Charge Scheduling of Electric Vehicles for Last-Mile Distribution of an E-grocer

Dalmijn, Menno; Atasoy, Bilge; Bijl, Peter; Negenborn, Rudy R.

DOI
10.1109/FISTS46898.2020.9264893

Publication date
2020

Document Version
Final published version

Published in
Proceedings of the 2020 Forum on Integrated and Sustainable Transportation Systems, FISTS 2020

Citation (APA)
Dalmijn, M., Atasoy, B., Bijl, P., & Negenborn, R. R. (2020). Charge Scheduling of Electric Vehicles for Last-Mile Distribution of an E-grocer. In *Proceedings of the 2020 Forum on Integrated and Sustainable Transportation Systems, FISTS 2020* (pp. 236-241). IEEE. https://doi.org/10.1109/FISTS46898.2020.9264893

2020 Forum on Integrated and Sustainable
Transportation Systems (FISTS)
November 3-5, 2020, Delft - The Netherlands

Charge Scheduling of Electric Vehicles for Last-Mile Distribution of an E-grocer

Menno Dalmijn[1], Bilge Atasoy*[1], Peter Bijl[2] and Rudy R. Negenborn[1]

Abstract— **This paper proposes a model for charge scheduling of electric vehicles in last-mile distribution that takes into account battery degradation. A mixed integer linear programming formulation is proposed that minimizes labor, battery degradation and time-dependent energy costs. The benefit of implementing charge schedule optimization is assessed for a real-life case study at e-grocer Picnic. It is shown that charging optimization yields an overall reduction of charging costs by 25.2% when compared to the current operational charging performance. Furthermore, the impacts of three different shift schedule types, the increase in vehicle battery size and the coordinated charging are investigated. It turns out that more energy demanding shift schedules result in higher average charging cost per charged amount of energy. The introduction of a larger battery size as well as coordinated charging show potential for decreasing overall costs.**

I. INTRODUCTION

The advances in information and communication technologies are changing the way transportation and logistics systems are operating. In the context of freight transportation, consumers are using online systems and becoming more time-sensitive even though they would like to keep the prices reasonable. This overall brings challenges to cities, e-commerce and logistics companies. Together with the environmental considerations, it is clear that we need a paradigm shift to increase the sustainability of operations without comprising on the efficiency. Freight transportation, currently dominated by fossil fuelled vehicles, contributes largely to sustainability problems, including noise and air pollution, global warming and oil dependency [1]. The adoption of electric vehicles (EVs) could solve these problems by enabling cleaner transport [2]. The attractiveness of EVs is related to [3]: total cost of ownership (TCO), technology readiness and local and national regulations. However, substituting conventional internal combustion engine (ICE) vehicles with EVs within the transportation and logistics sector is not straightforward. In contrast to ICE vehicles, EVs have to refuel frequently due to limited battery capacities. Moreover, the recharging process of an EV is more time consuming. These raise challenges in terms of strategic, planning, and operational perspectives [4].

The increased potential of EVs led to the development of optimization problems both at strategic and operational levels. We refer to a recent review by Schiffer et al. (2019) for both levels of models [5]. On the strategic side, the needed fleet size (e.g., [6]) and the location of the charging infrastructure (e.g., [7], [8]) are studied. When it comes to operational level models, electric vehicle routing problems (E-VRP) are introduced in order to consider the limited range of EVs while optimizing the routes. Some consider full charging of batteries at each charge event (e.g., [9]) whereas others enhance the model with partial charging possibilities. Montoya et al. (2017) [10] worked on E-VRP with piecewise linear representation of the nonlinear charging process. They were the first ones to consider nonlinearity and showed that more accurate representation of the charging process is important for reaching efficient operations with EVs. A different operational problem is the electric vehicle scheduling problem (E-VSP) with the assumption of pre-determined vehicle routes which is also what we focus on in this paper.

We focus on the depot charge scheduling from the perspective of the fleet owner. The fleet is considered to operate a multi-shift schedule, i.e., multiple trips per day. It is assumed that individual trips, which span a number of customer orders, do not exceed vehicle range which allows charging only at the depot. A relevant study is by Pelletier et al. (2018) [11] who introduce the Electric Freight Vehicle Charge Scheduling Problem (EFV-CSP). They focus on optimising the depot charge planning over the course of multiple days for a given set of routes for a small fleet of electric freight vehicles. Sundstrom et al. (2010) [12] propose a charge scheduling optimisation model with the goal of minimising charging costs, while ensuring satisfactory state-of-energy levels for the vehicles and not exceeding the amount of available wind power. A different type of problem discussed by Sassi et al. in (2014a) [13], (2014b) [14] and (2017) [15] that covers the subject of unidirectional depot charge scheduling for fleet owners is the Simultaneous Electric Vehicle Scheduling and Optimal Charging Problem.

Our model contributes to the charge scheduling literature in various dimensions. First, the labor cost is taken into account with a fixed penalty for each performed charging event. Second, the battery wear costs are considered as lithium-ion batteries are subject to deterioration of the electro-chemical properties over time, ultimately resulting in a performance and range deterioration of the vehicle [16]. We incorporate a SOC dependent battery degradation model proposed by Han et al. (2014) [17] by adopting a discrete wear cost function. The nonlinearity of the degradation cost with respect to SOC is handled with additional continuous decision variables. Furthermore, this paper is distinct with experiments based on real data from a Dutch e-grocer Picnic, that operates a last-mile distribution with over 700 EVs [18].

* Corresponding author: b.atasoy@tudelft.nl
[1] Transport Engineering & Logistics, Maritime & Transport Technology, Delft University of Technology, Mekelweg 2, 2628 CD, Delft, Netherlands
[2] Domain Lead Distribution Model, Picnic Technologies BV, Van Marwijk Kooystraat 15, 1114AG, Amsterdam-Duivendrecht, Netherlands

II. MODEL FORMULATION

The charge scheduling problem is formulated as a MILP. We first present the basic version and then the extensions with battery degradation and coordinated charging.

A. Basic Model Formulation

As mentioned before, vehicle routes are assumed to be decided prior to our model and that energy requirements of these trips are estimated to be inputs to the model. The entire time horizon is discretized into a number of fixed time periods $t \in T$. The periods corresponding to hub opening and closing times are defined as t_{open} and t_{close}. A set of homogeneous vehicles $k \in K$ is characterized by maximum and minimum allowable battery SOC, soc_{max} and soc_{min}, and battery energy capacity E (kWh). Moreover, the SOC at the beginning of an operational day is specified as soc_{start}. Every vehicle has to execute a known sequence of trips from the set $r \in R$. Trips can be further defined by their departure period β_r, arrival period α_r and energy requirement Δsoc_r (%). The vehicle that executes a certain trip r, is denoted by V_r and the preceding trip is defined as μ_r. Moreover, let the set A_k contain the arrival periods of all trips that belong to vehicle k. The charger types given by $s \in S$ are characterized by their charge rate P_s (kW), the SOC differential that can be charged in one period λ_s (%) and amount of available chargers per type $\mathcal{K}_s$. Let the binary decision variable $x_{t,k,s}$ be 1, if a charger of type s is charging vehicle k during period t, and 0 otherwise. A continuous variable $soc_{t,k}$ denotes the SOC of vehicle k at the start of period t. y keeps track of the peak charging power that is drawn from the grid during the entire time horizon. Binary variable $z_{t,k}$ equals 1 if a charge event starts for vehicle k in period t, and 0 otherwise. To count the number of charge events, an integer variable N is introduced. The peak power demand is constrained by the grid capacity G. The model minimizes the total costs:

$$\sum_{t \in T} \sum_{k \in K} \sum_{s \in S} x_{t,k,s} P_s \Delta_t c_t + N c^e \quad (1)$$

where the first term represents the cost of the charged energy as a function the total charged energy during a charging period (if $x_{t,k,s} = 1$ it is the charge rate, P_s, times the length of each time period, Δ_t) and the time-dependent energy costs c_t (€/kWh); the second term accounts for the labor costs with a fixed cost per charge event c^e.

Constraints (2) prevent a vehicle from being charged while serving the trips, i.e., maintains depot-charging. Constraints (3) limit the amount of chargers of type s that can be used during every period to $\mathcal{K}_s$, while constraints (4) enforce that each vehicle can be charged by only one charger at the same time. Constraints (5) keep track of the peak charging power that is drawn from the grid during the entire time horizon and constraint (6) limits this peak charging power to the grid capacity. Lastly, constraints (7) and (8) are used to identify the period that corresponds to the start of a charging event. Constraints (9) and (10) define the binary decision variables.

$$\sum_{t=\beta_r}^{\alpha_r} \sum_{s \in S} x_{t,V_r,s} = 0 \qquad \forall r \in R \quad (2)$$

$$\sum_{k \in K} x_{t,k,s} \leq \mathcal{K}_s \qquad \forall t \in T, s \in S \setminus \{1\} \quad (3)$$

$$\sum_{s \in S} x_{t,k,s} \leq 1 \qquad \forall t \in T, k \in K \quad (4)$$

$$\sum_{k \in K} \sum_{s \in S} P_s x_{t,k,s} \leq y \qquad \forall k \in K, t \in T \quad (5)$$

$$0 \leq y \leq G \quad (6)$$

$$z_{t,k} \geq x_{t,k,s} - x_{t-1,k,s} \qquad \forall k \in K, t \in T \setminus \{1\}, s \in S \quad (7)$$

$$z_{1,k} \geq x_{1,k,s} \qquad \forall k \in K, s \in S \quad (8)$$

$$x_{t,k,s} \in \{0,1\} \qquad \forall t \in T, k \in K, s \in S \quad (9)$$

$$z_{t,k} \in \{0,1\} \qquad \forall t \in T, k \in K \quad (10)$$

$$soc_{\alpha_r,V_r} = soc_{\beta_r,V_r} - \Delta soc_r \qquad \forall r \in R \quad (11)$$

$$soc_{t,k} = soc_{t-1,k} + \sum_{s \in S} \lambda_s x_{t-1,k,s} \qquad \forall k \in K, t \in T \setminus \{1\}, t \notin A_k \quad (12)$$

$$soc_{min} \leq soc_{t,k} \leq soc_{max} \qquad \forall k \in K, t \in T \quad (13)$$

$$soc_{1,k} = soc_{start} \qquad \forall k \in K \quad (14)$$

Constraints (11) relate the SOC of the vehicle at trip departure to the SOC at trip arrival by reducing it with the trip energy requirement Δsoc_r. During charging, constraints (12) enforce the increase of the SOC of a vehicle with the SOC differential that corresponds to a certain charge rate λ_s. Constraints (13) ensure that the SOC of a vehicle always stays between the minimum and maximum allowable SOC. Constraints (14) set the SOC of the vehicle at the start of the time horizon.

$$\sum_{t \in T} \sum_{k \in K} z_{t,k} = N \quad (15)$$

$$\sum_{t=t_{close}}^{t_{open}} z_{t,k} = 0 \qquad \forall k \in K \quad (16)$$

Constraint (15) counts the number of charge events for labor cost computation. Constraints (16) prevent charging events from occurring during the night closing times of the hub.

B. Model Extension I: Battery Degradation

Typically, battery manufacturers specify the cycle lifetime of batteries with the *Achievable Cycle Count* (ACC) for different *Depth of Discharge* (DOD) points, which indicates how many times a battery can be charged/discharged before it reaches the end of its lifetime. For defining the relation between ACC and DOD, it is typically assumed that the battery is always discharged from 100% SOC, which represents the situation in which a battery is always cycled from full charge. However, in reality batteries are cycled in different SOC ranges and the ACC-DOD characteristics need to be transformed into a practical battery wear model in order to

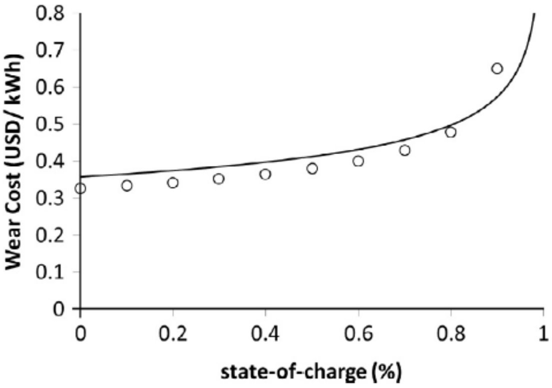

Fig. 1: Discrete and continuous wear costs [17]

facilitate its use in charge scheduling models. The battery wear model that was proposed by Han et al. (2014) [17] does exactly this and we use this model to incorporate battery wear behavior in the charge scheduling model. They propose a *wear density function* (WDF) that represents the average cost per unit of energy transfer based on SOC. A continuous and discrete time battery wear function are derived using both the battery price and ACC-DOD data as shown in Figure 1. In this work, we adopt the discrete-time model and extend the basic MILP with a discrete wear cost function. The formulation is applicable for cases when the wear cost function is increasing with respect to SOC, i.e., more battery degradation occurs during cycling at higher SOC values. The SOC of the batteries is split into a number of intervals $d \in D$ of equal size Δ_d (%), with the upper SOC value of an interval corresponding to U_d. The battery wear cost is represented by W_d in €/kWh for every SOC interval d. A new continuous variable, $soc^+_{d,r}$, is introduced that keeps track of the part of every SOC interval that is used to charge vehicle k between arrival of trip μ_r and departure of trip r. For example, if a vehicle is charged from 40% to 55% SOC between trip $r = \mu_x$ and $r = x$, the corresponding used SOC intervals become $soc^+_{3,x} = 10\%$ and $soc^+_{4,x} = 5\%$ respectively. Lastly, let a binary decision variable $x^{ch}_{d,r}$ equal 1, if the corresponding SOC interval is used for charging the vehicle before trip r and after μ_r, and 0 otherwise.

$$\sum_{t\in T}\sum_{k\in K}\sum_{s\in S} x_{t,k,s}P_s\Delta_t c_t + Nc^e + \sum_{r\in R}\sum_{d\in D} 2E soc^+_{d,r}W_d \tag{17}$$

The objective function now (17) comprises three terms of which the first two represent the energy costs and labor costs as in equation (1). The third term is introduced to take into account the costs related to battery degradation. The total charged amount of energy per interval is derived by multiplying the SOC variation in every interval $soc^+_{d,r}$ with the battery energy capacity E (kWh), and then the corresponding degradation cost is determined by multiplying those factors with the degradation cost W_d that depends on the SOC interval. Since cyclic aging affects the battery health during charging and discharging, a final multiplication by a factor of two is required to calculate the total battery degradation.

$$\sum_{d\in D} soc^+_{d,r} = soc_{\beta_r,V_r} - soc_{\alpha_{\mu_r},V_r} \qquad \forall r \in R \tag{18}$$

$$0 \leq soc^+_{d,r} \leq \Delta_d x^{ch}_{d,r} \qquad \forall d \in D, r \in R \tag{19}$$

$$soc^+_{d,r} \leq U_d - soc_{\alpha_{\mu_r},V_r} + 100 - x^{ch}_{d,r}100 \quad \forall d \in D, r \in R \tag{20}$$

Constraints (2) - (16) are still valid for this model extension. In addition, constraints (18) ensure that the total charged energy (the sum of all $soc^+_{d,r}$ over intervals) satisfies the energy need of vehicle k between trips μ_r and r. Constraints (19) limit the marginal SOC that can charged in a SOC interval between zero and the maximum amount that can be charged in one interval, Δ_d. Constraints (20) limit the amount that can be charged in interval $soc^+_{d,r}$ based on the upper SOC value of that interval and the SOC of the vehicle after the last trip. Note that this constraint will be binding only when the corresponding SOC interval is used (i.e., if $x^{ch}_{d,r} = 1$) and it is only valid in the case of non-decreasing wear cost with respect to SOC.

C. Model Extension II: Coordinated Charging

So far we focused on uncoordinated charging where the charging starts immediately after plugging in a vehicle or after a fixed start delay and continues until the battery is fully charged or disconnected [19]. This may lead to high peak demands and thereby overloading of the grid [20]. On the other hand, coordinated smart charging optimizes time and power demand with the objectives of minimizing charging cost, valley filling and peak shaving [19] without interfering with the scheduled vehicle use during the day [21]. To be able to leverage on the possible benefits of coordinated charging, smart chargers, connected vehicles and an energy management system that controls the charging of the vehicles are needed. Coordinated charging brings the flexibility to (i) stop and start charge events any moment in time including the hub closing times (ii) interrupt charge events without additional costs.

In order to consider the charging event cost in coordinated charging, not the number of charge events should be counted, but the number of used *charge opportunity intervals*. A charge opportunity interval is defined as the time between the arrival of the preceding trip α_{μ_r} and departure of the trip β_r. The total number of charge opportunity intervals is equal to the number of trips. The binary decision variable Nc_r equals 1 if the charge opportunity interval corresponding to trip r is used, and 0 otherwise. Multiple charge events may occur in a given used charge opportunity interval, however it does not incur any costs to stop and start. The only cost will be the plugging of the vehicle after the trip in case the charging opportunity interval afterwards is going to be used. As we are working with operational models, we did not consider the investment costs of smart charging infrastructure. The adapted objective function is given as follows:

$$\sum_{t\in T}\sum_{k\in K}\sum_{s\in S} x_{t,k,s}P_s\Delta_t c_t + \sum_{r\in R} Nc_r c^e + \sum_{r\in R}\sum_{d\in D} 2Esoc^{+}_{d,r}W_d \tag{21}$$

where the second term calculates labor cost by multiplying Nc_r with c^e. The remainder is the same as Equation (17).

$$\sum_{t=\alpha_{\mu_r}}^{\beta_r} z_{t,v_r} \geq -M(1-Nc_r) \qquad \forall r \in R \tag{22}$$

$$\sum_{p=\alpha_{\mu_r}}^{\beta_r} z_{p,v_r} \leq MNc_r \qquad \forall r \in R \tag{23}$$

$$Nc_r \in \{0,1\} \qquad \forall r \in R \tag{24}$$

Constraints (22) and (23) ensure that the binary decision variable Nc_r equals 1 if the term $\sum_{t=\mu_r}^{\beta_r} z_{t,v_r}$ is larger than 0 and that it is 0 if no charging is performed. The linearity of the constraints is maintained by the big constants M. Constraint (15) needs to be discarded as the counting of events is now different and constraints (16) are not valid anymore since the charging can start and stop during the closed times of the hub as long as it is plugged in. All other constraints remain valid (2) - (14), (18) - (20).

III. CASE STUDY

The charge schedule optimization is evaluated with a case study from a Dutch e-grocer, Picnic based on real-life instances. Starting in 2015 by just serving the city of Amersfoort, Picnic maintained an explosive growth reaching 90 cities in Netherlands and 13 cities in Germany. One distinct characteristic of Picnic is that the second-tier logistics from the hubs to the customers is carried out by EVs.

A. Experimental setup

Three different shift schedules, characterized by shift time windows, i.e., scheduled departure and arrival times for trips, are considered to have an analysis of the system under different operational profiles representing potential changes in the demand. All shifts in these schedules are strictly separated in time, which means trips from consecutive shifts can be executed by the same vehicle.

- **SS1** is an afternoon only schedule with 3shifts of equal duration. The shifts have time in between that enables vehicles to do depot charging.
- **SS2** contains 2 additional shifts (compared to SS1) in the morning, which are slightly shorter in time, i.e., less energy demanding, compared to the afternoon shifts.
- **SS3** includes 4 equal but longer duration of shifts with a longer break between shifts two and three. The shifts of SS3 are roughly 30% longer in time, i.e., more energy demanding than SS1 and SS2.

For every shift schedule, 7 instances are generated representing the execution of one operational week based on the database of Picnic. The time horizon is from 23:00 of the previous day until 23:00 of the current day and is discretized in steps of 10 minutes. Hub closing hours are 23:10 - 10:10

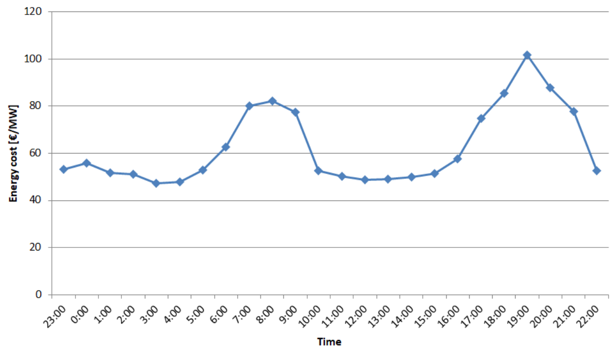

Fig. 2: Hourly energy prices

for the SS1 schedule and between 23:10 and 7:10 for SS2 and SS3. A uniform fleet of light commercial vehicles considered in the case of Picnic. The battery size is 12kWh and the charging curve is represented by a linear charge rate of 2kW, which sets λ_s to 2.78%. The SOC range of the vehicles is restricted to 10-100% SOC in order to have an extra safety margin to take into account the uncertainties in the predicted energy requirement of trips. The SOC at the start of an operational day is set at the lower bound of 10% for comparable results for battery degradation and energy costs.

The peak power that can be drawn from the grid G is set at $40kWh$. The hourly variable energy prices, c_t, are based on a sampled day of hourly prices from the Dutch day-ahead energy market (APX) given in Figure 2. For every performed charge event a fixed cost (c^e) is considered. The discrete wear density function for the battery under consideration is determined using the ACC-DOD curve from Han et al. (2014) as they work with a comparable battery type and size [17]. The entire SOC range is divided into 10 intervals of 10% SOC. Based on the battery price and size, the average wear costs W_d ($€/kWh$) is computed per SOC interval and presented in Table I. This average wear cost computation per kWh is more convenient in order to apply it for different battery capacities. The instance sets for different

TABLE I: The discrete wear cost per SOC interval.

SOC [%]	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
W_d [€/kWh]	0.32	0.33	0.34	0.36	0.37	0.38	0.40	0.425	0.485	0.65

shift schedules yield a different number of trips and total energy requirement. For a fair comparison, the results are reported as cost per consumed amount of energy, in €/kWh.

B. Base case

The base case represents the process at Picnic in which no charge schedule optimization is used. The costs for battery degradation and labor are derived using operational data. Since the SOC dependency is taken into account in the battery wear cost model, it is required to know in which SOC ranges the batteries are cycled during the current use of the vehicle to derive the current battery degradation cost. A discrete probability density function (PDF) of the SOC during driving is derived using data from actual trips. Using this PDF and the battery wear cost function, the average wear cost during driving can be obtained.

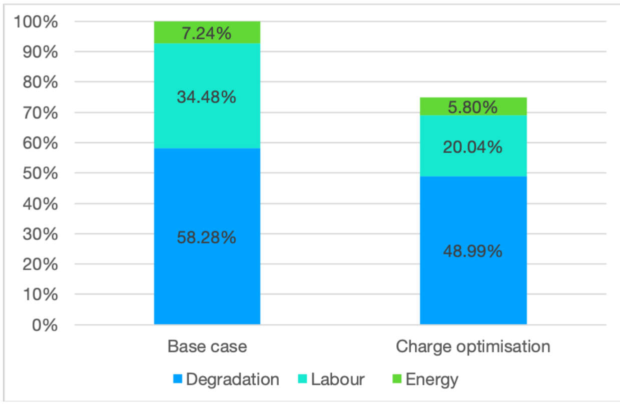

Fig. 3: The benefit of charge schedule optimization

For the determination of the labor cost, we need an understanding of the typical charge cycle currently performed at Picnic based on the operational trip data. First, to derive a realistic value for the average charge cycle, the average trip arrival SOC is used and all vehicles are assumed to be fully charged from this SOC, which is the case for Picnic. Subtracting the average arrival SOC from a 100% SOC yields the average charge cycle. Subsequently multiplying this with the battery capacity gives the quantity of charged energy that corresponds to this charge cycle. Lastly, this is divided by the cost related to one charge event to derive the cost per charged unit of energy, resulting in a charge event cost in €/kWh. It is assumed that, the average energy cost per charged amount of energy is equal to the average time-dependent energy prices. The base case is the benchmark for the experimental results with a total cost of 100% and the other cases are provided in reference to this. Based on the above assumptions for different cost components, 58.28% of the total cost corresponds to the battery degradation, 34.48% is the labor and 7.24% is the energy cost for the base case.

C. Experimental Results

We present a set of experiments for the proposed charge schedule optimization. Gurobi is used as a solver on a machine with Intel Core i7-4700MQ 2,4 GHZ processor with 8.0GB of RAM Windows 10. The maximum computational time is set at 3600 seconds, with a gap tolerance of 1.0%.

The impact of charge schedule optimization is compared to the base case for the SS1 schedule. The results are depicted in Figure 3, where the presented cost corresponds to average charging cost in €/kWh for seven operational days. An overall charging cost reduction of 25.2% is obtained, which is a result of a decrease of degradation, labor and energy costs of 15.9%, 41.9% and 19.9%, respectively. Furthermore, the reduction in battery wear can be translated into an extended lifetime of the batteries by 19.0% .

The results for charge schedule optimisation for 3 shift schedules are depicted in Figure 4. Note that, SS1 results are the same the optimized results in Figure 3. It is observed that the charging costs for SS2 and SS3 schedules are higher than the SS1 schedule by 7% and 10%, respectively as expected. The intensified use of vehicles throughout the day results in an increase in energy requirement and a reduction of the

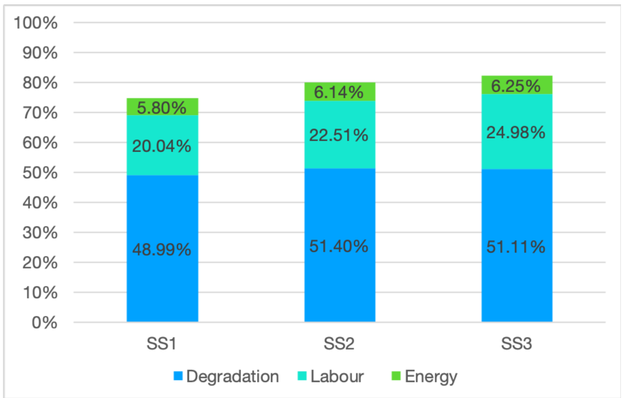

Fig. 4: Charging costs under different shift schedules

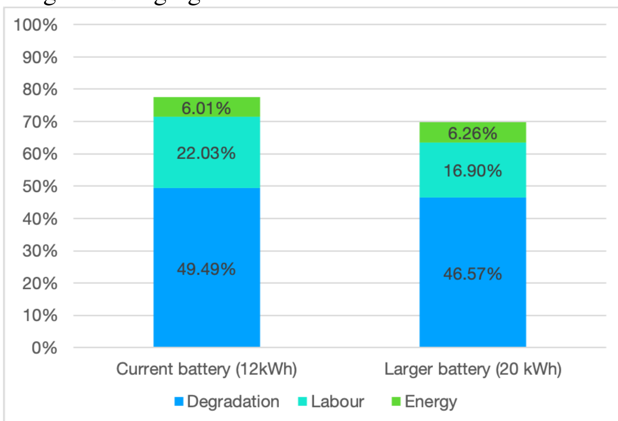

Fig. 5: The impact of an increased battery size

charging flexibility, which is defined as the idle time spent not charging [22]. This results in higher SOC cycling ranges, i.e., higher battery degradation costs, and a higher number of required charge events, i.e., higher labor costs. Moreover, there is also an increase in the energy costs since decreased time flexibility in SS2 and SS3 does not allow for selecting when to charge.

As the battery size is an important decision for EV users (in our case, an e-grocer), the impact of increasing the battery size on charging cost is investigated. Note that, higher investment costs with larger batteries and higher energy consumption due to the increased weight of the vehicle with a larger battery are not considered in the analysis. The experiments for all shift schedules are repeated for a battery of 20kWh. The average across all the shift schedules are presented in Figure 5. A decrease of 10% is observed on the overall charging cost as a result of the reduction in battery degradation cost (5.9%) due to the change in cycled SOC ranges, and more significantly the reduction of labor cost (23.3%) due to the less number of needed charge events.

The increased flexibility during the charging process that is enabled by smart chargers may help to reduce overall charging cost. On and off switching during coordinated charging may help to achieve the desired SOC levels at the right moments in time without using many charge events, and thereby reduce degradation and labor costs. Moreover, the increased charging flexibility can be leveraged to charge during times of low energy prices. Figure 6 shows a reduction

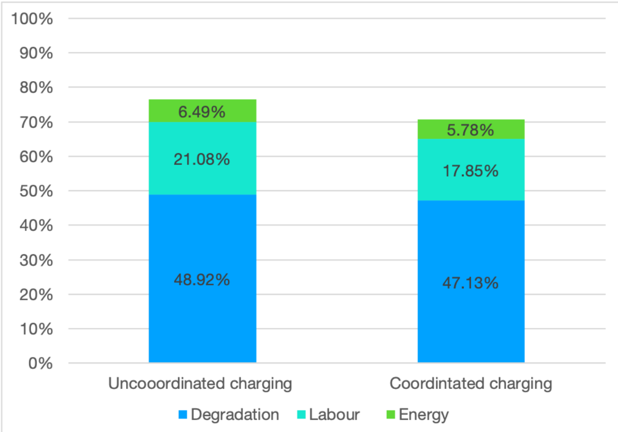

Fig. 6: The impact of coordinated charging

of 7% on the total charging costs due to a decrease of all cost components (battery degradation by 3.7%%, labor by 15.3% and energy costs by 10.9%) as expected.

IV. CONCLUSIONS

We proposed a charge schedule optimization model and investigated the impacts on overall charging cost (consisting of energy, labor and battery degradation costs) based on a real-life case study of the last-mile distribution of an e-grocer, Picnic. The proposed model outperforms the benchmark (which is the representation of actual operations) by 25.2% in total costs. This shows the potential of charge schedule optimization in last-mile services using EVs. An immediate consequence of reduced battery wear cost is that expected lifetime of the vehicles batteries is extended (19.0%). Furthermore, the impacts of 3 different shift schedules, the battery size and coordinated charging are investigated. It turns out that more energy demanding shift schedules result in higher average charging cost per charged amount of energy. The introduction of a larger battery size, shows potential for decreasing cost related to charging (10%). Moreover, coordinated charging yields a reduction of charging cost by 7%.

An interesting new area of research would be to consider the scheduling of vehicles to trips and the scheduling of charge events in a joint optimization problem. This could generate improved results, due to the increased flexibility of the vehicle schemes. On the other hand, these types of problems are more complex and therefore require efficient formulations and/or heuristics. Another area of interest lies in the implementation of more advanced battery degradation models, which take into account other operational factors other than cycling SOC or that incorporate degradation during storage. A very interesting future direction is to consider the uncertainty in various model components such as the required energy demand of the trips. Such a stochastic extension will be valuable to bring the study closer to reality and to develop robust strategies.

ACKNOWLEDGMENT

The authors would like to thank the collaborators from Picnic B.V. for providing the case study.

REFERENCES

[1] F. Liao, E. Molin, H. Timmermans, and B. van Wee, "Consumer preferences for business models in electric vehicle adoption," *Transport Policy*, vol. 73, pp. 12–24, 2019.

[2] V. Nian, M. Hari, and J. Yuan, "A new business model for encouraging the adoption of electric vehicles in the absence of policy support," *Applied energy*, vol. 235, pp. 1106–1117, 2019.

[3] C. Tryggestad, N. Sharma, J. van de Staaij, and A. Keizer, "New reality: electric trucks and their implications on energy demand," *McKinsey*, 2017.

[4] A. A. Juan, C. A. Mendez, J. Faulin, J. de Armas, and S. E. Grasman, "Electric vehicles in logistics and transportation: a survey on emerging environmental, strategic, and operational challenges," *Energies*, vol. 9, no. 2, p. 86, 2016.

[5] M. Schiffer, M. Schneider, G. Laporte, and G. Walther, "Vehicle and location-routing problems with intermediate stops: A review," *Transportation Science*, vol. 53, no. 2, pp. 319 – 343, 2019.

[6] M. Rogge, E. van der Hurk, A. Larsen, and D. U. Sauer, "Electric bus fleet size and mix problem with optimization of charging infrastructure," *Applied Energy*, vol. 211, pp. 282–295, 2018.

[7] J. Chen, B. Atasoy, T. Robenek, M. Bierlaire, and M. Thémans, "Planning of feeding station installment for electric urban public mass-transportation system," in *13th Swiss Transportation Research Conference (STRC)*, 2013.

[8] M. Schiffer and G. Walther, "Strategic planning of electric logistics fleet networks: A robust location-routing approach," *Omega*, vol. 80, pp. 31 – 42, 2018.

[9] J. Lin, W. Zhou, and O. Wolfson, "Electric vehicle routing problem," *Transportation Research Procedia*, vol. 12, pp. 508 – 521, 2016, tenth International Conference on City Logistics 17-19 June 2015, Tenerife, Spain.

[10] A. Montoya, C. Guéret, J. Mendoza, and J. Villegas, "The electric vehicle routing problem with nonlinear charging function," *Transportation Research Part B: Methodological*, vol. 103, pp. 87–110, 2017.

[11] S. Pelletier, O. Jabali, and G. Laporte, "Charge scheduling for electric freight vehicles," *Transportation Research Part B: Methodological*, vol. 115, pp. 246–269, 2018.

[12] O. Sundström and C. Binding, "Optimization methods to plan the charging of electric vehicle fleets," *Proceedings of the international conference on control, communication and power engineering*, pp. 28–29, 2010.

[13] O.-B. Sassi and A. Oulamara, "Simultaneous electric vehicles scheduling and optimal charging in the business context: Case study," 2014.

[14] O. Sassi and A. Oulamara, "Joint scheduling and optimal charging of electric vehicles problem," in *International Conference on Computational Science and Its Applications*. Springer, 2014, pp. 76–91.

[15] ——, "Electric vehicle scheduling and optimal charging problem: complexity, exact and heuristic approaches," *International Journal of Production Research*, vol. 55, no. 2, pp. 519–535, 2017.

[16] J. Vetter, P. Novák, M. R. Wagner, C. Veit, K.-C. Möller, J. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, and A. Hammouche, "Ageing mechanisms in lithium-ion batteries," *Journal of power sources*, vol. 147, no. 1-2, pp. 269–281, 2005.

[17] S. Han, S. Han, and H. Aki, "A practical battery wear model for electric vehicle charging applications," *Applied Energy*, vol. 113, pp. 1100–1108, 2014.

[18] T. Hallema, "'75.000 mensen op wachtlijst picnic'," Oct 2018. [Online]. Available: https://www.distrifood.nl/formules/nieuws/2018/10/75-000-mensen-op-wachtlijst-picnic-101119793?vakmedianet-approve-cookies=1&_ga

[19] M. Yilmaz and P. T. Krein, "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles," *IEEE Transactions on Power Electronics*, vol. 28, no. 5, pp. 2151–2169, 2013.

[20] A. R. Abul'Wafa, W. A. F. Mohamed, *et al.*, "Uncoordinated vs coordinated charging of electric vehicles in distribution systems performance," *International Journal of Engineering and Information Systems (IJEAIS)*, vol. 1, no. 6, pp. 54–65, 2017.

[21] D. Wu, D. C. Aliprantis, and L. Ying, "On the choice between uncontrolled and controlled charging by owners of phevs," *IEEE Transactions on Power Delivery*, vol. 26, no. 4, pp. 2882–2884, 2011.

[22] C. Develder, N. Sadeghianpourhamami, M. Strobbe, and N. Refa, "Quantifying flexibility in ev charging as dr potential: Analysis of two real-world data sets," in *2016 IEEE International Conference on Smart Grid Communications*. IEEE, 2016, pp. 600–605.