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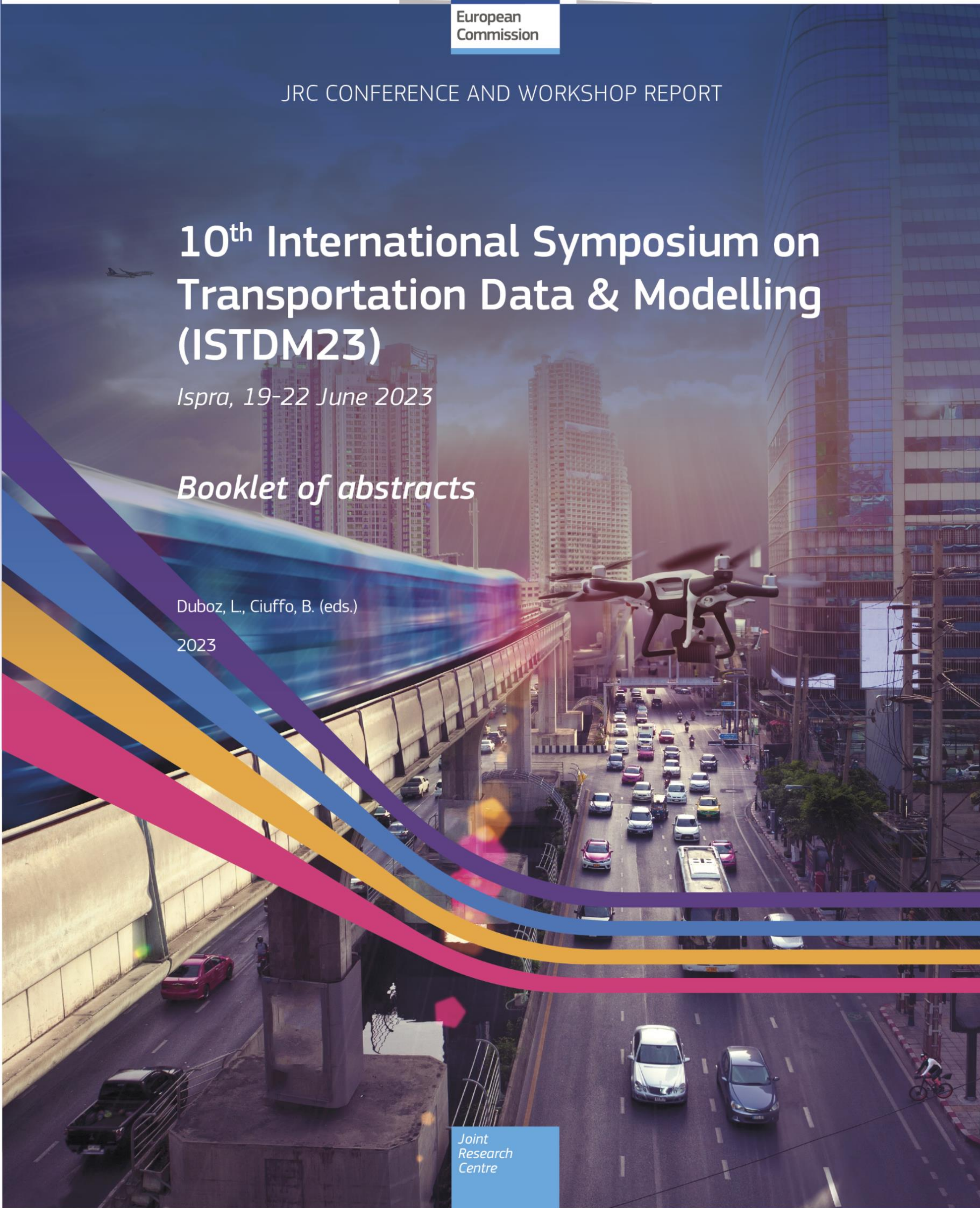

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An agent-based electric vehicle charging demand modelling framework to assess the needs for the energy transition in transport

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Introduction

The transport systems are being electrified: from infrastructure management to intelligent transportation systems to electric vehicles, including heavy trucks, personal cars, and bikes. Electric vehicles (EVs) do not still have a very high market share; however, there is up to a 40% year-on-year increase in the registered EVs (International Energy Agency, 2020), and many countries are in the process of designing policies to phase out vehicles that use fossil fuels (Netherlands Enterprise Agency, 2022). The feasibility of the widespread use of EVs highly depends on the capacity of the charging infrastructure and the ubiquity of charging stations. However, to a large extent, 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). For cost-effective and efficient investments, the setup of charging infrastructure (e.g., location and capacity of charging stations) should be based on the expected demand considering local conditions such as population, income level, socio-demographics, and travel behaviour. For a realistic assessment, temporal (e.g., preferred time of charging, day or night charging) and spatial (e.g., preferred charging location, residence or workplace) aspects should also be taken into consideration. On the other hand, the adoption of EVs and the availability of the infrastructure may influence the travel behaviour of individuals. Current technology does not allow for successive long-range trips with limited charging time. Consequently, individuals may need to reconsider their daily activities and travel choices, e.g., by changing routes considering the availability of charging stations in congested electricity grids.

Current models and frameworks for transportation fall short to address such complex situations and dependencies on other systems, such as the electric power infrastructure. Considering the steps taken by the European Union towards phasing out fossil fuel use and promoting a shift to electric transport (EEA, 2016), the need for models and frameworks capable of estimating spatiotemporal charging demand taking socio-economic conditions and travel behaviour into consideration becomes even more imperative. It is especially important to make easy-to-use and openly accessible tools available, which can be used by public and private stakeholders to assess different scenarios for data-driven decision-making processes. To address these needs, the objectives of this study are: 1) developing an analysis framework that can determine spatiotemporal EV charging demand considering the travel and charging behaviours of individuals; and 2) making the developed framework accessible to public and private stakeholders as open-source software. The developed framework and software are novel in terms of enabling the estimation of EV charging demand by utilizing an agent-based modelling approach, which provides a detailed spatiotemporal distribution of the demand and allows various scenarios to be analysed at scale.

Methodology

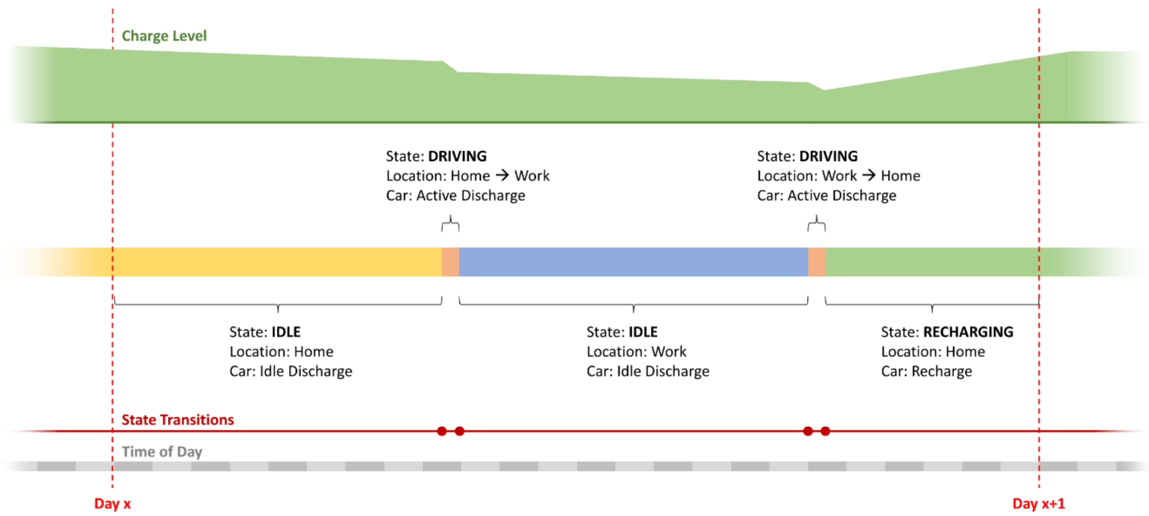
The framework, which is designed to allow a detailed analysis even with limited data, is based on agents mimicking the behaviour of individuals commuting between home and work daily. Each agent has a home location, a workplace location, a commuting behaviour (i.e., time to work and time to home), an EV with certain characteristics (e.g., charge capacity, maximum range, etc.), a location indicating its current spatial position and a state that is dynamically updated during an analysis based on various state transition rules.

There are three states defined by the framework that roughly correspond to different states of an EV:

- *Idle state* indicates that 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.
- *Driving state* indicates that the agent is travelling between two specific locations (e.g., from home to work) and the car is consuming the charge of its battery in driving mode.
- *Recharging state* indicates that the agent is located at a specific location and the car is parked similar to the idle state, but it is connected to a charging station; hence, its battery is recharged.

The framework follows the state transition mechanism illustrated in Figure 1 to model the actions of an agent. From midnight to the time to leave home for work (i.e., time to work), an agent can be either in idle or in recharge state at home. This state is either assigned as the initial state at the beginning of the analysis if the analysis start time is within this period, or otherwise relayed from the previous day. Then, a state transition occurs to a driving state from home to work for a duration that corresponds to the required travel time. Once the agent arrives at work, it enters either an idle or a recharge state and stays in this state until the time to leave work for home (i.e., time to home). To decide which state to select, the framework first checks if the agent *can recharge*, i.e., if there is a recharge station available to use. If it is possible to recharge, then the framework checks if the agent *wants to recharge*. If the outcome is positive, then a recharge state is started. Otherwise, the state is set as idle. The selected state changes into a driving state when the analysis time reaches the time to home, and the agent travels back to home, where it can enter again either an idle or a recharge state following the same probabilistic logic that is applied when it arrived at work. This state continues until the time to work the next day, which completes a full transition cycle.

Figure 73. Example state transition workflow for an agent



Source: Authors' elaborations (2023).

Implementation

An open-source research software is developed that implements the framework to enable the analysis of user-defined EV charging demand scenarios and to produce detailed as well as aggregated reports of the analysis results. The software, *EVDemand*, has an object-oriented architecture that facilitates modification of the existing methodology and further development of additional features easily. The self-documented source code, which is written in PHP, is available at https://github.com/ITC-CRIB/EVDemand.

To simplify the analysis, the software defines home and workplace locations by using regions (e.g., postcode zones). The number of agents commuting between the regions and the average commuting distance between the regions are required as input. To determine the time to work and time to home of each agent, a discrete intra-day commuting volume pattern is used for each commute direction. For each agent, first, discrete time periods (e.g., 08:00-10:00 and 16:00-18:00) are determined randomly for time to work and time to home considering the respective volume patterns, and then specific times within these periods are assigned randomly. This ensures a variation in the commuting behaviour of different agents, even if they commute the same route. For a more realistic analysis, the software also allows time to work and time to home of each agent to be modified slightly for each day by a small random delta time. At present, the travel duration is calculated by using the average commuting distance between the locations and a constant average speed.

A set of car models can be provided as input and for each car model, charge capacity (kWh), maximum travel range at full charge (km), recharge time from zero charge to full charge (h), and idle discharge rate (%/h) can be specified. A car of an agent is based on a car model, but the software allows these parameters to be customised for each car. For example, a car can have a charge capacity different from its base model, e.g., to simulate long-term fatigue. For the designation of car models, three different options are provided: 1) a single car model for all agents, 2) random distribution of car models to the agents, and 3) random distribution of car models to the agents based on a predefined probability for each car model (e.g., 50% for Model A and 50% for Model B). The software keeps track of the battery charge level of each car. The initial charge capacity can be specified either as a constant value for all cars (e.g., 100%) or can be assigned randomly. A minimum charge percentage can be specified in case of random distribution to guarantee that the assigned values are greater.

The software implements the logic illustrated in Figure 1. The location and state of each agent are updated regularly during an analysis period (e.g., 120 hours), which is divided into smaller time steps (e.g., 5 mins). The software allows each state to 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; hence, their temporal resolution is equal to the analysis time step. In contrast, the state transition is checked *during* a time step for each state with a definite duration, and a new state is assigned to the agent if the elapsed time of the state reaches its defined duration within the time step. The software iteratively performs this check enabling multiple consecutive state transitions during a single time step, which results in an improved temporal resolution. Each agent has a state history, and the software keeps track of previous states in addition to the current state, which can be utilised to define complex state transition rules.

An initial state is assigned to each agent based on the start time of the analysis. For this purpose, the software considers the time periods an agent is expected to be at home, at work, or commuting. For example, if the start time is later than the time to work of an agent, but earlier than the agent is expected to be at the workplace, then the initial state is set as driving from home to work. The elapsed duration of the state is also calculated, and the state variables are set accordingly. For example, if the start time is 5 mins after the time to work of an agent and if the total commute duration is 15 mins, then the elapsed duration of the initial driving state is set as 5 mins and the distance travelled is set as 1/3 of the travel distance. While assigning the initial state, the initial battery charge level is also controlled to ensure that it is sufficient to complete the assigned state.

Currently, it is assumed that sufficient charging points are available at home and workplace locations, as these locations are only known as regions (e.g., postcode zones) that prevent the assignment of specific capacities. To describe different recharge behaviours, recharge behaviour functions are utilized that define the willingness of an agent to recharge given the current charge level of the car. Each behaviour function is defined by a list of charge percentage vs recharge probability values that are interpolated for intermediate charge percentages. This allows non-linear rechange behaviours to be described easily. The software has the following options to assign recharge behaviours to agents: 1) a single behaviour for all agents, 2) random distribution of behaviours to the agents, and 3) random distribution of behaviours based on a predefined probability for each behaviour.

Conclusions and Discussion

The developed framework to simulate the commuting and recharge behaviours of EV owners allows estimation of the spatiotemporal distribution of EV recharge needs, hence the required charging capacity. Because the framework allows alteration of physical (e.g., charge capacity) as well as physiological (e.g., willingness to recharge) parameters, it can facilitate the planning and development of local or regional infrastructure to serve the needs in an effective and cost-efficient manner. Various scenarios, including socio-economic incentives to motivate people to follow certain recharging behaviour (e.g., the low cost during night time, high cost in case of extended recharge at the workplace), can be easily tested by using the developed open-source software.

The agent-based approach of the framework allows detailed analysis of the recharge needs of individuals but also enables the calculation of aggregated results for designated regions. The software implementing the framework can simulate a high number of agents and can scale up easily provided that sufficient computing resources are available. Therefore, it is suitable to perform simulations not only at a small scale (e.g., city level) but also at a large scale (e.g., country level). Depending on the precision required, the time step of the analysis can be altered to speed up the computation. The capability to simulate state transitions within each time step for states with definite durations helps to improve the accuracy in the case of large time steps.

Although it is currently not utilised for analysis, the framework also allows all parameters related to agents (e.g., commute times, car properties, recharge behaviour, etc.) to be altered dynamically during an analysis. This capability, together with the state history of the agents, can be exploited to generate 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). Because the framework is time-aware (i.e., knows the day of the week and time of the day), it can also be extended to simulate not only commuting during workdays but also travelling during the weekends and other holiday periods. The modular and object-oriented architecture of the software allows easy modification of the analysis logic by introducing additional actions (e.g., shopping) and locations (e.g., shopping malls). Hence, it can be enhanced through additional analysis components in the future, also through the involvement and collaboration of all interested parties thanks to the open-source approach.

Currently, we are working on two case studies to demonstrate the capabilities of the framework. The first case study is a regional study in the Overijssel province of the Netherlands located in the eastern part of the country with a population of 1.2 million people. The second case study, which is larger in extent, includes all provinces of the Netherlands that correspond to about 17.5 million people. For estimating the number of EV trips within these networks (i.e., the number of agents), we use a four-stage travel demand model (de Dios Ortuzar and Willumsen, 2011) based on MobiSurround (Tutert and Thomas, 2012). The four-stage transport model partitions the network into different postal code zones (neighbourhood level, so-called PC4 level), using land-use and socio-economic data to estimate the motive-dependent trip volume originating in each zone. Using a so-called deterrence function that aims to reflect an increased resistance to travel longer distances in general (de Dios Ortuzar and Willumsen, 2011), a gravity-based model determines the total commuter trips between all pairs of zones (origin-destination matrix) (Thomas and Tutert, 2013). We estimate, per origin-destination pair, the shares for cars, active modes (mostly cycling), and public transport (train); and utilise the shares for cars. These case studies will allow us to test the scalability of the framework and fine-tune the performance of the software implementation.

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