Modelling the urban mining potential of micromobility: A Finnish case study for e-scooters and e-bikes

Karhunen, M.*[1], Mosoni, C.[2], Patil, A.[3], Turkki, R.[4], Perämäki, S.[5], Väisänen, A.[6], Suomalainen E.[7]

[1] Senior Research Scientist, Built Environment Solutions Unit, Finnish Environment Institute (Syke), Finland
[2] Researcher, Climate Solutions Unit, Finnish Environment Institute (Syke), Finland
[3] Lecturer, Department of Chemistry, University of Jyväskylä, Finland
[4] Project Researcher, Department of Chemistry, Circular Economy, University of Jyväskylä, Finland
[5] Senior Lecturer, Department of Chemistry, Circular Economy, University of Jyväskylä, Finland
[6] Professor, Department of Chemistry, Circular Economy, University of Jyväskylä, Finland
[7] Leading Researcher, Built Environment Solutions Unit, Finnish Environment Institute (Syke), Finland

SHORT SUMMARY

Electric micromobility, or e-scooters and e-bikes may offer an alternative to the use of private cars. These micromobility devices, while lighter and less resource-intensive than cars, still require different metals and minerals. In this paper, we build a dynamic material flow model for shared e-scooters and private e-bikes in Finland, with an emphasis on their batteries, as these contain many critical raw materials. Our aim is to quantify the future urban mining potential of micromobility. We use Weibull distributions to model the lifetimes of micromobility devices and their batteries and discrete-time Bass diffusion to model the uptake of e-bikes as an innovation. In our baseline scenario, the outflow of used e-scooter batteries will be approximately 25,400 units and the outflow of used e-bike batteries some 217,000 units annually. For both types of devices, the main drivers of uncertainty are battery lifetime and the volume of future sales.

Keywords: Bayesian inference, e-bikes, e-scooters, fleet modelling, micromobility, shared mobility

1. INTRODUCTION

Transport produces 15% of the global greenhouse-gas (GHG) emissions (EDGAR, 2023) and as much as 33% in EU-27 and 24% Finland (European Environment Agency, 2024), when including aviation and shipping. Thus, there is an evident need for decarbonization of the transport sector. Yet, according to most forecasts, electric vehicles will still form only a minority of the global car fleet in 2040 (Kapustin & Grushevenko, 2020). Because the world is struggling to meet the 1.5°C target of the Paris agreement, it is natural to ask, if part of the transport-related emissions could be avoided by replacing private cars by other modes of transport. In this paper, we focus on electric micromobility which extends the range and speed of active mobility (walking and cycling) and does not possess many of the limitations of public transport (fixed schedules and routes etc.).

Electric micromobility involves most importantly e-bikes and e-scooters. In the UK, mass usage of e-bikes could have a potential to reduce CO2 emissions by 10%, significantly more than ordinary bikes (Philips et al., 2022). E-scooters seem to have less potential. Indeed, in Germany, it has been estimated that they can replace only 2% of car kilometers, and consequently little of the total CO2 emissions (Gebhardt et al., 2022). This is largely because e-scooters are typically used for shorter trips, the average distance being approximately 1.5 km (Zou et al., 2020). However, e-scooters are still an emerging technology and their popularity seems to be growing in Finland (Traficom, 2023).

Both e-bikes and e-scooters run on grid-based electricity and have predominantly lithium-ion batteries in Europe. Lithium-ion batteries contain many critical elements or strategic raw materials, such as cobalt, lithium, nickel and manganese (European Commission et al., 2023). Thus, the batteries of the electric micromobility devices may increase Europe's dependence on global supply chains, and on the other hand, used batteries contain valuable materials which could be recovered. Thus, there is potential for urban mining.

In this paper, we focus on modelling electric micromobility fleets, using shared e-scooters and private e-bikes in Finland as examples. Conceptually, our model could be termed as a dynamic material flow analysis (Deng et al., 2023). For the e-scooters, we build future scenarios around assumed fleet sizes of the e-scooter operators, using a result from recent literature (Reck et al., 2021). For the e-bikes, we build future scenarios using Bass diffusion to model their market penetration (Orbach, 2016; Lilien et al., 2000). Otherwise, both micromobility fleets can be modelled by using the same model structure.

2. METHODOLOGY

Model structure

The model is based on two fundamental equations written as

$$N_x(0,t) = s_x(t), \tag{1}$$

$$N_x(a+1,t+1) = (1-P_x(a))N_x(a,t) \tag{2}$$

where x denotes either an e-scooter, e-bike or a battery and $N_x(a,t)$ is the number of the objects of age a in year t. The first equation states that the inflow is determined by purchases (either by the operators or private consumers). We note that $s_x(t)$ is not necessarily the same for the batteries and corresponding devices, as extra batteries are typically bought with each shared e-scooter. The second equation describes how the fleet ages, given the breakdown probability $P_x(a)$. Each device must have at least one battery. Thus, at the end of each calendar year, we adjust the stock of new batteries $N_{nb}(0,t)$ as

$$N_{nb}(0,t) = N'_{nb}(0,t) + \max\{0, \textstyle\sum_{a=0}^{\infty}(N_{dev}(a,t) - N_{ob}(a,t) - N_{nb}(a,t))\} \tag{3}$$

where $N'_{nb}(0,t)$ is the unadjusted value, $N_{nb}(0,t)$ is the adjusted value, and $N_{dev}(a,t)$ and $N_{ob}(a,t)$ are the stocks of devices and old batteries, respectively. We distinguish between new and old batteries because e-scooters are typically bought to Finland as used, and thus, the batteries are old. The outflow of batteries is our main object of interest and is given by

$$OF(t) = \sum_{a=0}^{\infty}(P_{nb}(a)N_{nb}(a,t) + P_{ob}(a)N_{ob}(a,t)). \tag{4}$$

We use the Weibull distribution (e.g., Rinne, 2008) to model the lifetimes of devices and batteries alike. This distribution is given by the density function

$$f(a) = \frac{k}{\lambda}\left(\frac{a}{\lambda}\right)^{k-1} e^{-(a/\lambda)^k} \tag{5}$$

for $a, k, \lambda > 0$. (Note that the values of the parameters k and λ depend on x.) The mean and variance of the Weibull distribution are given by

$$\mu = \lambda\Gamma(1 + 1/k) \tag{6}$$

and

$$\sigma^2 = \lambda^2\left[\Gamma\left(1+\frac{2}{k}\right) - \left(\Gamma\left(1+\frac{1}{k}\right)\right)^2\right], \tag{7}$$

respectively. For each scenario, we assume that μ is known and $\sigma = 0.5\mu$. Thus, we can solve the primary parameters from the values of μ. We use the Broyden method (Dennis and Schnabel, 1996), implemented in the R package nleqslv (Hasselman, 2023), to solve the system of equations (6-7). Finally, the breakdown rate between ages a and $a + 1$ is given by

$$P_x(a) = \frac{F(a+1) - F(a)}{1 - F(a)} + v \tag{8}$$

where F is the cumulative distribution function of the Weibull distribution and v is the annual probability of vandalism. We calculate the breakdown rate of used devices and batteries as

$$P_x^{(u)}(a) = \frac{1}{c-b}\int_b^c P_x(a+u)\, du, \tag{9}$$

as we assume that their initial age is distributed uniformly in (b, c). We note that the rate $P_x^{(u)}(a)$ is a continuous function of age, even as the model is solved in discrete calendar time.

E-scooters

We consider only shared e-scooters, thus ignoring the privately owned ones due to lack of data. For the e-scooters, the model is stock-driven in the sense that a desired fleet size and a need to replace broken devices drives the e-scooter purchases of operators (Wiedenhofer et al., 2019). The total fleet size of shared e-scooters is known for years 2020–2022 (Traficom, 2023). However, the model is defined in terms of sales, and thus, we need to solve the sales' timeseries. To this end, we use the following rationale:

1. For 2020–2022, we use the Broyden method (Dennis and Schnabel, 1996) and the breakdown probabilities $P_x'(a)$ to calculate the sales which produce the desired fleet size, i.e., we run the model with different three-year timeseries, until the algorithm converges and the fleet size matches the target.

2. For each subsequent year, we assume that the size of the fleet must match a certain target and adjust the sales accordingly. This target is given by

$$T(t) = N_{2022}e^{-0.5(t-2022)} + N_{2030}\left(1 - e^{-0.5(t-2022)}\right), t = 2023, \ldots, 2029 \quad (10)$$

$$T(t) = N_{2030}, t \geq 2030 \quad (11)$$

where N_{2022} is the fleet size obtained from the data, t is the calendar year and N_{2030} is the final fleet size assumed in each scenario.

Table 1 presents the scenarios we consider in this study. The expert opinion cited in Table 1 corresponds to interviews conducted with various e-scooter operators and city representatives in Finland during the second half of 2023. The same set of questions was asked from all stakeholders. This included questions about the life cycle of shared e-scooters (manufacturing, use and logistics, and recycling). Note that individual answers cannot be identified from Table 1, as the scenarios are based on aggregated values.

The estimate of future sales in higher and business-as-usual (BAU) scenarios is based on a density estimate from Reck et al. (2021). They report that increasing the density of shared e-scooters beyond 114-171 km^{-2} does not increase the probability to use them. Thus, it seems logical to assume that the operators will not increase the e-scooter density beyond this limit. We multiply these figures by the highly urbanized area of Finland. Highly urbanized area is here defined as the sum of pedestrian zone of city centers, pedestrian zone of subcenters and the fringe zone of city centers (Information service Liiteri, 2023), totaling 588 km^2.

Table 1. Parameters of the fleet model. The format of the 'Values' column is: business-as-usual (BAU) scenario (low scenario – high scenario), where applicable.

Shared e-scooters

Parameter	Values	Justification
Expected lifetime	5 yrs (4–6 yrs)	Expert opinion (EO)
Expected lifetime of batteries	3 yrs (2–4 yrs)	EO
Vandalism rate	0.02 yr^{-1} (0.01–0.03 yr^{-1})	EO
Age of shared e-scooters imported to Finland	A uniform distribution in 0–2 yrs	EO
No. of batteries for each device	1.3 (1.2–1.4)	EO
Past sales	Calculated from fleet-size data	Data source from Traficom (2023)
Future fleet size in 2030	66,997 (stable fleet size–100,495)	BAU and the higher scenario are based on the density estimates from Reck et al. (2021) and highly urbanized area of Finland (Information Service Liiteri, 2023), the lower scenario from Traficom (2023)

Private e-bikes

Expected lifetime	10 yrs (5–15 yrs)	BAU value: Felipe-Falgas et al. (2022), lower value: Berjisian and Bigazzi (2019)
Expected lifetime of batteries	5 yrs (3–7 yrs)	EO
Vandalism and theft rate	0.02 yr^{-1} (0.01–0.03 yr^{-1})	Calibrated to the rate of bike theft in Finland (Bikesterredaktionen, 2024)
Past fleet size	Calculated from sales data	Data from Traficom (2022)
Increase of fleet size	Sales given by the Bass model, $s_0(t)$ ($s_1(t)$–$s_2(t)$)	Bayesian estimation: s_0 is the scenario based on posterior mean parameter values. s_1 and s_2 are the 5th and 95th percentile of the scenarios, as ranked by the total sales
Ultimate market size (M)	20% of population owns an e-bike (16%–28% of population owns an e-bike)	BAU scenario: e-bike density from Switzerland (Office fédéral de la statistique, 2023), lower scenario: e-bike density from Belgium (Goffinet, 2021), higher scenario: e-bike density from Netherlands (LEVA-EU, 2022)

E-bikes

The model is fleet-driven in the sense that we assume that sales are exogenous (Wiedenhofer et al., 2019). We have data on the sales of privately owned e-bikes from 2018–2022 (Traficom, 2022). We have imputed this timeseries with 4,000 for 2017 to model the early adopters. We assume that e-bike ownership follows the discrete-time Bass model of Lilien et al. (2000). To this end, we first run the model with BAU parameter values (Table 1), assuming that each broken e-bike is replaced. Thus, we obtain a timeseries of replacement sales $s_r(t)$. Subtracting this from the observed sales' timeseries, we get the innovation sales, i.e., the sales to new users as

$$g(t) = s(t) - s_r(t), t = 2017, \ldots, 2022. \tag{12}$$

We model this timeseries by using a Bass model with random noise. The market penetration at time t is

$$G(t) = \frac{1}{M} \sum_{u=-\infty}^{t} g(u) \tag{13}$$

where M is the total market size, with different scenarios given in Table 1. Using this definition, the innovation sales are modeled as

$$g(t+1) \sim NB\big((\alpha + \beta G(t))(1 - G(t))M, \vartheta\big) \tag{14}$$

where NB denotes a negative-binomial distribution, and α, β and ϑ are primary parameters to be estimated. We note that the dynamics of the model is such that $G(t) \to 1$ and $g(t) \to 0$ when $t \to \infty$, whereas the rate of convergence is determined by the values of α, β and ϑ. We parameterize the negative-binomial distribution so that the first term is the expectation and ϑ is a parameter known as 'size'. We thus have the likelihood

$$\mathcal{L}(\boldsymbol{g}|\alpha,\beta,\vartheta) = \prod_{t=2017}^{2022} \Gamma(g(t)+\vartheta)(\Gamma(\vartheta)g(t)!)^{-1} p(t)^{\vartheta}\big(1-p(t)\big)^{g(t)}, \tag{15}$$

$$p(t) = \vartheta(\vartheta + (\alpha + \beta G(t-1))(1 - G(t-1))M)^{-1}. \tag{16}$$

We first seek the maximum-likelihood estimate of $(\alpha, \beta, \vartheta)$ by using the Nelder-Mead method (1965) and then we assess the uncertainty of the parameter values by using the Haario-Saksman-Tamminen algorithm (2001). Thus, we can predict the innovation sales of the e-bikes for future years. Additionally, we assume that there are replacement sales, i.e., that each broken e-bike is replaced. Thus, we define the total sales as the sum of $g(t)$ and $s_r(t)$, the latter being equal to device outflow.

Otherwise, the model is the same as explained in the subsection 'Model structure'. The parameter values used for e-bikes are given in Table 1.

3. RESULTS AND DISCUSSION

Figure 1 demonstrates the dynamics of our model. The model for e-scooters is stock-driven, so that the number of e-scooters at the end of each year is given by Eqs. 10-11 and the purchases of the operators are adjusted accordingly. We observe that the sales are expected to decrease in the BAU scenario, as the fleet size stabilizes. The model for e-bikes is based on Bass diffusion and calibrated to sales data. We observe that peak sales in the model occur between 2025 and 2030, after which new sales are expected to decrease and the sales are driven by the need to replace broken e-bikes.

Figure 2 presents the simulation results for e-scooters. In the BAU scenario, the outflow of used batteries settles to approximately 25,400 units per year by 2030. The slight increase in the battery outflow after 2022 results from the fact that the age distribution of the fleet reaches the equilibrium state only gradually. The results show clearly that the main drivers of uncertainty are battery lifetime and the assumed future fleet size of e-scooters: In the lower sales scenario, the outflow of batteries stabilizes to some 20,900, and in the higher sales scenario, to some 38,100. We obtain 34,400 and 20,200 for the lower and higher battery lifetime scenarios, respectively. Vandalism has been omitted from Figure 2 because in these scenarios, it only has a minor effect.

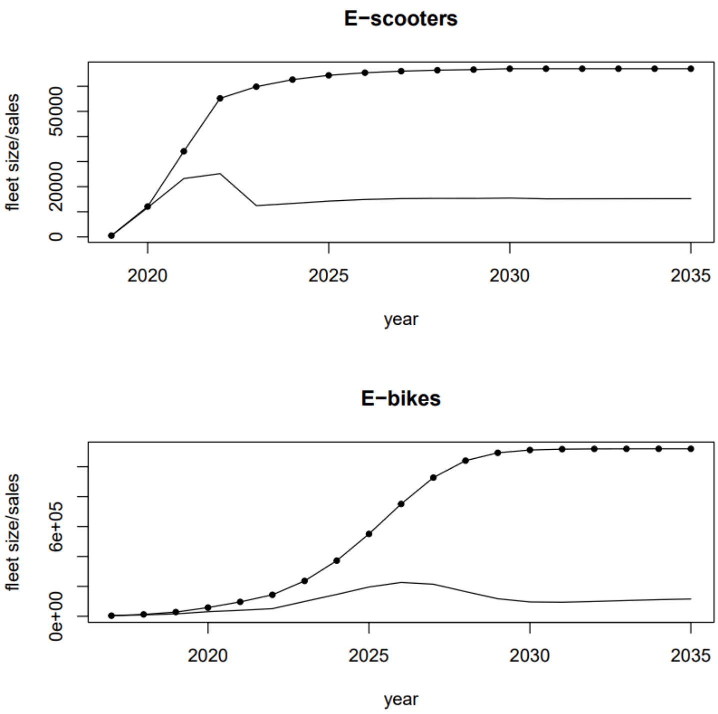

Figure 1. Dynamics of the model in the BAU scenario. The dotted lines represent the fleet sizes of e-scooters and e-bikes, whereas the solid lines represent sales, i.e., purchases of e-scooters by the operators and e-bikes by the consumers.

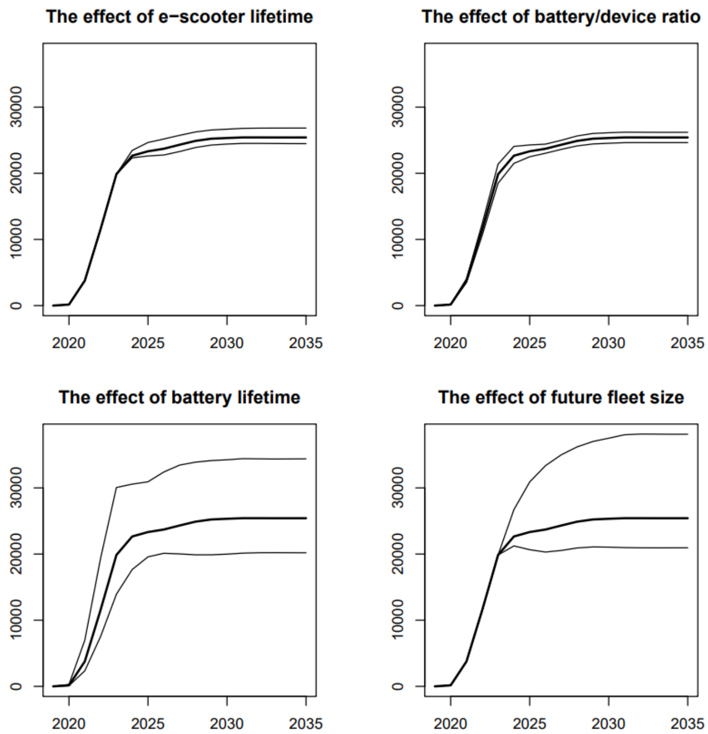

Figure 2. Simulation results for e-scooters. These results show the outflow of used batteries from shared e-scooters in Finland. In all panels, the bold line is the BAU scenario, whereas

the other two lines are the two scenarios corresponding to low and high alternative parameter values.

The picture is very different for private e-bikes (see Figure 3). First, the scale is greater than for the e-scooters. In the BAU scenario, the outflow of used batteries settles to 217,000 units by 2035. The main driver of uncertainty is battery lifetime, with the higher and lower scenarios stabilizing at 164,000 and 330,000, respectively. Perhaps surprisingly, the device lifetime has a minor effect (maximal difference in battery outflow: 2,200 units). The explanation is that the e-bike frame lasts much longer than the battery, so that the vast majority of the battery outflow comes from battery breakdowns. There are two types of uncertainty regarding future sales in the e-bike model: The parameter uncertainty related to the Bass model and the uncertainty related to the market size. Of these, the effect of market size is greater. Thus, if the market size is known, the parameters of the Bass model can be estimated fairly reliably. We note that the curves cross each other in the panel of the Bass parameters. This is because the peak sales occur in different years for different values of α, β and ϑ.

It should be noted that these results are based on few data points and would have benefitted from longer timeseries regarding the fleet sizes and/or sales. However, when comparing the BAU scenarios for e-scooters and e-bikes, e-bikes and the raw materials contained in their batteries are economically more important, with volumes almost 10 times greater, even without considering the fact that the e-bike batteries are typically larger than the e-scooters'.

We have used the Bass model (Lilien et al., 2000) and e-bike densities from different European countries to forecast the number of e-bikes in Finland. The logic of this model implies that the number of e-bikes will increase significantly. However, this is an extrapolation from a partially observed sales curve, and thus, there is a risk that the model may be misspecified.

We did not model privately owned e-scooters and shared e-bikes, since the number of shared e-bikes is minor in Finland and there is very little data on the ownership of private e-scooters. This is a major knowledge gap, and especially their future numbers might become significant. It seems that the uptake of private e-scooters has generally been studied little and constitutes an important research and data gap. Moreover, the effect of the battery lifetime is the largest source of uncertainty for both e-scooters and e-bikes. This constitutes another research gap, and to our knowledge, little data is publicly available.

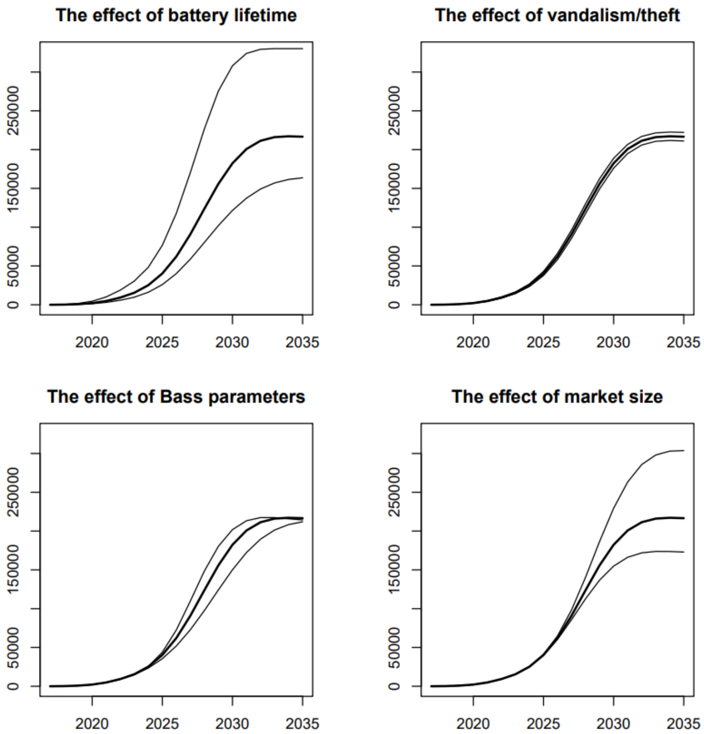

Figure 3. Simulation results for e-bikes. These results show the outflow of used batteries from private e-bikes in Finland. In all panels, the bold line is the BAU scenario, whereas the other two lines are the two scenarios corresponding to low and high alternative parameter values. The e-bike lifetime has been left out this figure because it has a negligible effect.

4. CONCLUSIONS

We built a dynamic material flow analysis model for electric micromobility devices in Finland. The model was combined with scenarios regarding device and battery lifetimes, vandalism rate, number of batteries per device, and future fleet or market size. The outflow of used batteries from e-scooters settles to some 25,400 units in the BAU scenario, and the outflow of used batteries from e-bikes to some 217,000. While there is unavoidable uncertainty in these figures, it is evident that battery lifetime and the projected fleet or market size are the most important factors in modelling the urban mining potential of micromobility.

ACKNOWLEDGEMENTS

Thanks are due for Mr. Antti Rehunen for his help with the definition of urban zones. We would also like to very much thank the experts who participated to our survey and interviews for their valuable knowledge that greatly helped to shape the scenarios.

REFERENCES

Berjisian, E., & Bigazzi, A. (2019). *Summarizing the Impacts of Electric Bicycle Adoption on Vehicle Travel, Emissions, and Physical Activity*. REACT (Research on Active Transportation) Lab, University of British Columbia.

Bikesterredaktionen. (2024). *Pyörävarkaus – Mitä tehdä kun polkupyörä varastetaan & miten minimoida varkauden mahdollisuus*. [Bike theft – What to do when a bike is stolen & how to minimize the chance of theft.] https://www.bikester.fi/fi/info/bikester-magazine/2024/03/13/pyoravarkaus-miten-toimia-kun-polkupyora-varastetaan, accessed 24 May 2024.

Deng, T., Zhang, Y., & Fu, C. (2023). Modelling dynamic interactions between material flow and stock: A review of dynamic material flow analysis. *Ecological Indicators, 156*, 111098.

Dennis, J.E. Jr., & Schnabel, R.B. (1996). *Numerical Methods for Unconstrained Optimization and Nonlinear Equations*, Siam.

EDGAR. (2023). *EDGAR (Emissions Database for Global Atmospheric Research) Community GHG Database, a collaboration between the European Commission, Joint Research Centre (JRC), the International Energy Agency (IEA), and comprising IEA-EDGAR CO2, EDGAR CH4, EDGAR N2O, EDGAR F-GASES*, version 8.0. [Data set]. European Commission, JRC. https://edgar.jrc.ec.europa.eu/climate_change, accessed 29 May 2024.

European Commission, Directorate-General for Internal Market, Industry, Entrepreneurship and SMEs, Grohol, M., & Veeh, C. (2023). *Study on the Critical Raw Materials for the EU 2023: Final Report*. Publications Office of the European Union. https://op.europa.eu/en/publication-detail/-/publication/57318397-fdd4-11ed-a05c-01aa75ed71a1, accessed 22 Nov 2023.

European Environment Agency. (2024). *EEA Greenhouse Gases – Data Viewer*. https://www.eea.europa.eu/data-and-maps/data/data-viewers/greenhouse-gases-viewer, accessed 24 May 2024.

Felipe-Falgas, P., Madrid-Lopez, C., & Marquet, O. (2022). Assessing environmental performance of micromobility using LCA and self-reported modal change: The case of shared e-bikes, e-scooters, and e-mopeds in Barcelona. *Sustainability, 14*(7), 4139.

Gebhardt, L., Ehrenberger, S., Wolf, C., & Cyganski, R. (2022). Can shared e-scooters reduce CO2 emissions by substituting car trips in Germany? *Transportation Research Part D, 109*, 103328.

Goffinet, L. (2021). Statistiques mobilité: Les belges et le vélo. [Mobility statistics: The Belgians and the bicycle.] https://www.gracq.org/actualites-du-velo/statistiques-mobilite-les-belges-et-le-velo, accessed 24 May 2024.

Haario, H., Saksman, E., & Tamminen, J. (2001). An adaptive Metropolis algorithm. *Bernoulli*, 223-242.

Hasselman, B. (2023). *nleqslv: Solve Systems of Nonlinear Equations*. R package version 3.3.4, https://CRAN.R-project.org/package=nleqslv.

Information service Liiteri. (2023). https://liiteri.ymparisto.fi/, accessed 24 Jan 2024.

Kapustin, N. O., & Grushevenko, D. A. (2020). Long-term electric vehicles outlook and their potential impact on electric grid. *Energy Policy, 137*, 111103.

LEVA-EU. (2022). *The Netherlands Has Nearly 5 Million E-bikes*. https://leva-eu.com/the-netherlands-has-nearly-5-million-e-bikes/, accessed 25 Jan 2024.

Lilien, G. L., Rangaswamy, A., & Van den Bulte, C. (2000). 12. Diffusion models: Managerial applications and software. *New-product Diffusion Models, 11*.

Nelder, J. A., & Mead, R. (1965). A simplex algorithm for function minimization. *Computer Journal, 7*, 308-313.

Office fédéral de la statistique. (2023). *Possession de Véhicules, de Permis et d'Abonnements des TP*. [Possession of vehicles, licenses and public transport subscriptions.] https://www.bfs.admin.ch/bfs/fr/home/statistiques/mobilite-transports/transport-personnes/comportements-transports/possession-vehicules-permis-conduire.html, accessed 24 May 2024.

Orbach, Y. (2016). Parametric analysis of the Bass model. *Innovative Marketing, 12*(1), 29-40.

Philips, I., Anable, J., & Chatterton, T. (2022). E-bikes and their capability to reduce car CO2 emissions. *Transport Policy, 116*, 11-23.

Reck, D. J., Haitao, H., Guidon, S., & Axhausen, K. W. (2021). Explaining shared micromobility usage, competition and mode choice by modelling empirical data from Zurich, Switzerland. *Transportation Research Part C: Emerging Technologies, 124*, 102947.

Rinne, H. (2008). *The Weibull distribution: A Handbook*. CRC press.

Traficom – Liikenne- ja viestintävirasto. (2022). Personal communication. Email from Virpi Ansio, 28.11.2022.

Traficom – Liikenne- ja viestintävirasto. (2023). *Yhteiskayttöisten sähkopotkulautapalveluiden tarjonta, kysyntä ja markkinatilanne*. [The suppy, demand and market situation of the shared e-scooter services.] https://tieto.traficom.fi/fi/tilastot/yhteiskayttoisten-sahkopotkulautapalveluiden-tarjonta-kysynta-ja-markkinatilanne, accessed 22 Nov 2023.

Wiedenhofer, D., Fishman, T., Lauk, C., Haas, W., & Krausmann, F. (2019). Integrating material stock dynamics into economy-wide material flow accounting: Concepts, modelling, and global application for 1900–2050. *Ecological Economics, 156*, 121-133.

Zou, Z., Younes, H., Erdoğan, S., & Wu, J. (2020). Exploratory analysis of real-time e-scooter trip data in Washington, D.C.. *Transportation Research Record, 2674*(8), 285-299.