

# Integrated Rail System and EV Parking Lot Operation with Regenerative Braking Energy, Energy Storage System and PV Availability

Alper Çiçek, İbrahim Şengör, *Member, IEEE*, Sıtkı Güner, *Member, IEEE*, Furkan Karakuş, Ayşe Kübra Erenoğlu, *Graduate Student Member, IEEE*, Ozan Erdiñç, *Senior Member, IEEE*, Miadreza Shafie-khah, *Senior Member, IEEE*, and João P. S. Catalão, *Fellow, IEEE*

**Abstract**—A significant advancement regarding the electrification of transportation has occurred in recent years due to technological developments, environmental concerns, and geopolitical issues in the energy areas all over the world. In this study, a new concept for the integration of rail-based public transportation systems with electric vehicle (EV) parking lots operated by a “park and ride” strategy is propounded, including also renewable resources based energy production. In the proposed structure, the charging power demand of the EV parking lot is supplied by different charging strategies considering the existing unused energy infrastructure capacity and the regenerative braking energy of the railway system, altogether. Here, the design of a photovoltaic (PV) based carport type renewable energy production unit is also realized in the existing local parking area. The development of an optimal energy management system to effectively manage these inputs is realized and the uncertainties pertaining to EVs' demand are also taken into account. To demonstrate its efficacy, the concept is tested considering a bench of case studies and comprehensive results are obtained. Conclusions are duly drawn.

**Index Terms**—Charging stations, electric vehicles, energy management, railway systems, regenerative braking energy, renewable energy resources.

## NOMENCLATURE

The used nomenclature in this study is alphabetically ordered and properly classified into groups, as follows.

### Abbreviations

ESS	Energy storage system.
EV	Electric vehicle.
PV	Photovoltaic.
RBE	Regenerative braking energy.

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A. Çiçek, S. Güner, F. Karakuş, A.K. Erenoğlu, and O. Erdiñç are with the Department of Electrical Engineering, Yildiz Technical University, Istanbul, Turkey (e-mails: alper\_cicek92@hotmail.com; sitkiguner@gmail.com, furkankarakus@yahoo.com.tr; ayseerenoglu94@gmail.com; ozanerdinc@gmail.com).

İ. Şengör is with the Environmental Research Institute, MaREI, University College Cork, Cork, Ireland, and also with the Electrical and Electronics Engineering Department, İzmir Katip Çelebi University, İzmir, Turkey (e-mail: ibrahimsengor.is@gmail.com).

M. Shafie-khah is with School of Technology and Innovations, University of Vaasa, 65200 Vaasa, Finland (e-mail: mshafiek@univaasa.fi).

J.P.S. Catalão is with the Faculty of Engineering of University of Porto, and INESC TEC, Porto, Portugal (e-mail: catalao@fe.up.pt).

### Sets and Indices

$h$	Set of EVs.
$l$	Set of day-ahead market price scenarios.
$s$	Set of EV behavior scenarios.
$t$	Set of time.

### Parameters

$Cap_t^{serv}$	Capacity of service transformer during period $t$ [kW].
$Cap_t^{trac}$	Capacity of traction transformer during period $t$ [kW].
$n^{Bus, ch, DC}$	Number of DC bus charger.
$n^{Car, ch, AC}$	Number of AC electric car charger.
$n^{Car, ch, DC}$	Number of DC electric car charger.
$p_t^{brk}$	Total regenerative braking power available during period $t$ [kW].
$p_t^{PV}$	Total PV power production during period $t$ [kW].
$p_t^{stat}$	Total station power demand during period $t$ [kW].
$p_t^{trac}$	Total traction power demand during period $t$ [kW].
$P_h^{EV, AC, max}$	Maximum AC charging power capacity for EV $h$ .
$P_h^{EV, DC, max}$	Maximum DC charging power capacity for EV $h$ .
$p_i$	Probability of day-ahead market price scenario $i$ .
$p_s$	Probability of EV behavior scenario $s$ .
$R^{ESS, ch}$	Maximum charging power capacity for ESS [kW].
$R^{ESS, disch}$	Maximum discharging power capacity for ESS [kW].
$SoE_{t,l}^{ESS, ini}$	Initial state of energy of ESS [kWh].
$SoE^{ESS, max}$	Maximum state of energy of ESS [kWh].
$SoE^{ESS, min}$	Minimum state of energy of ESS [kWh].
$SoE_h^{EV, ini}$	Initial state of energy of EV $h$ [kWh].
$SoE_h^{EV, max}$	Maximum state of energy of EV $h$ [kWh].
$SoE_h^{EV, des}$	Desired state of energy of EV $h$ at departure time [kWh].
$T_h^a$	Arrival time period of EV $h$ .
$T_h^d$	Departure time period of EV $h$ .
$u_{h,s}^{EV, avail}$	Binary parameter for the availability of EV $h$ in scenario $s$ : 1, if EV is available; else 0.
$\Delta T$	Time granularity.
$\lambda_t^{buy}$	Price of buying energy from the day-ahead market during period $t$ [\$/kWh].
$\eta_{ch}^{ESS}$	Charging efficiency for ESS.
$\eta_{disch}^{ESS}$	Discharging efficiency for ESS.
$\eta_h^{EV, ch}$	Charging efficiency for EV $h$ .
$\eta_{DC \rightarrow DC}$	Efficiency of DC-DC conversion unit.
$\eta_{AC \rightarrow AC}$	Efficiency of AC-AC conversion unit.

### Variables

$P_{t,l,s}^{AC, ch, tot}$	Total AC charging power demand during period $t$ for scenario $l$ and $s$ [kW].
$p_{t,l,s}^{brk2ESS}$	The portion of regenerative braking power assigned for ESS charging during period $t$ for scenario $l$ and $s$ [kW].
$p_{t,l,s}^{brk2EV}$	The portion of regenerative braking power assigned directly for EV charging during period $t$ for scenario $l$ and $s$ [kW].
$P_{t,l,s}^{DC, ch, tot}$	Total DC charging power demand during period $t$ for scenario $l$ and $s$ [kW].
$p_{t,l,s}^{ESS, disch}$	Discharging power of ESS during period $t$ for scenario $l$ and $s$ [kW].

$P_{h,s,t}^{EV, ch, AC}$	AC charging power of EV $h$ during period $t$ for scenario $s$ [kW].
$P_{h,s,t}^{EV, ch, DC}$	DC charging power of EV $h$ during period $t$ for scenario $s$ [kW].
$P_{t,s}^{PV, AC}$	The portion of PV power production assigned for assisting AC charging during period $t$ in scenario $s$ [kW].
$P_{t,s}^{PV, DC}$	The portion of PV power production assigned for assisting DC charging during period $t$ in scenario $s$ [kW].
$P_{t,l,s}^{serv, 2EV}$	Power drawn from the service transformer for EV charging during period $t$ in scenario $l$ and $s$ [kW].
$P_{t,l,s}^{serv, total}$	Total power drawn from the service transformer during period $t$ in scenario $l$ and $s$ [kW].
$P_{t,l,s}^{trac, 2EV}$	Power drawn from the traction transformer for EV charging during period $t$ in scenario $l$ and $s$ [kW].
$P_{t,l,s}^{trac, total}$	Total power drawn from the traction transformer during period $t$ in scenario $l$ and $s$ [kW].
$SOE_{t,l,s}^{ESS}$	State of energy of ESS during period $t$ in scenario $l$ and $s$ [kWh].
$SOE_{h,s,t}^{EV}$	State of energy of EV $h$ during period $t$ [kWh].
$u_{h,s}^{bus, ch, DC}$	DC charging decision for electric bus $h$ among EVs in scenario $s$ .
$u_{h,s}^{car, ch, AC}$	AC charging decision variable for electric car $h$ among EVs in scenario $s$ .
$u_{h,s}^{car, ch, DC}$	DC charging decision variable for electric car $h$ among EVs in scenario $s$ .
$u_{t,l,s}^{ESS}$	Binary variable for ESS power transaction during period $t$ in scenario $l$ and $s$ .

## I. INTRODUCTION

### A. Motivation

Among energy users, approximately 20 percent of universal energy consumption and greenhouse gas emissions are originated from the transportation sector [1], [2]. In order to tackle these issues, the widespread adoption of electric vehicles (EVs) has been promoted by a broad spectrum of actors all over the world, driven by the raising awareness of air contamination and a sustainable transportation system. In this sense, electric mobility has been growing exponentially and the global electric car fleet is expected to reach 35 million and 130 million worldwide in 2022 and 2030, respectively [3],[4].

However, despite all the aforementioned advantages of EVs, uncoordinated charging poses great challenges onto the power system, depending strongly on uncertain charging and driving behaviours [5]. The current status of the power system could not host a large volume of unmanaged EV charging, which could possibly result in “peak-to-peak” phenomena, overloading problems, line congestions and stability issues, i.e. all of them bring about significant performance degradation in a critical infrastructure system [6]. As an example, it has been deduced from the study performed in [7] that, under an uncontrolled charging scenario, the daily peak demand has increased by 35.8% with a 20% EVs penetration at a home charging platform on a standard network.

In order to reduce the installation cost of large-scale charging stations, as well as providing a sustainable transportation system, increasing energy efficiency and decreasing carbon footprint, integrated railway stations with EV charging carpots have attracted great attention in the last decade from the academic community and industrial stakeholders. Railway infrastructures are large-scale electricity consumers that meet their respective electrical energy demands with a separate connection directly from the transmission line level [8].

One of the significant benefits of such a design is that the transfer of the EV load to the operational weakest part of the power system, such as the distribution level, is relatively reduced. Moreover, adjacent substations installed for emergency conditions such as failure and maintenance can be utilized for feeding charging stations under normal operating periods.

Moreover, transforming mechanical braking of the train into electrical energy (called regenerative braking) increases energy efficiency of railway systems and decreases energy consumption, significantly. However, it is not always possible to inject this recovered energy to the catenary line if there is not a nearby train [9]. The regenerated electricity can either be stored in energy storage systems or may be dissipated in banks of variable resistors [10], [11].

Seemingly, there is an excellent opportunity for taking full advantage of existing railway electrical infrastructures in supplying the demand of charging stations by DC reference node and/or recoverable train braking energy.

Furthermore, local energy production such as photovoltaic (PV) panels can be integrated to the charging stations if it is established as an outdoor parking lot instead of multistorey car parks.

The power demand of EVs could be supplied with clean energy resources while grid dependences and power losses can be reduced in a substantial fashion. As a consequence, a smart energy management framework that incorporates the aforementioned concepts and approaches will provide a wise operation of both transportation and electrical grid systems.

### B. Literature Review

During braking operation in a railway vehicle, a great heat occurs. This heat is defined as the lost energy and also causes a decrease in system efficiency. For this reason, the method of recovering lost energy of regenerative braking has been a topic recently emphasized by several researchers and operators.

Lu et al. [12] proposed a method to increase the regenerative braking energy (RBE) obtained in both electrical and mechanical braking modes. In their study, they applied the Bellman-Ford algorithm to determine the brake speed curve of the train. By doing so, an increase of 17.23% was provided in the RBE. Kumagai et al. [13] suggested a structure in which RBE generated in one train is transferred to another train. The authors tested this system on the Chuo train line in Tokyo and performed simultaneous measurements at the Chuo train line and at the nearby transformer center. Liu et al. [14] presented a model in which the time schedule for using RBE in a metro line is determined.

However, in references [12]-[14], the subjects of renewable energy sources (RESs), energy storage systems (ESSs), and EVs were not addressed.

Wu et al. [15] presented a model of optimal sizing of onboard ESSs to minimize catenary energy consumption. The authors also examined the ESS consisting of supercapacitors, Li-ion batteries, and flywheels in the Beijing Changing line. Yang et al. [16] suggested an optimum energy management strategy for supercapacitors in the urban rail system, adjusting the control parameters. Eziani et al. [17] suggested a new method based on a neural network to estimate the state of charge of supercapacitors used for RBE recovery in railways.

Khodaparastan et al. [18] examined in detail the methods that can be used to recover the RBE. The authors stated that there are three methods for achieving this energy: optimizing train operating hours, using ESSs, and using reverse traction transformers.

However, in [15]-[18], while RBE and ESS are considered, EVs and RESs were not included in the model.

Aguado et al. [19] presented a model for the optimal operation of a railway power system, which includes a PV system, wind turbines, RBE option, and a supercapacitor-battery hybrid system. The authors applied a scenario-based approach to the uncertainty of RESs and integrated the whole model into an AC optimum power flow problem. They also analyzed the practice carried out on a high-speed train in Spain. They achieved an improvement of 33.22% and 9.63% in costs and energy savings, respectively, with the use of renewable energy and ESSs together. Şengör et al. [20] suggested a mixed-integer linear programming model of the energy management problem of a railway station with an ESS, RBE, PV system, and a separate grid line.

However, in references [19] and [20], while ESSs and RESs are included in addition to RBE, EVs were not addressed.

Calvillo et al. [21] modeled a region with metro, EV, and distributed generation facilities using linear programming. The aim of their study was the optimum use of RBE obtained from the metro in other trains or EVs. However, operation over nominal power of traction transformer, AC and DC charging units, electric buses, short-term economic operation problem, and purchasing energy from the day-ahead market are all neglected in [21].

Perez et al. [22] proposed a model for the integration of a train line for RBE into a DC micro-grid consisting of a PV system, a hybrid supercapacitor-battery system, and a DC local load. However, this study did not include EVs.

Mohamed et al. [23] presented a real-time energy management algorithm for a grid-connected EV charging park in a commercial workplace. However, they did not include the arrival and departure times of EVs in the model.

Hoarau and Perez [24] and Alghoul et al. [25] conducted virtual micro-grid research in which smart parking management systems were combined with RESs and EVs. It is to be highlighted that the studies presented in [24] and [25] are only review studies, not research paper.

Tulpule et al. [26] investigated the suitability of installing a PV generation system for parking lots in workplaces. They considered the annual solar radiation and financial structure of the Columbus and Los Angeles regions with different scenarios. The analysis showed an increased parking rate for access to the charging station. They also examined the contribution to the economy by using the most appropriate planning strategy. Sedighzadeh et al. [27] proposed a two-stage optimization system based on approximate dynamic programming and an hybrid algorithm, which takes into account an artificial neural network to design the most suitable energy management systems. Besides, they paid attention to the EV charging usage time in order to reduce the costs of the EV parking lot owner in the proposed energy management strategy.

It should be underlined that there are some studies in the existing literature including the combinations of the evaluated components in this study. However, none of them took into consideration the idle power capacity of the railway traction substation. Besides, none of the abovementioned studies considered the electric buses, AC and DC charging of EVs, and operation overrated power of traction transformer.

A detailed comparison of the studies in the specified literature and the presented study is given in Table I. It enables to better understand the motivation behind this study and the gaps in the existing literature.

### C. Contributions and Organization

In this study, an optimal energy management strategy is presented where the existing installed capacity for service and transportation purposes on the rail systems side, potential RBE, and ESS are used together with a local renewable energy generation unit located in the parking area in order to meet the demand for the EV parking zone.

TABLE I  
TAXONOMY OF THE PROPOSED METHODOLOGY COMPARED TO THE RESEARCH PAPERS IN THE LITERATURE

Case Studies	RES	RBE	ESS	EV	Electric Buses	EV Parking Lot	EV Behavior Scenarios	AC and DC Charge of EVs	Operation Over Nominal Power of Traction Transformer
[12]	-	✓	-	-	-	-	-	-	-
[13]	-	✓	-	-	-	-	-	-	-
[14]	-	✓	-	-	-	-	-	-	-
[15]	-	✓	✓	-	-	-	-	-	-
[16]	-	✓	✓	-	-	-	-	-	-
[17]	-	✓	✓	-	-	-	-	-	-
[18]	-	✓	✓	-	-	-	-	-	-
[19]	✓	✓	✓	-	-	-	-	-	-
[20]	✓	✓	✓	-	-	-	-	-	-
[21]	✓	✓	✓	✓	-	✓	✓	-	-
[22]	✓	✓	✓	-	-	-	-	-	-
[23]	✓	-	-	✓	-	✓	-	-	-
[26]	✓	-	-	✓	-	✓	-	-	-
[27]	-	-	-	✓	-	-	✓	-	-
<b>This Study</b>	✓	✓	✓	✓	✓	✓	✓	✓	✓

To the best of the authors' knowledge, this concept has not yet been addressed in any study in the literature. Hence, the novelties of this study are twofold:

- A framework is presented in which service and traction transformers provide energy to the rail system and RBE, ESS, and PV system are aimed to be utilized in charging for both EVs and electric busses in the parking lot. The uncertain nature of EV behaviors as well as electricity market prices are modeled in a stochastic-based approach. AC and DC fast charging units are also considered in the proposed model. DC energy from the railway to the EVPL comes from the railway system's catenary via a DC-DC converter. It should be highlighted that this is the first study in the literature in which the idle power of the traction transformer is evaluated for charging EVs. Moreover, the energy needs of EVs are matched by the power bought by the traction and service transformers from the day-ahead market.

- Due to the well-known redundancy-oriented design in railway systems, service and traction transformers are typically lightly loaded. Traction transformers can also provide 150% power for two hours, according to the EN50329 standard for railway systems. It is the first time that the extra capacity in lightly loaded railway transformers, which can even be overloaded for some times to match the charging demand of parking lots, is analyzed in the literature.

The rest of the paper is organized as follows. The mathematical model is given in Section II. In Section III, the evaluated case studies are defined, and related results obtained from comprehensive simulations are examined. Finally, the concluding remarks are evaluated in Section IV.

## II. METHODOLOGY

The general structure of the proposed model is given in Fig. 1. Herein, RBE from trains, PV production, ESS, traction transformer, and service transformer are used to charge the EVs, which consist of electric cars and electric buses in the parking lot in an economic manner.

It should be noted that electric buses and EVs can be charged in both AC and DC charging units in this scheme. The idle part of the traction and service transformer is also used to charge the EVs in the parking lot for the first time in the literature, even exceeding the traction transformer's rated power.

At train stations, service transformers are commonly used for supplying the demand of passenger information boards, station lighting, station offices, and other areas. A traction transformer, on the other hand, is the instrument that enables the train to move. The common bus distributes the parking lot's AC/DC charging power to the AC/DC charging units.

Firstly, a mathematical model of motion for the metro line is needed to determine the potential of RBE. In this respect, the mathematical model of the metro movement in [20] was used to determine the RBE. Herein, metro motion is based on Newton's one-dimensional laws.

### A. Objective Function

In the study, the objective function aimed at minimizing the cost of energy bought from the day-ahead electricity market through service and traction transformers to charge the EVs is given by (1).

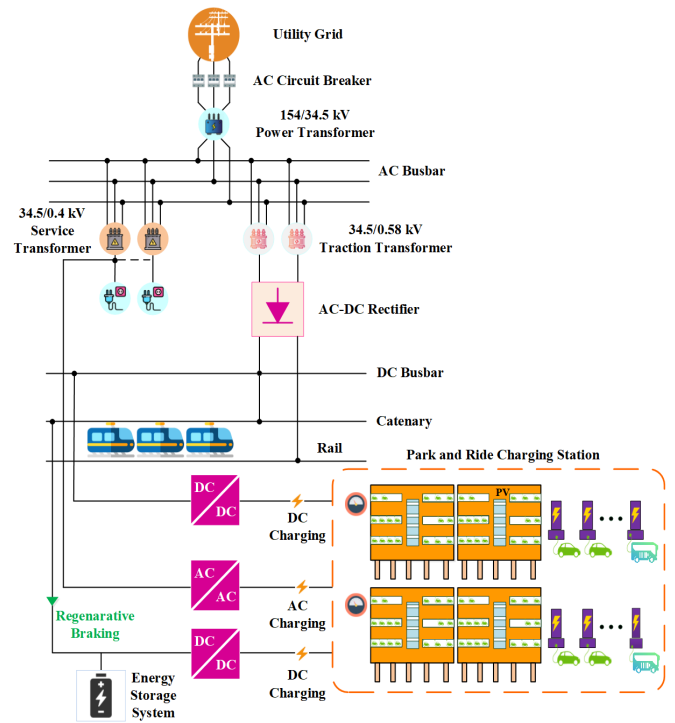


Fig. 1. A general structure of the proposed model.

$$\min(Cost) = \sum_t \sum_l \sum_s (p_{t,l,s}^{serv2EV} + p_{t,l,s}^{trac2EV}) \cdot p_l \cdot p_s \cdot \lambda_{t,l}^{buy} \cdot \Delta T \quad (1)$$

Namely, it is aimed to minimize the cost of purchasing energy used to charge EVs, except for train station energy use, through the service transformer, and the cost of energy purchased through the traction transformer used directly for train movement during the day, except for train operation cost.

It is worth underlining that the cost of RBE is not considered in the cost function since the energy regenerated by the braking during the normal operation of the evaluated metro line is being wasted via the resistances on the train. Here, regenerative braking power, PV system, ESS and EV charging optimization are evaluated as well, thus reducing the total cost. Besides, day-ahead market price and EV driving behavior scenarios are also taken into account, since the stochastic structure is considered.

### B. Power Limitations

It is expressed in (2) that the energy provided by the service transformer is used for the energy requirement of the station and charging of EVs. Inequality (3) defines the power limit that the service transformer can provide for each time interval  $t$ . Equation (4) defines how the energy supplied by the traction transformer is used for metro energy consumption and charging of EVs, while the power limit that this transformer can provide for each time interval  $t$  is determined by (5).

$$p_{t,l,s}^{serv,tot} = p_t^{stat} + p_{t,l,s}^{serv2EV}, \quad \forall t, l, s \quad (2)$$

$$p_{t,l,s}^{serv,tot} \leq Cap_t^{serv}, \quad \forall t, l, s \quad (3)$$



$$P_{t,l,s}^{trac,tot} = P_t^{trac} + P_{t,l,s}^{trac2EV}, \quad \forall t, l, s \quad (4)$$

$$P_{t,l,s}^{trac,tot} \leq Cap_t^{trac}, \quad \forall t, s \quad (5)$$

### C. Power Balance Constraints

The total DC charging power of EVs consists of the power provided by the traction transformer, the regenerative braking power, and the power provided by the ESS, which is expressed in (6). The efficiency of the DC-DC converter is also taken into account here. In (7), it is stated that the AC charging power for EVs is provided from the service transformer. Besides, the efficiency of the AC-AC converter is also taken into account. In other words, if the EVs are charged at the AC charging unit, the AC charging energy is only provided from the service transformer. In (8), it is stated that the sum of the charging power provided by regenerative braking, ESS, and traction transformer for EVs is obtained by subtracting the power generated in the PV system for DC charging from the sum of the DC charging power of all EVs. It is indicated in (9) that the total AC charging power provided by the service transformer for EVs is obtained by subtracting the power generated in the PV system for AC charging from the total of AC charging power of all EVs.

$$P_{t,l,s}^{DC,ch,tot} = (P_{t,l,s}^{trac2EV} + P_{t,l,s}^{brk2EV} + P_{t,l,s}^{ESS,dSCH}) \cdot \eta_{DC \rightarrow DC}, \quad \forall t, l, s \quad (6)$$

$$P_{t,l,s}^{AC,ch,tot} = P_{t,l,s}^{serv2EV} \cdot \eta_{AC \rightarrow AC}, \quad \forall t, l, s \quad (7)$$

$$P_{t,l,s}^{DC,ch,tot} = \sum_h P_{h,s,t}^{EV,ch,DC} - P_{t,s}^{PV,DC}, \quad \forall t, l, s \quad (8)$$

$$P_{t,l,s}^{AC,ch,tot} = \sum_h P_{h,s,t}^{EV,ch,AC} - P_{t,s}^{PV,AC} \cdot \eta_{DC \rightarrow AC}, \quad \forall t, l, s \quad (9)$$

### D. Charging/Discharging and SoE Constraints of the ESS

In (10), it is stated that the regenerative braking power is used in charging EVs or stored in the ESS for later use. The state-of-energy (SoE) expression of the ESS in period  $t$  is obtained by (11), where SoE is calculated by adding the energy at time period  $(t-1)$  and the stored RBE at time period  $t$ , or subtracting the energy discharged at time period  $t$ . The SoE level of the ESS at the beginning of the time period is determined in (12). Besides, the minimum and maximum energy limits for the charge and discharge conditions of the ESS are determined by (13). Because ESSs technically have a maximum capacity and it is generally desired that the energy level should not go below a certain level for an efficient use, a minimum limit is considered. The inequalities (14) and (15) prevent the ESS from charging and discharging in the same period, while also determining the maximum charge and discharge power. The simultaneous charging and discharging events are prevented by the binary decision variable  $u_{t,l}^{ESS}$ . The maximum charging power of the ESS is given on the device label and catalog, which is determined by the manufacturer.

$$P_t^{brk} = P_{t,l,s}^{brk2ESS} + P_{t,l,s}^{brk2EV}, \quad \forall t, l, s \quad (10)$$

$$SoE_{t,l,s}^{ESS} = SoE_{(t-1),l,s}^{ESS} + P_{t,l,s}^{brk2ESS} \cdot \eta_{ch}^{ESS} \cdot \Delta T - \frac{P_{t,l}^{ESS,dSCH}}{\eta_{dSCH}^{ESS}} \cdot \Delta T, \quad \text{if } t > 1, \forall l, s \quad (11)$$

$$SoE_{t,l,s}^{ESS} = SoE_{t,l}^{ESS,ini}, \quad \text{if } t = 1, \forall l, s \quad (12)$$

$$SoE_{t,l,s}^{ESS,min} \leq SoE_{t,l,s}^{ESS} \leq SoE_{t,l,s}^{ESS,max}, \quad \forall t, l, s \quad (13)$$

$$P_{t,l,s}^{brk2ESS} \leq R_{ESS,ch} \cdot u_{t,l}^{ESS}, \quad \forall t, l, s \quad (14)$$

$$P_{t,l,s}^{ESS,dSCH} \leq R_{ESS,dSCH} \cdot (1 - u_{t,l}^{ESS}), \quad \forall t, l, s \quad (15)$$

### E. Mathematical Model of Charging Operation

The SoE expression for EVs is given in (16). Herein, the energy state in period  $t$  is the sum of the energy in period  $(t-1)$  and the determined DC or AC charge energy in period  $t$ . While the SoE level at the beginning of the time period for EVs is determined by (17), the desired energy state for EV batteries when leaving the parking lot is determined by (18). Besides, the maximum energy level for EV batteries is determined by (19). The maximum DC and AC charging power limit of electric cars is determined by inequalities (20) and (21), respectively, while the maximum DC charging power limit for electric buses is determined by (22). The binary decision variable  $u_{h,s}^{EV,avail}$  refers to whether the EV arrives at the EV parking lot in the day. The value of this variable is 1 if the EV is coming to the EV parking lot, and 0 if it is not. In other words, if it is 0, no transaction is realized for that EV.  $u_{h,s}^{Car,ch,AC}$  and  $u_{h,s}^{Car,ch,DC}$  are binary decision variables for the DC and AC charging status of electric cars, while  $u_{h,s}^{Bus,ch,DC}$  is the binary decision variable for the DC charging status of electric buses. It is assumed that the DC charging unit of electric buses is different from the electric car DC charging unit. Considering that each electric car can be charged by either AC charge unit or DC charge unit and electric buses can be charged by only the DC charge unit, it is defined in (23) where the sum of the related binary decision variables is 1 for each EV. While the number of electric cars charged with the AC or DC charge unit can be equal to the number of AC or DC charge units in the EV parking lot is defined in (24) and (25), a similar situation for electric buses is expressed in (26).

$$SoE_{h,s,t}^{EV} = SoE_{h,s,(t-1)}^{EV} + (P_{h,s,t}^{EV,ch,DC} + P_{h,s,t}^{EV,ch,AC}) \cdot \eta_h^{EV,ch} \cdot \Delta T, \quad \forall h, s, t \in [T_h^a, T_h^d] \quad (16)$$

$$SoE_{h,s,t}^{EV} = SoE_h^{EV,ini} \cdot u_{h,s}^{EV,avail}, \quad \forall h, s, t = T_h^a \quad (17)$$

$$SoE_{h,s,t}^{EV} = SoE_h^{EV,des} \cdot u_{h,s}^{EV,avail}, \quad \forall h, s, t = T_h^d \quad (18)$$

$$SoE_{h,s,t}^{EV} \leq SoE_h^{EV,max} \cdot u_{h,s}^{EV,avail}, \quad \forall h, \forall t \quad (19)$$

$$P_{h,s,t}^{EV,ch,DC} \leq u_{h,s}^{Car,ch,DC} \cdot P_h^{EV,DC,max}, \quad \forall s, t, h \in \{Electric\ cars\} \quad (20)$$

$$P_{h,s,t}^{EV,ch,AC} \leq u_{h,s}^{Car,ch,AC} \cdot P_h^{EV,AC,max}, \quad \forall s, t, h \in \{Electric\ cars\} \quad (21)$$

$$P_{h,s,t}^{EV,ch,DC} \leq u_{h,s}^{Bus,ch,DC} \cdot P_h^{EV,DC,max}, \quad \forall s, t, h \in \{Electric\ buses\} \quad (22)$$

$$u_{h,s}^{Car,ch,AC} + u_{h,s}^{Car,ch,DC} + u_{h,s}^{Bus,ch,DC} \leq 1, \quad \forall h, s \quad (23)$$

$$\sum_h u_{h,s}^{Car,ch,AC} \leq n^{Car,ch,AC}, \quad \forall s \quad (24)$$

$$\sum_h u_{h,s}^{Car,ch,DC} \leq n^{Car,ch,DC}, \quad \forall s \quad (25)$$

$$\sum_h u_{h,s}^{Bus,ch,DC} \leq n^{Bus,ch,DC}, \quad \forall s \quad (26)$$

### F. Photovoltaic System Model

The power generated from the PV system is used as the DC and AC charging demand of EVs, which is expressed in (27).

$$P_t^{PV} = P_{t,s}^{PV,DC} + P_{t,s}^{PV,AC}, \quad \forall t, s \quad (27)$$

## III. TEST AND RESULTS

In this study, the problem that aims to charge the EVs in the EV parking lot in the most economical way is addressed in a Mixed-Integer Linear Programming (MILP) framework. The proposed methodology has been tested in GAMS environment. The input data and related results from the different case studies carried out to demonstrate the effectiveness of the proposed methodology will be discussed in the following subsections, respectively.

### A. Input Data

The power capacities of the traction and service transformers that can provide energy to the EV parking lot, which is considered to be located in the Esenler bus and metro station of İstanbul, Turkey, are 6.6 MVA and 1 MVA, respectively.

According to the EN50329 standard, a traction transformer used for train movement can be operated at 150% capacity for two consecutive hours, which is 50 percent greater than the nominal power specified on the label. Because the study discusses the most economical way to charge EVs, this operating condition is also taken into account in the optimum operating problem. It should be noted that this value was chosen to allow the transformer to operate safely without overheating.

In the study, there are 100 different electricity price scenarios within the stochastic approach, and these data are presented in Fig. 2. Electricity prices consist of actual data of Turkey's day-ahead market operated by EXIST [28], which includes data from January 1, 2020, to the next 100 days. The 15-minute production and consumption data regarding the RBE produced from the metros, the power consumption of the metro station and metro are given in Fig. 3. While the power consumption of the metro and the station is based on real data, regenerative braking data is generated through the RailSIM software using the real topology of the M1 Metro line in İstanbul.

The metro station located here is considered as the intermediate station so that the related figure includes the regenerative braking power of all trains passing here. Traction power refers only to the power drawn from the substation, excluding the other traction transformers in the rail system.

Data related to the PV production located in the EV parking lot is given in Fig. 4. The relevant data was obtained by using simulation software for the EV parking area in the Esenler bus and metro station. The month of December as the month in which energy generation is the lowest in İstanbul, Turkey, looking into the historical data, was chosen because the worst case is often taken into account for system design.

It is considered that there are 4 different types of electric cars and one type of electric bus in the EV parking lot. The technical specifications for EVs are given in Table II. Four different scenarios for EVs driving behavior are considered.

In these scenarios, the number of EVs arriving at the parking lot, the arrival/departure times, and SoE levels of EVs are taken into account as a stochastic-based approach. The arrival and departure times of EVs are generated via Weibull distribution and Kernel estimation, respectively. The detailed information about creating the scenarios is given in [29]-[31].

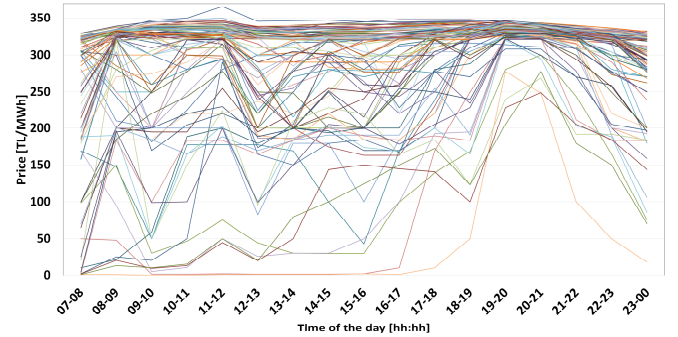


Fig. 2. Day-ahead market price scenarios (100 scenarios).

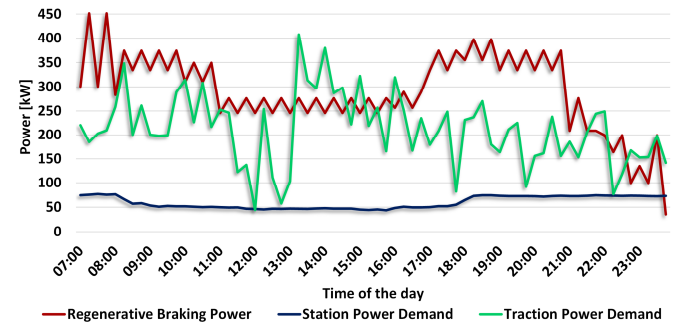


Fig. 3. Data of regenerative braking power, station and traction power demand.

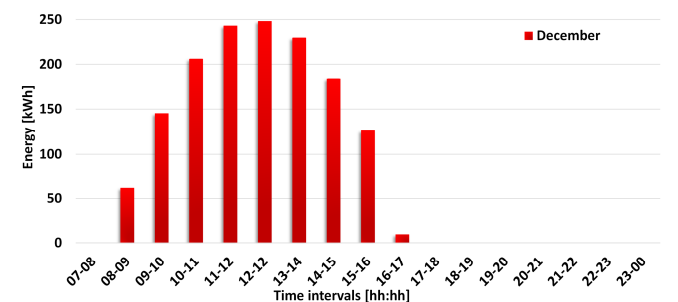


Fig. 4. Hourly energy generation of the PV system.

The real historic data including arrival/departure times extracted from the existing parking lot in Istanbul is also processed in the Weibull distribution for conducting more realistic assumptions. Furthermore, normal distribution ( $\mu=0.70$ ,  $\sigma=0.15$ ) is evaluated for randomly generating the value of the state of charge (SoC) of EVs when they arrive at the parking lot. The initial SoE of each EV is obtained by multiplying randomly generated SoC and individual battery capacity of each EV. The initial SoE used for EVs is given in Fig. 5. SoE data of the EVs that do not come to the EV parking lot is not shown.

It should be stated on the right-hand side of Fig. 5 that those with higher energy levels than others are electric buses. The EV parking lot is designed to accommodate 50 electric buses and 450 electric cars, that is, in total 500 EVs. In the scenarios, it is assumed that the EV parking lot includes 45 electric buses and 386 electric cars, at most.

It is assumed that EVs desire to leave the car park at a full charge level. There are 50 electric bus DC charge units with 120 kW, 350 electric car DC charge units with 50 kW, and 100 electric car AC charge units with power up to 7.4 kW in the EV parking lot. Besides, there is an ESS that can store RBE, and the technical specifications are given in Table III. Furthermore, the efficiency of DC-DC and AC-AC converters at the EV parking lot is taken as 0.95.

### A. Simulation Results

Five separate case studies demonstrate the feasibility of the proposed model, considering the existence of the PV system, ESS, RBE, and the operating time period of up to 150% of the nominal power of the traction transformer for 2 hours.

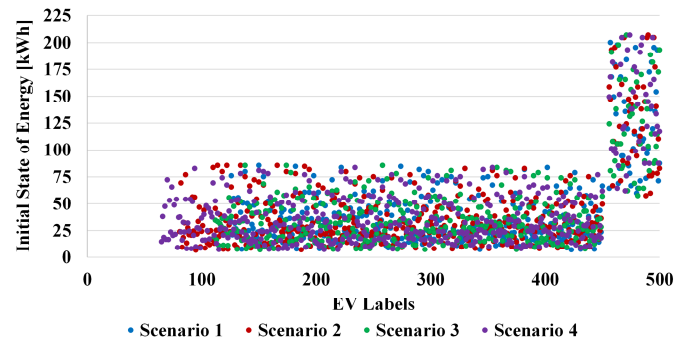


Fig. 5. Initial SoE level of EVs for all scenarios.

Features	Buses	BMW i3	Audi e-Tron	Kia Soul EV	Nissan Leaf Plus
$SoE_h^{EV,max}$	230 kWh	42.2 kWh	95 kWh	27 kWh	64 kWh
$p_h^{EV,AC,max}$	—	7.4 kW	7.2 kW	6.6 kW	7.2 kW
$p_h^{EV,DC,max}$	120 kW	50 kW	50 kW	50 kW	50 kW
$\eta_h^{EV,ch}$	0.95	0.95	0.95	0.95	0.95

Maximum battery capacity	500 kWh
Minimum battery capacity	100 kWh
Charge rate	500 kW
Charge efficiency	0.95
Discharge rate	500 kW
Discharge efficiency	0.95
Initial SoE	100 kWh

### B.1 Economic Comparison of the Results

Table IV contains the details on the case studies. Table V gives the results obtained from the case studies. According to the simulation results, the cost was the lowest (with 2121.54 Turkish Liras (TL)) in Case-1 where PV power generation is used; when RBE and ESS were also included, the most profitable situation is realized. In Case-4, the most expensive situation is where PV, RBE, and ESS were not included and the traction transformer worked between 13:00-15:00 hours above its nominal capacity, as in Case-1.

In this case, an expense of 3822.54 TL has been incurred for charging of EVs. It is seen that the period in which the traction transformer is operated above its nominal power is shifted from the range 13:00-15:00 to the range 12:00-14:00 in which electricity prices are relatively cheaper, in Case-5, so the charging cost is slightly reduced.

Hence, the presence of the PV system, ESS, and RBE had positive effects on the total cost because the best result was obtained in Case-1, in which they are all included. If Case-2 and Case-3 are compared, in order to assess the effects of the PV system, ESS and RBE on total charging cost, it can be seen that ESS and RBE are more effective in reducing the charging cost than a PV system.

### B.2 Utilization of the Regenerative Breaking Energy

The data showing how the RBE is used and the change of the energy state of the ESS in Case-1 for price scenario 39 and EV driving scenario 1, is given in Fig. 6. The RBE from the train is used in the charging of EVs and ESS. Herein, while RBE is mostly used for charging EVs, the ESS is charged in the range of 07:00-08:00, 08:30-08:45, and 23:00-00:00.

Between 12:00-13:00 and 22:00-23:00, there appears to be a decrease in the SoE of the ESS, which means that the discharged energy is used to charge the EVs. It should be highlighted that the ESS is fully charged between 08:45 and 12:00; It is discharged in the range of 12:00-12:30 and 21:45-22:45. Besides, after 23:00, the ESS is charged a small amount. This is because most of the EVs leave the EV parking lot, thus the excess energy generated from the PV system is stored.

The SoE levels of the Audi e-Tron electric car named Audi110 and Bus39 in each EV driving scenario for Case-1 are given in Fig. 7. It can be seen that each EV is charged at different times in each scenario.

Cases	PV	Working Time Above Nominal Power of Traction Transformer	ESS	RBE
Case-1	✓	13:00-15:00	✓	✓
Case-2	✓	13:00-15:00	—	—
Case-3	—	13:00-15:00	✓	✓
Case-4	—	13:00-15:00	—	—
Case-5	—	12:00-14:00	—	—

Cases	PV	ESS and RBE	Working Time Above Nominal Power of Traction Transformer	Cost [TL]
Case-1	✓	✓	13:00-15:00	2121.54
Case-2	✓	—	13:00-15:00	3409.87
Case-3	—	✓	13:00-15:00	2525.85
Case-4	—	—	13:00-15:00	3822.54
Case-5	—	—	12:00-14:00	3811.88

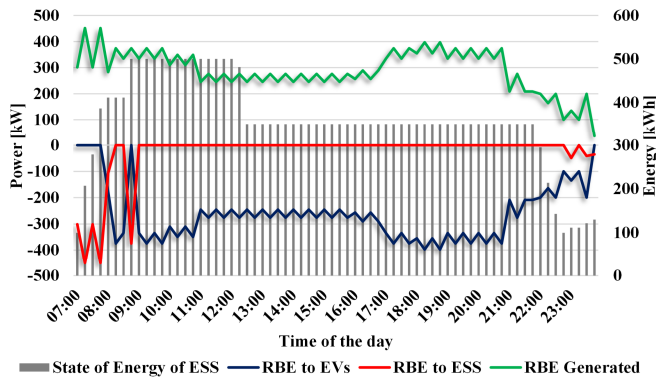


Fig. 6. Distribution of RBE usage and SoE of ESS in Case-1 for EV driving scenario 1 and price scenario 39.

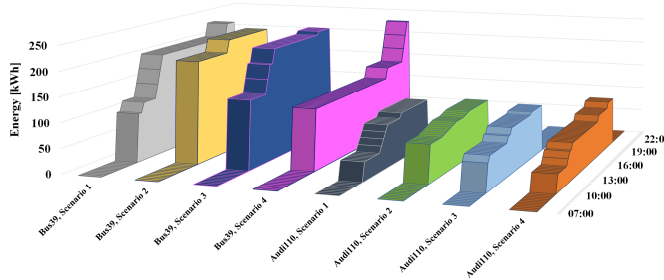


Fig. 7. SoE level of EVs selected in Case-1 for all EV driving scenarios.

The electric car is charged with the DC charging unit in Scenario 1, Scenario 3, and Scenario 4, while Bus39 is already charged with only the DC charging unit. In Scenario 2, where the EV is charged by an AC charge unit, it can be seen that the SoE level increases more linearly compared to other scenarios. Besides, in Scenario 4, EVs reached the full charge level later.

### B.3 EVs and the Related SoE Variations

In Case-1, EV driving scenario 1 and price scenario 47, the data on the DC and AC charging powers of EVs and where these energies are met are given in Fig. 8. PV, ESS, RBE, energy from traction and service transformer used to charge the EVs in the EV parking lot are shown on the positive side of the graph, while the energies consumed in AC and/or DC charging units are shown on the negative side. It should be noted that in all case studies, the power generated from the PV system is only evaluated for DC charging.

Moreover, although the traction transformer is allowed to provide power capacity above its nominal power in the range of 13:00-15:00, it does not exceed the 100% power limit. It can be stated that the traction transformer and RBE have an important share in DC charging. However, it should be underlined that the traction transformer is not used to charge EVs after 16:00.

For all case studies, 226 electric cars in Scenario 1, 270 electric cars in Scenario 2, 240 electric cars in Scenario 3, and 286 electric cars in Scenario 4 are charged at the DC charging stations, while 100 electric cars are charged at the AC charging stations. In addition, 45 electric buses are charged with DC charging power, which is the only alternative.

Fig. 9 shows the variation in SoE level of Bus40 for EV driving scenario 1 and Bus46 for EV driving scenario 2 in all case studies. It can be seen that the charging period of Bus40 is greater than Bus46 since it spends more time in the parking lot.

Therefore, a more flexible planning can be conducted for Bus40 depends on its departure time. In addition, SoE variation is remarkably similar throughout all case studies for each bus.

Further, for Cases 3, Bus40 and Bus46 reach a fully charged battery state relatively near to the time when they depart the parking lot. The data of charging powers in Case-1 and Case-4 for the electric car named Nissan Leaf 87 are given in Fig. 10. The EV was charged through the AC unit in Scenario 1 for Case-1, and in Scenario 1, Scenario 3, and Scenario 4 for Case-4, while it was charged through the DC charge unit in other scenarios in Case-1 and Case-4. All these results reveal the importance of examining different case studies and scenarios.

### B.4 Loading Conditions of Transformers

Fig. 11 shows how much power is allocated for charging EVs from traction and service transformers in Case-1, Case-2, Case-3, and Case-4.

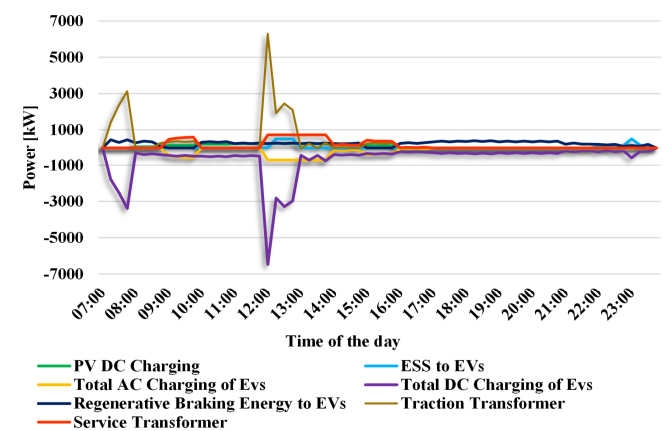


Fig. 8. Distribution of power transactions in Case-1 for EV driving scenario 1 and price scenario 47.

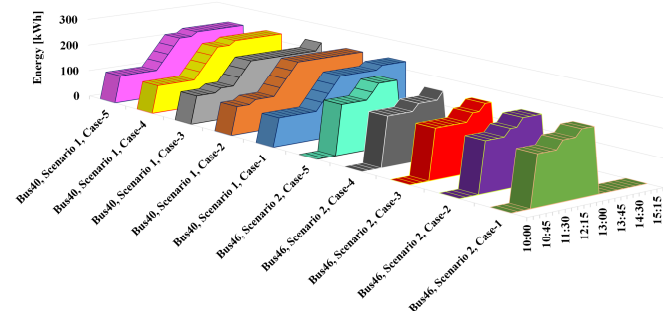


Fig. 9. The SoE variation of Bus40 for EV driving scenario 1 and Bus46 for EV driving scenario 2.

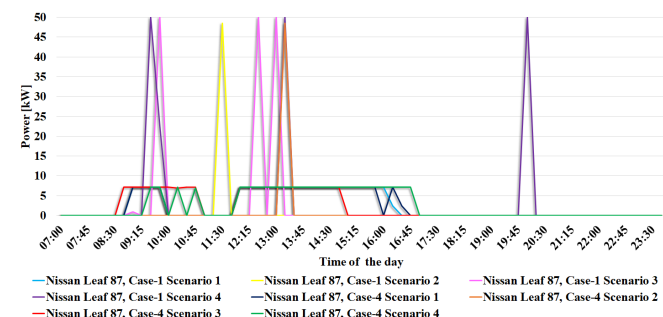


Fig. 10. Charging power of Nissan Leaf 87 in Case-1 and Case-4 for all EV driving scenarios.



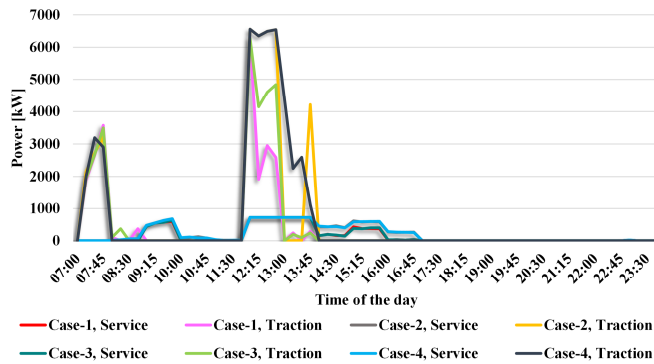


Fig. 11. Powers supplied from service and traction transformer to EVs in Case-1, Case-2, Case-3, and Case-4 for EV driving scenario 4 and price scenario 39.

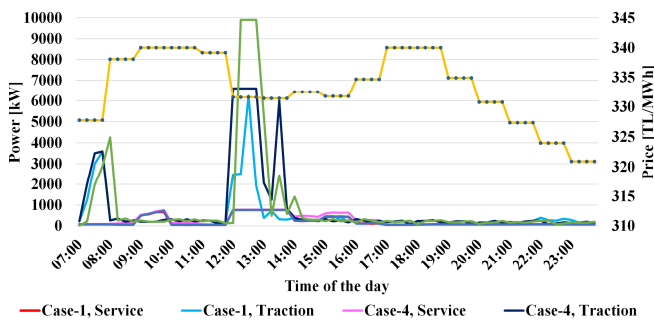


Fig. 12. Total power supplied from service and traction transformer in Case-1, Case-4, and Case-5 for EV driving scenario 3 and price scenario 15.

Herein, between the hours of 12:00-13:00, it is seen that the traction transformers provide more power in Case-2 and Case-4 than in other cases. An important result is that the traction transformer does not give power above its nominal power between 13:00 and 15:00.

The total power provided from the service and traction transformers in Case-1, Case-4, and Case-5 are given in Fig. 12. In Case-5, where the working hours of the traction transformer that can provide 150% power are shifted to the range of 12:00-14:00, after 12:00, 9.900 kW (full 150% power) was provided from the transformer. The cost of charging was reduced, as energy was purchased from the grid at relatively cheap hours. Besides, in Case-5, there is a 15-minute shift in the power provided by the traction transformer in the ranges of 07:00-08:00 and 12:00-13:00 compared to other cases.

#### IV. CONCLUSIONS

An innovative smart energy management framework was proposed in this study for integrated transportation and power system with the aim of increasing energy efficiency, decreasing carbon emission and reducing footprint of overall installations. Within the scope of the presented scheme, EVs were exploited as a storage system of the railway electrical infrastructure’s braking energy. That is, regenerative braking was aimed to be used in the EV charging located at the parking lot located nearby the train station. Also, idle capacity of internal service and traction transformers was considered as the other source for EV charging in normal operating conditions. The inherent advantages of the railway system and the renewable energy resources have been taken into consideration in developing an optimization-based strategy for the first time in the literature.

According to the results obtained, it was deduced that the use of service and traction transformers’ idle power capacity has the potential to keep installation costs low for the charging station infrastructure. Moreover, a PV equipped parking lot together with the RBE from the trains have significant impacts on reducing the operational cost of the parking lot. Last but not least, it is possible to decrease the operational cost even further by considering 150% power capacity for two hours due to the EN50329. When PV, ESS, and RBE were not considered in the proposed model, e.g. Case-4, the charging cost increased by approximately 80% compared to Case-1, which is significant. Thus, it can be indicated that the cost became lower in the studies that integrated RBE and ESS instead of PV systems. Besides, power usage on a rated power for the traction transformer resulted in a reliable power system operation. Finally, the RBE power can be considered in the cost function as well as the purchasing power through the service and traction transformers from the day-ahead electricity market in future studies. Also, the V2G option could be included into the optimal decision-making algorithm.

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