Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 70 (2023) 347–355

Transportation Research Procedia

www.elsevier.com/locate/procedia

8th International Electric Vehicle Conference (EVC 2023)

Feedback Indicators for Providing Carbon Impact of Vehicle Charging to Electric Vehicle Users

Nana Kofi Twum-Duah[a,b,] *, Lucas Hajiro Neves Mosquini[a,c], Muhammad Salman Shahid[a], Frédéric Wurtz[a], Benoît Delinchant[a]

[a] *Univ. Grenoble Alpes, CNRS, Grenoble INP, G2Elab, F-38000 Grenoble, France*
[b] *Univ. Grenoble Alpes, CNRS, Grenoble INP, G-SCOP, F-38000 Grenoble, France*
[c] *University of Applied Sciences of Western Switzerland, Energy Institute, HEIA-FR, 1700 Fribourg, Switzerland*

Abstract

The purpose of this article is to introduce two indicators designed to evaluate and consequently influence the indirect emissions related to the operation of an EV. The first indicator, denoted as "Electric Vehicle CarbonFlex Potential" indicator, evaluates an EV's maximum and minimum achievable carbon emissions using an optimization approach and compares the user's resultant indirect carbon emissions to these boundaries, therefore, this indicator compares the users behavior to the optimal best and worst cases. The second indicator is "EcoCharge Time" indicator, which provides feedback to an EV user based on their charging behavior on the best and worst times of charging the vehicle in a day. Since human behavior cannot be controlled, such indicators are essential tools for influencing the behavior of EV users toward a desired optimal, in this case, a charging schedule with the lowest possible overall indirect emissions. The proposed indicators were tested on an EV dataset using the carbon intensity data from a number of countries and the results show that there exists considerable flexibility potential. Additionally, the results also showed the best charging times, which were typically clustered around, allowing for ease of use and understanding.

Keywords: Indirect Carbon Emissions; Energy Transition; Carbon-free Transportation; Feedback Indicators; Linear Programming

1. Introduction

As the world continues to rely heavily on fossil fuels for transportation, the resulting greenhouse gas emissions are a major facilitator of climate change. The transportation sector is considered a major contributor to global warming

* Corresponding author.
E-mail address: nana-kofi-baabu.twum-duah@g2elab.grenoble-inp.fr

10.1016/j.trpro.2023.11.039

since it accounts for 23% of global CO_2 emissions (International Energy Agency, 2022). To mitigate this impact of transportation on climate change, electric vehicles (EVs) are becoming increasingly important in the fight against climate change. Battery Electric vehicles (BEVs) have consequently emerged as one of the most promising and prominent alternatives to traditional gasoline vehicles, as also illustrated in Figure 1 (European Environment Agency, 2018; International Energy Agency, 2021). Governments and private companies are investing heavily in EV technology to accelerate their adoption and ensure a sustainable future for our planet. Therefore, electric mobility is an important pillar to achieving the energy transition for mitigating climate change.

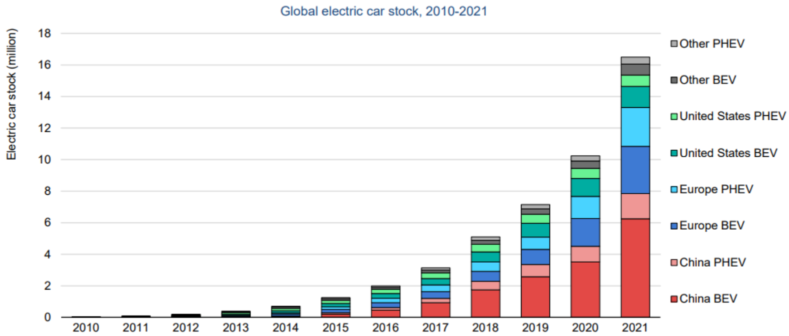

Figure 1. Global EV stock for passenger light-duty vehicles- Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEV) (International Energy Agency, 2022)

Compared to traditional ICE (internal combustion engine) vehicles, BEVs are a promising alternative that offers several benefits, including lower emissions, reduced reliance on fossil fuels, and potentially lower operating costs (Ingrid Malmgren, 2016). A key driver for the BEV revolution is that they have zero tailpipes (i.e. direct) emissions and are effectively more environmentally friendly in their operational phase. This benefit can be further enhanced by sourcing electrical energy from renewable sources, effectively making BEVs zero emissions. However, it is pertinent to take into account the production and end-of-life phases of the vehicle as well (i.e. the entire life cycle of a BEV). Literature shows that the manufacturing and end-of-life stages of BEVs have higher global warming potentials relative to conventional ICEs (Hawkins et al., 2013; Zerrin Günkaya et al., 2016).

Like all energy-dependent systems, the impact of BEVs on emissions is dependent on the source of electricity used to power them. EVs powered by renewable electricity sources, such as wind and solar energy, can significantly reduce emissions compared to ICEs. However, for high carbon-intensity grids, BEVs may have emissions similar to or even higher than that of a similar ICE (Li et al., 2019). This brings to light the importance of optimizing human behavior to minimize the indirect emissions associated with BEVs (Bohua et al., 2018). Effective energy or climate awareness indicators can play an important role in influencing human behavior toward more sustainable choices. Indicators can serve as a tool to nudge individuals towards more sustainable behaviors, such as charging EVs during periods of low carbon intensity. Additionally, indicators provide a clear and concise way to communicate complex information (i.e. reduce the cognitive strain associated with trying to process information (Calvo et al., 2022)) and can encourage individuals to adopt more sustainable behavior (Midden et al., 2014).

Multiple studies have been conducted to evaluate the effect of feedback on building occupants' behavior with regard to energy consumption. Nilsson et al and Westskog et al (Nilsson et al., 2014; Westskog et al., 2015) concluded that providing feedback resulted in no significant reduction in electricity consumption, whilst Lin et al (Lin et al., 2016) recorded a 16.7% reduction in electricity consumption for a group of participants in their study. Effectively, these studies point out the fact that indicators can be effective if they are well-designed (simple and easy to understand) by incorporating the right socioeconomic factors (income, education, and cultural values) (Capellán-Pérez et al., 2016; Twum-Duah et al., 2019). Thus, the purpose of this article is to provide feedback in the form of indicators to EV owners and fleet operators, which would serve as a tool for assessing their performance relative to the best and worst cases. The best case refers to the minimum possible indirect emissions given the historical charging behavior of the EV user and vice versa for the worst case. Subsequently, Section 2 of this article provides details on the datasets used in this article, Section 3 is the methodology, Section 4 presents the results and discussions and Section 5 is the conclusion.

2. EV and Grid Carbon Intensity Datasets

For this article, we consider two datasets, the EV dataset, and the grid carbon intensity dataset, for the period between January 2021 and December 2021 (i.e. one year). The considered dataset is sampled at a one-hour timestep and has undergone some pre-processing to remove outliers. All authors and as such this article adhere to the principles of Open-Science, implying that all datasets, notebooks, and code associated with this article will be published following the guidelines prescribed by ORUCE (Open and Reproducible Use Cases For Energy) (Hodencq et al., 2021). This study considered a 2013 Renault Zoe with a battery capacity of 22 kWh that was primarily used in the southeastern part of France. Figure 1 is a visualization of the EVs data and shows some usage patterns. Figure 1 (a and d) shows the charging behavior of the EV user, Figure 1 (b and e) demonstrates the discharge patterns of EV's battery and Figure 1 (c and f) is a visualization of the distance traveled by the EV. From Figure 1 (d), it can be observed that charging frequently happened in the early mornings (9:00 – 12:00). The driving (discharging) of the car usually happened between 7:00 – 8:00 and 17:00 – 19:00 (Figure 1 (e)) with a typical distance less than 50 km. The data infers that this vehicle was typically used for commutes to work based on the driving time and distances traveled. The driver of the car also validated this inference.

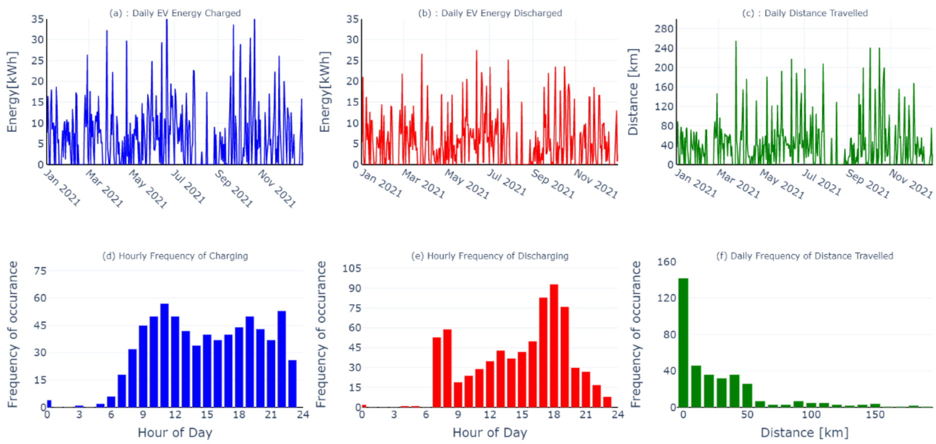

Figure 2: Daily usage summary of EV (a) Energy charged, (b) energy discharged, and (c) distance traveled and the distribution of EV (d) hourly count of vehicle charging, (hourly count of vehicle discharge, (f) frequency of distance traveled data – typical daily distance less than 50km

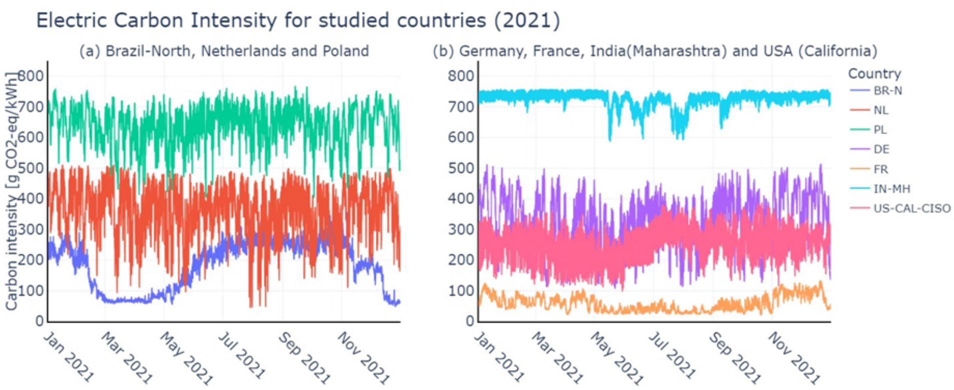

Figure 3: Hourly carbon intensity for the electricity grids of (a) Brazil-North, Netherlands, and Poland, and (b) Germany, France, India (Maharashtra), and USA (California)

The grid carbon intensity was sourced from the electricity map (Electricity Maps, 2022) for the following countries; India (IN-MH), the USA (US-CAL-SISO), France (FR), the Netherlands (NL), Brazil (BR-N), Germany (DE), and Poland (PL), see Figure 2. The data shows that India had the highest carbon intensity (with low levels of variations) whilst France had the lowest levels of carbon emissions (also with low levels of variations). The German, Dutch, and American (Californian) grids were also of high interest as they had high renewable energy penetration rates.

3. Methodology

Considering the dataset, two indicators, namely, (i) the Electric Vehicle CarbonFlex Potential Indicator (EV-CP) and (ii) the EcoCharge Time indicator (ECT) were proposed.

3.1. Electric Vehicle CarbonFlex Potential Indicator (EV-CP)

The EV-CP is an indicator that provides information on the potential an EV user has to improve the indirect carbon emissions from their electric vehicle. It ranges from 0 – 1 (0 indicating optimal charging behavior and 1 indicating the worst possible charging behavior) This indicator is computed using the Mixed Integer Linear Programming (MILP) approach to minimize the carbon emissions related to charging (i.e. the best case) and the maximum carbon emissions (the worst case) based on the charging behavior of an EV user. The MILP approach is explained further in section 3.3. The EV-CP is then expressed mathematically as:

$$EV - CP = \left[\frac{Emissions_{real} - Emissions_{best}}{Emissions_{worst} - Emissions_{best}}\right] \tag{1}$$

Such that $Emissions_{real}$ are the real emissions obtained from the available data and $Emissions_{worst}$ and $Emissions_{best}$ are the emissions from the worst-case and best-case scenarios respectively and are denoted as

$$Emissions_{best} = min\left[\sum\sum P_{charge}(pd,t) \times CO2_{grid}(pd,t)\right] \tag{2}$$

$$Emissions_{worst} = max\left[\sum\sum P_{charge}(pd,t) \times CO2_{grid}(pd,t)\right] \tag{3}$$

where $P_{charge}(pd,t)$ and $CO2_{grid}(pd,t)$ are the charging power (in kW) and grid carbon intensity (g-co2 eq/kwh) at time step $'t'$ respectively.

3.2. EcoCharge Time indicator (ECT)

The ECT indicator, on the other hand, makes use of the results from the two optimizations (i.e. optimal and worst-case scenarios) and evaluates the best hour and worst hour to charge based on the frequency of charging based on the two optimizations. It ranges from -100 to +100, with -100 denoting the highest likelihood for high grid emissions (i.e. bordering on the worst-case scenario), and +100 denoting the highest likelihood for low emissions for a given hour (i.e. bordering on the best-case scenario). Thus, for the worst-case scenario, the most frequently used charging time would yield the worst results and as such should be avoided. Similarly, using the results from the optimal scenario (minimize emissions), the best charging time can be determined based on how frequently the optimizer decided to charge for a specific hour. The goal of this indicator is to provide very generalized information (based on an EV users charging behavior) which would serve as a guide and nudge an EV user to charge at the most optimal time with respect to grid-related emissions. The ECT indicator is computed as the difference between the likelihood of a best-case charge and the likelihood of a worst-case charge for each hour of the day and is given mathematically as:

$$ECT = \frac{Count_{best\ case\ charge}(t) - Count_{worst\ case\ charge}(t)}{T} \times 100 \tag{4}$$

where $Count_{best\ case\ charge}(t)$ and $Count_{worst\ case\ charge}(t)$ refer to the number of times during the evaluation period that the optimizer chose to charge for hour $'t'$ for the best and worst case scenarios respectively. 'T' represents the total number of hours $'t'$ present in the evaluation period (in this case 365).

3.3. Mixed Integer Linear Programming approach for computing best and worst case

As highlighted in the previous section, a mixed integer linear programming approach is applied to either determine the scheduling of charging which would allow the indirect emissions to be maximized (worst-case) or minimized (best-case). Figure 4 shows a block diagram representation of the system under consideration. For this optimization, we considered two time scales, the main horizon of 1 year (365 days) and the sub-horizon of 1 day (24 hours), allowing for the daily demand of the EV user to be respected. Thus, the proposed charging strategy will not be the global optimal (it would be possible to improve results by removing the constraint of respecting the daily demand) however, this strategy allows us to take into account human behavior in the optimization.

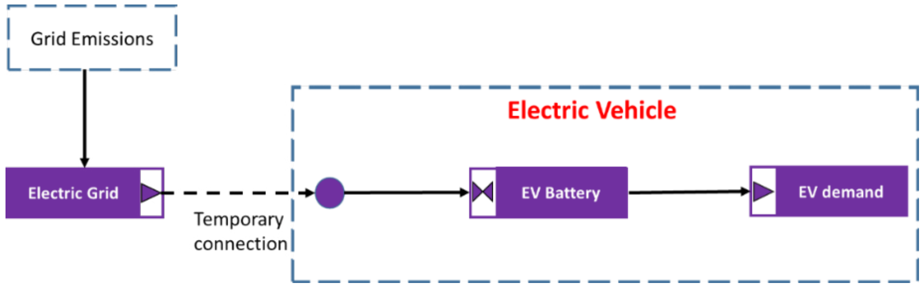

Figure 4. Graphical representation of the energy system for optimization

The objective function of the proposed optimization was defined for the best case and worst case as:

$$objective_{best} = min\left[\sum\sum P_{charge}(pd,t) \times CO2_{grid}(pd,t)\right] \quad (5)$$

$$objective_{worst} = max\left[\sum\sum P_{charge}(pd,t) \times CO2_{grid}(pd,t)\right] \quad (6)$$

where $\boldsymbol{P_{charge}(pd,t)}$ is the charging power from the grid and $\boldsymbol{CO2_{grid}(pd,t)}$ is the grid carbon intensity for the horizon $\boldsymbol{pd}$ and belongs to the set$\{\mathbf{0},\mathbf{1},\mathbf{2},\cdots,\mathbf{364}\}$ at time step $\boldsymbol{t}$. Moreover, to ensure that the battery state of charge (SOC) stays within defined operational bounds:

$$\mathrm{SOC_{Min}} \times Cap_{bat} \leq \mathrm{E}_{bat}(\mathrm{pd,t}) \leq SOC_{Max} \times Cap_{bat} \quad (7)$$

where $\mathbf{SOC_{Min}} \times \boldsymbol{Cap_{bat}}$ and $\boldsymbol{SOC_{Max}} \times \boldsymbol{Cap_{bat}}$ refers to the minimum and maximum bounds of battery energy respectively and $\mathbf{E}_{\boldsymbol{bat}}(\mathbf{pd,t})$ is the electric charge in the battery. The energy in the battery $\mathbf{E}_{\boldsymbol{bat}}(\mathbf{pd,t})$ is given as:

$$\mathrm{E}_{bat}(pd,t) = \mathrm{E}_{bat}(pd,t-1) + \left[P_{charge}(pd,t) \times \eta_{charge} - \frac{P_{discharge}(pd,t)}{\eta_{discharge}}\right] \times ts \quad (8)$$

where, $\boldsymbol{P_{discharge}(pd,t)}$ is the discharge power of the battery for the sub-horizon $\boldsymbol{pd}$ at time $\boldsymbol{t}$, $\boldsymbol{\eta_{charge}}$ and $\boldsymbol{\eta_{discharge}}$ are the battery charge and discharge efficiencies respectively and $\boldsymbol{ts}$ is the timestep coefficient (defined as the ratio of time step in minutes to 60 minutes). In addition, to ensure charging and discharging respect the technical constraints of the battery and the vehicle movement:

$$P_{charge}(pd,t) \leq \mathrm{P}_{max-charge} \times availability(pd,t) \quad (9)$$

$$P_{discharge}(pd,t) \leq \mathrm{P}_{max-discharge} \times availability(pd,t) \quad (10)$$

where, $\mathrm{P}_{max-charge}$ and $\mathrm{P}_{max-discharge}$ are the maximum charging and discharging power of the EVs battery and $availability(pd,t)$ is a binary value which determined by the discharge power of the EV (i.e., it has a value of one when the vehicle is not being discharged and zero when the vehicle is in motion). To ensure an energy balance in the system:

$$P_{grid}(pd,t) - P_{charge}(pd,t) + P_{discharge}(pd,t) - P_{demand}(pd,t) = 0 \tag{11}$$

where $P_{grid}(pd,t)$ and $P_{demand}(pd,t)$ are the power imported from the grid and consumed by the EV, respectively. Lastly, to ensure continuity in the battery's State of Charge (SOC), particularly in the day strategy, an additional constraint was added to ensure that the battery SOC charge stayed within the defined operating bounds.

$$E_{bat}(pd+1\,,0) = E_{bat}(pd,T+1) + \left[P_{charge}(pd,T) \times \ \eta_{charge} - \frac{P_{discharge}(pd,T)}{\eta_{discharge}}\right] \times ts \tag{12}$$

where T is the last time step in the set defined by the sub-horizon given by$\{0,1,2\ldots T\}$, and the final battery energy is constrained as defined in Equation (2). Thus, the starting battery energy for the various periods was defined as:

$$\mathrm{E}_{bat}(\mathrm{pd,t}) = \begin{cases} E_{bat}(pd,T) \leq Cap_{bat}, & if\ pd = 0\ and\ t = 0 \\ \mathrm{E}_{bat}(pd-1, \quad T+1), & if\ pd > 0\ and\ t = 0 \end{cases} \tag{13}$$

To carry out the optimization, the following technical parameters outlined in Table 1 were considered. Both day and annual strategies were modeled as PYOMO (Python Optimisation, Modelling Objects) (Hart et al., 2011) concrete models and were solved using the Gurobi solver (Gurobi Optimization, LLC, 2021).

Table 1. Technical parameters and assumptions considered for the optimization

No.	Parameter	Unit	Value
1	Max Charging Power	kW	20.0
2	Max discharging power	kW	40.0
3	Charging Efficiency	%	85.0
4	Discharging Efficiency	%	100.0
5	Sub-horizon	days	1
6	Horizon	days	365

The discharging efficiency was kept at 100% since the sensors measured the energy being drawn out of the battery, thus the losses have been accounted for in the measurements. The subsequent section details the results of the optimizations.

4. Results and Discussion

Figure 5 (a) illustrates the actual results regarding the CO_2 emissions of the reference-charging schedule with minimum optimal schedule and maximum (worst case) schedule. Figure 5 confirms the earlier assertion about Poland and India (Maharashtra) having higher indirect CO_2 emissions and vice versa for France. Additionally, Figure 5 (a) provides an indication of how much potential flexibility there exists (generally, the Netherlands and the USA have the highest potential whilst France and India have the lowest potential).

Building on this premise, the EV-CP indicator was calculated for each of the studied grids and is shown in Figure 5 (b). It can be observed that for the French grid, the EV had a high (second highest potential (since the higher the value the higher the flexibility potential available). Whilst the flexibility potential was lowest in the Brazilian grid. The EV-CP in no way indicates that the actual emissions of the EV were lower in Brazil compared to the Emissions in France. It does, however, indicate that for the given charging behavior, an EV's emissions would be closer to the optimal (i.e. the best case) emissions for the Brazilian grid as compared to the French grid.

The ECT indicator was thus computed for France, the Netherlands, Brazil, and India, From Figure 6, we can see that for France, the best times to charge were found to be midnight to 4 AM, whilst the worst times to charge were between 7 and 11 PM. Similarly, for the Netherlands, the best times were 12 noon to 4 PM whilst the worst times were between 5 and 9 AM and 7 to 11 PM. In the case of Brazil-North, the best times to charge were between 4 and 7 PM whilst the worst times were between midnight and 5 AM. Lastly, for India, 10 Am to 2 PM were seen to be the best times with most other hours falling in the negative zone hence not an ecological time to charge. The difference in best and worst time to charge is dependent on the energy mix of the respective grids. For example, Brazil has a high penetration of hydro-electric energy supply, whilst India is highly dependant on fossil-fuel based electricity production technology.

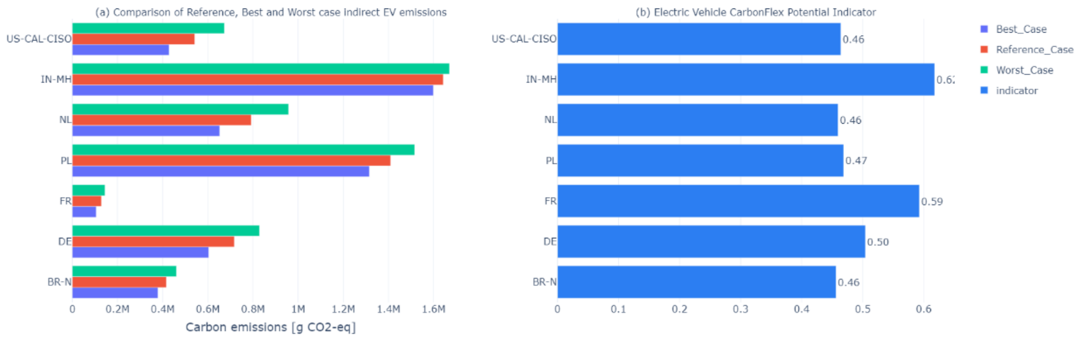

Figure 5. (a) Comparison of CO_2 emissions (gCO2-eq/km) of reference charging schedule with minimum optimal schedule and maximum optimal schedule, (b) Comparison of Electric Vehicle CarbonFlex indicator for studied countries.

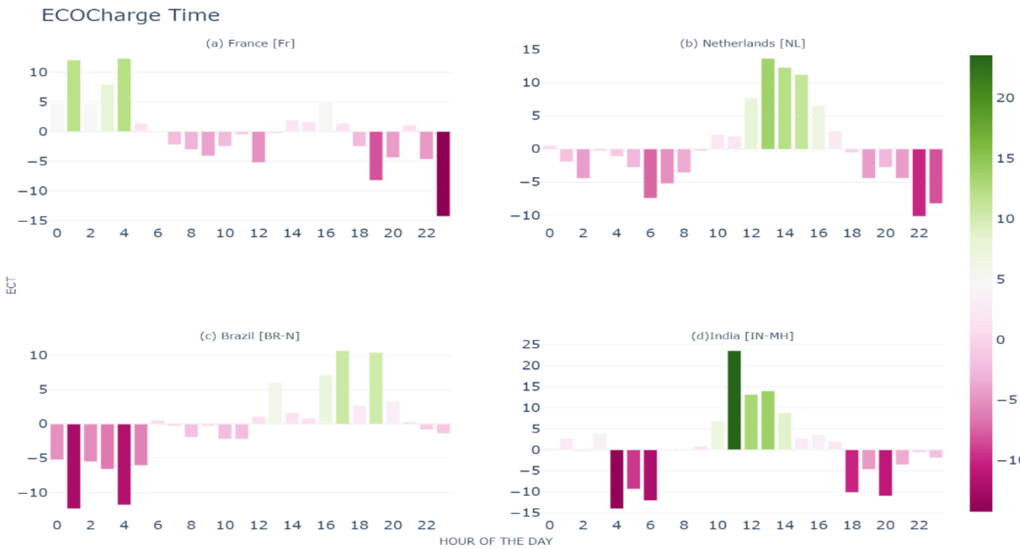

Figure 6. EcoCharge Time (ECT) for (a) France, (b) Netherlands, (c) Brazil-North, and (d) India

5. Conclusion

EVs have an associated operational global warming potential, though indirect yet it exists depending on the grid. There exists a potential to further improve the performance of an EV by potentially giving EV users some feedback. Using the EV-CP indicator, we propose a means of evaluating the behavior of EV users with respect to the emissions related to the electricity used to charge the EV. To promote desirable behavior, the ECT indicator provides information on behavioral change that would nudge an EV user in the desired optimal direction in terms of their indirect emissions.

These indicators have been proposed taking into account the behavior of one driver, and the results depicted here may not be generally applicable. However, the methodology should be replicable and the feedback also applicable to different users. A further study to evaluate the effectiveness of the proposed indicators and their potential consequence on the behavior of EV users would be required and is planned as a future perspective of this study.

Acknowledgments

The authors acknowledge that this study is realized only for academic and research purposes, and has no connection to any commercial interest. This work was partially supported by the ANR project ANR-15-IDEX-02, eco-SESA program (https://ecosesa.univ-grenoble-alpes.fr/), Observatory of Transition for Energy (https://ote.univ-grenoble-alpes.fr/) and a grant from the French government under the PIA, IRT Nanoelec, bearing the reference ANR-10-AIRT-05.

Supplementary Materials

The data, code and associated notebooks related to this study can be found here: https://gricad-gitlab.univ-grenoble-alpes.fr/NanaKofi/ev_study/-/blob/main/EV_Indicators/EV_Carbon_Study_indicator.ipynb

References

Bohua, S., Deng, W., He, R., Wu, J., & Li, Y. (2018). *Personalized Eco-Driving for Intelligent Electric Vehicles*. https://doi.org/10.4271/2018-01-1625

Calvo, L., Christel, I., Terrado, M., Cucchietti, F., & Pérez-Montoro, M. (2022). Users' Cognitive Load: A Key Aspect to Successfully Communicate Visual Climate Information. *Bulletin of the American Meteorological Society*, *103*(1), E1–E16. https://doi.org/10.1175/BAMS-D-20-0166.1

Capellán-Pérez, I., de Castro, C., Carpintero, Ó., & Miguel, L. J. (2016). Socio-economic factors in energy system modeling: A review. *Renewable and Sustainable Energy Reviews*, *62*, 1209–1229. https://doi.org/10.1016/j.rser.2016.05.024

Electricty Maps. (2022, December 1). *Electricity Maps – The leading resource for 24/7 CO2 grid data*. https://www.electricitymaps.com/

European Environment Agency. (2018). *Electric vehicles from life cycle and circular economy perspectives* (Transport and Environment Report 13/2018; Transport and Environment Report). European Environment Agency. https://www.eea.europa.eu/publications/electric-vehicles-from-life-cycle

Gurobi Optimization, LLC. (2021). *Gurobi Optimizer Reference Manual*. https://www.gurobi.com/wp-content/plugins/hd_documentations/documentation/9.0/refman.pdf

Hart, W. E., Watson, J.-P., & Woodruff, D. L. (2011). Pyomo: modeling and solving mathematical programs in Python. *Mathematical Programming Computation*, *3*(3), 219–260.

Hawkins, T. R., Singh, B., Majeau-Bettez, G., & Strømman, A. H. (2013). Comparative Environmental Life Cycle Assessment of Conventional and Electric Vehicles. *Journal of Industrial Ecology*, *17*(1), 53–64.

Hodencq, S., Delinchant, B., & Wurtz, F. (2021). Open and Reproducible Use Cases for Energy (ORUCE) methodology in systems design and operation : a dwelling photovoltaic self-consumption example. *Building Simulation*.

Ingrid Malmgren. (2016). Quantifying the Societal Benefits of Electric Vehicles. *World Electric Vehicle Journal*, *8*(4), 996–1007. https://doi.org/10.3390/wevj8040996

International Energy Agency. (2021). *Global EV Outlook 2021 – Analysis - IEA*. https://www.iea.org/reports/global-ev-outlook-2021

International Energy Agency. (2022). *Global EV Outlook 2022* (Global Electric Vehicle Outlook) [Technology Report]. https://www.iea.org/reports/global-ev-outlook-2022

Li, Y., Ha, N., & Li, T. (2019). Research on Carbon Emissions of Electric Vehicles throughout the Life Cycle Assessment Taking into Vehicle Weight and Grid Mix Composition. *Energies*, *12*(19), 19. https://doi.org/10.3390/en12193612

Lin, J., Li, N., Ma, G., & Zhou, J. (2016). The impact of eco-feedback on energy consumption behavior: A cross-cultural study. *ISARC 2016 - 33rd International Symposium on Automation and Robotics in Construction*, 274–281. https://doi.org/10.22260/isarc2016/0034

Midden, C. J., Kaiser, F. G., & McCalley, L. (2014). Encouraging sustainable behavior: the role of nudging, feedback, and information. *Frontiers in Psychology*, *5*, 1205.

Nilsson, A., Bergstad, C. J., Thuvander, L., Andersson, D., Andersson, K., & Meiling, P. (2014). Effects of continuous feedback on households' electricity consumption: Potentials and barriers. *Applied Energy*, *122*(June), 17–23. https://doi.org/10.1016/j.apenergy.2014.01.060

Twum-Duah, N. K., Amayri, M., Wurtz, F., & Ploix, S. (2019). Indicators for Evaluation of Energetic Performance of Net Zero Energy Buildings. *2019 IEEE International Smart Cities Conference (ISC2)*, 136–142. https://doi.org/10.1109/ISC246665.2019.9071782

Westskog, H., Winther, T., & Sæle, H. (2015). The effects of in-home displays-revisiting the context. *Sustainability (Switzerland)*, *7*(5), 5431–

5451. https://doi.org/10.3390/su7055431

Zerrin Günkaya, Alp Özdemir, Aysun Özkan, & Banar, M. (2016). Environmental impacts of electric vehicles in Turkey: A life cycle assessment. *Sustainability (Switzerland)*, *8*(11), 1097. https://doi.org/10.3390/su8111097