Critical Power Demand Scheduling for Hospitals Using Repurposed EV Batteries

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Received: 1 December 2020 / Accepted: 30 September 2021 / Published online: 11 October 2021
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Abstract
Without a doubt, the healthcare sector is one of the most vulnerable sectors of electricity outages. A microgrid system to be installed in hospitals, if well planned, may offer a continuous and low electricity cost solution for health-care. By constructing an Energy Management System (EMS) specific to the hospitals, this study aims to present the significance of using an energy storage system and an optimum schedule for power utilization to prevent the lethal consequences arising from cut-offs and power quality issues. EMS is a linear (LP) scheduling model including PV panels and re-purposed EV batteries, and its target is to meet the electricity demand of the hospital with the lowest cost for every hour. The proposed scheduling model was run for a 150-bed hospital in Istanbul, Turkey under 5 different scenarios for every hour based on the data of 2016. According to scenario results, it is possible to achieve a 9.4% and 13.4% reduction in electricity bills and the grid electricity usage, respectively.

Keywords Linear programming · Scheduling · Energy management system · Energy storage · Reuse of eV batteries · Microgrid

Introduction
A microgrid is a group of localized energy sources and energy distribution systems in which the load works synchronously with the main grid, and also operates autonomously in “island mode” independent of the main grid if physical and economic conditions are met. In the framework of grid-connected or off-grid distributed energy utilization, microgrid systems using renewable energies are emerging to meet the energy demand for the last decade. However, because of the uncertainties of Renewable Energy Sources (RES), such as the amount of wind speed and solar irradiance, and the limits of electricity transmission and distribution systems, electricity grids have been facing some difficulties [56].

To solve these issues, Energy Storage Systems (ESS) has become prominent with the ability to balance supply and demand. Microgrids with ESS are utilized in a wide array of implementations, including campuses, public buildings, residential and commercial buildings, etc. Although there are many different types of microgrids, the technologies used in microgrids, the main factors in the setup, and the benefits they provide vary depending on the purpose of the setup. For instance, while the purpose of establishing public microgrids is the management of power outages, integration of RES and combined heat and power (CHP) systems to the grid, topics such as power quality, reliability, and energy efficiency come to the fore in industrial applications [10].

Energy security and quality problems, as well as the imbalance of supply and demand, may cause many lethal damages. Without a doubt, the healthcare sector is one of the most vulnerable sectors of electricity outages. Accordingly and naturally, the electricity infrastructures of hospitals and medical centers are supported by various backup systems such as generators and Uninterrupted Power Supply (UPS) units. Despite the existence of generator backup power systems, the start-up time of the best generator in the market is about 8 to 10 s which is insufficient for the healthcare sector [46]. The critical effect of a power outage that will last up to 10 s on hospital units is investigated and it is reported that the most fragile departments to power outage are operating theaters, resuscitation units, and intensive care units, whereas, the least affected ones are administrative units and corridors [24].

Many unfortunate events indicate how essential electricity supply is for healthcare services. 21 patients died in the
and falling prices, the cost of batteries constitutes 35–50% of the entire cost of the vehicle [26]. However, these batteries lose about 20% of their beginning capacity within 8 years as seen from Fig. 1. After 8 years, their usage in EVs is terminated, whereas, they maintain approximately 80% of their beginning capacities [1]. The re-use of these batteries taken from EVs as stationary batteries may benefit both economically and environmentally.

Repurposed lithium-ion EV batteries, when used as stationary batteries, provide many advantages, including voltage support, frequency regulation, power continuity and quality [44]. The feasibility studies of re-using old EV-batteries as stationary batteries have been increasing in recent years. For instance, Toyota and Yellowstone National Park started to utilize the batteries used in Toyota Hybrid vehicles in the guard watch stations and training buildings in the national park. In a similar application, General Motors (GM) has integrated the repurposed EV batteries from Chevrolet Volt vehicles into the IT buildings that GM has opened for new use [33].

The contribution of this paper is three-fold:

- First of all, in similar studies conducted for hospitals, scheduling and sizing analyses were carried out only by looking at the demand, which emphasizes profit maximization or cost minimization (see, for example, Pradhan et al. [42]), yet neglected the critical loads. However, the critical loads of the hospitals must be taken into account as constraints. This paper exactly addresses this issue by scheduling the specialty wards of hospitals (intensive care units, resuscitation units, operating rooms) to ensure uninterrupted and regulated electricity, especially during the era of pandemics.
- Second, to the best of our knowledge, the use of repurposed EV batteries in hospitals as a storage system is also not previously studied.
- Finally, adding the calculations of the release of CO₂ gas from grid electricity and the social cost of CO₂ on an hourly basis strengthens the contribution of the study.

In this study, it is aimed to present the significance of the ESS for the healthcare sector to prevent the lethal consequences arising from electricity cut-offs and power quality issues. While doing this, it is also intended to construct an Energy Management System (EMS) specific to the hospital. EMS is a scheduling model including PV panels and repurposed EV batteries, and its target is to meet the electricity demand of the hospital with the lowest cost for every hour, where carbon emissions are kept under the European standards. This paper is organized as follows. An overview of microgrid optimization studies depending on different storage and resource types is given in the second section. The third section will be saved for reviewing the method, establishing the model, and explaining the data and assumptions. The
results of the different scenarios will be presented in section 4. Finally, the conclusion and recommendations will be given in section 5.

**Literature Review**

The number of studies for DERs and microgrid systems is gradually increasing in the literature. These studies can be grouped under three different types of problems, namely, investment, design, and scheduling. Within the scope of investment problems, capacity optimization of renewable energy resources and/or energy storage systems is mentioned. In the studies under the title of design problems, it is aimed to decide on the most optimal design parameters for both energy resources and storage systems and their integration into the system. In scheduling problems, two things: (i) in which time interval the storage systems and/or energy resources will be activated and deactivated, and (ii) if it is possible to buy/sell from/to the grid, when to buy/sell are decided.

In the literature, many studies have been carried out for microgrid optimization with ESS systems and renewable energy resources. Different methods were used in these optimization studies, however; in this study, especially studies using linear programming methods are included.

Using linear programming (LP) method, Nottrott et al. [38] implemented a scheduling model to dispatch electricity supply and demand for a grid-connected microgrid system which consists of PV panels and a battery storage system. They calculated that the energy cost management system can be only financially feasible in case the lithium-ion battery costs are about $400–$500/kWh. For an off-grid microgrid including both conventional and photovoltaic energy resources, Torres et al. [51] designed a linear programming model to optimize the scheduling problem. The model combined the optimal scheduling of energy generation and battery charging/discharging to meet the demand with the maximum profit.

In a similar study, Wu et al. [57] aimed to minimize the electricity cost by applying a linear programming method to a grid-connected microgrid which consists of solar panels and battery storage units. They revealed that optimized energy management systems may provide considerable cost savings. With a similar method, Hanna et al. [20] presented an energy discharge chart covering the periods of July 2012–November 2012 to reduce peak energy demand levels by using RES and ESS. In light of this data; they compared the results obtained with and without using an energy storage system in a grid-connected microgrid.

Mixed-integer linear programming (MILP) method is also a very widely used method in scheduling problems. For instance, Tenfen and Finardi [49] proposed a MILP scheduling model to minimize operation costs of a microgrid involving micro-turbines, wind turbines, solar panels as well as batteries and fuel cells as ESS. The result showed that the scheduling model is very suitable for microgrid energy management. In another study, Gruber and Prodanovic [19] presented an energy scheduling management model to minimize energy costs. They applied the scheduling model into a hotel microgrid which includes two diesel generators, PV panels, and battery storage unit. The simulation results manifested 19.5% and 25.6% reduction in total energy costs for two different scenarios. To increase the local consumption of renewable energy, Sabillon et al. [45] introduced a dynamic scheduling model for optimum operation of solar panel units and EVs in an unbalanced residential electrical distribution grid using energy storage systems.

Unlike the previous studies, Talent and Du [48] developed a new MILP for optimal solar panel-battery sizing and energy...
scheduling. It was optimized under the Time of Use (ToU) and demand schedule structures, separated from other formulations. The optimization model was based on the highest net present value (NPV) of the system. A residential and a commercial customer were analyzed as case studies in optimization under these tariff structures. It was determined that the optimum solar panel-battery dimensioning is not affected by the tariff structure, and the most suitable solutions in both tariffs suggest that larger solar panel systems are preferred in the combination with small battery systems. Using the same method, Tu et al. [52] aimed to minimize the general levelized electricity cost for a microgrid including solar panels, wind turbines, diesel generators, and ESS. The outputs of the model are to determine both the optimum system sizing and scheduling for each system component with demand management control in case of power loss and load shifting. More recently, Faraji et al. [14] exhibited an EMS to find an optimal solution for the operation costs of prosumers using Discrete Nonlinear Programming (DNLP). This study showed that the operation cost of Li-ion batteries would be higher than Lead-acid batteries.

Distinct from the scheduling problems, there are also investing and design studies for microgrids in the literature. In this context, Ferrer-Martí et al. [15] propose a MILP model to optimize the location of the wind turbines and PV panels while minimizing the initial investment cost of the microgrid. The model shows a significant cost reduction in a real case study in Peru. Instead of scheduling models, Omu et al. [39] combine design parameters with the investment problem in their study. They develop a MILP model to facilitate the design of a solar hot water system. The purpose of the model is to optimize the area of the roof-mounted flat plate solar thermal collectors and the required thermal energy storage volume, the capital of the total energy system and the annual operating cost. In another study, Mashayekh et al. [35] presented an optimization model that determines the optimal technology portfolio, optimal technology placement, and the related optimal task distribution in a microgrid with different types of energy sources. The developed model uses a multinode modeling approach (as opposed to a unified single-node approach) that includes electrical power flow and heat flow equations. Therefore, optimum positioning capability is offered considering the physical and operational constraints of the electrical grid and heating/cooling systems. Förstl et al. [17] aimed to analyze the profitability and lifecycle of a residential PV system with battery ESS based on the different tariff regimes in Australia and Germany. This study showed that the site conditions, such as geography and energy-economic conditions, have very significant impacts on the system configuration and lifetime of the battery system.

In Table 1, there is a summary of some examples of microgrids with energy storage unit optimization studies. In the problem type section; I, D, S indicates investment, design, and scheduling, respectively. In the storage unit part; B, T, O stands for battery, thermal energy storage, and other storage types, respectively. In the energy source part; W, SP, G and O are abbreviations for wind, solar, grid, and other energy sources, respectively.

Methodology, Model and Data

Methodology

To schedule the integrated system structure, it is proposed to use a linear programming (LP) model. In this context, LP is one of the most widely used methods of deterministic approaches.

LP is a mathematical method shown in the form of linear relationships, used to determine the best result or solution from a particular parameter set or list of requirements. It is the most commonly used method in computer modeling or simulation to find the best solution to allocate finite resources such as money, energy, manpower, machine resources, time, space and many other variables. Decision variables vary as continuous ones and the binary or integer ones. Linear decision variables indicate the amounts to be determined by the model, whereas the integer variables indicate if a source is used or decision is considered based on certain conditions. The constraints show the capacity limits, resource limits, demand or supply limits.

Model and Problem Definition

Microgrids with ESS are regarded as very useful solutions to eliminate the very well-known dilemmas such as energy security, quality and supply. However, energy planning has become very complicated due to uncertainties in microgrids with integrated renewable energy sources. Therefore, for better planning and solutions, a model that will facilitate decision making in planning is necessary. This model can work as an EMS in hourly energy load, state of energy storage system and network usage.

The main purpose of this model is to provide uninterruptible electricity to the hospital all the time. In addition to the main purpose, an EMS based on the LP scheduling model is presented to meet the electricity demand of the hospital microgrid system, which consists of solar panels, grid electricity and repurposed lithium-ion batteries taken from EVs, with the lowest cost. The structure of the hospital microgrid system is shown in Fig. 2.

As aforementioned, operating theaters, resuscitation units, and intensive care units are the most sensitive hospital departments to power outages. Thus, they constitute the critical electricity loads of the scheduling model in this study.
Decision Variables

With the decision variables shown in Table 2, the energy flow is assigned to a specific target from a source. At time “t”, it is predetermined where to direct the electricity that is either received from the grid and/or generated by the solar panels. Similarly, and simultaneously, filling or discharging the battery system will be decided.

Table 1 Summary of some microgrid optimization studies

| Reference                        | Method     | Problem Type | Storage Unit Type | Source of Energy |
|----------------------------------|------------|--------------|-------------------|------------------|
| Ferrer-Marti et al. [15]         | MILP       | X            | X                 | X                |
| Nottrott et al. [38]             | LP         | X            | X                 | X                |
| Torres et al. [51]               | LP         | X            | X                 | X                |
| Pousinho et al. [41]             | MILP       | X            | X                 | X                |
| Hanna et al. [20]                | LP         | X            | X                 | X                |
| Gruber and Predanovic [19]       | MILP       | X            | X                 | X                |
| Wu et al. [57]                   | LP         | X            | X                 | X                |
| Tenfen and Finardi [49]          | MILP       | X            | X                 | X                |
| Brahman et al. [4]               | MILP       | X            | X                 | X                |
| Ho et al. [21]                   | MILP       | X            | X                 | X                |
| Omu et al. [39]                  | MILP       | X            | X                 | X                |
| Awad et al. [3]                  | LP         | X            | X                 | X                |
| Mashayehk et al. [35]            | MILP       | X            | X                 | X                |
| Zheng et al. [59]                | LP         | X            | X                 | X                |
| Sabillon et al. [45]             | MILP       | X            | X                 | X                |
| Talent and Du [48]               | MILP       | X            | X                 | X                |
| Lesko et al. [30]                | MILP       | X            | X                 | X                |
| Cheng et al. [7]                 | MILP       | X            | X                 | X                |
| Luo et al. [31]                  | Robust MILP| X            | X                 | X                |
| Cardoso et al. [5]               | MILP       | X            | X                 | X                |
| Wang et al. [55]                 | IMMOP      | X            | X                 | X                |
| Kumar and Saravanand [28]        | LP         | X            | X                 | X                |
| Tu et al. [52]                   | MILP       | X            | X                 | X                |
| Förstl et al. [17]               | MILP       | X            | X                 | X                |
| Fescioglu-Unver et al. [16]      | MILP       | X            | X                 | X                |
| Dorahaki et al. [9]              | MINLP      | X            | X                 | X                |
| Pimm et al. [40]                 | LP         | X            | X                 | X                |
| Faraji et al. [14]               | DNLP       | X            | X                 | X                |
| Wang et al. [54]                 | MILP       | X            | X                 | X                |

Fig. 2 The structure of micro grid system
Table 2 Decision variables and their explanations

| Decision Variable | Description |
|-------------------|-------------|
| $E_{GD,t}$        | Electricity taken from the grid to meet demand at time $t$ |
| $E_{GB,t}$        | Electricity taken from the grid to charge battery at time $t$ |
| $E_{PVD,t}$       | Electricity taken from the PV system to meet demand at time $t$ |
| $E_{PVBD,t}$      | Electricity taken from the PV system to charge battery at time $t$ |
| $E_{DCH,t}$       | Electricity drawn from the battery to meet demand at time $t$ |

Objective Function

The objective function tried to be minimized is given in Eq. 1 and Eq. 2. Cost items in the objective function (Eq. 1) are the cost of electricity generation from solar panels ($M_{PV}$), the depreciation, and maintenance cost of the battery system ($M_B$) and the costs of the energy purchased from the grid ($M_{pur}$).

$$\text{Min} Z = \sum_{t=0}^{T} \{ M_{PV,t} + M_B,t + M_{pur,t} \}$$

The expanded version of the objective function is shown in Eq. 2 based on the equations given in Section 3.2.4.

$$\text{Min} Z = \sum_{t=0}^{T} \left\{ \alpha \text{DoD}_t \left[ \eta_b \left( E_{PVBD,t} + E_{GB,t} \right) + \frac{E_{DCH,t}}{\eta_{dis}} \right] C_{\text{maintenance}} + C_{PV} \left( E_{PVD,t} + E_{PVBD,t} \right) + \left( P_{pur} + C_{\text{carb}} \right) \left( E_{GB,t} + E_{GD,t} \right) \right\}$$

Constraints

The objective function given in Eq. 2 minimizes the cost subject to the following constraints. As mentioned before, the main purpose of this model is to provide uninterruptible electricity to the hospital. Therefore, in virtue of demand constraint formulated in Eq. 3, it is ensured that the hospital is never de-energized. In Eq. 4 and Eq. 5, battery capacity and discharge constraints are given. The critical load constraint specific to a hospital is shown in Eq. 6. With this constraint, the critical electricity loads are supported by the battery unit in case of a power outage. This constraint provides an uninterruptible electricity for the critical loads of the hospital. In Eq. 7, electricity taken from solar panels is limited by the PV panels capacity. In Eq. 8, battery charge constraint is given depending on the grid electricity price criteria (Eq. 9). With this constraint, it is aimed to charge the batteries fully when the grid electricity price is below a specific value.

Demand constraint : $E_{PVD,t} + E_{GD,t} + E_{DCH,t} = D_t$, $\forall t$ (3)

Battery capacity constraint : $SoC_t \leq B_{c}$, $\forall t$ (4)

Battery discharge constraint : $E_{DCH,t} \leq \left[ SoC_t - B_{s} \right] \eta_{dis}$, $\forall t$ (5)

Critical load constraint : $SoC_t \geq D_{crit,t}$, $\forall t$ (6)

Equations

To perform the scheduling model, balancing constraints are used in the background. Some features of the lithium-ion batteries used in the energy storage system have been added to the equations in the model. The used capacity of the battery system at time $t$ varies. In addition to the energy entering and leaving the battery, the self-discharge rate of the battery should also be considered. In Eq. 10, the State of Charge ($SoC_t$) variable that shows the energy level in the ESS at the time $t$ is given. In Eq. 11, the Depth of Discharge (DoD) is given. Eq. 12 gives the cost of wear on the battery depending on this discharge depth, whereas Eq. 13 gives the maintenance and operating cost depending on the total charge / discharge cycle amount.

$$SoC_t = \left[ SoC_{t-1} + E_{CH,t} - E_{DCH,t} \eta_{dis} \right] (1 - k_{loss}) \quad \forall t$$

$$\text{DoD}_t = \frac{E_{DCH,t}}{B_{c} \eta_{dis}} \quad \forall t$$

$$f_{dep,t} = \frac{\text{DoD}_t \eta_{carb}}{N} \quad \forall t$$

$$f_{maint,t} = \left[ E_{CH,t} \eta_{ch} + E_{DCH,t} \eta_{dis} \right] C_{\text{maintenance}} \quad \forall t$$
from solar panels and grid are shown in Eq. 15 and 16, respectively. Moreover, total battery charge amount at time $t$ is calculated as in Eq. 17.

$$D_{crit,t} = D_{cur,t} + D_{res,t} + D_{cum,t}, \forall t$$  \hspace{1cm} (14)

$$E_{PV,t} = E_{PVD,t} + E_{PVB,t}, \forall t$$  \hspace{1cm} (15)

$$E_{G,t} = E_{GD,t} + E_{GB,t}, \forall t$$  \hspace{1cm} (16)

$$E_{CH,t} = E_{PVB,t} + E_{GB,t}, \forall t$$  \hspace{1cm} (17)

The available electricity production from PV panels is calculated based on the European Commissions’ Photovoltaic Geographical Information System [13]. The peak output power of PV panels is decided as 250 kWp and the efficiency of the solar panel system involving efficiencies of inverters, cables and charge controllers are taken as 86%. Furthermore, levelized cost of electricity from PV panels is assumed as $0.024/kWh [53].

Levelized cost consists of investment expenditures, operation and maintenance expenditures and fuel expenditures and it is calculated as

$$LCOE = \frac{\sum_{t=1}^{n} (I_t + O_t + F_t)}{(1 + r)^t}$$

where $I_t$, $O_t$, $F_t$, and $E_t$ stand for investment expenditures, operation and maintenance expenditures, fuel expenditures, and electricity generation in year $t$, respectively. Furthermore, $r$ is the discount rate, while $n$ is lifetime of the system.

Different from other studies, in this study, lithium-ion batteries with reduced efficiency from EVs are used as stationary energy storage units because of the reasons mentioned in prior sections. The characteristics of this storage unit are shown in Table 3. The capacity, charge/discharge rate and number of cycle amounts are their available values considering the battery aging. It means that the battery with 125 kWh initial capacity (20% capacity fade) is utilized in this micro grid system.

To calculate the yearly electricity consumption of the hospital, Gonzalez et al. [18] gives based on the number of beds (NB) as

$$EC = 33.548NB - 2633.6$$

According to Eq. 21, the yearly electricity consumption of the selected hospital is found as 2398.6 MWh. From this point forth, the monthly electricity consumption coefficients are determined based on the study of Hu et al. [22]. The hourly electricity consumption is calculated by multiplying these

### Table 3 The characteristics of the battery unit

| Characteristic       | Value |
|----------------------|-------|
| Capacity (kWh)       | 100   |
| Hourly self-discharge rate (%) | 0.2   |
| Charge/discharge rate (%) | 90    |
| Number of life cycle | 4000  |
| Maintenance cost ($/kWh) | 4000  |
| Capital cost ($/kWh) | 0.001 |
|                         | 50    |
coefficients with hourly consumption coefficients specific to the hospitals and the time-series of hourly consumption is shown in Fig. 3. Hourly consumption coefficients are gathered from EPIAS [12]. The price of electricity purchased from the grid is also obtained from the hourly Market Clearing Price (MCP) data published by EPIAS. However, the distribution fee in electricity received from the grid is not taken into account.

According to the International Energy Agency, 33.62%, 32.5% and 0.7% of electricity generation in Turkey are provided in 2016 from coal, natural gas, and oil, respectively [23]. Considering Eq. 20, gas emission amounts depending on the resource type are shown in Table 4 [25].

The monetary value of the ton CO2-eq amount obtained as a result of each scenario will be handled in two different ways, namely, social cost and carbon tax. For Turkey, the social cost of carbon emission is given as 4.46 $/ton CO\textsubscript{2} regarding the SSP3/RCP8.5 scenario [43]. In addition to the social cost of carbon emission, the carbon tax savings as a result of the optimization model will be examined. However, in Turkey, the carbon market is not established yet. To calculate the price equivalent of the carbon saved by the model, the carbon tax price is taken as 15 $/ton CO\textsubscript{2}-eq regarding the Medium Tax Scenario of Report of the High-Level Commission on Carbon Prices [47].

Results and Discussions

The schedule model given in the previous section was run in 5 different scenarios for every hour of the year (8760 h) in the Excel Solver program based on the same hospital data. Below, the scenarios in which the model is run are given with their descriptions and the results obtained. Scenarios are designed considering the best use of the storage system and hence, the scheduling base, the charging price and the number of charging changes.

Scenario 1

In this scenario, it is considered that the critical loads of $D_{\text{res},t}$ and $D_{\text{icu},t}$ are active for every hour, and the critical load of $D_{\text{sur},t}$ is active during only office hours, both on weekdays and weekends. The battery system has been restricted to energize critical loads for at least one hour. The battery system will be charged completely, when MCP is below 0.03 $/kWh ($P\text{_{criteria}} = 0.03$).

As a result of the scheduling model running for 8760 h, the battery system had to discharge 2580 times while a total of $10,665.46 was saved. In Fig. 4, the saving/loss status of this scheduling model is shown for every hour. 321,411 kWh less grid electricity was used in this scenario and as a result, 144.15 tons of CO2-eq direct emission reduction was achieved.

Scenario 2

Now, the distribution of critical loads and the battery charge constraint remain the same as in the previous scenario.

![Fig. 3 The hourly electricity demand of the hospital](image-url)
However, in case the battery charge price is below 0.025 $/kWh, the number of savings and discharges were examined ($P_{\text{criteria}} = 0.025$).

It was observed that almost the same amount of profit was achieved as the previous scenario with a saving of $10,755.01. However, in this scenario, the number of battery discharges dropped to 2095. The low battery discharge amount allows the batteries in the system to cycle less and thus wear less. In Fig. 5, the saving/loss status of this scheduling model is shown for every hour. As a result of this scenario, 322,348.6 kWh less energy was drawn from the grid and a total of 144.6 tons of CO2-eq direct emission reduction was achieved.

**Scenario 3**

The critical load distribution and battery constraint in Scenario 3 are the same as in previous scenarios. The battery charge price was set at 0.02 $/kWh in this scenario and the model was run for 8760 h ($P_{\text{criteria}} = 0.02$). Hourly data is shown in Fig. 6. As a result of the schedule, $10,809.13 savings were achieved with 1651 discharges. Besides, a total of 322,259.93 kWh less grid electricity was used in this scenario, resulting in a direct reduction of 144.98 tons of CO2-eq.

**Scenario 4**

Unlike previous scenarios, a more realistic situation is emphasized in this scenario. Provided that the battery charge limit remains the same, the scheduling of the batteries in which $D_{\text{res},t}$ and $D_{\text{ICU},t}$, which are the critical loads, are active for every hour, and the critical load of the $D_{\text{emr},t}$ is active only during office hours on weekdays and Saturdays. The model was run for 8760 h, considering that there was no surgery on Sundays in many hospitals, but the intensive care and resuscitation units are available 24/7. As in Scenario 3, it is ensured that the batteries are filled most efficiently by making the battery filling in MCP (Market Clearing Price) below 0.02 $/kWh. In Fig. 7, the hourly saving/loss graph is given for this scenario.

In Fig. 7, the hourly saving/loss situation graph is given for this scenario. In this scenario, a total of $10,817.87 was saved with 1485 battery discharge. According to this scenario, while 323,506 kWh less grid electricity is used, 145.09 tons of CO2-eq direct emission reduction has been made.

**Scenario 5**

In the last scenario, in addition to the previous scenario, a schedule was made for the batteries to provide critical loads for at least 2 h of uninterrupted energy. In this scenario, due to the stricter storage constraint, a relatively low $10,596.53 was saved as a result of 1763 discharge.

While 323,389 kWh less grid electricity is used, 145.04 tons of CO2-eeq direct emission reduction has been made with this scheduling model.

**Output Analysis and Discussion**

To analyze the performance of the established scheduling model, the year 2016 is selected because of the nationwide electricity outage that occurred in Turkey on December 23,
2016. As seen from Figs. 4, 5, 6, 7 and 8, despite the electricity outage on December 23, 2016, and the increasing electricity prices, the hospital was not de-energized during this period thanks to the ESS. This is a striking indicator of the importance of the energy storage system not only for hospitals but also for many public institutions, services, and industrial facilities.

The number of discharges, saving amounts, and emission savings of each scenario are given in Table 5. It will be reasonable to use the model obtained in the 4th scenario of the hospitals with the highest savings target, and the hospitals that demand more electricity supply security to use the model in the 5th scenario.

To see the differences between the scenarios better, all results are normalized based on the 4th scenario and shown in Table 6.

Regarding the 4th scenario, it is possible to save approximately $13,500 (carbon tax and social cost savings included) per year for the selected hospital. With this system installed in the hospital, an annual decrease of 9.4% was achieved in the electricity bill. Furthermore, a more than 13% reduction in grid electricity usage is implemented during this period.

With the Energy Efficiency Obligation Schemes (EEOSs), which is planned to be implemented for Turkey in the near future and has been a binding agreement in the European Union as of 4 December 2012 in 13 countries, it is to achieve savings by reducing energy sales. As a matter of fact, with EEOSs, a 1.5% reduction is aimed at the energy distribution stage in the EU. At this point, the result of this study, if EEOS is applied in our country one day, it responds better-than-aimed with the saving rate it provides.
None of the above scenarios reckon the value of reutilizing the used EV batteries as these scenarios are solely based on the minimization of private cost functions. Minimizing the negative externality of the used-EV batteries, which were presumably be thrown away otherwise, could be achieved simply by reutilizing them. Providing a longer economic life for the used batteries hence, will benefit the social welfare simply by internalizing them within the circle, in particular, socially in a more sensitive field like the health services. Figure 9 briefly pictures how the society could benefit from this circulation.

The model presented in this study is totally under the control of the consumer. The hospital uses the optimization model for dispatching the load that responds to the demand by optimizing the operating costs under the capacity constraints and environmental concerns. The optimization model decides the energy use from the Grid, Solar Panels or the Storage system without allowing any Grid-caused Black Outs. The proposed LP model makes the system more resilient by using constraints that limit the capacity of power resources. The Grid is activated automatically when electricity demand surpasses the capacity of the panels and/or the battery state is insufficient to provide the required power. The fact that “batteries can only be utilized when they are over the 20% efficiency level” guarantees that the model gives no option for a power cut.

### Summary and Conclusion

This study was conducted to demonstrate the importance of securing electricity supply, which is vital for hospitals, with

| Scenario: | Number of Discharge | Saving amount ($) | Emission saving (ton CO₂-eq) | Carbon Tax saving ($) | Social Cost saving ($) |
|-----------|---------------------|-------------------|-----------------------------|----------------------|------------------------|
| 1         | 2580                | 10,665.46         | 144.15                      | 2162.25              | 642.91                 |
| 2         | 2095                | 10,755.01         | 144.57                      | 2168.55              | 644.78                 |
| 3         | 1651                | 10,809.13         | 144.98                      | 2174.70              | 646.61                 |
| 4         | 1485                | 10,817.87         | 145.09                      | 2176.35              | 647.10                 |
| 5         | 1763                | 10,596.53         | 145.04                      | 2175.60              | 646.88                 |

| Scenario: | Saving amount ($) | Emission saving (ton CO₂-eq) | Carbon Tax saving ($) | Social Cost saving ($) |
|-----------|-------------------|-----------------------------|----------------------|------------------------|
| 1         | 6138.84           | 82.97006                    | 1244.551             | 370.047                |
| 2         | 7623.48           | 102.4756                   | 1537.134             | 457.0398               |
| 3         | 9722.325          | 130.403                    | 1956.045             | 581.5965               |
| 4         | 10,817.87         | 145.09                     | 2176.35              | 647.1                  |
| 5         | 8925.608          | 122.1693                   | 1832.539             | 544.8762               |

Fig. 9 Life cycle of eV battery in case of reuse
energy storage systems. Because nothing is more important than human life.

An Energy Management System based on the LP scheduling model is established to meet the electricity demand of the hospital microgrid system, which consists of solar panels, grid electricity and repurposed lithium-ion batteries taken from EVs, with the lowest cost. The energy storage system integrated into the system was provided to feed critical electrical loads in the hospital continuously, thus preventing electricity outages that would risk human life. Also, electricity was saved by coordinating solar panels and battery systems. The proposed scheduling model was run for a 150-bed hospital under 5 different scenarios for every hour based on the data of 2016. According to scenario results, it is possible to achieve a 9.4% and 13.4% reduction in electricity bills and the grid electricity usage, respectively. Moreover, as a result of the re-evaluation of the lithium-ion batteries from the EVs, which constitute the main structure of the system proposed in this study, the economy of Turkey gains an important saving item. Recycling the batteries, which completed their first life cycle in EVs, while capable of using 80% capacities, would be a great loss for the country’s economy. Considering the high exchange rates costs caused by the supply of batteries from abroad as well as high recycling costs, it will be beneficial for the economy to serve the batteries as fixed batteries for many years.

Human life is invaluable. With this system, many people’s lives are protected against electrical problems that may occur in hospitals, while both economic and environmental benefits can be created. This paper is original in considering the critical loads of hospitals to secure human life. To the best of our knowledge the power cut-off in critical units were not prevented by using the repurposed EV batteries. Furthermore, the study has the ecological concern shown by the calculation of social cost of CO$_2$ on an hourly basis.

In the future, it will be possible to recalculate the costs and savings once the carbon markets are set in Turkey. This study is open to development by designing a model that integrates carbon markets and taxes and/or developing the model to include the uncertainties in operation of the system.

Acknowledgements The authors would like to thank anonymous reviewers and editor for their very helpful and strong suggestions.

Funding Not applicable.

Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Conflicts of Interest/Competing Interests The authors declare that they have no known competing for financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Code Availability The code that support the findings of this study are available from the corresponding author upon reasonable request.

Nomenclature

- $E_{PV,t}$: Total electricity production from PV panels at time $t$
- $E_{PVB,t}$: Electricity taken from the PV system to charge the battery at time $t$
- $D_{PV}$: Area of PV Panels
- $E_{PVD,t}$: Electricity taken from the PV system to meet demand at time $t$
- $B_{C}$: Battery capacity
- $f_{dep,t}$: Depreciation cost of battery at time $t$
- $B_{s}$: Battery safety limit
- $f_{m}$: Maintenance cost of battery at time $t$
- $b_{n}$: Binary parameter to charge battery fully
- $k_{loss}$: Battery self-discharge rate
- $C_{cap}$: Capital cost of battery
- $P_{grid}$: Electricity capacity of solar panels depending on $r_{t}$ at time $t$
- $C_{maintenance}$: Maintenance cost of battery
- $M_{B,t}$: Total cost of battery usage at time $t$
- $C_{GB,t}$: Cost of electricity production from PV panels ($/kWh$)
- $P_{grid}$: Cost of grid electricity at time $t$
- $C_{carb,t}$: Social cost of carbon emissions released from grid electricity generation ($/kWh$)
- $C_{PV}$: Cost of electricity production from PV panels at time $t$
- $D_{crit,t}$: Total Critical load at time $t$
- $N$: Number of battery cycle
- $D_{dis,t}$: Electricity demand for Surgery rooms at time $t$
- $E_{CH,t}$: Total charge amount at time $t$
- $P_{pur,t}$: Grid electricity price at time $t$
- $E_{G,t}$: Total electricity taken from grid at time $t$
- $r_{t}$: Solar irradiance at time $t$
- $E_{GD,t}$: Electricity demand for resuscitation units at time $t$
- $E_{CH,t}$: Total charge amount at time $t$
- $P_{rand}$: Grid electricity demand for Surgery rooms at time $t$
- $E_{PVB,t}$: Electricity taken from the PV system to charge the battery at time $t$
- $D_{res,t}$: Electricity demand for intensive care units at time $t$
- $E_{ch,dis}$: Discharge efficiency of battery
- $D_{c,OL}$: Electricity demand for resuscitation units at time $t$
- $E_{ch,DIS}$: Efficiency of the PV system
- $DeD_{c}$: Depth of Discharge at time $t$
- $E_{ch,DIS}$: MCP criteria to charge battery fully based on scenario
- $E_{ch,G}$: Total charge amount at time $t$
- $E_{PVD,t}$: Grid electricity price at time $t$
- $E_{DCH,t}$: Electricity drawn from the battery to meet demand at time $t$
- $SoC_{t}$: State of Charge at time $t$
- $E_{OL}$: Electricity taken from the grid to charge battery at time $t$
- $y$: How much of the battery depreciation is associated with controlled wear cost
- $E_{C2D,t}$: Electricity taken from the grid to meet demand at time $t$

References

1. Ahmadi L, Fowler M, Young SB, Fraser RA, Gaffney B, Walker SB (2014) Energy efficiency of Li-ion battery packs re-used in stationary power applications. Sustain Energy Technol Assess 8: 9–17. https://doi.org/10.1016/j.seta.2014.06.006
2. Arabi YM, Murthy S, Webh S (2020) COVID-19: a novel coronavirus and a novel challenge for critical care. Intensive Care Med 46: 833–836. https://doi.org/10.1007/s00134-020-05955-1
3. Awad A, Bazan P, German R (2016) Optimized operation of PV/T and Micro-CHP hybrid power systems. Technol Econ Smart Grids Sustain Energy 1:2. https://doi.org/10.1007/s40866-016-0004-3
4. Brahman F, Honarmand M, Jadid S (2015) Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system. Energy Build 90:65–75. https://doi.org/10.1016/j.enbuild.2014.12.039
5. Cardoso G, Brouhard T, DeForest N, Wang D, Heleno M, Kotzur L, Christe S, (2018) Battery aging in multi-energy microgrid design using mixed integer linear programming. Appl Energy 231:1059–1069. https://doi.org/10.1016/j.apenergy.2018.09.185
6. Chauhan A, Saini RP (2014) A review on integrated renewable energy system based power generation for stand-alone applications: configurations, storage options, sizing methodologies and control. Renew Sust Energ Rev 38:99–120. https://doi.org/10.1016/j.rser.2014.05.079
7. Cheng C, Su C, Wang P, Shen J, Lu J, Wu X (2018) An MILP-based model for short-term peak shaving operation of pumped-storage hydropower plants serving multiple power grids. Energy 163:722–733. https://doi.org/10.1016/j.energy.2018.08.077
8. Cristiansen N, Kalschmiet M, Dzukowski F (2016) Electrical energy consumption and utilization time analysis of hospital departments and large scale medical equipment. Energy Buildings 131: 172–183. https://doi.org/10.1016/j.enbuild.2016.09.023
9. Dorahaki S, Dash R, Shaker HR (2020) Optimal energy management in the smart microgrid considering the electrical energy storage system and the demand-side energy efficiency program. J Energy Storage 28:101229. https://doi.org/10.1016/j.est.2020.101229

10. Driesen J, Katiiraie F (2008) Design for distributed energy resources. IEEE Power Energy Magazine 6(3):30–40. https://doi.org/10.1109/MPE.2008.918703

11. ECDC-European Centre for Disease Prevention and Control (2020) COVID-19: Situation update worldwide. https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases. Accessed 01 December 2020

12. EPIAS (2016) Transparency Platform: Profile coefficients. https://seffatlik.epias.com.tr/transparency/tuketim/profil-katsayilari/caran-degeri.xhtml

13. European Commission (2016) Photovoltaic Geographical Information System. https://re.jrc.ec.europa.eu/pvg_tools/en/tools.html#MR.

14. Faraji J, Ketabi A, Hashemi-Dezaki H (2020) Optimization of the scheduling and operation of prosumers considering the loss of life costs of battery storage system. J Energy Storage 31:101565

15. Ferrer-Martí L, Domenech B, Garcia-Villoria A, Pastor R (2013) A MILP model to design hybrid wind-photovoltaic isolated rural electrification projects in developing countries. Eur J Oper Res 226(2):293–300. https://doi.org/10.1016/j.ejor.2012.11.018

16. Fescioglu-Unver N, Barlas A, Yilmaz D, Demli UO, Bulgan AC, Karagol EC et al (2019) Resource management optimization for a smart microgrid. J Renew Sustain Energy 11(6):065501

17. Fürst M, Azzatallah D, Chapman A, Verbic G, Jossen A, Hesse H (2019) Assessment of residential battery storage systems and operation strategies considering battery ageing. Int J Energy Res 44(2):718–731. https://doi.org/10.1002/er.4770

18. Gonzalez AG, Garcia-Sanz-Calcedo J, Salgado DR (2018) Evaluation of energy consumption in German hospitals: benchmarking in the public sector. Energies 11(9):1–14. https://doi.org/10.3390/en11092279

19. Gruber JK, Prodanovic M (2014) Two-stage optimization for building energy management. In: Smart energy control Systems for Sustainable Buildings. Springer, Cham, pp 225–243. https://doi.org/10.1007/978-3-319-52076-6_10

20. Hanna R, Kleissl J, Nottrott A, Ferry M (2014) Energy dispatch schedule optimization for demand charge reduction using a photovoltaic-battery storage system with solar forecasting. Solar Energy 103:269–287. https://doi.org/10.1016/j.solener.2014.02.020

21. Ho WS, Macchietto S, Lim JS, Hashim H, Muis ZA, Liu WH (2016) Optimal scheduling of energy storage for renewable energy distributed energy generation system. Renew Sust Energ Rev 58:1100–1107. https://doi.org/10.1016/j.rser.2015.12.097

22. Hu SC, Chen JD, Chuach YK (2004) Energy cost and Consumption in a large acute hospital. Int J Arch Sci 5(1):11–19

23. IEA - International Energy Agency (2018) World Energy Balances 2018. https://doi.org/10.1787/25186442

24. Imal N, Kale MC (2013) Kesintisizlik Analizi Île Hastaneler Icin Elektrik Enerjisi Kalitesiyle iliskilene [improvement of electrical energy quality for hospitals by continuous analysis]. Chambers of electrical engineering III. Electrical fitting National Congress and exhibition, Izmir: November 21-24

25. IPCC - Intergovernmental Panel on Climate Change (2014) Annex IE: Metrics & Methodology. In: climate change 2014: mitigation of climate change. Contribution of working group III to the fifth assessment report of the intergovernmental panel on climate change. Cambridge: Cambridge University Press, 2014

26. Kampker A, Deutschens C, Nee C (2013) Produktion von Elektrofahrzeugen. Elektromobilität: Grundlagen einer Zukunftstechnologie 46

27. Kimutai G (2018) fatal hitch: three die after power outage at hospital. Standard digital. www.standardmedia.co.ke/article/2001282254/three-die-after-power-outage-at-hospital accessed 8 November 2020

28. Kumar KP, Saravanan B (2019) Day ahead scheduling of generation and storage in a microgrid considering demand side management. J Energy Storage 21:78–86. https://doi.org/10.1016/j.est.2018.11.010

29. Lai CC, Shih TP, Ko WC, Tang HJ, Hsueh PR (2020) Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and coronavirus disease-2019 (COVID-19): the epidemic and the challenges. Int J Antimicrob Agents 55(3):105924. https://doi.org/10.1016/j.ijantimicag.2020.105924

30. Lesko M, Bujalski W, Futyma K (2018) Operational optimization in district heating systems with the use of thermal energy storage. Energy 165:902–915. https://doi.org/10.1016/j.energy.2018.09.141

31. Luo Z, Gu W, Wu Z, Wang Z, Tang Y (2018) A robust optimization method for energy management of CCHP microgrid. J Modern Power Syst Clean Energy 6(1):132–144. https://doi.org/10.1007/s40565-017-0290-3

32. Madhusudhanakar K (2017) 20 die during 12-hr power cut at Kurnool Hospital in Andhra Pradesh. The new Indian express. https://www.newindianexpress.com/states/andhra-pradesh/2017/jun/23/20-die-during-12-hr-power-cut-at-kurnool-hospital-in-andhra-pradesh-1619975%2D2D1.html accessed 19 September 2020

33. Madsloer R, Kirmas A (2017) Economic viability of second use electric vehicle batteries for energy storage in residential applications. Energy Procedia 105:3806–3815. https://doi.org/10.1016/j.egypro.2017.03.890

34. Manikandan M (2019) After power failure, 3 patients on ventilator die at Madurai hospital. Hinduist times. https://www.hinduistimes.com/india-news/after-power-failure-3-patients-on-ventilator-die-at-madurai-hospital/story-G1u6W3yjRm6nPS17rQaARN.html accessed 21 September 2020

35. Mashayekh S, Stadler M, Cardoso G, Heleno M (2017) A mixed integer linear programming approach for optimal DER portfolio, sizing, and placement in multi-energy microgrids. Appl Energy 187:154–168. https://doi.org/10.1016/j.apenergy.2016.11.020

36. Morgenstern P, Li M, Raslan R, Ruyssevelt P, Wright A (2016) Benchmarking acute hospitals: composite electricity targets based on departmental consumption intensities? Energy Buildings 118:277–290. https://doi.org/10.1016/j.enbuild.2016.02.052

37. Ministry of Health (2002) Regulation of private hospitals (24708). http://www.mevzuatgovtr/MetinAspx?MetinKod=754854&Mevzuatliski=0&source=XmlSearch=%C3%B6zel%20hastane Accessed 28 September 2020

38. Nottrott A, Kleissl J, Washom B (2013) Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems. Renew Energy 55:230–240. https://doi.org/10.1016/j.renene.2012.12.036

39. Omu A, Hsieh S, Orehoungi K (2016) Mixed integer linear programming for the design of solar thermal energy systems with short-term storage. Appl Energy 180:313–326. https://doi.org/10.1016/j.apenergy.2016.07.055

40. Pimm AJ, Palczewski J, Morris R, Cockrell TT, Taylor PG (2020) Community energy storage: a case study in the UK using a linear programming method. Energy Convers Manag 205:112388. https://doi.org/10.1016/j.enconman.2019.112388

41. Poussinol HMI, Silva H, Mendes VMF, Pereira M, Cabrita CP (2014) Self-scheduling for energy and spinning reserve of wind/CSP plants by a MILP approach. Energy 78:524–534. https://doi.org/10.1016/j.energy.2014.10.039

42. Pradhan AK, Kar SK, Mohanty MK (2016) Off-grid renewable hybrid power generation system for a public health centre in rural
43. Ricke K, Drouet L, Caldeira K, Tavoni M (2018) Country-level social cost of carbon. Nat Clim Change 8:895–900. https://doi.org/10.1038/s41558-018-0282-y
44. Rohit AK, Rangnekar S (2017) An overview of energy storage and its importance in Indian renewable energy sector: part II – energy storage applications, benefits and market potential. J Energy Storage 13:447–456. https://doi.org/10.1016/j.est.2017.07.012
45. Sabillon C, Franco JF, Rider MJ, Romero R (2018) Joint optimal operation of photovoltaic units and electric vehicles in residential networks with storage systems: a dynamic scheduling method. Electr Power Energy Syst 103:136–145. https://doi.org/10.1016/j.ijepes.2018.05.015
46. Sechilariu M, Locment F, Sechilariu M, Locment F (2016) Backup power resources for microgrid. In: urban DC microgrid: intelligent control and power flow. Elsevier science optimization, pp 93-132
47. Stiglitz JE, Stern N, Duan M, Edenhofer O, Giraud G, Heal GM, ... Shukla PR (2017) Report of the high-level commission on carbon prices. https://doi.org/10.7916/d8-w2nc-4103
48. Talent O, Du H (2018) Optimal sizing and energy scheduling of photovoltaic-battery systems under different tariff structures. Renew Energy 129:513–526. https://doi.org/10.1016/j.renene.2018.06.016
49. Tenfen D, Finardi EC (2015) A mixed integer linear programming model for the energy management problem of microgrids. Electr Power Syst Res 122:19–28. https://doi.org/10.1016/j.epsr.2014.12.019
50. The Times of India (2016) 21 die in Hyderabad govt hospital, staff blame power cut https://timesofindiatimescom/india/21-die-in-Hyderabad-govt-hospital-staff-blame-power-cut/articleshow/53359874.cms Accessed 26 September 2020
51. Torres D, Crichigno J, Padilla G, Rivera R (2014) Scheduling coupled photovoltaic, battery and conventional energy sources to maximize profit using linear programming. Renew Energy 72:284–290. https://doi.org/10.1016/j.renene.2014.07.006
52. Tu T, Rajanatham GP, Vassallo AM (2019) Optimization of a stand-alone photovoltaic-wind-diesel-battery system with multi-layered demand scheduling. Renew Energy 131:333–347. https://doi.org/10.1016/j.renene.2018.07.029
53. Ufluglu EE, Kayakutlu G (2016) Mathematical model for a microgrid consisting of wind turbine, PV panels, and energy storage unit. J Renew Sustainable Energy 8(5):1–14. https://doi.org/10.1016/j.1464309
54. Wang J, Liu J, Li C, Zhou Y, Wu J (2020) Optimal scheduling of gas and electricity consumption in a smart home with a hybrid gas boiler and electric heating system. Energy 204:117951. https://doi.org/10.1016/j.energy.2020.117951
55. Wang L, Li Q, Zhang B, Ding R, Sun M (2019) Robust multi-objective optimization for energy production scheduling in microgrids. Eng Optim 51(2):332–351. https://doi.org/10.1080/0305215X.2018.1457655
56. Weitzel T, Glock HC (2018) Energy management for stationary electric energy storage systems: A systematic literature review. Eur J Oper Res 264(2):582–606. https://doi.org/10.1016/j.ejor.2017.06.052
57. Wu Z, Tazvinga H, Xia X (2015) Demand side management of photovoltaic battery hybrid system. Appl Energy 148:294–304. https://doi.org/10.1016/j.apenergy.2015.03.109
58. Young K, Wang C, Strunz K (2013) Electric vehicle battery technologies. In: Electric vehicle integration into modern power networks. Springer, New York, pp 15–56. https://doi.org/10.1007/978-1-4614-0134-6_2
59. Zheng Y, Jenkins BM, Kornbluth K, Træholt C (2018) Optimization under uncertainty of a biomass-integrated renewable energy microgrid with energy storage. Renew Energy 123:204–217. https://doi.org/10.1016/j.renene.2018.01.120

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