



# Infrastructure and Policy Design for Electric Vehicles

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## Motivation

Battery and Plug-in Hybrid Electric Vehicles (EVs) are seen by many as a key component to a future transport sector with lower greenhouse gas emissions. These vehicles do not only have a more efficient driving cycle than conventional vehicles, but also allow a diversification of energy sources for driving [1]. Several governments have announced national goals regarding the number of EVs they want to have on their roads. Examples include the USA with one million EV until 2015 [2] and Germany with the same number of vehicles until 2020 [3]. Furthermore, currently all major car manufacturers have either introduced a plug-in electric vehicle or are planning to do so [4].

While these numbers highlight the fact that a shift towards an era probably dominated by EVs has started, there are also many uncertainties on this path. Especially the charging infrastructure for EVs is still limited, and it is unclear which policies could render highest cost-benefit in this regard.

Most available models for infrastructure and policy design today operate either within a simplified optimization framework, e.g. minimize number of charging stations for given boundary conditions [5], or just simulate single scenarios for assumed future boundary conditions [6].

While these models help to acquire new insights for planning, one of their major drawback is that they do not have a long-term temporal component integrated in them, e.g. years. For example, while one can simulate scenarios for 2010 and 2035 with such frameworks [6], the possibility to evaluate, which kind of policies applied in 2010 might have led to the desired target boundary conditions in 2035 is still missing.

**Main Contribution:** The presented work tries to bridge this gap and presents a framework which allows temporal and spatial evaluation of policies, especially for short and long-term scenarios within transportation in general and for electric vehicles in particular. One of the main goals is to design policies, which lead to a desired outcome with high probability (e.g. CO2 reduction). For our modelling we envision to use an agent-based approach (described in next section), which can help to uncover possible policy flaws/hidden loop holes by inspecting complex emerging behavior of subsystem interactions.

## Background

The most sophisticated approach for modelling large-scale travel demand, where people are represented as virtual entities, is called agent-based modelling. The traffic demand model developed at our institute at ETH Zurich (together with TU Berlin) is called MATSim [7] and is outlined in the following (see Figure 1).

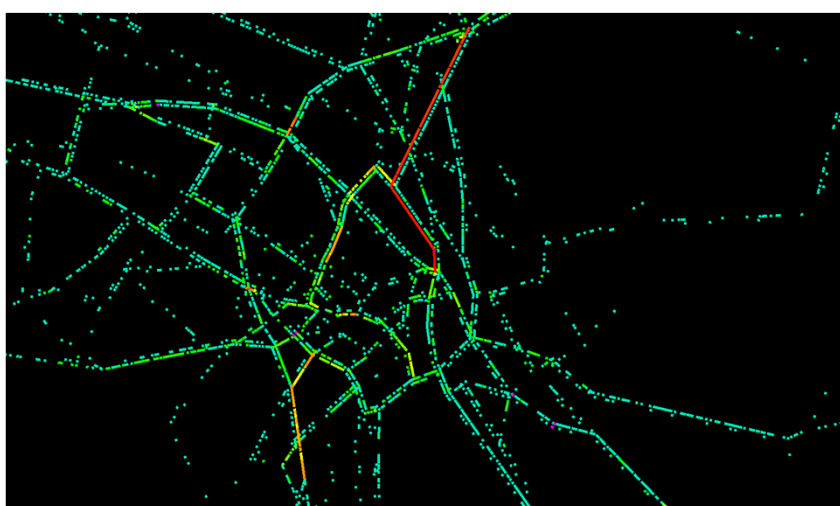


Figure 1: Agent-based traffic simulation with MATSim for Zurich

Figure 2 shows MATSim's simulation process: Each agent in MATSim has a daily plan of trips and activities, such as going to work, school or shopping. The initial daily plans of agents are provided as input in the initial demand step together with supply models, e.g. street network and building facilities. These initial plans can be based on, for example, activity/ travel diaries of people. The goal of the MATSim simulation process is to optimize the plan for each agent while respecting supply side constraints and the preferences of each agent. The plans of all agents are executed by a micro-simulation, resulting in traffic flows along network roads, which can cause traffic congestion. The execution of these plans is then scored and assigned a utility value. For example, a person with lower travel time has a higher utility than one who has a longer congested travel time. Additionally, working and other activities increase the utility. The goal of each agent is to maximize the utility of its daily plan by replanning it after each iteration, e.g. changing routes, working time, travel mode or location choice. In this step, either a new plan is assigned to an agent by adapting a previously executed plan, or a previously executed plan is reselected. Plans with a higher score have a higher chance of reselection, while plans with a lower score are deleted over time, as only a limited number of plans per agent are kept. This idea corresponds conceptually to mutation, selection and survival of the fittest in a co-evolutionary algorithm [8]. This iterative process approaches a point of rest corresponding to a user equilibrium called relaxed/optimized demand.

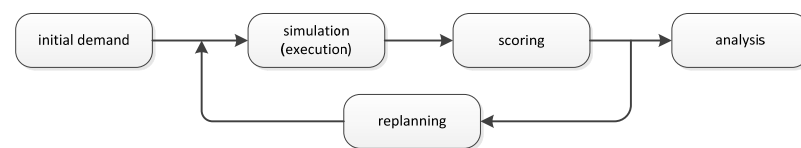


Figure 2: Co-evolutionary simulation process of MATSim

## Proposed Model

Whereas the MATSim model presented in the previous section only supports evaluation of single day scenarios, we propose an extension to MATSim, which is capable of simulating both short-/mid-term decision during the day and long-term decisions (months/years). The goals of the framework are as follows:

- Dynamic scenario creation: Instead of simulating discrete future scenarios for given boundary conditions, one can model future scenarios starting from a given scenario.
- System boundary conditions can change during the simulation, e.g. population growth, policy change, agents changing behavior to cope with new reality, car ownership changes, changing home and work locations, etc.
- Support for policy design: Create policies, which lead to desired outcome with high probability; uncover possible policy flaws/hidden loop holes by inspecting complex emerging behavior of agents and subsystem interactions
- Incremental approach, which allows to update model to match new reality and provides help for new forward guidance, policy design, etc.

The proposed design of the proposed Model is shown in Figure 3.

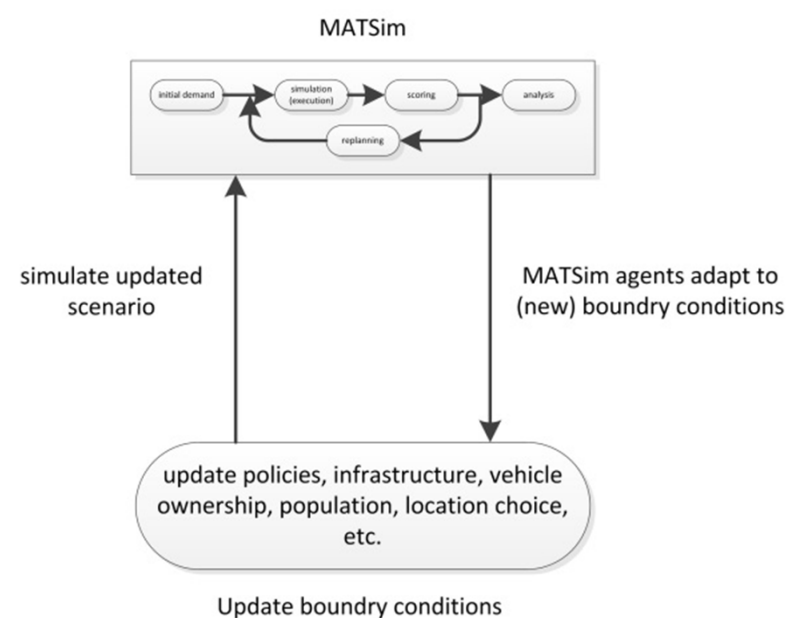


Figure 3: Dynamic scenario creation and evaluation of policies

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