Optimal Operation of Battery Exchange Stations for Electric Vehicles

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Abstract

Due to environmental and energy security concerns, low emission vehicles present a vital necessity for clean transportation. In particular, electric vehicles (EVs) are the most promising solution due to the fact that the electrical power system is the most ready infrastructure to supply their requirement. Two possible energy delivery solutions to the EVs, namely the charging stations and the battery exchange stations (BESs) are the focus of research nowadays. In this paper, a new optimal operation approach is proposed for the BESs. The proposed new model determines the optimal charging, discharging, and exchange decisions for the battery stock throughout the day taking into consideration the customers' arrivals, the variations in the grid price, the grid connection limitations, and the self-degradation of the batteries. The objective of the proposed approach is to maximize the BES owner profit while satisfying the EV owners' requests. The BES operation optimization problem is formulated as mixed-integer programming (MIP) and is solved as a day-ahead scheme. The performance of the BES is compared to conventional EV charging stations, where the BES shows superior customer satisfaction and higher profit.

Keywords Battery Exchange Stations, Charging Stations, Electric Vehicles, Optimization, Smart Grid

1. Introduction

Global warming due to Green-House-Gas (GHG) emissions raised critical

https://doi.org/10.1016/j.epsr.2020.106935

environmental concerns in the last few decades. In addition, several concerns regarding the security of energy resources are raised due to the dependency of some essential sectors (e.g. transportation) on a single source of energy (e.g. fossil fuel) [1],[2]. To lower the GHG emissions and to increase energy security by diversifying the energy sources, electric vehicles (EVs) represent the most promising solution [3]. This is due to the availability of electric power systems' infrastructure almost everywhere and the electricity generation sector has well established and economically feasible low-emission energy resources such as solar panels and wind turbines. An EV is any vehicle with an electric motor as a source of propulsion. There are three main types of EVs classed by the degree that electricity is used as their energy source, the hybrid electric vehicles (HEV), the plug-in hybrid electric vehicles (PHEV) and the battery electric vehicles (BEV) [4]. HEV's source of energy is petrol or the electric energy generated by the braking system [5]. The PHEV, which is also known as extended-range EVs, is similar to the HEV; however, it can recharge the battery through both regenerative braking and plugging-in to an external electrical charging outlet. On the other hand, BEVs are pure EVs, meaning they are only powered by electricity and do not have a petrol engine, fuel tank, or exhaust pipes [6]. EVs are moving forward in the market and people are using these cars more and more. However, the percentage on roads is almost negligible and most people are still not comfortable with this technology [7]. This is due to many factors that make EVs users have a different life pattern compared to the normal fuel cars we use nowadays. Some of these factors that limit the widespread of EVs are the time required to charge the EVs' battery and the limitation of the available charging stations. Also, the energy consumed by the high penetration of EV may cause severe consequences on the electrical grid, such as thermal overloading, under-voltage, and fuse failure [8], [9]. Therefore, the charging technology and the charging stations should be managed carefully to decrease the negative impacts on the grid side, increase the users' satisfaction, the charging stations' owners' profit, and service quality.

Table 1 Comparison between charging stations and BESs [14]-[16]

	Charging Stations	Battery Exchange Stations
Advantages	• Lower capital investment. • Easy to install. • Have different sizes.	• Very fast service about 5 minutes. • Provide ancillary services to grid. • More reliable. • Low operational cost.
Disadvantages	• May have negative impact on the electric power system. • Very long service time.	• Two to three times more capital investment. • Needs complicated and expensive robots for swapping. • The measurement of the charging curve and charging capacity is required. • Ownership of batteries.

EV stations can be categorized into two types: charging stations and BES. The best EV conventional charging stations have fast chargers, which can charge the battery fully in as low as half an hour [10]. Battery exchange stations work in a different way where the service needs only few minutes by exchanging the battery with a previously charged one [11]. However, BES is still under research in its primitive stages and further intensive research is required to be practically feasible. The main difference between them is the service time which is very short for the BES. Table 1 shows the advantages and disadvantages of the charging station and the BES.

As described in the next section, most of the existing research lacks optimal operational model for the BES, which considers the charging, discharging of batteries, replacement of batteries, and operation of multiple batteries and customers' arrival over the day as well as the grid limit and demand charges and their impacts on the optimal decisions. The optimal operation of BES is related to optimal decisions about charging, discharging and replacement of batteries available on BES such that increasing the profit of BES and customer satisfaction. The main contributions of this work are summarized as follows:

- Propose a new operation approach for the BES to satisfy customers' requirements and minimize the operation costs.
- We investigate the integration of the operation of multiple batteries while being exchanged in BES, and the arrivals of different customers over the day, and the grid power limitation on the chargers into the proposed operation approach.

2. Literature review

The difference between the charging station and BES in terms of the cost and technical factors has been investigated in [12]. In addition, the load scheduling schemes for hybrid electric vehicle BESs in smart grid have been studied in [13]. In [14], the authors built a model that estimates the energy consumption of an EV based on the driving style of the user. Also, many other papers considered using a renewable source of energy with BESs. In [15] and [16], the authors focused on building a model to provide the foundation for the planning and design of Photovoltaic (PV) system as a source of energy in the BES by modeling an optimization tool for finding the annual profit and the power generated by the PV system. Furthermore, an optimization model for minimizing the cost of an off-grid connected wind power system along with the BES has been discussed in [17]. With a different approach, the authors in [18] analyzed the historical sensing data of taxi routes and evaluated the battery swapping demand profile and the power consumption of individual taxis to propose a method to calculate an optimized battery-swapping station scheme. Also, in [19], the aim was to minimize the total cost considering three factors: the number of batteries taken from the stock to serve all the swapping orders from incoming EVs, potential charging damage with the use of high-rate chargers and electricity cost for different periods of the day.

A new method is proposed in [20] to locate and size BES to maximize the present value. In [21], an optimization model was presented to maximize the total profit by considering both selling energy to the grid and buying energy from the grid to charge the batteries. The energy price and the battery demand uncertainties were considered in this model. In [22], the optimal scheduling for both batteries charging and discharging was obtained. However, it considered a combined operation between BES and conventional charging station and considered also logistics that facilitate this operation. The work in [23] implemented an approach to assign each customer to certain BES to minimize the path taken by the vehicle to the station and to minimize the generation cost. In [24], it considered the operation of both microgrid and BES. Further, the obtained model was used to minimize the microgrid cost and to minimize the BES cost considering the battery degradation cost, the replacement cost, and the charging cost. Moreover, it didn’t consider the battery characteristics, the different arrival times of the customers, the number of batteries dedicated to serving the customers in the BES, and the state of charge (SOC) of each battery at each instant. In [25], decentralized demand-side management was proposed to force the residential load to follow a predetermined energy profile. The game theory was used in two stages. The first stage allowed the customers to make the day ahead predicted demand. In the second stage, the renewable energies, energy storage and charging/discharging of electric vehicles were availed to mitigate the deviation between the predicted and actual demand. The authors in [26] introduced optimal allocation of BES to minimize the implementation cost of BES, the travel time of EVs and the waiting time of EVs at BES. They divided the area into candidate regions and introduced the effect of varying both the number of regions and the number of BES on the objective function. The authors in [27] presented a model that only determined the number of battery to be charged or discharged according to the grid price and didn't consider the operation of BES, for example, the battery should be replaced, the customers’ arrival and the effect of charging/discharging on SOC of batteries and hence on the decision of replacement.

Based on the previous discussion and the limited work in this area, it is obvious that the research in the field of BES is still in its early stages. All the previous work didn’t consider the optimal operation of BES. The work in [21] presented the most relevant operational model for BES. The authors considered the charging, discharging and replacement of batteries. However, they didn't consider the customers’ arrival, swapping time, possibility that the number of customers throughout the day may be higher than the number of batteries, the demand charge and the grid limit. They only considered the swapping process as energy demand required to be supplied.

Accordingly, this research proposes to develop an operational approach for smart BES to maximize the total revenue for the investor. The proposed models and approaches will include consideration of the charging and discharging cycles of the battery pack, the operation of multiple batteries while being exchanged in BES, the arrivals of different customers over the day, and the grid technical constraints. In addition, the approach will consider the self-degradation factor of the batteries and the grid power limitation on the chargers. The necessity of proposing a new operation approach for the BES is the need for a day head plan to decide charging, discharging, and replacing the batteries in stock of BES. The aim of the approach should focus on serving as many customers as possible and on the maximizing revenue of the BES owner. However, the grid limit and demand charges should be considered in this model due to their impact on the optimal decisions obtained from the optimization problem.

3. Problem and solution descriptions

In this section, the structure of the BES and the proposed operation approach are described. All possible technical and economic aspects are discussed along with the proposed approach.

3.1. BES System Structure

The design of the BES is similar in some aspects to the available gas stations. For example, a typical BES may have n exchanging units so that a maximum of n cars can exchange their batteries at the same time and the rest will be waiting in the queue as shown in Fig. 1. The exchange can be done manually or automatically. The system structure shown in Fig. 2 consists of five main parts: the grid-side unit, the battery-side unit, the EVs/customers, the optimization unit, and the control unit. The grid-side unit is a bidirectional AC/DC converter to be used to maintain a fixed DC link voltage at the point of the common coupling (PCC) and the desired power factor at the grid side. The battery-side unit is a DC/DC converter that follows the battery characteristics for charging/discharging. These converters work in charging mode or discharging mode depending on the reference signal from the control unit.

The charging and discharging cycles are dependent on the limitation of the power system, grid price, and the customers' arrivals. The third unit receives the coming EVs to exchange the EV battery with the assigned battery to meet the station requirements trying to serve all incoming customers. The assigned battery must be disconnected from the battery-side unit before being exchanged with the depleted battery in the EV. The optimization unit is responsible for developing the optimal decisions based on the inputs assigned from the control unit. Finally, the control unit gets the data from the other three units and takes decisions about the charging, discharging, and exchanging decisions [13].

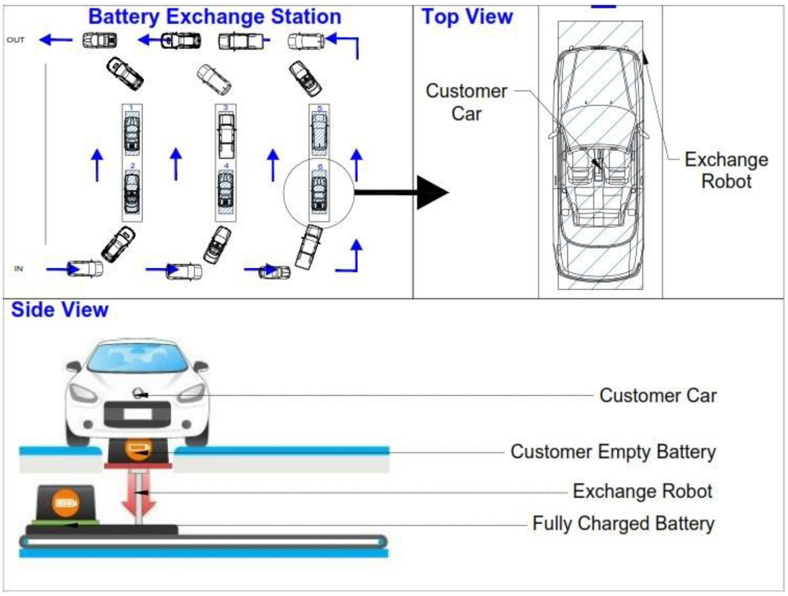

Fig. 1. *BES schematic diagram.*

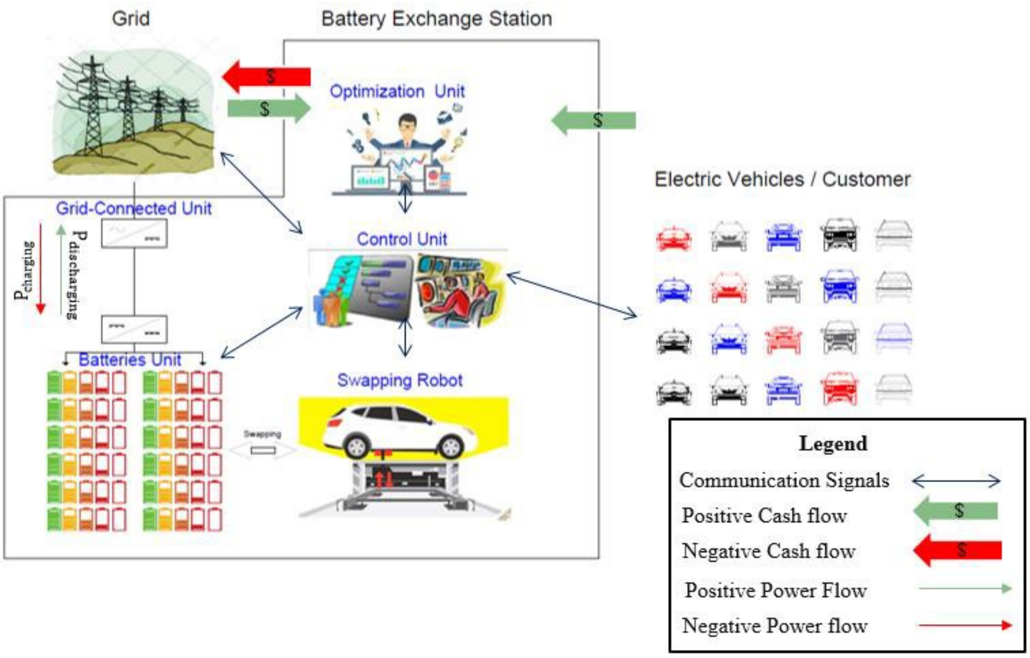

Fig. 2. *BES system structure.*

3.2. BES Operation

For the BES operation stage, all the assets are assumed to be available. Therefore, the inputs to the operation approach include economic aspects such as

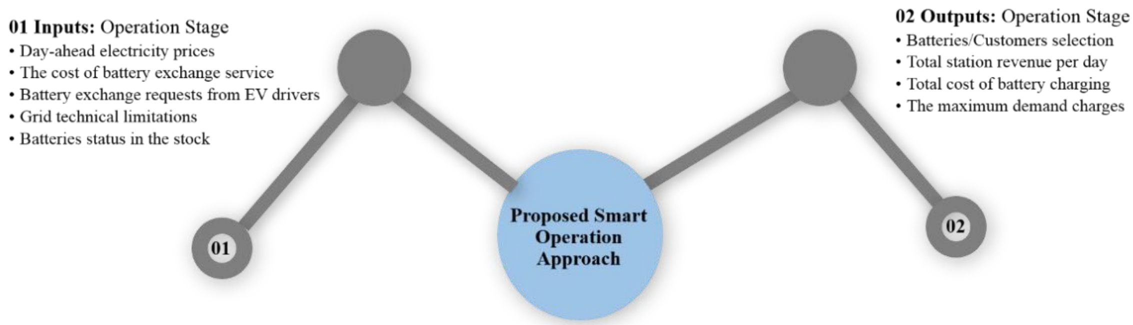

Fig. 3. *Proposed BES operation approach.*

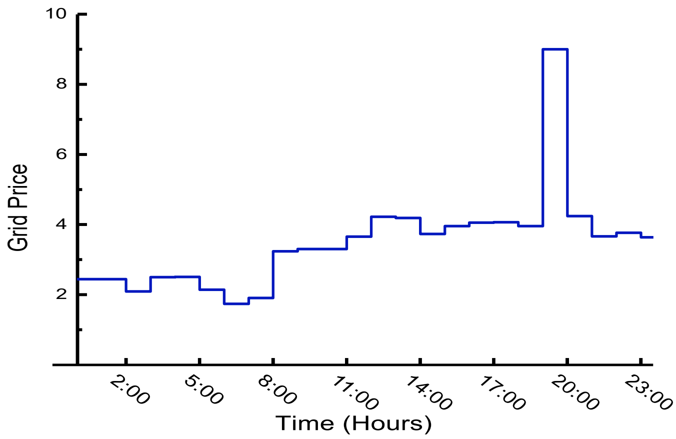

Fig. 4. *Grid price per hour for one day.*

the day-ahead electricity prices and the cost of battery exchange service. Also, the inputs include technical aspects such as the battery exchange requests from EV drivers, batteries status in the stock, and the grid technical limitations. All the inputs and outputs of the proposed smart operation approach are shown in Fig. 3.

One of the input parameters to the proposed approach is the grid energy price. The battery exchange station is considered as an industrial customer to the grid. Thus, the industrial tariff should be adopted as an input to the smart operation. As an example, an industrial customer in Ontario, Canada, would pay the real-time energy price [14] in Fig. 4, in addition to, the charges shown in Table 2.

Also, the EV arrivals schedule and their required energy should be known day-ahead. Furthermore, the status of the batteries that are being charged and replaced in the station should be tracked to serve the customers accordingly. For example, consider a battery with 35% State of Charge (SOC) is being replaced with a fully charged one. If the battery needs an hour to be fully recharged again, then this battery should be eliminated from the active service during that hour. However, the

Table 2 Monthly Charges for industrial customers [15]

Description	Amount
Hourly market price	Varies hourly as given in Fig.4.
Global adjustment (¢/kWh)	3.00
Wholesale market service (¢/kWh)	0.05
Transmission charges ($/kW)	5.10
Distribution charges ($/kW)	4.00

Table 3 EV battery specifications

Type: Laminated lithium-ion battery			
Parameter	Symbol	Value	Unit
Maximum Depth of Discharge	MDOD	80	%
Maximum Power	Pmax	10	kW
Maximum Energy	Emax	50	kWh
Efficiency	η	80	%
Initial State of Charge	SOCo	Varies	%

system will include this battery in the service for the customers coming in the next few hours.

At the end of the day, the outputs of the proposed smart operation approach will include the total cost of charging the batteries using the grid and the revenue of replacing and selling the energy to the customers. In addition, a full analysis of the customers that have been served with the corresponding battery that was used will be reached to help in future analysis and design. For instance, if the customer/battery selection during this day reached to a conclusion that one customer cannot be served for any reason, such as the customers' queue was long, or unavailability of a charged battery when the customer arrived, a study will be conducted on it to prevent this problem in the next day analysis. In this case, different solutions may appear. For example, the battery/customer selection may be done differently to optimize the outputs or the number of batteries in the station may be increased to serve more customers. An example of the battery parameters is shown in Table 3.

3.3. Proposed Approach Description

The inputs to the proposed smart operation approach are the technical and economical parameters mentioned before. The decisions that need to be taken are charging, discharging, or replacing the battery. When a customer arrives, the third decision, which is exchanging a battery, will be valid. But, the decision of serving that customer or not depends on the availability of the required charged battery, the customer can be served by a battery with SOC in the range of 90 % to 100 % depending on the availability. By this, the approach should assign the batteries to the customers depending on their known daily arrivals in order to maximize the number of customers being served during the day as well as the operational profit. Furthermore, the maximum energy extracted from the grid is controlled in order not to exceed a specific limit. This limit is known from historical data for the station. The time segment is adjusted to be Δt minutes, so the scheduling period is N_t time segments through a day, i.e. $t \in \mathbb{T} = \{1,2, \dots , N_t\}$, where t and $\mathbb{T}$ are the index and the set of time segments respectively. The index and set of the batteries in the station are b and B respectively. Finally, the index and the set of the customers coming to the station are c and C respectively. It is assumed that the number of batteries in the BES remains unchanged, where a battery b can experience a sudden drop in energy when being exchanges with another depleted battery from an EV.

4. Problem formulation

In this section, the proposed problem formulation for optimal BES operation as a mixed integer programming (MIP) is explained in detail. The approach is used to optimize the charging, discharging, state of charge, and the energy replacement for each battery in the station depending on a specific customers' arrival and the grid price. In addition, a test on the effect of different factors such as grid power limitation and battery self-degradation is discussed. Moreover, the conventional charging station formulation is included to be compared with the BES.

4.1. Objective Function

The objective of the proposed operation approach is maximizing the net profit of the BES, z, in \$. It's formulated as shown in (1) – (7). The decision variables are the charging, discharging, and battery exchange decisions. The revenue, R, is for the sold energy by the battery replacement as in (2). The included costs in the BES are the demand charges, C^{kW}, and the charging/discharging costs, C^{kWh}. C^{kW} is determined based on the maximum demand consumed from the grid. The demand charges are paid monthly; thus, to include the impact of the daily operation on the demand charges, we use the targeted or historical peak demand of the BES, $P^{MAX}_{Historical}$, in kW. As shown in (3), the peak demand charged are only considered for the maximum consumption that exceeded $P^{MAX}_{Historica}$ Note, that (3) involves Non-differentiable function; thus, it is replaced by (4). In (4), the maximum excess demand, defined by $P^{ExMax} - P^{MAX}_{Historical}$, above $P^{MAX}_{Historical}$ is defined. This term is zero if the maximum consumption is below $P^{MAX}_{Historical}$ and is the difference if the maximum consumption is above $P^{MAX}_{Historica}$. Thus, P^{ExMax} should be the higher of the maximum consumption or $P^{MAX}_{Historical}$ as in (5) and (6).

For the energy charges, it is assumed that the energy purchased or sold to the grid has the same price as in (7).

$$\underset{P^{Charging}_{(t,b)},P^{Discharging}_{(t,b)},x_{(b,c)}}{\text{maximize}} \quad z = R - (C^{kW} + C^{kWh}) \tag{1}$$

Subject to:

$$R = \sum_{t\in\mathbb{T}} \sum_{b\in\mathbb{B}} \sum_{c\in\mathbb{C}} E^{rep}_{(t,b,c)} \times p^{grid-Rep} \tag{2}$$

$$C^{kW} = p^{grid-kW} \times max\ (0, (\max_t (\sum_{b\in\mathbb{B}} \frac{P^{Charging}_{(t,b)}}{\eta}) - P^{MAX}_{Historical})) \tag{3}$$

$$C^{kW} = p^{grid-kW}(P^{ExMax} - P^{MAX}_{Historical}) \tag{4}$$

$$P^{ExMax} \geq P^{MAX}_{Historical} \quad \forall t \in \mathbb{T}\ \&\ b \in \mathbb{B} \tag{5}$$

$$P^{ExMax} \geq \sum_{b\in\mathbb{B}} \frac{P^{Charging}_{(t,b)}}{\eta} \forall t \in \mathbb{T}\ \&\ b \in \mathbb{B} \tag{6}$$

$$C^{kWh} = \sum_{t\in\mathbb{T}} \sum_{b\in\mathbb{B}} p^{grid-kWh}_{(t)} (\Delta t) (\frac{P^{Charging}_{(t,b)}}{\eta} - P^{Discharging}_{(t,b)} \times \eta) \tag{7}$$

where, $p^{grid-Rep}$ is replacement energy price (\$/kWh), $p^{grid-kW}$ is demand power from grid price (\$/kW), $p^{grid-kWh}_{t}$ is charging/discharging energy price (\$/kWh), $P^{MAX}_{Historica}$ is the maximum historical demand consumed from the grid (kW). $P^{Charging}_{(t,b)}$, $P^{Discharging}_{(t,b)}$ are the charging and discharging powers (kW) from the grid for each battery b at time t. $E^{rep}_{(t,b,c)}$ is the energy drop due to replacing the battery which is a positive variable. In addition to the above constraints, there are other constraints related to battery charging/discharging constraints, battery exchange constraints, grid limit constraint, and battery self-degradation constrains which will be discussed in the following sections.

4.2. Battery Charging/Discharging Constraints

In (8), the stored energy in a battery b at end of time slot t, $E^{stored}_{(t,b)}$, is calculated as the sum of three terms: 1) the previously stored energy at $t-1$, 2) the added energy by charging the batteries or the subtracted energy by discharging the batteries from the grid, and 3) the energy drop due to replacing the battery, $E^{rep}_{(t,b,c)}$, with a customer battery. The energy stored at the end of the first time slot $E^{stored}_{(t=1,b)}$ is related to the initial energy as in (9). The state of charge, $SOC_{(t,b)}$, for each battery is related to the stored energy and the maximum battery capacity E^{max} as in (10). The charging and discharging powers are limited by the maximum charger power, P^{max}, as formulated in (11) – (12). Also, the state of charge is limited by the maximum depth of discharge, $MDOD$, for each battery as shown in (13).

$$E^{stored}_{(t,b)} = E^{stored}_{(t-1,b)} + \Delta t(P^{Charging}_{(t,b)} - P^{Discharging}_{(t,b)}) - \sum_{c\in\mathbb{C}} E^{rep}_{(t,b,c)} \quad \forall t \in \{2,3,\dots,N_t\} \;\&\; b \in \mathbb{B} \;\&\; c \in \mathbb{C} \tag{8}$$

$$E^{stored}_{(t=1,b)} = E^{stored-int} + (\Delta t)(P^{Charging}_{(t=1,b)} - P^{Discharging}_{(t=1,b)}) \quad \forall\, b \in \mathbb{B} \tag{9}$$

$$SOC_{(t,b)} = E^{stored}_{(t,b)} \times \frac{100\ \%}{E^{max}} \forall t \in \mathbb{T} \;\&\; b \in \mathbb{B} \tag{10}$$

$$P^{Charging}_{(t,b)} \leq P^{max} \forall t \in \mathbb{T} \;\&\; b \in \mathbb{B} \tag{11}$$

$$P^{Discharging}_{(t,b)} \leq P^{max} \forall t \in \mathbb{T} \;\&\; b \in \mathbb{B} \tag{12}$$

$$100\ \%(1 - MDOD) \leq SOC_{(t,b)} \leq 100\ \% \;\forall t \in \mathbb{T} \;\&\; b \in \mathbb{B} \tag{13}$$

4.3. Battery Exchange Constraints

The replaced energy is limited by the maximum energy capacity of the battery as mentioned in (14) as the replaced energy must be less than the available capacities of the batteries. The decision of serving the customer or not depends on the customers' arrival pattern, $ar_{(t,c)}$, and the availability of the batteries. $ar_{(t,c)}$ is generated based on the customer requests and it has a value of 1 if customer c is arriving at time t and 0 otherwise. This decision is controlled by the binary variable $x_{(b,c)}$, where $x_{(b,c)}$ of one indicates serving customer c by battery b as illustrated in (16). In (15), three cases may occur:

- Case 1 of no customer request, i.e. $ar_{(t,c)} = 0$, will enforce $E^{rep}_{(t,b,c)} = 0$.
- Case 2 of customer request but service is denied, i.e. $ar_{(t,c)} = 1$ and $x_{(b,c)} = 0$, will enforce $E^{rep}_{(t,b,c)} = 0$.
- Case 3 of customer request and service is granted, i.e. $ar_{(t,c)} = 1$ and $x_{(b,c)} = 1$, will enforce $E^{rep}_{(t,b,c)} = E^{stored}_{(t-1,b)} - E^{arrival}_{(t,c)}$.

Thus, for case 3, if $E^{rep}_{(t,b,c)} = E^{stored}_{(t-1,b)} - E^{arrival}_{(t,c)}$ is substituted in (8), it will lead to $E^{stored}_{(t,b}$ being the same as the arrival battery stored energy, which implies that the batteries have been exchanged. In (17), it is assumed that the customer will be served by only one battery. As in (18) and (19), which represent modified constraints to replace (11) and (12), the charging and discharging cycles cannot happen at the same time with the replacement. Also, the customer satisfaction factor, γ, which reflects the minimum SOC of a battery in stock to be acceptable for exchange, is included in (20) as the stored energy must be at least equal to the desired energy by the customer for the replacement to occur (case 3).

$$E^{rep}_{(t,b,c)} \leq E^{max} \ \forall t \in \mathbb{T} \ \& \ b \in \mathbb{B} \ \& \ c \in \mathbb{C} \tag{14}$$

$$E^{rep}_{(t,b,c)} = ar_{(t,c)}\, x_{(b,c)} (E^{stored}_{(t-1,b)} - E^{arrival}_{(t,c)}) \quad \forall t \in \mathbb{T} \ \& \ b \in \mathbb{B} \ \& \ c \in \mathbb{C} \tag{15}$$

$$x_{(b,c)} \in \{0,1\} \tag{16}$$

$$\sum_{b \in \mathbb{B}} x_{(b,c)} \leq 1 \tag{17}$$

$$P^{Charging}_{(t,b)} \leq P^{max} (1 - ar_{(t,c)}\, x_{(b,c)}) \quad \forall t \in \mathbb{T} \ \& \ b \in \mathbb{B} \ \& \ c \in \mathbb{C} \tag{18}$$

$$P^{Discharging}_{(t,b)} \leq P^{max}\,(1 - ar_{(t,c)}\, x_{(b,c)})$$
$$\forall t \in \mathbb{T}\ \&\ b \in \mathbb{B}\ \&\ c \in \mathbb{C} \tag{19}$$

$$E^{stored}_{(t,b)} \geq \gamma\, E^{max}\,(\sum_{c\in\mathbb{C}} ar_{(t,c)}\, x_{(b,c)})$$
$$\forall t \in \mathbb{T}\ \&\ b \in \mathbb{B}\ \&\ c \in \mathbb{C} \tag{20}$$

The nonlinear equation (15) can be converted to the following three linear constraints in order to make the model MIP rather than mixed integer nonlinear programming (MINLP):

$$E^{rep}_{(t,b,c)} \leq ar_{(t,c)}\,(E^{stored}_{(t-1,b)} - E^{arrival}_{(t,c)}) \tag{21}$$

$$E^{rep}_{(t,b,c)} \geq ar_{(t,c)}\,(E^{stored}_{(t-1,b)} - E^{arrival}_{(t,c)}) - E^{max} * (1 - x_{(b,c)}) \tag{22}$$

$$E^{rep}_{(t,b,c)} \leq E^{max} * x_{(b,c)} \tag{23}$$

If $x_{(b,c)} = 1$, so $E^{rep}_{(t,b,c)}$ will be equal $[ar_{(t,c)}\,(E^{stored}_{(t-1,b)} - E^{arrival}_{(t,c)})]$ from constraints (22) and (23). While constraint (24) is utilized to make $E^{rep}_{(t,b,c)} = 0$ if $x_{(b,c)} = 0$ as $E^{rep}_{(t,b,c)}$ is a positive variable.

4.4. Grid Connection Limit constraint

The charging power supplied from the grid at any time t shouldn't exceed the grid connection $P^{grid-max}$, as indicated in (24):

$$\sum_{b\in\mathbb{B}} P^{Charging}_{(t,b)} / \eta \leq P^{grid-max}\ \forall t \in \mathbb{T} \tag{24}$$

4.5. Battery Self-Degradation constraints

The batteries in the BES undergo many charging/discharging cycles which reduce the ability for the battery to store energy inside it causing an effect on the maximum capacity of the battery. This is called the battery degradation. As a result, the battery self-discharge rate and the internal resistance increase, which causes the battery to heat up due to power loss and lowers the output voltage. The degradation effect is added to the formulation by replacing (1) with (25). The battery lifetime is assumed by the number of charging/discharging cycles. So, the number of cycles for each battery, $Cyc_{(b)}$, is utilized to evaluate the loss in SOC caused by degradation using (27), which is fitted from previous data in [28]. This is updated every time the battery is charged to keep track of the health of the battery which is required for a proper replacement. Then, the change in the price of the battery due to degradation can be defined as C^{DEG} as in (28), where

$$\underset{P_{(t,b)}^{Charging}, P_{(t,b)}^{Discharging}, x_{(b,c)}}{\text{maximize}} \quad z = R - (C^{kW} + C^{kWh} + C^{DEG}) \tag{25}$$

Subject to:

$$\text{Constraints (2) – (10), (13), (14), (16) – (24)} \tag{26}$$

$$\Delta SOC_{(b)}^{deg} = -8.954 \times 10^{-10} \times Cyc_{(b)}^{3} + 7.883 \times 10^{-7} \times Cyc_{(b)}^{2} - 2.814 \times 10^{-4} \times Cyc_{(b)} \tag{27}$$

$$C^{DEG} = \sum_{b \in \mathbb{B}} 100\ \% \times \Delta SOC_{(b)}^{deg} \times p_{(b)}^{deg} \tag{28}$$

4.6. Charging Price Uncertainty

BES purchases energy from the grid which is used to charge the batteries in BES when the charging price is low and sells energy to the grid through discharging the batteries when the charging price is high. Price uncertainty should be considered in the objective function to avoid a profit missing or increasing cost incurred by BES. The multi-band robust optimization approach is used to embrace this uncertainty [21]-[29].

The price range for each band $[p_{(t)}^{grid-kWh\,(\min)}, p_{(t,ba)}^{grid-kWh\,(\max)}]$ is utilized to represent the deviations in the prices. Where $p_{(t,ba)}^{grid-kWh\,(\max)} = p_{(t)}^{grid-kWh\,(\min)} + \Delta p_{(t,ba)}$ and $\Delta p_{(t,ba)}$ is the variation in the charging price for each band $ba \in \mathbb{A}$. ba and $\mathbb{A}$ are index and set of bands, respectively. The multi-band robust optimization approach utilizes multiple bands where these bands are controlled by robustness parameter $\varphi_{(ba)}$. The modified objective function can be expressed as follow:

$$\underset{P_{(t,b)}^{Charging}, P_{(t,b)}^{Discharging}, x_{(b,c)}}{\text{maximize}} \quad z = R - (C^{kW} + C^{kWh} + C^{DEG}) - \sum_{ba \in \mathbb{A}} \varphi_{(ba)} v_{(ba)} - \sum_{t \in \mathbb{T}} q_{(t)} \tag{29}$$

Subject to:

$$\text{Constraints (2) – (10), (13), (14), (16) – (24), (27), (28)} \tag{30}$$

$$\varphi_{(ba)} \in \{0 \quad |\mathbb{U}_{(ba)}|\}, \qquad \forall ba \in \mathbb{A} \tag{31}$$

$$\sum_{ba\in\mathbb{A}} \varphi_{(ba)} \leq N_t \tag{32}$$

$$v_{(ba)} + q_{(t)} \geq \Delta p_{(t,ba)} * \sum_{b\in\mathbb{B}} P^{Charging}_{(t,b)} \quad \forall t \in \mathbb{U}_{(ba)} \ \&\ ba \in \mathbb{A} \tag{33}$$

where $\mathbb{U}_{(ba)}$ is set of time periods during which the uncertainty in electricity prices might occur for band ba, $v_{(ba)}$ is auxiliary non negative variable for linearity in band ba, $q_{(t)}$ is auxiliary variable to compute the uncertainty in the price of electricity during period t.

In constraint (31), for each band $\varphi_{(ba)}$ can take value from 0 to upper limit of uncertainty time set $\mathbb{U}_{(ba)}$ for this band. If $\varphi_{(ba)} = 0$, the effect of price uncertainty is ignored and If $\varphi_{ba} = |\mathbb{U}_{(ba)}|$, the effect of all price uncertainties during uncertainty time set $\mathbb{U}_{(ba)}$ are considered. The summation of total periods of price uncertainty for all bands are less than or equal total number of time segments according to constraint (32). Constraint (33) guarantees feasibility for any deviation $\Delta p_{(t,ba)}$.

4.7. Conventional Charging Station Operation

In the charging station, the only decision that can be taken is charging the batteries from the grid once the customer plug in his EV based on First come first serve (FCFS) as described in [30]. In this case, discharging isn't allowed, and grid connection limit is respected.

We formulate this problem as a preemptive goal programming [31]. Each customer is prioritized based on the arrival time, i.e. earlier customers receive higher priority. The following problem is solved for each customer k from highest priority to lowest in order. The objective is to minimize the weighted charging power, as in (34), where the power is weighted according to the time slot. Earlier time slots receive lower weight; thus, in a minimization problem, the charging will occur as early as possible limited to the constraints.

The stored energy is updated as in (35) and (36). The charging only can occur after the customer arrives at the station as in (37), where $\delta_{(t,c=k)}$ is a vector of length N_t containing zeros before the customer arrives and ones afterward. The SOC is limited as in (38) and (39). The grid limit is presented in (40) and the charging power is equated to the outcome of previous sub-problems, as in (41), of higher priority customers, where $\mathbb{K}_k \subset \mathbb{C}$ is the subset of customers with higher priority with respect to customer k.

$$\max_{\Omega} z = \sum_{t \in \mathbb{T}} \beta_t \frac{P_{(t,c=k)}^{Charging}}{\eta} \tag{34}$$

$$E_{(t,c=k)}^{stored} = E_{(t-1,c=k)}^{stored} + \Delta t(P_{(t,c=k)}^{Charging} - P_{(t,c=k)}^{Discharging}) \quad \forall t \in \mathbb{T} \tag{35}$$

$$E_{(t=1,c=k)}^{stored} = E^{stored-int} + \Delta t(P_{(t=1,c=k)}^{Charging} - P_{(t=1,c=k)}^{Discharging}) \tag{36}$$

$$P_{(t,c=k)}^{Charging} \leq \delta_{(t,c=k)} P^{max} \, \forall t \in \mathbb{T} \tag{37}$$

$$SOC_{(t,c=k)} = E_{(t,c=k)}^{stored} \times \frac{100\ \%}{E^{max}} \forall t \in \mathbb{T} \tag{38}$$

$$100\ \%(1 - MDOD) \leq SOC_{(t,c=k)} \leq 100\ \% \, \forall t \in \mathbb{T} \tag{39}$$

$$\sum_{c \in \mathbb{B}} P_{(t,c)}^{Charging} \leq P^{grid-max} \, \forall t \in \mathbb{T} \tag{40}$$

$$P_{(t,c)}^{Charging} = P_{(t,c)}^{Ch*} \forall t \in \mathbb{T}, c \in \mathbb{K}_k \tag{41}$$

5. Results and analysis

Different cases will be studied to investigate the effect of several aspects on the technical and economical features of the BES under the proposed operation approach. The first case study will be conducted on 30 customers and 13 batteries, which is considered as the base case and will be used for the comparison with the following cases. It is worth mentioning that using more than 13 batteries is useless as only 13 batteries are needed to serve the 30 customers. The second case study will focus on the effect of the grid power limitation on the charging power and the revenue of the station. The third case study will focus on the impact of maximum historical demand and grid limit variations on the total revenue obtained by BES. Finally, a comparison between the conventional charging station and the BES is conducted. All cases include the battery self-degradation factor and study its negative effect on the state of charge of the battery and the maximum capacity. Finally, a summary of the different case studies and their results will be discussed. The replacement for each customer is done within a one-time segment. The General Algebraic Modelling Software (GAMS) was used to solve the optimization problems. The GAMS is a very powerful tool as well as it is an effective and simple platform for optimization problems regarding the power system applications [32]-[33]. It has many solvers to solve the different types of optimization problems. BARON is one of the solvers embedded in GAMS which is used for solving MINLP, NLP, MIP problems. BARON implements deterministic global optimization algorithms of the branch-and-bound type that are guaranteed to provide global optima under fairly general assumptions.

5.1. Case 1: Base Case

This case study represents the base case. The case includes 13 batteries, i.e. $b \in \mathbb{B} = \{1,2, \dots ,13\}$, with 100 % SOC at the beginning and at the end of the complete cycle. Furthermore, the batteries need to serve 30 customers, i.e. $c \in \mathbb{C} = \{1,2, \dots ,30\}$, throughout the day. The charging and discharging occur at different rates and different periods of the day depending on the grid price and the customers assigned for each station. Fig. 5 and Fig. 6 show the charging and discharging cycles for the 13 batteries. Most of the batteries have the discharging during the day that has the highest grid price as shown in Fig. 6.

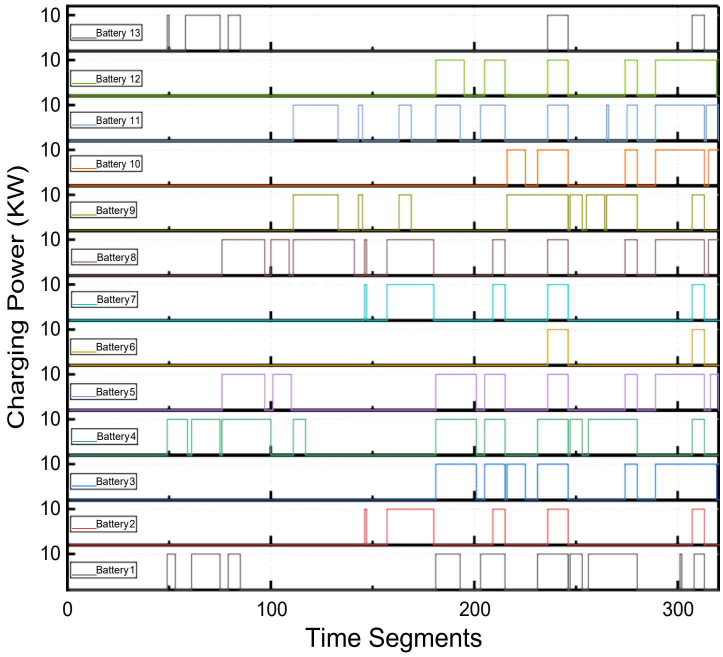

Fig. 5. *Charging cycles vs. time segments for the 13 Batteries.*

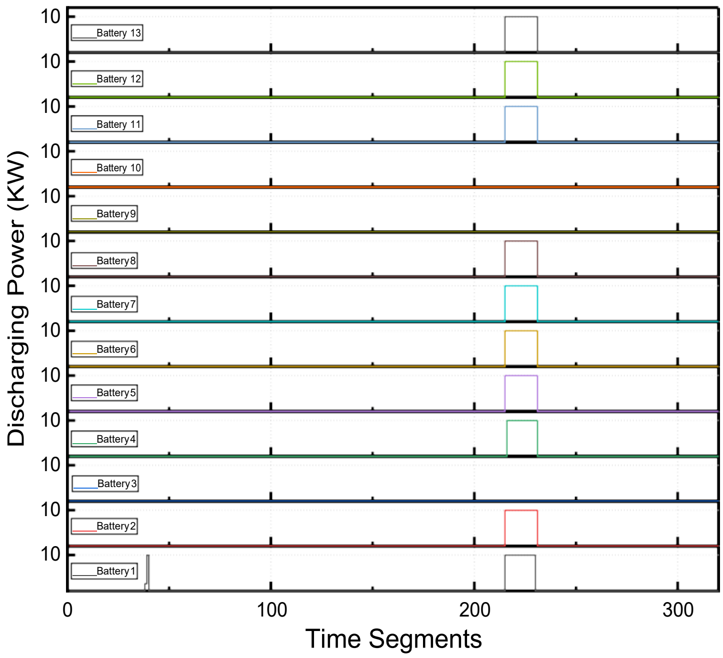

Fig. 6. *Discharging cycles vs. time segments for the 13 Batteries.*

The SOC variation with time is shown in Fig. 7. The direct drops indicate the replacements as mentioned before. Fig. 8 shows the batteries/customers' selection. Some batteries are chosen to serve two customers like station 10 but others are The SOC variation with time is shown in Fig. 7. The direct drops indicate the replacements as mentioned before. Fig. 8 shows the batteries/customers' selection. Some batteries are chosen to serve two customers like station 10 but others are serving 4 customers like battery 4. This depends on the battery availability in each station, the required energy by each customer, and the time segment when the customer will reach the station. Customers 14, 15, 16, and 17 are being served by four different stations since they arrive at the station at the same time. All the 30 customers are being served without using all the 13 batteries. The maximum revenue from this case is about \$125.9. The cost of purchased energy from the grid to charge the batteries is \$70.5775, the cost of selling energy to the grid by discharging the batteries is \$12.7371, and the cost of selling energy by replacing

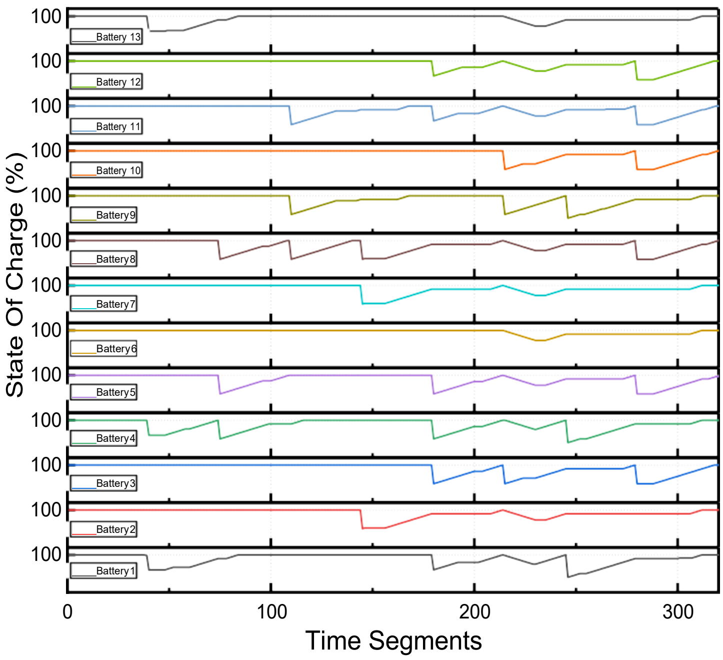

Fig. 7. *State of charge variation vs. time segments for the 13 Batteries.*

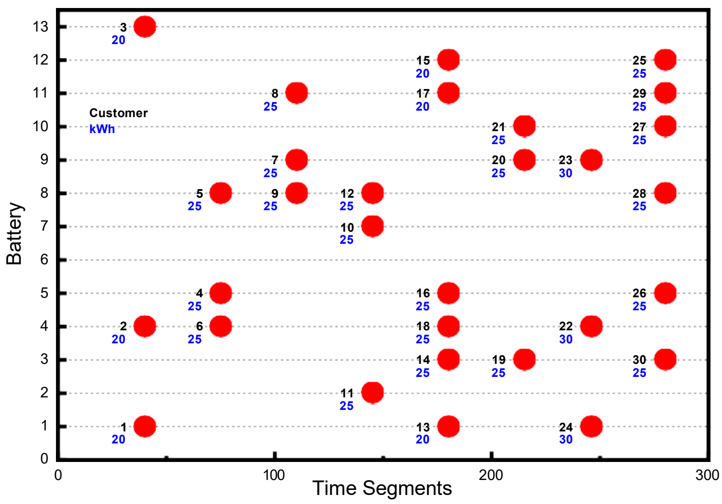

Fig. 8. *Batteries/Customers selection*

batteries is \$183.75. To study the effect of the charging price uncertainty, the modified objective function regarding the charging price uncertainty is considered. Two bands of 10% and 15% are considered in the uncertainty part. The two robustness parameters $\varphi_{(10\%)}$ & $\varphi_{(15\%)}$ can take any value in range of $\{0 \quad |\mathbb{U}_{(ba)}|\}$ for price deviation of $\Delta p_{10\%}$ & $\Delta p_{15\%}$. However, the values of these parameters have to satisfy constraint (32) [$\varphi_{(10\%)} + \varphi_{(15\%)} \leq N_t$]. The maximum revenue from this case will be \$121.41 (3.7% decrease). Furthermore, the cost/revenue of purchased energy, selling energy and replacing batteries will be \$63.88, \$5.54, and \$183.75, respectively. Therefore, price uncertainty hasn't a great impact on the revenue obtained by BES as the major superiority of BES is the flexibility in the starting time of charging of each battery and the main part of the profit is profit obtained from the replacement process.

5.2. Case 2: Grid Power Limitation Effect

In this section the grid power limit and the demand charges C^{kW} due to the maximum demand consumed from the grid are considered. In this case, the maximum power that can be consumed from the grid is 60 kW, i.e. $P^{grid-max} = 60$ kW and the maximum historical demand consumed from the grid is assumed to be 50 kW, i.e. $P^{MAX}_{Historical}$= 50 kW.

As shown in Fig. 9, the optimal decisions for the BES choose to limit the total consumed power at 50 kW, i.e. $C^{kW} = 0$. As the main merit in the BES is the flexibility in the starting time of charging of each battery. Consequently, only five batteries can be charged from the grid simultaneously. Fig. 9 shows the charging power variation with time with and without the grid power and the maximum historical demand limitations. With these limitations, the width of the charging cycles is bigger to overcome the periods where the power was greater than 50 kW. As a result, the batteries/customers' selection has been changed as shown in Fig. 10. With the grid power limitation, the station needs 13 batteries to serve the same customers. So, battery 6 is now serving customers 19, and 27. Adding the grid power limitation in this case study did not affect the revenue of the station (\$124.97). However, it changed the decisions of the control unit. The cost of

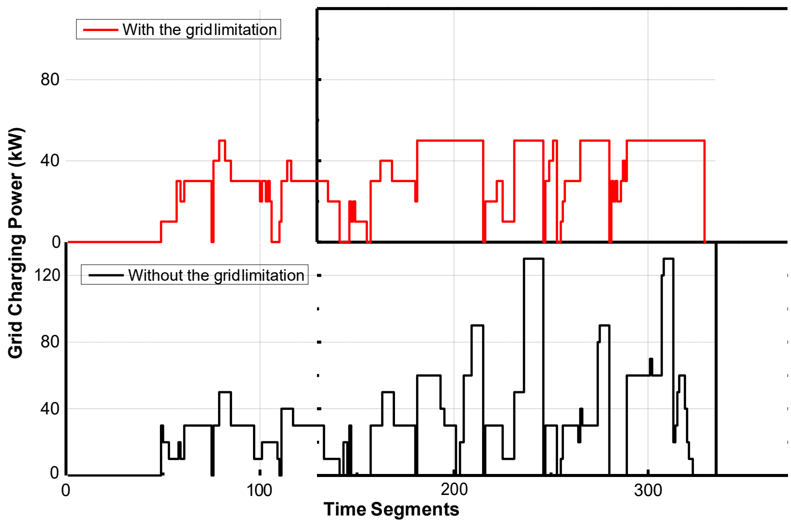

Fig. 9. *Charging Power vs. time with and without the grid power limitation.*

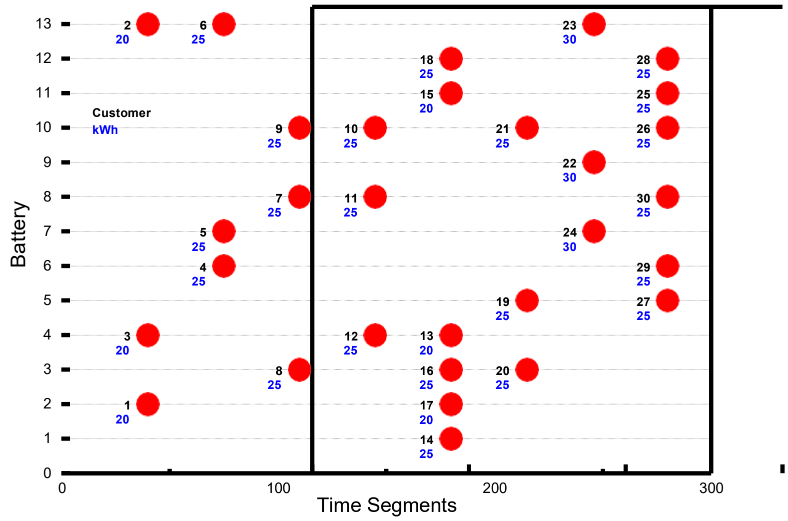

Fig. 10. *Batteries/Customers selection with grid power limitation.*

purchased energy from the grid to charge the batteries is \$64.5598, the cost of selling energy to the grid by discharging the batteries is \$5.784, and the cost of selling energy by replacing batteries is \$183.75. In the case of the charging price uncertainty, the maximum revenue from this case will be \$119.7 (4.6% decrease). Furthermore, the cost/revenue of purchased energy, selling energy, and replacing batteries will be \$60.22, \$0.08, and \$183.75, respectively.

5.3. Case 3: Sensitivity Analysis

The aim of this case study is to evaluate the impacts of different parameters' variations on the optimal decision and thus on the revenue obtained by BES while considering the charging price uncertainty. In this subsection, we investigate the

TABLE 4 IMPACT OF PARAMETERS' VARIATIONS ON TOTAL REVENUE

Grid Limit	Cost/Revenue	Maximum Historical Demand		
		30 kW	**50 kW**	**70 kW**
40 kW	Total Revenue ($)	89.52	108.66	108.66
	Charging costs ($)	45.08	56.09	56.09
	Discharging Revenue ($)	0	0	0
	Replacement Revenue ($)	137.5	168.5	168.5
	No. of Served Customers	23	28	28
	Maximum power consumed from grid (kW)	30	40	40
80 kW	Total Revenue ($)	89.52	119.7	120.99
	Charging costs ($)	45.08	60.22	61.63
	Discharging Revenue ($)	0	0.0803	2.65
	Replacement Revenue ($)	137.5	183.75	183.75
	No. of Served Customers ($)	23	30	30
	Maximum power consumed from grid (kW)	30	50	70

effect of varying both demand charge and grid limit on the charging, discharging and replacement cost/revenue. Table 4 demonstrates the results obtained in case of parameters' variations. AS illustrated in Table 4, if the maximum historical demand is lower than the grid limit, the optimal decisions will be always limiting the total power consumed from the grid at the maximum historical demand limit so that no extra charges are incurred. However, the results indicate that if the power consumed from the gird is limited at 50 kW or higher, the BES will be able to serve all customers in our case. Furthermore, the change in power consumed from the gird over this value hasn't a significant effect on the total revenue obtained by BES in our case study. Moreover, this value depends on the BES configuration including the number of batteries and the number of served customers per day. In case of power consumed from the grid is limited at a value lower than 50 kW, this will lead to not serving some customers due to this value have an impact on the batteries which can be charged simultaneously. Therefore, the batteries will not satisfy the customers' satisfaction expressed in equation (20).

5.4. Case 4: Comparison Between BES and Charging Stations

In this case study, a comparison between the charging stations and the BESs is conducted in case of the grid limitation and maximum historical demand consumed from the grid. The charging curve for the BES and the charging station can be illustrated in Fig. 11. The maximum revenue from this case for BES and the charging station is about $124.97, and $35.37 respectively. For the charging station, each customer has to wait until its battery is charged. The mean waiting time for the customers in this case study is 147 minutes. While the waiting time for each customer in BES is only 5 minutes, the duration of the battery replacement service. However, each customer in the charging station may wait a delay time until the starting of the charging process as a result of the operation of the station with its maximum charging power. In this case study, the customers 28-30 have to wait 15 minutes to start the charging process. If the owners of the charging station decide to limit the power at 50 kW to not charge extra cost due to maximum historical demand consumed from the grid. The total profit will increase and becomes $125. The revenue, in this case, will be nearly the same with the BES as the energy replacement price is considered to be fixed for this comparison although unrealistic of this condition. However, the delay time for the customers until the beginning of batteries charging will increase. For example, the customer 18 has to wait 125 minutes to start the charging process while the customer 30 has to wait 155 minutes in addition to the charging duration as shown in Fig. 12. This may lead to making these customers leave this station and charge at another station.

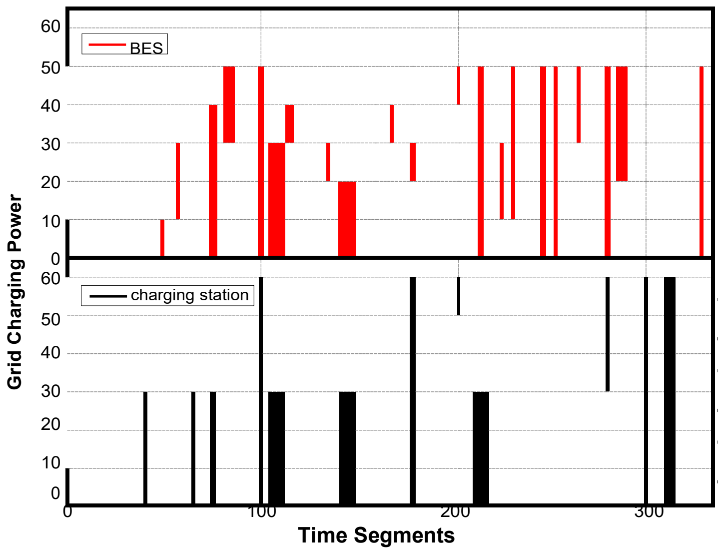

Fig. 11. *Charging power variation vs. time for the BES and the charging station in case of a 60 kW limitation.*

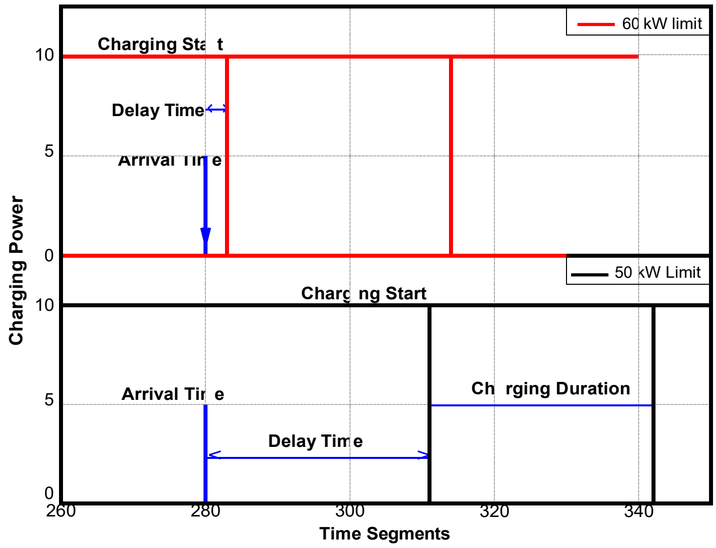

Fig. 12. Charging profile for customer 30 in case of 50 kW and 60 kW limitations.

6. Conclusion

This paper proposes a new approach for operating a BES to determine the optimal charging, discharging, and replacement decisions in order to maximize the profit based on the grid price and the customers’ requests. The optimization problem is formulated as MINLP with the objective of maximizing the BES investor profit while satisfying the EV owners’ requests. The variation of charging/discharging power, the state of charge, and the stored and replaced energy for all batteries in the station with time is analyzed considering different case studies. The results from the case studies on a typical BES demonstrate the effectiveness of the proposed approach while considering practical grid tariffs for industrial customers representing the BES owner. Moreover, a comparative study between conventional charging stations and BES is conducted, which shows that BES outperforms the conventional charging stations in terms of the service time, number of served customers, and the operational cost. Also, the grid power limitation and battery self-degradation are all considered to represent a practical BES structure. The results highlight the effectiveness of the proposed approach in satisfying the EV owners' requests while maximizing the BES investor profit.

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