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Technical Coordination of Aggregated Electric Vehicle Charging and Residential Loads at the Medium Voltage Level

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***Abstract*—Despite the coronavirus pandemic, the market share of electric vehicles (EV) has increased in recent years. For this reason, planning of new charging stations and active operation of charging stations have become more important. Studies about the integration of electric vehicles are very common, but the parameters and models adopted in these studies are simplified and analyses are made by making contradictory general assumptions. Therefore, there is a need for electric vehicle studies to be carried out with more detailed and realistic parameters. This study includes a wide range of normal and fast charging sessions and the housing demand of several customers. An aggregated charging management solution is developed, to keep the overall demand below the maximum limit at the medium voltage transformer level. This study provides a way to determine the suitability of the infrastructure or the integration challenges in the areas where the installation of parking and charging stations is aimed and proposes solutions. Initial simulation results show peaks at specific time intervals, especially in evening hours and these peaks cause overloads. To solve this problem two different methods were used. The first method is the random selection method, the second method is the sorted selection method. After the solutions are applied, high load values decrease, both worked successfully but the sorted selection method was more flexible and obtained more usable results. On the other hand, random method generally gave mix of good and bad results.**

Keywords— charging station, electric vehicle, energy management, fast charging, residential demand.

I. Introduction

The development of EVs has been considerably accelerated in the recent years. During the pandemic period, while vehicle sales have been decreased by %6, the EV sales have been increased by %41. Increasing energy storage capacity of a newly developed car, plans to ban combustion engines in some countries, deployment of fast-charging stations, and widespread use of fast charging are the main reasons for the growth of the EV industry. For these reasons, the total number of EVs is predicted to reach nearly 145 million in 2030 [1]. Due to rapid growth in the EV industry, EV charging and energy management have become an important part of the operation of electric grids.

Several closely related topics, such as integration of EVs into the existing grids, planning of new electric grid capacity expansions considering the availability of electric vehicles in the region, the construction and operation of charging stations suitable for the infrastructure of the region, the power management of charging stations, charging time and V2G applications have become more dependent on up-to-date data and a high level of details. There are research that have revealed charging behaviour based on real-time events and the observations gained during research are of importance for new studies. Otherwise, the results of these studies are limited due to the considered period, different models of EVs, a limited number of consumers (for example only people living in a certain area), and results do not provide a general scope.

There are several related studies in the literature with different methods and techniques such as real-life observation, and compilation of real-life statistics. In [2] and [3], more than 200 Nissans have been deployed across the UK and their behaviours such as start/end charging time, initial/final SOCs, etc. are observed. Another study [4] observed the distance travelled and the time elapsed between two charging events. In [2] and [3] start/end SoC and start/end charging time are important because interventions into ongoing charging sessions will be made based on these results. In [5], household electricity demand analysis was made based on real-life statistics such as the number of households, appliances, and time spent at home. These parameters make it more comprehensive and reliable. [6] is a general view of the data collected from charging stations. [6] will provide a lot of support to this study, especially about important parameters such as charging time and idle time. In [7], it is aimed to create a more effective electricity grid management by bringing together data such as fast and normal charging statistics and charging times of vehicles. In [8], certain inferences and results were formed by considering statistics such as the places where the vehicles perform the charging process according to the seasons, charging times, and waiting times. In general, it has been observed that vehicles are charged at parking stations, this study was one of the starting points in this research. In [9], the charging types of the common parking areas, the models of the charging equipment used, and the

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charging processes over the years were statistically interpreted, and inferences were made.

For EVs, a database with realistic information about all electric vehicles with characteristics such as charging time and charging capacity was used [10]. Although these data are constant for vehicles, they vary from model to model. In this way, a specific result can be obtained for each vehicle. This data from [10] is used both as an intermediate step to determine a more realistic scenario and combine normal charging and fast charging. By using the statistics and probabilities from these studies, the basis of an analysis that realistically interprets the charging behaviour of electric vehicle users and vehicle uses is constructed.

In this work, the main contributions are detailed models of EVs and a combination of the fast and normal charging events. The average consumption data of 30 houses and 11 electric vehicles simulated using the data obtained from previous studies correspond to the medium voltage level. This value is between about 1kV and 100kV. One of the goals is to reduce the overload that occurs in medium voltage networks, especially in places exceeding 100kV, by managing electricity consumption with smart grid. Aggregate residential demand and several EV charging stations overall demand is aimed to be managed at upstream network substations at the MV level. Results of this study is important to electric distribution companies because of market share has increased rapidly and users need new charging stations. Establishing new charging stations is critical for both vehicle sales and distribution companies. From the results of this study, they will be able to foresee undesired overload situations in the charging stations, and they will have solutions to instantly prevent overloads that occur after charging stations are installed. This simulation that can run different daily scenarios stochastically, using MATLAB coding and Excel simulations. In this way, companies will have the chance to foresee any situation. Results of the simulation will help generate solutions for management of electric demands by managing the EV charging system.

Section 2 presents the details of the developed EV charging, driving, and parking behaviour modelling approach. Section 3 explains the case study and presents the results. The last section discusses the findings and concludes the paper.

II. Creating Algorithm for Household and Vehicle Charging Demand Simulations

The methodology followed in the study is explained under two subsections on residential demand profile generation and EV charging profile generation respectively.

A. Residential Demand Profile Generation Methodology

In [5], there is an Excel simulation that creates dwelling load profile for a house in one day range. It is possible to select number of household, appliances, and other parameters, and assign these parameters randomly. But in our simulation, appliances were assigned randomly because, it will be more realistic and appliances rates are based on real-life statistics. 30 different house load graphs were created and repeated the same procedure for one-day period. Figure 1 shows average hourly consumption rate of 30 houses in a day. Before each simulation, appliances were randomly selected.

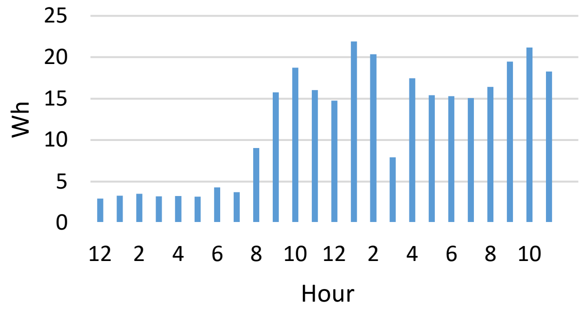

Fig.1 One day electricity consumption of 30 houses

B. EV Charging Profile Generation Methodology

In this part, MATLAB was used to write the algorithm. Many different functions were created to make it more flexible and usable. Firstly, our assumption includes 11 EVs considering market shares in the country. After models were assigned, characteristics of EVs were implemented into the MATLAB code. These characteristics were taken from [10] such as battery capacity, average power of fast and normal charging. Later, these parameters will be used to calculate final SoC values. In the second function, the initial SoC and start charging time were assigned according to [2] and [3]. 11 highest probabilities of start-charging time, initial and final SoC percentages were selected. After the selection, algorithm compares initial and final SoC. If final SoC is lower than initial SoC, goes back a step as shown in Figure 2. Next steps are calculating $t_{charging}$ and t_{end} using equations (1), (2), and (3).

$$\%\Delta SoC = \%Final\ SoC - \%Initial\ SoC \tag{1}$$

$$t_{charging} = \%\Delta SoC * t_{\text{charging time of vehicle for \%1}} \tag{2}$$

$$t_{end} = t_{start} + t_{charging} \tag{3}$$

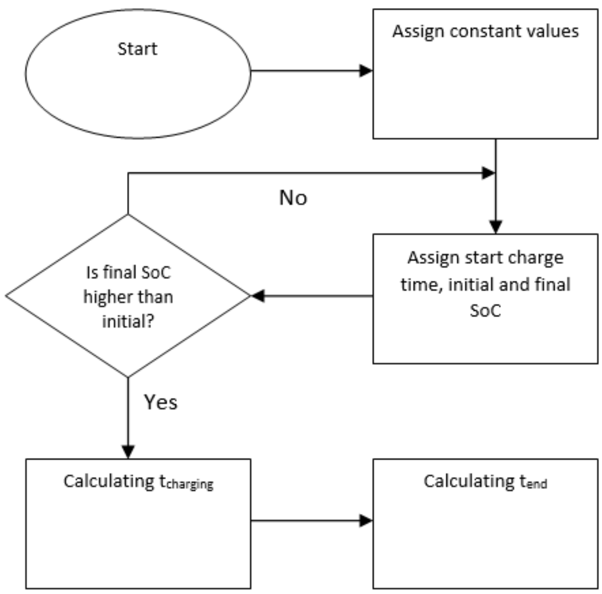

Fig. 2 Flowchart of the main algorithm

After finding t_{end} using the formulas and graphs will be drawn the slow charge. Code imports dwelling profile file which were found in II-A and combines dwelling load profile and EVs charging demand together. This process has only been done for the normal charge state so far.

C. Combination of Normal and Fast Charging Events

In this part, some data were taken from previous studies [4]. Now, some parameters will be added such as distance since the last charge event and time since the last charge event. These parameters will be used to find the SoC before fast charging starts and the percentage of charge used. Equation (4) will be used to find the SoC of vehicles just before fast charging starts.

$$P_{final} = P_{initial} - (x_{trip} * P_{consumptionperkm}) \qquad (4)$$

P_{final} is the SoC of vehicles just before fast charging starts and we set the end SoC of the fast charge to 100% and found the time elapsed between charges again using the previous equations (1), (2), (3), and data were imported from the same source [10]. One important difference here is the average power of fast charging and normal charging, the average power of fast charging is higher than normal charging and the normal charging power is 7.4kW constant. So, this time charging demands will show higher peak values. Also, there are some important points to simulation. Our scenario is considered as a one-day, so when the charging time of the vehicles exceeds 24 hours, the hours exceeded will not be included in the simulation. This is important because some slow charging scenarios may exceed 24 hours, therefore must be prevented.

III. Energy Management Methodology and General Results

A. Household and Charging Demand Results

In Figure 1, household demand data came from [5]. Thirty different household demands were obtained and repeated all procedures for one day period. All those data are different from each other, but there are certain similarities, such as increased electric consumption at the same hours. These will improve our results and make them comparable to real-life situations. Between 1 p.m. and 7 p.m. demand is higher in other time periods. Therefore, solutions must consider this period. As shown in Figure 1, the maximum household consumption is around 20kW. It is a normal level for medium voltage. Another important point here is that three electric vehicles that perform the normal charging process consume as much energy as approximately 30 houses. This is an indicator of how low household consumption is compared to the consumption of electric vehicles. Household consumption does not create an excessive load at medium voltage level by itself. However, the realization of fast charging will put a load on the system, almost twice the household consumption.

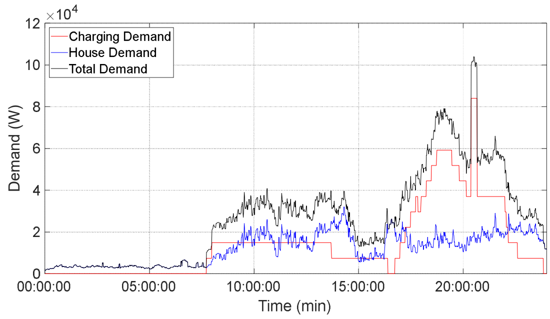

Fig. 3. Total demand, charging, demand, and house demand per minute

In Figure 3, the periods when electric vehicle users charge their vehicles and the periods when the amount of household consumption increases are the same time intervals. Especially the increase in the time intervals when more vehicles are charged, and fast charging stand out compared to other times of the day. Result of that, there are quite high peak values such as 90 kW,100kW and 110kW. As we mentioned, fast charging consumes huge energy in a short period, even if these time intervals are short, it has enough time to cause damage to the infrastructure and system due to overload. These will be the points that will be concentrated and regulated by the solutions applied. Another thing is household demand is seen as quite stable consumption. Therefore, it is necessary to solve vehicle consumption that causes the main source of overload.

In Figure 4, there are hourly charging demand graph. The situation mentioned in Figure 3 is also seen in this graph. In the evening, the charging of vehicles puts a heavy load on the grid. As can be seen in Figure 4, there is a significant difference in consumption between the hours when the charging process takes place and the hours when it is not. Hourly average consumption between 40kW and 60kW is seen in the periods where the charging process takes place.

The household consumption graph seen in Figure 5 is considerably lower than the electrical power consumed by the charging process of the vehicles at certain times. There are also some points where the average hourly household consumption is quite low compared to electric vehicle consumption. This point is very important because it is the clearest example of how electric vehicles put a load on the grid. In Figure 6, it is seen that Figure 4 and Figure 5 are overlapped. Peak times can be determined from the graph, the applications of the solutions will take place in these time intervals.

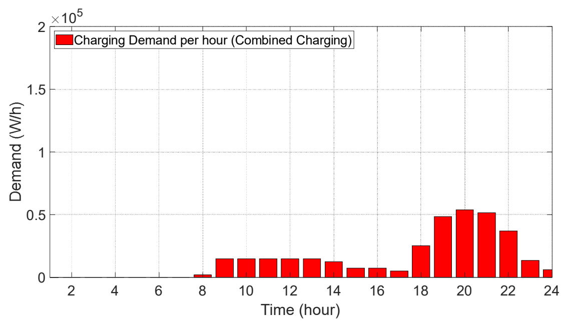

Fig. 4. Hourly charging demand

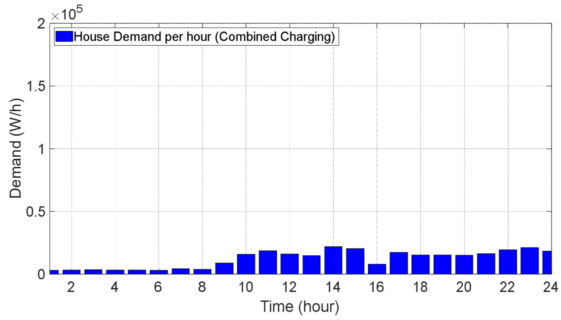

Fig. 5. Hourly house demand

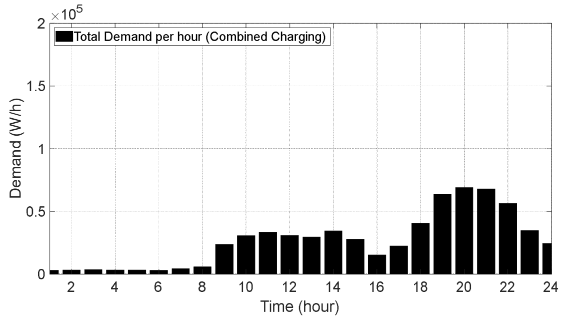

Fig. 6. Hourly total demand

In general, it is seen that there is an intensified energy use in the evening hours. Charging consumption is the main source of overload on the grid. As seen in Figure 3, general consumption peaks at points where the consumption of electric vehicles is at its peak.

B. Solution Methodology

In Figure 7, there is a flowchart showing solution steps.

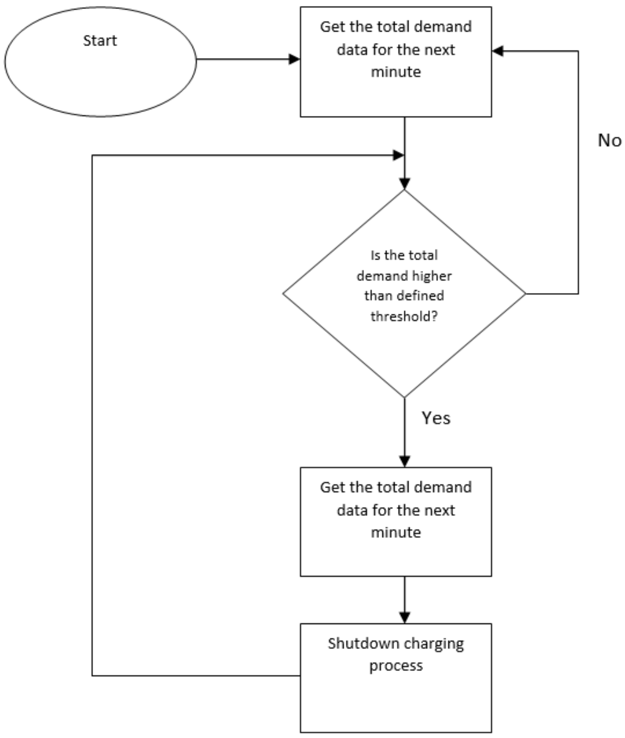

Fig. 7. Flowchart of solution idea

Code start gets total demand one by one and checks if it is higher than the threshold. If the value of total demand is higher than the threshold, checks at active vehicles and shuts down the charging process until the value of total demand is lower than the threshold. During this process, two different methods were used to determine which vehicles to stop charging. In the first method (random selection method) vehicles were selected randomly, in the other method (sorted selection method) vehicles were selected considering some parameters such as idle time and charging power.

In the random selection method, it randomly selects one of the vehicles that perform the charging process at that minute, in the minutes exceeding the stimulation threshold, and stops the charging process. This process continues until the total demand falls below the threshold value. Parameters such as charging power, parking time, and remaining charging time of the selected vehicle are not considered here. Therefore, it does not always give the best and most logical solution, and vehicles with a short time remaining for the charging process can also shut down, so it may result in a prolonged charging process.

On the other hand, in the sorted selection method, the data received in [10] were sorted in descending order according to their charge power. Although the normal charging power of all-electric vehicles is about 7.4 kW, the fast-charging power generally varies between 30kW and 50kW according to the model of the vehicle. The overloads that the fast-charging vehicles put on the network in a short time generally create an overload in the system. Therefore, the order of charging powers is one of the parameters that is considered first here. When we stop the charging process of fast-charging vehicles that are active at overload, the total demand often falls below the threshold value, so there is no need to stop the charging process of another vehicle. In this way, a more effective solution is presented by disabling less vehicles. The result of the sorted selection method is shown in Figure 8. As can be seen in Figure 8, the decrease from the threshold value is not as much as random selection method. Reason of that is fast charging shuts down first due to the sorting algorithm. The results of the random selection method are shown in Figures 9, Figure 10, Figure 11, and Figure 12. There are differences in the demands dropping below the threshold due to shutting down different vehicles each time. In cases where the decrease from the threshold value is too high, we can say that the charging process of many vehicles were shut down. The reason for that is during the overload, shutting down the normal charging process of a randomly selected vehicle is not enough alone, and fast-charging vehicle shuts down after two or three normal-charging vehicles. As an example, when normal-charging processes are shut down, 100kW consumption decreases to 93kW, 86kW, 79kW, and 71kW, respectively when these shutdowns are not enough consumption decreases to 20kW or 30kW by shutting down fast-charging vehicle. As a result, both solutions gave the desired results, but the functionality of both solutions is different from each other.

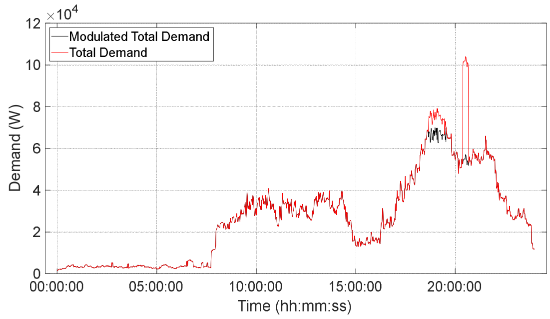

Fig. 8. Result of sorted selection method

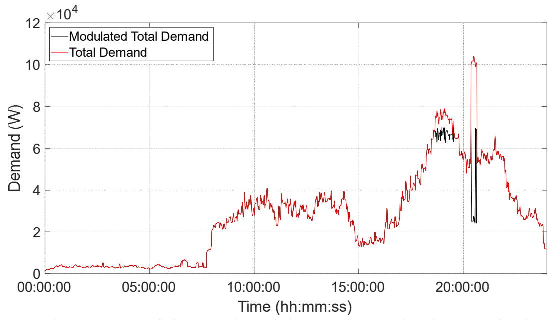

Fig. 9. One of the results of the random selection method

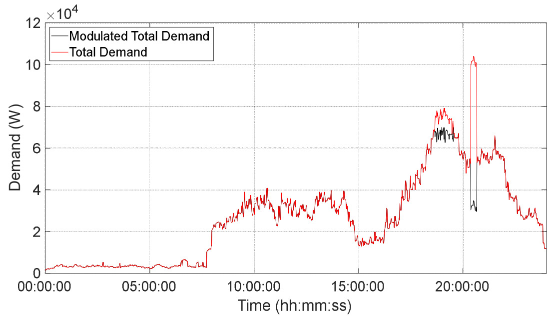

Fig. 10. One of the results of the random selection method

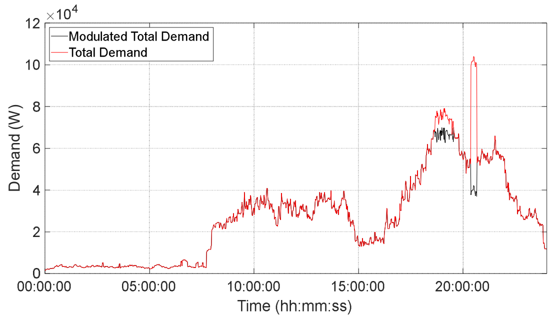

Fig. 11. One of the results the of random selection method

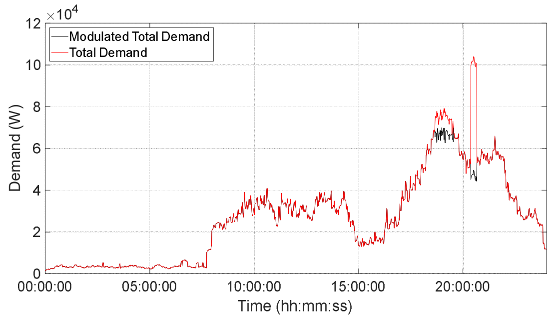

Fig. 12. One of the results of the random selection method

IV. Conclusion

This study provided insights into the joint management of household and EV consumption. According to household and EV consumption simulation results, there are some important points. Firstly, peak values occur at the same period, therefore the overlap of electric vehicles and household consumption puts an extra load on the grid. But most of the load comes from the charging of EVs. Overload problems caused by EVs charging will be solved. As shown in Figure 8, Figure 9, Figure 10, Figure 11, and Figure 12 even short-term spikes in the electric grid can damage the grid infrastructure, therefore the solutions must interfere immediately. For this reason, the fastest and most functional solution would be to stop the charging process of vehicles that are charging at the time of overload, because the electric consumption of houses is considerably lower than the charging consumption of vehicles. Two different methods were created, analysed, and compared to each other. In the random selection method vehicles were selected randomly, in the sorted selection method vehicles were selected according to their idle time, remaining charging time, and charging power. As a result, both methods achieved their goal, however, the sorted selection method is more functional than the random selection method. Because having randomness in the solution is not something to be desired in real-life. The fastest and most functional solution should be applied for daily usage. Nevertheless, sometimes the solution produced by the random selection method may be the same as the results of the sorted selection method. In ten different simulations, provided that the data we had found at the beginning, such as vehicle charging consumption and household consumption, remained the same, the random selection method provided the same result two times as the sorted selection method, whereas other results are worse than sorted selection method. This result shows that, when the data which were obtained in previous steps change, the similarity of the random selection method to the sorted selection method may also vary.

The results for the energy consumption and peak points of the electric vehicles are in parallel with the previous study [7]. Therefore, our base data which was obtained by using [2] [3] [4] [5] also contributed to the real-life usage of the study. Using the data of previous studies and obtaining the same data on some subjects with recent studies [7] proves that our study is up to date. In this way, the presented methods will be easily applied and solved first-hand, while adapting them to real-life or developing tangible applications to solve real-life problems.

Especially distribution and maintenance companies and companies investing in electricity infrastructure will be able to directly benefit from the results of this study. The simulation results of this study can be used as an additional resource for planning the new electric charging stations while planning for the population, the number of houses, and consumption in the region. However, the main goal is to ensure the use of certain charging stations and infrastructures of the region in a longer-lasting and less malfunctioning manner by using a smart grid system. In the future, systems will be developed based on the field testing of these methods, and the results of real-life applications of the two solutions will be analysed, and a more stable solution will be presented.

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