

*EVS36 Symposium Sacramento,  
CA, June 11-14, 2023*

## **Charging Infrastructure of Electrified Public Transport - a Case Study of Linköping City**

Daniel Jung<sup>1</sup>, Hampus Alfredsson<sup>2</sup>, Joakim Nyman<sup>3</sup>, Christofer Sundström<sup>4</sup>, and Jan Åslund<sup>5</sup>

<sup>1</sup>(Corresponding author) *Vehicular Systems, Linköping university, Linköping, Sweden, daniel.jung@liu.se*

<sup>2</sup>*RISE Research Institutes of Sweden, hampus.alfredsson@ri.se*

<sup>3</sup>*RISE Research Institutes of Sweden, joakim.nyman@ri.se*

<sup>4</sup>*Vehicular Systems, Linköping university, Linköping, Sweden, christofer.sundstrom@liu.se*

<sup>5</sup>*Vehicular Systems, Linköping university, Linköping, Sweden, jan.aslund@liu.se*

---

### **Executive Summary**

In this work, optimization of charging infrastructure and battery size is performed for the public transport in the Swedish city of Linköping. It is investigated how the total cost varies including charging infrastructure and batteries but also how different solutions affect battery aging. Real data on the driving patterns of the buses in the existing public transport system is used to analyze how the charging infrastructure should be distributed such that all buses can fulfill their driving missions. Both static and dynamic charging is considered, and it is shown that also a relatively small amount of charging infrastructure significantly decreases the required battery size in the buses. The results show that the optimization distributes charging infrastructure along one of the main roads where most buses pass during the day and the end bus stops along some of the bus routes where the buses are parked between the driving missions. A cost analysis shows that the total cost is reduced by selecting a smaller battery size and installing charging infrastructure. However, simulations indicate that smaller battery sizes will speed up battery aging due to deeper cycling.

---

## **1 Introduction**

Electrification of transport in cities has several advantages in addition to the reduction of  $CO_2$  and emissions, for example, the reduction of local emissions and noise. One such example is public transportation in cities, such as buses. Buses operate along predetermined routes and follow a known schedule. This is suitable for electrification since it allows for planned charging and optimized charging infrastructure. Compared to conventional internal combustion engines, electric machines are more suitable for driving patterns that include many starts and stops. The energy efficiency of buses is also increased when an electrified powertrain is used due to recuperation during braking and the low average speed.

Today, many electrified public transport systems only use depot charging and therefore require large batteries in the vehicles. The benefit is high flexibility, but with the potential drawback of using unnecessary large batteries. As alternatives, a system including smaller batteries and additional charging infrastructure available along the bus lines is to be analyzed [1, 2]. Examples of such infrastructure are electric road systems (ERS) or charging at bus stops.

Charging infrastructure must be distributed such that all buses can fulfill their driving missions. This could mean rescheduling the timetable to have time for charging. However, it is not acceptable that electrification should reduce the availability of public transportation due to charging. There are also other constraints such as possible locations for installing charging infrastructure, where it can be connected

to the grid, how much power is available during the day, etc. At the same time, the solution should be as cheap and resource effective as possible. The complexity of the problem requires mathematical optimization to find the most economical solution that fulfills all requirements.

Another important aspect of the operation of battery-electric vehicles is battery aging. As more access to charging infrastructure reduces the needed battery size it can also accelerate battery aging due to deeper cycling of the batteries. Thus, when analyzing the total lifetime cost of electrified public transportation, it is relevant to consider the expected battery lifetime when evaluating different solutions.

## 1.1 Problem formulation

The objective of this work is the optimization of charging infrastructure and battery size for an electrified public transportation system. It is assumed that charging stations are available at the depot and that each bus that is parked at the depot is charging. The main objective is then to distribute charging infrastructure along the bus routes such that all buses can fulfill their driving missions for a given battery size. The total cost of electrified public transportation includes both charging infrastructure and battery costs for all vehicles. Formulating the optimization problem requires some decisions regarding simplifications and modeling assumptions while still finding a practical solution.

Here, an optimization-based approach is used to investigate the trade-off between battery size and charging infrastructure in a mid-sized city. The objective is to minimize the total length of the charging infrastructure such that all buses can fulfill their driving missions without depleting their batteries. By analyzing the results for different battery sizes, a sensitivity analysis should be performed to evaluate the optimal solution depending on the total cost. The case considered in this work is the public transportation in the city of Linköping, Sweden. Driving patterns of the current public transport system are used to simulate the energy consumption of the individual buses and models of the electric powertrain and battery are used to simulate losses and the battery state of charge.

Both charging infrastructure placement, charging power, and battery size, will affect how the bus batteries are cycled during operations. As the battery degrades through usage (cycle aging) and due to calendar aging, the maximum available capacity will fade over time. This will in turn dictate the longevity of the batteries. Therefore it has been of interest in this work to also analyze to what extent degradation might impact the attractiveness of a proposed system solution. This is done by using a battery system and capacity fade model developed for LiFePO<sub>4</sub> (LFP) battery cells in earlier studies [3].

## 1.2 Limitations

The existing public transport system of Linköping consists of 15 fully electric buses and 80 bio-gas buses. In this study, all buses are modeled as fully electric and the simulated energy consumption is based on the assumption that all buses are operated in the same way as today. This implies that the scheduling of the timetables of the buses as well as the drivers are not to be modified, for example, longer charging stops. Furthermore, all buses are to have the same battery size due to the flexibility constraints of the system.

## 1.3 Related research

A review of the charging infrastructure localization problem for electric vehicles is given in [4]. The authors in [5] analyze charging infrastructure for different types of electrified transportation where the peak loads were identified as a risk to grid stability and high costs. In [6], different types of charging infrastructure for electric buses are evaluated, including charging stations, electric roads, and battery swapping. Electric roads were identified as cost competitive, especially for bus networks with high service frequency and low vehicle speed.

The authors in [7] considered an electric bus scenario with only depot charging. To avoid load peaks when many buses arrive at the depot at the same time, two different heuristic charging strategies were proposed. In [8], a nonlinear optimization problem is formulated for overnight charging of an electric bus fleet at the bus depot that considers battery aging.

In [9], the number of electric buses and locations of charging stations are optimized by formulating a stochastic integer program assuming stochastic charging demand. The authors in [10] formulated an optimization problem where the grid infrastructure and the distribution of charging stations were optimized simultaneously. In [11], the size of the battery pack, location of charging infrastructure, and charging power was done to minimize the total cost of ownership by including battery aging.

The size of the battery pack and charging using electric roads were optimized in [12] using integer programming. The authors in the mentioned work, state that uniform battery size and joint scheduling was the most cost-effective solution.

## 1.4 Data

Data for the GPS position and speed of the buses in the city is available for one full day (September 16, 2020). The position data is sampled at 1Hz. In this case study, 76 buses are considered that are operated

on 46 different bus routes, covering a total of 177 bus stops. Figure 1 illustrates the bus routes (blue lines) as well as the bus stops (purple circles). In addition, information about the road topology, as well as the outdoor temperature is collected to be used in the computation of the power consumption of the individual buses considering the vehicle propulsion and climatization of the compartment.

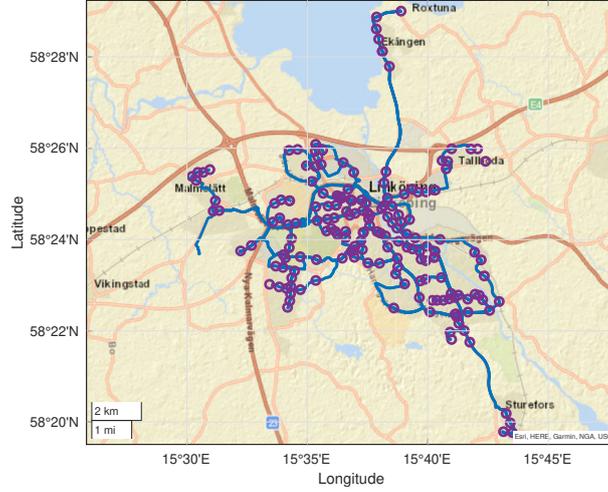


Figure 1: The figure shows the distribution of bus routes (blue curves) and bus stops (purple circles).

## 2 Models

Optimizing energy consumption requires simulation models of the vehicle and battery and a model of the charging infrastructure. Also, simulating battery aging requires a battery degradation model. The models used in this work are summarized in this section.

### 2.1 Vehicle model

A longitudinal bus model is used to compute the energy consumption based on vehicle speed  $v$ , and topology resulting in the road inclination  $\alpha$ . The energy flows to the battery is computed based on the energy required from the electric machine, but the power also depends on the availability of charging infrastructure. The power for the vehicle propulsion includes rolling resistance, air drag, topology, and acceleration. The air drag force is computed by

$$F_d = \frac{1}{2} \rho A_d C_d v^2 \quad (1)$$

where  $\rho$  is the air density,  $A_d$  the frontal area, and  $C_d$  the drag coefficient. The rolling resistance is modeled to be proportional to the vehicle mass  $m$  as

$$F_r = m g C_r \quad (2)$$

where  $g$  is the gravitational constant and  $C_r$  is the rolling resistance coefficient. The force acting on the wheels due to the topology is computed by

$$F_\alpha = m g \sin \alpha \quad (3)$$

and the force to longitudinal acceleration or deceleration

$$F_a = m a = m \frac{dv}{dt} \quad (4)$$

The total power needed at the wheel for a given route and velocity profile is given by

$$P_w = (F_d + F_r + F_\alpha + F_a) v \quad (5)$$

The powertrain is modeled using constant efficiencies except for the battery where the losses depend on the power. Based on  $P_w$  the input power to the gearbox is computed by

$$P_{gb} = \begin{cases} \frac{1}{\eta_{gb}} P_w & \text{if } P_w > 0 \\ \eta_{gb} P_w & \text{if } P_w < 0 \end{cases} \quad (6)$$

where  $\eta_{gb}$  is the gearbox efficiency. The electrical power to the electric machine is computed by considering the electric machine efficiency  $\eta_{em}$  as

$$P_{em} = \begin{cases} \frac{1}{\eta_{em}} P_{gb} & \text{if } P_{gb} > 0 \\ \eta_{em} P_{gb} & \text{if } P_{gb} < 0 \end{cases} \quad (7)$$

The battery current when there is no charging infrastructure available  $I_{b,noCharge}$  is computed based on  $P_{em}$  and the battery voltage  $U_b$  that is assumed constant when computing  $I_{b,noCharge}$

$$I_{b,noCharge} = \frac{P_{em}}{U_b} \quad (8)$$

The current is used to compute the losses in the battery. When charging infrastructure is available it is assumed that the vehicle receives a constant power,  $P_{charge}$ , that depends on both the charging infrastructure and the vehicle configuration. The battery current when charging infrastructure is available,  $I_{b,charge}$  is computed by

$$I_{b,charge} = \frac{P_{em} - P_{charge}}{U_b} \quad (9)$$

The energy stored in the battery is computed considering the losses in the battery, which are modeled using an internal resistance  $R_b$ . The change in stored energy in the battery when no charging infrastructure is available is computed by

$$P_{b,noCharge} = P_{em} + R_b \cdot I_{b,noCharge}^2 \quad (10)$$

and the corresponding power when charging infrastructure is available is computed as

$$P_{b,charge} = P_{em} - P_{charge} + R_b \cdot I_{b,charge}^2 \quad (11)$$

The power consumption for auxiliary loads, including, e.g., the HVAC system, is highly temperature dependent. Auxiliary power  $P_{aux}$  consumption data used in this project is delivered by a bus operator. The state of energy calculation depends on if charging infrastructure is available or not and is computed by

$$S\dot{O}E = \begin{cases} -(P_{b,noCharge} + P_{aux})/E_b & \text{if no charging infrastructure} \\ -(P_{b,charge} + P_{aux})/E_b & \text{if charging infrastructure available} \end{cases} \quad (12)$$

where  $E_b$  is the energy storage capacity of the battery.

The velocity, elevation profile, and battery State of Energy (SOE), for one of the buses, are presented in Figure 2. The x-axis is the time in seconds since midnight. The figure thereby illustrates the signals for almost one hour at approximately 2 pm.

## 2.2 Modeling of charging infrastructure

The considered charging infrastructure is static charging at the depot, bus stop chargers, and dynamic charging using electric road systems (ERS). The charging power is assumed to be 300kW independent of the type of charging infrastructure. To model the distribution of the electric road is available or not, a grid of the city map is constructed. The grid is dividing the road map into regions with dimensions 25 times 25 meters, as illustrated in Figure 3. The paths of the different bus lines are used to identify which regions that are candidates for electric roads. All the squares containing roads that are part of a bus route can be electrified. The locations of bus stop chargers are modeled by one of these 25 m x 25 m squares being electrified.

The bus GPS position is used to simulate when a bus is in an area where charging infrastructure is available. If the GPS position is inside a region that has charging capabilities, the vehicle is charged with the maximum power if the battery is not fully charged. This approach thereby handles both static and dynamic charging, where static charging includes both depot charging and bus stop charging.

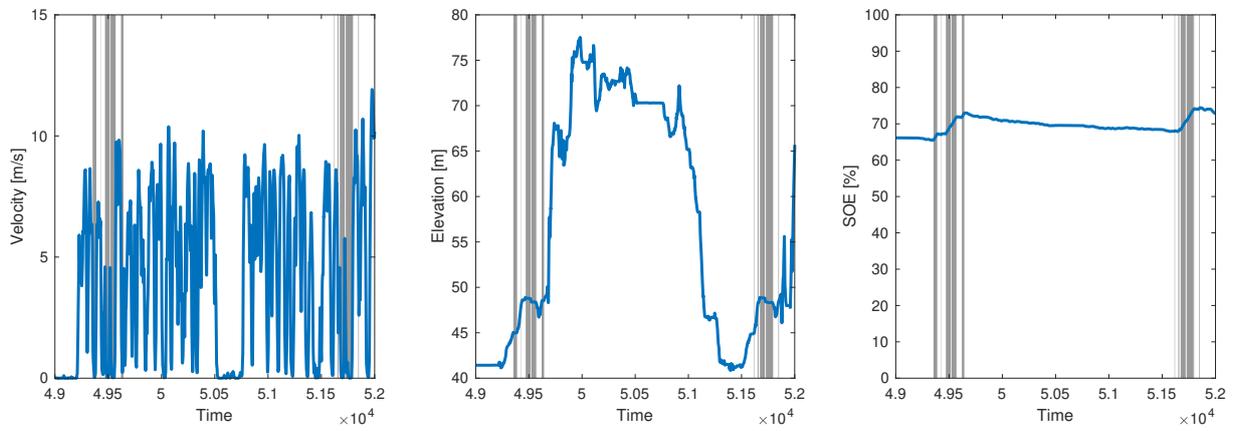


Figure 2: Example of bus data. The left figure shows logged velocity and the right figure shows simulated battery SOE. The marked intervals correspond to charging using ERS. The time is in seconds since midnight.

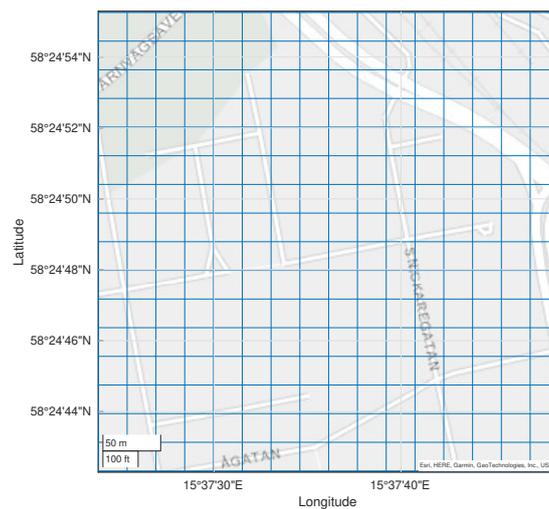


Figure 3: Example of how the road network is divided into regions using a grid.

## 2.3 Modeling of battery degradation

The battery cells considered in this work are LFP cells with a capacity of 14 Ah each, connected in series and in parallel to form the battery pack. A capacity-loss model is implemented according to earlier studies [13, 14] as

$$Q_{loss\%}(p, Ah) = \sigma_{funct}(p) Ah^z \quad (13)$$

$$\sigma_{funct}(p) = (\alpha SOC + \beta) \cdot \exp\left(\frac{-E_a + \eta I_c}{R_g \theta}\right) \quad (14)$$

$$I_c = \frac{|I|}{Q_{max}} \quad (15)$$

where  $Ah$  is the Ah throughput in the battery cell,  $z$  is the power law factor,  $\alpha, \beta$  define SOC dependence,  $E_a$  is the activation energy,  $\eta$  models the current rate  $I_c$  (or C-rate),  $R_g$  is the universal gas constant, and  $\theta$  is the battery pack's temperature in Kelvin. From experimental data and curve-fitting, earlier studies have identified suitable parameter values for modeling capacity fade of LFP batteries with  $E_a = 31700(J \text{ mol}^{-1})$ ,  $\eta = 202.5$ , and  $z = 0.57$ . The temperature is assumed to be kept constant at  $25^\circ C$  ( $298.15K$ ). The parameter values of  $\alpha, \beta$  are defined for different ranges of SOC as

$$\begin{cases} \alpha = 1287.6, \beta = 6356.3 & \text{if SOC} \leq 0.45 \\ \alpha = 1385.5, \beta = 4193.2 & \text{if SOC} > 0.45 \end{cases} \quad (16)$$

This study aims to simulate how the maximum capacity of the bus batteries changes over time due to cycling, which means summing very small capacity fade contributions as each bus traverses along the route network. However, since (13) is not linear, it cannot be used in this manner straight away. Using the approach taken in [3], equations (13)-(15) are combined and rewritten as an *aging intensity factor* as

$$\dot{Q}_d(t) = (\alpha' SOC + \beta')^{\frac{1}{z}} \cdot \exp\left(\frac{-31700 + 202.5 \frac{|I|}{Q_{max}}}{R_g \theta z}\right) \cdot |I(t)| \quad (17)$$

$$Q_{max}(t) = Q_{rated} - Q_d(t)^z \quad (18)$$

where  $\dot{Q}_d(t)$  is the resulting aging contribution for a very small timestep, which is continuously summed for each step throughout the simulation to form  $Q_d(t)$  at time  $t$  for the full drive cycle. Values for  $\alpha', \beta'$  are modified by a scaling factor. Before repeating the drive cycle, the maximum remaining capacity,  $Q_{max}(t)$ , is updated. The process is repeated until  $Q_{max}(t)$  has dropped to 80% of the rated capacity ( $Q_{rated}$ ) for a new battery, which is commonly used as a definition of the so-called End-of-Life (EoL), for when the battery needs to be replaced due to performance losses.

## 3 Optimization

To optimize the charging infrastructure, the models of the vehicle and battery are used to compute the energy consumption when each bus is driving. Each bus is passing through a given sequence of regions, which is evaluated by using GPS data to track where each bus is located in the city based on a grid. In each region of the grid, the total energy flow through the battery depends on the simulated propulsion to follow the given speed profile and if the bus is driving on an electric road. Here, the total energy flow is lumped together for each region. To formulate change in SOE (12) as a linear constraint depending on if the segment is an electric road or not, the total change in SOE when bus  $k$  is in the region  $i$  is modeled as

$$x_{SOE,k}[t+1] \leq x_{SOE,k}[t] + x_i dSOE_{k,ER}[t] + (1 - x_i) dSOE_{k,noER}[t] \quad (19)$$

where  $x_{SOE,k}[t]$  is the initial SOE of the bus when entering region  $i$ ,  $x_{SOE,k}[t+1]$  is the SOE when the bus  $k$  is leaving the region,  $dSOE_{k,ER}[t]$  is the total change in SOE when the bus is passing that region when there is electric road and  $dSOE_{k,noER}[t]$  is the change when there is no electric road. The index  $t$  represents the chronological order the bus is passing the different regions. The new SOE when entering the next region  $x_{SOE,k}[k+1]$  is upper bounded where the inequality is used to avoid that the battery is not charged more than  $x_{SOE,k} \leq 100\%$ . The SOE variables  $x_{SOE,k}$  are continuous while  $x_i$  are binary representing if a region has an electric road  $x_i = 1$  or not  $x_i = 0$ . The cost of electrifying each road segment is proportional to the length of the road in each region  $i$  which is given by multiplying  $x_i$  with a cost  $c_i$ .

Table 1: Optimized total length of electric road for different battery sizes using operational data from 76 buses.

Electric road	Battery size
1514 m	50 kWh
1049 m	100 kWh
720 m	150 kWh
545 m	200 kWh
302 m	250 kWh
230 m	300 kWh
37 m	400 kWh
27 m	500 kWh

To avoid finding solutions where the electric road is scattered along the road network, which would result in the extra cost of e.g. power supply to all the electric roads, an additional cost is added when  $x_i - x_j = \pm 1$ . This will act as a regularization term that will gather the electric road to a few roads, i.e., when two neighboring grid segments  $x_i$  and  $x_j$  are both neither regular roads nor electric roads. The optimization problem is formulated as a Mixed Integer Linear Program (MILP) as follows:

$$\begin{aligned}
 & \min_{x_i, x_{SOE}, s_{ij}} \sum_i c_i x_i + \beta \sum_{ij} s_{ij} \\
 & \text{s.t. } x_{SOE,k}[t+1] \leq x_{SOE,k}[t] + x_i dSOE_{k,ER}[t] + (1 - x_i) dSOE_{k,noER}[t], \forall k, t \\
 & \quad -s_{ij} \leq x_i - x_j \leq s_{ij}, \text{ for all neighboring regions } i \text{ and } j \\
 & \quad 0\% \leq x_{SOE,k}[t] \leq 100\%, \forall k, t \\
 & \quad x_i \in \{0, 1\}, \forall i
 \end{aligned} \tag{20}$$

where  $s_{ij}$  is included as a penalty when  $x_i - x_j \neq 0$  and  $\beta$  can be interpreted as related to a fixed cost of each segment of the electric road (a set of neighboring regions with electric road).

The optimization problem (20) is implemented and solved for 76 buses operated during one day using Gurobi [15].

## 4 Results

The first analysis compares the optimized charging infrastructure for different battery sizes in the buses and the predicted cost of the total solution. Then, it is investigated how the different solutions will impact battery aging.

### 4.1 Optimized charging infrastructure

The investigation is done by optimizing the distribution of electric roads for different battery sizes and calculating the total length of the electric road. In the analysis, batteries in the range of 50 - 500 kWh are evaluated. The total cost of batteries and the electric road is computed based on an estimated cost of 1 200 000 €/km for the electric road.

Figure 4 shows the solutions, i.e. the distributed charging infrastructure from the optimization, for the different battery sizes. The trend of the solution with increasing battery size draws similar conclusions. Electric roads are distributed along one of the main roads in the center of Linköping where many of the bus routes pass, and at some of the final bus stops. Figure 5 shows plots that are zoomed in on the center of Linköping. The solution for smaller battery sizes includes a longer section of the street and charging at more final bus stops.

In 2022, the battery cost is approximately 140 €/kWh and it is predicted to cost 80€/kWh in 2030. Increasing demand and shortage of resources could in the worst case increase the cost of batteries. It is assumed that the price of charging infrastructure will not change as much as the cost of batteries.

To evaluate the impact of the battery cost on the optimal trade-off, a sensitivity analysis is done by varying the cost of the batteries between 60 - 160 €/kWh. The result is shown in Figure 6 where the left plot shows the trade-off between battery size and the total length of the electric road. It is interesting to observe that the total length of the electric road varies for battery sizes below 400 kWh. The battery size that is used today by the electric buses in Linköping is approximately 600 kWh. The results of the optimizations show that the currently used battery size is sufficient to fulfill the current driving patterns without the need for additional charging infrastructure along the routes besides depot charging.

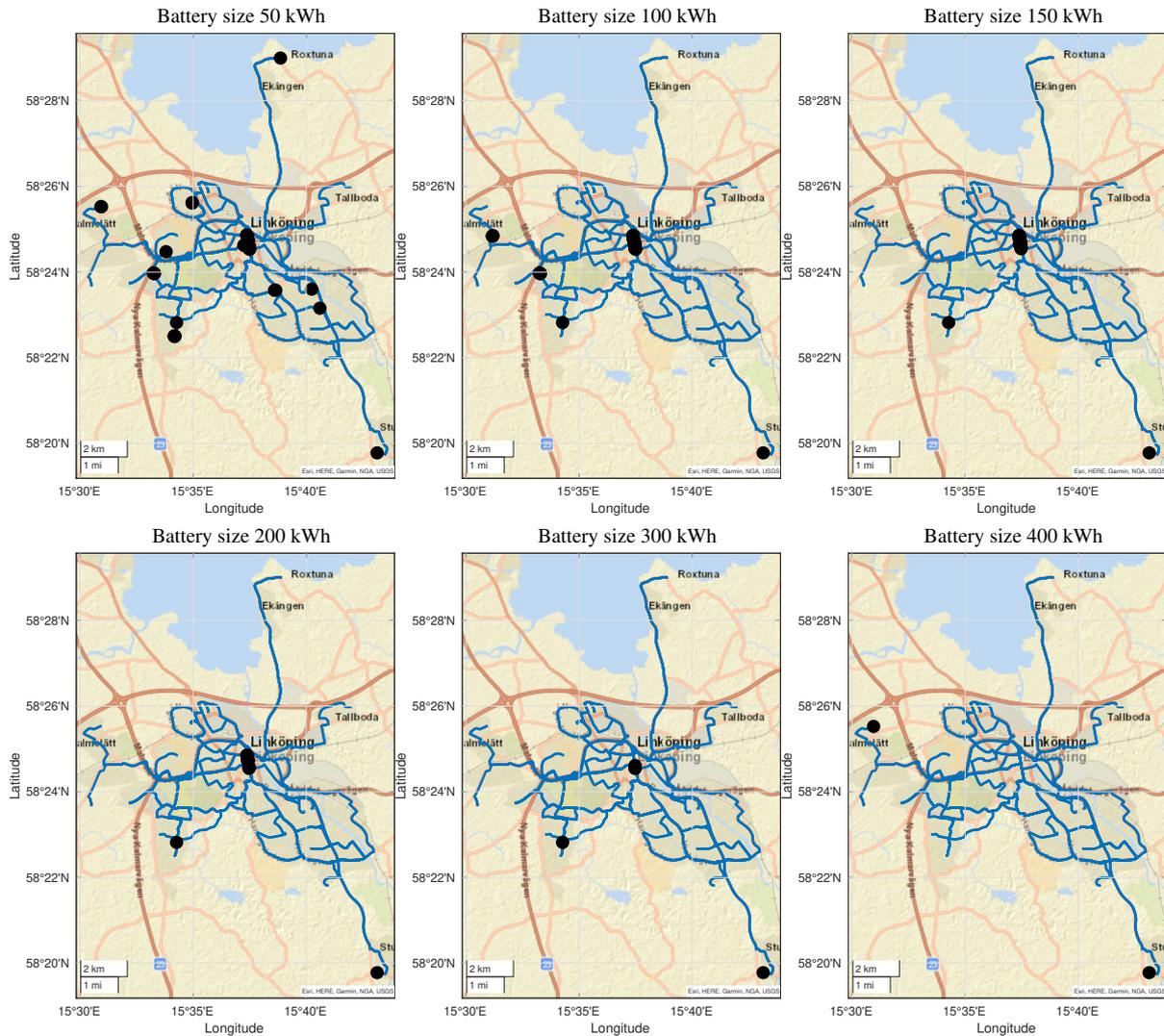


Figure 4: Optimized electric road. The electric road is distributed along one street in the central of Linköping where many buses pass and the last bus stop on some of the bus routes.

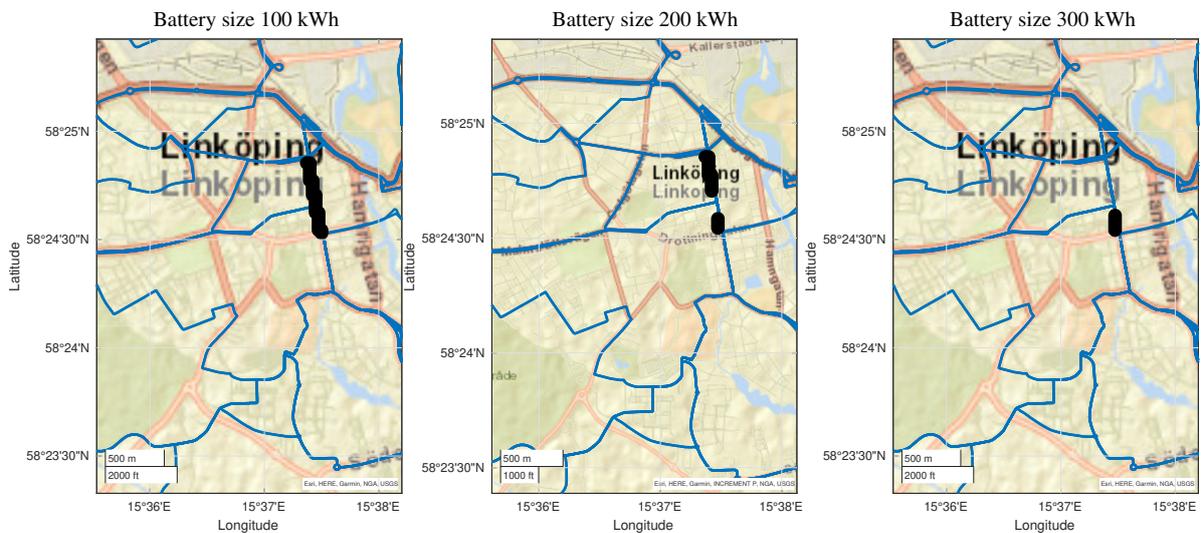


Figure 5: Zooming in on the distribution of electric road in the center of Linköping. The electric road is distributed on the street that passes one of the main town squares where many of the buses pass.

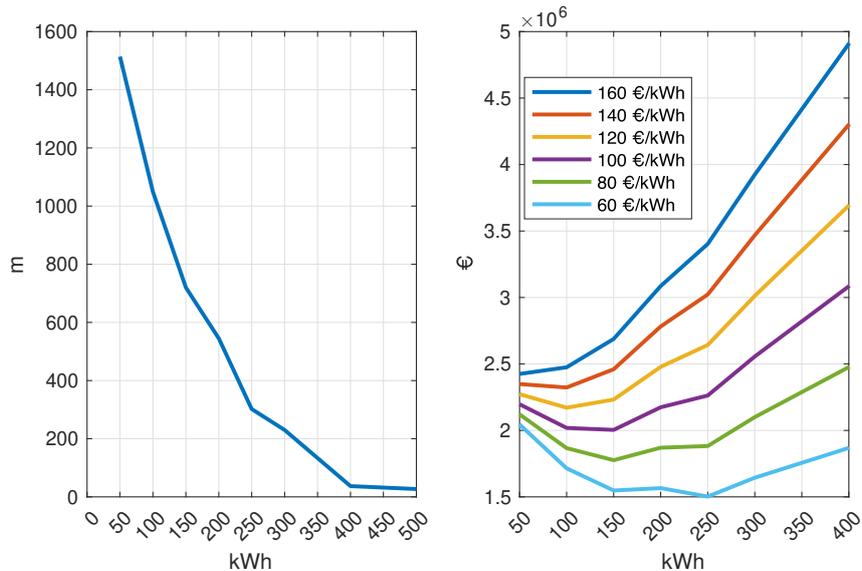


Figure 6: The left plot shows the trade-off in Table 1 between battery size and required electric road. The right plot shows the computed total cost of charging infrastructure and batteries for different battery sizes and battery cost per kWh.

## 4.2 Battery aging

Depending on the bus battery size and optimized charging infrastructure placement, the cycling pattern of the battery will differ, which in turn affects degradation (i.e. how long the battery will last). Hence, if a certain solution leads to fast battery degradation, it might not be an attractive option. Ultimately this should therefore be considered in some way as part of the optimization problem. A larger battery means higher investment cost, though it does not experience as deep cycles as a smaller battery, meaning it can deliver more energy over its lifetime.

In Figure 7, the optimized charging infrastructure result for 100 kWh bus batteries has been used to simulate battery degradation, as the number of cycles until EoL. To further investigate how an increase in battery size would affect this result, the charging infrastructure is kept constant, whilst the bus batteries are increased step-wise up to 250 kWh. Colored intervals represent the difference between the minimum and maximum number of cycles until EoL amongst the 76 buses, for each battery size.

For a 150% increase in battery size from 100 kWh to 250 kWh, the average number of cycles increased by roughly 15%, which is quite small compared to the increased capital cost of a more than twice as big battery pack. Still, since more cycles with a larger pack can deliver more energy over its cycle lifetime, it is important to compare costs on a unit base between different configurations. The optimization model behind this work is to be further developed to effectively consider both charging infrastructure costs and battery degradation costs when optimizing the system.

## 5 Conclusions

The results from the optimization show that the required battery size of the buses can be reduced significantly by adding electric roads. The optimization found solutions where the electric road was distributed along the main road where many of the buses pass during the day. It also identified final bus stops on routes where buses are parked between the scheduled driving missions. The credibility of the solution is also strengthened by the fact that the solutions are not dramatically different when the battery size is changed. The cost analysis shows that installing electric roads can significantly reduce the total cost by reducing the battery sizes. The analysis shows that the solution has a significant impact on battery aging. In future work, the plan is to include the impact of battery size on aging in the optimization problem.

## Acknowledgements

The authors would like to acknowledge Elina Rönnerberg for her support in implementing the optimization problem with Gurobi.

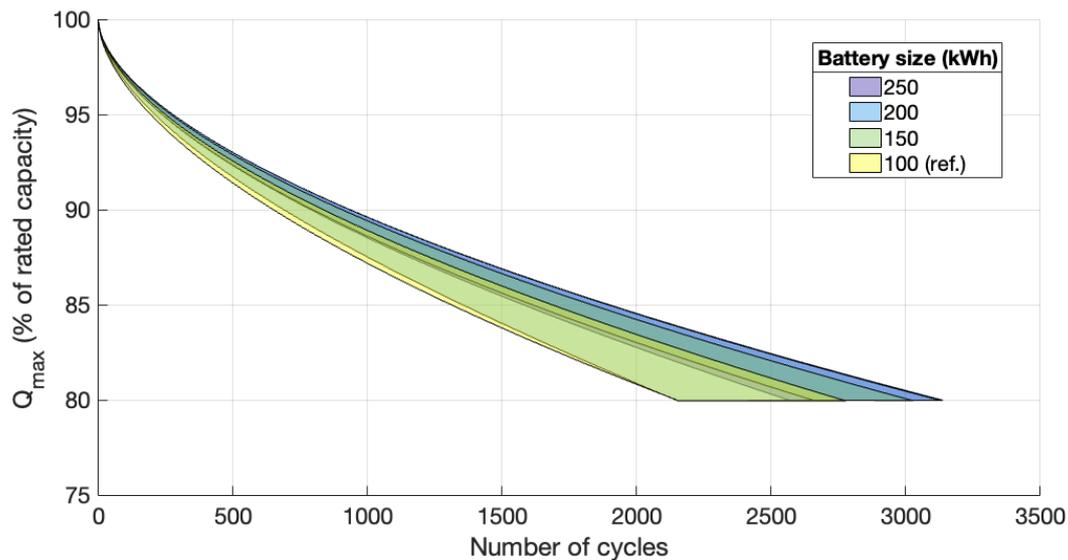


Figure 7: Number of cycles until EoL with altered battery sizes and same charging infrastructure solution. Results are obtained using the battery degradation model described in Section 2.3.

## References

- [1] L. Lindgren, “Electrification of city bus traffic – a simulation study based on data from linköping,” Lund University, Tech. Rep., 2017.
- [2] A. Kunitz, R. Mendelevitch, and D. Goehlich, “Electrification of a city bus network—an optimization model for cost-effective placing of charging infrastructure and battery sizing of fast-charging electric bus systems,” *International Journal of Sustainable Transportation*, vol. 11, no. 10, pp. 707–720, 2017.
- [3] I. Shafikani, “Energy management strategy design for series hybrid electric vehicles,” PhD dissertation, No. 2165, Linköping University, Department of Electrical Engineering, 2021.
- [4] R. C. Majhi, P. Ranjitkar, M. Sheng, G. A. Covic, and D. J. Wilson, “A systematic review of charging infrastructure location problem for electric vehicles,” *Transport Reviews*, vol. 41, no. 4, pp. 432–455, 2021.
- [5] A. Palomino and M. Parvania, “Advanced charging infrastructure for enabling electrified transportation,” *The Electricity Journal*, vol. 32, no. 4, pp. 21–26, 2019.
- [6] Z. Chen, Y. Yin, and Z. Song, “A cost-competitiveness analysis of charging infrastructure for electric bus operations,” *Transportation Research Part C: Emerging Technologies*, vol. 93, pp. 351–366, 2018.
- [7] A. Jahic, M. Eskander, and D. Schulz, “Charging schedule for load peak minimization on large-scale electric bus depots,” *Applied Sciences*, vol. 9, no. 9, p. 1748, 2019.
- [8] A. Houbbadi, R. Trigui, S. Pelissier, E. Redondo-Iglesias, and T. Bouton, “Optimal scheduling to manage an electric bus fleet overnight charging,” *Energies*, vol. 12, no. 14, p. 2727, 2019.
- [9] K. An, “Battery electric bus infrastructure planning under demand uncertainty,” *Transportation Research Part C: Emerging Technologies*, vol. 111, pp. 572–587, 2020.
- [10] Y. Lin, K. Zhang, Z.-J. M. Shen, and L. Miao, “Charging network planning for electric bus cities: a case study of shenzhen, china,” *Sustainability*, vol. 11, no. 17, p. 4713, 2019.
- [11] O. Teichert, F. Chang, A. Ongel, and M. Lienkamp, “Joint optimization of vehicle battery pack capacity and charging infrastructure for electrified public bus systems,” *IEEE Transactions on Transportation Electrification*, vol. 5, no. 3, pp. 672–682, 2019.
- [12] Y. Alwesabi, Y. Wang, R. Avalos, and Z. Liu, “Electric bus scheduling under single depot dynamic wireless charging infrastructure planning,” *Energy*, vol. 213, p. 118855, 2020.

- [13] G. Suri and S. Onori, “A control-oriented cycle-life model for hybrid electric vehicle lithium-ion batteries,” *Energy*, vol. 96, pp. 644–653, 2016.
- [14] M. Jafari, A. Gauchia, S. Zhao, K. Zhang, and L. Gauchia, “Electric vehicle battery cycle aging evaluation in real-world daily driving and vehicle-to-grid services,” *IEEE Transactions on Transportation Electrification*, vol. 4, no. 1, pp. 122–134, 2018.
- [15] Gurobi Optimization, LLC, “Gurobi Optimizer Reference Manual,” 2023. [Online]. Available: <https://www.gurobi.com>

## Presenter Biography



Hampus Alfredsson (presenter) works as a researcher and project leader in electromobility at RISE Research Institutes of Sweden, Gothenburg. He received an MSc in Environmental Engineering and Energy Systems at Lund University in 2018. In his daily research, he works primarily with questions around charging infrastructure for electrified vehicles, including modeling and analyzing localization and smart utilization of the infrastructure from a fleet perspective.