AN AGENT BASED MODEL FOR LONDON: EXPLORATORY CASE STUDY COLLABORATION WITH TRANSPORT FOR LONDON

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1 ABSTRACT

Agent based modelling is a modelling paradigm which may transform how key transport decisions are made. Agent Based Models (ABMs) simulate actions and interactions of individual agents with a view to assessing the emergent effects on the system as a whole. For macro (city, region or country) transport modelling they allow unique consideration of population heterogeneity and complex interactions of individuals between each other and their environment. This advance is made possible by recent leaps in the availability of data and compute. ABMs are well suited to answer current transport planning challenges and the arising challenge from new transport technologies and services. This paper sets out the fundamental principles behind ABMs with particular consideration of their potential application for transport planning. The methodology and learnings from an exploratory project (a collaboration between Arup and Transport for London) to develop a proof of concept ABM for London are discussed.

2 INTRODUCTION

Traditional 4-step transport modelling (trip generation, trip distribution, modal choice, and route assignment) is ubiquitous for planning and assessment of policy options and major transport projects. The 4-step approach was developed 50 years ago (McNally, 2007) and as such is influenced by both data and computational restrictions at the time, principally using significant abstraction and aggregation of real-world movements, decision making and population heterogeneity.

Modern transport decision makers are increasingly challenged to tackle questions of (i) equity, such as the distribution of impacts by demographic, (ii) complex behaviours, such as those resulting from dynamic road pricing or hopper fares, (iii) interactions between different modes and services, and (iv) temporal precision, such as at peak-period shoulders. The 4-step framework is extendable through segmentation and combination of specialised models to tackle many of these questions. Such extension creates a sprawling interaction of processes resulting from the fundamental unsuitability of these models to represent the decision making of the underlying drivers of these scenarios - heterogenous, irrational, unpredictable, and complex humans.

Modelling challenges are only likely to increase as new technologies and models of transport provision, such as electric vehicles, autonomous vehicles and mobility as a service, add new interactions and complexity. The impacts of these changes are not currently well understood and the complexity of the resulting interactions challenging to model with traditional approaches.

The ABM approach also makes use of recent advances in availability of compute and micro-level data.

In late 2018, Arup and Transport for London (TfL) engaged in a collaborative effort to explore the development of a proof of concept Agent Based Model (ABM) for London. This was based on previous Arup experience developing an ABM of Melbourne for Transport Victoria and on TfL's work on activity-based plan estimation and population synthesis. The joint team developed a synthetic population and built a UK-wide network to simulate travel in London. One of the key objectives of the collaboration was knowledge-share and learning.

3 LITERATURE REVIEW

3.1 Agent Based Models

ABMs are a class of computational models which simulate the interactions of autonomous agents within a system of constraints with an aim to assess the resulting behaviour of the whole system. Crucially, ABMs are able to simulate complex emergent patterns based on simple behaviours of individuals.

Definitions of ABMs vary across different fields, but all generally describe some sort of simulated environment in which virtual agents act and interact based on some rules. Agents are autonomous, typically have heterogeneous attributes and behaviours, and crucially interact both with the environment and each other. In the context of transport, ABMs are able to simulate complex systems such as congestion or travel behaviours emerging from relatively simple low-level decision making of individuals.

Agent-based modelling is not a new concept. In the 1970s, Shelling (1971) used a simple ABM to model how complex real-world patterns of segregation could be observed to emerge from simple behaviours. Such simple early application has been preceded by a plethora of models, of generally increasing scale and complexity, exploring a diverse range of fields from politics to biology, including human movement (M. Torrens, 2012) and transport (Zhao et al., 2012).

ABMs are increasingly accepted as a vital tool for exploring complex systems such as cities and their transport systems (Batty, 2007 & 2008, Silva, 2010). They are already common for micro level simulations such as modelling pedestrian movements in or through a location, as described by M. Torrens (2012). But their adoption as a tool both for research and application has historically been limited by practical matters. Specifically, a lack of individual level data and of compute required to build and run the models.

In recent years, these restrictions have started to fall away; individual level data (for example from mobile devices) and massive computing power (for example from cloud computing providers) has become both cheaper and easier to access. Casey et al. (2017) describe a framework using big data and ABMs to model cities in the future and there are now some city level examples of their implementation (Zhao et al, 2019).

3.2 ABM Implementation

In seeking a useful toolkit for future transport modelling with ABMs, this project has implemented open source and bespoke software. The Multi-Agent Transport Simulation (MATSim, 2016) project software is used for the core modelling process. This is combined with Python projects for processing inputs (such as population synthesis) and generation of outputs (such as model benchmarking).

The MATSim project is a Java based open source software (Matsim, 2016), it has been in development since 2006 and is now a highly extendable software used by over 40 groups worldwide (Axhausen et al., 2016). MATSim has a catalogue of successful transport modelling research and applications, such as for dynamic road pricing (Zheng et al., 2012), air travel (Grether et al., 2013), evacuation (Taubenböck et al., 2013) and air quality (Grether et al., 2013). MATSim has also been used to model a number of cities, including London (EUNOIA, 2015), providing extensive literature on the framework of theoretical foundations and of model calibration.

At its core MATSim is an ABM, based around the idea that emergent traffic and congestion patterns can be simulated from the actions and interactions of individuals. MATSim combines a number of modelling components: (i) traffic modelling, used to simulate traffic flow and congestion on given networks, (ii) activity-based modelling of agent schedules, used to simulate demand for travel (typically for a single day) and (iii) a co-evolutionary algorithm to search for a simulation equilibrium.

Similar to traditional traffic assignment, MATSim simulates the competition in space and time for transport availability. Compared to traditional models, MATSim implements a highly capable combination of dynamic, queue-based and equilibrium traffic assignment as described by (Bliemer et al., 2017). However, MATSim goes beyond regular practice by allowing agents to vary time choice, mode selection and even destination alongside route assignment. This effectively combines all choice from traditional 4-step modelling steps within the same optimisation.

A single MATSim run consists of multiple iterations of the same simulated day, during which agent's activity-based plans are optimised using a co-evolutionary algorithm (Paredis, 1995). An optimised plan is the achievement of the agent's activity-based schedule so as to maximise the net utilities from undertaking activities and undergoing travel as described by Charypar and Nagel (2005), also referred to as scoring. Within the co-evolutionary algorithm process, agents undertake some level of random selection and mutation of behaviours in order to seek an optimum score. This results in a globally stochastic equilibrium, in which agents have essentially learnt how to best score with consideration of all other agents also competing for transport resource.

By modelling individual state and decision making dynamically within the simulation, MATSim allows for complex mechanisms to be implemented, such as realistic chains of trip modes, attribute (such as income) dependant decision making, and charging from innovative charging schemes. The dynamic nature of the simulation also allows an event-based output, with precision to the second. This allows useful consideration of traffic and congestion at both a fine level and also throughout the day.

4 METHODOLOGY

As part of our collaboration we build a proof of concept ABM for modelling London transport. The model building process developed can be usefully split into several components: (i) generation of transport supply, (ii) generation of transport demand, (iii) model configuration and (iv) validation. Model configuration and subsequent validation is an iterative process, also described here in combination as calibration. Once calibrated, the model can be used for scenario simulation as required by altering the input transport supply, demand or the configuration.

4.1 Transport Supply

We implement a UK wide multimodal network. The various transport networks are extracted from Open Street Map (OSM), The spatial network is simplified to reduce unnecessary detail, while maintaining travel distances. The road network outside the Greater London Authority area is filtered to only include arterial roads, whereas for within London all links are maintained. Where road attributes such as speed and capacity are not available from OSM, defaults are used based on the road type. Restricted turns and signals are not modelled at this point.

Public Transport service is extracted from a General Transit Feed Specification (GTFS) and merged to the OSM network as per Poletti (2016) creating an inter-modal representation. Bus, cable-car, ferry, train, tram and underground services are all included. Vehicle or service capacities are based on sensible estimates with a view to improve these in the future. During simulation, walking and cycling legs are not mapped to the network. Effectively making them non interactive and therefore not susceptible to congestion. Mid-week congestion charging is implemented for all cars entering the London Congestion Charging Zone.

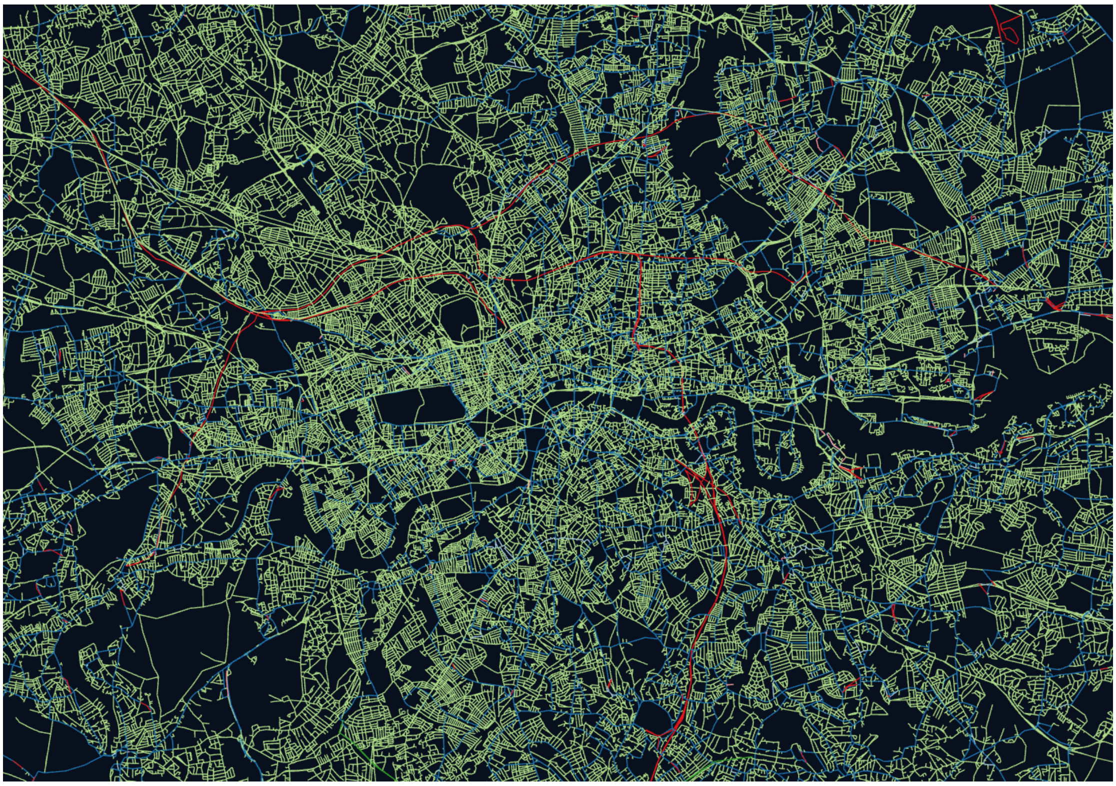
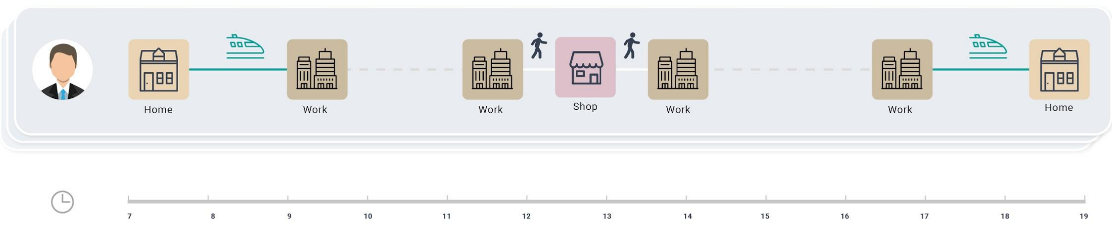


Figure 1 - Visualisation of sample Multi-Modal Transport Network

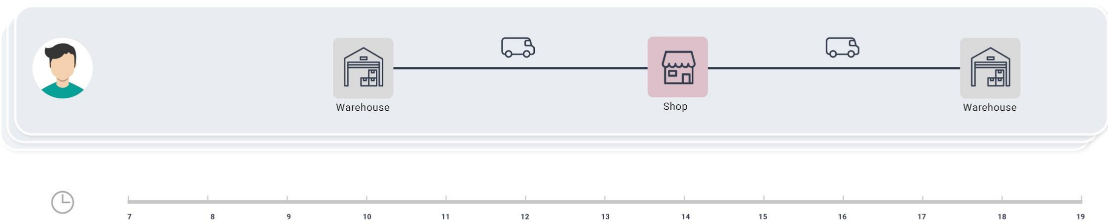
4.2 Transport Demand

We use an activity based approach as per (Guo and Bhat, 2007) to model transport demand, where ‘agent plans’ are the core container of this demand. Agent plans consist of chains of desired activities undertaken at different locations, connected by travel legs. Figure 2 shows two example plans. Within the ABM simulation, as agents seek to achieve their plans, they drive demand for transport. The generation of this population of agents, with representative plans is referred to here as population synthesis.

We do not synthesise a full population for this proof of concept. Instead we use populations as low as 0.01% of total for development and testing, 1% for preliminary calibration and 10% for full benchmarking and output. This 10% population comprises around one million agents. For simulation the transport network capacity is reduced proportionally to reflect the sampled population.



(i) Example commute like activity pattern



(ii) Example freight activity pattern

Figure 2 - Example Agent Activity Plans

4.2.1 Population Synthesis

We sample (without replacement) a representative population from TfL’s London Population Synthesis (LoPopS) dataset. LoPopS uses household and individual attributes and travel plans from the London Travel Demand Survey (LTDS) from 2005 to 2017. The population is synthesised by making the population attributes (characteristics such as gender and income) representative by area as best as possible.

LoPopS is a detailed activity-based representation of travel demand for members of London Households (agents), including realistic and complex plans, where a plan is a sequence of chained trips to activities at various locations, such as for home, work or shopping. LoPopS also provides these agents with personal attributes such as car ownership and income which are then used to influence behaviour in the model and provide detailed output.

Activity locations from LoPopS are defined by Lower Super Output Area (LSOA), but for the purpose of modelling exact origins and destinations, we sample a point randomly from the described LSOA. If an agent returns to the same LSOA for the same activity, then the same point location is used. In the future, more realistic selection of location can be implemented using data about land-use and real facility locations.

4.2.2 Supplementing the Population

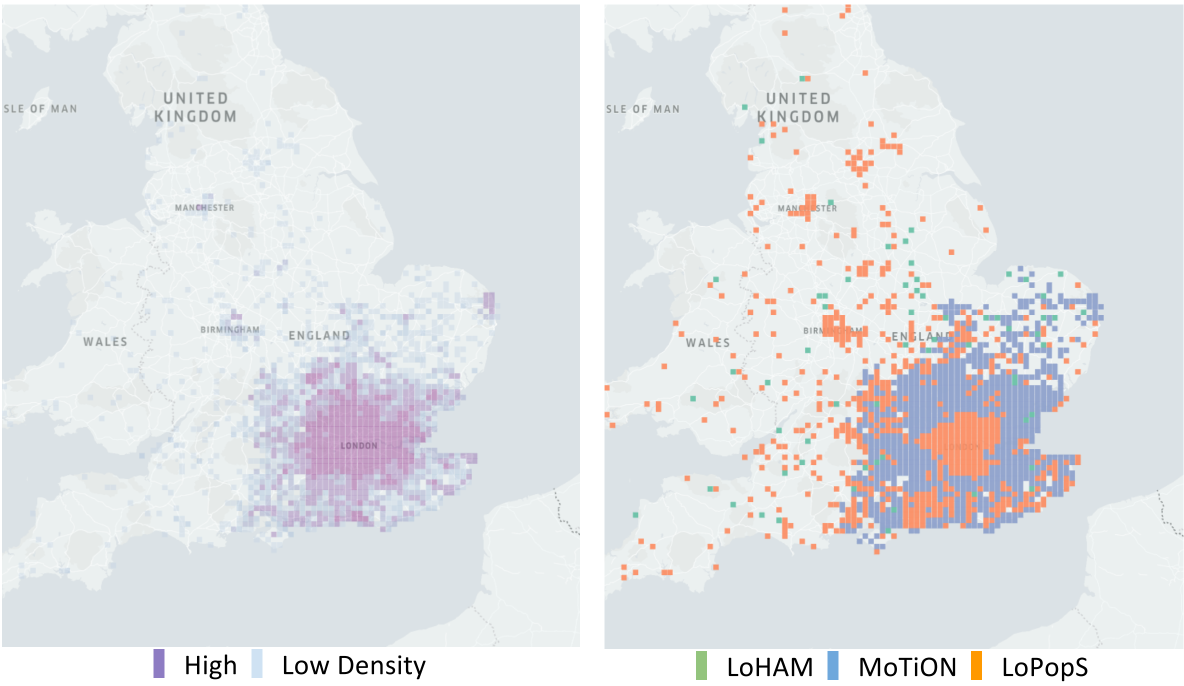
LoPopS is derived from the LTDS so can only be considered as representing London Households. We therefore supplemented the population with freight and non-London household plans synthesised from regular demand models also supplied by TfL. Figure 3 and Table 1 describe this breakdown of input sources for all population activities. It is worth noting that LoPopS includes travel plans from London household members who have activities outside London (for example, business trips) and that the supplementary plans include home locations outside of London.

Simple freight vehicle plans are synthesised from the London Highway Assignment Model (LoHAM) and non-London plans from the new London demand model MoTiON. Plans and population attributes are built from origin-destination pairs and model segmentation attributes, sampled according to model weights and data randomly sampled (from sensible distributions) as required. Freight is either classified as Heavy or Light Goods Vehicle and non-Londoners as per the MoTiON aggregation classes. This supplementary synthesis is does not capture the same quality of information as LoPopS. MoTiON provides only simple chaining of trips and freight plans generated from LoHAM are synthesised as basic single activity (delivery) return trips.

In both cases only trips entering the London area are extracted. This supplementary synthesis includes significant influence from agents residing outside of London as shown in Figure 3 below. It is for this reason that we input a UK wide transport network.

Table 1- Activity Source Summary

Source	Breakdown
LoPopS	85.47%
LoHAM	6.47%
MoTiON	8.06%



(i) synthesised population plans: activity density

(ii) modal (majority) activity source by 5km grid

Figure 3 - Activity Locations and Data Source, England and Wales

4.2.3 Sub Populations

In addition to plans, agents are labelled with attribute classes, such as age, gender and income, based on LoPopS labels. These attributes are available for model results post-processing, for example allowing breakdown of vehicle flows or other modelled outcomes by income class or occupation type.

Population attributes (income and driving license) are also used to break the population down into subpopulations as described in Table 2. These subpopulations are configured with different behaviours and scoring, providing detailed heterogeneity of model interactions to better reflect reality. This breakdown is highly extendable, potentially to the level of the individual.

Table 2 – Population Sub-population Breakdown Summary

Source	Income	Driving License	Breakdown
LoPopS	<10k	Yes	3.30%
		No	7.27%
	10-20k	Yes	10.57%
		no	6.74%
	20-35k	Yes	9.51%
		No	7.53%
	>35k	Yes	32.89%
		No	7.66%
LoHAM	NA	Yes	6.47%
MoTiON	20-35k	Yes	2.25%
		No	0.40%
	>35k	Yes	4.76%
		No	0.66%

4.2.4 Population Validation

A bespoke python software has been developed to implement the above sampling and synthesis of population plans and attributes and output correctly formatted MATSim inputs. Key population information such as mode shares, trip distances, temporal and spatial distribution of different activity types (such as Figure 4 and Figure 5) are also output for validation of the synthesised populations.

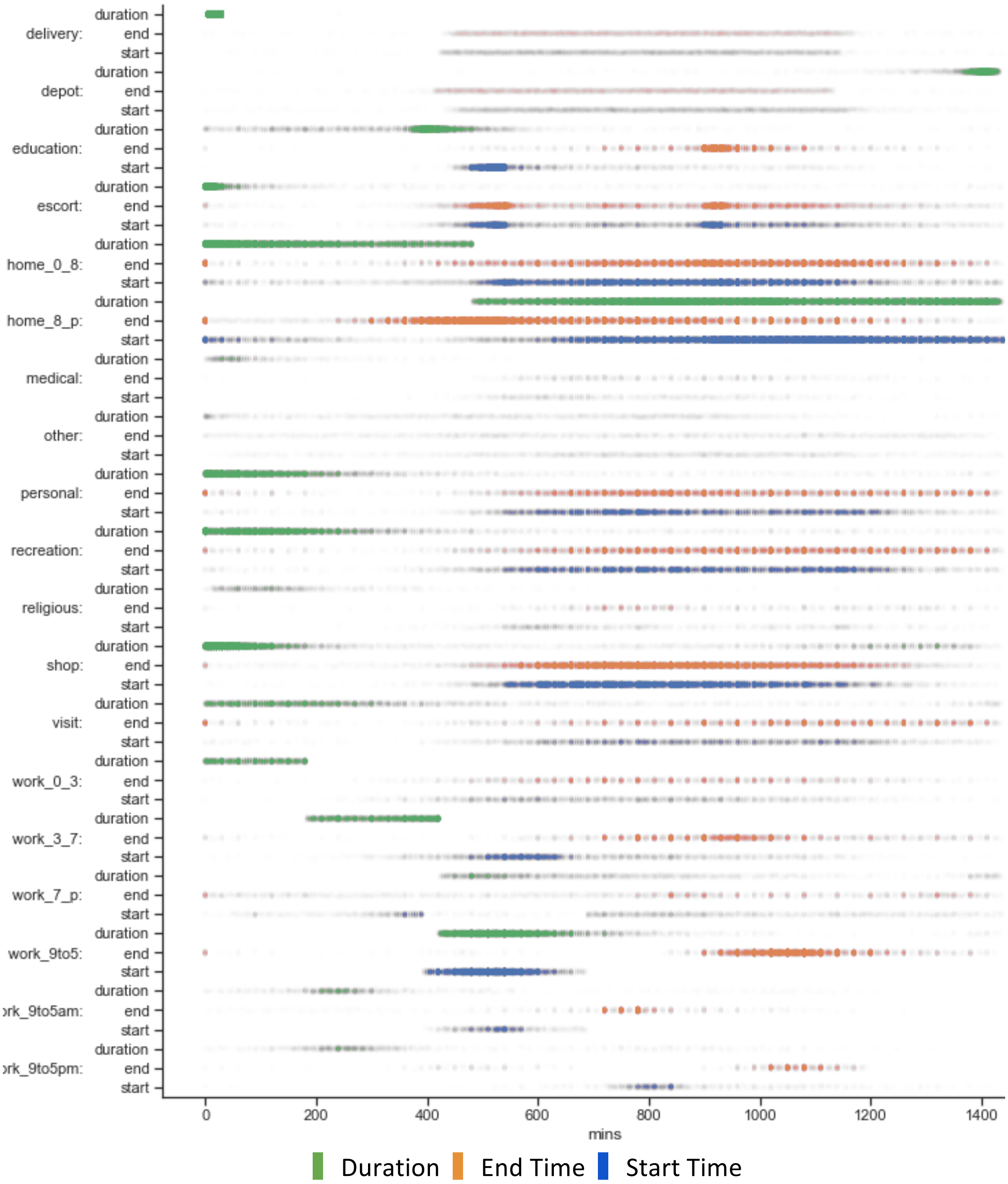
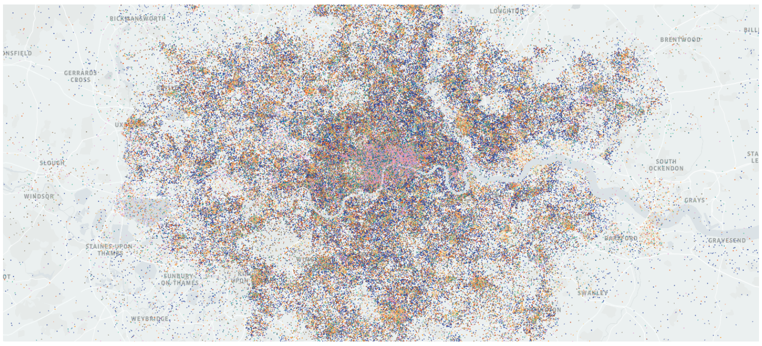
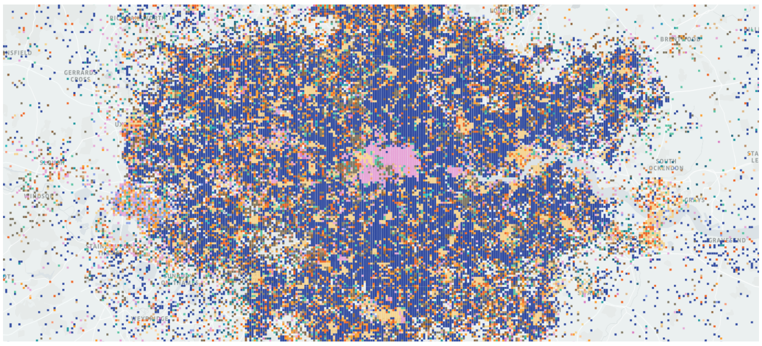


Figure 4 - Temporal Distributions (time of day and duration, all in minutes) of Agent Activities by Type

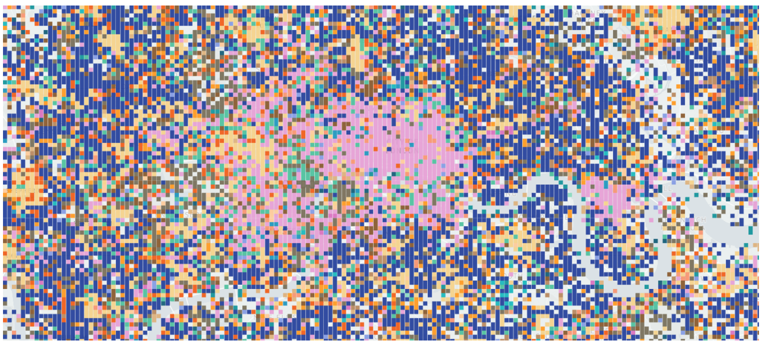


(i) London activity locations

(ii) Central London activity locations



(iii) London modal activity locations (200m grid)



(iv) Central London modal activity locations (100m grid)

Home Shop Work

Figure 5 - Spatial Distributions of Activities from 1% Sample and Supplementary Synthesis

4.3 Configuration

In addition to varying input travel demand and supply, MATSim is highly configurable via an input configuration. Of particular importance in this configuration is the reasonable calibration of agent behaviours and scoring for different activities and travelling by different modes. Configuration can be usefully broken down into (i) agent behaviour, (ii) activity scoring and (iii) modal scoring.

4.3.1 Agent Behaviour

As a proof of concept we implement unique subpopulation scoring and behaviour via the configuration: (i) Income class is used to vary agent marginal utility of money so that response to costs is heterogenous, (ii) freight vehicles are restricted from shifting mode and (iii) absence of a driving license is used to incur additional costs for car travel. This additional cost for car travel is intended to represent taxi or other mobility as a service which is otherwise not modelled at this time.

Subpopulations can also be given unique activity and modal scoring. However, this has not been implemented at this time - with the exception of additional cost of car travel for non-driving license holders as described above. Instead we use population level scoring as described in the next sections.

4.3.2 Activity Scoring

Activity scoring is configured for each activity type through expected activity opening time, closing time, typical duration and minimal duration. The basic activity types and their configuration are shown in Table 3. Two main activity types; home and work, are further categorised based on sensible and observed patterns of start times, end times and durations. This extends the 13 basic activity types from LoPopS into 19 total activity types.

Each activity is calibrated with times and durations based on observed patterns in LoPopS. This detailed breakdown and calibration of activities is intended to maintain the high level of information from the activity-based input - about people's preferences for activity times and durations.

Table 3 – Activity Scoring Summary

Activity	Breakdown	Note	Opening Time	Closing Time	Typical Duration	Minimal Duration
delivery	2%	freight only			0:30	0:30
depot	2%	freight only			10	1
education	4%		08:30	17:00	6	6
escort	6%				0:10	0:01
medical	1%		08:00	19:00	2	1
other	1%				1	1
personal	5%				2	1
recreation	7%				2	1
religious	1%		08:00	19:00	2	1
shop	12%		08:00	19:00	2	1
visit	3%				2	1
Home:						
home_8	12%	<8 hours			8	1
home_8p	30%	>8 hours			10	8
Work:						
work_9t5	7%	~9am-5pm	08:00	18:00	9	8
work_9t5_am	1%	~9am-5pm with lunch break (am)	08:00		5	3
work_9t5_pm	1%	~9am-5pm with lunch break (pm)		18:00	3	2:30
work_3	2%	<3 hours			2	0:30
work_3_7	3%	3-7 hours			6	3
work_7p	2%	>7 hours			11	7

4.3.3 Modal Scoring

MATSim allows calibration of (dis)utility from using the available car, public transport, bike or walking modes. Exact public transport mode is determined during the simulation.

Scoring parameters include modal utility costs by travel time, travel distance, waiting time and monetary cost. For this proof of concept, we use modal configuration based on previous literature and do not implement heterogeneity by subpopulation, although response to travel costs will be subject to marginal utility of money which we link to income group.

5 Results

MATSim has a huge potential parameter space to explore, particularly with added complexity through unique subpopulation scoring. Validation through benchmarking of model calibrations is therefore important.

5.1 Outputs

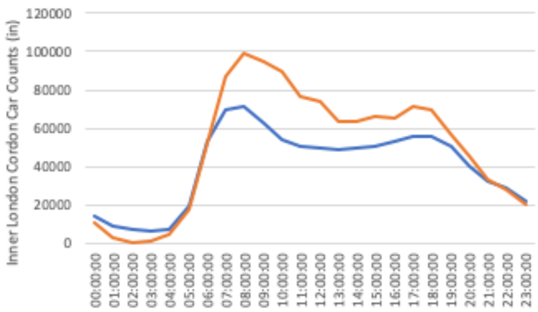
Model outputs are post-processed using bespoke Python software to create a number of useful and traditional outputs such as link vehicle-kilometres travelled and cordon counts. In fact, by processing raw events from the model it is possible to produce detailed outputs for unique, groups or sequences of vehicles or individuals, including individual or group attributes, such as vehicle types or incomes. In addition to these attributes, outputs are spatial and temporal, allowing the production of maps and animations showing agent and vehicle movements and actions.

5.2 Benchmarking

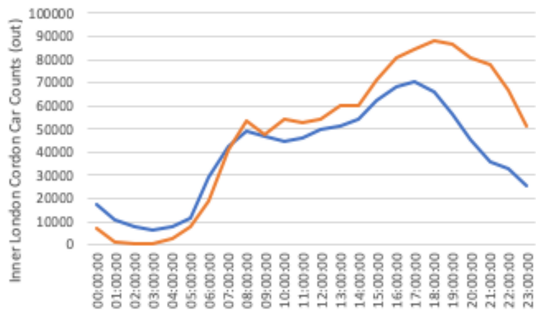
5.2.1 Macro benchmarking

Included in the post-processing software is a framework for adding observed data for benchmarking results, such as cordon counts and mode choice statistics. These benchmarks are automatically scored and output. Additionally, a combined 'meta-score' describing overall model quality is output by combining all benchmark scores. It is the intention that, in addition to aiding fast turnaround when comparing and iterating model configurations, this scoring pipeline will eventually facilitate automated parameter exploration and optimisation for a given base case.

(i) Cordon Counts by Hour, Both Directions



(ii) In direction only

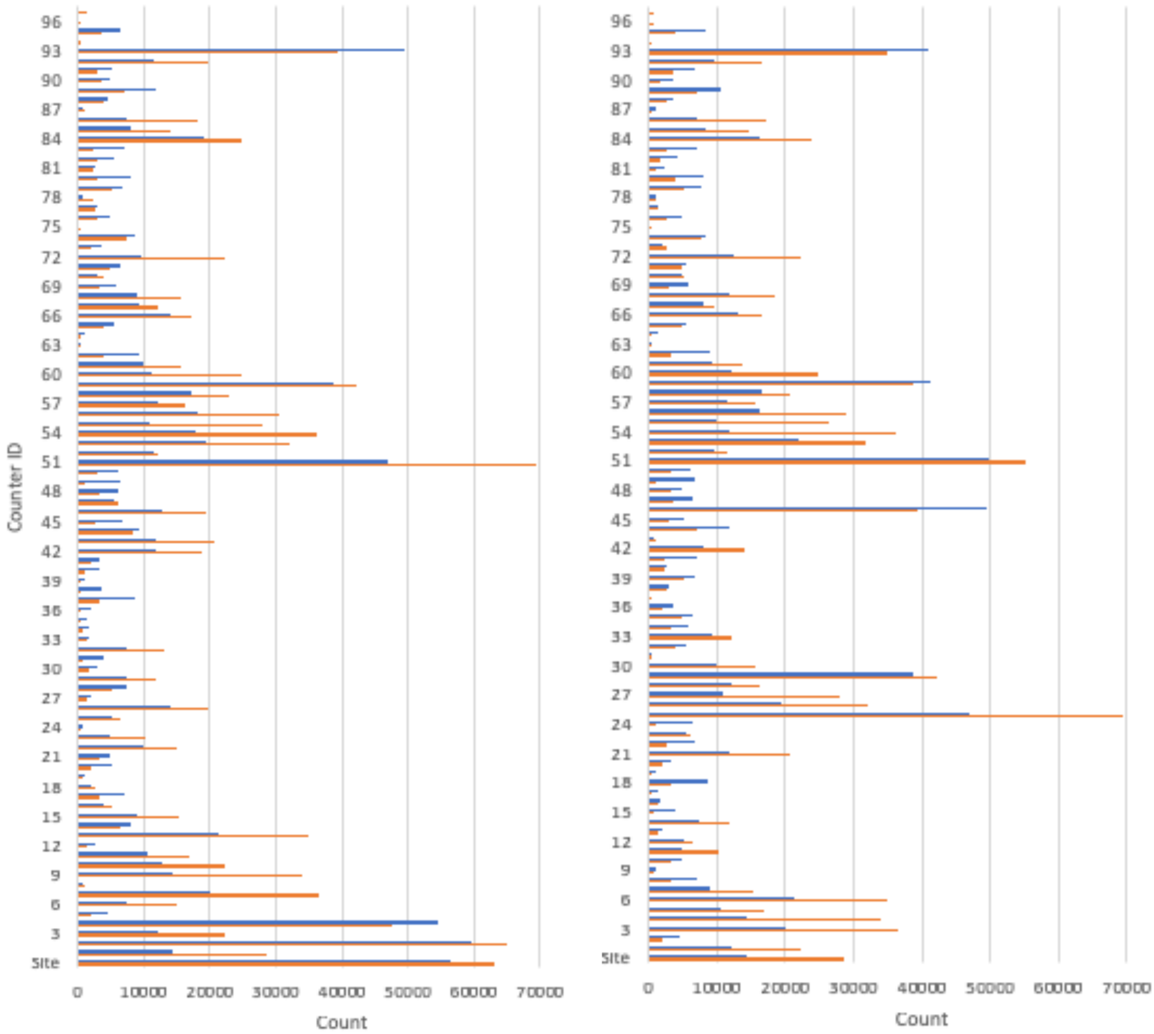


(iii) Out direction only

Benchmark Model

Figure 6 - Preliminary Inner London Cordon Benchmarking (Cars Only, 1% Sample, 100 Iterations)

Preliminary benchmarking against the London Inner Cordon has been positive as shown in Figure 6, where the temporal pattern of counts is well represented. Additionally, Figure 7 shows that the spatial or network patterns are well represented.



(i) Inner Cordon Site Counts (Cars - In)

(ii) Inner Cordon Site Counts (Cars - Out)

Benchmark Model

Figure 7 - Preliminary Inner London Cordon Benchmarking by Counting Site (Cars Only, 1% Sample, 100 Iterations)

5.2.2 Micro benchmarking

A key feature of our ABM is the level of detail and scale that can be interrogated from the model. Individual agents record on average ~750 events each, detailing their behaviours and actions within the simulation. These records include movements around the networks and interactions such as arriving at transit stops and waiting for the next service.

These ‘micro’ outputs from a macro model allow us to interrogate behaviours in the model at unique detail but also sensically. For example, poor configuration causing unlikely behaviours such as waiting too long at transit stops or poor route choice are easily interpretable from the output and corrected. Figure 8 shows the distribution and duration of waiting times through the day of agents interchanging from bus to train.

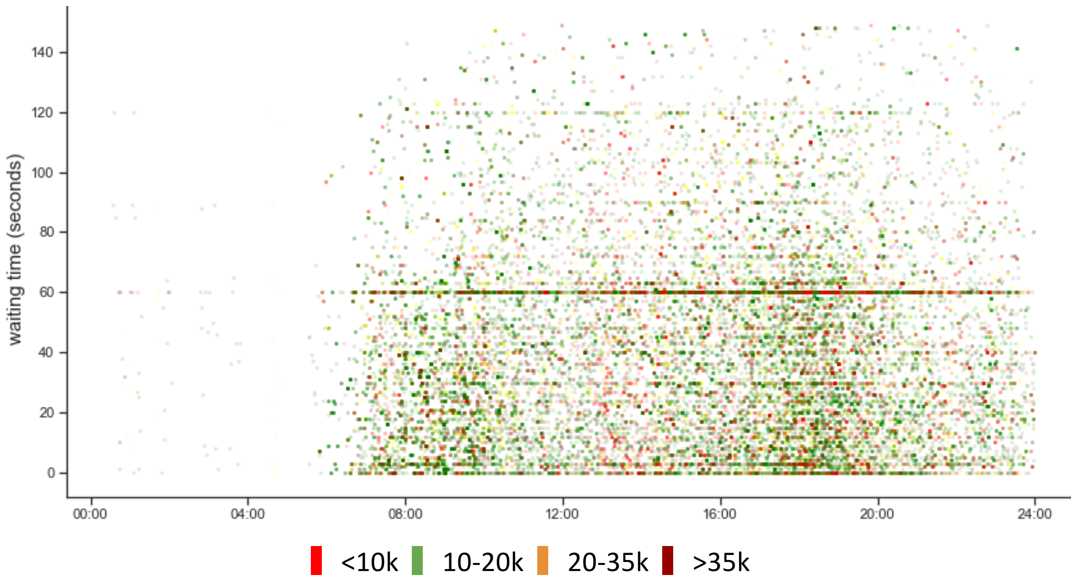
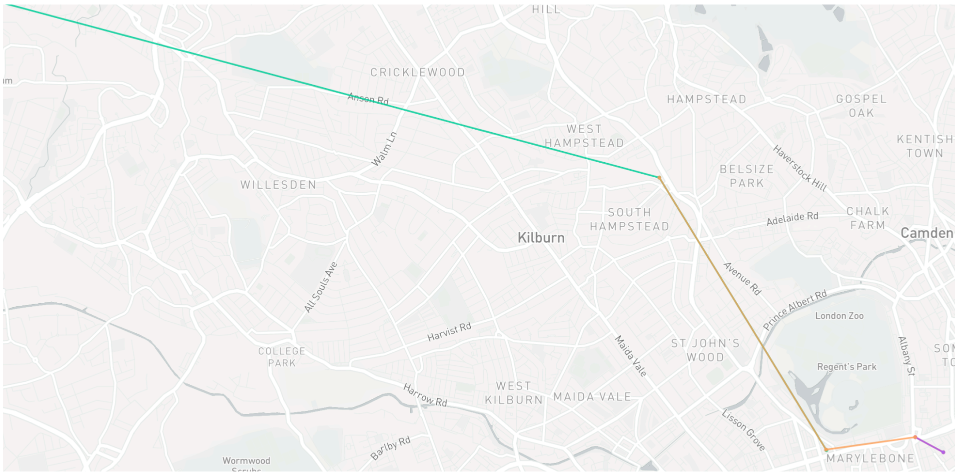


Figure 8 - Temporal Distribution and Duration of Waiting Times (<3 min) for Bus to Train Interchanges, for different Income Classes, from 10% Sample and Supplementary Synthesis

We are able to extract and visualise the complex chains of daily events and activities for individual agents. Figure 9 (i) shows an example chain of movements for an individual agent. By adding the plans of real agents (derived from GPS traces) we are then able to compare these simulated chains of movements to known movements, as shown in Figure 9.

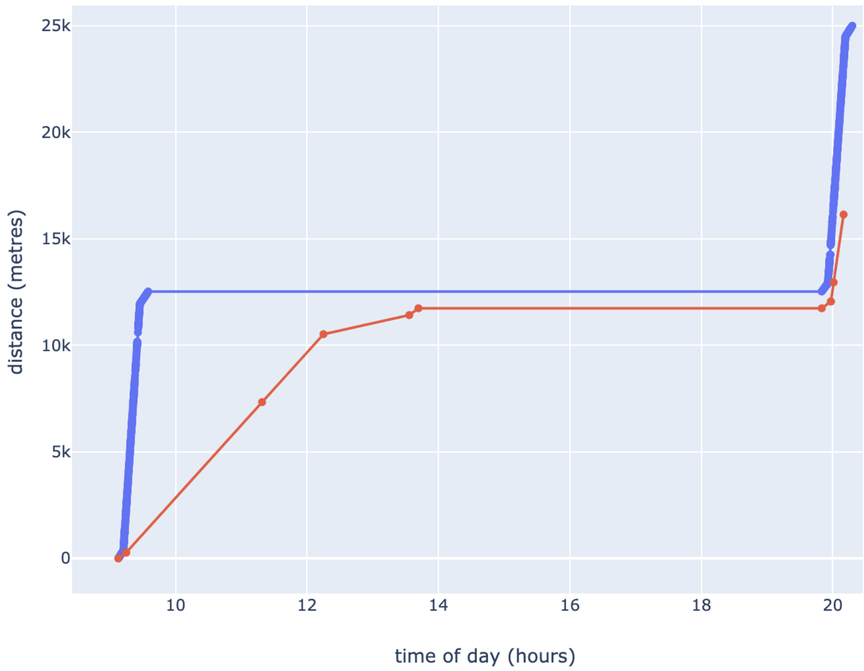


(i) Example Agent Event Trace

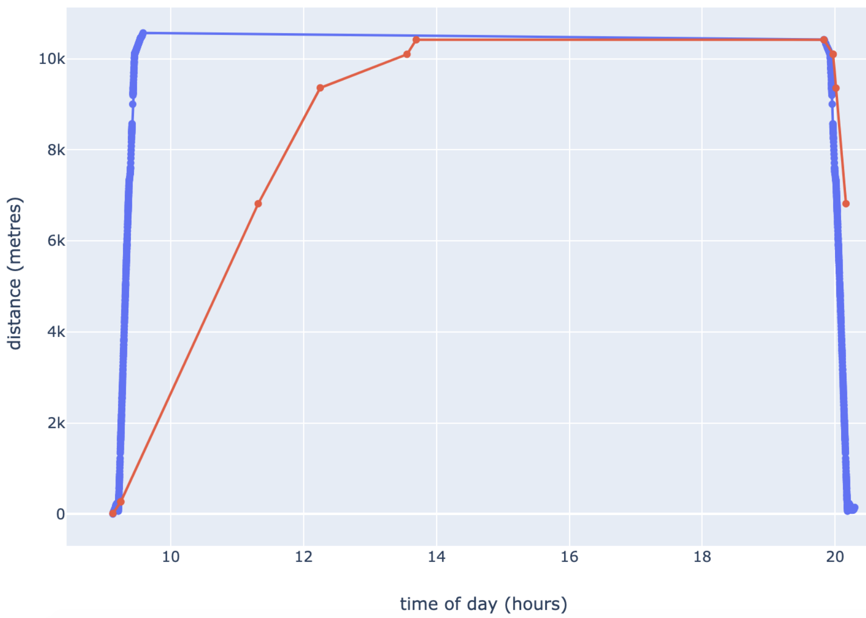
(ii) Real Agent Event Trace

Figure 9 - 'Micro' Simulation Evaluation - example comparison between real agent movements (from GPS) and simulated movements (from our Simulation)

In future we hope to supplement traditional benchmarking (for example of vehicle flows across counting points) with new micro benchmarks. This might include both the distribution of discrete micro level events, such as waiting times as shown in Figure 8 or chains of events for known individuals, as shown in Figure 9. Figure 10 demonstrates two metrics for evaluating temporal and spatial closeness of agent activity chains.



(i) Cumulative Distance Travelled



(ii) Distance from Home Location

GPS Simulated

Figure 10 - Proposed spatial and temporal distance metrics for comparing agent event chains (for example for scoring difference between Simulated and GPS).

Micro validation and benchmarking will be important for ABMs as they seek to incorporate more and more detailed interactions and mechanics. Similarly micro validation allows for more transparent and sensical validation of models for non-practitioners.

5.3 Compute

5.3.1 Population Synthesis

Population synthesis (sampling from LoPopS and synthesis from LoHAM and MoTiON) takes around 6 hours for 1 million individuals (~10% sample), varying significantly depending on the input source. Because synthesis is typically a one-off operation in the modelling process, no effort has been made to parallelize or otherwise speed up this process, but significant time savings are certainly achievable.

5.3.2 Core MATSim

The core model is containerised and run in large multi-core graphical processing units using cloud compute services. Our latest model with a 10% representative population (~1 million agents) stabilises after 150 iterations in only 30 hours.

Work is ongoing to profile the run time for larger scenarios. We expect response to additional agents to be linear or better. Experimentation shows that network complexity, particularly from numerous interacting public transport services is the primary driver of compute and therefore work is ongoing to optimise both the network representation and the graph computations that are carried out on the network.

Most experiments to date suggest that 150 iterations are enough for the model to stabilise, however, experimentation with ‘warm starting’ (using good plans already discovered from previous model runs) show this requirement can be significantly reduced when iterating. Of course, the definition of model stability is nuanced, and it is important for this to be continuously assessed.

6 DISCUSSION

6.1 Results

Benchmarking of early results from the developed London ABM are extremely positive, comparing well to the 2016 Inner London Cordon with minimal calibration. Model results have also been used to drive animations of agent behaviour, provide link level output of vehicle kilometres travelled as well as breakdowns by population income level, such as Figure 11.

MATSim produces an event-based output, making possible the extraction of any information about any interaction in the model for an agent or agents with a leg or activity or any combination. This output can be additionally labelled by attributes, spatially and temporally such as Figure 12. This makes feasible the consideration of new results such as changes to activity start times or complex interactions such as chained bus legs.

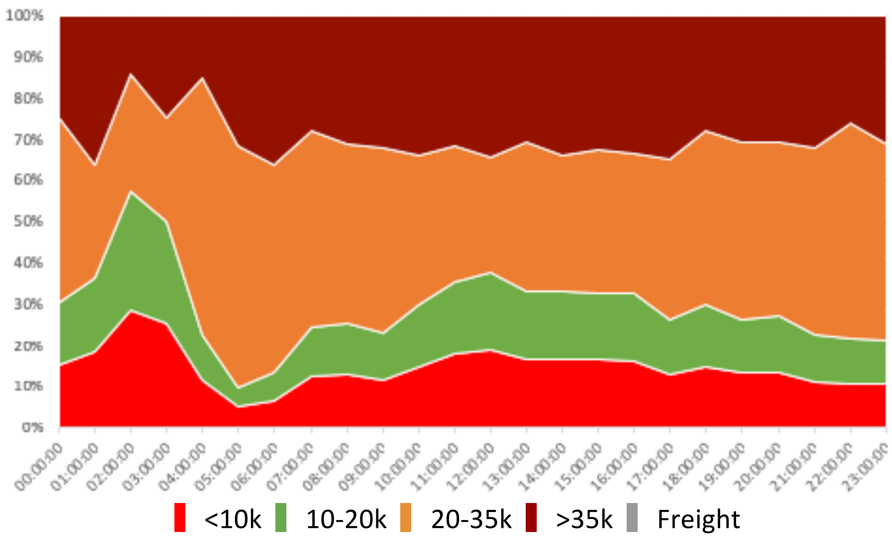


Figure 11 - Breakdown of cars passing Inner London Cordon by Income Class and Time of Day (1% sample, 100 iterations)

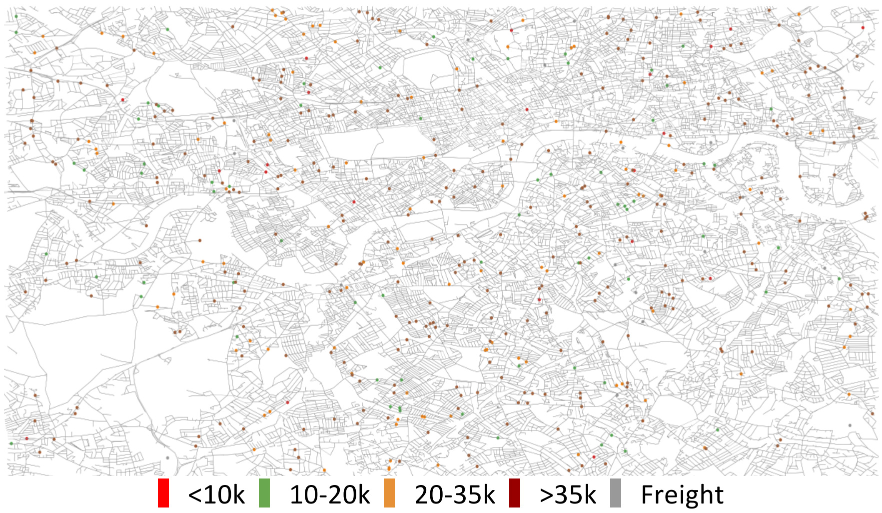


Figure 12 - Central London car drivers at 7am by Income Class (1% sample, 100 iterations)

6.2 Reusability

The ABM approach simulates behaviour from bottom up interactions. As such a calibrated model or components of a calibrated model can be reused or added to, provided the existing interactions still hold true, which they generally will. This capability is already exploited by the MATSim project (MATSim, 2019), which is already well extended, for example for air quality modelling (Gerike, 2014) or evacuation (Lämmel et al., 2009). This makes feasible the iteration or reuse of ABMs rather than complete rebuild, even for new applications.

6.3 Pipeline

The application of ABMs for real transport planning projects has been a core consideration of this collaboration, in particular the ease and speed with which modelling projects with an ABM approach can be undertaken.

Further to the simulation capability of ABMs, the overall framework of model development used in this proof of concept compares favourably to the traditional transport modelling approach, despite requiring considerably more computation. This is driven by a combination of; (i) open-source data, (ii) open-source software and data formats, (iii) modern cloud service engineering and (iv) adoption of modern data-engineering good practices such as distributed version control, reproducibility and early validation.

The use of open source data reduces the requirement for expensive and difficult data collection. Additionally, the creation of tools for building inputs from a variety of possible sources reduces dependency on such data, accelerating a project and adding redundancy to the synthesis process.

By combining non-proprietary software and scalable cloud compute this project demonstrates the removal of restrictions from licenses and user hardware. Projects can run multiple simulations in parallel using flexible and huge compute, accelerating tuning or quickly exploring many scenarios.

By combining open data formats and good data-engineering principles, this project demonstrates a robust pipeline with reduced intermediate data stages and interacting processes. The traditional 4-step process is replaced by a 2-step process of synthesis and simulation. The traditional combination of various specialised models is also replaced by a single simulation. This makes rapid iteration quicker and easier.

7 CONCLUSIONS

This collaboration between Arup and TfL successfully demonstrates the application of a city scale ABM for transport modelling. A preliminary model with approximately one million agents is benchmarked and used to extract results with detail and precision not achievable from traditional 4-step modelling.

The framework developed combines activity-based demand synthesis and an ABM to expose city-wide transport conditions from the bottom up - from the interactions, decisions and actions of individuals. This framework allows for the heterogeneity and complexity of the real world to be more accurately modelled.

This new modelling paradigm is arguably better than the traditional 4-step approach for many modern-day requirements, such as temporal precision and assessing impact equity. Additionally, emerging modelling challenges, such as from autonomous vehicles and mobility services can be incorporated into this new framework more naturally.

In addition to technical feasibility, this collaboration demonstrates a practical pipeline of model delivery from input to benchmarking. Open source, cloud computing and modern data engineering techniques are used in a flexible and fast pipeline of model building and development. If the transport planning profession of the future wishes to make use of the growing availability of compute and data, such pipelines will be crucial.

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