CHEMICAL ENGINEERING TRANSACTIONS

VOL. 94, 2022

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Petar S. Varbanov, Yee Van Fan, Jiří J. Klemeš, Sandro Nižetić

ISBN 978-88-95608-93-8; **ISSN** 2283-9216

DOI: 10.3303/CET2294175

Plug-in Hybrids vs Battery Powered Vehicles – Optimisation Model for Charging Infrastructure at a University Campus

Matouš Cabalka[a,*], Pavel Charvát[b], Jan Fišer[b], Pavel Popela[a], Martin Pešek[c]

[a]Institute of Mathematics, Faculty of Mechanical Engineering, Brno University of Technology, Technická 2896/2, Brno 616 60, Czech Republic
[b]Energy Institute, Faculty of Mechanical Engineering, Brno University of Technology, Technická 2896/2, Brno 616 60, Czech Republic
[c]EGÚ Brno, a.s., Hudcova 487/76a, Brno, 612 00, Czech Republic
Matous.Cabalka@vutbr.cz

University campuses, as well as other workplaces, provide great opportunity for electric vehicle (EV) charging. A simulation model was created in GAMS (General Algebraic Modeling System) for the optimization study concerning charging infrastructure at the Faculty of Mechanical Engineering at Brno University of Technology. The study was conducted for 20 plug-in hybrid electric vehicles (PHEVs) and 20 battery electric vehicles (BEVs). This assumption was based on the similar sales of PHEVs and BEVs in the EU in 2021. The PHEVs could only be charged at alternating current (AC) chargers (using the EV's built-in chargers) while the BEVs could be charged at both the AC chargers and the high-power DC (direct current) chargers. The AC chargers are much cheaper to install but because of the relatively small power of the BEV's built-in chargers the charging at AC chargers takes a long time. As the university employees have flexible working hours, varying arrival times of the EVs as well as the varying duration of their stay on the campus was considered. The state of charge (SOC) of the EV's batteries at the time of arrival on the campus was also considered. For the considered sets of parameters 3 DC chargers and 6 AC chargers covered 96 % of the total demand. A replacement of one DC charger with two AC chargers led to the decrease of coverage to 95 % but with significant reduction of capital costs.

1. Introduction

The long-term strategy of the EU to become an economy with net-zero greenhouse gas (GHG) emissions by 2050 will bring about significant changes in many sectors of the economy (Ringel et al., 2021). One of the sectors that will be significantly influenced by the net-zero emission strategy is transportation. The mitigation of greenhouse gas emissions in the transportation sector is already in progress. Main European railway lines have been electrified and public transport in cities moves toward electrification and cleaner fuels; such as natural gas and eventually green hydrogen. The main transformation, however, can be expected in the area of personal vehicles. Several major carmakers have already announced their plans to significantly reduce GHG emissions by the increased production of electric vehicles. Electrification of transportation brings about many challenges. Electric vehicles are only as clean as the electricity they use and without cleaner means of electricity production, the electrification of transportation would only transfer the GHG emissions from the transportation sector to the energy sector (Gryparis et al. 2020). In the short-term, the GHG emissions (carbon intensity) of power generation lower than 600 tCO2e/GWh are needed for the EVs to "produce" less GHG emissions than the vehicles with internal combustion engines (Kennedy, 2015). Hamels et al. (2021) conducted a critical literature review focusing on the use of primary energy factors and the CO2 intensities for electricity in the European context. The authors presented an overview of national CO2 intensities in the EU countries. The Czech Republic with the carbon intensity of 431 t/GWh was above the EU average but below the threshold presented by Kennedy (2015). The environmental benefits of EVs in the Czech Republic were shown in the study presented by Hromádko and Miler (2012). The authors used a well-to-wheel approach and reported a 56 % reduction of carbon emissions in case of an EV in comparison to a car powered by a direct injection compression ignition

Paper Received: 17 April 2022; Revised: 22 June 2022; Accepted: 22 June 2022
Please cite this article as: Cabalka M., Charvat P., Fiser J., Popela P., Pesek M., 2022, Plug-in Hybrids vs Battery Powered Vehicles - Optimisation Model for Charging Infrastructure at a University Campus, Chemical Engineering Transactions, 94, 1051-1056 DOI:10.3303/CET2294175

engine. However, the considered EV was a small four-seat car with an average energy consumption of 0.093 kWh/km.
One of the challenges, during the introduction of electric mobility, is providing a sufficiently dense network of charging stations. Customers are hesitant to buy EVs unless there is a network of charging stations and the investors are hesitant to invest into the charging network because of the uncertainties of such investments (Perera, et al. 2020). Though the public charging stations are a backbone of the EV charging infrastructure, there are other EV charging options. People spend most of their time at home and homes provide the largest time window for electric vehicle charging. In densely populated urban areas, however, the majority of the population lives in apartment buildings where it is more difficult to install EV chargers than it is in detached dwellings. For working-age people, the workplace is a location where they usually spend most time out of home. Therefore, workplaces have a significant potential for electric vehicle charging. This fact has been reflected in optimization studies published in recent years. An optimisation framework for workplace charging (WPC) strategies was developed by Huang and Zhou (2015). The authors considered three groups of employees, according to their daily commuting distances, and two types of charging technologies. The simulation case study for 10 EVs showed a 70 % total cost reduction of running WPC when optimization framework was used in comparison to a non-optimized scenario based on the DOE’s guidelines. Erdogan et al. (2021) employed integrated multi-objective optimization and a multi-criteria decision-making model for optimal planning of the workplace electric vehicle supply equipment (EVSE) configuration. The authors considered 5 types of chargers. Direct current fast charging was chosen as the best option for the considered workplace mobility pattern. Another study of the authors (Erdogan et al, 2022) focused on the smart charging strategies and the scheduling policies. The authors reported 7.8 % cost saving on the EVSE when the multi-objective model was used instead of single-objective optimal models. The authors also reported higher sensitivity of the unit costs to the scheduling than to the charging strategies. Unlike the present study, the above-mentioned studies did not distinguish between the PHEVs and BEVs when optimizing workplace charging infrastructure.

2. Problem description

The sales figures for 2021 show that about the same number of battery-electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) were sold in the EU that year (each category accounting for about 9 % of new personal vehicle sales). Both BEVs and PHEVs are generally more expensive than similar-size vehicles with internal combustion engines. As a result, BEVs and PHEVs will be, in the early stages of their market penetration, adopted by people with above-average incomes. One of such groups of potential BEV and PHEV users are tenured academic staff at universities.
Unlike BEVs, the PHEVs are not intended to operate 100 % of the time in the purely electric mode. However, in order to reduce the GHG emissions, it is beneficial when the PHEVs operate in the purely electric mode as much as reasonably possible. The PHEVs have much shorter electric driving ranges than the BEVs and thus they require more frequent charging in order to increase the distance driven in purely electric mode. This has implications for the charging infrastructure. The present study was conducted with focus on the potential situation at the Faculty of Mechanical Engineering of Brno University of Technology (FME BUT), see the campus map on Figure 1 illustrating the potential for future charging network related to parking places between the building, see shadow areas. Although the analyzed situation focuses on the particular university campus, the designed model can be generally applied.

Figure 1: The map of the FME BUT Campus buildings and related parking areas, (FME BUT).

No detail survey has yet been conducted about the daily commuting distance of the employees who park their vehicles on the FME BUT campus only expert-based considerations are given. Chiara et al. (2019) cite a questionnaire survey about the home to work driving distance reported by Politecnico di Torino. Of the 812 people working at the university, who responded to the questionnaire, 64.3 % reported a driving distance of fewer than 10 km (one way), and only 2.9 % reported a driving distance of more than 50 km. The situation at the FME BUT is not likely to differ significantly from the findings reported for Politecnico di Torino. The most important information is that the vast majority of people commuting to the university by car live within the electric range of PHEVs. The opportunity to recharge the PHEV at work (on the campus) increases the daily distance driven in the pure electric mode.

The problem considered in the present study follows the main ideas and related formal models introduced in Cabalka et al. (2021). The paper originally details ideas of the second model therein and the obtained results for the initial input data sets are presented and discussed. The model defined in Section 3 represents the keystone for the further its refinement and development of subsequent models involving uncertainty, investment planning and multistage decision structure. The basic assumptions used for the actual model design are the following ones. The basic assumptions used for the actual model design are the following ones. Two types of EV chargers were considered; DC chargers and the AC chargers. Both BEV and PHEVs are equipped with built-in chargers that can be connected to AC chargers. However, BEV can also be charged by DC chargers, which provide significantly larger charging power (shorter charging time), but DC chargers are significantly more expensive. See the charging scheme on Figure 2 that is further utilized in the model of Section 3.

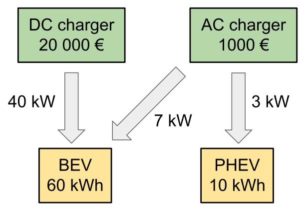

Figure 2: Charging scheme for BEV and PHEV.

3. Model description

Inspired by the previously discussed ideas, the following model Eq(1) - Eq(13) has been designed for optimal decision making about charging capacities and their distribution at the FME BUT campus:

$$\max \sum_{j\in J}\sum_{t\in\tau} y_{jt} - \sum_{t\in\tau}\frac{t}{10\cdot|\tau|+1}\cdot\left(\sum_{i\in I}\sum_{j\in J} x_{ijt}\right) - \sum_{i\in I} pen_i\cdot\left(\sum_{j\in J}\sum_{t\in\tau} x_{ijt}\right) \quad (1)$$

$$\sum_{i\in I} x_{ijt} \leq 1, \qquad \forall\, j\in J, \forall\, t\in\tau, \quad (2)$$

$$\sum_{j\in J} x_{ijt} \leq 1, \qquad \forall\, i\in I, \forall\, t\in\tau, \quad (3)$$

$$v_{ijt} = x_{ij(t+1)} - x_{ijt}, \qquad \forall\, i\in I, \forall\, j\in J, \forall\, t\in\tau, \quad (4)$$

$$v_{ijt} = v_{ijt}^{+} - v_{ijt}^{-}, \qquad \forall\, i\in I, \forall\, j\in J, \forall\, t\in\tau, \quad (5)$$

$$\sum_{i\in I}\sum_{t\in\tau} v_{ijt}^{+} + v_{ijt}^{-} \leq 2, \qquad \forall\, j\in J, \quad (6)$$

$$\sum_{t\in\tau} x_{ijt} - \delta_{ij} \geq 0, \qquad \forall\, i\in I, \forall\, j\in J, \quad (7)$$

$$\sum_{t\in\tau} x_{ijt} - (|\tau| - 1 + \varepsilon_1)\cdot\delta_{ij} \leq 1 - \varepsilon_1, \qquad \forall\, i\in I, \forall\, j\in J, \quad (8)$$

$$\sum_{j\in J} v_{ijt}^{+} + \sum_{j\in J} v_{ijt}^{-} + \sum_{j\in J} v_{ij(t-1)}^{-} \leq 1, \qquad \forall\, i\in I, \forall\, t\in\tau, \quad (9)$$

$$y_{jt} \le \sum_{i \in I} cr_{ij} \cdot x_{ijt}, \qquad \forall\, j \in J, \forall\, t \in \tau, \tag{10}$$

$$y_{jt} \ge x_{ijt} \cdot \varepsilon_2, \qquad \forall\, i \in I, \forall\, j \in J, \forall\, t \in \tau, \tag{11}$$

$$\sum_{t \in \tau} y_{jt} \le a_j, \qquad \forall\, j \in J, \tag{12}$$

$$x_{ijt}, \delta_{ij}, v_{ijt}^{+}, v_{ijt}^{-} \in \{0,1\},\ x_{ijt} \le x_{Uijt},\ y_{jt} \ge 0,\ v_{ijt} \in \mathbb{R}. \qquad \forall\, i \in I, \forall\, j \in J, \forall\, t \in \tau, \tag{13}$$

where $j \in J$ are car indices, $i \in I$ are charger indices, and $t \in \tau$ are indices of time periods. Then, x_{ijt} are binary decision variables identifying whether the car j is charged ($x_{ijt} = 1$) on the place i in time t and the related upper bounds modeling car arrivals and departures and the feasibility of charging by Figure 2 are denoted by x_{Uijt}, see Eq(13). Obviously, the car j can use at most one charger in time t, see constraints Eq(2). Symmetrical constraints Eq(3) say that charger i can be used at most by one car in time t. Subsequently, v_{ijt}, v_{ijt}^{+}, and v_{ijt}^{-} variables identify moments when the car j starts or leaves charging place i in time t, see introducing constraints Eq(4), Eq(5), and constraints Eq(6) that guarantee continuity of charging period. Then, δ_{ij} are indicator variables inspired by Williams (1999) modelling tricks, see $|\tau|$ i.e. cardinality of set τ and ε_1 value near to 0. The constraints Eq(7) and Eq(8) indicate whether the charging place i is anytime used by car j and the breaks between charging cycles are set to two time periods, i. e. thirty minutes, to let employees to have enough time to change at the charging station by constraints Eq(9). Finally, y_{jt} variables describe the amount of energy charged in the battery of car j in time t and their values are implied by constraints Eq(10) and Eq(11) where cr_{ij} in Eq(12) are coefficients allowing to set up charging capacities of AC and DC chargers in time period t, see Figure 2. In addition,ε_2 in Eq(11) represents a small positive real number identifying a minimal allowed charge within the period t. The total charged amount of energy is bounded in Eq(13) by coefficient a_j. Finally, the objective function, which value is maximized, combines 3 terms, see Eq(1). The first one represents maximization of totally charged capacity. The second term introduces penalties for delayed car charging. The third one allows selected suppression of extra (unnecessary) chargers by user chosen penalty coefficients pen_i .

4. Results and discussion

The model computations have required data preprocessing to make the test model instance smaller and easier to solve in terms of number of used variables, constraints and computational difficulty caused by binary and integer variables. First, the charging demand of a particular EV (the amount of energy an employee wants to charge that day) needs to be determined. PHEVs battery capacity is expected to be small enough such that every employee is coming to work with completely discharged battery. BEV owners are expected to come to work with at least 20 % state of charge (SOC) of the battery in order to maintain the battery capacity. BEVs with state of charge over 80 % will not be connected to any charger as they do not necessarily need to be charged as they want to maintain battery lifespan. Values a_j for BEVs are generated from $N(0.5, 0.15^2)$ and then multiplied by 60 such that the generated values from Normal distribution belong to interval $(0, 1)$ with probability almost one and after multiplication the values from interval $(0, 60)$ are obtained as it fits to a capacity of the battery to be charged. If the obtained value for particular a_j is more than 48 kWh (i.e. the j-th car is charged for less than 20 % of the battery capacity) or less than 0 kWh the value is generated again. Finally, the parameter a_j ranges from 0 to 48 kWh for BEVs. Considered working hours ranging from 6 a.m. to 8 p.m. are divided to fifteen minute periods. Further values of t_{j1} and t_{j2} denoting employee arrival to work and length of work hours were generated. The value t_{j1} is given by uniform distribution $U(1, 17)$ and then rounded down such that any employee comes to work between 6 and 10 a.m. The work hours of all employees t_{j2} come from uniform distribution $U(24, 49)$, also rounded down such that any employee works from 6 to 12 h. If the value $t_{j1} + t_{j2}$ overcomes the considered time horizon it is set to the maximum possible value of 56. All employees are assigned vector jv_{jt} of ones and zeroes where ones describe presence of the employee, where the first one is in position t_{j1} and the last one is in position $t_{j1} + t_{j2}$. Later artificial parameter m_{ij} giving the information if employee can charge at particular charging station as PHEV owners cannot charge at DC chargers was introduced. Knowledge of the presence at work and the possibility of charging cars at charging stations enabled setting upper bound on the variablex_{ijt}, as a product of m_{ij} and jv_{jt}, that is 1 if employee works and can charge at the right charging station, otherwise it is set to 0. The last introduced condition deals with the fact employee cannot connect to the charging station less than hour before leaving the university, hence the value v_{ijt}^{+} is set to zero for $t \geq t_{j1} + t_{j2} - 4$.

The aforementioned model has been repeatedly solved for two different scenarios. For both of them abovementioned computations were utilized. In addition, 40 cars (20 BEVs and 20 PHEVs) and 56 charging time periods (from 6 a.m. till 8 p.m. so 14 h and time periods per 15 min) were considered. The values of cr_{ij} were chosen by the combination of the type of charger and the type of car (40 for DC and BEV, 7 for AC and BEV, and 3 for AC and PHEV, see Figure 2). At the end, a_j. values are equal to 10 for PHEV and for BEV randomly generated by expert chosen normal probability distribution that is truncated as above. Two computed scenarios differ only by number and type of chargers that can be installed in the university parking lot - 6 AC (1 - 6) and 3 DC (- 9) chargers for scenario 1, 16 AC (1 - 16) and 2 DC (17 - 18) chargers for scenario 2 where the numbers in brackets are indices of charging stations for particular scenario.

The results of the assumed scenarios are shown in the following figures. Each block means some car is connected to certain charging station. As mentioned above in the model description, no car can be charged by more than one charging station and also the charging has to be continuous, hence different blocks describe different cars. Spaces between blocks, caused mainly by different work hours of university employees and at least thirty-minute mandatory breaks between charging, denotes no car is charged at that time.

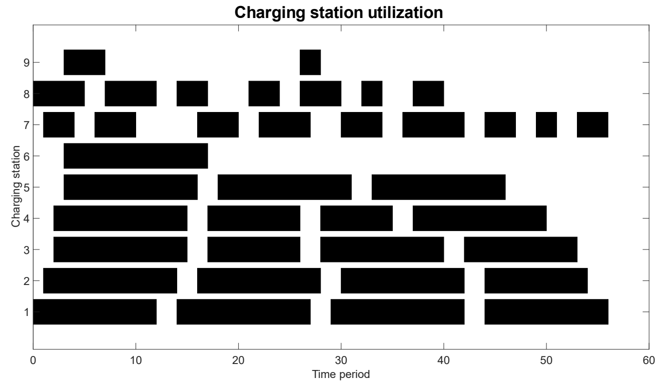

Figure 3: Gantt chart of EV charging for the first scenario.

The first studied scenario is based on higher investment in charging stations where 3 AC chargers and 6 DC charger are assumed to be installed on the university parking lot with 66,000 € total cost. All cars requiring charging were assigned to a charger and time period. In the first scenario 95.98 % of total charging demand was satisfied. Furthermore, the second, more realistic, scenario was examined as described above. Figure 4 shows that it is not necessary to install all AC chargers (indexed 1 - 16).

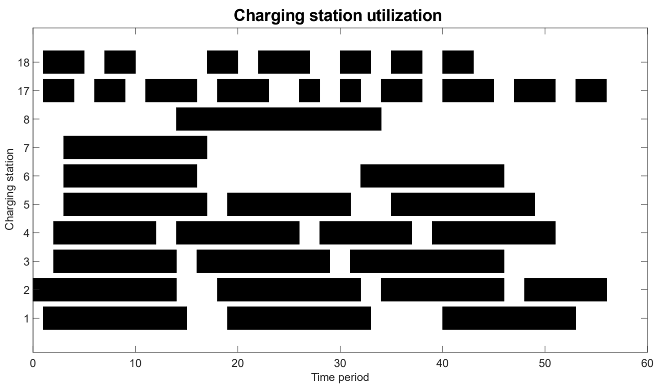

Figure 4: Gantt chart of EV charging for the second scenario.

Installed chargers in the second scenario covered 95.04 % of total charging demand. Even though the optimal solution for the second scenario comprises of installation of 10 charging stations covering 1 % less of total charging demand than the first scenario, the total savings are 16,000 €. The optimal numbers of charging stations were found by aforementioned model under an economical constraint represented by the upper bound of possible installed AC and DC charging stations.

5. Conclusions

In the beginning of the modelling and gathering data, more than eight chargers were expected to be installed because of different working hours of university employees. Optimal solutions obtained by solving the original MILP for both scenarios made our expectation quite realistic even though the fleet of forty EVs consisting of twenty PHEVs and twenty BEVs based on trend of penetration of EVs to the employees' fleet was expected. It was also shown that the installation of 6 AC and 3 DC chargers can cover almost 96 % of total charging demand, while exchanging one DC charger for two AC chargers leads to covering total charging demand slightly over 95 % with the 16,000 € savings.

It is important to emphasize the fact that the size of employees' fleet plays the key role as well as economic constraints. The further analysis will focus on the economic issues. It does not make a sense to satisfy the charging demand at any costs. An objective function would have to be formulated for the search of an optimal balance between the demand satisfaction and the total costs of charging infrastructure which will lead to utilization of a two-stage stochastic programming approach in the future modeling.

Acknowledgments

This work was supported by the project Computer Simulations for Effective Low-Emission Energy Engineering, reg. no. CZ.02.1.01/0.0/0.0/16_026/0008392 funded by Operational Programme Research, Development and Education, Priority axis 1: Strengthening capacity for high-quality research.

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