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Optimal Siting and Sizing of Electric Vehicles Charging Stations in a Logistic Network

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Abstract: In the last decade, special attention has been paid to electric vehicles and renewable resources to reduce pollutant emissions. Road transport (particularly regarding heavier, long-haul vehicles) is the sector that is required to make the greatest effort to achieve the ambitious decarbonization targets, and managers of fleets are currently planning to convert, partially or totally, their vehicles with electric or hybrid systems. In this paper, we propose a new approach for the location and sizing of charging stations in a logistics network served by heavy trucks. Logistic data from an optimal route planner are used to optimally size and locate charging stations above customers and in the depot. The proposed approach has been tested over a year using data from a real case study in Northern Italy.

Keywords: Charging Stations, Electric Vehicles, Optimal Planning, Logistics

1. INTRODUCTION AND STATE OF THE ART

To achieve climate neutrality by 2050, the European Union (EU) has set two important intermediate targets: to reduce net greenhouse gas emissions by at least 55% compared to 1990 levels by 2030 and to plant 3 billion new trees in the EU (European Commission, 2019). Moreover, as part of the 2023 revisions of the Emission Trading System (ETS) Directive, a new emissions trading system named ETS2 was created, which includes the CO_2 emissions from fuel combustion in buildings, road transport and additional sectors. Thus, transportation companies are now looking at ways of quantifying and reducing their emissions, and are planning to convert, partially or totally, their vehicles with electric, hybrid or hydrogen-based systems.

Globally, the transport sector is responsible for about 25% of the total CO_2 emissions in Europe, which around 70% depend on wheeled transport (European Environment Agency, 2024). Road transport, particularly regarding heavier, long-haul vehicles, is the sector that is required to make the greatest effort to achieve the ambitious decarbonization targets. In 2023, the total number of electric cars reached 40 million, electric car sales in 2023 were 3.5 million higher than in 2022, a 35% year-on-year increase. Sales of electric trucks increased 35% in 2023 compared to 2022, and China is the leading market for electric trucks, accounting for 70% of global sales in 2023, down from 85% in 2022.

This paper focuses on the perspective of a manager of a fleet of vehicles who wants to reduce emissions by optimizing the routes and using electric vehicles. In particular, we propose an optimization model for the optimal sizing and siting of charging stations in a logistic network, and in particular for the case in which, from a warehouse, it is necessary to deliver products to different stores. The optimization model is able to take into account the information related to the routes and decide how many charging stations (CSs) and of which types should be installed at the depot or at the stores.

In literature, several papers focus on the optimal siting and sizing of CSs for EVs transport goods. The location-routing problem has also been investigated for electric vehicles to determine optimal routes and CS locations that enable vehicles to fulfil customer delivery requests without running out of charge (Kchaou-Boujelben, 2021). Given customer demand at different network nodes and considering the limited driving range of vehicles, most models in this category involve battery state-of-charge (SOC) tracking constraints. These constraints help evaluate the remaining energy at each segment of a candidate route and decide, at each network node, whether to place a charging station (Arias et al., 2018; Hof et al., 2017).

Generally, the transportation problem in a logistic network consists in defining the optimal route assigned to each vehicle on the basis of the demands of goods at the different nodes (i.e., stores in the considered decision problem).

Vehicle Routing Problems (VRP) comprise a class of problems for solving optimisation models in which a given fleet of vehicles must serve a number of customers with the aim of minimising the total cost of transport, which may depend on the distance travelled, the time taken and the number of vehicles used for transport. There are several variants that allow the algorithm to describe different combinations and create models that fit the case study under consideration, and, in particular, in the last years attention is focused on the so-called Electric Vehicle Routing Problem (EVRP) and the Green Vehicle Routing Problem (GVRP). For example, in (Eslamipoor, 2024), the authors propose a model in which hybrid vehicles, which are powered by conventional fuel and/or electricity, are used. The work in (Al-Hanahi et al., 2024) considers a fleet of electric vehicles which, having to make certain routes, can be recharged at public charging stations and at the central depots.

Together with the studies of VRP and its variants, it is important to implement studies that enable the optimal siting and sizing of CSs. An important aspect that these algorithms must take into account is related to, as already mentioned, both the dimensioning and positioning aspect and the various factors that characterise the local power grid as it is particularly influenced by the configuration adopted. In fact, one issue that must be considered when positioning recharging areas relates to possible peaks in electrical demand that may occur and may cause problems to the public grid. In this sense, in the article (Sadeghi-Barzani et al., 2014), the authors attempt to find an optimal solution in terms of positioning and

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sizing of fast charging stations, also considering their interaction with the electric grid.
Looking further into the optimal sizing of electric vehicle CS in residential car parks, it is worth to consider the (Borhani et al., 2021) article which presents a model to optimise the number of stations and the charging strategy while reducing the investment and maintenance cost as much as possible. Although this model considers the costs associated with the installation of the different types of CS, it does not take into account those related to the connection to the distributor.
Another class of problem is the one that refers to simultaneously solving the CS location selection and EV routing optimization problems (EVCS-LRP) (Schiffer and Walther, 2017). Yang and Sun (2015) formulated an integer programming model to simultaneously decide the locations of battery swap stations (BSSs) and the route plan of EVs. Yıldız et al. (2016) developed an enhanced deviation flow refuelling location model to handle the refuelling location station problem with routing by setting a tolerable shortest routing deviation. Schiffer and Walther (2017) discussed the impact of different objective functions, such as the distance, the number of EVs and the required CSs, and the cost minimization, on the EV routing plan and CS location decisions. He et al. (2018) proposed a bi-level programming model to determine the CS locations by maximizing the routing flow and balancing the routing plan under the constraint of the driving distance. Zhang et al. (2019) introduced two resource strategies based on battery and loading capacities to determine the optimal number and locations of BSSs and the routes for the BSS location routing problem. Guo et al. (2020) developed a mathematical planning model based on user satisfaction and the detour limitations to solve the selection of service station locations and route planning for EVs.
In this paper, attention is focused on the definition of a new optimization model for the optimal sizing and siting of CSs in a logistic network, and the main contributions are:

- The formalization of an optimization problem for CSs sizing and siting that considers the optimal results of a vehicle routing problem and the calculation of energy consumption in each part of the logistic network.
- The inclusion of costs related to the connection to the distribution grid (low or medium voltage) as a function of the decision variables.
- The application to a real case study of a company that has to deliver products from a warehouse to stores.

The remaining part of the paper is divided as follows: Section 2 defines the problem, while Section 3 details the optimization model. Section 4 presents the case study, along with results and analysis. Finally, Section 5 concludes the paper.

2. THE CONSIDERED DECISION PROBLEM

The aim of this study is to design the installation of CSs in a logistic network in which it is supposed to substitute fossil-fuelled trucks with electric ones. The CSs can be installed at the depot and/or at the stores in which the products should be delivered. Supposing to use electric trucks, it is necessary to know electric trucks' routing to quantify the energy needs. To define the optimal sizing and siting of CSs, the results of the vehicles' optimal routing are input data (i.e., which vehicle serves which node). Figure 1 shows the input data necessary for the developed optimization problem that can be found applying for example the model reported in (Jafari et al., 2024).

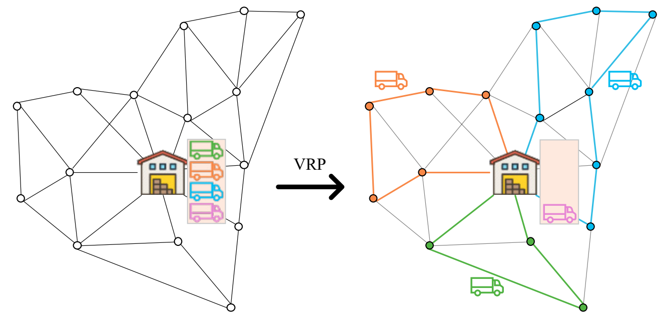

Figure 1. Vehicle Routing Problem architectural scheme

Other relevant input data are those related to each vehicle's energy consumption and at each route link. Thanks to them, it is possible to derive the energy request that should be satisfied by the different CSs in the different nodes of the logistics network, with the final aim of the optimal siting and sizing.
Specifically, in this paper, the mathematical formulation described in (Ferro et al., 2020) has been used to estimate the energy consumption of a heavy electric vehicle, which takes into account: the vehicle's total mass, including kerb mass and transported load; the gradient of the terrain; the speed that influences rolling and aerodynamic resistance; the specific characteristics of the engine and electrical equipment that influence the total efficiency of the vehicle.

3. THE PROPOSED OPTIMIZATION MODEL

The optimization model presented in this section is a mixed integer nonlinear programming model and aims to determine the optimal size and best location to meet the energy demand of the vehicles that must travel through the routes, minimising investment and operating costs. In addition to the consumptions evaluated in the previous section, it is necessary to carry out research on the main charging stations available on the market, keeping track of the power that can be delivered, the type of socket, and the cost of the infrastructure and the installation. In particular, the proposed optimization model includes different possible contracts with the distribution system operator as a function of the necessary power and meters to be installed at a specific site. The price, indeed, varies depending on the voltage at which the electricity is supplied; for example, in Italy, till 100kW, the distributor must supply the energy with low voltage (i.e., 400V for a three-phase system), while for higher values, it is supplied at medium voltage (i.e., 15 or 20kV). In the case of medium voltage supply, the connection price (power share) and energy price are lower because the voltage transformation is not the responsibility of the distributor, but of the user. It is important to consider that in addition to the power share, the installation and supply of a transformation cabin must also be considered. The price of the latter varies according to the size of the transformer to be installed, considerably affecting the total cost of the installation. The considered sets are:

- $N^{day} = \{1, \dots, N^D\}$: Set of the considered days,

- $N_d^{routes} = \{1, \dots, N^R\}$: Set of the optimal paths for each day d,
- $N^{nodes} = \{1, \dots, N^N\}$: Set of nodes of the optimal paths,
- $N^{ch} = \{1, \dots, N^C\}$: Set of the kinds of CSs that can be installed at the store,
- $N^{ch,dep} = \{1, \dots, N^{C,dep}\}$: Set of the kinds of CSs that can be installed in the depot.

3.1 The considered objective function

The objective function aims to minimise the summation of the different types of costs, as follows.

$$\min J = C^{inst} + C^{conn} + C^{en} + C^{dep} \tag{1}$$

where:
- C^{inst}: the cost of installing the charging stations in the various stores;
- C^{conn}: the cost of connecting to the national grid for each store where the infrastructure is installed;
- C^{en}: the actual cost of the electricity used;
- C^{dep} : the cost relating to the installation in the central depot.

The installation cost (C^{inst}) is given by the summation of fixed costs related to CSs and installation's works for each CS ($C_z^{cs}, C_z^{cs,w}$), multiplied by the binary variable $\sigma_{j,z}$ that is equal to 1 if CS z is installed at store j as follows.

$$C^{inst} = \sum_{j \in N^{nodes} \setminus \{1\}} \sum_{z \in N^{ch}} \left(C_z^{cs} + C_z^{cs,w} \right) \sigma_{j,z} \tag{2}$$

The connection cost (C^{conn}) to the electrical grid differs according to the type of contract stipulated (i.e., medium or low voltage). It is thus necessary to calculate the power installed at the specific site (P_j) and then to multiply it by the corresponding costs (C^{bt}, C^{mt}). A specific threshold ($\bar{P}$) is parametrized to separate low and medium voltage level. In the case in which the power required is greater than $\bar{P}$ a medium-voltage connection is necessary, the supply and installation cost of an electrical cabin (C_j^{cab}) must also be considered. On the overall, the connection costs are given by

$$C^{conn} = \sum_{j \in N^{nodes}} C^{bt} P_j \, \sigma_j^{bt} + \sigma_j^{mt} \left(C^{mt} P_j + C_j^{cab} \right) \tag{3}$$

where σ_j^{bt} and σ_j^{mt} are defined as

$$\sigma_j^{bt} = \begin{cases} 1 & if \quad P_j \le \bar{P} \\ 0 & otherwise \end{cases} \quad j \in N^{nodes}$$
$$\sigma_j^{mt} = \begin{cases} 1 & if \quad P_j > \bar{P} \\ 0 & otherwise \end{cases} \quad j \in N^{nodes} \tag{4}$$

In the proposed model, size of transformation cabin is a data of the decision problem which depends on the installed power (P_j) so that its cost (C_j^{cab}) is a piecewise constant function as

$$C_j^{cab} = \overline{C_k^{cab}} \quad for \quad \overline{P_{k-1}} \le P_j \le \overline{P_k} \quad k \in K, j \in N^{nodes} \tag{5}$$

Such that for each k-th voltage level ($\bar{P}_k$) within K number of levels, a constant value of transformation cabin cost is given. It is important to recall that the optimal siting of charging stations takes as an input the routes of vehicles that have to deliver material to stores. Thus, each route i is associated to each store j. Defining $t_{i,j,d}$, as charging time of vehicles of route i in charging station at store j in each day d, the overall energy consumed is given by the installed power P_j multiplied by $t_{i,j,d}$. Then, it is necessary to multiply the energy consumed by the unit cost ($C^{en,bt}$ or $C^{en,mt}$) and the binary variable (σ_j^{bt} or σ_j^{mt}) that considers low and medium voltage cases. The model considers energy consumed data for all the days, thus, the overall cost is given by

$$C^{en,tot} = \sum_{y \in [1,Y]} \frac{C_y^{en}}{\left(1+d\right)^y} \tag{6}$$

where

$$C_y^{en} = \frac{N^{op}}{N^D} \sum_{d \in N^{day}} \sum_{i \in N^{routes}} \sum_{j \in N^{nodes}} P_j \, t_{i,j,d} \left(C^{en,bt} \sigma_t^{bt} + C^{en,mt} \sigma_t^{mt} \right)$$

and:
- $C^{en,bt}$ [€/kWh]: Unit low voltage energy cost,
- $C^{en,mt}$ [€/kWh]: Unit medium voltage energy cost,
- N^D [day]: Number of considered days,
- N^{op}[day]: Number of operative days in one year,
- y: discount rate.
- Y: number of years considered.

Regarding the installation costs at the depot, considering that several CSs can be installed in the depot and even of the same type, the variable $n_z^{cs,dep}$ has been introduced to quantify the number of CS of each type considered, and multiplied by the cost of the charging station c_z^{cs} and installation costs $c_z^{cs,w}$ as

$$C^{dep} = \sum_{z \in N^{ch}} \left(c_z^{cs} + c_z^{cs,w} \right) n_z^{cs,dep} \tag{7}$$

3.2 Model constraints

Different kinds of constraints should be taken into account. The total power available in each store is given by the summation of the known nominal power for the z-th charging station P_z^{cs} multiplied by the binary variable representing the presence of the CS at store j ($\sigma_{j,z}$). That is

$$P_j = \sum_{z \in N^{ch}} P_z^{cs} \, \sigma_{j,z} \quad j \in N^{nodes} / \{1\} \tag{8}$$

The total number of charging stations in each store can't overcome a maximum number $\overline{N_j^{cs}}$ due to territorial characteristics.

$$\sum_{z \in N^{ch}} \sigma_{j,z} \le \overline{N_j^{cs}} \quad j \in N^{nodes} / \{1\} \tag{9}$$

As regards the depot, different charging the power installed at the depot is given by the summation of the necessary power P_i^{dep} that serves all routes.

$$P_1 = \sum_{i \in N^{routes}} P_i^{dep} \tag{10}$$

The power that can be delivered to each vehicle that serves each route depends on the fact if a charging station is associated to a specific route. A binary variable is defined ($\sigma_{i,z}^{dep}$), equal to 1 if the z-th CS is related to route i, and 0 otherwise, and a continuous parameter ($P_z^{cs,dep}$) as the known power that can be delivered. Thus P_i^{dep} is given by

$$P_i^{dep} = \sum_{z \in N^{ch}} P_z^{cs,dep} \sigma_{i,z}^{dep} \quad i \in N^{routes} \tag{11}$$

It is important to note that only 1 charging station can be associated to a route, thus

$$\sum_{z\in N^{ch}} \sigma_{i,z}^{dep} \le 1 \quad i\in N^{routes} \tag{12}$$

Moreover, the number of charging stations in the depot is equal to

$$n_z^{cs,dep} = \sum_{i\in N^{routes}} \sigma_{i,z}^{dep} \quad z\in N^{ch} \tag{13}$$

If a CS is installed in the stores, there must be a low or medium voltage connection with the national grid, thus

$$\sum_{z\in N^{ch}} \sigma_{j,z} = \sigma_j^{bt} + \sigma_j^{mt} \quad j\in N^{nodes}/\{1\} \tag{14}$$

Elsewhere, i.e. if no CS is installed, the charging time is equal to zero for both depot and stores.

$$t_{i,1,d} - M \sum_{z\in N^{ch}} n_z^{cs,dep} \le 0 \quad i\in N^{routes}, d\in N^{day} \tag{15}$$

$$t_{i,1,d} - M \sum_{z\in N^{ch}} \sigma_{j,z} \le 0 \quad i\in N^{routes}, d\in N^{day}, j\in N^{nodes}\backslash\{1\} \tag{16}$$

where M is a big number. The charging time in the store is limited by a maximum value $T_{j,d}^{max}$ calculated a-priori, and the charging time must have positive values. That is,

$$0 \le t_{i,j,d} \le T_{j,d}^{\max} \quad i\in N^{routes}, d\in N^{day}, j\in N^{nodes}\backslash\{1\} \tag{17}$$

The constraints related to each vehicle battery and power exchange are

$$soc_{i,j+1,d} = soc_{i,j,d} + t_{i,j+1,d} P_{j+1} - E_{i,j,d}$$
$$i \in N^{routes}, d \in N^{day}, j \in N^{nodes} \tag{18}$$

$$\underline{SOC} \le soc_{i,j,d} \le \overline{SOC} \quad i \in N^{routes}, d \in N^{day}, j \in N^{nodes} \tag{19}$$

where $soc_{i,j,d}$ [/] is the vehicle state of charge, $E_{i,j,d}$ [kWh] is the energy used at previous arc ($j \rightarrow j+1$), $\underline{SOC}$ and $\overline{SOC}$ [/] are vehicle state of charge lower and upper limits. To ensure the success of the considered route, the state of charge of the vehicle at the departure node $soc_{i,j}$ must be higher than the estimated energy $E_{i,j}$ used in the considered arc as follows:

$$soc_{i,j,d} \ge E_{i,j,d} \quad i \in N^{routes}, d \in N^{day}, j \in N^{nodes} \tag{20}$$

The initial state of charge $SOC_{i,1,d}$ of each vehicle in the departure node $(i, 1)$, which is the depot, is equal to the energy supplied in the central depot ($P_i^{dep} t_{i,d}^{dep}$) to which the arrival status SOC^{in} from the previous trip has been added. That is,

$$soc_{i,1,d} = SOC^{in} + P_i^{dep} t_{i,d}^{dep} \quad i\in N^{routes}, d\in N^{day} \tag{21}$$

Moreover, a maximum recharging time limit on vehicles parked in the depot is formulated as:

$$t_{i,d}^{dep} \le T^{\max,dep} \quad i\in N^{routes}, d\in N^{day} \tag{22}$$

Finally, in the optimization problem the function to be minimized is (1) s.t. constraints (2)-(22).

4. CASE STUDY

The application of the proposed model is used to study the possibility of converting a company's vehicle fleet to electric propulsion only, assessing the required investment to enable this replacement and optimizing decisions on the needed charging infrastructure. The considered logistic network is composed by 1 central depot and 24 stores, and 3 different kinds of electric trucks are considered and used to supply the goods from the depot to the stores. The problem has been implemented by using the software LINGO on an AMD Ryzen 7 5800H 3.2 GHz with 16GB RAM.

4.1 Input data

To model the problem, the information related to the number of items needed by the considered store is converted into the number of pallets, which have standard dimensions and that allow to estimate the right type of truck to use. Assuming pallet capacity of 400kg, the daily number of pallets needed by each store are shown in Figure 2, as average over the entire year 2023. A worst-case scenario is considered by analysing five representative days with highest demand for goods and greatest number of shops to be supplied, thus requiring the vehicles to travel a longer distance.

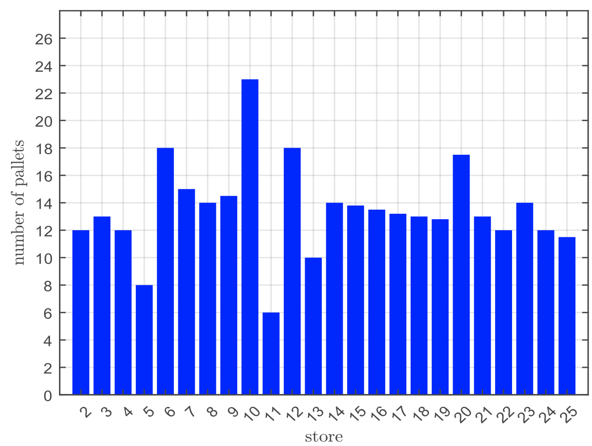

Figure 2. Average number of supplied pallets per day for each store

The VRP model, using data related to position and demand of each store, time windows and traveling times, minimizes the associated costs and distances of the logistic network. Optimal routes are, thus, returned as outputs encompassing the type and number of EVs needed and their arcs between stores.

Figure 3 and Table 1 show an example of optimal routing results. In Figure 3, results for day 1 are shown, and 7 optimal routes are depicted. For each route, Table 1 shows: the total distance related to the entire route, the amount of related electrical energy consumed in [kWh], and the unitary consumption, which is the amount of energy that is needed to travel 1km, measured in [kWh/km].

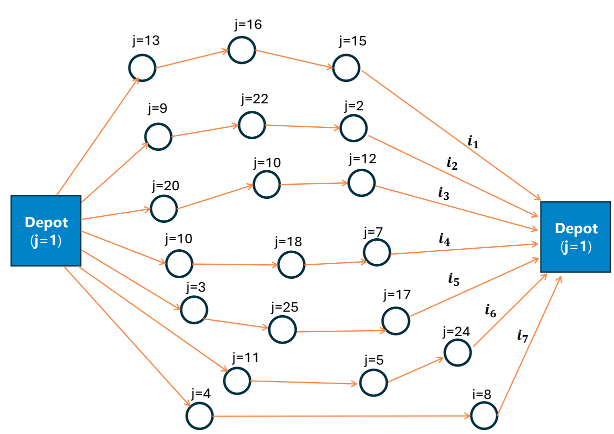

Figure 3. Optimal routes used as inputs – day 1

Table 1. Example of data from optimal routes energy assessment

Optimal route (i)	Total energy [kWh]	Total distance [km]	Consumption [kWh/km]
1	688	515	1.34
2	691	505	1.37
3	157	104	1.51
4	405	301	1.35
5	439	326	1.35
6	244	183	1.33
7	457	357	1.28

The estimation of routes energy consumptions, take several parameters into account, among which the most relevant are distance, slope and total vehicle mass is performed as in (Ferro et al., 2020). The resulting unit consumption can vary among different routes.

Figure 4 shows the consumption in relation to the distance travelled for all the considered days. As an example, on the first day considered, which results are shown in Figure 4, it can be seen that the longest journey, that is route i_1, is not characterised by the highest consumption: the reason is that the route is characterize by a higher load of the truck and the slope of the road is not completely flat.

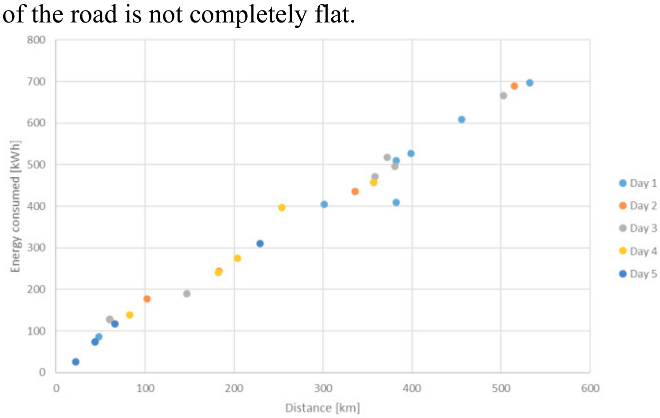

Figure 4. Total energy consumed related to entire routes

As for power level threshold, between low and medium voltage ($\bar{P}$), a value of 100 kW is used.

4.2 Optimization results

Considering that an initial SOC of the vehicles was assumed to be 70kWh (a little more than 10% of the battery vehicle capacity), and analysing the results of the energy consumption calculation, it can be seen that it is not strictly necessary to recharge the vehicle entirely in the depot, but that this is more convenient. In fact, if a vehicle was not fully charged it could still make the first few arcs but would need to use an intermediate recharge at some store on the route, but this would be more expensive. The convenience of choosing the central depot for recharging depends on the costs of civil and electrical works, mainly due to the cost of installing the transformer station. The choice of recharging in shops, taking into account of the shorter time available compared to the hypothesis based on the central depot, would require the use of high-powered charging stations and therefore a medium-voltage supply. The medium-voltage supply, while costing less in terms of unitary connection costs (€/kW) and energy consumption (€/kWh), requires the installation of a transformer cabin, which has a significant impact on the overall investment costs of the charging station.

As shown in Figure 5, in the case of the depot the required power exceeds 100kW and therefore requires the installation of a transformer cabin, thus the investment is less impactful as it is spread over several charging stations.

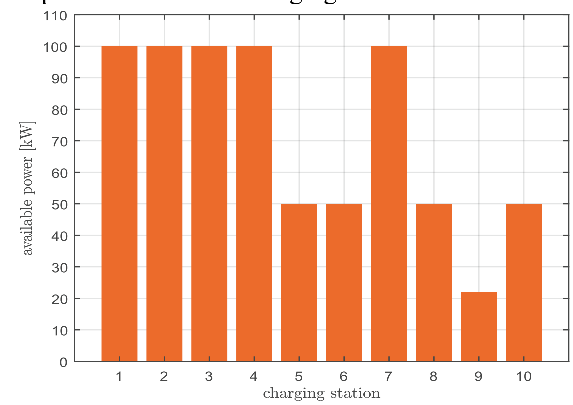

Figure 5. CS optimally installed power at the depot

Analysing the energy consumption, it is possible to notice that most of it does not exceed the maximum battery capacity of the vehicle in question, such as 550kWh. For this reason and because of the economic issues described above, it appears that the installation of the charging infrastructure in the stores should only be carried out in those stores where it is strictly necessary to allow the vehicles to complete the route, which is in store number 15, which needs to be refuelled 3 days out of the 5 considered.

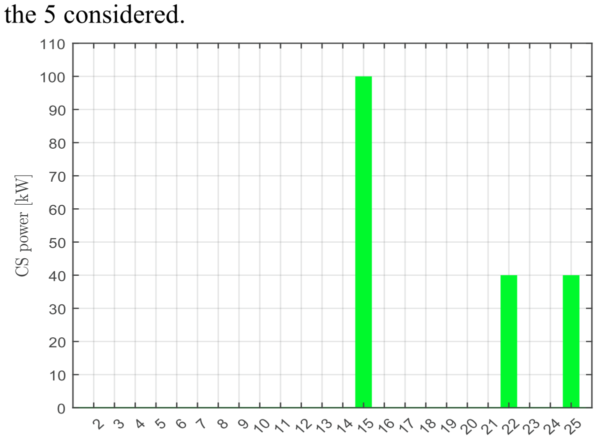

Figure 6. Charging station installed power in the stores

In Figure 6, the types of CS to be installed in the nodes of the logistics network are shown, precisely on the x-axis the 24 stores considered are indicated, while on the y-axis the power is displayed, which identifies the charging station to be installed in order to complete the predefined routes. The runtime for the proposed instance is about 15 mins.

5. CONCLUSIONS AND FUTURE DEVELOPMENTS

This paper introduces a novel approach for determining the optimal location and sizing of charging stations within a logistics network. The key innovation lies in leveraging logistics data from an optimal route planner to strategically place and size charging stations at customer locations and the depot. The proposed method has been validated over a year using real-world data from a case study in Northern Italy. Numerical results indicate that full recharging at the central depot is not possible, but it would be more cost-effective compared to intermediate charging at stores, which are required by VRP output. This is due to the high installation costs, which increase in case of medium-voltage supply.

Future developments will be related to the simultaneous routing and optimal location of CSs in a logistic network.

REFERENCES

Al-Hanahi, B., Ahmad, I., Habibi, D., Pradhan, P., Masoum, M.A.S., 2024. A Charging Strategy for Large Commercial Electric Vehicle Fleets. IEEE Access 12, 46042–46058. https://doi.org/10.1109/ACCESS.2024.3382219

Arias, A., A., J., Granada Echeverri, M., 2018. Integrated planning of electric vehicles routing and charging stations location considering transportation networks and power distribution systems. International Journal of Industrial Engineering Computations 9. https://doi.org/10.5267/j.ijiec.2017.10.002

Borhani, A., Ouadi, H., Najoui, M., 2021. Optimal Sizing of Electric Vehicle Charging Stations in Residential Parking, in: IECON 2021 – 47th Annual Conference of the IEEE Industrial Electronics Society. IEEE, Toronto, ON, Canada, pp. 1–6. https://doi.org/10.1109/IECON48115.2021.9589453

Directorate-General for Climate Action, European Commission, 2019. Going climate-neutral by 2050 – A strategic long-term vision for a prosperous, modern, competitive and climate-neutral EU economy. Publications Office. https://doi.org/doi/10.2834/02074

Eslamipoor, R., 2024. Direct and indirect emissions: a bi-objective model for hybrid vehicle routing problem. Journal of Business Economics 94, 413–436. https://doi.org/10.1007/s11573-023-01168-2

European Environment Agency, 2024. Road transport.

Ferro, G., Paolucci, M., Robba, M., 2020. Optimal Charging and Routing of Electric Vehicles With Power Constraints and Time-of-Use Energy Prices. IEEE Transactions on Vehicular Technology 69, 14436–14447. https://doi.org/10.1109/TVT.2020.3038049

Guo, F., Huang, Z., Huang, W., 2020. Integrated location and routing planning of electric vehicle service stations based on users' differentiated perception under a time-sharing leasing mode. Journal of Cleaner Production 277, 123513. https://doi.org/10.1016/j.jclepro.2020.123513

He, J., Yang, H., Tang, T.-Q., Huang, H.-J., 2018. An optimal charging station location model with the consideration of electric vehicle's driving range. Transportation Research Part C: Emerging Technologies 86, 641–654. https://doi.org/10.1016/j.trc.2017.11.026

Hof, J., Schneider, M., Goeke, D., 2017. Solving the battery swap station location-routing problem with capacitated electric vehicles using an AVNS algorithm for vehicle-routing problems with intermediate stops. Transportation Research Part B: Methodological 97, 102–112. https://doi.org/10.1016/j.trb.2016.11.009

Jafari, M.J., Ferro, G., Magni, A., Mereu, A., Minciardi, R., Paolucci, M., Robba, M., 2024. Optimizing a Capacitated Vehicle Routing Problem with Scheduled Arrival, Split Deliveries within Time Windows and Emission Consideration. IFAC-PapersOnLine 58, 180–185.

Kchaou-Boujelben, M., 2021. Charging station location problem: A comprehensive review on models and solution approaches. Transportation Research Part C: Emerging Technologies 132, 103376. https://doi.org/10.1016/j.trc.2021.103376

Sadeghi-Barzani, P., Rajabi-Ghahnavieh, A., Kazemi-Karegar, H., 2014. Optimal fast charging station placing and sizing. Applied Energy 125, 289–299. https://doi.org/10.1016/j.apenergy.2014.03.077

Schiffer, M., Walther, G., 2017. The electric location routing problem with time windows and partial recharging. European Journal of Operational Research 260, 995–1013. https://doi.org/10.1016/j.ejor.2017.01.011

Yang, J., Sun, H., 2015. Battery swap station location-routing problem with capacitated electric vehicles. Computers & Operations Research 55, 217–232. https://doi.org/10.1016/j.cor.2014.07.003

Yıldız, B., Arslan, O., Karaşan, O.E., 2016. A branch and price approach for routing and refueling station location model. European Journal of Operational Research 248, 815–826. https://doi.org/10.1016/j.ejor.2015.05.021

Zhang, S., Chen, M., Zhang, W., 2019. A novel location-routing problem in electric vehicle transportation with stochastic demands. Journal of Cleaner Production 221. https://doi.org/10.1016/j.jclepro.2019.02.167