Critical Power Demand Scheduling for Hospitals Using Repurposed EV Batteries

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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

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Gandhi Hospital in India, with a capacity of 1200 beds, due to the electricity outage in 2016. Most of these deaths happened in specialty wards such as respiratory intensive care units and surgical intensive care units [50]. In another example, 20 patients, including 8 children, lost their lives because of the 12-h electricity outage in Kurnool Hospital in 2017 [32]. As a result of a 7-h power outage in Longisa, Kenya, 3 patients died in Longisa County Hospital. One of the patients was on a life support machine in the Intensive Care Unit [27]. In another example in India, 3 patients connected to a ventilator in the intensive care unit (ICU) died after an electricity outage due to the heavy rain accompanied by thunderstorms [34]. There are many more records about the negative situations caused by electricity outage in hospitals.

More recently, in December 2019, the third coronavirus outbreak in the last 20 years has appeared as a pandemic, so-called *SARS-CoV-2*. This novel coronavirus causes a disease labeled as *COVID-19* (nCoV). With the COVID-19 pandemic, the respiratory intensive care units grow in importance in hospitals. More than 25% of patients with nCoV require ICU admission and approximately 90% of these patients need to receive mechanical ventilation [2, 29]. The increasing number of COVID-19 cases (More than 62 million as of December, 1st 2020) imposes a burden for the hospitals' electricity infrastructure [11]. In the case of an electricity outage in hospitals throughout this pandemic period, it may cause many COVID-19 patients in ICU to die. In order to avoid such events, the critical units in hospitals need to have continuous and regulated access to electricity.

A microgrid system with integrated RES and ESS to be installed in hospitals, if well planned, may offer a continuous and low electricity cost solution for the hospitals. For the system to be installed to be both economically and technically feasible, a well-designed operation model is required. A well-designed operation model provides a stable cost-effective integrated energy infrastructure with high efficiency [6].

Setting up a scheduling model, which we aim to do here, may help mitigate such horrific events mentioned above. A not so much related sector may assist this solution by providing invaluable resources through its wastes. It is the Electric Vehicles (EVs)-era, which we are at the beginning of, and its used car batteries. In addition to the evolution in energy demand and supply, the automotive sector also is experiencing a revolutionary change in terms of the penetration of EVs into the market. Batteries used in electric vehicles are quite different from batteries used in mobile consumer electronics such as laptops and mobile phones. While these batteries provide high power up to 100 kW and high energy capacity of tens of kWh, it is also expected to meet volume, weight and reasonable price constraints [58]. In this context, the most widely used battery technologies in EVs are nickel-metal hydride and lithium-ion batteries. Despite their developing technologies 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

Fig. 1 Capacity fade ratio based on Ah-processed over battery lifetime

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 leveled 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-Marti 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 multi-node 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.

Table 1 Summary of some microgrid optimization studies

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

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.

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
$E_{PVB,t}$	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}).

$$\text{Min.} Z = \sum_{t=0}^T \{M_{PV,t} + M_{B,t} + M_{Pur,t}\} \quad (1)$$

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

$$\text{Min.} Z = \sum_{t=0}^T \left\{ \alpha DoD_t + \left[\eta_{ch} (E_{PVB,t} + E_{GB,t}) + \frac{E_{DCH,t}}{\eta_{dis}} \right] C_{maintenance} + C_{PV} (E_{PVD,t} + E_{PVB,t}) + (P_{pur,t} + C_{carb,t}) (E_{GB,t} + E_{GD,t}) \right\} \quad (2)$$

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.

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

$$\text{Battery capacity constraint : } SoC_t \leq B_c, \forall t \quad (4)$$

$$\text{Battery discharge constraint : } E_{DCH,t} \leq [SoC_t - B_s] \cdot \eta_{dis}, \forall t \quad (5)$$

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

$$\text{PV production constraint : } E_{PVD,t} + E_{PVB,t} \leq L_{PV,t} \quad (7)$$

Battery fully charged constraint

$$: b_t [\eta_{ch} E_{CH,t} + E_{DCH,t} / \eta_{dis}] (1 - k_{loss}) = B_c - SoC_t \quad (8)$$

$$\text{where } b_t = \begin{cases} 1, & P_{pur,t} < P_{criteria} \\ 0, & \text{Otherwise} \end{cases} \quad (9)$$

Non negativity constraint: All variables ≥ 0 , $\forall t$.

b_t is a binary parameter to decide whether battery should be charged fully or not at time t . In case of grid electricity price is below a certain value ($P_{criteria}$), b_t will be 1 and thus, EMS will charge the battery system fully. On the other hand, if grid electricity price is above the $P_{criteria}$, b_t will be zero and EMS will not charge the battery system.

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_t) 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.

$$SoC_t = [SoC_{t-1} + E_{CH,t} \cdot \eta_{ch} - E_{DCH,t} / \eta_{dis}] (1 - k_{loss}), \forall t \quad (10)$$

$$DoD_t = E_{DCH,t} / [B_c \cdot \eta_{dis}], \forall t \quad (11)$$

$$f_{dep,t} = [DoD_t \cdot \gamma \cdot C_{capital}] / N, \forall t \quad (12)$$

$$f_{mnt,t} = [E_{CH,t} \cdot \eta_{ch} + E_{DCH,t} / \eta_{dis}] C_{maintenance}, \forall t \quad (13)$$

The equation of the total critical electricity loads at time t is presented in Eq. 14. The equations of the total electricity taken

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.

$$D_{crit,t} = D_{sur,t} + D_{res,t} + D_{icu,t}, \forall t \quad (14)$$

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

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

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

M_{Pur} variable, which shows the cost of electricity purchased from the grid at time t , is shown in Eq. 19. The total battery cost M_B (Eq. 20) in the objective function consists of the sum of f_{dep} in Eq. 12 and f_{mnt} cost items in Eq. 13.

$$M_{PV,t} = E_{PV,t} \cdot C_{PV}, \forall t \quad (18)$$

$$M_{Pur,t} = E_{G,t} \cdot (P_{Pur,t} + C_{carb,t}), \forall t \quad (19)$$

$$M_{B,t} = f_{dep,t} + f_{mnt,t}, \forall t \quad (20)$$

$$C_{carb,t} = \frac{\sum_{i=1}^{13} P_{i,t} \cdot Carb_i}{\sum_{i=1}^{13} P_{i,t}}, \forall t \quad (21)$$

where $P_{i,t}$ is power output from i^{th} electricity resource at time t and $carb_i$ is the carbon emission coefficient (g CO₂-eq/kWh) of i^{th} resource. Hence, Eq. 21 shows the carbon emissions released by the use of grid electricity for time t .

Data and Assumptions

The data used in this study was collected from European energy standards, Turkish energy authorities, the Turkish Ministry of health and a particular hospital. In addition to the data, some assumptions are made to construct a more realistic model. The data and assumptions are explained in this section.

To apply this model to a hospital, a sample should be selected. A middle-size hospital that has 150 inpatient capacities, 4 resuscitation units, 7 operating theaters and an intensive care unit with 25 beds in Istanbul, Turkey is chosen. The size of these hospital units and operating theaters are decided according to the regulation of the Ministry of Health [37]. In this context, the area of an operating theater, an intensive care unit, and a resuscitation unit is decided as 45m², 12m², and 10m², respectively. Moreover, peak electricity demand of the intensive care unit, operating theater and resuscitation unit are taken as 28.9, 17 and 68.7 Wh/m² [36]. The critical load of these units is calculated by taking into consideration that the working hours of operating theaters are similar to the office hours (08.00–12.00/13.00–17.00) and the other critical loads are active all the time [8].

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

$$LCOE = \frac{\sum_{t=1}^n \frac{(I_t + O_t + F_t)}{(1+r)^t}}{\sum_{t=1}^n \frac{E_t}{(1+r)^t}} \quad (22)$$

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

$$EC = 33.548NB - 2633.6 \quad (21)$$

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)	0.001
Capital cost (\$/kWh)	50

Fig. 3 The hourly electricity demand of the hospital

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 CO₂ 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 CO₂-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 $D_{res,t}$ and $D_{icu,t}$ are active for every hour, and the critical load of $D_{sur,t}$ 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. In addition, the battery system will be charged completely, when MCP is below 0.03 \$/kWh ($P_{criteria} = 0.03$).

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.

Table 4 Gas emission amount depending on the resource

i	Resource	g CO ₂ -eq/kWh
1	Natural gas	370
2	Hydro with reservoir	10
3	Lignite	810
4	Hydro	10
5	Import coal	750
6	Wind	8
7	Solar	19
8	Oil	600
9	Geothermal	30
10	Asphaltite coal	750
11	Hard Coal	810
12	Biomass	40
13	Naphtha	500

Fig. 4 Saving/Loss status of Scenario 1

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 323,259.93 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 $D_{\text{sur},t}$ 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-eq 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,

Fig. 5 Saving/Loss status of Scenario 2

Fig. 6 Saving/Loss status of scenario 3

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.

Fig. 7 Saving/Loss status of Scenario 4

Fig. 8 Saving/Loss status of Scenario 5

Table 5 Summary of scenarios results

Scenario:	Number of Discharge	Saving amount (\$)	Emission saving (ton CO ₂ -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

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

Table 6 Normalized scenario results

Scenario:	Saving amount (\$)	Emission saving (ton CO ₂ -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 CO₂ 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.

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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 ; A_{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; $f_{mnt,t}$, Maintenance cost of battery at time t ; b_t , Binary parameter to charge battery fully; k_{loss} , Battery self-discharge rate; $C_{capital}$, Capital cost of battery; $L_{PV,t}$, Electrical 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_{PV} , Cost of electricity production from PV panels (\$/kWh); $M_{Pur,t}$, Cost of grid electricity at time t ; $C_{carb,t}$, Social cost of carbon emissions released from grid electricity generation ((\$/kWh); $M_{PV,t}$, Cost of electricity production from PV panels at time t ; $D_{crit,t}$, Total Critical load at time t ; N , Number of battery cycle; $D_{sur,t}$, Electricity demand for Surgery rooms at time t ; η_{ch} , Charge efficiency of battery; $D_{icu,t}$, Electricity demand for intensive care units at time t ; η_{dis} , Discharge efficiency of battery; $D_{res,t}$, Electricity demand for resuscitation units at time t ; η_{PV} , Efficiency of the PV system; DoD_t , Depth of Discharge at time t ; $P_{criteria}$, MCP criteria to charge battery fully based on scenario; $E_{CH,t}$, Total charge amount at time t ; $P_{pur,t}$, Grid electricity price at time t ; $E_{DCH,t}$, Electricity drawn from the battery to meet demand at time t ; r_t , Solar irradiance at time t ; $E_{G,t}$, Total electricity taken from grid at time t ; SoC_t , State of Charge at time t ; $E_{GB,t}$, Electricity taken from the grid to charge battery at time t ; γ , How much of the battery depreciation is associated with controlled wear cost; $E_{GD,t}$, Electricity taken from the grid to meet demand at time t

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