**ACS332-003**
**160141094**

The University Of Sheffield.

# Individual Assessed Work Coversheet

**Assessment Code: ACS332**

**Description: Assignment 3**

**Staff Member Responsible:**

**Due Date: 10-12-2018 16:00:00**

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**Student Registration Number:**

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**Assessment Code:**

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CONTENTS

# ACS332 Agent-based modelling and multi-agent systems: Final Report

Automatic Control and Systems Engineering
University of Sheffield

## I. Introduction

As is common in many cities, the travel choices of it's residents could bring significant improvement to the health and well being of said residents, as well as positively impacting the economic and environmental health of the city [3]. Sheffield city council intend to create a "modal shift" in the transport choices of it's citizens from cars to "active transport", such as walking and cycling, bringing about a variety of positive environmental, public health and traffic changes [2]. Policies to improve the adoption of a certain intervention in a city (particularly in the public health domain) can benefit from models. Broadly, cities can be seen as a network of sophisticated interactions and are therefore suited to be modelled as a complex system. In this paper. agent based modelling is suggested as an appropriate model, capable of forming a sufficiently realistic representation of the dynamics of the real world system. Of course, a variety of information is required to inform the structure and interaction of such a model and in accordance with this the model has been developed from the relevant literature. Unlike many models in this domain, instead of focusing on utility maximisation this paper focuses on decision making with imperfect information [agent based route choice]. Agents make decisions in a similar way to humans using heuristic rules, based on their knowledge of their environment. Although validation is beyond the scope of this work, methods are discussed and critical data sources identified for future work.

## II. Final version of the conceptual design

### A. Understanding of System

The system under investigation is broadly defined as the mode choice of Sheffield over the period of 2018 to 2040 [2]. In reality this system is likely to be highly dimensional and contains thousands of featured but it is likely that a small number of features dictate the majority of the behaviour of the system.

As a starting point for this case, A variety of documents reflecting the motivation of Sheffield city council were looked at and other cases where similar modelling techniques have been used to inform public health policy as well as studies more closely related to the task. Sheffield city council released a transport strategy using census data to give a picture of where the cities modal choice is now, and where they want it to be by 2040 [2]. In particular, they want to create policies to move cycling from 2% mode share to 11%. A key part of the model is to identify starting points for mode share and looking at census data is probably the most accurate way of assessing this. Fortunately, Sheffield's transport consults used census data to create easy to interpret figures for mode share. They have also collated information on injuries resulting from the various forms of transport from 2005 - 2016.

Much of the literature suggests that an important design property of the model is for it to be highly specialised. This study [8], reviews a variety of public health interventions and highlights that local projects are often sensitive to local issues. It also draws attention to the role that income had on transport. In order for the model to be useful to Sheffield council, the model must account for attributes of travelling within Sheffield specifically. The paper contained a variety of case studies concerned with various public health interventions in urban environments. It highlighted a few key points to take forward when modelling urban environments, these will be discussed further in the next section of the report.

Firstly, local projects can be sensitive to local issues, it is unlikely that highly specialised studies of this nature will be directly applicable to a new environment. It also touched on the relationship that income had on the likelihood for an individual to engage in active forms of transport. As this paper has been published in a reputable journal with a high impact factor, it is reasonably likely to contain reliable information. However, it is worth noting that many of the case studies identified are not directly comparable, what is of greater importance is the process by which decisions were made, for example, how the role of policy, urban planning, management etc. are considered in the system's model.

One study [5] was able to show the effects of various policies over a period of 40 years in Auckland, New Zealand. Their model was primarily based on a series of structured interviews and consultations. with experts, this allowed them to identify various potential factors that influence peoples decision to cycle within their city. The importance of expert opinion here is made apparent when certain factors are identified that the average member of the population may not realise influences (such as the normality in numbers effect). There are a number of factors (which will be discussed in the next section) that can be reused in our model, however, there are concerns about the suitability of their approach to our case. Firstly, the accuracy of the identified relationships is likely to be very limited with such a small sample size, it is good to be aware of the small sample size bias which often results in many published studies not reproducing as small sample sizes tend to highlight noteworthy relationships that happen by chance and large studies tend to be more accurate but less noteworthy [11]. It is possible, due to the small sample sizes used, that this work may fall into the former category leading to uncertainty in any findings. Steps that could be taken to address this issue would be to make use of technological advances such as the wide adoption of social media resulting in large data-sets or the prevalence of smart-phones which could lead to more citizens being able to give more feedback on their reasons for certain choices of transport to reduce uncertainty by increasing the sample size. Although this is understandable and common in many social studies, journals are increasingly apprehensive of the conclusions of these studies although a portion of this is alleviated when trends can to some degree be verified using data. Another concern is that the topographical features of the area concerned in the case study are significantly different to that of Sheffield, as Sheffield appears to have a very high change in elevation over many journeys whereas Auckland appears to be flatter [10], and changes in elevation appear to play a role in people's decision to cycle (far more than walking and motorised form of transport) [7].

Census data has become the standard tool for gathering high-quality data from a large population. However, as the census is only taken every 10 years, information with respect to time in yearly steps has been taken from an amalgamation of other sources. As stated in the report these sources are only so accurate. This study was able to get access to the raw data that the transport strategy was based upon and it is likely that this data will be used in future work.

### B. Prioritised Set of Features

In reality this system is likely to be affected by a very large number of features, the dynamics of which will be difficult to characterise and time consuming to validate. Fortunately models do not need to be perfect in order to provide insight into a system. It is therefore useful to prioritise a set of features that will be particularly desirable to be incorporated into the model. Broadly these features fit into at least one of three categories.

1) Features with important effects on the dynamics of our model (in this case this could be concentration of cyclists creating a safety in numbers effect).
2) Features that are easy to measure or reliable data already exists for (in this case this could be census data such as age and residence location data).
3) Features that are critical to the use of the model (in this case features that can be directly affected by policy makers such as availability of bicycles).

Looking first at features that are likely to apply to a variety of cities, a normality or safety in numbers effect is likely to exist in this scenario for two reasons[4]. The first is that of safety. There are a number of articles proposing that increasing the number of cyclists increases the safety of cycling [4]. This is generally attributed to a behavioural change in motorists in the presence of people walking and cycling. This safety in numbers effect is likely to reduce the real and perhaps more relevantly the perceived risk of cycling which will increase the number of people cycling in a positive feedback loop. However, as the number of cyclists on the road increases, the number of injuries also increases which may increase the perceived risk. This is an example of a negative feedback loop.

One of the policies Sheffield city council specifically want to investigate concerns cycling friendly infrastructure. In Macmillan's work [5], the introduction of such infrastructure reduces the perceived risk resulting in more cyclists. There is a distinction created between road conversion cycle paths and separate cycling infrastructure. Particularly when looking at cyclists sharing roads with motor vehicles, the number of motorists on the road during commute time and their average speed are likely to contribute to perceived risk. Policy is also likely to have an impact on this so it would be beneficial to test their effects in our model. For example, if the number of motorists is a very sensitive feature, separate cycling infrastructure may be more beneficial.

There are also a number of features highlighted in the strategy consult and Shaping Cities for Health that are that are more tailored to Sheffield. Looking at the topographical map of Sheffield [topographic map Sheffield] and a paper investigating[7] it is likely that topography, due to many journeys within Sheffield containing a significant change in elevation, will play a part in people's choice of transport. Including this as a feature in our model will also let us investigate whether the introduction of electrically assisted bikes would be an effective intervention. This paper also highlights the effect of economic income on transport decisions. According to the index of multiple deprivations (IMD), Sheffield has a range of affluence. As income seems to influence an individual's transport choice it is worth including as a feature of our model. Another significant factor affecting modal transport choice taken from census data is the journey distance [2].

Another paper looking at applying agent based modelling modal choice and departure time in Beijing [12] highlighted the importance of the current mode choice when making a decision to switch to a new form of transport. For example an agent that is currently walking may be more likely to switch to cycling than an agent that is currently commuting by car. The rationale behind this paper was particularly influential the design of agents in this model as is discussed below.

### C. Agent Decision Making

Traditional travel theory is often based on utility maximisation. Where all agents are assumed to be perfectly rational and are capable of making choices that optimise well for their own utility. In reality is it rare to find people who think perfectly rationally but some researchers have suggested that this effect of rationality doesn't average out across a population and instead agents should be considered to have bounded rationality and operate on incomplete information [1] [6]. Zou [12] suggests the SILK method which considers Search,Information, Learning, and Knowledge. The model developed for this article uses use a modified version of this method to control agent decision making.

The proposed model in figure 1 shows the sequence of actions that an agent takes for each step in the simulation. First the agent will decide whether it is worth considering other forms of transport. if it decides it is worthwhile it will then choose a mode of transport to consider based on a set of fuzzy search rules. The agent then decides based on previous experience if it wants to switch to the new mode of transport. The agent then is given the opportunity to interact with the network, this lets the agent gather information on the world. It's experience is then added to it's knowledge base using Bayesian updating. The rationale for each step in this process is discussed in more detail below.

*1) Evaluating the value of searching:* The agents decision to search is based on the relationship between the agents perceived search gain and search cost (perceived as the agents have imperfect information). This has the benefit of reflecting that people in the real world forming habits, in general people don't continually re-evaluate and search for the best options, instead people often exhibit habitual behaviour and and normally prompted to change these habits [9].

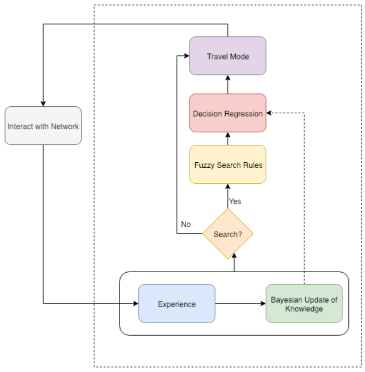


Fig. 1. Framework for Agents in Model

If the agent choices not to search the habitual behaviour is executed.

*2) Searching for other forms of transport:* This step represents the influence that the individual combination of an agents parameters, has, on it's adoption of a certain mode. If the agent decides to search then the agent searches for other modes using a sequence of if-then search rules. This type of decision making was chosen for a number of reasons but mainly that they have been shown to capture heuristic decision making as shown by humans , they are computationally efficient which is important when running large simulations, and rules can be express the knowledge of humans in a very natural way. To illustrate the number and function of each set of search rules a state transition diagram is shown in figure 2.

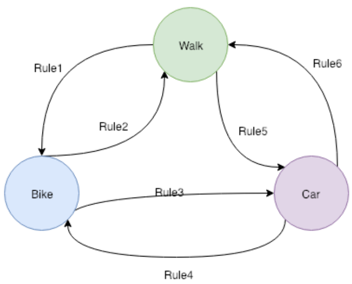


Fig. 2. State transition diagram for agents

The agent has a small amount of memory in that it knows which mode it used in the last run, but knowledge of previous states before that are not accounted for in the model. The set of heuristic rules are dependent on the state that the agent was previously in as a person switching from a car is likely to have different reasons to switch to a bike than a person switching from walking (e.g. environmental concerns vs speed) .

*3) Deciding whether to switch given some experience:* In order to account for social effects, such as normality in numbers the agent must have some knowledge of it's environment. For now assume that the agent has this knowledge, we will explain later why this is. At this stage the agent assesses the suitability of it's decision made in the search section against the world. In practice the agent may be more likely to cycle if it thinks there are a lot of cyclists in the world, or less likely to cycle if ti thinks that there are a lot of cars around. The rationale behind this is that an agents knowledge of the environment is critical in it's decision making but is generally separate to the many of it's internal features (i.e. both old and young people know that lots of people use cars in their world, even if they themselves do or do not use a car).

*4) Interacting with the network:* Perhaps the critical feature most critical to the suitability of agent based modelling for this task is that agents are able to take actions that influence the behaviour of other agents in the network. In this case the network is spatial and can be visualised as a Cartesian plane in two dimensions. Agents are distributed across this plane and are able to interact with other agents in the plane. Agents that are nearby are likely to have a greater influence on the agent than agents that are further away. When agents interact with other agents they are able to build up a spatial representation of the world. This is similar to how people are influenced more by the people they spend the more time with. Often families and communities will adopt similar modes or have other attributes that are similar, such as income that affect their mode choice. Agents are only able to initiate interactions with a limited number of agents per turn to simulate the growing but incomplete information of the world contained in each agent.

*5) Bayesian Inference:* It can be proven mathematically that the best way for one update the probability of a hypothesis is via Bayesian inference. In this case the prior hypothesis is that whatever transport the agent is using is the 'best' choice. When the agent accumulates more information from the world it should update it's opinion on the likelihood of this hypothesis being true so as to then take a rational action. Probabilities are updated in the following way (please note that the term 'best' has been used to loosely represent a question the agent wants to know the answer to, in reality this may be which mode is most proliferate in the world).

$$P(A|B) \propto P(B|A)P(A)$$

Where $P(A|B)$ is known as the posterior (how likely is a bike to be the best choice given the knowledge of the world that we have), $P(B|A)$ is the likelihood (how likely is it that you see the evidence you see if bikes are the best form of transport) and $P(A)$ is the prior (how likely is it that bikes are the best form of transport). The prior is updated on each iteration so that although initially there is a $\frac{1}{3}$ probability that it is the 'best' option this is updated when new evidence is encountered by the agent.

### D. Agent Interaction

As was mentioned previously agents are distributed spatially. This is of relevance for two reasons. Firstly, an agents location may have some secondary influence on their decision, for example a certain region on the grid may be associated with a steep gradient reducing the likelihood of the agent choosing to use non-motorised transport. Secondly, an agents ability to interact with another agent is primarily governed by it's proximity to said agent.

The likelihood of an agent interacting with another agent is governed by the following formula.

$$p = C \cdot exp\left[\frac{D(a,b)}{\lambda}^2\right]$$

Where $\lambda$ is a negative connection parameter, and $D(a,b)$ is the Euclidean distance (straight line distance) between agents a and b. This means that an agents perceived knowledge of the world is based on the world being correlated with the agents surroundings. This is likely to be inaccurate but is reflective of how people view the world, in general it is hard to make optimal decisions when your knowledge of the world is biased in some way, but this is a reasonable reflection of how people actually make decisions.

Figure 3 illustrates the diminishing influence of an agent on the ego agent (agent of interest) with distance. In one turn the agent is unlikely to interact with all of these agents, as there is some stochasticity which influences which agent the ego agent interacts with.

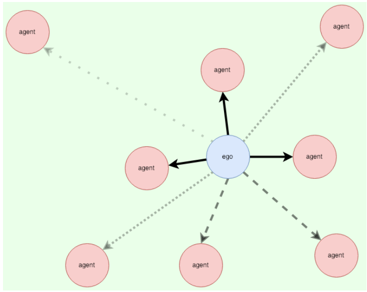


Fig. 3. Relationship between Euclidean distance and interaction likelihood in the spatial model

## III. Final version of the detailed design

As previously discussed the model consists of agents making decisions using the SILK framework with Bayesian learning. Agents are distributed in space, which influences their interactions with other agents. The details of the design and implementation will now be presented.

### A. Structure of Program

The implementation of the model leans heavily on object orientated programming with each agent being represented as an individual object. Agents are well suited to this as objects support encapsulation, allowing the states of agents to be kept private and only shared with the world when intended. Data abstraction will also be useful in this case, allowing for cleaner, more usable code in the higher level parts of the program.

Figure 4 shows how classes in the program interact with one another. The purpose of each class will now be discussed.

*1) Agent:* The agent class contains the code that governs all actions and construction of agents in the model. Agents are constructed using the provided constructor with a set of initial parameters describing the prioritised set of features discussed above such as age, current mode choice, income, travel distance, car and bike ownership. They also contain a vector which is where information they collect about their world is stored. The agent also contains setter and getter methods for accessing a subset of this data so that it can be modified and used in other parts of the

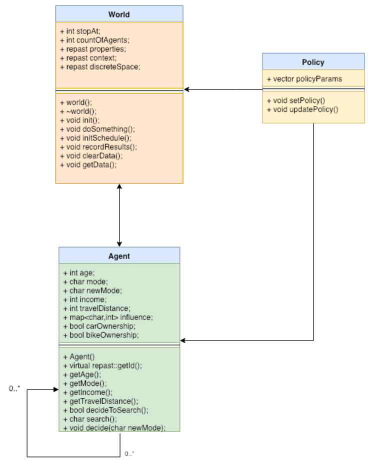


Fig. 4. UML diagram describing the structure of the program

program. The most notable methods are the ones implementing the SILK framework which are decideToSearch(), search() and decide(). Decide to search evaluates whether it is worthwhile for the agents to perform a search it does this by using it's experience and tracking the rate at which perception of the world changes. If the agent notices that world is changing significantly then the agent will be more likely to search, if the agent is more assured of it's knowledge of the state of the world as it is not rapidly changing it is more likely not to search. In order to provide some clarity, a mathematical example of one component of the algorithm is shown below where $f(n)$ is the proportion of bikes the agent thinks is present in the world on iteration $n$, $g$ is the proportion of cars and $l$ is the likelihood of deciding to search.

$l \leftarrow 0$
$f(n) \leftarrow 0.5$
$g(n) \leftarrow 0.5$
**if** $(f(n) - f(n-1)) \geq 0.1$ **then**
  *increase likelihood of deciding to search*
**end if**
**if** $(g(n) - g(n-1)) \geq 0.1$ **then**
  *increase* $l$
**end if**
**if** $l \geq$ *someThreshold* **then**
  *return true*
**end if**

If the function returns true then the agent has decided to initiate some search. It is worth noting there is some influence of random variables in this process so occasionally an agent will decide to search despite not reaching the threshold.

*2) World:* The purpose of the world object is to provide a space in which agents are able to interact with each other, the world is also able to measure the states of the agents within it and is therefore useful for data collection and getting insight from our simulations, this is done by a combination of the getData and clearData methods. The first method invoked from the world object (after construction) is named init, which is responsible for creating agents with a variety of parameters and distributing them in the discrete space. The method responsible for the mechanics of the simulation is named doSomething. Here the methods associated with the SILK framework are invoked. After completing internal actions agents are then given the opportunity to interact with the network. This is done iteratively so that all agents are able to initiate a number of one way interactions. Generally agents that are located nearby are likely to have a greater influence on the ego agent than agents situated further away. As connections are one way only the parameters of the agent that initiates the action is affected by the interaction, however, there is no limit to the number of interactions an agent can be the recipient of so some agents may have a larger effect on the knowledge of other agents and dynamics of the model, than other agents.

*3) Policy:* In order to test the effect of a variety of policies, the policy class is created to test various policies in a sensible work flow. It is beneficial to define what is meant by policy at this point. Policy makers are likely to define policy as course of action proposed by an organisation. The policy objects in this model have a similar purpose, but they are meant to impose the effects of a certain policy. For example, a local government may create a policy encouraging the development of bike paths is a certain. The role of the policy class is to impose the effects of this policy, which in this case could be an increase in the range of ages able to cycle and/or reduced perceived risk of cycling. The class modifies parameters governing the way in which the agent searches the world for new transport options, this will involve interacting with the agent directly, in order to modify it's capabilities (for example if the council decide to invest in electric bikes the agent will be able to travel longer distances), but also modify the world (for example if the council incentivise group cycle to work schemes there is likely to be an increase in the number of interactions the agent makes).

### B. Repast Considerations

The model will be implemented in Repast HPC. Although agents represent individuals making regular commutes it would be impractical and beyond the scope of this work to represent every individual in Sheffield as an individual agent. It may be helpful to understand why increasing the number of agents adds a non-trivial compute time to the simulation. In order to understand this better we will run through a short mathematical illustration. For simplicity we will only evaluate the algorithmic intensity with respect to calculations involved with agents interaction as algorithmic intensity scales approximately linearly with the number of agents in the network with respect to internal agent decision making. For every extra agent in the simulation. Let $n$ be the number of agents in the model and $f(n)$ be the number of calculations (interactions) performed by the model. As all agents have some probability of interacting with each other it is easier to depending on their distance from other agents and a random quantity consider the case where all agents interact with all other agents. In this case $f(n) = n^2 - n$,as agents can not interact with themselves, resulting in a algorithmic intensity of $f(n) = \mathcal{O}^2$. A layer of abstraction is used so as to simplify the simulation computationally. The simulation initially uses 1000 agents to represent Sheffield's population of 518,000. One tick (or iteration) of the model represents 1 week in the model, resulting in the model being run for 1144 iterations. However, if the system reaches steady state before this time the simulation may be aborted at this point.

### C. Agent Decision Making

The reasoning of the agents mode choice is contained in the search and decide methods of the agents. The search method is influenced by attributes of the agent, whereas the decide method is concerned with the agents knowledge of the world.

*1) Search method:* The search method uses fuzzy modelling to represent human decision making. Fuzzy logic is often used to describe heuristic decisions and is well suited to validation by experiment. Attributes of the agent are classified into a member of a fuzzy set. Fuzzy sets associated with an attribute (for example age) have an associated membership function. It is likely that agents will belong partially to multiple members of the same fuzzy set. A rule base decides whether the agents searches for a certain new mode of transport while using a certain mode. These rules are described by following rule base.

**if** *age is not old and the travel distance is short* **then**
  Search Walk;
**end**
**if** *age is not old and travel distance is not long and bike ownership is true* **then**
  Search Bike;
**end**

**Algorithm 1:** Current mode is car

**if** *Car ownership is true and income is moderate and travel distance is long* **then**
  Search Car;
**end**
**if** *age is not old and travel distance is not long* **then**
  Search walk;
**end**

**Algorithm 2:** Current mode is bike

**if** *age is not old and travel distance is moderate and bike ownership is true* **then**
  Search Bike;
**end**
**if** *Car ownership is true and income is not low and travel distance is not short* **then**
  Search Car;
**end**

**Algorithm 3:** Current mode is walk

It is worth noting that these algorithms serve as a base case but will be influenced by policy objects.

*2) Decide method:* The decide method leverages the experience that the agent has built up by interacting with other agents in the network. The result of the search method acts as a suggestion, which the agent will then decide if it wants to act on.

**if** *Search suggests bike and weighting of bikes in knowledge satisfies the bike threshold* **then**
  change mode to bike ;
**end**
**if** *Search suggests car and weighting of cars in knowledge satisfies the car threshold* **then**
  change mode to car ;
**end**
**if** *Search suggests walk and weighting of walks in knowledge satisfies the walk threshold* **then**
  change mode to walk ;
**end**

**Algorithm 4:** Method for deciding whether to follow search

The base case for this method is based on a normality in numbers effect. Where an agent is more likely to change it's behaviour if it knows of other agents exhibiting that behaviour.

### *D. Interaction with Network and Bayesian Inference*

The agent learns about it's surrounding by interacting with other agents. As discussed above, an agents knowledge of the world is most heavily influenced by the behaviour of agents that are nearby. An agent will make a interaction with another agent in the network if the Euclidean distance multiplied by a random variable is above a certain threshold. This means that agents will occasionally interact with agents that are further away from it. Agents learn using Bayesian inference using the equation previously described. In Bayesian learning all samples are weighted equally. It is worth noting that although this is a mathematically accurate description of a rational agents it is not necessarily how people think in the real world. It is somewhat likely that the population acts rationally to a degree, and the incorrect weighting of evidence cancels out over time.

### *E. Verification*

As previously stated model was implemented in C++ using RepastHPC. Subsequently verification testing was performed in line with AGILE methodologies. Due to the complexity of the model it is impractical to describe in detail the results of the hundreds of tests performed during a post development. Instead the approach will be described in detail, with a few results provided to provide clarity.

*1) Unit Testing:* The first level of testing used was unit testing. At this level individual components were tested, normally using just a single input variable and measuring a single output variable. The generic process used was to create a set of 'test cases'. This would normally be a small subset of the input space. Then predict outcomes for each test case. At the unit test level the results of all tests should be normally predictable, however, as our model does incorporate some stochastic behaviour some unit test may be repeated to obtain a predictable output distribution. All functions were individually tested in this fashion. In general the performance of unit tests was done by printing the relevant results to the command line. Most unit tests have now been commented out in the code base. A few examples of unit tests that were performed involved adding agents to the context, assigning agents ID values, placing agents in a certain location in 2D space. A combination of these unit tests has been shown in figure 5. When unit tests failed future results were treated with a greater level of uncertainty (results of previously failed tests were made to pass many times instead of just once or twice).

```
AgentId(23, 0, 0, 0) b at Point[-86, -89]
```

Fig. 5. A combination of simple unit tests

*2) Integration Testing:* The next level of testing was integration testing. This was generally done at the class level. The purpose of integration testing to monitor the behaviour of a set of interaction components. This was often achieved through stringing together a chain of unit tests. This was done for a variety of cases and particular attention was paid to 'special cases'. A case could be identified as special if it was sufficiently differentiated from other tests. Practically this often came down to how memory was managed in the program, discrepancies between creating objects on and off the heap and agents being placed near to the edges of the 2D space. Figure 6 shows one example of the output of an integration test performed to assess the agent class. In this test the agent is initialised, made to search and decide on it's mode.

```
AgentId(86, 0, 0, 0) Age: 4.24695 Mode: w Income: 428309 Travel distance: 8
Agent Deciding whether it is worth Searching...
Agent Decided to Search
Agent Searching ...
Current mode is walk, searching for new mode ...
Keep current mode
Agent Completed Search
Agent Deciding ...
AgentId(86, 0, 0, 0) w at Point[-77, -90]
```

Fig. 6. An example of an integration test

*3) System Testing:* Testing was finally performed on a system level. On the system level it becomes more difficult to work back from to establish bugs, so an emphasis was placed of showing predictable behaviour. The idea of system testing was to engage a wide variety of nodes in the map of the system. The policy class was used to implement these tests. Examples of system level test include increasing age of all agents sufficiently so that they are not able to cycle, seeing the effect of reducing network connectivity to 0 and towards infinity. Tests did not necessarily also serve as potential policy but a test that served as both has been shown below. In this case bicycle proliferation has been increased so as to see the predictable effect of more people using bicycles.

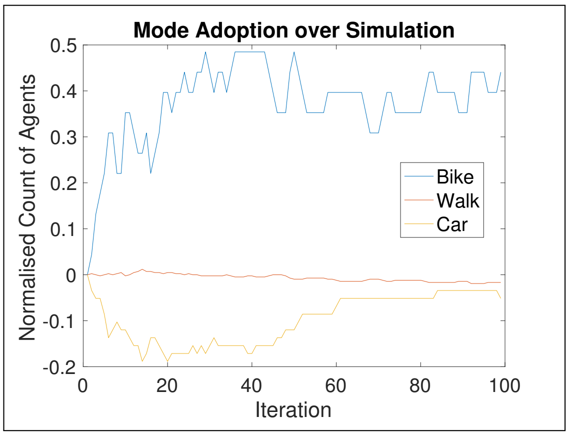


Fig. 7. An example of a system test

The model was then used to show the effect of various policies on modal choice. This section presents the rational behind scenarios that were run from the perspective of the local council, the changes made to the model to reflect the intervention, results of the simulation and suggestions of insights can be drawn from them. Simulations were generally run until steady state was reached, in most cases this was around 100 iterations.

## IV. Scenarios and Results

### A. No Intervention

*1) Reasoning:* This scenario represents the natural behaviour of the system with no intervention. This is used to illustrate how modal change is expected to naturally happen and will serve as a control for which to assess the effectiveness of policies against. The model is initialised with the following configuration.

| | |
|---|---|
| Bike Age | 60 |
| Bike Dist | 5 |
| Walk Age | 60 |
| Walk Dist | 3 |
| Car Dist | 10 |
| Bike Proliferation | 0.4 |
| Communal Effect | 1 |

TABLE I: Parameters for Control Case

Bike age and Walk age represent the maximum age at which an agent can choose to cycle or walk respectively, walk distance, bike distance represent the maximum distance that agents can travel by walking and cycling respectively. Bike proliferation represent the distribution of bicycles within the population. Communal effect describes the effect of cycling in a group regularly, a setting of one corresponds to no effect (as the group size is 1). As few parameters as possible were changes between scenarios so as allow for a greater interpretatbility of results, (as it is easier to attribute changes to a small subset of parameters).

*2) Results:* Figure 8 shows the adoption of various modes in the control case, where no policy has been implemented. As stated above this will serve as a reference for which to assess our policies by. We have normalised the plots by dividing each quantity by the mean value, allowing us to compare the effect of each policy more fairly.

Cycling becomes more and more popular increasing by 36% with a rise time of around 60 iterations. Walking stay roughly the same with a small depreciation (less than 2%), it converges to steady more quickly that cycling (within 2%

almost instantly). Motorists suffer a slight depreciation of 6% and converge relatively quickly.

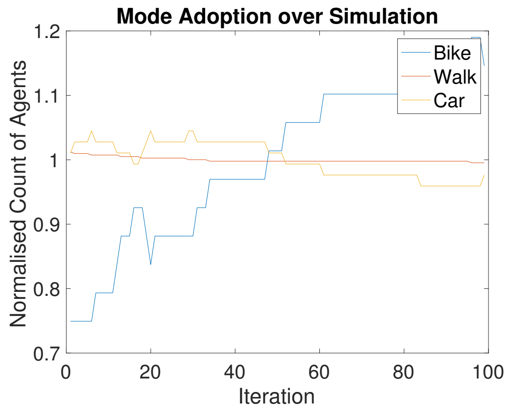


Fig. 8. Mode Adoption in Control Case

The search data of agents has also been provided in figure 9, recall that an agent must both choose to search and search for a category for it to be considered search for said category. We can see that at the start of the simulation agents are very curious and search a lot, as a population they are particularly interested in cycling, this soon converges with few and fewer agents searching until just under 300 agents are searching at any time. Steady state is reached after around 8 iterations of the simulation with respect to bikes, whilst motorists and walkers deviate very little from their starting point.

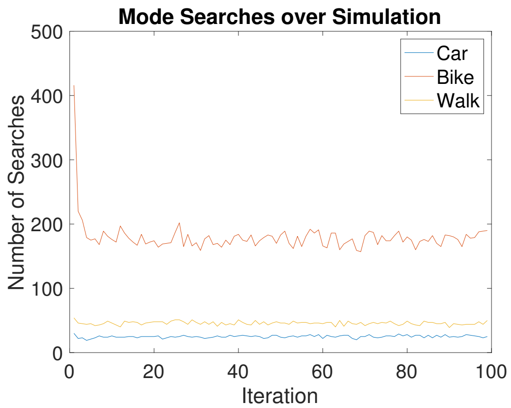


Fig. 9. Searches in Control Case

### B. *Docked Electric Bicycles*

*1) Reasoning:* Many journeys within Sheffield are difficult by active modes of transport. This is often due to either to either the travel distance being great of the change in altitude being large (as many regions in Sheffield are very hilly). One strategy the council could adopt to address this could be to invest in electric bicycles. The rationale is that docked pay per use electric bicycles make these journeys more convenient (leading to wide adoption) at a small cost (far exceeded by the cost of using motorised methods). The parameters for this simulation are as follows.

| | |
|---|---|
| Bike Age | 60 |
| Bike Dist | 30 |
| Walk Age | 60 |
| Walk Dist | 3 |
| Car Dist | 10 |
| Bike Proliferation | 0.4 |
| Communal Effect | 1 |

TABLE II: Parameters for Electric Bikes

Only the bike Dist variable (representing the subjective difficulty of journey by bike, with respect to both distance and altitude), is changed. Arguments could be made to also increase bike proliferation but this was decided against as the small charge for bike use is likely to negate this effect, and our results will be more useful for the reasons stated above.

*2) Results:* Plots of mode adoption from this point unless otherwise stated are generated by first taking the difference between having a policy and the control and then dividing by the mean of the control. For reproducibility the formula is provided below where $n$ is the point to be plotted.

$$n = \frac{\text{policy} - \text{control}}{\text{mean of control}}$$

Figure 10 shows mode adoption after the electric bike policy has been implemented. As we can see bike adoption in the new paradigm, rapidly grows as motorists switch to cycling. There is also a small increase in walkers but this quickly steadies out. This is likely due to cyclists switch to walking initially, but soon the effect of the network increases the normality of cycling, allowing the cycling population to grow significantly (by about 40%).

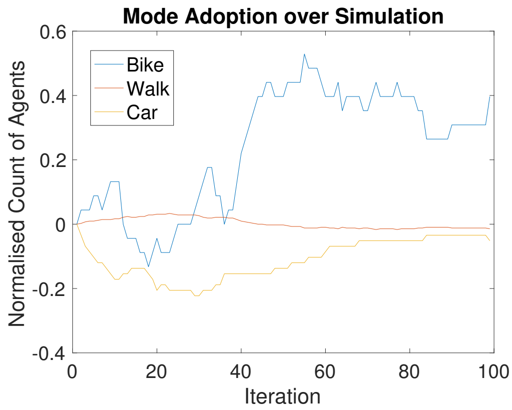


Fig. 10. Mode adoption in Electric Bike Case

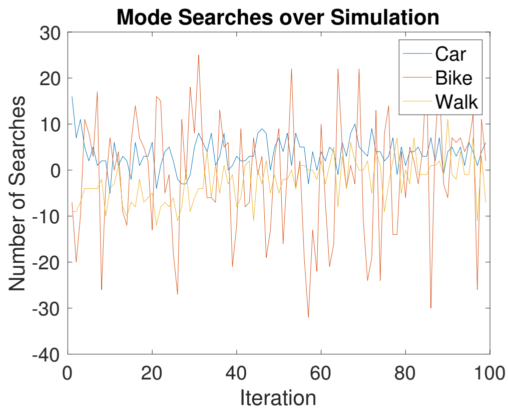


Fig. 11. Searches in Electric Bike Case

The policy influences the agents tendency to search very little. The mean number of searches for all modes are very close to 0 (bike:3.6364, car: -1.1818, walk: -2.4444) indicating there was little effect on the model. From now on assume this is the case for all policies unless otherwise stated and discussed.

### *C. Dedicated Cycle and Walk Paths*

*1) Reasoning:* Travel infrastructure within cities in the UK is generally biased towards motor vehicles.Certain journeys can be logistically difficult to take by active modes of transport and can be off putting to certain groups due to the need to cycle on roads. Affected most by this are younger members of the population, when cycling on roads is deemed unnecessarily dangerous and older members of the population. Dedicated paths make cycling and walking available to a wider variety of ages. They also increase the distance at which these modes are desirable as travel is quicker, less dangerous, and more pleasant.

The parameters for this simulation are as follows.

| | |
|---|---|
| Bike Age | 80 |
| Bike Dist | 15 |
| Walk Age | 80 |
| Walk Dist | 5 |
| Car Dist | 10 |
| Bike Proliferation | 0.4 |
| Communal Effect | 100 |

TABLE III: Parameters for Walk and Cycle Paths

For this simulation we increased the ages at which people take journeys by active modes, as well as the distance people travel by these modes. An argument could be made for also increasing the normality effect. Take the case where agents will be more exposed to cycling on the first few cycles, so they are influenced in a positive direction for cycling and decide to cycle more. This effect has not been implemented here and instead a separate policy was created to see the effectiveness of this type of approach.

*2) Results:* Changes to these parameters increased the adoption of cars by around 28% relative to the control case (in the simulation the absolute number of motorists actually did decrease by a small amount). The number of bikes dips by a small amount relative to the control case before increasing to a steady state increase of 10%. The number of walkers decreases trivially despite a larger proportion of agents being able to take walking journeys. I suspect this is because many of the previous walkers now see cycling as a more attractive option.

### *D. Investment in group schemes (e.g. cycle to work groups))*

*1) Reasoning:* It is common to find people who regularly exercise, incorporate exercising in some kind of group activity. It is thought there is some kind of boost to moral that aids formation of these positive habits, as well as accountability, where failing to reach a certain goal has some

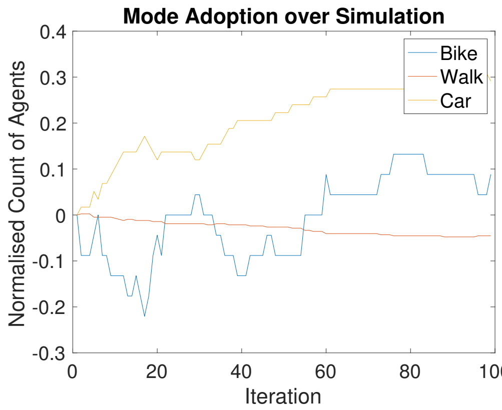


Fig. 12. Adoption of modes in Paths Case

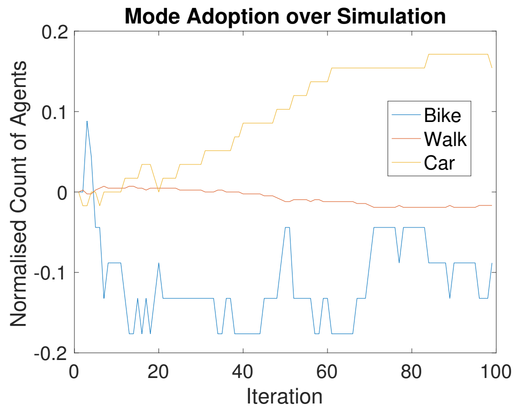


Fig. 13. Adoption of modes in Groups Case

kind of social penalty. Running and cycle groups are becoming more and more popular, and it seems likely there may be a similar effect by which groups are pushed to adopt active modes of transport rather than individuals.

The parameters for this simulation are as follows.

| | |
|---|---|
| Bike Age | 60 |
| Bike Dist | 5 |
| Walk Age | 60 |
| Walk Dist | 3 |
| Car Dist | 10 |
| Bike Proliferation | 0.4 |
| Communal Effect | 100 |

TABLE IV: Parameters for Groups Case

For this simulation we changed the community factor. This changes the connectivity in the network and means that agents that the ego agents interacts with that are using active modes of transport have a far higher effect on the agents decision to adopt similar habits (when they see one person cycling they effectively see 1 hundred people cycling as there are likely to work with the person who they see cycling).

*2) Results:* Although the results of this simulation are initially discouraging, as we see an increase in motorists by about 20% an a decrease in cyclists by around 10% the search data may provide a more valuable insight.

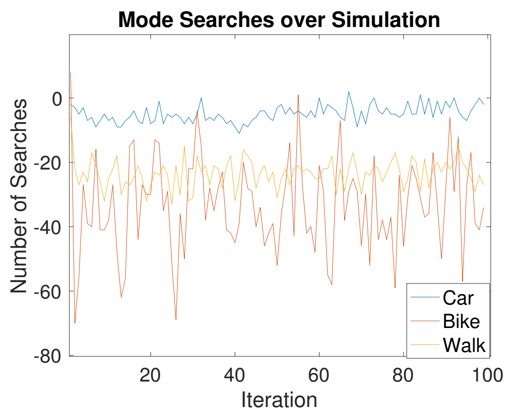


Fig. 14. Search initiation in Groups Case

This is the first time a significant change to the search dynamics of the agents is seen. The mean number of bike searches decreases by 33.5455 and the mean number of walk searches decreases by 23.4242. This is actually a promising result, to clarify why it may help to think of search frequency as a measure of an agents certainty of it's opinion on that mode. If an agent searches for bikes a lot, it frequently thinks about switching to cycling. An increase in the agents certainty indicates that agents are making 'smarter' choices, they are second guessing themselves less. Essentially biasing the network in a certain direction has allowed agents to reach decisions they are happier with for longer. It is likely in this paradigm driving turned out to be a 'better' option for agents that did decide to cycle or walk at some point. If this paradigm was combined with more attractive active mode conditions (such as docked electric bikes) it is likely that as a population agents would decide to adopt this mode more frequently than without the communal effect.

*3) Increased Bike Proliferation:* According to recent data, around 40% of Sheffield's commuting residents own or have access to a bicycle. There are many schemes the council could adopt to incentivise an increase in this such as cycle to work schemes allowing bicycles at a cheaper price (where the price reduction comes from tax breaks) to be gradually paid back in monthly instalments from the residents salary. Innovative services like 'Offo bikes' also allow for a greater accessibility of bicycles. In this case an increase in the proliferation of bicycles is investigated.

The parameters for this simulation are as follows.

| | |
|---|---|
| Bike Age | 60 |
| Bike Dist | 5 |
| Walk Age | 60 |
| Walk Dist | 3 |
| Car Dist | 10 |
| Bike Proliferation | 0.8 |
| Communal Effect | 1 |

TABLE V: Parameters for Groups Case

*4) Results:* From figure 15 we can see a clear increase in the adoption of cycling by around 40%. This reaches steady state after around 30 iterations. We see a decline in motorists relative initially, however, as this settles it does reach roughly the same point as the controlled scenario (after around 80 iterations). We also see a small decline in the number of walkers. It is unlikely to shock policy makers that an increase in accessibility to bicycles results in more people using bicycles. It is worth noting that in this increased bike proliferation case, added bicycles are allocated randomly. More targeted bicycle dispersal may result in a larger increase in cyclists (with a 100% increase in bicycles a 40% increase in users is arguably disappointing). In fact, a more targeted approach could results in greater than 100% increase if the interactions of cyclists are better leveraged.

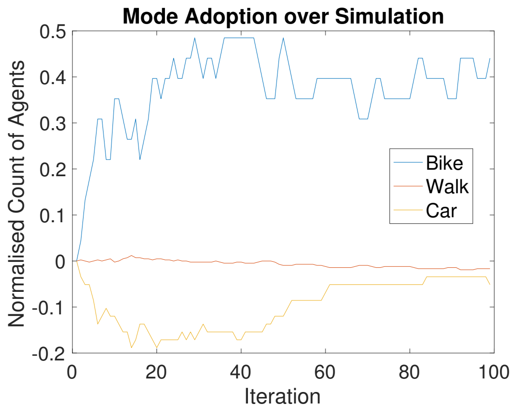


Fig. 15. Adoption of modes in Bike Proliferation Case

## V. Discussion

### *A. Critical Evaluation of Model Design*

As with any system, there is a level of abstraction before which a mathematical model is impractical and too computationally expensive, but after which models are inaccurate do not sufficiently capture the dynamics of the system to be useful in the real world. Although without validation it is difficult to show that an appropriate level of abstraction is set, a case can be made that there is good reason for this to be the case. Firstly, this model accounts for agents having imperfect knowledge of the world. Unlike many models implementing some kind of rationality framework, like in the real world, agents form opinions of the world through Bayesian inference rather than having access to a common objective function that they figure out how to optimise. This is likely to be significant as in the real world people have a tendency to make irrational decisions. There must be a compromise between the predictability of rational responses that can be modelled with relative ease and and what we know from epistemology.

Another potential weakness of the model is with regard to the accuracy of implemented policies. The policy class clearly makes assumptions of the effects that certain policies have on the world, but it can be difficult to get a sense of what realistic parameterisation looks like without doing any validation. This will be discussed further in the next section of the report. One redeeming quality of the model is that these parameters can be easily changed when information does become available. It would also be beneficial to map the input space in order to optimise the model and see if there are any overtly sensitive parameters which are of particular importance to verify the degree to which they are likely to be true.

Fundamentally, the future can be difficult to predict. There are limitations to what simple models can do. However, as without these simple models decisions are likely to be highly heuristic and therefore inconsistent across councils, models based off these heuristic rules provide a framework which is quantitative and reproducible. The use of fuzzy logic is particularly important to this as fuzzy logic is a suitable mechanism by which heuristics can be mathematically expressed. It is often found that 'experts' often agree in principle but when it comes to quantifying parameters (which is vital to the use of most models), there is sometimes a high degree of variation. Fuzzy logic and the use of membership functions are able to account for this, and multiple data sources could be used for calibration.

### B. Calibration and Validation

In order for our model to be useful, it must be representative of a real world system over the predefined time period. It is therefore necessary to train our model to show that results produced are representative of the real world. Representatives is determined by looking at evidence, the idea is to get a sense of the degree to which predictions of the model match observed data. A parametric representation for decide to search, search and decide methods can be produced. Hyperparameters in this model can then be changed the work out the differences between agents required for the model (heterogeneity). Hyperparamters it is important to consider in the case of this model are fuzzy parameters governing transitions between modes, weightings in the decide function for acting on the search function and weightings in the decide to search functions, agents are also effectively initialised with differing beliefs (as their parameters affect thresholds in the model) which must also feature in parameterised calibration model.

Techniques for model calibration can broadly split into Bayesian and emulation methods.

*1) Approximate Bayesian Computation Methods:* Conceptually, hyperparamters are represented as probability distributions that reflect our intuition for possible values hyper parameters in our model should take. This produces probability distributions for out model outputs. We can then characterise these distributions by measures like expectation and deviation to get a sense of how the model behaves with respect to our uncertainty. The core principle behind this condition probability approach is how likely is the output of our model given the evidence available to us (calibration data) and therefore how likely are our hyperparameters.

The first method that will be discussed at Markov chain Monte Carlo methods. This class of methods involves sampling the probability distribution by constructing a Markov chain. The Markov chain should feature the desired distribution as it's equilibrium distribution. In this case we are able to construct the posterior from samples when we cannot produce an analytically description of the posterior. A well known example from this class of algorithms in the Metropolis-Hastings algorithm. After a suitable period, the algorithms will start to generate samples from the posterior distribution. One disadvantage of this method is that it's speed is largely dependent on the choice of initially proposed distribution. The use of interacting MCMC methods are sometimes able to speed up these algorithms by an order of magnitude by taking into account previous iterations as essentially MCMC methods are run in parallel with each other. Another interpretation is as mutation selection genetic particle algorithms. Any MCMC should be implementable as a interacting chain.

Another method that could be used is rejection sampling where a large number of samples a taken from the sample space. On approach is latin hypercube sampling where one sample is taken from every columns and row in the sample grid. Like in the previous method the distance between the observed and modelled data is calculated and the rmse is used as a metric.

In our case arguably the most suitable method is history matching. In this method we gradually reduce the size of the posterior distribution in an iterative fashion. The implausibility of of each output is then calculated (at various time intervals). This process is conducted in waves to locate regions of non implausibility. MCMC can then be used to construct the posterior distribution.

*2) Emulation:* One of the weaknesses of our model is the long time it takes to run, even for 500 agents. This makes the aforementioned methods problematic as in a typical case they may require of the order of $10^6$ samples. Although Repast HPC has the functionality of allowing us to leverage multi-core processing, in our case emulation may offer a better solution. Relatively slow agents like ours can be replaced with faster more computationally simple agents. Emulation methods are generally black box methods in which outputs for each time point are generated given a set of inputs (which are the hyper parameters of our model). Distance metrics are then calculated for each hyper parameters in the vector.

One popular emulator is the radial basis function (RBF). The principle is that a complicated function can be composed of a weighted sum of smaller functions. A variety of basis functions exist. As this is essentially a machine learning paradigm so K-fold cross validation can be employed, where the input is folded into subsets and part of the input space is left out on each iteration, an optimisation algorithm can then be used to identify a good choice of basis function guided by the rmse. Other popular method is the Kriging model approximation which is based on RBF which is well suited to stochastic models, like this one, where the basic principle is that points that a close together in the input space are more highly correlated than points that are further apart.

### *C. Data for Model Parameterisation*

In order to parameterise the model using the methods previously described it is important to identify data sources. Data for various parts of the model are likely to require different sources.

The fuzzy part of the model is designed to reflect heuristic decisions. Web based surveys have been used for this part of the kind of data collection in the past. We will now outline the design for a potential questionnaire. Data on the personal attributes of the and socio-economic statuses will need to be collected. This can also be used for initialisation which will be discussed further later on. Data on age, gender and income and address will need to be collected. Also travel information like ability to drive, car ownership, bike ownership, public transport cards.

Another useful feature of the survey would be collecting basic information around travellers commutes, such as destination, travel time, and cost. It would also be useful to ask for information to be about the last commute for accuracy.

The final part of the survey is most useful to determining the fuzzy rules and the switching behaviour between states. One way in which to do this is to ask for mode, travel time and cost. Then present a policy randomly by multiplying a series of random parameters on the basis of most recent trip information. The subject is then given the opportunity to change their behaviour. These binary choices will enable us to highlight parameters which caused agents to switch. Data from the personal information of respondents can then be compared to census data which is publicly available to assess how representative the population was.

Another useful data source, particularly for calibration, is census data. The last census was carried out in 2011 and contains a large amount of multivariate data. Particularly useful to us is commuting data showing where people commute to and from within Sheffield. This will aid us in distributing travel distances by agent location. There is also age data, which can be combined with data form previous censuses to show how the UK's population is ageing. There is also data on car or van availability, economic activity, hours worked (to give an idea of time between commuting each way and frequency of commutes). This data is likely to be of a high quality but it is still likely that some cleaning will need to take place.

Data will be divided in a 60-20-20 split between training, validation and test data. If fewer than 500 samples are available it is likely that a cross validation technique will be used (such as leave one out) to reduce the need for different validation and test sets.

### *D. Implications for decision makers in Sheffield City Council*

The effectiveness of policies will be compared with respect to bike adoption. Figure 16 shows the various policies and their effect on bike usage over the course of the simulation.

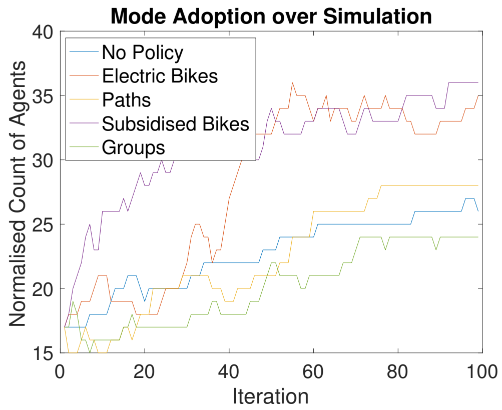


Fig. 16. Comparison of the effect of policy on bike adoption

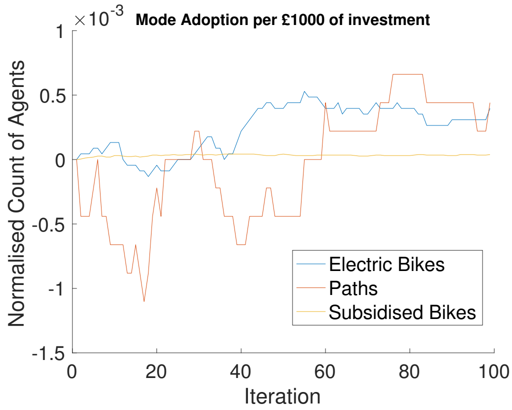


Fig. 17. Cost effectiveness of policies

From the results presented subsidies bikes seems like a very promising policy. More investigation is required to validate the results, but of the policies investigated it seemed particularly promising. It is worth noting that the metric of most value is the integral each response as opposed to the absolute value at the end of the simulation. A subsidised bikes have the largest area the current implementation would suggest that they are the most effective intervention. It is closely followed by implementation of electric bicycles, which lags behind but quickly matches the performance of subsidised bicycles. Bicycle paths seem to have relatively little effect and the implementation of group schemes seems to have a small negative effect. Perhaps the largest issue in local government is on of economics, it is becoming increasingly difficult for local councils to secure the necessary funding to deliver the required services. The cost effectiveness of policies is therefore likely to be of more use to the council. Figure 17 show some back of envelope cost effectiveness calculations based on the likely costs that would be incurred by the council.

The figure above suggests that a better policy with respect to cost effectiveness could be the implementation of electric bikes and possibly paths as there is a larger integral per £1000 of predicted investment. A parallel could be drawn between other types of investment. Traders of equities in stock markets use a variety of measures to predict the profitability of their portfolio. Perhaps the critical measure in this paradigm is one of risk. To get a sense of the risk the signal to noise ratio of each policy was calculated.

| | |
|---|---|
| Electric Bikes | 3.8770 |
| Paths | 3.3805 |
| Bike Subsidies | 11.2245 |

TABLE VI: Signal to Noise ratio for various policies

Our portfolio can be optimised to alleviate risk of certain policies. In this case as bike subsidies seem to look relatively risk free it is suggested that they along with Electric Bikes take the majority of investment. The actual weightings of each policy are down to the quantity of risk the local council wish to leverage.

Another interesting policy is the implementation of cycling and walking groups. This seems to have a positive impact on the network but it is more difficult to characterise the dynamics. A suggestion in future work would be the combination of such a policy with other policies to see the effect on modal shift. As this is very cheap to implement it is likely to be worth wile implementing in an A/B test style (as are many of these policies for validation). Randomised controlled trials have become the gold standard for measuring impact. These trials could be done across Sheffield in an A/B test style whilst accounting for local effects by incentivising certain services to randomly selected households. The main take-away from this investigation is that it looks likely that policies are able to influence modal choice, but more data is required to validate models.

## VI. Conclusion

An agent based model was developed to illustrate the effect of various policies on modal choice. The model can be used by policy makers to aid informed decision making. Furthermore a variety of quantitative metrics can be calculated from generated data to form a better understanding of the possible effect of policies taking into account the stochastic nature of the real world. The model incorporates fuzzy set theory as a way of mimicking heuristic decision making. It also trades traditional utility maximisation methods in favour of the silk framework, in which agents use Bayesian inference to build a picture of their world. Methods have also been suggested for model validation, and useful data sources such as census data have been identified. The creation and necessity for more tailored data sources through online surveys has also been discussed. A variety if policies have been discussed and a discussion of the various strengths and weaknesses of the model with respect to each policy has been discussed.

Beyond validation there are a variety of ways future work could build on this model. One was in which the model could be extended was through the use of of API's and web scraping to better inform the model. The Google maps API could allow us to distribute agents in 2D space in a very tangible way as there could be a direct correlation between population density and agent density in various regions of the 2d space. There are also changed in the model that would be interesting to investigate. A better understanding of how people in the real world change their own network connectivity's is likely to provide useful insight to better inform the model and produce more useful insights with respect to various policies.

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