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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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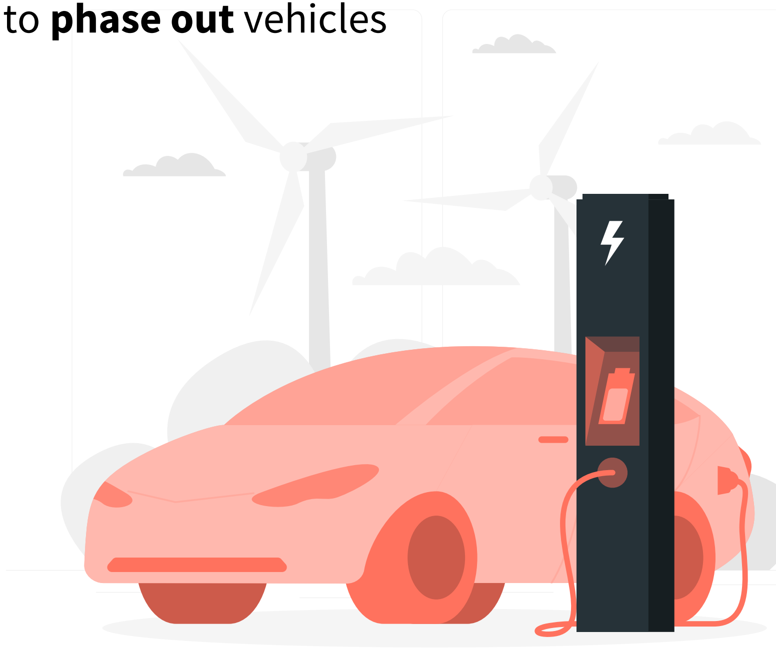
The transport systems are being **electrified**

- 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).



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Demand analysis is crutial 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)

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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.

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

Objectives of the study

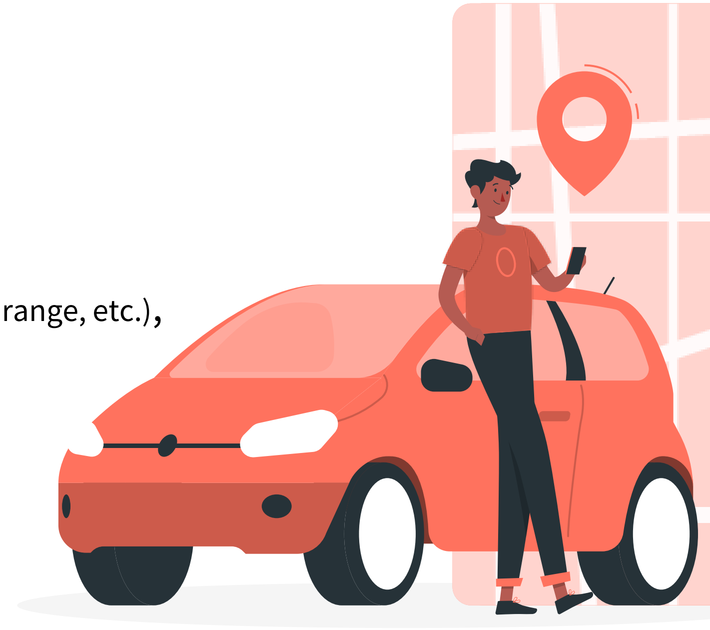
1. Developing an analysis framework that can determine **spatiotemporal EV charging demand** considering the travel and charging **behaviours of individuals**.
2. Making the developed framework accessible to public and private stakeholders as **open-source software** enabling various scenarios to be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

Illustration by Storyset.com

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.



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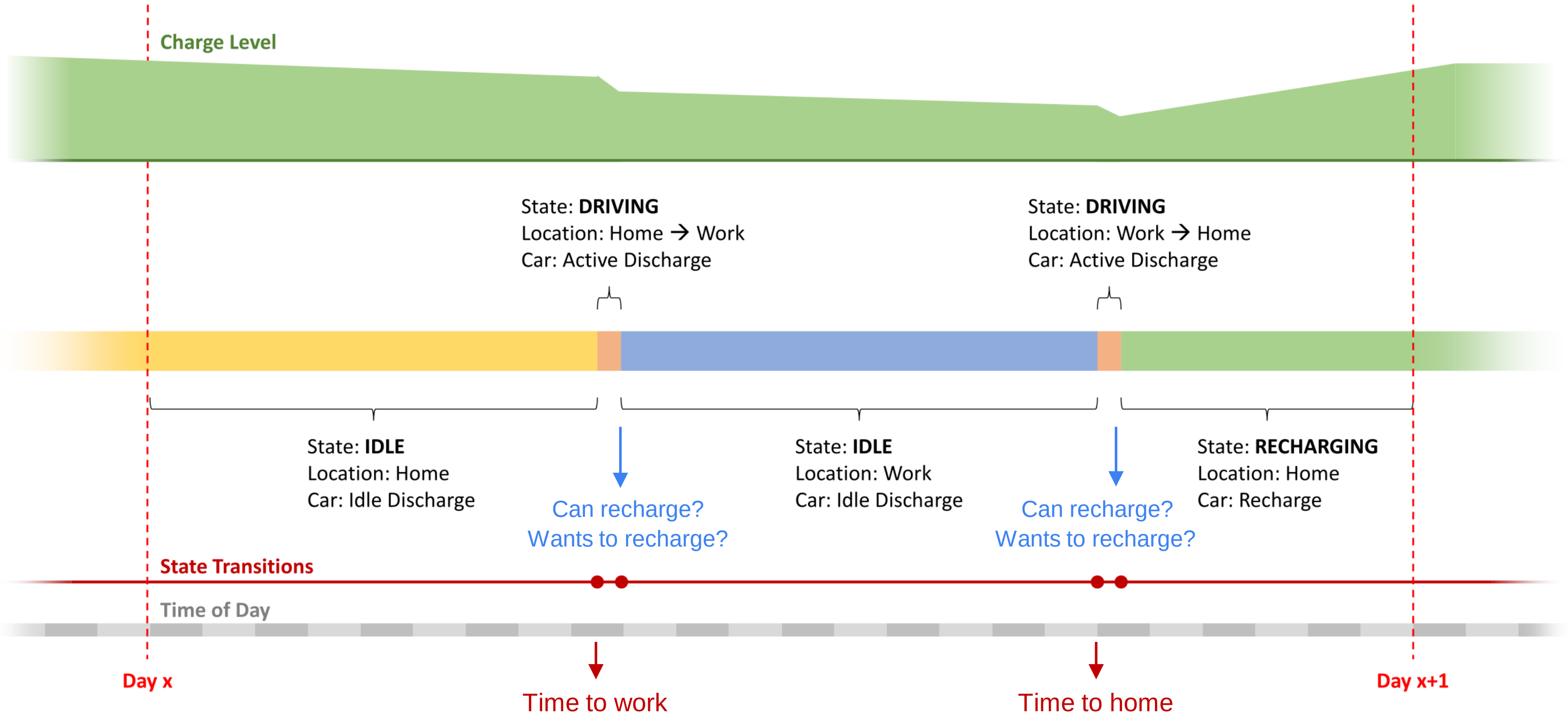
The **agent states** simulate different recharging states of an EV

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**.

Illustration by Storyset.com

State transitions are used to model the actions of an agent



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.

Illustration by Storyset.com

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.

Illustration by Storyset.com

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.

Illustration by Storyset.com

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 rechange 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 are 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)

Illustration by Storyset.com

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.

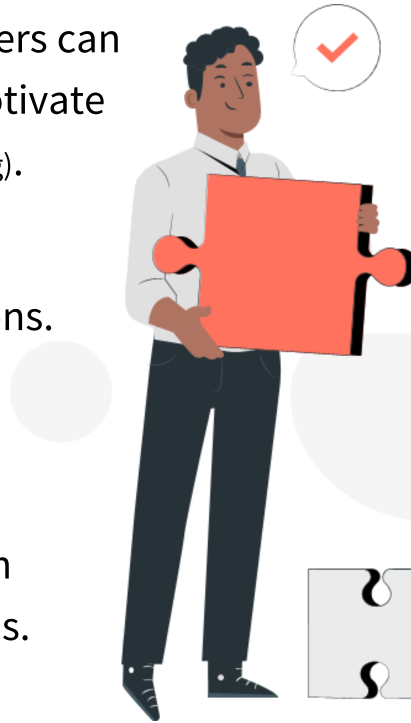


Illustration by Storyset.com

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**.

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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.

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Thanks for your time!

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

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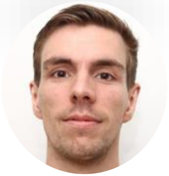

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