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Mobile EV Charging: Design, Optimization and Evaluation of Battery-Integrated Robots to Improve Electric Mobility

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***Abstract*—This study explores the potential of mobile charging systems to overcome the challenges of traditional Electric Vehicle (EV) charging infrastructures, such as the scarcity of charging points, lengthy charging times, and urban space constraints. It introduces an autonomous mobile system tailored to satisfy daily charging demands in various conditions, presenting a flexible alternative to fixed charging stations.Through an optimization process, the operational effectiveness of a robot-like mobile charging system is assessed under different grid capacities and battery configurations. The results indicate that these systems can significantly reduce peak grid demand and improve the charging experience by increasing availability and reducing waiting times. Profitability varies with seasonal changes and grid capacity. A switchable battery configuration, which utilizes fewer carriers to mobilize batteries, is shown to lower investment costs and boost financial returns when compared to traditional charging poles, making mobile charging systems a viable and efficient solution to meet the increasing demands of urban EV charging.**

***Index Terms*—Electric Vehicles, Mobile Charging, Optimization**

I. Introduction

The escalating climate crisis, highlighted by a record 36.8 $GtCO_2$ in global carbon emissions in 2022, underscores the urgent shift toward sustainable technologies and policies. The transport sector, a significant contributor with 7.95 $GtCO_2$ emissions, necessitates rapid advancements in sustainable mobility [1], [16]. The Paris Agreement aims to limit the temperature rise to below 2°C, driving initiatives like the EU's plan to eliminate the sale of new internal combustion engine vehicles by 2035 [2], [3]. While electric vehicles (EVs) are pivotal in this transition, there are certain challenges in developing sufficient charging infrastructures.

Collaborative efforts are essential to scale and enhance charging infrastructure, aiming to make EVs more accessible. The European Automobile Manufacturers' Association proposes installing 7 million charging points by 2030, facing a significant financial challenge [4], [24]. This underscores the need for sustainable business models that minimize reliance on public funding.

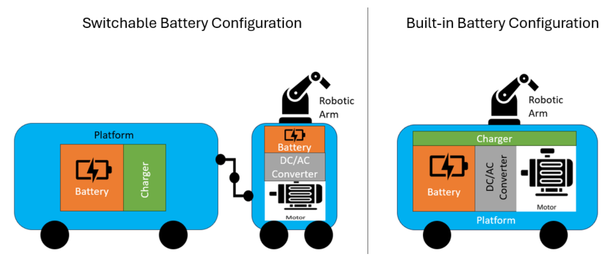

Fig. 1: General layout of the Switchable and Built-in Battery configurations

Challenges persist, notably in urban areas where space is at a premium and the growing number of EVs may lead to significant spatial demands. Moreover, the need for fast charging introduces additional complications, including heavy cable management and substantial grid impacts, potentially leading to voltage drops and grid instability [5], [6], [9], [17], [18].

Innovations such as mobile EV charging systems are emerging to address these needs by providing flexible, scalable, and efficient charging solutions, reducing reliance on fixed charging stations, and integrating seamlessly with urban infrastructure and smart grids [6], [7], [9], [18]–[21]. Mobile EV charging systems present a strategic alternative, enabling better utilization of urban space and enhancing grid flexibility. These systems can operate as mobile energy storage units, absorbing surplus energy during low demand and supporting the grid during peak times, thus facilitating a more stable energy distribution and integration of renewable resources [18]–[22]. By reducing the reliance on fixed charging infrastructure, mobile chargers offer a scalable solution that can adjust to dynamic demand and potentially reduce the need for future grid enhancements [7], [9]. While the push for more charging stations addresses some barriers to widespread EV adoption, the integration of mobile charging solutions could provide a more adaptable and economically viable approach to supporting the growing demand for EVs and renewable energy integration.

Autonomously navigating in the urban environment, robot-like systems are designed to provide flexibility. Employing the sensors and automation, the system can locate and dock with EVs and deliver power without necessitating today's fixed charging infrastructure. This system can dynamically adapt and adjust to different locations and charging demands, without necessitating an extensive infrastructure and optimizing the use of urban space. By functioning as a charger and mobile battery storage, it supports the grid stability and the integration of renewable generation.

These systems effectively manage the demands typically served by extensive networks of fixed stations, thus enhancing urban space efficiency and reducing infrastructure demands [18]. Using their inherent flexibility, mobile chargers not only fulfil basic charging needs but also serve as dynamic energy storage devices when they are equipped with batteries. They can absorb excess power during off-peak periods and supply it during peak demand, promoting the potential integration of renewable energy sources. This dual functionality positions them as crucial tools in reducing emissions from major sectors like transportation and energy production [18]–[22].

The charging tasks can be fulfilled using two different mobile charging configurations studied in this research. First, the built-in battery configuration requires a heavy-duty robotic platform with integrated sensors for autonomy, a chassis and wheels for heavy loads, a battery, a DC/AC converter to drive the motor, a high-power DC/DC charger, and a robotic arm for docking. The switchable battery configuration uses two platforms: one for the battery and another for mobilization. It omits the motor, DC/AC converter, and robotic arm found in the built-in setup, which are instead part of the carrier robot responsible for towing the battery platform. A small battery powers the carrier robot, with additional energy possibly sourced from the larger battery. The layout of these configurations is depicted in Figure 1.

II. Sizing Optimization

The main objectives of the problem are to decide on the most feasible number of robots, battery capacity, and the best action sequence to cover all charging operations on a typical day. The system also allows for bidirectional flow between the batteries used to charge EVs and the grid. In this case, the system is expected to sell energy to the grid whenever it is profitable and there is time and energy available, pointing out peak demand hours throughout the day. Dutch day-ahead electricity market prices on different days are used to implement the price-incentivised decision-making in the system [8].

The system's performance is studied by employing a summer price scenario with cheap electricity to reflect on price fluctuations as shown in Figure 3 and a winter scenario. The summer data set exhibits negative price instants, which are set to zero, as the system is not acting directly on the wholesale market, but using the same prices.

To make a realistic sizing decision and practical business assessment, it is vital to address the costs associated with the battery energy storage system. It is possible to express the effect of increasing the battery capacity on its monetary value in terms of the economies-of-scale principle [23]. Furthermore, this approach makes it also possible to define a monetary value for battery degradation, since this phenomenon implies a loss of bought capacity. A market search is conducted to reproduce an overall price function. The options found along with their capacities and prices are plotted and fitted linearly. As a consequence, the cost function shown in Equation 1 is obtained to be used in the degradation and investment cost calculations.

$$C_{\text{battery}}(Q) = 170.69 \cdot Q + 175.37 \tag{1}$$

A. Optimization Problem

An optimization problem is developed to study the performance of a mobile charging system with EVs and the grid under varying conditions. In the mobile charging system model, the decision variables are essential for controlling operations. The binary variables $B2V_{\mathrm{r,t,o}}$, $G2B_{\mathrm{r,t}}$, $B2G_{\mathrm{r,t}}$, and $T_{\mathrm{r,t}}$ indicate whether a robot is engaged in charging an EV (Battery to Vehicle), charging from the grid (Grid to Battery), selling energy back to the grid (Battery to Grid), or travelling between locations, respectively, at each time step. The power variables $P_{\mathrm{B2V}_{\mathrm{r,t}}}$, $P_{\mathrm{G2B}_{\mathrm{r,t}}}$, $P_{\mathrm{B2G}_{\mathrm{r,t}}}$, and $P_{\mathrm{T}_{\mathrm{r,t}}}$ specify the amount of power involved in these respective transactions. The state variable $SoC_{\mathrm{r,t}}$ denotes the State of Charge of the robot's battery at each time step. On the other hand, $A_{\mathrm{r,o}}$ is a binary variable indicating the assignment of a specific charging task o to a robot r. The simulation is conducted repeatedly with fixed battery capacities ranging from 70 to 400 kWh and the number of units varying between 3 and 5.

The objective function maximizes daily profits from energy transactions, considering battery degradation as shown in Equation 2. Revenues from charging EVs and selling energy to the grid are R_{B2V} and R_{B2G}, respectively, while costs include electricity purchases C_{G2B} and battery degradation C_{D}. Daily electricity prices C_{G}, and EV charging price C_{C}, taken as 0.65 €/kWh, are considered, alongside battery degradation, L, cost per kWh, based on Li-ion battery prices and degradation rates as explained in Section III-C. The time step duration Δt is set at 5 minutes.

$$\max(R_{\mathrm{B2V}} + R_{\mathrm{B2G}} - C_{\mathrm{G2B}} - C_{\mathrm{D}}) \tag{2}$$

Where:

$$R_{\mathrm{B2V}} = \sum_{r=1}^{R}\sum_{t=1}^{T} P_{\mathrm{B2V}_{\mathrm{r,t}}} \Delta t C_{\mathrm{C}} \tag{3}$$

$$R_{\mathrm{B2G}} = \sum_{r=1}^{R}\sum_{t=1}^{T} P_{\mathrm{B2G}_{\mathrm{r,t}}} \Delta t C_{\mathrm{G}} \tag{4}$$

$$C_{\mathrm{G2B}} = \sum_{r=1}^{R}\sum_{t=1}^{T} P_{\mathrm{G2B}_{\mathrm{r,t}}} \Delta t C_{\mathrm{G}} \tag{5}$$

$$C_{\mathrm{D}} = \sum_{r=1}^{R}\sum_{t=1}^{T}[P_{\mathrm{B2V}_{\mathrm{r,t}}} + P_{\mathrm{B2G}_{\mathrm{r,t}}} + P_{\mathrm{G2B}_{\mathrm{r,t}}}]\Delta t L \quad (6)$$

The following constraints are aimed at transforming real-world phenomena into mathematical formulations, enabling comprehensive understanding and accurate predictions of system behaviour.

1) A unit has 4 degrees of freedom: charging an EV, charging from the grid, selling energy, and travelling between locations. The constraint ensures a unit can only perform one activity at a time.

$$\sum_{o=1}^{O} B2V_{\mathrm{r,t,o}} + G2B_{\mathrm{r,t}} + B2G_{\mathrm{r,t}} + T_{\mathrm{r,t}} \leq 1 \quad (7)$$

2) This constraint governs the SoC evolution of batteries, increasing with the energy intake from the grid and decreasing with discharge. η_{B2V} stands for battery to vehicle charging efficiency, η_{G2B} and η_{B2G} for grid to battery and battery to grid efficiencies, while η_{M} for powertrain efficiency and Q for battery capacity:

$$\begin{aligned} SoC_{\mathrm{r,t+1}} = SoC_{\mathrm{r,t}} + \frac{P_{\mathrm{G2B}_{\mathrm{r,t}}}\Delta t}{Q}\eta_{G2B} - \\ \frac{P_{\mathrm{B2G}_{\mathrm{r,t}}}\Delta t}{Q\eta_{\mathrm{G2B}}} - \frac{P_{\mathrm{B2V}_{\mathrm{r,t}}}\Delta t}{Q\eta_{\mathrm{B2V}}} - \frac{P_{\mathrm{T}_{\mathrm{r,t}}}\Delta t}{Q\eta_{\mathrm{M}}} \end{aligned} \quad (8)$$

3) The constraint ensures the power drawn by the motor matches the powertrain's average demand during a travel cycle. $P_{\mathrm{T_{avg}}}$ indicates average power consumption per driving cycle:

$$P_{\mathrm{T}_{\mathrm{r,t}}} = P_{\mathrm{T_{avg}}} T_{\mathrm{r,t}} \quad (9)$$

4) The unit should be identified as travelling one time step before a charging operation starts as well as one time step after the charging session ends:

$$T_{\mathrm{r,t+1}} \geq \sum_{\mathrm{o=1}}^{\mathrm{O}} B2V_{\mathrm{r,t,o}} - \sum_{\mathrm{o=1}}^{\mathrm{O}} B2V_{\mathrm{r,t+1,o}} \quad (10)$$

$$T_{\mathrm{r,t-1}} \geq \sum_{\mathrm{o=1}}^{\mathrm{O}} B2V_{\mathrm{r,t,o}} - \sum_{\mathrm{o=1}}^{\mathrm{O}} B2V_{\mathrm{r,t-1,o}} \quad (11)$$

$$B2V_{\mathrm{r,t,o1}} + B2V_{\mathrm{r,t+1,o2}} \leq 1 \quad (12)$$

5) According to the implemented logic, the net power drawn from the grid, as well as fed to the grid, should be smaller or equal to the grid capacity, denoted by G:

$$\sum_{\mathrm{r=1}}^{\mathrm{R}} \left(P_{\mathrm{G2B}_{\mathrm{r,t}}} - P_{\mathrm{B2G}_{\mathrm{r,t}}}\right) \leq \mathrm{G} \quad (13)$$

$$\sum_{\mathrm{r=1}}^{\mathrm{R}} \left(P_{\mathrm{G2B}_{\mathrm{r,t}}} - P_{\mathrm{B2G}_{\mathrm{r,t}}}\right) \geq -\mathrm{G} \quad (14)$$

6) This set of constraints defines the maximum power an individual unit can feed or draw. The maximum battery power rating $P_{\mathrm{B_{MAX}}}$ averages the top charging powers of the 10 most popular EV models in the Netherlands, varying by SoC:

$$P_{\mathrm{G2B}_{\mathrm{r,t}}} \leq P_{\mathrm{B_{MAX}}} G2B_{\mathrm{r,t}} \quad (15)$$

$$P_{\mathrm{B2G}_{\mathrm{r,t}}} \leq P_{\mathrm{B_{MAX}}} B2G_{\mathrm{r,t}} \quad (16)$$

7) A unit can only charge one vehicle at a time. When it conducts a charging operation, the binary variable corresponding to this operation, $B2V_{\mathrm{r,t,o}}$ takes 1, while that of other operations must be 0:

$$\sum_{\mathrm{o=1}}^{\mathrm{O}} B2V_{\mathrm{r,t,o}} \leq 1 \quad (17)$$

8) Each charging operation must be assigned to a unit, and only one unit can charge an EV:

$$\sum_{\mathrm{r=1}}^{\mathrm{R}} A_{\mathrm{r,o}} = 1 \quad (18)$$

9) The constraint merges assignment logic with charging power, stating that the binary variable for power flow between a unit and an EV can be nonzero only if assigned to that unit.

$$\sum_{t=Start_{\mathrm{o}}}^{End_{\mathrm{o}}} B2V_{\mathrm{r,t,o}} \geq A_{\mathrm{r,o}} \quad (19)$$

10) To regulate energy flow between units and vehicles, constraints ensure that power flow is monitored individually per charging operation. Units cannot share charging tasks, necessitating distinct definitions of power indexed by unit, time, and operation. These constraints relax non-convexity using the auxiliary variable, $P_{\mathrm{x}_{r,t,o}}$:

$$P_{\mathrm{x}_{r,t,o}} \leq P_{\mathrm{B_{MAX}}} B2V_{r,t,o} \quad (20)$$

$$\sum_{\mathrm{o=1}}^{O} P_{\mathrm{x}_{\mathrm{r,t,o}}} = P_{\mathrm{B2V}_{\mathrm{r,t}}} \quad (21)$$

$$P_{\mathrm{x}_{r,t,o}} \geq P_{\mathrm{B2V}_{r,t}} - P_{\mathrm{B_{MAX}}}(1 - B2V_{r,t,o}) \quad (22)$$

11) Together with the previous three constraints, this ensures that the charging demand of each EV, based on their required energy, E_{o}, is met within the connection time:

$$\sum_{t=Start_{\mathrm{o}}}^{End_{\mathrm{o}}} P_{\mathrm{x}_{\mathrm{r,t,o}}}\Delta t = E_{\mathrm{o}} \quad (23)$$

12) This constraint forces the power flow value between a unit and an EV corresponding to a battery at a time step to be zero if it is not conducting a charging operation:

$$P_{\mathrm{B2V}_{\mathrm{r,t}}} \leq P_{\mathrm{B_{MAX}}} \sum_{\mathrm{o=1}}^{\mathrm{O}} B2V_{\mathrm{r,t,o}} \quad (24)$$

III. Results

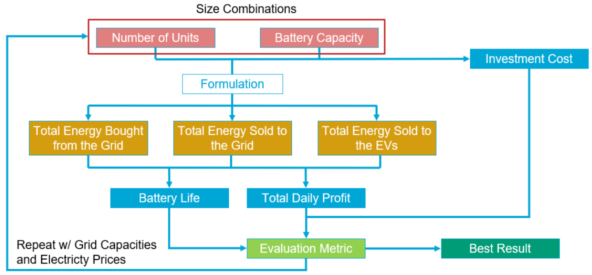

Fig. 2: Study framework

To simulate the system's daily operation, and evaluate the results, a study framework is developed as shown in Figure 2.

A. Energy Arbitrage

The winter scenario has lower daily price gaps. This small price gap is not enough to profit notably from energy arbitrage. Meanwhile, the emerging price gap in summer gives the system great potential to do energy arbitrage. Furthermore, as this transaction is mainly dependent on the daily price gap, the demand from the battery side is price-driven, hence increasing by the surplus and decreasing by the deficit. The plot in Figure 3 demonstrates the impact of daily electricity prices on the transactions between one of three 270 kWh batteries and the grid with 50 kW capacity, as well as its charging interactions with electric vehicles. Positive power values indicate the battery is charging, while negative values show discharging phases. The secondary axis displays the electricity prices, underscoring their influence on the battery's charging and discharging decisions in the summer scenario.

As shown in Figure 3, when the electricity price increases later in the day, the direction of this flow changes so that the system sells the purchased and stored energy back to the grid when the demand is higher. As the amount of energy available for sale is finite and constrained by the battery and grid capacities, it only exhibits a positive flow to the grid during the two highest price periods. Since the transaction is not profitable at other non-zero price instances, the system strategically limits energy sales to mitigate battery wear and maintain its longevity.

B. Daily Profits

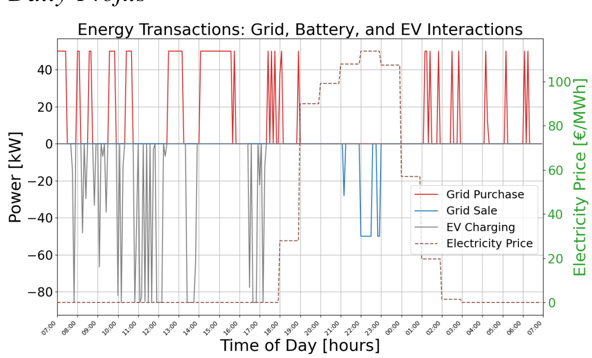

Fig. 3: Exchange power of a 270 kWh battery and grid with daily electricity price

Battery capacity and the number of units in the system have a critical effect on the daily profits that can be realised as a consequence of providing charging services to EVs and energy arbitrage. Generally, more battery capacity and units give the system flexibility. At this point, sometimes energy could be purchased to store just enough energy to charge the upcoming vehicles, not because it is very cheap, since the charging demand must be fulfilled under any conditions. As the total capacity of the system increases, the system gains enough flexibility to take full advantage of low prices. However, increasing system capacity no longer improves profitability after a point, as the purchased energy is mainly restricted by the capacity of the grid.

Daily profits can be further improved by increasing the grid capacity to 100 kW. This allows for cheaper battery charging and reduced energy costs. For example, daily profits in the winter scenario reach approximately €424.6 with 50 kW and €437.4 with 100 kW, while zero electricity prices in the summer scenario raise profits to €490.5 and €538.4.

C. Product Life

Product life can be described as the time it takes to reach the end-of-life point of a critical component of the system. In this case, this duration is mainly described by the capacity fade of the Li-ion battery utilised.

Li-ion battery degradation mechanisms, being highly non-linear and affected by various conditions, are extensively studied to develop degradation models and understand capacity loss [10], [11], [12], [13]. Considering the C-rate the battery undergoes during charging operations, assuming optimal temperature management a specific rate of 0.000175 kWh per kWh cycled is adopted for this study. Consequently, when energy arbitrage is not viable due to an unsuitable price gap, battery life extends due to fewer cycles, as in the winter scenario, where the price gap prevents energy arbitrage, battery life varies from 1 to 6 years with 70% capacity retention as the end-of-life (EoL) criterion, as shown in Figure 4. Furthermore, as the energy arbitrage becomes infeasible in this scenario, grid capacity therefore does not affect the battery life significantly.

Furthermore, Figure 4 shows that higher battery capacity correlates with longer service life due to less cycling and material degradation. Adding more batteries spreads the load, extending product life. However, increasing grid capacity has minimal impact on service life in the winter scenario, as batteries are used solely for charging EVs.

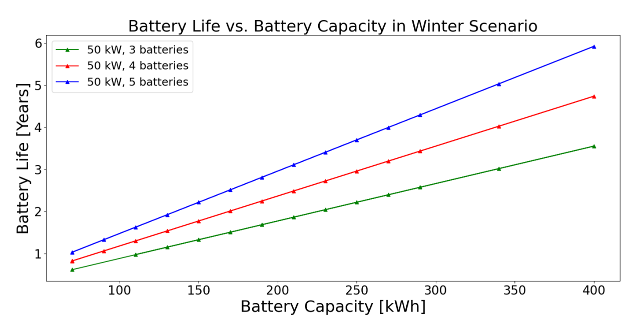

Fig. 4: Battery life in the winter scenario

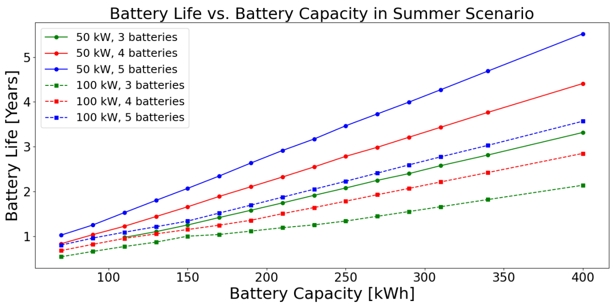

Fig. 5: Battery life in the summer scenario

On the other hand, summer prices enable energy arbitrage, leading to more cycles and quicker capacity loss, as shown in Figure 5. Particularly, the 100 kW case shows the shortest lifespan due to excessive daily energy transactions with the grid, yielding more, but at the cost of faster degradation.

To verify the accuracy of linear capacity loss approximation, an empirical battery model is employed to compare the cyclic ageing as shown in Equation 25 [14]. Despite the two ageing models yielding slightly different product life spans, the relative difference is minimal at 1.75% in the example scenario, affirming that the linear model used in the optimization is a sufficiently accurate simplification.

$$C_{\text{cyc}} = 0.021 \cdot e^{-0.01943 \cdot \text{SoC}_{\text{avg}}} \cdot \text{cd}^{0.7612} \cdot \text{nc}^{0.5} \qquad (25)$$

IV. Financial Assessment

For a mobile system with built-in batteries, investment costs depend on the number of robots equipped with batteries. Switching to a system with switchable batteries, the number of carriers can be fewer than the batteries since carriers only transport batteries as needed. Analysis shows it is feasible to reduce carrier units to two for three batteries, covering 99.64% of travel needs and reducing investment costs without any significant service disruption. Similarly, using three carriers for four and five batteries meets 99.9% of travel requirements, reducing investment and improving operational efficiency.

The evaluation should consider profit potential, required investment, and the system's lifespan. Various financial metrics like Net Present Value and Return on Investment assess performance, but their reliance on product life can bias results.

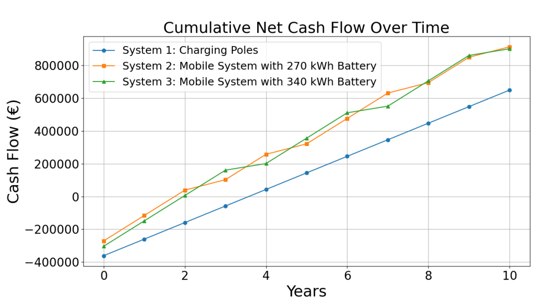

Fig. 6: Cumulative cash flow of different systems in the winter scenario

To address this, a fixed evaluation period, like a year, is recommended. This approach allows investors to compare investment efficiency and return speed accurately. Consequently, yearly Return on Investment (ROI) values are calculated for different battery units and capacities to determine optimal sizing.

Data analysis shows that using a 100 kW grid capacity increases profits by 9.7% in Summer and 3% in Winter but it increases peak demand and shortens system lifespan due to more frequent energy arbitrage. Additionally, heavy use of battery material for grid arbitrage proves financially inefficient, leading to significantly faster degradation in the long term despite higher returns. Conversely, a 50 kW grid capacity extends product life by 52% on average and significantly reduces peak demand by 73%, with minimal profit loss. High grid capacities also triple hub costs due to higher hardware and installation expenses. Given these factors, a 50 kW grid capacity is recommended for effective peak reduction and cost-effectiveness.

Due to their lower initial investment costs, three batteries in switchable configuration are considered. For each price scenario, it is assumed that the system will sustain earning the same amount of daily profits until it reaches the EoL point. The growing EV market accelerates the development of a second-life market for Li-ion batteries, supported by increasing volumes of batteries reaching EoL thresholds, typically 70% State of Health (SoH), which can be sold for $70/kWh [15], [25]. As soon as it reaches the minimum capacity retention, it is further assumed that the battery units will be sold at the second-life market for circular use. Yearly ROI in the winter scenario reaches 26.2% when 270 kWh battery capacity is used and after that point, further increasing the capacity only brings along limited improvement. In addition, the maximum is observed when the capacity is increased further by 70 kWh in the winter scenario, just before a slightly decreasing trend starts due to overinvestment. The net cash flow of these configurations is plotted in Figure 6 and compared with a system with charging poles. Positive cash flow arises from operational profits and end-of-life battery sales, while negative cash flow stems from battery replacements and maintenance costs. On the other hand, the system's performance improves in Summer due to cheaper electricity, reaching the peak value at 310 kWh. Table I shows that despite lower initial costs, the mobile system has a shorter service life due to capacity loss, reducing the years of higher daily profits compared to charging poles, which yield returns over a longer period of 10 years. Charging poles face risks from potential technological disruptions over their decade-long expected life, whereas the mobile system allows investors to reassess and potentially reinvest every 2-3 years, providing comparable or higher annual profits and greater flexibility.

The expenditures for the hub are one-time costs. The system's main recurring expense is battery replacement, which is cheaper than the initial investment as other components last longer. Replacement costs are €126,294.36 for a 270 kWh system and €158,913.22 for a 340 kWh system.

Comparison of Mobile Systems and Charging Poles							
System Type	Scenario	Capacity	Init. Life	Init. Investment	Revenue per Round	Total Life	Total Profit
Mobile	Winter	270 kWh	2.398 Yrs	€271,430.46	€407,791.58	9.59 Yrs	€978,234.15
Mobile	Winter	340 kWh	3.02 Yrs	€304,275.41	€513,409.96	12.07 Yrs	€1,269,327.83
Mobile	Summer	270 kWh	2.247 Yrs	€271,375.52	€438,149.33	8.99 Yrs	€1,099,884.86
Mobile	Summer	340 kWh	2.81 Yrs	€304,200.58	€549,366.63	11.25 Yrs	€1,413,453.82
Pole	Winter	-	10 Yrs	€361,861.5	€1,011,743.5	10 Yrs	€649,882
Pole	Summer	-	10 Yrs	€361,861.5	€1,231,437	10 Yrs	€869,575.5

TABLE I: Consolidated Financial Performance of Mobile Systems and Charging Poles Over Initial and Reinvestment Periods

After three reinvestment periods, the mobile system matches the 9 to 12-year lifespan of charging poles. Despite higher initial costs, it achieves significantly higher profits due to slightly increased charging rates compared to traditional AC charging poles. Although these profits benefit investors, customers may view it unfavourably due to higher costs compared to traditional AC charging poles. Nonetheless, it remains 13.3% less expensive than the average DC charging rates in the Netherlands [26]. Consequently, the 270 kWh system, requiring 1.8 times the investment, generates 1.51 to 1.26 times the profits of charging poles with a faster return. The 340 kWh option increases annual profits slightly but with just a 2.85% improvement in average annual profits over the 270 kWh setup and demands 20.12% more investment for a longer operational life.

V. Conclusion

This study introduces a mobile charging system as a viable alternative to traditional infrastructure, aimed at improving EV adoption. The analysis reveals that mobile chargers, particularly those with robot-like features, offer enhanced accessibility, reduced urban space requirements, and support for electrical grids. While excessive energy arbitrage might increase short-term returns, it also accelerates battery degradation, hindering the system's financial performance. Conversely, lower grid capacities diminish peak demands and present better economic performance. These configurations, especially those involving switchable batteries, strike an optimal balance between investment efficiency and operational flexibility, thereby highlighting the profound economic benefits of mobile charging solutions.

VI. Acknowledgements

We gratefully acknowledge the contributions of Ken Gould, whose innovative work on the charging system for EVs is encapsulated in Patent No. WO2023/140730 A1. This patent develops a concept of a mobile EV charging system that can be realised and deployed, providing valuable insights and demonstrating practical applications. The study has benefited from the foundational concepts illustrated in this patent.

References

[1] International Energy Agency, "Global CO2 emissions from transport by sub-sector in the Net Zero Scenario, 2000-2030,".
[2] United Nations Environment Programme, "Paris Agreement,", 2015.
[3] European Parliament, "EU ban on the sale of new petrol and diesel cars from 2035 explained,", 2023.
[4] European Automobile Manufacturers' Association, "ACEA Position Paper Proposal for the Alternative Fuels Infrastructure Regulation (AFIR),", 2021.
[5] Egbue, O. and Long, S., "Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions,", vol. 48, pp. 717-729, 2012.
[6] Walzel, B. and Sturm, C. and Fabian, J. and Hirz, M., "Automated robot-based charging system for electric vehicles," , 2016.
[7] Saboori, H. and Jadid, S. and Savaghebi, M., "Optimal Management of Mobile Battery Energy Storage as a Self-Driving, Self-Powered and Movable Charging Station to Promote Electric Vehicle Adoption," , vol. 14, no. 3, 2021.
[8] Epex Spot, "Market data," , 2023.
[9] Liu, Q. and Li, J. and Sun, X. and Wang, J. and Ning, Y. and Zheng, W. and Li, J. and Liu, H., "Towards an Efficient and Real-Time Scheduling Platform for Mobile Charging Vehicles," Eds., Algorithms and Architectures for Parallel Processing, vol. , no. , pp. 402–416, 2018.
[10] Farzin, H. and Fotuhi-Firuzabad, M. and Moeini-Aghtaie, M., "A Practical Scheme to Involve Degradation Cost of Lithium-Ion Batteries in Vehicle-to-Grid Applications," , vol. 7, no. 4, pp. 1730-1738, 2016.
[11] Peterson, S. B. and Whitacre, J. and Apt, J., "The economics of using plug-in hybrid electric vehicle battery packs for grid storage," , vol. 195, no. 8, pp. 2377-2384, 2010.
[12] Bryden, T. S. and Holland, A. and Hilton, G. and Dimitrov, B. and de León Albarrán, C. P. and Cruden, A., "Lithium-ion degradation at varying discharge rates," , vol. 151, pp. 194-198, 2018.
[13] Gandoman, F. H. and Kalogiannis, T. and Berecibar, M. and Mierlo, J. V. and Bossche, P. V. d., "Quantitative analysis techniques for evaluating the reliability of Li-ion battery: challenges and solutions," , 2020 IEEE Vehicle Power and Propulsion Conference (VPPC), pp. 1-5, 2020.
[14] Stroe, Daniel Ioan., "Lifetime Models for Lithium-ion Batteries used in Virtual Power Plant Applications,", 2014.
[15] Haram, M. H. S. M. and Lee, J. W. and Ramasamy, G. and Ngu, E. E. and Thiagarajah, S. P. and Lee, Y. H., "Feasibility of utilising second life EV batteries: Applications, lifespan, economics, environmental impact, assessment, and challenges," , vol. 60, no. 5, pp. 4517-4536, 2021.
[16] International Energy Agency, "CO2 emissions in 2022," , 2022.
[17] Schoenberg, S. and Dressler, F., "Reducing Waiting Times at Charging Stations With Adaptive Electric Vehicle Route Planning," , vol. 8, no. 1, pp. 95-107, 2023.
[18] Afshar, S. and Macedo, P. and Mohamed, F. and Disfani, V., "Mobile charging stations for electric vehicles — A review," , vol. 152, pp. 111654, 2021.
[19] Moghaddam, V. and Ahmad, I. and Habibi, D. and Masoum, M. A., "Dispatch management of portable charging stations in electric vehicle networks," , vol. 8, pp. 100112, 2021.
[20] Wang, F. and Chen, R. and Miao, L. and Yang, P. and Ye, B., "Location optimization of electric vehicle mobile charging stations considering multi-period stochastic user equilibrium," , vol. 11, no. 20, pp. 5841, 2019.
[21] Vempalli, S. K. and Deepa, K. and others, "A novel V2V charging method addressing the last mile connectivity," , 2018 IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), pp. 1–6, 2018.
[22] Diouf, B. and Pode, R., "Potential of lithium-ion batteries in renewable energy," , vol. 76, pp. 375-380, 2015.
[23] Mauler, L. and Duffner, F. and Leker, J., "Economies of scale in battery cell manufacturing: The impact of material and process innovations," , vol. 286, pp. 116499, 2021.
[24] Transport & Environment, ""Charging" for phase-out,", 2022.
[25] Q. Dong, S. Liang, J. Li, H. C. Kim, W. Shen, and T. J. Wallington, "Cost, energy, and carbon footprint benefits of second-life electric vehicle battery use," iScience, vol. 26, no. 7, Art. no. 107195, 2023.
[26] European Alternative Fuels Observatory, "Electric vehicle recharging prices," European Commission, 2024.