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An agent-based electric vehicle charging demand modelling framework to assess the needs for the energy transition in transport

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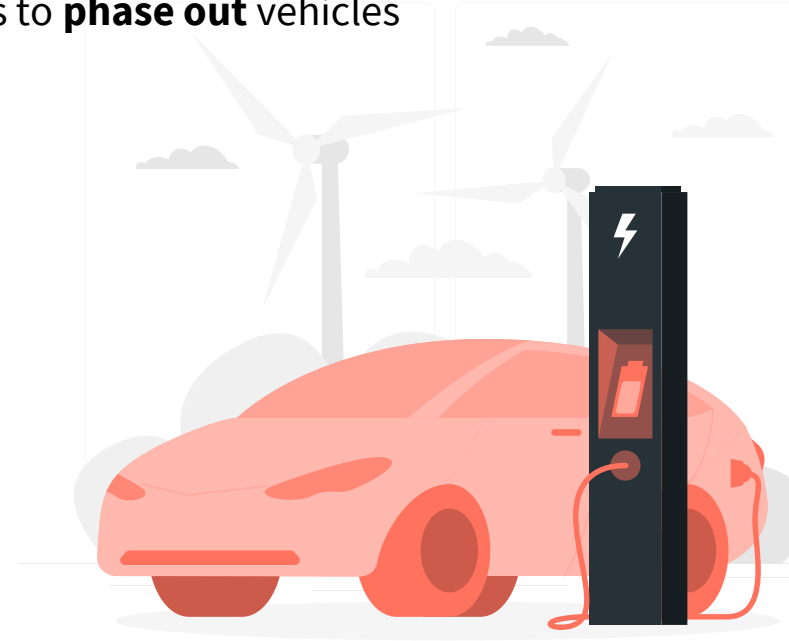
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The transport systems are being **electrified**

- There is up to a **40% year-on-year increase** in the registered electric vehicles (EVs) (IEA, 2020).
- Many countries are in the process of designing policies to **phase out** vehicles that use **fossil fuels** (RVO, 2022).
- However, the current charging **infrastructure is not adequate** to satisfy future demand, indicating the need for **technical improvements** and **financial investments** (Muratori, 2018; Gilleran et al., 2021).



Demand analysis is crucial for building **cost-effective and efficient** charging infrastructure

- The **setup of charging infrastructure** should be based on the expected demand considering conditions such as **socio-demographics and travel behaviour**.
- **Temporal** and **spatial** aspects should be considered.
(e.g., preferred time of charging, preferred charging location)
- **Dynamic nature** of the personal habits and preferences should be considered.
(e.g., people may change their routes based on the availability of charging stations in congested electricity grids)



Existing tools fall short to address the **complex analysis needs**

- Current **models and frameworks are not adequate** to estimating spatiotemporal charging demand considering socio-economic conditions and travel behaviour.
- It is especially important to **make easy-to-use and open-access tools available** that can be used by public and private stakeholders to assess different scenarios for **data-driven decision-making** processes.



We aim to lessen the gap by developing an open-access agent-based EV charging demand **modelling framework**

Objectives of the study

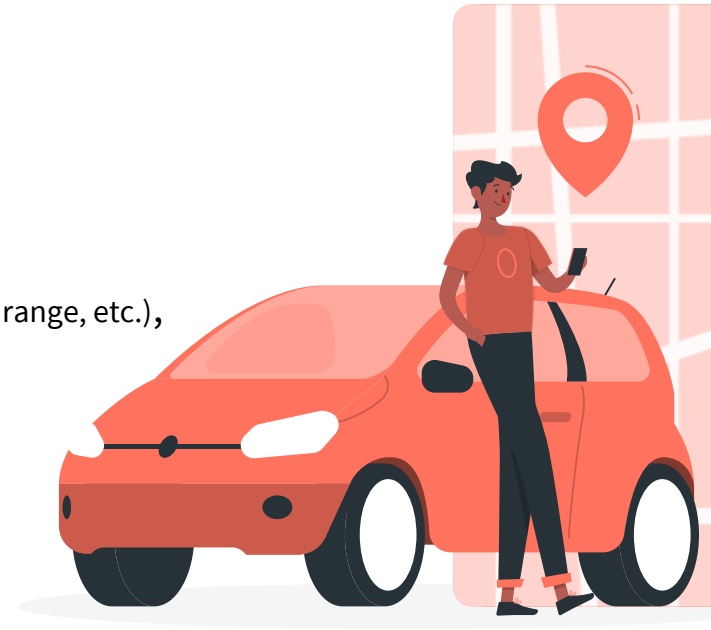
1. Developing an analysis framework that can determine **spatiotemporal EV charging demand** considering the travel and charging **behaviours of individuals**.
2. Making the developed framework accessible to public and private stakeholders as **open-source software** enabling various scenarios to be analysed at scale.



The agents simulate the behaviour of **individuals commuting between home and work daily**

Each agent has:

- **Home** location,
- **Workplace** location,
- Commuting **behaviour** (i.e., time to work and time to home),
- **EV** with certain characteristics (e.g., charge capacity, maximum range, etc.),
- Location indicating its current **spatial position**, and
- **State** that is dynamically updated based on state transition rules.



The **agent states** simulate different recharging states of an EV

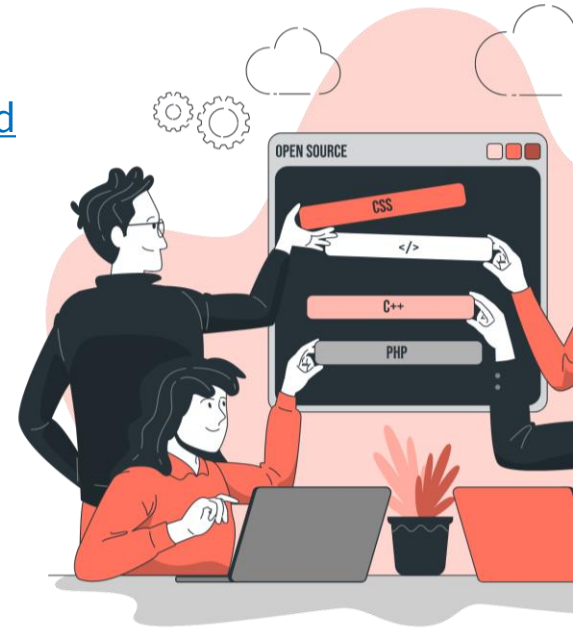
There are 3 states defined by the framework:

- At **idle** state the agent is located at a specific location (e.g., home, workplace) and the **car is parked and not recharging**; hence, subject to **idle discharge**.
- At **driving** state the agent is travelling between two locations (e.g., from home to work) and the **car is consuming its battery in driving mode**.
- At **recharging** state the agent is located at a specific location and the **car is parked and connected to a charging station**.



Open-source software allows modelling by using the framework

- **EVDemand** software implements the framework to enable the analysis of user-defined demand scenarios and to produce detailed as well as aggregated reports of the results.
- Source code is available at <https://github.com/ITC-CRIB/EVDemand>
 - Documented PHP code.
 - Easily extendable object-oriented architecture.
 - No dependency on 3rd party packages.



Commuting behaviour of the agents can be specified easily

- Home and workplace locations are defined by **regions** (e.g. postcode zones)
- The number of agents **commuting between the regions** and the average **commuting distance between the regions** are taken as input.
- A discrete **intra-day commuting volume pattern** is used for each commute direction to determine the **time to work** and **time to home** of each agent.
 - First, discrete time periods (e.g., 08:00-10:00) are determined by using the pattern.
 - Then, specific times within these periods are assigned randomly.
- Time to work and time to home of each agent can be **modified slightly for each day** by a small random delta time.
- **Travel duration** is calculated by using the average commuting distance and a constant average speed.



Characteristics of the cars of the agents can be easily specified

- A set of **car models** can be indicated and for each car model, charge capacity (kWh), range at full charge (km), full recharge time (h), and idle discharge rate (%/h) can be specified.
 - A single car model for all agents,
 - Random distribution of car models to the agents, and
 - Random distribution based on a predefined probability for each car model (e.g., 50% for Model A).
- The car parameters can be **customized for each agent** (e.g., for long-term fatigue).
- The **initial charge capacity** can be specified as constant for all cars (e.g., 100%) or can be assigned randomly with an optional minimum charge percentage.



The implementations aims to **perform analysis quickly**

- The location and state of each agent are updated regularly during an analysis period (e.g., 120 h), which is divided into smaller **time steps** (e.g., 5 min).
- Each state can have a **definite duration** (e.g., idle at work for 8 hours) at the end of which a state transition occurs, or an **indefinite duration** which requires a temporal trigger to initiate a state transition (e.g., idle at work until time to home).
 - Indefinite duration states are checked for state transition at the beginning of each time step (i.e., their temporal resolution is equal to the analysis time step).
 - The state transition is checked during a time step for each definite-duration state, and a new state is assigned to the agent if the elapsed time of the state reaches its duration within the time step.
 - This check is performed iteratively enabling multiple consecutive state transitions during a single time step, which results in an improved temporal resolution.
- Each agent has a **state history** (i.e., previous states in addition to the current state is stored).

Charging behaviour of the agents can be specified easily

- An **initial state** is assigned to each agent based on the start time of the analysis.
 - The time periods an agent is expected to be at home, at work, or commuting are considered.
 - The elapsed duration of the state is also calculated, and the state variables are set accordingly.
- The **initial battery charge level** is adjusted to ensure that it is sufficient to complete the state.
- Sufficient **charging points** are assumed to be available at home and workplace locations, as they are only known as regions that prevent the assignment of specific capacities.
- **Recharge behaviour functions** are used to describe the willingness of an agent to recharge given the current charge level of the car.
 - They are defined by a list of charge percentage vs recharge probability values that are interpolated.
 - This allows non-linear recharge behaviours to be described.
- Recharge behaviours can be **assigned to the agents** by the same methods used for car models.

Modelling results can be **monitored** at the agent level

- The software provides **detailed logs** for each time step, including inter-time step state transitions.
- Individual agents or groups of agents can be **tracked** during an analysis run.
- Temporal **recharging demand can be summarized** for each region.
- Analysis results can be obtained in **standard output formats**.
(e.g. CSV, JSON)



The developed framework **facilitates planning** of cost-effective and efficient EV recharging infrastructure

- Physical (e.g., charge capacity) and physiological (e.g., willingness to recharge) parameters can be altered and **various scenarios**, such as socio-economic incentives to motivate certain recharging behaviour, can be tested easily (e.g., low-cost nighttime charging).
- The agent-based approach allows detailed analysis at the **individual level** but also enables the calculation of **aggregated results** for designated regions.
- The software can simulate a **high number of agents** with limited computing resources, making it suitable for large scale analysis.
- The capability to simulate state transitions within a time step for states with finite duration helps to **improve the accuracy** in the case of large time steps.



Object-oriented open-source software enables rapid **further development**

- Parameters related to agents (e.g., commute times, car properties, recharge behaviour) can be **altered dynamically** during an analysis programmatically.
- Together with the state history of the agents, this can be exploited for more complex simulations, during which the agent states can be altered based on **previous actions** of the agent, as well as the **actions of other agents** (e.g., commuting the same route).
- The analysis logic can be extended with **additional actions** (e.g., shopping) and **locations** (e.g., shopping malls), as well as travelling during the **weekends and holidays**.



We are working on two **case studies** to demonstrate the capabilities of the framework

- **Regional** study in the Overijssel province of the Netherlands, 1.2 million people
- **National** study in the Netherlands, 17.5 million people.
- A 4-stage travel demand model based on Mobi Surround is used to estimate the number of EV trips (de Dios Ortuzar & Willumsen, 2011; Tutert & Thomas, 2012).
 - Motive-dependent trip volume originating from each postal zone (PC4 level) is estimated by using land use and socio-economic data.
 - A gravity-based model with a deterrence function favoring shorter travel distances is used to determine the commuter trips between all pairs of zones.
- The case studies will allow us to test the **scalability** of the framework and **fine-tune** the performance of the software implementation.



Join us to develop the framework in a **collaborative** way

- **Co-design**

Voice your ideas to improve the methodology according to your research and application needs.

- **Testing**

Test the framework and provide feedback to correct issues and improve features.

- **Co-development**

Take part in the co-development effort with your programming and writing skills to improve code and documentation.

- **Visibility**

Promote the framework if you find it useful.



Thanks for your time!

Please contact us for further **questions** or **collaboration options**:



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