# International Workshop on Agent-Based Modelling of Urban Systems (ABMUS) Proceedings: 2022

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ABMUS is a workshop where urban and geo-spatial modellers get together in a focused session, during the International Conference on Autonomous Agents and Multiagent Systems (AAMAS). The central goal of this workshop is to bring together the community of researchers and practitioners who use agent-based models and multi-agent systems to understand and manage cities and urban infrastructure systems. Through the exchange of ideas and state-of-the-art within this area, we will pool together current thinking to discuss avenues of fruitful research and methodological challenges we face in building robust, realistic, and trusted models of urban systems. Drawing from recognised challenges faced by the modeling community through the COVID-19 pandemic and similar public policy crises, the overarching theme for the workshop this year will be '**Trust, Transparency and Translation**'. Participants will be asked to describe how their models are creating a bridge between the synthetic and real worlds, and making their way into real-world policy and decision-making. This year, we invite presentations that describe how researchers construct their models, demonstrate results, work with policy and decision-makers, and how these processes either facilitate or hinder the process of urban systems model building from the modeller's perspective. We will discuss challenges associated with model development, data interoperability, consistent representation of space and time, as well as developments in interfaces and stakeholder engagement.

Further details are available at: `http://modelling-urban-systems.com/abmus2022/`

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# 1 Session 1: Methodology

## 1.1 Synthetic generation of individual transport data: the case of Smart Card data

**Minh Kieu, Iris Meredith and Andrea Raith**

# Synthetic generation of individual transport data: the case of Smart Card data

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## 1 Introduction

The acquisition and dissemination of individual data are key for research in many disciplines, including social simulation. Wide access to individual data has unprecedented benefits for the analysis and modelling of heterogeneous individual behaviour and is highly valuable when supporting decision making. However, governments across the globe have increasingly become concerned over privacy and the exchange of personal data. Simple data de-identification measures such as data-masking, top-coding, adding noise or random data swapping are not sufficient to protect individual confidentiality Drechsler and Reiter (2011). This poses a major risk of privacy breaches for vulnerable individuals and thus prevents the wider dissemination of personal data to the wider research community and limits the impacts of research on policymaking. On the other hand, as the risks of personal data disclosure increase, the alterations made by data owners may impact the usefulness of the released data.

To address the limitations of standard de-identification measures, literature has offered various approaches aiming at generating partially synthetic or fully synthetic data from real data. The idea is to retain the probability distributions in the data, but each synthetic data sample does not represent a real person in the raw data. Synthetic data enables public dissemination of the data while protecting individual privacy and preserving data utility. With higher quality synthetic data, analysts can develop meaningful and relevant research that can contribute to decision making. Data owners, who are generally policymakers, can also benefit from access to cutting-edge models and synthesis methods that can be directly implemented on the real data.

While synthetic data generation has attracted great interest and proved effective for images Karras et al. (2020), music Briot et al. (2020) and texts McKeown (1992), synthetic data is often poorly understood in transportation. Human mobility-related data in transport is relatively unique compared to popular personal data such as census data, health records or financial data because individual transport data such as Smart Card data often have operational information such as travel routes and modes, which are strictly spatially constrained, e.g. train travels occur only to and from train stations. Analysts generating and working with synthetic transport data must be aware of the confidentiality of this spatial element while aiming to retain the spatial information in the data.

This paper compares two of the most advanced methods for data modelling and synthetic data generation: Bayesian Network and Generative Adversarial Network for the generation of the most popular individual data in transportation: the Smart Card data. Smart Cards have become the de facto standard for modern public transport systems. The availability of Smart Card data has recently enabled novel research in intelligent transport systems, such as the analysis of travel behaviours (Kieu et al. 2015, 2018), inference of trip purposes (Lee and Hickman 2014), or intention to transfer (Kieu et al. 2017). However, the research community has not widely benefited from the ubiquitous availability of Smart Card data to support decision making while policymakers, who may have access to the raw data, have not yet been informed by the cutting-edge research on their data. The framework in this paper connects Smart Card data owners to a much wider community of researchers through synthetic data modelling and generation. It enables researchers to work on a synthetic dataset that is reasonably similar to the real data, having the same distributions and retaining the spatial-temporal activity sequence in the real data, but with data points not representing real people. On the other hand, this paper provides public transport agencies, research centres, local councils and other Smart Card data owners with a better alternative for public data dissemination. The scientific contributions of this paper are three-fold:

- We introduce a new data pipeline to process raw Smart Card data into sequential spatiotemporally constrained trip data
- We apply a Generative Adversarial Network, a Bayesian Network to model and generate synthetic smart card data
- We compare and contrast the two methods mentioned above, discussing the advantages and disadvantages of each for the data synthesis problem

## 2 Generative Adversarial Network (GAN)

Generative Adversarial Networks (GANs) are generative models in deep learning that aim to discover the patterns in input data and then generate new data observations that are very similar to the original dataset. The core idea of GANs is the use of two sub-models: a generator model that generates new observations, and a discriminator model that classifies the generated observations as either real or fake data. The two sub-models are trained subsequently in a zero-sum game (based on game theory), until the discriminator cannot differentiate the generated from the real observations for half of the time, which means that the generator is capable of generating valid observations. More details on GAN can be found in the original paper by Goodfellow et al. (2014).

Among the latest GAN-based algorithms in the literature, we adopt Tabular Conditional GAN (CTGAN) for modelling and generating of Smart Card data (Xu et al. 2019). CTGAN excels in modelling and generating mixed tabular data of continuous and discrete variables, similar to our Smart Card data. CTGAN has been proven to outperform many other data generative methods in the original paper (Xu et al. 2019) and several specific applications, such as insurance data (Kuo 2019).

## 3 Bayesian Networks

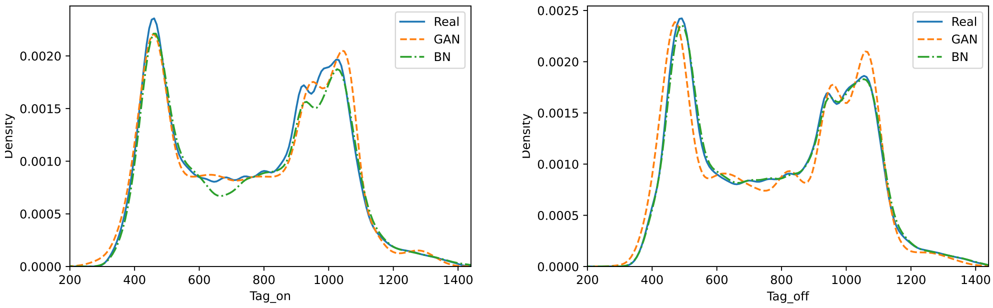
A Bayesian Network is a directed acyclic graph with a variable and a conditional probability associated with each node: the distribution for each variable is conditioned on the variables upstream of it in the DAG. A joint probability distribution for the variables can then be fitted on the graph and sampled from, generating a synthetic sample. In this paper, shape learning on the dataset was performed using the hill-climbing and constraint-based search approaches, with parameter fitting being performed by expectation-maximisation and forward sampling being used to generate the synthetic datasets.

## 4 Evaluation of generated data

In this section, we analyse and compares the generated Smart Card data from BN and GAN. We hypothesise that the generated data should have the same probabilistic distributions as the real Smart Card data.

Figure 1 displays the generated distributions of the tag-on times and tag-off times (in minutes from midnight) for each of the models discussed above against the real data:

Both BN and GAN broadly fit a mixture of normal distributions similar to the underlying data, it is clear from the plots that the real dataset's distribution is best approximated by the BN, which has almost



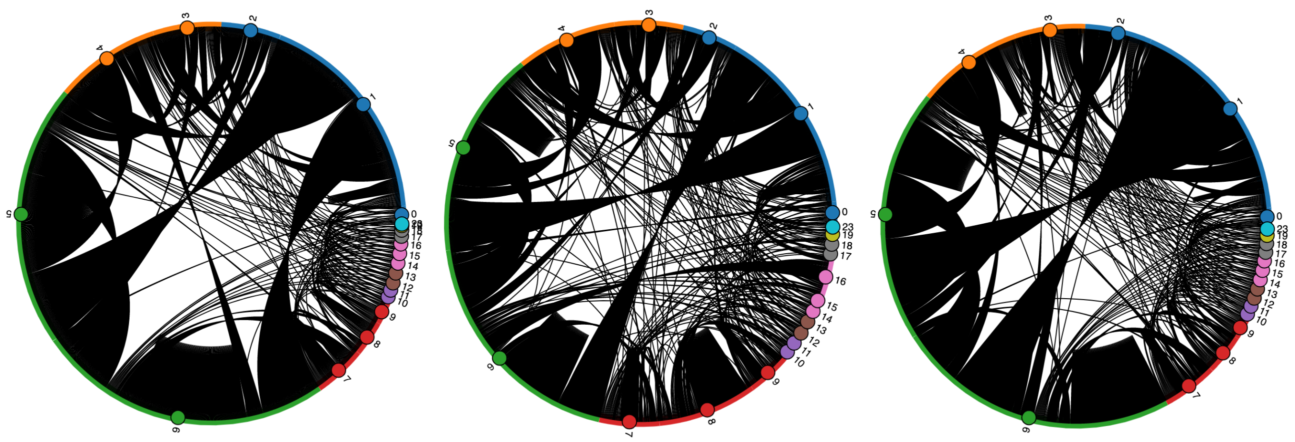

(a) Tag on time distributions for the real dataset and three models

(b) Tag off time distributions for the real dataset and three models

Figure 1: Tag off time distributions for the real dataset and three models

identical properties. GAN fits a similar structure, though it appears to overestimate and misplaces the peaks. GAN overemphasise peaks in the data, meaning that a dataset generated from the GAN would underpredict uncommon events.

We then look at the distribution of origin and destination zones. These variables are categorical, as the zones vary from 1 to 23. If the algorithms can retain the distributions of origin distribution, they can reproduce the spatial distribution of trips. Figure 2 shows three Chord diagrams of public transport trips from the real data (Figure 2(a)), generated data from GAN (Figure 2(b)) and generated data from BN (Figure 2(c)). The larger the chords, the more trips are there in the data.



(a) Real distribution of Origin-distribution

(b) Generated distribution of Origin-distribution from GAN

(c) Generated distribution of Origin-distribution from BN

Figure 2: Tag off time distributions for the real dataset and three models

Both GAN and BN can replicate the overall spatial travel patterns, where the majority of the trips are between and within a few zones. Figure 2 show that zone 1, 5 and 6 are popular zones, and there are a lot fewer trips started or ended in zones 10 to 23. While both GAN and BN can replicate those patterns, BN seems to more accurately generate the proportion of trips from each zone. In GAN the most popular zones (zone 1,5 and 6) are slightly less popular, whereas the remaining zones have a larger share than the real data.

Finally, we look at the distribution of travel time at each travel zone in Figure 3. This is the most challenging variable for GAN and BN to capture, as we are interested in a temporal by-product (travel time) that is spatially constrained (travel zones). Figure 3 shows the real and generated distribution of travel time at the first 6 travel zones in the data.

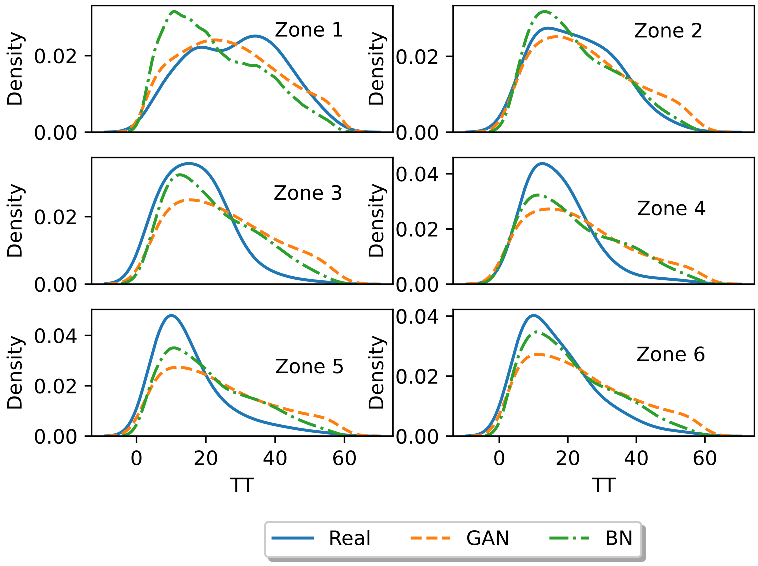



Figure 3: Distribution of travel time at each zone

Figure 3 shows that each zone has a unique distribution of travel time. Zone 1 and Zone 2 has more trips at higher travel time than the rest, while the travel time of trips from Zone 4 to 6 is highly concentrated at lower values. Both GAN and BN struggle to learn the complex travel time distribution at different zones, with BN performing slightly better than GAN. The generated travel time is relatively stable across the zones. We leave the spatial learning of by-product temporal variable (e.g. travel time) to a future study, where spatial interaction data synthesis models may need to be introduced for this purpose.

## 5 Conclusion and future works

This abstract describes the current progress of an ongoing project "Synthetic Big Data of Human Activities (SynAc)". The comparison between Bayesian Network (BN) and Generative Adversarial Network (GAN) shows that both methods can model and generate data that have the same distributions with the real data, both spatially and temporally. The synthetic data from Smart Card can be used as the synthetic population for an Agent-Based Models of public transport.

The next step in SynAc is to retain the sequential structure of transportation data, such as individual travels at a certain time from one area to another. This structure expresses the individuality of each person in as much as their activities are associated with travelling. The sequential travel activity from Smart Card data is even more challenging to synthesise as a person's travel itinerary will be incomplete if some of the travel is not done on public transport. We are currently exploring BN, GAN and various other methods in synthetic data modelling and generation for sequential transport data.

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## 1.2 Data-driven agent-based model development to support human-centric TOD design

**Liu Yang and Koen van Dam.**

# Data-driven agent-based model development to support human-centric TOD design*

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**Abstract.** This paper proposes an agent-based simulation model of an urban environment to evaluate alternative transport-oriented development (TOD) designs for infrastructure proposals prepared by urban planners. The model is tested by the students as model users, and the generated model output on the use of the city infrastructure, occupancy of public space and key data around the pedestrian and vehicle movements results can be translated to design modifications. A particular challenge with this approach is the inclusion of realistic data for the behaviour of the transport system users. To this end, an experiment was conducted in which data on the individual behaviour and activities was collected, which could be integrated in the simulation model to capture realistic responses to TOD proposals. Illustrative results are shown, demonstrating the model can produce results that are meaningful to planners, but also highlights the role of agent-based simulation models to steer the data collection process and engage with decision-makers.

**Keywords:** TOD, agent-based model, data collection, decision-support tool.

## 1 Introduction

The issue of integrated design of transit stations and affiliated urban areas such as transit-oriented development (TOD) have gained increasing attention worldwide [1]. The design of a new generation TOD emphasizes improving access to active travel and high-quality public spaces to promote human comfort [2]. To appraise whether a planning scenario achieves such improvements, there is a need for urban design support tools for studying the impact of different design scenarios and examining how people use the infrastructure and public space under different design alternatives. Agent-based

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modelling (ABM) is a suitable modelling methodology to create a heterogeneous population with activity patterns which lead to transport decisions (including mode, route, time) for a given environment and infrastructure options. Collectively, the individual decisions lead to insights on key indicators that can support planners in evaluating different alternatives and ensure new developments are attractive, efficient for users but also meet sustainability and economic targets. One of the challenges for ABM applications in this domain is how to build data-driven models and explore human behaviour.

Model development itself can help guide data collection [3] by showing what data is required to test a theory. Moreover, models can often be built as generic frameworks which are then instantiated for a specific case study by providing relevant case-specific input data. The ODD protocol specifically refers to this as “initialisation” and “input data” to describe part of the model [9]. However, there remains several methodological challenges, for example, in collecting data that matches the specification of the model, linking data sets together, analysing the data to extract significant drivers and behaviours [4], deriving agent-rules from data, and integrating human-environment models [5]. Kagho et al. highlighted that “the data collection process is one way error can be introduced into the model” and data bias (e.g. introduced by preference surveys) could cause bias in models [6].

This paper therefore aims to: 1) build a data-driven ABM decision-support tool for urban designers, especially in designing and evaluating people-centric TOD plans; and 2) discuss the role of data in the development of the urban simulation model, and the use of output data to help influence decision-making in a case study in Nanjing, China.

## 2 A prototype ABM

To meet these aims, we firstly developed a prototype model “Transport, Spaces, and Humans-system (TSH-system)” and implemented the model in the GAMA platform (documented in https://gama-platform.org/wiki/Projects). Fig.1 shows the model interface. The model was built as a generic framework to support students and practitioners in urban planning and design, architectural design, and other fields to analyse urban systems and to quantitatively evaluate design schemes [7, 8]. It allows the simulation of private car drivers and pedestrians for a given TOD plan to predict the usage of the space and relevant activities, as well as automobile travel demands, active travel demands, and transport mode choices.

Input data includes GIS files (land use, walking routes, and driving road network), population statistics (e.g. density), activity patterns, walking and driving speeds, mode choice parameters (e.g. weight of money cost in mode choice), personal parameters (e.g. shoulder width), and pedestrian parameters (e.g. the repulsive force in social force model). The model then outputs hourly data in terms of users over the urban space (occupancy/dwelling time), automobile traffic volumes and pedestrian population on each road segment.

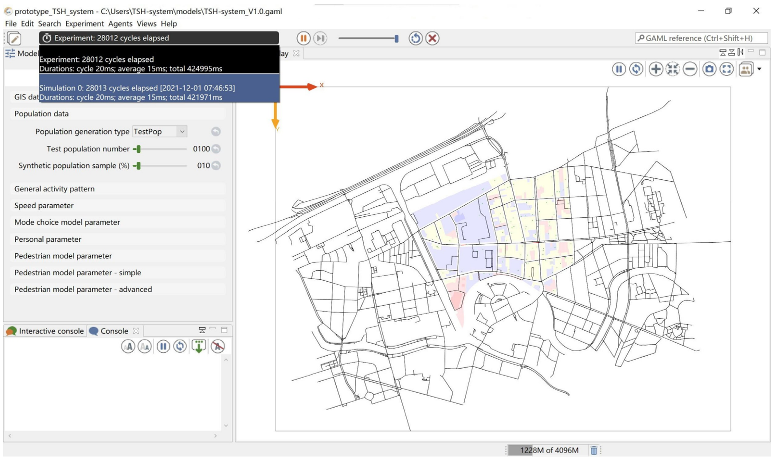

**Fig. 1.** Interface of the TSH-system model

## 3 Case study

The model was tested in a regular MSc course at the School of Architecture in Southeast University, China, which attempts to explore the future development model of the surrounding plots of transit stations [8]. This year, a case study was conducted in Shanghai, China (see Fig.2). Research site is located at plots X101-01 and X102-02 of Shanghai West Railway Station. It is not only the location of the Shanghai West Railway Station, but also a transfer station of Metro Lines 11, 15 and 20; thus, it is an important hub for the local and wider area.

Students conceived their designs based on a primary aim, for instance, to improve spatial orientation and wayfinding, to combine two grid road systems, and to create a high-quality microclimate. To test the effectiveness of their plans, they changed the GIS input files in terms of the land uses, activities, road network and pavement network, and ran the simulation model for their scenario. The model then presents hourly number of users in urban spaces, traffic volume over the road network, and walking demands across the pavement network which provided the designers with relevant metrics to help them revise their plans iteratively.

## 4 Data collection and initial results

The GIS data was based on a baseline of the built environment, with the modifications and designs prepared by the user as part of their proposed intervention. In addition to the spatial data, agent-behaviour data was required to enable a user to simulate the use of the urban system. To collect relevant behavioural data, an experiment was set up for which 30 participants (10 are students from the MSc course and 20 are volunteers) were recruited. It was conducted in Nanjing city in China. The experiment aims to explore the pedestrians' walking behaviour in affiliated areas of rail transit stations as well as the impact of the design of such areas (underground/semi-underground/open outdoor space) on their behaviour, cognition, and comfort. Each participant visited the different spaces of three subway stations and one railway station freely for 10 minutes while being monitored.

The ErgoLAB human-machine environment platform and a series of wearable physiological recording modules were used to collect and analyse multi-dimensional human factors data synchronously. The factors of time-space trajectories, electroencephalography, eye movement, electrodermal activity were investigated. Activity pattern data was collected by a survey. For the first step of building data-driven ABM, we will extract features of pedestrians' walking behaviour from the time-space trajectories including for example the movement direction angle.

By using the TSH-system agent-based model, Fig.3 shows the initial results of simulating the number of users of each urban space (darker blue plots means a higher amount of people) and walking behaviour (darker green lines means heavier traffic) for the baseline scenario, simulating how users would interact with the current TOD layout.

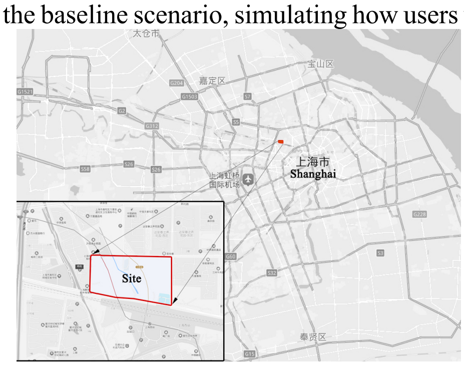


**Fig. 2.** Location of the case study site in Shanghai city, China.

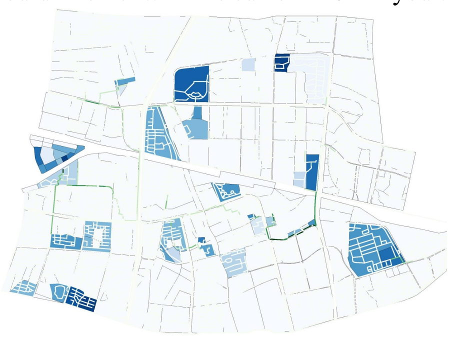

**Fig. 3.** Baseline scenario simulation of walking behaviour: the blue plots show the number of users per hour in a workday; the green lines show the traffic volume over the walking network.

## 5 Discussions and conclusion

These initial results illustrate the potential of enriching the prototype TSH-system model with the data from the experiment to generate more reliable output for evaluating a given design. This enables designers to compare alternatives for the physical design of TOD projects for a given population. Besides, the time-space trajectories, physiological, and psychological data we got matches the specification of the model, that is, simulating human behaviour in the public spaces around transit stations. Also, the way of collection was designed to avoid data bias by not only delivering surveys but also recording individual behavioural data using wearable physiological recording devices.

To incorporate the collected data into the model, we are analysing the data to extract significant drivers of individual behaviour in the TSH system and derive agent-rules. As always with such complex systems, there is uncertainty around key input parameters especially when these are based on an analysis of human behaviour. In the next stage of this project, using sensitivity analysis, we can test the impact of these parameters on the final result and use that to guide design updated data collection strategies and experimental setup. For TOD this specifically refers to mode choice and journey purpose, but also the agent's views on the quality and attractiveness of the space.

There are, however, some challenges in developing data-driven ABM. For example, it is time-consuming to prepare and cleaning the GIS files before integration with agent-based models. Standardisation of data formats, quality checks, and scaling up data to population level are also challenging issues. To this end, we aim to integrate this work with a geospatial data platform to take advantage of other relevant datasets (e.g. on the environment), linking this with the simulation model, and to presenting simulated data in the platform, providing a coherent picture to key decision-makers.

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### 1.3 AgentsX.jl — An Extended Julia Framework for Exploring Urban and Social Systems

**Rajith Vidanaarachchi, Jason Thompson, Branislava Godic and Rod McClure**

# AgentsX.jl — An Extended Julia Framework for Exploring Urban and Social Systems *

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**Abstract.** Agent-Based Modelling (ABM) is applied successfully in various use cases, including but not limited to economic modelling, socio-behavioural modelling, ecological modelling, public health, and urban design. We draw attention to the emerging ABM platform Agents.jl, written in Julia — an accessible, high-level programming language. We identify Agents.jl as a promising package for interfacing, customising and extending for specialised uses. We present the key design ideas for a proposed extension and interface to the Agents.jl framework for ABM for urban and social systems simulation — AgentsX.jl — that provides greater flexibility of agent definitions for urban and social researchers. Our primary motivation is to formalise ABM design through a "Code as the Model" approach, reducing barriers to documentation and increasing reproducibility. Our proposed design entails a structured means of defining an ABM based on layers modelled after spheres of influence, clearer constructs to coding an ABM as interfaces to Agents.jl, and an insightful visualisation toolkit that uses dimension reduction techniques.

**Keywords:** Agent-Based Modelling · Urban Simulation · Social Simulation · Julia · Agents.jl

## 1 Introduction

Agent-Based Models (ABMs) are useful tools for modelling urban and social systems. ABMs are often used in an interdisciplinary manner to inform large-scale policy decisions, to understand complex behaviours, and to aid in planning and designing within socio-technical systems. ABMs at their core involve the creation of an artificial society containing 'agents', which can represent any decision-making entity that acts along with a set of 'rules' or 'behaviours' defined by the modeller and reveals emergent phenomena [1]. ABMs are useful for understanding urban systems as they allow the 'agents' or the entities within the model to have a unique set of characteristics which leads them to be located

* Supported by The University of New England and The University of Melbourne

in a simulated 'neighbourhood'. Each neighbourhood can have its own characteristics which influence the agents' interactions with their environment, with emergent consequences on factors such as the health and financial status of the agent [2]. There are extensive examples of applications of ABMs in the context of urban systems, including transport, residential choice, urban growth and expansion, urban food access, urban planning and health, and urban systems generally [3–8].

### 1.1 Background

There are a host of Agent-Based Modelling platforms available, including Netlogo [9], Swarm [10], MASON [11], Repast [12], Mesa [13], and the newly minted Agents.jl [14]. Among these, we identify Agents.jl as a platform with much potential (for review, see [15]). It has a simple back-end, is fast, and the underlying language — Julia — is a well-supported general programming language.

As ABMs are often used interdisciplinarily, it is crucial that a human-readable definition accompanies them. A proper definition of an ABM has two roles. Firstly, it allows for a better understanding of the model by users. Secondly, it increases reproducibility. We identify two noteworthy approaches to these issues. First is the ODD (Overview, Design Concepts, Details) by [16], which is the formal documentation method in the ABM field. Second is the "Code as the Model" approach argued for in [17]. Both have documented strengths and weaknesses [18]. The latter of which may be overcome using this extension.

Formal methods are often employed where computational methods are applied in critical systems. When ABMs are used in urban and social simulations that affect policy decisions, it is not unreasonable to expect a certain degree of formalisation. [19–21] present attempts to formalise ABMs.

### 1.2 Motivation and Contributions

In this paper, we introduce AgentsX.jl, which is an extension to an ABM framework based on the Agents.jl platform. The framework's design reflects an effort to formalise ABMs and improve the ease of human readability. We achieve these goals through the extension and interfacing of the Agents.jl platform and present a framework specifically suitable for urban and social simulation.

We are influenced by the arguments presented in [17] that code is the ultimate definition of a computational model. However, we believe that code needs to be structured in a manner that serves as a robust, readable definition. Hence, we provide infrastructure to generate ABMs that would represent unambiguous models. We also recognise the importance of visual documentation as mentioned in ODD [16]. We, therefore, also provide infrastructure for model developers to generate simple automated visual representations of ABMs, reducing barriers to visual documentation.

A complementary contribution that stems from the layered structure we introduce is the visualisation of Agent movement and behaviour beyond the traditional spatial domain, which allows analysis and actuation in spatial and alternate (e.g., social) domains, as visualised in Fig. 2.

## 2 Methods

This paper discusses the design and the initial development of work-in-progress that is available at github.com/rajithv/AgentsX.jl. This work is an actualisation of a conceptual framework that seeks to formalise ABMs. The Julia language implementation of the framework eases barriers into coding a robust Agent-Based Model through facilitating formalisation through code generators.

We present AgentsX.jl as an extension and an interface to the Agents.jl platform that would cater specifically to urban and social simulation paradigms. Primary reasons to keep the work distinct from the base Agents.jl package is due to the specialisation into social simulation support that would be unnecessarily complicated for simulations solely dedicated to the spatial domain that is already well supported through Agents.jl.

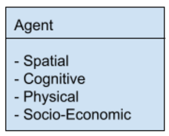


**Fig. 1.** A layered agent

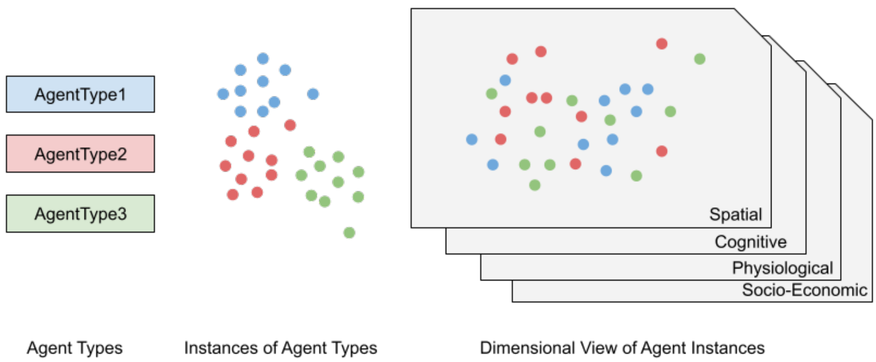


**Fig. 2.** Multiple agent types provide instances to the ABM that inhere independently in different dimensions

As part of our extension, we propose a structure that separates the agent definition in attributes and actions through clearly defined source code files. To formalise the definition of attributes, we introduce a new abstract agent type — LayeredAgent — that recognises the heterogeneity of agent attributes. A standard example is an agent with Spatial, Cognitive, Physiological and Socio-Economic attributes as seen in Fig. 1. Each layer is modelled as a parametric layer, enabling agents to be visualised through any subset of layers, not just in the spatial domain, as is the case with traditional visualisations. We formalise the actions by separation of responsibilities in the source code from the attributive definition of the agent and by defining the scope of the actions as intra- or inter-layer actions taking place between agents and the environment.

We facilitate this formalised structure through a code generator similar to that of PkgTemplates.jl package generator and use Mustache.jl based templates in its implementation.

```
create_agent_template(;agent_class, num_agents, space,
    random_seed = 250, layers = Nothing, actions = Nothing)
```

We provide two main interfaces to the existing Agents.jl architecture. Firstly, we provide a generalised step function and defer the definition of an agent's 'step' to the definition of the agent itself through an ordered list of actions or a function that describes a sequence of actions. Secondly, we provide a simpler construct to adopt multi-agent models by overriding the AgentBasedModel() function.

```
ABM(agents::Array{<:AbstractAgent}, args...; kwargs...)
```

We propose the following rules for layers and actions — and enforce the same in AgentsX.jl — to ensure a robust ecosystem for ABMs.

**Layers**

1. All agents share a single environment.
2. Agents in a model can be of different types.
3. Agents have layers describing different internal domains.
4. Different agent types have different subsets of layers.
5. The environment has a set of corresponding layers that is equivalent to the superset of the union of layers of each agent type.
6. Layers are described through parameters.

**Actions**

1. The environment is omniscient.
2. Interactions could be within the agent (self-interactions), between multiple agents, or between the agent and the environment.
3. Agent-agent interactions must be facilitated through the environment.
4. Interactions could be inter- or intra-layer interactions.

## 3 Conclusion

The design of the AgentsX.jl framework allows the formalisation of Agent-Based Models in a programming language that is fast, easy to use and future-proof. Together with the code generator, the proposed structure would allow the reproduction of ABMs with minimal ambiguity. Moreover, the layered agent design would improve the overall design of agents with respect to clarity of agent behaviour, data collection, isolation of agent domains, experimentation, and analysis. These properties would ensure a high level of trust in the model, allowing translation into high-impact real-world results.

We suggest that the proposed interfaces to Agents.jl would facilitate coding practices that contribute to the "Code as the Model" approach and enhance clarity, communication, and reproducibility for users. The layer-based reduced dimension visualisations would allow modellers to look beyond the spatial arrangement of agents in single domains, allowing more sophisticated agent interactions in other (any) parameterised agent domains.

### 3.1 Future Work

The current design of the Agents.jl and AgentsX.jl, as well as the design principles of the Julia language, allows modular improvements resulting in ambitious possibilities for development and future work. These may include a centralised representation of agents that can be converted to human readable documentation as well as computer-readable code with minimal effort. Another direction relates to perception and actuation interfaces for interactions. This is based on the idea that the actual environmental conditions are perceived by the agents with an individual bias, resulting in variations of perception. Similarly, actions taken by the agents will have an intention-actuation gap, resulting in variations of actuation.

We note that in the most recent Agents.jl publication [15] it is suggested that the multi-agent simulation architecture may be upheaved in the future. We believe the work presented and the proposed future works can positively influence the modelling of complex social behaviours within urban and social systems.

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## 1.4 Simulating civil emergency evacuation with Inverse Generative Social Science

**Gayani Senanayake and Minh Kieu**

# Simulating civil emergency evaluation with Inverse Generative Social Science

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## 1 Introduction

Emergency evacuations are increasingly becoming problematic and complex in cities (Batty 2008; Borja 2007). It is because the population of the cities and coastal states is steadily growing (Chang & Lo 2016) while transportation infrastructures fail to keep pace with this growth (Dow & Cutter 2002). Under severe emergencies, evacuation is the most important and effective method to save human lives within limited time and space (Lämmel 2011). Mass evacuations often rely on automobiles which usually presents a complex process, sometimes leading to undesirable and chaotic outcomes (Lämmel 2011) where injuries or deaths are caused by crowding, crushing and congestion during emergencies (K. Wang, Shi, Goh, & Qian 2019). The unique characteristics of evacuation traffic; large number of agents, their panic or herding behaviour (Lämmel 2011), and traffic flow including accidents, damaged, and emergency vehicles (Bani Younes, Boukerche, & Zhou 2016) need to be incorporated into the design of generic traffic simulation (Yin, Wang, & Ouyang 2020). This highlights the necessity and significance of a better understanding of traffic flow dynamics, which can be used to facilitate human safety and evacuation management and planning.

Various techniques have been proposed in the existing literature to model and understand the emergency evacuation process (Chiu, Zheng, Villalobos, Peacock, & Henk 2008). Computer simulation has been an effective experimental means for evacuation planning and management due to its low cost and high speed to improve the evacuation process (Zhang, Chan, & Ukkusuri 2014). Among the computer simulation methods, Agent-Based Modelling (ABM) is particularly suitable for simulating individual behaviours and exploring emergent collective phenomena in evacuation. To capture the phenomena and complexities during evacuations, modellers often have to craft the rules of individual behaviours in ABMs from limited post-disaster surveys (Zhao, Lovreglio, & Nilsson 2020) and modellers' knowledge (Zhao et al. 2020). Although the machine-learning-based solutions reduce such a bias and provide better performance in terms of prediction accuracy (K. Wang et al. 2019), these methods fail to provide mechanistic explanations of human evacuation behaviour (Rand 2019), and only a few studies have used machine-learning techniques to investigate evacuation behaviour (Zhao et al. 2020; Şahin, Rokne, & Alhajj 2019). We argue that the existing theoretical understanding of human behaviours during evacuation is insufficient for us to effectively simulate, because of two unsolved challenges:

- Existing data about evacuation behaviours are often scarce and unreliable
- Classical models of complex systems can be highly predictive at the overall system level (i.e. black box) but fail to offer a theoretical explanation of the stochastic human behaviours

This paper presents a work-in-progress research in development of Inverse Generative Social Science (IGSS) (Gunaratne & Garibay 2017; Vu, Davies, Buckley, Brennan, & Purshouse 2021; Vu et al. 2020, 2019) for simulating human behaviours during an emergency. It first reviews the literature on agent-based modelling in simulating human evacuation behaviours and highlights the possibility of credible and falsifiable knowledge discovery frameworks to offer a theoretical explanation and modelling of human behaviours during an emergency evacuation. Instead of crafting the exact equations or rules governing human behaviours (like in classical ABMs), we hypothesise that if we can systematically generate an ensemble of potential human behaviours from the limited observed data that we have, then we can evaluate these propositions to understand how people will behave. We believe that there are still two major scientific challenges that we will address in this research:

- While other IGSS-based frameworks rely on a large volume of aggregated data, where various methods can be used to explore the behavioural space (e.g. genetic algorithms (Smith 2008), conventional genetic programming (Vu et al. 2020, 2019) or regression (Gunaratne & Garibay 2017)), we often have limited data for evacuation scenarios.
- Evacuation scenarios often involve a large number of agents, with a high diversity of behaviours, which lead to computational problems from evaluating many generated behavioural propositions, and from performing expensive bi-level optimisation of both model structure and model parameters.

## 2 Literature Review

There is a considerable amount of research that has proposed solutions to model pre-evacuation decision-making during an emergency (Zhao et al. 2020). Of them, several Agent-Based Models (ABMs) have been developed to investigate emergent evacuation scenarios (Dawson, Peppe, & Wang 2011; Lovreglio, Ronchi, & Nilsson 2016; Wood & Schmidtlein 2013; Zhang, Chan, & Ukkusuri 2009). Although existing ABMs can capture the dynamics during an evacuation process and offer a detailed analysis of agent interactions, each agent's evacuation decisions are based on a set of rules (Dawson et al. 2011; Zhang et al. 2014). However, the possible linear or nonlinear trends of each factor of the model outcomes need to be specified by the modellers (modeller's bias), and this may reduce the possibility to investigate the actual trends (Zhao et al. 2020). Under evacuation circumstances, drivers and pedestrians act in an unexpected panic situation and the traditional driver behaviour models such as car-following and lane-changing behaviour might fail to capture the conditions in emergency Li and Wang (2020). Apart from that, ABMs are not designed to produce behaviours that the designer can interpret and require intensive computational power with the complexity of the simulation (Cummings n.d.).

A very small literature exists on the "model discovery" (Gunaratne & Garibay 2017), and "inverse generative social science" (Vu et al. 2019)) of mechanism-based models. Both approaches use evolutionary computing (EC) methods to steer the search for good model structures. In a handful of studies on IGSS, evolutionary computing has also been used to search for ABM structures recently – the agents' internal rules and structuring computational architectures. In an early study, Smith used a genetic algorithm to evolve the rules in a classifier to reproduce the observed social assortativity of birds (Smith 2008). More recently, Zhong and colleagues used gene expression programming to optimise the structure of a reward function used by agents to evaluate behavioural choices, such that the ABM could better reproduce empirically observed crowd behaviours (Zhong, Luo, Cai, & Lees n.d.). Later, Gunaratne and Garibay used genetic programming to evolve agents' farm selection rules to identify new model structures for a NetLogo implementation of the seminal Artificial Anasazi ABM to reproduce the archaeological population demography of Long House Valley, Arizona (Gunaratne & Garibay 2017). Vu et al. (2019) develop an IGSS approach using genetic programming, decision trees, causal state modelling, and machine learning and artificial intelligence. It used multi-objective genetic programming to identify alternative situational mechanisms for a social norms model of alcohol use, aimed at both improved representation of observed drinking patterns in the US over 15 years and theoretical interpretability. The application of multi-objective genetic programming represents a starting point for building the tools needed to perform the model discovery process of IGSS. Further, IGSS is a new approach, its applicability in traffic simulation to model complex human behaviour has not yet been tested and is the most difficult aspect of the evacuation process and hard to model in mathematical equations (Mas, Imamura, & Koshimura 2011). IGSS is situated to offer meaningful insights into the mechanisms and evolve the rules to best fit the decision-making processes under pressure and panic.

Given this background, this study mainly focuses on dynamic traffic conditions among the agents during the evacuation process. The objective of this study is to build the preliminary evacuation simulation model to prove the applicability of the IGSS concept in capturing and discovering the rules of agents' evacuation behaviours and interactions between them under data scarcity. This toy simulation model will be the base to develop a complex IGSS model that tests and analyses different case study scenarios and grasp the characteristics and effects of human traffic behaviours during the evacuation.

## 3 Methodology

Preliminary analysis of the study are made to simulate traffic evacuation with limited empirical data by establishing the form of the basic algorithm and determining the range of the various system parameters. The evacuation toy model uses a NetLogo modelling environment (Tisue & Wilensky 2004). We adapt the agent-based tsunami evacuation model developed by H. Wang, Mostafizi, Cramer, Cox, and Park (2016) for a case study in Auckland, New Zealand. Figure 1 shows a snapshot of the developed toy model.

Fig. 1: Toy Model on Tsunami Evacuation

The above tsunami evacuation model platform includes five components: the transportation network, the population distribution, the evacuation shelters, the tsunami inundation, and casualty model. The simulations are capable to capture evacuees' socio-demographic characteristics which are related to the evacuees' decisions, such as choice of evacuation mode, milling time which marks the start time of their evacuation, and walking speed which represents the physical ability of the evacuee. The platform is capable of simulating a tsunami evacuation scenario with variable tsunami and behavioral characteristics. In addition, the city of Auckland has been used as a case study because of its high risk of experiencing a tsunami in the foreseeable future.

Figure 1 depicts the agents behaviour after several minutes of simulation process. At the beginning of the simulation, at time (t) = 0, it shows the distribution of initial population in brown. The ocean is on the top, and the evacuation shelters (yellow) are placed outside the inundation zone on the bottom and left. There are fictitious six horizontal evacuation areas located outside of the tsunami inundation zone and three fictitious vertical evacuation structures within the inundation zone where they are optional for the user to add. After the earthquake, depending on the milling time, people evacuate either by car (blue) or on foot (orange), and the tsunami inundates the city causing casualties (red). We focus on the consequences of the tsunami hazard on the road infrastructure, by providing options to break the road link during tsunami, and not on the building infrastructures.

The model can simulate several options related to human decisions and mobility characteristics. For instance, evacuation mode choice (foot, car) is one of the critical decisions, independently made by each agent, which have major impacts on the overall evacuation life safety. Equally important, and especially for near-field tsunami evacuations with less preparation time, milling time is another critical variable that is associated with evacuees' decision-making process. To capture the evacuation preparation time, as suggested by Mas et al. (2011), departure times in this work follow a Rayleigh distribution where values of t and s respectively represent the minimum milling time and the spread of the departure times. The larger is s, the larger the tail of the distribution towards later departure times will be. Further, the model provides option for the user to select immediate evacuation in which evacuees start the evacuation immediately after the tsunami alarm. Two other mobility characteristics affecting the efficiency of evacuation and the mortality rate of the scenario are the walking speed of the pedestrians and details of vehicular movement such as the maximum driving speed and other traffic flow variables (Wood & Schmidtlein 2012). In this work, the movement of vehicles is governed by a classic car-following model, the General Motors model, the details of which are documented by Mostafizi, Wang, Cox, Cramer, and Dong (2017). In addition, it is assumed that walking speeds follow a normal distribution with varying mean.

### 3.1 Study Site

The Auckland city is chosen as the study site for this work, mostly because of its special geographical and topographical characteristics and higher population of Seaside which is estimated to be 205,608 (*Population of North Shore in 2021 2022 - statistics* n.d.). The close proximity of the Auckland, within the next 10 years, there is a 10 percent to 60 percent chance (best estimate is 30 percent) of a magnitude 7 or higher earthquake occurring in the area(*GeoNet Earthquake forecasts* 2017), which makes this city prone to tsunami evacuation in the foreseeable future.On top of these, the flat topography of the city would allow the tsunami inundation to reach a long distance inland in a relatively short time.

### 3.2 Data for the simulation

The model uses GIS data as input for transportation network, population distribution and evacuation shelters in the shape-file format.

## 4 Future Plan and Conclusion

This toy model is developed to investigate the feasibility of using IGSS to simulate individual's behaviours in an emergency, where we would need to overcome data scarcity and modeller bias. We will use the toy model to provide the *pseudo-truth* data for an machine-learning-based IGSS model to learn the action rules used in the toy model. If the model can systematically generate the hypothesised evacuation behaviour in the developed agent-based model using IGSS concepts, then these preliminary model propositions can be evaluated to understand how people will behave in an emergency, while addressing major scientific challenges of using existing IGSS-based frameworks with limited data for evacuation scenarios and computational problems with a high diversity of behaviours.

With its success, a complex IGSS model will be developed in the future to continue this research. It will execute several simulations on different scenarios and test the influence of the evacuation behaviour of agents. Hence, this toy model will be the base to consider more realistic evacuation actions in the future.

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# 2 Session 2: Urban Development

## 2.1 No Hope for First-Time Buyers? Towards Agent-Based Market Analysis of Urban Housing Balance

**Erik Wiegel and Neil Yorke-Smith.**

# No Hope for First-Time Buyers? Towards Agent-Based Market Analysis of Urban Housing Balance

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**Abstract.** The Dutch housing market comprises three sectors: social-rented, private-rented and owner-occupied. The contemporary market is marked by a shortage of supply and a large subsidised social sector. Waiting lists for social housing are growing, whereas households with income above the intended limit do not or can not leave the social sector. Government policy and market regulations change frequently, not least for political reasons. We examine the effects of government policy by means of an exploratory agent-based simulation. Results provide perspectives on how internal demand is impacted by regulations in a housing market suffering from a shortage, and weigh the pros and cons of policy measures.

## 1 Introduction and Background

The Dutch residential market is experiencing a housing shortage at the time of writing – an imbalance which is expected to grow in the medium term. The market comprises three sectors: social-rented (managed directly or indirectly by municipal governments), private-rented (regulated by a combination of municipal and national government), and owner-occupied (affected by the mortgage market).

Regulations for the social housing sector and for mortgages have resulted in a situation where first-time home buyers ('starters') with a middle-income in the market are both ineligible for social housing and unable to purchase a property [8]. Combined with the limited supply in private renting, this situation leaves a starter with very few options.

Starters who are eligible for social housing experience that the social-rented market has growing waiting lists in every major urban area [4]. We term 'external demand' those wishing to enter the housing market, notably starters. Occupying social housing are families with children living in one-bedroom houses, some waiting for their turn for a larger houses; others who got their turn but are now ineligible for larger social housing because they earn above the maximum income to qualify, but who are also unable to afford to rent privately or to purchase a property [6]. We term 'internal demand' those having a home currently but are dissatisfied with it. At the same time, however, there are 'empty nesters', parents whose children have moved out, who keep living in social houses that are big enough to support a family with children.

The shortage of supply causes imbalance: some households will not have a home to own or will pay more for the few available dwellings than they would otherwise; some households under-pay and others over-pay; some households lack space while others have space to spare.

The question we investigate is: how is internal demand impacted by regulations in a housing market suffering from a shortage? We address this question by developing an agent-based model (ABM) of the Dutch housing market, in particular the city of Amsterdam. This simulation model intends to achieve four purposes: 1. Contrast with economical models through the use of a different modelling technique. 2. Investigate the effects of regulations on specific household groups. 3. Provide a flexible approach in which policy changes and new policy can be easily studied.

## 2 Methodology and Related Work

We adopt agent-based modelling as it allows a focus on the choices of and effect on individual households within the regulations – renters, buyers and sellers – and the emergent city-level effects. The choice of ABM as a methodology is recommended by Boelhouwer and Hoekstra [2] who highlight the influence of regulations in both the rental and home-ownership sector on tenure choice. Additionally, the use of an ABM allows unexpected interactions between regulations to emerge. Boelhouwer [1] reviews the government policy in the Dutch housing market and concludes that the current policy creates social inequality. Further, he concludes: "Many citizens, and more specifically low-middle income groups and young households, do not understand the current policy choices which leads to an increasing distrust in government and to instability in society."

The majority of research on the housing market is either social–anthropological or economic in nature, and done at a *macro level*. The econometric models analyse the relationships between housing prices and market fundamentals. These models can analyse specific policies, as long as those policies can be described in terms of the economic variables; however, econometric models cannot accommodate individual-level behaviour and results. Because of this, these models are unable to predict emergent patterns caused by policy.

An important precedent for ABM is the work of Gilbert et al. [3]: an ABM of the English home-ownership sector. The authors show that a simplified model of the housing market can replicate key behaviours observed in the real market. Their model provides effective ways to model income and home-owner behaviour when income changes. However, from a spatial perspective, Gilbert et al. assume that buyers that cannot buy a home leave the local market to some alternative municipality. But if this alternative does not exist, such as in a scarce market, these buyers would not leave the market and keep providing pressure on the market. The second reason that the model of Gilbert et al. cannot be used for our research question is that it does not consider the rental sector.

A number of other works model aspects of the housing market or urban housing development using ABM. To our knowledge, none address the case of

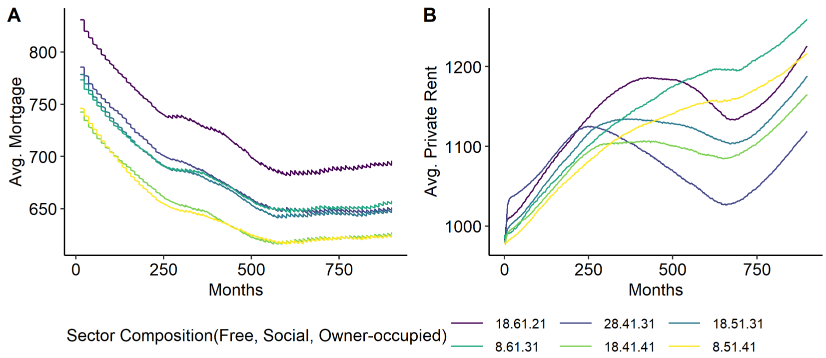


**Fig. 1.** Mean mortgage payment and monthly rent paid in the private sector.

a Dutch municipality setting with all three of social-rented, private-rented and owner-occupied dwellings. The closest are Ziengs and Yorke-Smith [10], who look at negotiation in Dutch property purchases using ABM, and Overwater and Yorke-Smith [7], who look at the peer-to-peer rental market in Amsterdam, again using ABM; Ligtenberg et al. [5] use ABM to study land planning but not residents' decisions.

## 3 Results and Outlook

In the context of the Dutch housing market, we argue that the interaction between choices of households and regulations in the social-rented, private-rented and owner-occupied sectors shapes the choices of households. The agents in the model are: households (as home-owners, sellers, renters), housing corporations (the non-profit organisations who manage social housing), and private landlords. The processes in the model are the households' search for a new place to live, the allocation of social housing, and the transactions in the private housing market. The processes are subject to current municipal and national regulations. ABM provides a convenient way to explore effects of what-if changes to regulations at both levels. A challenge is to traverse the temporal scales between the frequency of decisions of different types of agents – buying a property is not a weekly occurrence for most households! – the pace of regulatory changes, and the market effects to be observed beyond the short-term.

A full description of the model and results are found in Wiegel [9]. Figure 1, for example, examines ownership and rental costs in the private sector, between various sectoral compositions. The results find that in the social sector, selection may be preferable to lottery due to its bias towards households that already own a home. The metric of 'secondary waiting time' can be effective in helping split households find a home, but has unclear effects on other households. Third, increasing the income limit for the social sector is found to favour older households.

Last, market policies that encourage a change to behaviours – designed to increase housing stock utilization – can instead spur demand.

This work engages ABMUS participants by, first, providing a case study of urban agent-based micro-modelling and its interface with public policy. An open discussion is how (Dutch) policy makers can be informed by such modelling, during a period where the over-demand in the housing market is a current political topic. Second, discussing how construction of such ABMs strongly draws on public data portals e.g., data.amsterdam.nl, which are sometimes incompatible. Third, by furthering discussion of spatial and temporal ABM design for housing market micro-simulation [3]. Fourth, by continuing the discourse from previous ABMUS editions [10].

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## 2.2 Agent-Based Modelling of People's Behaviour in Public Parks Sabine Timpf and Marie-Rose Degg.

# Agent-Based Modelling of People's Behaviour in Public Parks

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**Abstract.** Public parks are important urban spaces to promote physical and mental health, in addition to inducing social interaction between visitors. Within the context of geo-design and sustainability issues, urban designers are interested in designing parks for visitor's use as well as easy management – a bottom-up approach often resulting in public participation processes. As an alternative, people's behaviour may be simulated during the design process thereby testing different design alternatives. This course of action is also feasible when renovating or redecorating parks. However, validated models simulating people's behaviour in public parks at a very local level are very scarce. In this project, we use geodata on people's activities collected in three public parks in a European city to derive a model of behaviour for an agent-based simulation. We discuss this process as well as the problem of modelling human behaviour at the local scale.

**Keywords:** urban public parks, behaviour, activities, geodesign

## 1 Modelling behaviour in public parks – the challenge

Urban green spaces play an important role in the discussion on sustainable and resilient urban systems. Especially public neighbourhood parks are said to promote physical and mental health when visited regularly. In addition, public parks may induce social interaction between visitors. Analytical approaches (in the form of surveys and interviews, see e.g. [5]) show these benefits of urban public parks for existing parks. Public participation planning processes allow potential park users to express their preferences for the design of planned parks. However, these processes are time- and resource-consuming for an urban planning department.

Within the context of geodesign and urban sustainability, urban designers and city officials are interested in designing parks for visitor's use as well as easy management. As an alternative to public participation processes, we propose to simulate people's behaviour during the design process thereby testing different design alternatives. This course of action is also feasible when renovating or redecorating parks. However, validated models simulating people's behaviour in public parks, i.e., at a very local level, are very scarce. Existing models often focus on specific behaviours, such as walking [3], place selection [6], space appropriation [4], or others.

The challenge for modelling behaviour at a local level is that generic models for typical park activities, such as strolling, supervising children or playing catch, as well as more structured activities such as climbing, badminton or soccer (passing the ball), are missing. Furthermore, some of these activities may be carried out anyplace within a public park and the selection process for these places is not well understood. While we believe that theories from environmental psychology and anthropology may be helpful in this regard, we still have to contend with the problem that these theories are not (yet) implemented.

In our research, we use geodata on observed people's behaviour that was collected in three public parks in a European city. Within the project the observed behaviour was classified into activities [1]; from these we derive initial models of activities for an agent-based simulation in section 2. It is important to note that these models are based partly on the observations, partly on some knowledge about human-environment interactions as well as common knowledge about these activities. In section 3, we sketch the current implementation of the activities in an agent-based model. In the final section 4, we discuss the process of deriving models of activities from observation data as well as the problem of modelling human behaviour at the local scale.

## 2 People's activities in public parks derived from case studies

The case studies were undertaken from 2005 to 2007 in close collaboration with the administrative department responsible for the design and maintenance of public parks, i.e., GrünStadtZürich, as part of a larger research project. The three parks were selected on the basis of four criteria: their function in the city context as neighbourhood parks, their age (established vs. new), their style of design, and their suitability for observations (size, visibility). Figure 1 shows the model of the Bäckeranlage as an example of one of the oldest parks in Zurich, located in a densely built neighbourhood with a potentially precarious social constellation of low income and ethnically diverse population.

The observations were realised over a period of three years, including a pilot study. Each of the three parks was observed on 7-14 days for 2-4 hours. As two parks were observed in consecutive years, this amounts to almost 150 hours of observations with over 8000 park visitors recorded. The results of the extensive analysis may be found in [1].

The observations recorded individual visitors, their age, gender, time, location, type of activity, and group affiliation (groups of park visitors that know each other and spend their stay together). Age was classified into the broad groups of children, teenagers, adults and elderly (retired). The 26 observed activities were grouped into Static Solitary (e.g. reading, sleeping), Static Interactive (communicating), Eat/Drink, Dynamic Irregular (e.g. running around), Dynamic Regular (some kind of playing field, e.g. football), Playgrounds and Water after a pilot study. All observers had to undergo special training in order to be able to conduct the surveys according to the specifications.

## 3 Implementing the activities in an agent-based model

The agent-based model shows the activities of people in three different parks in Zurich (Switzerland) that were derived based on the data described above. It visualises how spaces are used in parks and how agents (spatially) interact with each other and with features in the park. The model was created with NetLogo 6.2.1 and its GIS-extension. Please note that the model itself is not attached to a GIS (there is no need for a coupling) - the data we use is derived from a GIS. At the beginning of the simulation the park is set up with all its observable features according to Shapefiles that were created using satellite images of the respective parks. Figure 1 shows an annotated screenshot of the model of the Bäckeranlage. This geodata forms the input for the setup of the agent-based model.

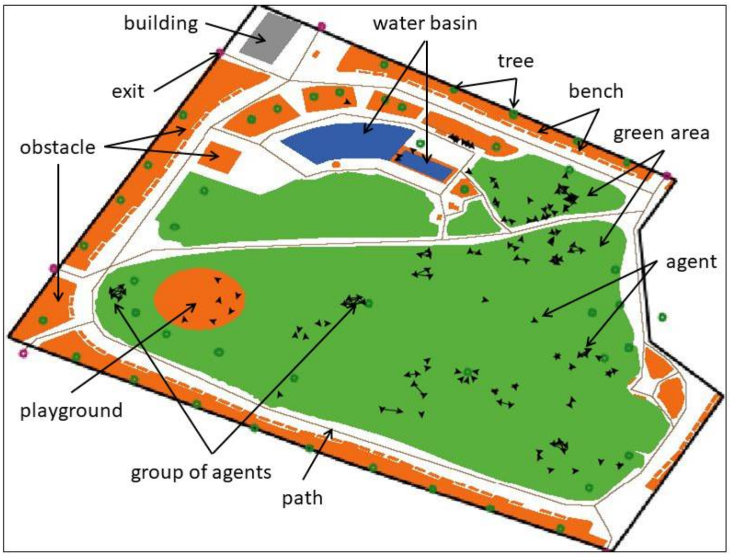


**Fig. 1.** Annotated screenshot of agent-based model of Bäckeranlage, Zurich

The park is populated with agents carrying out different individual and group activities - this setup is based on the collected geodata. The initial location of agents corresponds with the first recorded observation; subsequent observations of the same agent are currently disregarded.
There are 26 different activities. For stationary activities, the individual or group stays at their original location without movement (e.g., sleeping, picnicking)

or they move inside a circumscribed area represented as a polygonal feature (e.g., playgrounds) or area defined by the agent's locations (e.g., romping, football). For dynamic activities, individuals or whole groups move freely (randomly) through the park without (currently) being restricted to certain features or group areas (e.g. running around, chasing around) or follow a path until they reach an exit point (biking). They adapt their direction if they encounter an obstacle.

## 4 Discussion and Conclusions

In this project we endeavour to model activities of agents at a local level within a public neighbourhood park. Our approach is data-driven in that we use observations of real people's activities and locations in three parks in Zurich, Switzerland. We identified different types of activities and recreate their spatio-temporal footprints using a combination of theory and empiricism. However, the current initial implementation is lacking especially in the rich type of interaction between agent and environment that expresses a diversified understanding (or ontology) of the environment. We distinguish between obstacles, other agents, and free space. This minimalist interpretation already provides verisimilitude to some agent's movements, but we still needed to add specific concepts (such as boundary and exit). To make things potentially more complicated, each activity may require a different interpretation of obstacle, boundary, and free space, thus enforcing a "functional perception" on our agents.

The distinction between stationary and location-changing activities allows us to ignore all stationary activities, where the most important part, i.e. selecting a suitable location, is not modelled due to initialising all agents at the observed locations. The location selection process is mostly cognitive and may be modelled using the notion of affordances [2, 6].

The models for the location-changing activities currently use random movement, which needs to be substituted by rules for suitable moves (for that specific activity). This kind of "suitability assessment" will take much more processing time in addition to (again) changing the ontology.

A point to discuss is the need to adhere to/be informed by the data for validation purposes while at the same time freeing ourselves from the data in order to arrive at generic rules for modelling people's behaviour. How much difference between modelled and observed behaviour is still acceptable?

In conclusion, we have to admit that we are still rather far from using our agent-based model for geodesign simulations. It is however encouraging that the initial implementation shows expected and verisimilar movement patterns. We will therefore continue to work on implementing rules for the different activities with the goal to transfer these implementations to other case studies and serve as basis for geodesigning public parks.

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## 2.3 An agent-based model of greening a city for reducing pluvial flooding at a cultural heritage site

**Emily West, Rembrandt Koppelaar, Aitziber Egusquiza Ortega, Angela Santangelo and Eleonora Melandri.**

# An agent-based model of greening a city for reducing pluvial flooding at a cultural heritage site

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**Abstract.** We present an agent-based model which explores the impact of greening a city for pluvial flood risk reduction, to inform planning decisions in cities. In particular we focus on the location of an archaeological site lying 2 meters below ground level in the city centre of Ravenna, Italy, which is subject to pluvial flooding. A map of Ravenna was divided into cells which could be eligible for modelled greening if they contained a car park, a street or a pedestrianised area. The number and location of cells greened varied with each run of the model. This was combined with precipitation and temperature data from Ravenna, and subsequently estimated scores for evapotranspiration and permeability. In general, the greater number of greening measures introduced corresponded to a reduced volume of excess rainwater. There was a particular effectiveness of greened streets at reducing excess runoff compared to car parks and pedestrian areas. Our results demonstrate the usefulness of ABM in the field of disaster risk management.

**Keywords:** Agent-based, Pluvial, Cultural Heritage.

## 1 Background

Sites of cultural and natural heritage represent important records of the past [1]. Despite having historically survived numerous hazardous natural events, anthropogenic climate change is placing increasing stress on cultural heritage sites and their users. Agent-based modelling, or ABM, is useful in this context by enabling a structured exploration of disaster and post-disaster scenarios and different impact prevention measures, to quantify their benefits before resources are committed to their implementation [2].

The impact of pluvial flooding from precipitation is especially severe in urban areas of heritage due to impermeable ground surfaces causing high runoff [3]. The Santa Croce Church and archaeological site of Ravenna, Italy, is one such cultural heritage area at which pluvial flooding has become a problem [4],[5]. Since the 1990s the whole city of Ravenna and its surroundings have been subjected to the subsidence phenomenon. Moreover, due to being situated below both street and sea level, ground water levels are particularly high, meaning that water drains into these important areas from the above-ground street following heavy rainfall. Greening impermeable parts of the city can improve water infiltration and thus reduce surface runoff and flooding risk.

By simulating areas of the ground surface as agents with surface type as a characteristic, our agent-based model aims to be an explorative device to examine the usefulness of ABM as a tool for urban planners. Important to note is that this model is explorative since it is without empirical validation. The interpretation of which measures are most effective is based on deduction since the developed impacts in the models are based on expert logic and literature where available.

## 2 Methods

The model was built with the Python ABM libraries Mesa [6] and Mesa-geo [7]. In our model, a map of Ravenna was divided into areas or 'cells' of ground surface, determined by census data classifications, which here acted as the agents. Each one is characterised by its percentage of green land, streets, pedestrian areas and car parks. Depending on how many cells the user decides to green in each model run, a selection of cells are randomly chosen. Hourly totals of precipitation and means of temperature for a 2-month time series was taken in August 2018, when Ravenna saw greater than average rainfall. Each cell has a permeability score based on its land use, which enables it to absorb a given amount of rainfall. Rainfall in excess of this forms pools which remain on the ground surface and are slowly reduced by transpiration. If the cell is selected for greening, its permeability score changes and so does its absorption capacity. For a cell to be eligible for greening, it had to meet two criteria: Less than 70% of the cell had to have been already greened, and the cell must also be covered by at least 10% of either car park or street, or at least 5% of a pedestrianised zone, to model a justifiable amount of greening. In total 294 out of 664 cells were eligible for greening each run, broken down into 231 streets, 42 car parks and 21 pedestrian areas (fig 2). Each cell was simulated as a block of ground with natural processes and the following characteristics:

**Static characteristics:** Area ($m^2$), Amount of greened land in each cell (%), Amount of cell covered by car parks, by streets and by pedestrian areas (%).
**Dynamic characteristics**: Overall amount of greened land in each cell, after greening the city (%), Whether cell is flooded or not (yes/no), Permeability (a static coefficient which changes depending on the percent of green space in the model).

Important to note here is that the runoff absorption was estimated based on how much of the respective area could realistically be greened. This meant that pedestrian areas were modelled as being able to absorb 15% of runoff if greened, for example by installing vegetation barriers at kerbsides and in the middle of paved areas. It was assumed that car parks could be greened in a similar way but to a greater extent, leading to this value being estimated at a 30%. Due to the narrowness of many streets in Ravenna, however, it was assumed that these could not be greened in a typical sense and instead the more intrusive measure of installing permeable concrete or asphalt was assumed to be the most appropriate. This meant that the entire street area could in theory be ‘greened’ and as such streets were assumed to have an absorption capacity of 80%. The model was run as a batch with a series of variables. The consistent parameters included weather and temperature, and the variable parameters were as follows:

- Number of car parks being greened: Tested at values of 0, 10, 20, 30 and 40.
- Number of pedestrian areas being greened: Tested at values of 0, 5, 10, 15 and 20.
- Number of streets being greened: Tested at values of 0, 50, 100, 150 and 200.

These variables were each run for 5 values, with every combination between the three variables, 100 times. This resulted in **12,500 runs** of the model being carried out. For each of these model runs, 10 parameters were recorded. These were the number of cells which were greened during a model run, the total volume of excess flooding in the model, and the average runoff per cells with differing percentages of areas greened.

## 3 Results

The areas of Ravenna which were modelled as greenable can be seen in figure 2. Firstly, the more cells have greening measures applied to them, the less excess runoff occurred. This is because as heavy rainfall occurs, urban surfaces are unable to drain this water away quickly enough before more occurs. Thus, as surfaces become on average greener, more drainage can occur and hence less flooding (fig 1). Secondly, cells which have less than 5% of their area greened are more likely to flood with a higher number of greening measures applied to other cells. Similarly, cells which are over 10% greened benefit from less flooding as more greening measures are introduced.

The cells categorised as streets had the highest impact on flooding reduction when greened. This is partly attributable to the sheer quantity of these cells, and also because the streets were modelled as having a higher modelled runoff reduction per greened cell compared to pedestrian areas or car parks.

Finally, there is a greater impact from greening streets than other surfaces. This can be largely explained by the sheer quantity of streets compared to the other surfaces.

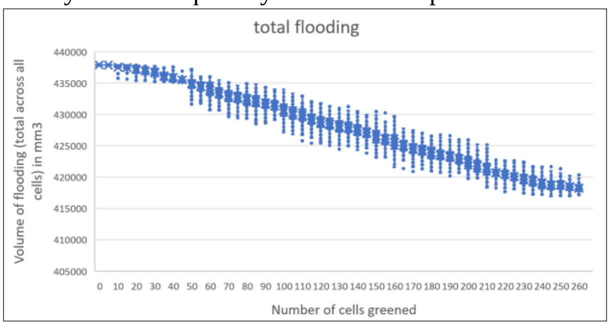


**Fig. 1.** Volume of flooding against number of greened cells in place.

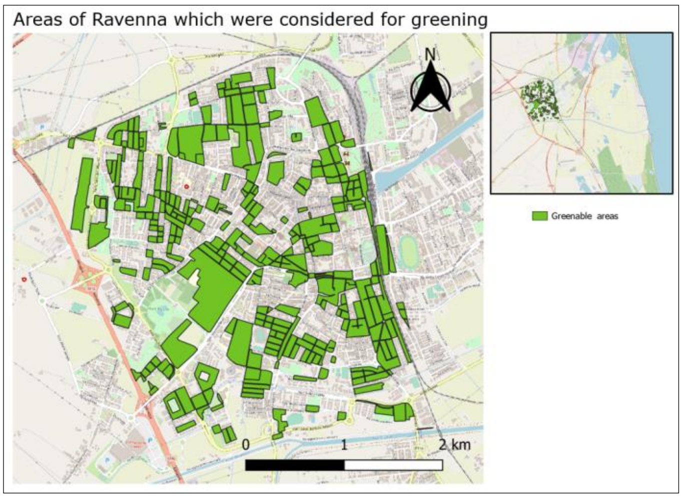


**Fig. 2.** Map with proposed cells for applying greening measures

## 4 Uncertainties and difficulties encountered

Several uncertainties must be considered alongside result interpretation. Firstly, rainfall parameters used were based on historic events, and thus do not account for climate change. Secondly, the role played by sewage systems was not accounted for. This may increase the drainage potential of certain parts of the city and worsen it in others due to Ravenna's generally high level of ground water. Neighbourhood interaction between cells was also not accounted for, but in reality greener cells are likely to influence the drainage of nearby cells. Thirdly, elevation and aspect were not considered. In reality, areas which are more sloped will drain into low-lying areas where water accumulation will be greater. This could be solved by incorporating digital elevation datasets. The greened factor for different types of land, as well as the coefficient of permeability, were also estimated. To improve this would require calculating how much of each greenable area could realistically be greened in practice. Finally, some cells will either be privately-owned or logistically impossible to green. A land survey could be carried out to determine which cells it would be feasible to green.

Despite several areas of proposed further development, our exploratory model demonstrates the usefulness of agent-based modelling to local decision-makers as well as to the research community for its exploration of city greening.

## 5 Conclusions and next steps

Our model explores the interaction between rainfall, surface type and flooding volume in Ravenna, Italy. Although several uncertainties limit the direct applicability of final results to justify specific planning actions on behalf of the local authority, our model is useful as a discussion tool for land use planning from a risk reduction perspective. The model's key conclusions include the relative effectiveness of greening streets compared with other surface types. Similarly, at least 10% of the cell must be greened to cause a tangible reduction on runoff. Other urban rainfall models include the SCS-CN model which similarly finds that increasing urban green space correlates with runoff reduction, and also finds that periods of heavy rainfall result in higher water retention by green spaces [8]. Our study did not consider individual rainfall events but rather focused on monthly totals, and this is worth considering in future iterations.

If more detailed information such as elevation can be incorporated into future model iterations, then the insights gained could allow an understanding of where and how many impervious surfaces should be greened to reduce pluvial flooding at the Santa Croce Church and archaeological area. The model can then be used as a discussion tool for organisations in Ravenna to incentivise the greening of public and private land.

The use of agent-based modelling as an explorative tool in disaster risk management was demonstrated for pluvial flooding, for the purpose of testing disaster management greening interventions. The value of using ABM in this way is the rapid testing of random behaviour of using different combinations of cells being greened each model run.

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## 2.4 Real World Traffic Optimization by Reinforcement Learning: A Concept

**Henri Meeß, Jeremias Gerner, Daniel Hein, Stefanie Schmidtner and Gordon Elger.**

# Real World Traffic Optimization by Reinforcement Learning: A Concept *

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## 1 Issues in Real Traffic Light Systems

Due to the growing urban population [22], the existing infrastructure and traffic control are successively reaching their limits, making an optimization of the traffic flow by intelligent control of Traffic Lights (TL) increasingly important. Previous research has already shown the basic suitability of Deep Reinforcement Learning (DRL) methods for TL control, for both, the optimization of single intersections [13, 14] and the optimization of traffic networks using Multi Agent Reinforcement Learning (MARL) [1, 19, 10, 15, 2, 11, 7]. A major gap in research concerning this area is the training and usage in real-life systems due to several challenges [18, 20, 23]: (1) Training in real systems is difficult since agents cannot perform unrestricted arbitrary actions. (2) It cannot always be guaranteed that the learned policies are sufficiently robust. (3) DRL controllers must ensure that existing safety and operational constraints are enforced at all times. Thus, DRL-based TL controllers have been implemented mostly simulation-based [23]. However, these simulation-based approaches can only be transferred to reality to a limited extent since [6]:

- *Multimodality:* In most simulations only car traffic was simulated, neglecting other traffic participants.
- *Baselines:* DRL methods have rarely been compared with state-of-the-art traffic-actuated controls that are already used in the real-world.
- *State and actions:* In reality, data collection is considerably more difficult. Furthermore, the action space is not correctly aligned with current TL control units.
- *Simulation environments:* Most implementations were only done in symmetric networks with distribution-based traffic demand, oversimplifying real traffic situations. Traffic state information was directly taken from simulation, neglecting the lack of this data in real systems. Therefore, training on simulations and inference in reality can lead to inconsistencies [24, 8].

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This work picks up the concept, presented in [16], to combine state-of-the-art DRL methods with existing traffic engineering methods to overcome the issues mentioned above and extends it by a description how to specifically close the gap between simulation and reality.

## 2 Closing the Simulation to Reality Gap

To enable a system that can be used effectively in real-world traffic systems, the RL framework to optimize the traffic lights is intended to build upon and extend established systems and procedures of traditional traffic engineering. In particular, this concerns the extraction of state and reward data and the actions definition. For the extraction of the state and reward data it is planed to use a traffic estimation model named DRIVERS [9]. DRIVERS creates a microscopic state representations based on raw detector data from real world traffic systems. Therefore it generates Origin-Destination (OD) matrices from the detector data which highly correspond to the real traffic on a macroscopic level. Based on the OD matrices traffic is simulated by a microscopic simulation model. This makes it possible to obtain microscopic state information which is coherent to the real-life traffic. Figure 1 shows the planned structure of the system for training and operation. In the core RL-System DRIVERS serves as the main data source for the state and reward information. The RL components and DRIVERS are closely linked, because the state and reward definitions are based on the DRIVERS output and the DRIVERS model is therefore an inherent part of the learned policy. To achieve a save operation of the system it will be first trained and evaluated in a simulation-based environment. In this environment a simulation serves as a surrogate for the real traffic network. This allows to train and optimize the core RL-System without affecting the real traffic network. To enable a realistic traffic representation in the simulation, a second DRIVERS instance is used. This instance is used to generate OD matrices from the sensor data of the real network, which serve as the demand definition for the simulation.

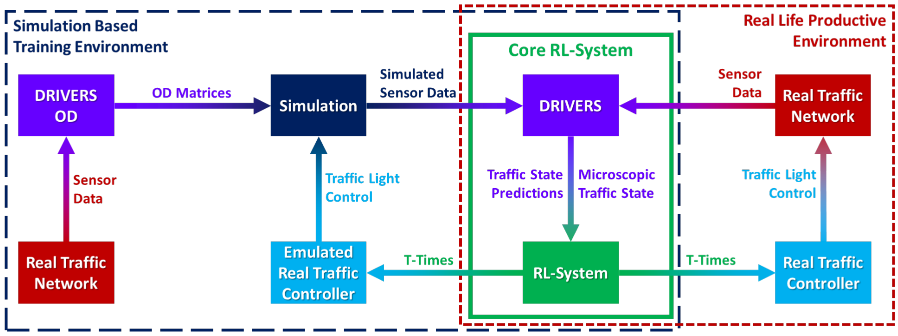


**Fig. 1.** Architecture of the proposed framework

After the configuration of the core RL-System has been optimized and tested in the simulation framework, it can seamlessly be integrated in the real traffic environment by switching the sensor data source and the control interface for the core RL-System from the simulation to the real system.
For both, the simulation based training and real life productive system, microscopic traffic generated by DRIVERS is transferred to the RL-System and refined through state representation methods known from the literature. Specifically Discrete Traffic State Encoding (DTSE) [5, 19, 4] and feature-based representation [12, 6] methods will be critically evaluated, especially for their theoretical justification and applicability in a real-world setting. For a multimodal optimization, all traffic participants are to be represented for this purpose, enabling a fair distribution of green times for all road users. Another important point for the applicability of RL systems in reality is the action definition. To achieve a compatibility with real control systems the action definition will be based on the widely spread time gap control [17]. This control method is based on frame signal plans, witch consist of T-times. T-times are lower and upper time limits, in which the local controller can independently switch the phases. For each phase $i$ from crossing $k$ there is a minimum ${T_{min}}_i^k$ and maximum ${T_{max}}_i^k$ admissible T-time. We define the set of actions $A^k = \{a^k_{i,min}, a^k_{i,max}\}$ for a single agent at crossing $k$ with the following condition: ${T_{min}}_i^k \leq a^k_{i,min} \leq a^k_{i,max} \leq {T_{max}}_i^k$. After $a^k_{i,min}$ has been exceeded and no further vehicles are registered for a defined time, or if $a^k_{i,max}$ is reached, the traffic controller switches to the next phase $i+1$. As the actions can only vary in an interval that takes the minimum and maximum admissible T-times of the phases into account, the safe operation and a minimal performance of the traffic lights is guaranteed with all possible combinations. The RL agent's goal is to find the optimal T-times for the given traffic situation. Thus, we obtain a continuous action space with two values per phase where all actions follow the reasonable phases and transitions of the existing systems.
Such an action space comes with several challenges: (1) a (dis-) continuous action space; the majority of papers deal with discrete action spaces [3] (2) a constrained action space (3) actions depend on other actions that are defined at the same time (4) a high number of actions at the same time; compared to different approaches.
To ensure that the constrains hold and generic Actor Critic methods can be used we define the actions as:

$$a^k_{i,min} = rnd(sig^k_{out i,min} \times ({T_{max}}_i^k - {T_{min}}_i^k)) + {T_{min}}_i^k \tag{1}$$

$$a^k_{i,max} = rnd(sig^k_{out i,max} \times ({T_{max}}_i^k - a^k_{i,min})) + a^k_{i,min} \tag{2}$$

Where $sig_{out}$ is the respective outcome of the last actors NN-Layer with a sigmoid activation function for the distinctive element of the agent's action set. Based on domain knowledge and theoretical considerations derived from traffic engineering, this approach aims to achieve the following:

1. The constrained action space can ensure that agents achieve a minimum level of performance in all situations. Even completely unknown traffic scenarios

do not lead to a full failure of the system while safety is secured by the T-times concept.
2. The occurrence of a green wave is simplified by the specification of allowed T-times.
3. This approach can be ported directly into the real application. Following the concept stated in Figure 1.

## 3 Cooperative Optimization

To ensure goal-directed cooperative optimization, an incentive for cooperation must be created. Usually, common rewards or reward sharing between the neighbors [21] are used. Furthermore, the state space can get enriched with relevant information of the neighbors [2]. To extend this basic setup, new approaches for the cooperation of multiple agents will be explored. These apply different concepts of shared critics, e.g.: (1) The actors and critics outputs are fed into a shared critic. The actors updates are based on a weighted gradient of own and shared critic. (2) The actors output are fed into their respective and a shared critic. Additionally, the shared critic gets superordinate state representations. The actors updates are based on a weighted gradient of own and shared critic. Additionally, we will investigate to what extent a benefit is created by providing information about outflowing edges to overcome deadlocks caused by not sufficient informed policies[4]. By this, streets or regions shall be jointly optimized as clusters or common routes. We thereby encourage direct cooperation as a shared critic directs the gradients for optimization.

## 4 Outlook

In this paper, we outlined a concept to bring RL from simulative applications to real use in the field. To solve the stated problems we propose a detailed consideration of individual intersections, multimodality, and specific configurations of MARL for practical implementation. Through the consideration and combination with current techniques for traffic control we increase the applicability of our concept for real-world traffic networks. To ensure compatibility we train in simulations on real data derived by online traffic estimations as well as random generated traffic. We use DRIVERS in the simulation to estimate the traffic behavior even though the actual traffic is available in the simulation and further add a simulation of the actual traffic controller. By this, we strongly adapt to the later in-field implementation even while training and try to overcome the simulation to reality gap in this field. Finally, the real deployment in Ingolstadt's road network is planned, where we after all want to prove the applicability of RL for real-world traffic optimization.

[4] A more detailed overview and presentation of the concepts will be provided in the full version of this work.

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# 3 Session 3: Transport

## 3.1 Transport electrification and fast-charging expansion: A case study in Alaska

**Ilya Turchaninov, Koen van Dam, Gonzalo Bustos Turu and Salvador Acha.**

# Transport electrification and fast-charging expansion: A case study in Alaska*

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**Abstract.** Research on the use of electric vehicles (EVs) typically focuses on urban areas only with a lack of case studies in areas that are not highly populated. This paper presents an agent-based model of EV users in Alaska, USA, combining a city with more remote areas and characteristics which lack representation in the literature. The developed agent-based model, supported by interviews and questionnaires, produces specific, relevant recommendations for local regulators and policymakers, showing that adding fast-charging stations in remote areas can support leisure use, and workplace charging can reduce peak demand. The methodology proposed in this work can serve as a baseline for other communities looking to make impactful policy and regulatory decisions regarding their EV transition.

## 1 Introduction

With the push to decarbonise energy generation, transport has become the highest-emitting sector globally, now accounting for almost a quarter of carbon dioxide emissions and contributing significantly to air pollution [2]. As a result, more focus is now being placed on the decarbonisation of the transport sector, and hence the electric vehicle (EV) market has grown substantially in the last decade [3]. However, there are still many barriers to widespread electric vehicle adoption [7, 4]; even in the presence of available charging infrastructure, it has been shown that EV uptake was lower than expected from a lack of consumer willingness to accept disruptions in their daily routines for charging purposes [1].

Fast-charging, while a ubiquitous solution to improve usability of EVs, has a limited business case arising from high capital and operational costs. Additionally, uncertainty regarding negative grid impacts have stifled widespread expansion of such infrastructure. An important issue for many communities attempting to transition to electric mobility is the lack of case studies focused on areas that are not highly-populated and urbanised. Such a limited scope is reasonable when considering the priority to decarbonise high-density communities producing significant carbon emissions; nevertheless, an understanding of the

* Supported by Imperial College London and the Alaska Center for Energy and Power

impacts of unique lifestyles in atypical environments and climates is crucial to promoting an equitable transition to electrification.

In response, this study aims to understand the systemic challenges with transport electrification and expansion of public fast-charging infrastructure as perceived by the stakeholders within a unique EV system. Furthermore, it offers specific, relevant guidelines and recommendations through the implementation of an agent-based model that focuses on individual driving and charging behaviours of residents for a variety of activity types. The model focuses on a case study of the Municipality of Anchorage (MoA) in Alaska. Anchorage is Alaska's largest city with a population of nearly 300k and it is currently rapidly gaining interest in transport electrification, but has many barriers to overcome for EVs to become mainstream. The remote setting as well as the local climate make this an interesting case study.

## 2 Methodology

To understand the barriers to charging infrastructure expansion in Alaska, a three-pronged approach was chosen which seeks to understand the problem from multiple perspectives and viewpoints. The methodology consists of stakeholder interviews, a survey of drivers in MoA, and an agent-based model to evaluate different interventions.

Firstly, stakeholder interviews were conducted to identify commonalities and differences in opinion between the major players in the Alaskan EV infrastructure landscape regarding public charging infrastructure and the promotion of electric mobility. Interviews were procured with a private charging station installer, a utility representative, a state energy agency representative, an elected state representative, and three local researchers. The viewpoints presented in the interviews influenced scenarios modelled.

Secondly, a survey of MoA drivers, in the form of an online questionnaire, was developed (based on [6]) with the main goals of understanding driving behaviour and charging preferences, to potentially use as input into the agent-based model and as a reference for future policy-making decisions.

Finally, an agent-based model (Fig. 1) of the Municipality of Anchorage and its drivers (based on the driver survey) was developed in NetLogo building on a previous application in Swindon, UK [5] adding fast charging, impact of external temperatures, and behaviour linked to EV use in remote locations. The goal of the model is to determine the EV load of drivers in the MoA and the utilisation of the public charging network based on the travel behaviour of electric vehicle drivers for a typical weekday and weekend using the current and potential future EV fleet, following the scenarios from the stakeholder interviews.

## 3 Results and Discussion

The model was ran for the year 2021 and 2025. The results of the model indicate that weekday travel needs in the MoA are met primarily without the aid of public

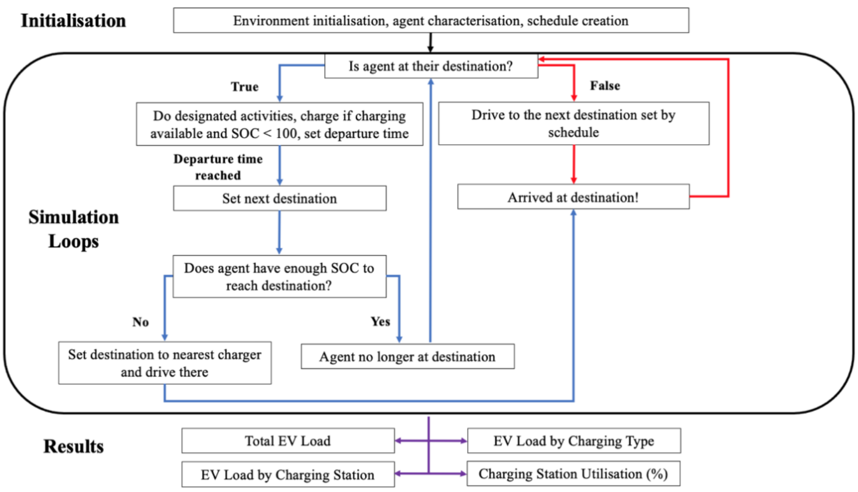


**Fig. 1.** Overview of the agent-based model of EV drivers.

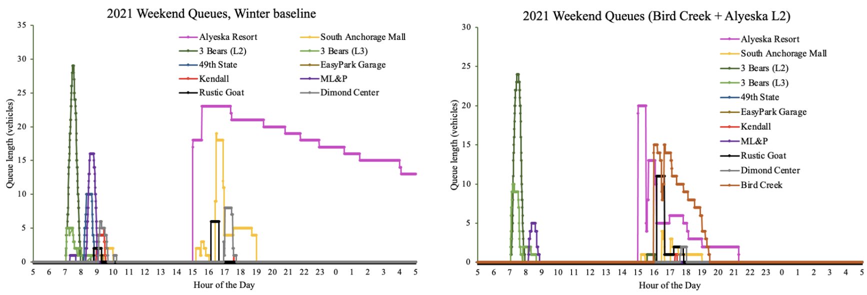


**Fig. 2.** Improvements to charging network lead to queue reduction.

charging infrastructure, with 86% of charging occurring at home during the weekday in 2021. On the other hand, the existing public infrastructure is limited in its capacity to handle weekend recreational travel, with clear limitations on the charging options available to drivers. The limited infrastructure located south of the MoA produced long queues for charging, which left some agents who travelled away from the city unable to make it home by the end of the simulation (Fig. 2).

Improvements in this area of the network were proposed through an additional fast-charging station and a supplementary charging port at the most congested station (Alyeska Resort, 40 miles out of Anchorage), which significantly reduced queuing and improved the feasibility of recreational EV use. These improvements even had success with higher penetration of EVs, seeing less queuing with the 2025 EV fleet than what was observed with the unimproved 2021 baseline infrastructure. Additionally, it was shown that the addition of workplace

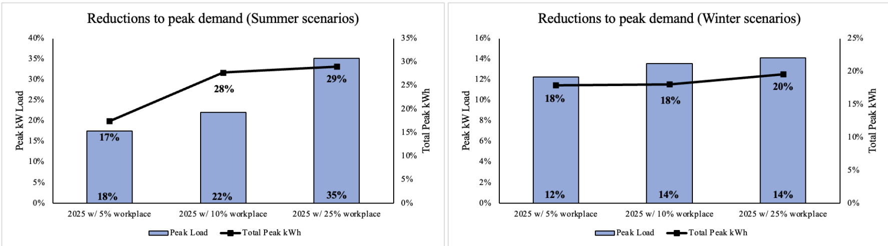


**Fig. 3.** Reduction in peak load and peak kWh consumed.

charging infrastructure has the potential to reduce negative grid impacts of increased EV penetration in 2025 (Fig. 3). With a 25% penetration of workplace charging, summertime peak demand and peak energy consumption were reduced by 35% and 29% compared to the baseline, respectively. On the other hand, increasing workplace charging past 5% did not produce consistent improvements in the winter, with reductions to peak demand and total peak energy consumption stagnating at approximately 14% and 20% from the baseline, respectively.

## 4 Conclusion

From the results of the case study we can conclude that existing infrastructure does not support weekend recreational travel, but simple improvements to the public charging network can significantly improve its feasibility within MoA. Moreover, environmental conditions are an important consideration for driver behaviour and charging network utilisation. Simple mitigation strategies for EV grid impacts are less effective in the winter and alternative methods must be considered to reduce peak demand with higher EV penetration.

The methodology proposed in this study can be applied broadly to case studies concerning EV impacts and utilisation of public charging infrastructure. Through the three-phase approach, the analysis produced can serve as a baseline to make specific, impactful policy and regulatory change through an understanding of local stakeholder needs and a foundation of end user requirements and preferences. The use of qualitative results from stakeholder interviews and the model initialisation based on driver surveys meant that the model could be used to explore relevant scenarios and provide input in the decision-making process, while also gaining trust in the model output from their involvement.

Future work on this agent-based model can more accurately assess EV impacts on the grid system by integrating network data into the model, such as feeder limits and substation capacity. Moreover, A simulation which considers all major travel destinations will have a better view of the limitations of the planned charging network, with important implications for charger roll-out. Finally, the model can be applied to other geographies to compare recommendations for less-densely populated areas in cold climates.

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### 3.2 Learning a Robust Multiagent Driving Policy for Traffic Congestion Reduction

**Yulin Zhang, William Macke, Jiaxun Cui, Daniel Urieli and Peter Stone**

# Learning a Robust Multiagent Driving Policy for Traffic Congestion Reduction

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**Abstract.** In most modern cities, traffic congestion is one of the most salient societal challenges. Past research has shown that inserting a limited number of autonomous vehicles (AVs) within the traffic flow, with driving policies learned specifically for the purpose of reducing congestion, can significantly improve traffic conditions. However, to date these AV policies have generally been evaluated under the same limited conditions under which they were trained. On the other hand, to be considered for *practical* deployment, they must be robust to a wide variety of traffic conditions. This paper establishes for the first time that a multiagent driving policy can be trained in such a way that it generalizes to different traffic flows, AV penetration, and road geometries, including on multi-lane roads.

**Keywords:** Autonomous Vehicles · Traffic Optimization · Deep Reinforcement Learning· Multiagent Systems

## 1 Introduction

According to Texas A&M's 2021 Urban Mobility Report, traffic congestion in 2020 in the U.S. was responsible for excess fuel consumption of about 1.7 billion gallons, an annual delay of 4.3 billion hours, and a total cost of $100B [3]. A common form of traffic congestion on highways is *stop-and-go waves*, which have been shown in field experiments to emerge when vehicle density exceeds a critical value [6]. Past research has shown that in human-driven traffic, a small fraction of automated or autonomous vehicles (AVs) executing a controlled multiagent driving policy can mitigate stop-and-go waves in simulated and real-world scenarios, roughly double the traffic speed, and increase throughput by about 16% [5]. Frequently, the highest-performing policies are those learned by deep reinforcement learning (DRL) algorithms, rather than hand-coded or model-based driving policies.

Any congestion reduction policy executed in the real world will need to perform robustly under a wide variety of traffic conditions such as traffic flow, AV penetration (percentage of AVs in traffic, referred to here as "AVP"), AV placement in traffic, and road geometry. However, existing driving policies have generally been tested in the same conditions they were trained on, and have not been thoroughly tested for robustness to different traffic conditions. Therefore, it remains unclear how to create a robust DRL congestion-reduction driving policy that is practical for real-world deployment.

Fig. 1: a single-lane merge road.

In this extended abstract (of full paper[7]), we establish for the first time the existence of a robust DRL congestion-reduction driving policy that performs well across a wide variety of traffic flows, AVP, AV placement in traffic, and several road geometries. Moreover, we investigate the question of how to come up with such a policy and what degree of robustness it can achieve. We create a benchmark with a diverse, pre-defined collection of test traffic conditions of real-world interest including the single-lane merge scenario shown in Figure 1. Such merge scenarios are a common source of stop-and-go waves on highways [4]. While there are different approaches to training robust DRL policies in other domains with different levels of success, our approach is to systematically search for a robust policy by varying the training conditions, evaluating the learned policy on our proposed test set in a single-lane merge scenario, and selecting the highest performing one. The highest performing policy outperforms the human-only baseline with as few as $1\,\%$ AVs across different traffic conditions in the single-lane merge scenario. We further investigate the policy's generalization to more complex roads it has not seen during training, specifically with two merging ramps at a variety of distances, or on a double-lane main road with cars able to change lanes. Notwithstanding negative prior results showing that a policy developed in a single-lane ring road fails to mitigate the congestion on a double-lane ring road [2], the learned policy outperforms human-only traffic and effectively mitigates congestion in all of these scenarios defined by our benchmark. Taken together, this paper's contributions and insights take us a step closer towards making the exciting concept of traffic congestion reduction through AV control a practical reality.

## 2 Robustness evaluation conditions and metrics in merge road

Similarly to past work [1], our baseline setup consists of simulated human-driven vehicles only. In contrast to past work, which typically showed improvement over this baseline in a *single* combination of traffic conditions, our goal is to develop a robust AV driving policy that improves over this baseline across a *range* of realistic traffic conditions in the merge road shown in Figure 1, characterized by:

- *Main Inflow Rate*: the amount of incoming traffic on the main artery (veh/hour),
- *Merge Inflow Rate*: the amount of incoming traffic on the merge road (veh/hour),
- *AV Placement*: the place where the AVs appear in the traffic flow; the AVs can either be distributed evenly or randomly among the simulated human-driven vehicles.
- *AV Penetration*: the percentage of vehicles that are controlled autonomously,
- *Merge road geometry:* the distance between two merge junctions (in relevant scenarios), and the number of lanes.

In this paper, we fix the merge inflow rate to be $200\,\mathrm{veh/hour}$ (small enough to cause traffic congestion on the main road) and set the range of the main inflow to be [1600, 2000] veh/hour (resulting in minimal to maximal congestion in our simulations), AV penetration (AVP) to be within [0, 40] percent (for a realistic amount of controllable AVs in the coming years). The placement of the AVs can either be random or even. For *even placement*, AV are placed every N human-driven vehicles in a lane. For *random placement*, AVs are placed randomly among simulated human-driven vehicles. Merge road geometries include one or two merges at distances that vary between [200, 800] meters, and the main road can have one or two lanes.

## 3 Learning a robust policy in the single-lane merge scenario

While real-world congestion-reducing driving policies need to operate effectively in a wide variety of traffic conditions, most past research has tested learned policies under the same conditions on which they were trained. Since in the real world it is impractical to deploy a separate policy for each combination of conditions, our primary goal is to understand whether it is feasible to learn a *single* driving policy that is robust to real-world variations in traffic conditions.

The performance of an RL-based driving policy depends on the traffic conditions under which it is trained. We hypothesize that the policy trained under high inflow, medium AV penetration, and random vehicle placement is robust in a range of traffic conditions defined in Section 2 for a single-lane merge scenario. To verify our hypothesis, we discretize the training traffic conditions along their defining dimensions to a total of 30 representative combinations of conditions, as follows. We consider main inflows of 1650, 1850, and 2000 $\mathrm{veh/hour}$ which result in low, medium, and high congestion. We discretize AV placement in traffic to be random or even-spaced. Finally, we discretize the training AV penetration into 5 levels: $10\,\%$, $30\,\%$, $50\,\%$, $80\,\%$, $100\,\%$. Based on this $3 \times 2 \times 5$ discretization, we train 30 policies, one for each combination.

By comparing $30$ policies, we verfied our hypothesis and identified a policy that generalizes well across training conditions (which will be termed as identified robust policy). Next, we evaluate the identified robust policy on road geometries different from its training scenario.

## 4 Deployment to roads with two merging ramps

We first deploy the selected policy on more complex merge roads (with $1500$ meters' main road and $250$ meters' merge road), which have two merging roads at varying distances (200, $400$, $600$, or $800$ meters), and evaluate the performance of the learned policy with respect to the distance between these two ramps. An example road with two merging on-ramps is shown in Figure 2. We tested the identified robust policy with random AV placement, main inflow of $1800\,\mathrm{veh/hour}$, merge inflow $200\,\mathrm{veh/hour}$, across a range of AV penetrations and the above gaps between the two merging roads. The identified robust policy is better than the human baseline even when the merging ramps are just 200 meters away.

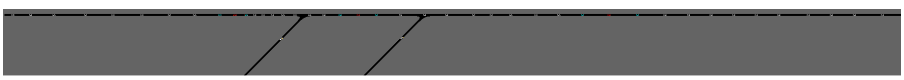

Fig. 2: A more complex road with two merging on-ramps.

## 5 Deployment to double-lane merge roads

Next, we deploy our identified robust policy on a double-lane merge road by adding a second lane in the main road. Similar to that of the single-lane merge scenario, the vehicles in the right lane must yield to the vehicles from the merging lane and may cause potential congestion in the right lane, while the vehicles in the left lane have the right of way when passing the junction. As a consequence, the vehicles in the left lane tend to move at a faster speed, and there will be more vehicles changing from right to left for speed gain than the number of vehicles changing from left to right. Those lane-changing vehicles cause additional stop-and-go waves in the left lane. To test the robustness of the selected policy in this new road structure, we deploy the learned policy to control the AVs on the right lane. During evaluation, there are only human-driven vehicles in the left lane with inflow $1600\,\mathrm{veh/hour}$, and $10\,\%$ of the vehicles in the right lane are AVs, each of which is controlled by our learned policy. The experimental results shows that the performance of the deployed policy is always significantly better than that of the human-only traffic, regardless of the right main inflow. Hence, the policy trained on the single-lane merge road generalizes well in the double-lane merge scenario.

## 6 Conclusion

We presented an approach for learning a congestion reduction driving policy that performs robustly in road merge scenarios over a variety of traffic conditions of practical interest. Specifically, the resulting policy reduces congestion in AV penetrations of $1\,\%$–$40\,\%$, traffic inflows ranging from no congestion to heavy congestion, random AV placement in traffic, single-lane single-merge road, single-lane road with two merges at varying distances, and double-lane single-merge road with lane changes. The process of finding this policy involved identifying a single combination of training conditions that yields a robust policy across different evaluating conditions in a single-lane merge scenario. We find, for the first time, that the resulting policy generalizes beyond the training conditions and road geometry it was trained on.

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### 3.3 Preference-Aware Dynamic Ridesharing

**Yi Cheng Ong, Nicos Protopapas, Vahid Yazdanpanah, Enrico H. Gerding and Sebastian Stein**

# Preference-Aware Dynamic Ridesharing

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**Abstract.** Smart mobility and, in particular, automated ridesharing platforms, promise efficient, safe and sustainable modes of transportation in urban settings. To make such platforms acceptable by the end-users, it is key to capture their preferences not in a static manner (by determining a fixed route and schedule for the vehicle) but in a dynamic manner by giving the riders the chance to get involved in the routing process throughout a journey. To that end, this work provides a toolbox, enabling riders to interact with the ridesharing service and have a say in the routing process.

**Keywords:** Dynamic Ridesharing · Preference Elicitation · Agent-Oriented Smart Mobility

## 1 Introduction

Ridesharing is a promising means towards reducing carbon emissions and mitigating climate change [5]. Integrating preference-awareness into ridesharing systems enhances the satisfaction of the end-users and, in turn, enables the efficient use of spare capacity in urban transportation services [14]. However, although the potential gains are known, some traditional urban transportation systems—such as bus services—are not benefiting from preference-aware ridesharing technologies. Our buses are still operating based on fixed schedules and, in the best cases, use historical data on the behaviour of riders to improve their routes. However, determining routes based on data about *past* users does not necessarily fit how *present* riders want to use the service. For example, arguably, bus schedules generated based on travellers' behaviour in 2019 (i.e., before the COVID-19 pandemic) do not satisfy what we want for riders in 2022. While gathering data more frequently and then fixing a static schedule is an option, in this work, we go a step further and suggest dynamic schedules that are determined based on the preferences of the *current* users/riders. Doing this will allow buses to provide customised services to riders, avoid wasting resources by visiting unnecessary stations, and find compromises for pickup and drop-off locations that users see preferable.

Ridesharing can be considered a vehicle routing problem that is typically solved by optimising a given global objective function. Most studies focused on optimising operational-based objective functions [11] which usually benefit the ridesharing service provider rather than the passengers. Optimising based on the provider's incentives

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would not lead to widespread adoption of this service, as passengers' preferences are not taken into consideration. Thus, recently, there have been studies regarding incorporating passengers' preferences or incentives into the ridesharing problem. These studies specified constraints such as passengers' maximum travel distance and maximum waiting time to ensure some level of quality of service, as well as incorporating new terms in the objective function, encapsulating the overall satisfaction of passengers [11]. This method, however, does not guarantee fairness among the passengers. For example, a ridesharing system might choose route *A* because it minimises the total waiting time and travelling time of all passengers. However, route *A* might lead to a longer travel time for a subset of passengers; for the sake of minimising the overall objective function, their preferences have been neglected, such that route *A* results in more inconvenience to them. In principle, assuming that the ideal route needs to be optimal merely based on the characteristics of the city in an objective sense (e.g., in terms of distances), ignores how satisfied riders are in a subjective sense. In such a view, ridesharing is approached and accordingly solved as a merely *technical* problem with no intention to take into account the *social* and preferential dimensions. In view of human-centred AI techniques and the need for developing trustworthy human-AI partnerships [13], we see ridesharing as an inherently sociotechnical problem and argue that its acceptance by society depends on the ability to capture riders' preferences throughout the journey.

Against this background, this is the first contribution that develops algorithms for determining ridesharing routes in participation with riders, allows dynamic routing through the journey by integrating voting mechanisms, and relaxes the expectation that riders need to compromise their privacy by sharing information with other riders. The current work focuses on riders with temporal preferences; however, all presented algorithms can handle complex utility functions, a capability we intend to employ in future work.

## 2 Main Approach

We consider the case of generating a route for a single bus that is part of a 24-hour ridesharing service. The route generated is a sequence of visited stations, taking into account the temporal preferences of the current riders. The map is defined as a graph that links bus stations. The riders are fully satisfied when their most preferred departure and arrival time is met, and suffer a disutility when the schedule deviates from that. Additionally, the riders have different senses of urgency and patience. We present 3 different algorithms, capturing various aspects of this problem. The algorithms are evaluated using simulation-based experiments.

The main building block of our schedules is the notion of *TourNode* as a list. The $i$-th TourNode defines the location of the $i$-th station in the schedule, as well as arrival and waiting times and the sets of riders for pick-up and drop-off. The list of TourNodes should meet certain constraints; the locations of two adjacent TourNodes should be different, as well as the arrival time at the $i$-th TourNode should be no smaller than the departure time of the $(i-1)$-th TourNode.

Our first approach, the *Randomized Greedy Algorithm* examines the riders according to a random ordering, and builds a list of TourNodes, as the bus schedule. More specifically, consider the case where the $i$-th rider is examined. A provisional schedule of TourNodes has been constructed when the previous riders were examined. At this point, the algorithm first creates a temporary set of valid TourNodes (these could be new or already exists in the provisional schedule) for the departure and the arrival of the rider. Then, the algorithm finds two valid TourNodes, one for the departure and one for the arrival, which maximize the utility for rider $i$ and assigns rider $i$ to them. If any of these two TourNodes does not exist in the provisional schedule, it is then added by the algorithm. The final route of the bus is the sequence of TourNodes created this way.

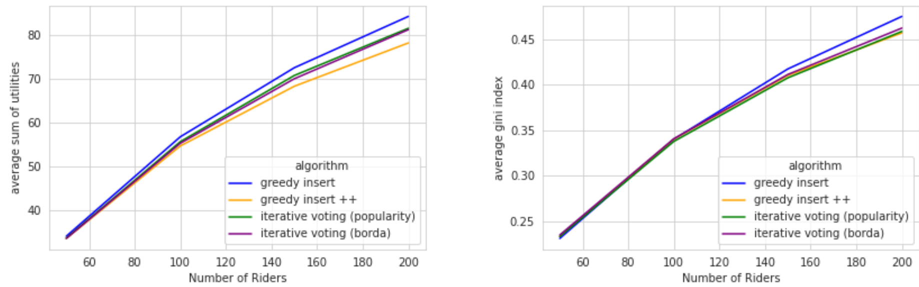
While this algorithm takes preferences into account, it does not consider any fairness aspects. The riders assigned first benefit the most from the scheduling, since the schedule for the first riders is not dense, and there is a higher chance of allocating a departure and arrival TourNodes to maximize the early scheduled riders' utility. To mitigate this impact, we firstly propose the *Randomized Greedy ++ Algorithm*. This algorithm works similarly to the Randomized Greedy Algorithm, with a slight modification: it firstly assigns TourNodes for the departure of the riders according to a random ordering, and then allocates TourNodes for the arrival, according to the reverse order. This form of allocation is also known as *picking sequences* [3]. This way, a rider whose departure was scheduled late, gets more flexibility in the scheduling of her most preferred arrival time.

A second algorithm designed to enhance fairness is the *Iterative Voting* algorithm. This algorithm follows a voting procedure that is repeated until all riders are allocated in a departure and an arrival TourNode. At each iteration, and given a provisional schedule of TourNodes, all unallocated riders propose the TourNode that suits them the best, first for their departure and then for their arrival, in a pool of candidate TourNodes. Observe that the proposed TourNodes should respect any constraints imposed by the previously scheduled TourNodes. After the pool of candidate TourNodes is built, the riders vote to select one of them to be added to the schedule. The voting is done either using the Borda method or plurality voting [3]. When all riders are allocated (i.e. they are allocated in a TourNode for departure and a TourNode for arrival time) the final sequence of TourNodes is returned, as the bus route.

## 3 Evaluating Fairness and Efficiency

We evaluate the performance of the algorithms experimentally. As a measure of efficiency, we focus on the sum of utilities [10]. To measure fairness we follow [8] and use the Gini Index [6, 10], a popular measure of equity in the transportation literature [16]. We use the locations of 66 bus stations in Westminster, London from the Naptan dataset [4] to create a fully connected graph. Finally, we generate riders with different patience levels and various departure and arrival times, simulating peak and off-peak demand.

Our preliminary observations on fairness and efficiency are presented in Figure 1. The Randomized Greedy algorithm worked the best with respect to efficiency, while all fairness-aware algorithms performed the best with respect to the Gini index, with small differences between them.




(a) Sum of Utilities

(b) Gini Index

Fig. 1: Sum of Utilities and Gini index vs Number of Riders.

## 4 Future Directions

In this work, we presented preliminary algorithms and results from an ongoing project on preference-aware dynamic ridesharing, aiming to promote rider participation. Such algorithms can be implemented in ridesharing services to improve riders' satisfaction and, in turn, foster the financial and environmental benefits of smart mobility. Future work can build on these algorithms to explore more realistic preference models.

Our approach is also privacy-conscious as it intentionally neither assumes that riders have complete knowledge about other riders nor expects them to share such sensitive information with others. While this perspective respects privacy concerns in general, in some specific settings (e.g., sharing a ride with others in a social network), sharing information may lead to improved performance of the service. As an extension of this work, we aim to integrate methods for sharing more information with other trusted riders on the service (e.g., using multiagent negotiation techniques [9]) to achieve meaningful consent over a shared route [15, 1]. Another extension is to work towards the design of sustainable preference-aware dynamic ridesharing systems by applying mechanism design methods [12], (e.g., as in [7]). Under this perspective, the riders are represented by computational agents [2] which act in real time on their behalf.

*Data Access Statement* This study was a re-analysis of data that are publicly available from the national public transport access nodes (NaPTAN) [4].

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### 3.4 Multi-Agent Traffic Signal Control via Distributed RL with Spatial and Temporal Feature Extraction

**Yifeng Zhang, Mehul Damani and Guillaume Sartoretti**

# Multi-Agent Traffic Signal Control via Distributed RL with Spatial and Temporal Feature Extraction*

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## 1 Introduction

The aim of traffic signal control (TSC) is to optimize vehicle traffic in urban road networks, via the control of traffic lights at intersections. Efficient traffic signal control can significantly reduce the detrimental impacts of traffic congestion, such as environmental pollution, passenger frustration and economic losses due to wasted time (e.g., surrounding delivery or emergency vehicles). At present, fixed-time controllers, which use offline data to fix the duration of traffic signal phases, remain the most widespread. However, urban traffic exhibits complex spatio-temporal patterns, such as peak congestion during the start and end of a workday. Fixed-time controllers [8, 10] are unable to account for such dynamic patterns and as a result, there has been a recent push for adaptive TSC methods.

Reinforcement learning (RL) is one such adaptive and versatile data-driven method which has shown great promise in general robotics control. Recent works which applied reinforcement learning to the traffic signal problem have shown great promise in alleviating congestion in a single traffic intersection [5–7, 9, 11]. A traffic network is composed of multiple such intersections and a network optimization problem can be broadly formulated as a centralized (single-agent) or decentralized (multi-agent) RL problem. In the centralized RL formulation, a global agent controls the entire traffic network and tries to minimize a global objective such as average trip time. However, centralized solutions for adaptive TSC are infeasible in practice due to the exponentially growing joint action and state space and the high latency associated with information centralization. To avoid the curse of dimensionality , decentralized approaches frame traffic signal control as a multi-agent RL (MARL) problem, where each agent controls a single intersection, based on locally-sensed real-time traffic conditions and communication with neighboring intersections [1, 14]. In this work, we propose a framework for fully decentralized multi-agent TSC (MATSC) based on distributed reinforcement learning with parameter sharing [4], for improved scalability and performance. We design a spatial and temporal neural network, by relying on an attention mechanism and a recurrent unit, to extract spatial and temporal features about local traffic conditions at each intersection. We compare our

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framework with state-of-the-art MATSC methods in simulation, and show that our approach results in decreased average queue lengths and trip times, as well as increased average vehicle speeds and trip completion rates, both overall and during peak periods.

## 2 Method

### 2.1 Problem Formulation

We use a decentralized MARL formulation for MATSC. Each traffic intersection is controlled by a RL agent which only has access to local traffic conditions i.e., the agents have partial observability.

More formally, we consider the multi-agent extension of a MDP, which is characterized by a set of states, $S$, action sets for each of $N$ agents, $A_1, ..., A_N$ , a state transition function, $P : S \times A_1 \times ... \times A_N \rightarrow S'$, which defines the probability distribution over possible next states, given the current state and actions for each agent, and a reward function for each agent that also depends on the global state and actions of all agents, $R_i : S \times A_1 \times ... \times A_N \rightarrow R$.

We consider a partially observable variant in which an agent, $i$, can observe part of the system state $s_i \in \mathbf{S}$ as its observation $o_i \in \mathbf{O}$. The *state* of junction $i$ at time step $t$ comprises two vectors: The first one is a one-hot vector representing the current traffic phase, and the second indicates the number of vehicles on each incoming lane. In line with recent works [2], the observation space of each agent is composed of the state of its assigned junction, as well as the state of all directly connected neighboring intersections.

The action space $\mathbf{A}$ is defined as a set of non-conflicting phases . Specifically, at time step $t$, agent $i$ will choose an action $a_i^t$ from its own action space $A_i$ as a decision for the next $\Delta t$ period of time i.e., the intersection will be in the chosen phase from time step $t$ to time step $t + \Delta t$. After the fixed duration of a given phase has elapsed, the agent may choose to continue with the same phase or choose a different phase and incur a 3 second transitional yellow phase penalty.

Following [2], we define the reward structure as a short term metric which is calculated as the sum of the number of halting vehicles on the lane-area detectors.

### 2.2 Spatial and Temporal Perception Network

Given the dynamics of a traffic network, an agent (junction) needs to have both spatial and temporal awareness to make informed decisions. To enable this, we propose a network that comprises two units, a message aggregation unit for spatial feature extraction, and a RNN-based memory unit for temporal awareness. The detailed network structure is shown in 1. The attention-based message aggregation unit [13] allows the agent to learn to assign higher weights to essential parts of the observations, i.e, concentrate more on the traffic states of neighboring intersections that might cause significant impacts on itself in future steps, while the recurrent unit allows it to utilize historical information to inform its current decision-making.

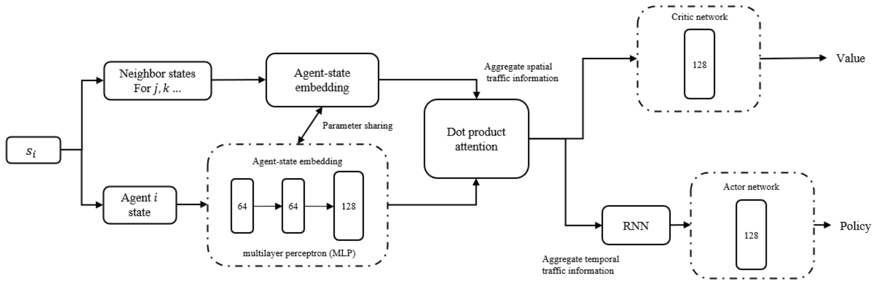


**Fig. 1.** Structure of the spatial-temporal perception neural network used in this work.

Specifically, we first map all the raw observations to a higher dimensional feature space i.e., mapping from low dimensional $o_i$ to high dimensional $e_i$ through multiple fully connected layers. Then, we obtain the query, key, value vectors of the attention mechanism (with same dimensions), by using three different sets of learned weights: $q_i = W_i \cdot e_i, k_i = W_k \cdot e_i, v_i = W_v \cdot e_i$. In our work, the parameters of the key, query, and value layers are shared among agents.

Next, we calculate the compatibility $u_{ij}$ between the query $q_i$ and $k_j$ based on scaled dot production mechanism: $u_{ij} = (q_i^T \cdot k_j)/\sqrt{d}$, where $d$ is the dimension of the vectors used for normalization. The attention weights for each query-key pair can be computed by: $\alpha_{ij}^h = softmax\,(u_{ij})$.

Finally, we calculate the output vector as the weighted sum of all the value vectors, using these learned attention weights: $h_i = \sum_{j \in \mathcal{N}_i} \alpha_{ij} \cdot v_j$. Second, we rely on a recurrent neural network (here, a Gated Recurrent Unit, GRU) [3] to extract temporal features from the agents' observations. Overall, through the proposed network structure, we are able to extract features in both the spatial (using attention) and temporal (using GRU) dimensions.

### 2.3 Learning Framework

We use the popular PPO algorithm for training the policy [12]. PPO's update rule prevents large changes to the policy, which is particularly desirable in our distributed, parameter-sharing setting where there is significant noise in computed gradients. We use the Adam Optimizer with learning rate $5e{-}5$, an episode length of 720 and a discount factor($\gamma$) 0.95.

Inspired by some of our previous works [4], we developed a hierarchical distributed learning framework to make use of parallelization and parameter sharing. Instead of learning a separate policy for each intersection, we use parameter sharing between intersections to learn a single, universal policy common to all agents (junctions) in the network. Our distributed framework instantiates multiple low-level "workers" (meta-agents) and a high-level coordinator called the driver. Each worker is regarded as a multi-agent system and works in an identical but independent environment. The goal of the worker is to collect the experience of all learning agents in an environment. The driver uses the shared experience of all workers to update a global shared network at the end of each episode.

In addition to significant gains in wall-clock training time, our distributed learning framework has two main advantages. First, parameter sharing between agents reduces the instability of distributed MARL associated with independent learning by preventing drastic updates to the global network and thus ensuring that the environment is relatively stable from any single agent's perspective. In addition, the (shared) network weights are updated at the end of each episode to improve the individual rewards of each agents, implicitly leading to a common policy that aims at optimizing their common decisions, thus encouraging the formation of cooperative behaviors.

Second, the structure of the distributed framework is modular and can easily be adapted to run multiple state-of-the-art RL algorithms such as A3C and SAC.

Third, we note that our learning framework aims at off-line (centralized) training before online (decentralized) execution. That is, our learning agents will first be trained in simulation. Then, the trained policy can be frozen and deployed in the real world in a fully decentralized manner, i.e., based on local sensing and communication among neighboring agents. The advantages of this offline, centralized training, decentralized execution design choice are:

1. Off-line training is cheap, since we do not need to concern about the potential threats (e.g., congestion, accidents) caused by unreasonable behaviors that would result from agents freely exploring their state-action space during early training.
2. Off-line training can still allow a sim-to-real solution with high portability: the policy can be trained in simulation by relying on real-world data, if available; alternatively, the trained policy may be fine-tuned under real-world traffic conditions after deployment, to truly reach a near-optimal controller.

## 3 Experiments and Discussion

We conducted our simulation experiments using the same Manhattan traffic network and similar traffic distribution as the benchmark method MA2C [2].

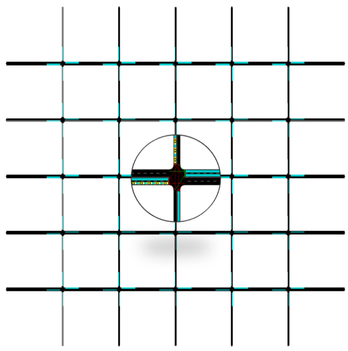

**Fig. 2.** Simulated grid traffic scenario with 25 homogeneous intersections, adapted from the benchmarks used in [2].

As illustrated in 2, there are a total of 25 homogeneous signalized intersections in this grid network, where each one is formed by two-laned, horizontal arterial streets with a speed limit of $20m/s$, and one-laned, vertical avenues with a speed limit of $11m/s$. Each intersection contains five permissible phases: East-West straight phase, East-West left-turn phase, and three straight and left-turn phases for East, West, and North-South, respectively. Besides, the lane-area detectors are install near the stop line

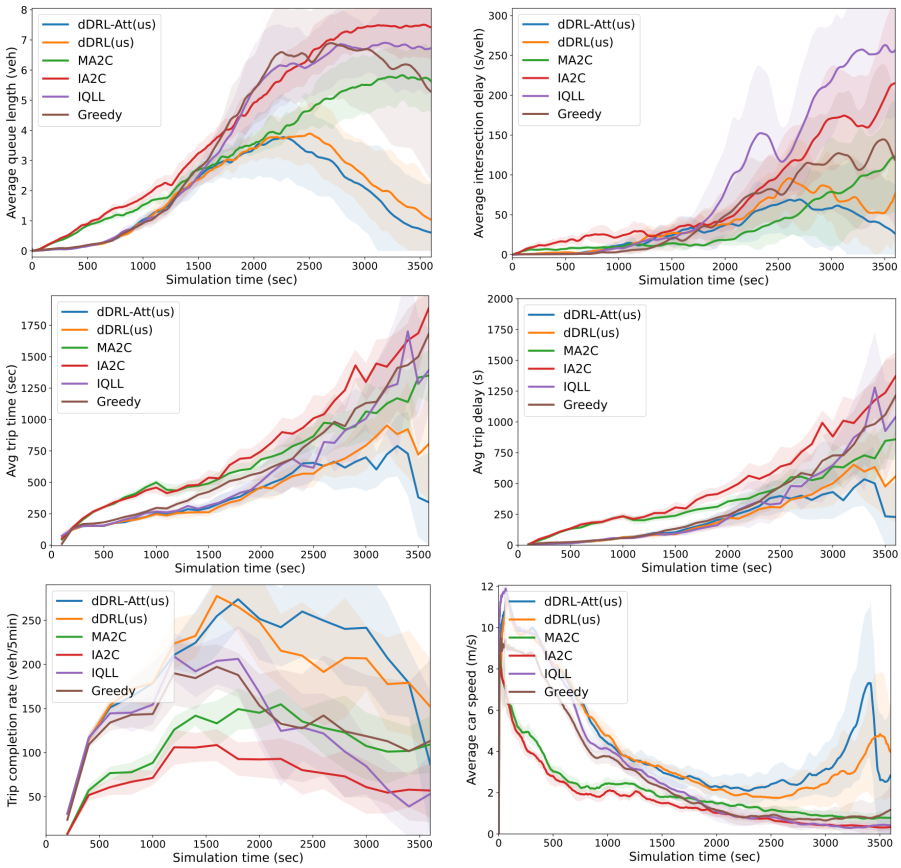


**Fig. 3.** Evaluation results for 10 episodes in the considered $5 \times 5$ Manhattan network. The solid lines show average values, while the standard deviations are shaded.

of the intersection, with the length of 50 meters, which are shown as the blue rectangles in  2.

We compare our method (dDRL-Att) with a conventional greedy controller (one-step optimal controller with respect to the same metric used by our dDRL approach) and three learning based methods (MA2C, IA2C, and IQL-LR) [2]. We also include a non-attention version of our method (dDRL) for a simple ablation study on this aspect. The comparison test results are shown in Fig. 3, where we measure and record the traffic metrics at each simulation step and then calculate the averages and deviations over a fixed set of 10 test episodes (i.e., same traffic conditions for all algorithms for fair comparison).

From these evaluation results, we first observe that the queue length and delay time curves of both IQL-LR and IA2C show a monotonically increasing trend. This trend indicates that as the simulation time increases, the vehicles gradually start accumulating on the incoming lanes, leading to growing congestion. Com-

| Metrics | Temporal Averages | | | | | Temporal Peaks | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| (Average) | dDRL-Att(us) | dDRL(us) | MA2C | IA2C | IQL-LR | dDRL-Att(us) | dDRL(us) | MA2C | IA2C | IQL-LR |
| Queue length (veh) | **1.800** | 1.974 | 3.204 | 4.214 | 3.762 | **3.816** | 3.939 | 5.944 | 7.555 | 6.942 |
| Speed (m/s) | **4.468** | 4.223 | 2.003 | 1.571 | 3.041 | 13.361 | **14.176** | 11.656 | 11.513 | 13.978 |
| Intersection delay (sec) | **30.984** | 38.837 | 34.985 | 72.959 | 92.591 | **70.929** | 98.612 | 124.005 | 216.112 | 266.912 |
| Trip completion rate (veh/s) | **0.990** | 0.955 | 0.546 | 0.366 | 0.634 | **2.300** | **2.300** | 1.700 | 1.400 | 2.100 |
| Trip time (sec) | **447.519** | 460.735 | 727.387 | 788.501 | 462.862 | **2330.000** | 2745.000 | 2938.000 | 3445.000 | 2373.000 |

**Table 1.** Temporal averages and peaks of all algorithms averaged over 10 episodes in the considered $5 \times 5$ Manhattan traffic network (best value on each line in bold).

pared to IQL-LR and IA2C, the queue length and delay time curves for MA2C rise significantly slower, indicating that MA2C is able to learn an effective policy. However, it still lacks the ability to reduce congestion in saturated networks, especially when the traffic gets heavier after 2000s. Finally, our distributed deep RL methods (dDRL-Att and dDRL) outperform the above-discussed baselines on handling peak-time traffic as well as recovering from saturated and congested traffic networks. This is evident from the queue length curve for dDRL-Att and dDRL, which rapidly trends downwards after 2400s, showing that the policy learned by our method is more sustainable and stable. In particular, compared to dDRL, dDRL-Att shows better performance in detecting and handling high-volume traffic, as evidenced by the fact that our approaches are able to handle peaks of traffic and return to baseline conditions faster (see Fig. 3, top left). We also observe that dDRL outperforms MA2C and other methods on completion rate, highlighting its effectiveness at maximizing throughput while minimizing congestion. The same conclusion can be obtained from the average speed metric, with higher values signalling fewer halts and higher overall vehicle flow.

Second, Table 1 summarizes the quantitative results for comparing different methods. From the table, we observe that our proposed dDRL-Att method performs better than all baselines in all the temporal average metrics. Finally, compared to dDRL, our multi-head-attention-based spatial and temporal network performs better, which showcases its effectiveness at extracting features that allow for more informed decision making.

## 4 Conclusion and Future Work

In this work, we introduced a framework for fully decentralized multi-agent TSC (MATSC) based on distributed reinforcement learning with parameter sharing, which relies on an attention mechanism and a recurrent unit for the extraction of spatial and temporal features. Through experimental results, we demonstrated that our proposed framework results in decreased average queue lengths, and increased average vehicle speeds and trip completion rates. Future work will focus on developing and improving techniques such as credit assignment that allow for increased cooperative behavior between agents in an effort to achieve better performance on global long-term metrics while staying in the regime of partial observability and local sensing.

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