A Coordinated EV Charging Scheduling Containing PV System

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Abstract- The two main reasons for the increase in carbon emissions are the use of fossil fuel resources in the transportation and energy sector. It is possible to reduce these emissions significantly by expanding Electric Vehicles (EVs) in the transportation sector and renewable energy sources (RES) in electric power generation. While the adoption of EVs is still struggling for various reasons, such as battery costs and reduced range, rising fuel prices combined with government policy sanctions and incentives are increasing the need for EVs. The increased penetration of EVs on the grid is likely to pose a very complex operational problem. Therefore, this penetration can result in overloading of the infrastructure equipment in the distribution system and a power outage. This study focuses on the coordinated charge scheduling for EVs with a photovoltaic (PV) system as one of the Renewable energy sources for seamless integration of EVs into the grid. In this paper, charge scheduling of EVs has been made by considering the EV battery state of energy (SoE) value. Mixed Integer Linear programming (MILP) technique is used for the charge scheduling model of EVs. Thus, the charge scheduling of EVs is made within the allowable limits in the grid. It is also a systematic reference work in the proposed approach because of the load balancing of the EVs with the power supplied from the PV system.

Keywords Scheduling, monte carlo simulation, PV system, coordinated charging, load balancing.

1. Introduction

Today, the power generation and transportation sectors face various challenges related to greenhouse gas emissions, climate change and the fuel crisis [1]. People tend to prefer electric vehicles (EV) for transportation due to increasing fuel costs in the world [2,3]. Day by day, the use of EVs, which provide longer range travel, is becoming more and increasingly interesting as battery technologies improve and become cheaper. However, the increase in the number of electric vehicles on the roads increases energy demand in the distribution network [4]. Due to the stochasticity of EV users' movement behavior and charging habits, their aggregate demand in power grids remains uncertain. An EV penetration higher than expected can have negative effects such as voltage drop, power losses and overloads in the power system [5]. It was previously thought that production capacity and infrastructure could be upgraded to reduce and minimize these effects [6]. However, this approach is significant in terms of both time and cost for grid operators, EV users and homeowners.

EV chargers are classified as onboard, or off-board chargers based on the location of the battery power converter unit. While onboard chargers charge from the mains in a few hours at normal power, off-board chargers are used for fast charging at high power and in a shorter time. The maximum charging power of an EV powered by most on-board EV chargers is about 4 times the load demand of an average household [7]. The overall charging power profile of EVs has two peaks per day, based on session times at work and at home. The large energy demand from many EVs, with its addition to the baseload profile, can overload the power grid or affect the daily load profiles at a common node in the distribution line [8].

Most EV users park their vehicles for most of their daily mobility behavior. It is assumed that charging most EVs with high-battery capacities for approximately 1.7 h at 12 kW or 7 kW is sufficient to meet transportation needs [7]. This could allow flexible charging scheduling of EV charging, showing that the vehicle does not need to start charging immediately after plugging in. In this way, the charging power can be shifted to different time zones.

Various data about EVs are produced by recording EV charging session data and daily motion behavior [9]. The use of this data is critical in determining the peak load and hours of increasing EVs in the grid. [10]. Additionally, power reduction strategies can be deployed in the grid as needed, owing to the predictions made based on these data [11]. However, recording and storing these data are considered an additional network cost for distribution network operators and charging stations. Additionally, data analysis companies allow very limited or limited sharing of high-resolution EV charging session data collected from charging station and network operators due to their privacy policies [12]. For this reason, the travel data of conventional internal combustion engine (ICE) vehicle users specified in the national household travel survey (NHTS) are used instead of EV charging session data in the literature [13]. information such as arrival time and departure times of real EVs is produced by using the probability distributions of these travel data. However, the actual EV charge load profile is created by obtaining useful information from vehicle manufacturer catalogs, such as driving distance, maximum charge power and EV battery capacity [14]. Based on these catalog data, the researchers created real EV charge-load profiles with synthetic data generators [15].

Optimal EV charge scheduling using real EV charge session data [16] or synthetic data generator data [15] to create EV charge-load profiles is a potential area of study. Thus, load reduction, load limiting, and load shift strategies can be implemented for increased EV penetration in the grid. Additionally, load balancing with renewable energy sources is of great importance at this stage. In the literature, predictive load balancing of electric vehicles with an intelligent coordination has been proposed [8]. However, these tools have not yet evaluated load balancing and load scheduling together.

An optimal scheduling would operate to keep the bulk charge power of incremental EVs on the grid within allowable limits [17, 18]. Therefore, charge scheduling is a potential solution to mitigate the negative impact of large-scale EV charging demand on the grid [19]. The movement behavior of each EV user and the charging power of their vehicles can be taken as the basic parameters in charge scheduling [20, 21]. To estimate these two parameters, Monte Carlo Simulation (MCS) was used to determine the EV travel times of ICE vehicles according to a probability distribution function in the NHTS questionnaire [22, 23]. To accurately model and predict EV charge times, waiting times of EVs is generated by MCS according to NHTS probability distribution functions in this study. Additionally, real EV data are used for the initial energy states in EV batteries. Thus, it is aimed to increase the performance in EV charge scheduling with real EV battery energy states and NHTS survey data.

In this study, charge scheduling of EVs is performed using Photovoltaic (PV) based coordination. The EVs are intended to be charged on the grid under a certain power limit. Mixed Integer Linear Programming (MILP) technique [23-25] was used to model the charging demand of total electric vehicles. A coordinated charge scheduling of the PV system and EVs has not yet been investigated in the literature. This study offers the opportunity to examine the charge scheduling of PV system powered EVs at a node in a distribution grid. order for the charging power to be at the allowable level in the grid, the charge load of the EVs is always distributed within the limits. The main contributions of this article can be summarized as follows:

• Load balancing of EVs by using the PV system.

• Individual coordinated charge scheduling considers the standby times and battery energy states of the EVs.

• Introducing many EVs into the grid in one day, relative to the cap on aggregate EV charging demands on the grid.

The remainder of this paper is structured as follows: The aggregated charging demands of EVs are described in Section 2 using MCS-based waiting times and battery initial state of energy. Coordinated charge scheduling of the PV system and EVs sample IEEE test system model and simulation results are given in Section 3. Finally, the results are presented in detail in Section 4.

2. Aggregated EV Charging Demands

The increasing fossil fuel prices ensure that EVs and RES with low carbon emissions are preferred in energy and transportation [26]. Interest in environmentally friendly EVs in transportation and their charging from PV systems are increasing day by day [27]. Additionally, incentive decisions for solar PV systems and EVs in line with zero emission target countries have recently resulted in a sharp increase in EVs on the roads. However, the increasing number of EV points to many difficulties in the electrical grid. Electric vehicles can draw an average of 8 kW of power per hour in a charging session [7]. According to the load profiles of EVs, the bulk charging demands generate two peak loads, morning, and evening. Accordingly, EV charge demand management with an appropriately coordinated charge scheduling can both reduce grid overload situations of EV charging and enabling the integration of more EVs into the grid. However, the EV user charging behaviors, which include charging start time, dwell time, and energy demand, is stochastic. Therefore, this section aims to model EV user behavior to improve the performance of data-driven charge-load profiles before scheduling EVs.

2.1. Battery Charging Model and Charging Sessions for EVs

The aim of this section is to obtain with MCS each EV user mobility model based on the NHTS survey [22]. Accordingly, the EV user behavior model is based on the probability distribution function of the NHTS. The i. EV user charging behavior is included to charge start time, t_i^s waiting time, t_i^w maximum charging power P_i^{max} and expected state of energy (SOE) C_i for each EV. These charge parameters are of great importance for making decisions of EV user attend scheduling.

More specifically, when a charging session begins for an EV user, a coordinated charge scheduling tool within energy management considers the waiting time and battery SOE value to determine the energy delivery process. It is assumed that the EV users in our model drive all day of the week. The charging start time and waiting times are expressed using frequency values by time of day, as in the case studies on NHTS [28–30]. Therefore, the waiting time of the i. EV calculation can be expressed by Eq. 1 using the charging start time t_i^s and the charging end times t_i^e.

$$t_i^w = t_i^e - t_i^s \tag{1}$$

Also, the hourly instantaneous SoE value of the i. EV SoE_i^h relates to the initial state of energy of each EV battery SoE_i^{init}, the charging start time, the instantaneous charge power, P_i^{ch} and the waiting time, such that the sum of the SoE_i^h values and the initial state of energy for the i. EV gives the maximum SOE value.SoE_i^{max} The SoE_i^h and the total energy consumption for each EV are given in Eq. 2 and Eq. 3, respectively. However, the cumulative energy consumption of an EV battery is limited to the maximum battery capacity SoE_i^{max}. Additionally, it is assumed that the minimum SoE of each EV will start to charge above 20%.

$$SoE_i^h = SoE_i^{init} + \sum(P_i^{ch} \cdot t) \qquad t \in [t_i^s, t_i^s + t_i^w] \tag{2}$$

$$SoE_i = \sum SoE_i^h \qquad 0.20 \cdot SoE_i^{max} \le SoE_i \le SoE_i^{max} \tag{3}$$

Similarly, EVs are charged within the range of values specified in Eq. 4 in the coordinated charging schedule. the authors previous study was given detailed about this methodology in [31]. In the proposed method, maximum charging power P_i^{max} is used before the specified value of $SoE_i = 73\% \cdot SoE_i^{max}$ as the starting point of the constant voltage charging mode. However, the EV maximum charging power may vary within the limits of the distribution grid and the charging station. When the total SoE value SoE_i of an EV is more than 73%, the battery continues with 3.17 times the inverse function of the natural logarithm based on the actual charge data. It is assumed that the EVs plug out at the sum of the instantaneous SoE values drawn from the grid and the initial SOE values are equal to SoE_i^{max}, or at the end of their waiting time.

$$f(C_i) = \begin{Bmatrix} if\ SoE_i < 73\% \cdot SoE_i^{max},\ P_i^{ch} = P_i^{max} \\ if\ SoE_i \ge 73\%,\ P_i^{ch} = 3{,}17. P_i^{max}. \text{In}(SoE_i / SoE_i^{max}) \end{Bmatrix} \tag{4}$$

2.2. The Aggregated EV-Charging Demand Model with MCS

EV user behavior is a key determinant of stochastic EV charging demand. Users' stochastic charging behavior also makes many parameters uncertain, such as charging start times, standby times, and battery start-up SoE. At work or on arrival at home, the charging start times of EVs reach their peak value. Therefore, the approximate charging start times of the EVs appear to be a two-piece wise normal distribution after curve-fitting tool via MATLAB software.

EV users can charge their vehicles at work, in public and at home. However, studies advocating that EV users use charging behavior at home are in the majority. In this study, home charging is considered. Additionally, the arrival time of the EVs, the time to start charging and the time they stand in the park are considered as charging standby time. According to the NHTS survey [26], charging start times are expressed as a two-part normal distribution in 12-hour time periods in a day, as in Equation 5 and Equation 6. Accordingly, the curve obtained using the curve fitting method is shown in Fig. 1. Linear interpolant $f(t_s)$ equals a piecewise polynomial computed from probability where x is normalized by mean 12.5 and standard deviation 7.07. Additionally, the starting times of charge according to the probability distribution functions are presented in Table 1 by calculating the mean and standard deviation values in the form in the morning and the afternoon.

$$f(t_s) = \frac{e^{-\frac{(t_s-\mu_s)^2}{2\sigma_s{}^2}}}{\sigma_s\sqrt{2\pi}}, \quad \mu_s - 12 \le t_s \le 24 \tag{5}$$

$$f(t_s) = \frac{e^{-\frac{(t_s+24-\mu_s)^2}{2\sigma_s{}^2}}}{\sigma_s\sqrt{2\pi}},\ 0 \le t_s \le \mu_s - 12 \tag{6}$$

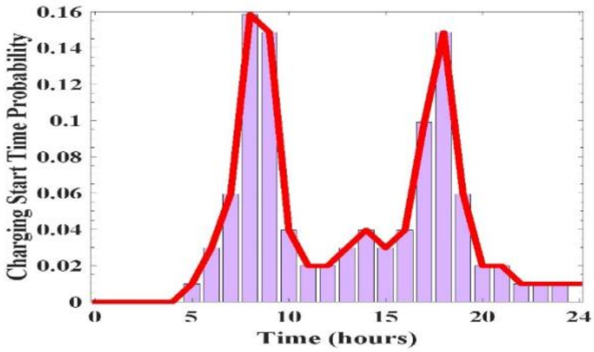

Fig. 1. The probability distribution curve of charging start time

Table 1. Calculated standard deviations and means

Time	Mean (σ)	Standard Deviation (μ)
$0 \le t_s \le 12$	8.4	1.2
$12 < t_s < 24$	18	1.33

The initial SoE value of the EVs is calculated by subtracting the battery SoE value consumed while commuting to and from the workplace from the maximum SoE value of the EVs. In [24], the probability curve of the initial SOE values of the EVs when they come to charge is a beta probability distribution with a beta value of 3.27 and an alpha value of 3.28. The probability distribution of EVs versus battery initial SoE values is shown in Fig. 2.

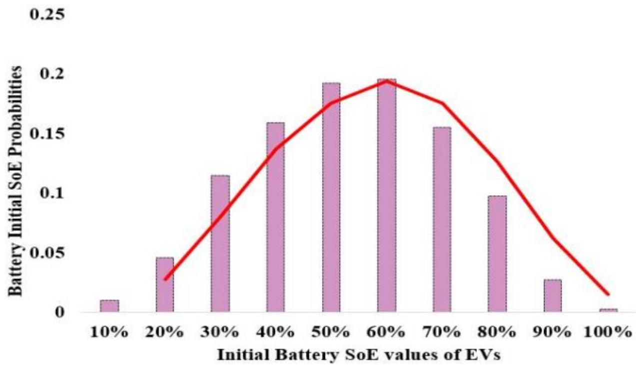

Fig. 2. The probability distribution curve of battery initial SoE

In this paper, MCS simulations are used to model the charging behavior of 50-EV users. Accordingly, it is assumed that the maximum battery capacity of all EVs is equal to 50 kWh and the charging power is equal to 7 kW. Charging sessions of EV users are sampled according to the MCS results. In this context, charging start times, standby times and first battery SoE values of 50 EVs are summarized in Table II with their standard deviation and average values. As seen from this table, the charge starts and initial battery capacities of all EVs are very close to the average and standard deviation values in the probability distribution function. In the next section, a coordinated charge scheduling will be made, considering grid, EV user and EV battery constraints, using charge start times, waiting times and initial SOE values for all EVs.

Table 2. Monte Carlo simulation results

EV Specifications at the charging sessions			
Statistical Parameters	***Morning***	***Afternoon***	***Unit of parameter***
Mean of waiting time (hours)	8.91	17.11	hours
Standart Deviations of charging start time (hours)	1.41	2.76	hours
Mean of charging waiting time (hours)	6.47	10.74	hours
Standart Deviations of charging waiting time (hours)	2.91	3.42	hours
Mean of Battery initial SoE (kWh)	26.3	24.81	kWh
Standart Deviations of Battery initial SoE (kWh)	6.94	8.44	kWh

3. Scheduling of EV Charging

The uncoordinated charging of EVs can strain the local grid without an appropriate charging scheduling strategy. That's why researchers are increasingly focusing on charge scheduling strategies to enable coordinated charging of EVs with the grid. Large-scale EV charge allocation is a challenging area of research that has yet to be resolved. This is because, as discussed in section 2, various uncertainties exist due to the behavior of stochastic EV users, such as battery state of charge, charge travel and waiting times. Therefore, it cannot be predicted exactly when the increasing EVs will generate a large power demand that exceeds the grid capacity. PV system supported charging stations can be recommended as a suitable control method for prevent these uncertainties in a way. Additionally, dynamic electricity price and EV charging times can be changed significantly during the day to take advantage of the PV system. Shifting EV users' movement habits, such as commuting and arriving times during the day, is not a flexible solution. However, performing power management with an appropriate EV charge scheduling may be one of the most effective EV charge coordination methods.

In EV charge scheduling studies, researchers have studied two main approaches, centralized and distributed architectures. decentralized architecture manages EVs [32]. The purpose function of each charging station may differ. The centralized architecture directly controls all EVs from a main control center. It also solves a single control center optimization problem. The centralized architecture has the principle of exchanging information from all EVs and centrally optimizing charging schedules. Therefore, the information privacy problem arises for centralized architectural EV owners. Also, data processing is difficult with high EV penetration. However, the distributed architecture is more flexible to control large population EV charging. In this method, the control center can communicate with the EV charger to perform coordinated charge scheduling.

Recently, distributed architecture has been studied in EV charge scheduling. Therefore, in this study, EV load scheduling was performed in a distributed architecture. In EV load scheduling, EV dwell time and battery start SoE samples are obtained by MCS considering the probability distributions of user behavior. Additionally, the charge period of each EV is cumulatively summed by considering time zones to create a realistic EV bulk charge profile based on the MCS results. This coordinated charge planning algorithm combined with EV user behavior is proposed to avoid grid overload. Additionally, charge-load balancing of EVs was ensured with the PV system having a peak power generation capacity of 60 kW. Here, the total EV charge demand cap is assumed to be 100 kW per hour. Eq. 7 defines the total charging costs of the EVs and imports them into the General Algebraic Modeling System (GAMS) software environment, along with the constraints in the previous equations. Coordinated charge scheduling adjusts the charge powers within the standby times of the EVs. Additionally, the total charging power here is reduced by balancing the load with the PV system. thus, peak occurrences in the grid are always kept within the allowable values, allowing more EVs to be integrated into the grid.

$$Minimize\ F(x) = \sum_{i=1}^{50} \sum_{t=1}^{36} X.(P_{EV}^{ch}(i,t)) \tag{7}$$

In the GAMS code, three basic components are defined as inputs, structures, and results. Data types such as scalar numbers, sets, variables, and tables are defined in the input component. As a scalar, the constant X value of the charging cost per kWh is equal to 1.5 TL. During scheduling, the t time interval is 1 h and the total t value is taken as a one-and-a-half-day period and 36-hour time zone. Thus, the sum of the instantaneous SoE values for each EV as it leaves the charging station is given in Fig. 3. The minimized energy consumption cost that all EVs will pay to the distribution company within the specified one-and-a-half-day period is equal to 1535.71 TL.

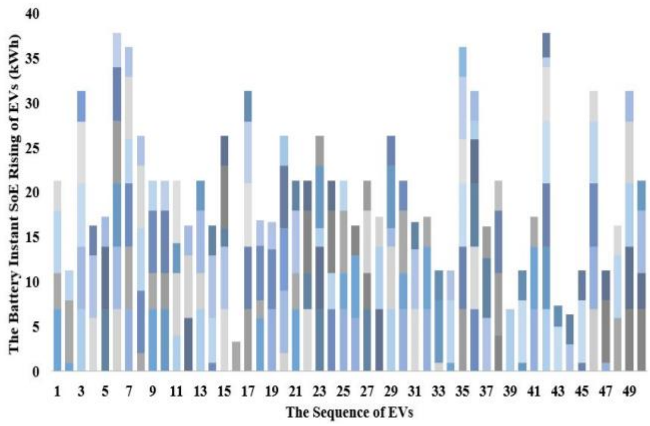

Fig. 3. The sum of the instantaneous SoE values for each EV.

The EV 16, EV 30, EV 32, and EV 49 batteries could not reach the maximum SoE value due to the short charge standby times.

3.1. IEEE 33 Test System Model and Simulation Results

The charging sessions of the EVs in a one-and-a-half-day period over the digsilent software are modeled as in Fig. 4 over the IEEE 33 busbar test system.

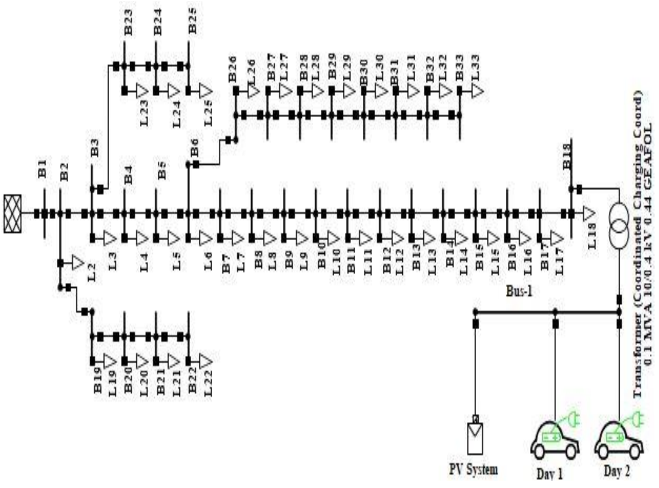

Fig. 4. Integration of EVs into the grid test system.

Performing the modeling on IEEE 33 bus test system, a transformer at a voltage level of 10/0.4 kV with a power of 0.1 MVA on bus 18 is used for the grid integration EVs. After simulation, the hourly total charging power of the EVs over a one-and-a-half-day period is shown in Fig. 5.

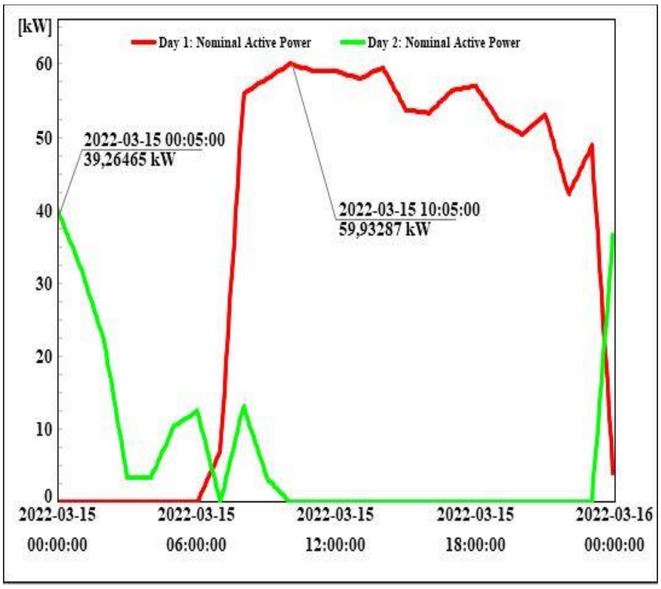

Fig. 5. The total charging power of the EVs.

In the case of uncoordinated charging without coordinated charge scheduling, the total charge demand of EVs can stochastically reach up to 350 kW at maximum power at any time. For this reason, as the total grid reaches its limit, a power outage or overload may occur in the grid equipment as a result. However, the proposed coordinated charge scheduling ensures that all EVs operate within grid allowable limits of approximately 60% of the total charge demand.

The final SoE values of each EV battery versus the charging waiting time are presented in Fig. 6 with a three-dimensional view.

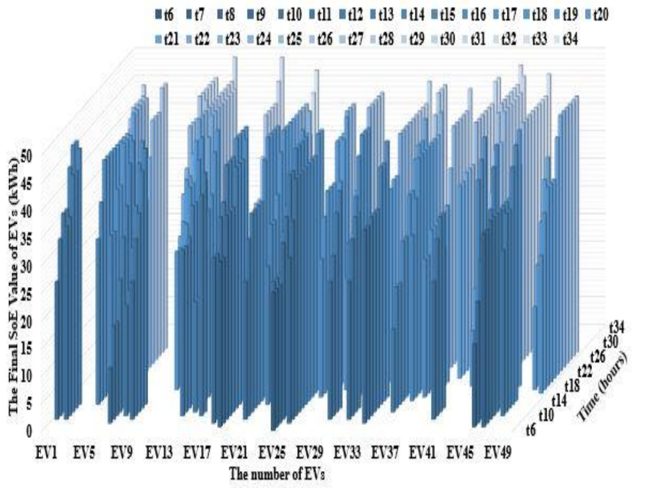

Fig. 6. The final SoE values of each EV battery versus charging waiting times.

It can be seen from Fig. 5 above that EV batteries are not always charged during their charging waiting time. Therefore, most of the waiting times between the arrival and departure times of the vehicles are spent as idle time.

3.2. Load Balancing with PV System

Coordinated charge scheduling can allow EV users to charge while the PV system is running, benefiting from a lower cost of charging. Also, the load balancing capability of the PV system, the proposed scheduling approach can further reduce the total charging demand, which is beneficial for distribution grid operators. Thus, new electric vehicles on the grid are also allowed to be charged and existing EV users will be relieved of their charging concerns and needs. In this way, a PV system with a peak power generation capacity of 50 kW [8] is connected to the busbar to which the EVs are connected in the IEEE 33 busbar test system. The power produced by the PV system in the real world and the total EV demand in the grid are given together in Fig. 7.

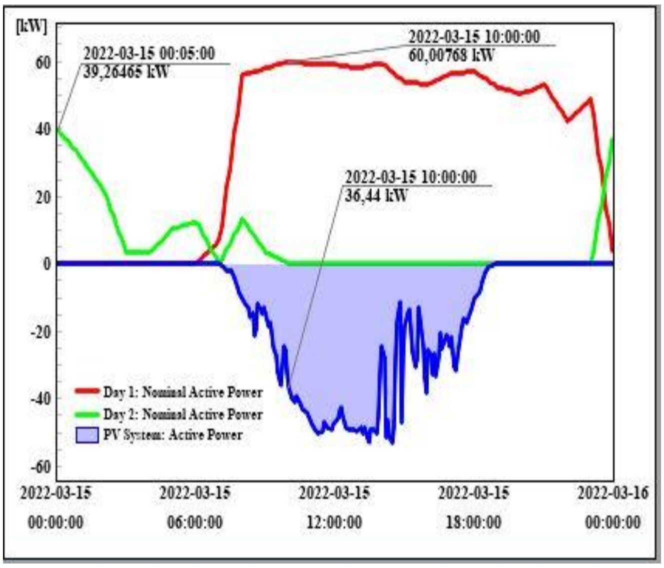

Fig. 7. The PV system generation and total charging power of the EVs.

With the load balancing capability of the PV system, the maximum peak load of the EVs was further reduced. Additionally, the load level in the distribution transformer is shifted to a different point during the day as in Fig. 8.

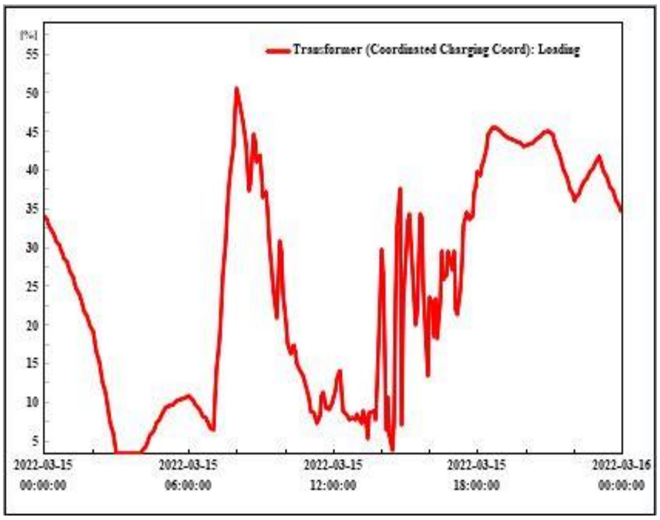

Fig. 8. The loading conditions of the transformer.

Also, this loading condition on the transformer was reduced by 10% more at peak times. As a result, with coordinated charge scheduling for EVs, the load situation on the grid can be reduced to a certain level. However, if more EVs are included in the grid, incorporating the PV system and load balancing strategy into the recommended charge scheduling prevents overloading of grid equipment such as transformers. Additionally, the power outage problems of the increasing EVs in the grid can mostly be avoided thanks to the PV system.

4. Conclusion

Recently, plug-and-charge strategies of electric vehicles have become a problem for grid operators. Charging electric vehicles with the coordinated charging schedule proposed in this study makes a great contribution to grid operators in terms of relieving the distribution grid. 50 EVs coordinated charge planning was carried out in the GAMS software using mixed integer linear programming and the EV load on the grid was reduced to 60%. Additionally, the load balancing strategy with the PV system further reduces the charge load and facilitated grid integration of new or outstanding EVs. As a result, the proposed method has the great advantage of reducing overload situations in grid equipment, allowing for greater EV integration. It is a vital work for future studies that apply both load smoothing and load balancing strategies under a single roof by making charge scheduling in coordination with the PV system.

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