A Simulation of Road Traffic to Model Causes of Congestion

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Bachelor of Science in Computer Science with Honours
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April 2009
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Submitted by: Daniel Shipp

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Declaration
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Abstract

For many drivers, joining the back of a traffic jam may pose just one question; who had the accident? Unfortunately, despite the convenience of placing blame on a single person, research into the causes of congestion reveals that the phenomena known as ‘shockwave’ traffic jams can often occur when there is no physical bottleneck limiting traffic flow, such as a lane closure or vehicle collision. Instead, this special form of congestion is closely linked to vehicle density and the human behavioural characteristics that determine individual driving habits. Research into the psychology of driving suggests that human reaction times and the inability of a driver to maintain constant speed may be two of the largest factors that affect the efficiency of vehicle flow on our roads, although concrete proof to support these claims is still to be shown. An experiment carried out by Sugiyama appears to support these ideas, though the simulation approach could be argued to be limited in the results it shows (Sugiyama, Fukui, Kikuchi, Hasebe, Nakayama, Nishinari, ichi Tadaki and Yukawa, 2008). In this paper, we investigate existing technologies and previous work carried out in the area of traffic modelling, leading to the design and development of our own simulation of a typical three lane motorway. In comparison to control scenarios utilising only basic car-following and lane-changing strategies, we investigate the extent to which vehicle density and human behavioural characteristics affect traffic flow in the simulation. We make further comparisons between our simulation data and prior observations of real motorway traffic flow to validate the accuracy of our implementation.
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Acknowledgements

I would like to thank my main supervisor, Dr. Marina De Vos, for her continued help and support throughout the project. Similarly, I am hugely grateful to my assistant supervisor, Ashley Mills, for giving me the initial research idea and inspiring me to develop the project further.

I would also like to thank my friends Tom Sheldon and Ben Whittard for keeping me motivated and focused, and my father for his help proof reading the final submission.
Chapter 1

Introduction

As any driver will tell you, traffic congestion and jamming is an everyday occurrence on our motorways. With growing pressure on governments around the world to increase the level of service offered by their road networks, the academic community is attempting to understand the real causes of congestion and their respective solutions.

A major concern is the supposed myth that increasing the length of a transport network by building new roads will ease congestion. In actual fact, there will be very little effect seen due to the simultaneous increase of road users as more and more cars are bought and used every year. Subsequently, a large amount of research has been conducted around the area of simulating vehicle interaction and driver behaviour to understand how new rules and regulations can help relieve our roads of heavy congestion. This has led to systems such as the variable speed limits seen on the M25 motorway in Britain to help lower travelling times during peak commuting hours.

Unfortunately, the main focus of understanding traffic and queuing behaviour has been placed on the development of ever more accurate models to describe how vehicles follow each other and make lane changing decisions. Despite hinting at the importance of human driver behaviour, in particular the inability to make accurate judgements, such advanced models remain relatively undeveloped. This introduces a huge potential for error in projecting figures for flow rate and congestion likelihood, as simulations will not be true to life.

In order to advance this area of research, we look to develop a new simulation of motorway traffic that allows various basic and behavioural models to be enabled or disabled as required. Part of our research will focus on car-following and lane-changing models that determine where a driver positions his vehicle relative to others on the road. On a multi-lane road such as a motorway, this is not just limited to vehicles in front of the driver, but
also vehicles in adjacent lanes based on the driver’s desire to overtake or return back to the far inside lane. Additionally, we will look at using behavioural characteristics for drivers in order to measure a more stochastic flow of traffic. Although there is much speculation as to the effects of these behaviours, there appears to be little evidence to explain the extent of their impact on the build up of congestion and traffic jams. This project aims to provide experimental findings for the effect of these behaviours on traffic flow.

In Chapter 2 we will review a range of existing traffic simulation software and the current research that supports various models of driver interaction. We also investigate the exact meaning of congestion and any methods available to measure it. Chapter 3 will outline our proposal for building a new simulation to expand on existing implementations of traffic modelling, followed by a detailed account of the development process in Chapter 4. A review of the validity of the behavioural characteristics will be detailed in Chapter 5 followed by a detailed look in Chapter 6 at the test results obtained from running a range of scenarios through the simulation. Finally, we conclude with our findings in Chapter 7 and an overall evaluation of the project (including suggestions for future work) in Chapter 8.
Chapter 2

Literature Survey

2.1 Overview

Traffic modelling and simulation has become a popular area of research in recent years, with the very first models of traffic flow and behaviour being developed over fifty years ago. In this section we present a description of the principles of traffic flow and congestion, and then move on to the more scientific explanations for them. A summary of the literature and its relevance to the project will be presented at the end.

2.2 Introduction to Traffic Simulation

2.2.1 Congestion and Bottlenecked Systems

Before trying to understand how traffic flow can be modelled, we will look first at the causes for the formation of traffic jams and congestion. This will include taking a brief look at basic vehicle dynamics in a bottlenecked system and existing definitions of congestion.

For this survey, we will state that road layouts are seen to have bottlenecks if a particular section enforces a slower speed limit than previous or subsequent sections or attempts to converge multiple streams of traffic together into a fewer number of lanes. In many cases this causes little inconvenience to drivers if the road in question only carries a low volume of traffic. In the case of two lanes merging, low volume traffic should be spaced adequately enough for drivers to filter in turn without slowing down to give way to other
vehicles. However if the volume of traffic is high in the same scenario, each vehicle would be required to wait in a queue to filter, as two vehicles cannot occupy the same space in a single lane. Some of the more noticeable physical road properties that cause a bottleneck are highway and motorway on-ramps and lane closures due to road maintenance or traffic collisions. Good examples of these can be found on Martin Treiber’s website that looks at simulating such scenarios (Treiber, 2008). We will look at Treiber’s work around this area in more detail later on.

So what exactly do we mean by traffic congestion, and how can we measure it? An example definition states that “Traffic congestion is a condition on any network as use increases and is characterized by slower speeds, longer trip times, and increased queuing”, such that road congestion occurs when “a volume of traffic […] generates demand for space greater than the available road capacity” (Wikipedia, 2008b). It is important to note that without the characteristic of increased queuing, slower speeds and longer trips times can often occur without a road being in a state of congestion, such as a single car travelling on a motorway at intentionally slow speed.

An initial approach that may be considered for measuring traffic congestion would be in comparing the speed of vehicles against a normal value. Chen tells us that “measures of congestion delay compare the actual time travelled to some standard”, where “one [standard] is travel time under free flow conditions (nominally 60 mph), and the other is travel time under maximum flow” (Chen, Jia and Varaiya, 2001). In his paper, Chen provides evidence to show that certain sections of highway observed in Los Angeles obtain their maximum flow at an average vehicle speed of 60 mph. Data was collected by sensors placed in the road that measure vehicle speed, flow rate and road occupancy. By analysing the period of time where the highest flow rate was observed, the average speed was obtained. Consequently, using the maximum flow standard allows us to measure congestion on a scale relevant to the section of road observed, given that we are able to calculate the corresponding optimal vehicle speed.

Unfortunately this relies on the initial knowledge of a road being in a congested state; in the extreme case, such a standard cannot be applied to a motorway with only a single vehicle travelling at speed intentionally lower than the optimal speed. Although perhaps obvious to a person when a road section is in a state of congestion, we must be careful when trying to draw such conclusions computationally. The problem we face is that there is no fine line between the states of free flow and congestion. In comparing the speed and travel time of vehicles against a normal, it should be understood that congestion can occur without every vehicle being involved, yet vehicles can be forced to slow down for reasons other than a general state of congestion. Therefore any attempt to evaluate the state of traffic may require the combined use of both computational results (such as notifications when critical ranges are exceeded, most likely based on the percentage of traffic affected in a certain way) and human interpretation.
CHAPTER 2. LITERATURE SURVEY

2.2.2 Types of Traffic Modelling

Before looking at existing software products in this domain, we should gain a basic understanding of the options available for simulating traffic. As a rule, there are two general scales of traffic simulation; microscopic and macroscopic. These are sometimes abbreviated to macro-simulation and micro-simulation respectively. The analysis of traffic is not just limited to road sections, but other fields such as network traffic in computing and taxation and pension modelling by government bodies.

Macro-simulation involves taking a high level view of traffic flow, modelling vehicles as a combined group of entities. This form of simulation will generally use factors such as vehicle density and average vehicle velocity to measure clusters of traffic, with little emphasis on the behaviour of individual vehicles. An overview of macro-simulation in the introduction of Erol’s paper on agent based traffic simulation tells us that using these models has the advantage that “run-time can be fairly short, as the computation is based on aggregate, abstract parameters” (Erol, Levy and Wentworth, 1999). Due to this, macro models have very low computational requirements, but consequently restricting the output to a coarse set of results. This is often evident in the variation of results obtained as even “infinitesimal perturbations to initial conditions can have arbitrarily large impact on the global system behavior”. As a basic example, a simulation of a multilane motorway may involve modelling each lane individually and applying to the model a certain global probability of vehicles overtaking each other (Helbing, Hennecke, Shvetsov and Treiber, 2002).

Micro-simulation is very different to its counterpart in that it revolves around modelling system entities at an individual-level (IMA, 2008). In general, individuals may have differing characteristics and attributes to others, as well as rules for behavioural change over time. It should however be noted that micro-simulation is considered to be very closely related to both Cellular Automata and Agent Based Models. The former places each entity inside its own grid space in a given system, whereby changes in behaviour are generally determined by the presence of entities in neighbouring grid spaces. Agent Based Models look more closely at the interaction between entities, where behaviour changes are based mainly on the failure or success of previous interactions. Combined, these three models have overlapping simulation capabilities, offering their own unique approaches to simulation that should be considered collectively when implementing the project software. For our purposes, when we talk about micro-simulation, we will refer to the general area covered by these three models.

Most papers written around the area of traffic micro-simulation (including Erol’s on agent based traffic simulation) acknowledge that the focus is mainly on car-following and lane-changing models, two areas we will be looking at in more detail later on. Because each entity in the system will display different behaviour depending on its immediate environment, it is easy to see how the computational costs could prove to be astronomically high compared
to macro-simulation if these two models are overly complex. An example basic simulation would require the collective modelling of any adjacent lanes, allowing each vehicle to have its own goals and objectives for overtaking and following other vehicles and reaching a desired velocity. Additional behaviours to these could restrict the ability to run the simulation in real time, depending on the scale of the road system.

For the purposes of this project, it is unlikely that the proposed simulation of a multilane motorway will be complex or large enough in scale that the computational requirements will not be able to be fulfilled by a reasonably powered machine, going by today’s personal computing standards. Regardless of this, Erol’s paper entitled “Application of Agent Technology to Traffic Simulation” makes some interesting points in the way that simulation of road traffic should be approached that are applicable to the project (Erol et al., 1999). Erol describes a traffic simulator that models each road section, vehicle and traffic signal as an agent inside the system, acting as an individual software program within a much larger framework. Agents are clustered in communities that encompass a small chunk of the entire road network being simulated. Communications are held both within and between communities, with agent vehicles migrating to adjacent communities when they reach the border of theirs. Using this model, multiple computers on a network can handle the modelling of communities in a distributed fashion, allowing the simulation of entire city road networks without the need for some kind of supercomputer. This poses many questions that need to be addressed during the design, in the way that interactions are handled in the simulation. Depending on the strengths and limitations of the language the software is built with, it may prove more efficient to build the simulation in an agent oriented way and experiment with both single and multi threaded engines to see which proves most effective.

2.2.3 Existing Traffic Modelling Software

Some of the earliest models of traffic flow were proposed around fifty years ago, and even now there does not appear to be a one-size-fits-all model that can applied to traffic flow in general. Various software systems have been developed to support such models, ranging from complete simulation frameworks for city-wide transport systems to simple web-based applets controlling a single crossroad junction. As such, an entire global market now exists for such software products.

One such product with a rather high profile is VISSIM, simulating city-wide traffic, used by city councils and transportation planners to devise the most efficient traffic network layouts (VISSIM, 2008). VISSIM is reported to be the market leader in transportation planning, using microscopic- and multi-modal- simulation techniques to model a wide range of types of traffic, including trams, bicycles and pedestrians (Wikipedia, 2008c). However, many other products make such claims as to their popularity and applicative value in different scenarios. In their paper entitled “Traffic flow simulation using CORSIM”, Owen et al. list a selection
of these including MITSIM, WATSIM, PARAMICS and TRANSIMS (Owen, Zhang, Rao and McHale, 2000). CORSIM (CORridor SIMulation) is unsurprisingly described as “the most widely used microscopic traffic simulation program in U.S. and all over the world”. The paper goes on to describe the product’s strengths, for example CORSIM is reportedly strong in its abilities to model complicated geometry conditions such as multi-lane freeway segments.

One thing that most of these products have in common is that they use the same core modelling techniques, as mentioned in an earlier section: car-following and lane-changing models. These are considered to be at the heart of traffic simulation software, but as we will see later they come in many different flavours. This begs the question as to whether each model is consistent with all the others, or whether some are more or less accurate than others. In Section 2.2.4 we will look at the comparisons between these models and how the Highway Capacity Manual (HCM) lends itself to them.

In addition to the large scale commercial software applications available, the internet plays host to a number of smaller applets designed for the sole purpose of replicating certain traffic scenarios. These are generally different in that they are looking to create and explain congestion as opposed to commercial software that wishes to avoid it however best it can. Currently undertaking research and publishing a number of papers in the field of traffic simulation, Martin Treiber hosts a variety of online resources with the hope of explaining various anomalous traffic behaviours (Treiber, 2008). Of particular note is a Java applet that attempts to simulate two-lane traffic congestion on a ring-road, an uphill gradient and a slip road amongst others. The applet uses a slightly simplified model of traffic to show how scenarios with and without bottlenecks can lead to the breakdown in free flowing traffic, depending on certain environmental variables.

2.2.4 Accuracy of Existing Software and the HCM

We mentioned previously that many existing micro-simulation models use a range of different models based on two main principles, and so are liable to provide different results for certain scenarios if the models do not work on a like-for-like basis. The issue of simulation accuracy will be important for validating the software developed for this project, so it will be necessary to find ways of evaluating the results.

A paper by Loren Bloomberg et al. looks at comparing various simulation models (or rather the software that apply these models) to the HCM, or Highway Capacity Manual. The HCM is published by the Transportation Research Board in the U.S. and contains “concepts and guidelines, and computational procedures for computing the capacity and quality of service of various highway facilities” (Dowling, 2008). There were six participants altogether; CORSIM, INTEGRATION, MITSIMLab, Paramics, VISSIM and WATSIM
(Bloomberg, Swenson and Haldors, 2003). Each developer was given a range of traffic scenarios (including freeway sections) and respective values for traffic volume and asked to simulate the performance of each road system. They were also asked to model the future performance in each scenario given traffic volumes of approximately 10-20% higher. For comparison, the same scenarios were modelled using the guidelines presented in the HCM.

The comparative analysis looked at measures for travel time, average speed and lane density. The author notes that “the six models were able to match reasonably well to the HCM results with respect to travel speeds and lane densities. For future conditions with increased volumes, the six models showed an increase in the variability and standard deviation”. Bloomberg goes on to conclude that in general, the model chosen for testing traffic scenarios was not particularly important, as the results obtained from each of the six tested simulation models were reasonably similar. There was also no indication that any particular model was notably better or worse than any other, indicating that the ability to “effectively code, test, calibrate and apply these models” is more important.

Unfortunately this paper is somewhat beyond the scope of this project as we are not trying to evaluate performance of a particular road system but rather simulate the conditions that could lead to a breakdown of efficient traffic flow. Consequently, the HCM would be of little use in evaluating the simulation proposed here as it consists of guidelines to be followed when designing road networks, where as we will not be evaluating the road layout in any way. We have however seen that different scientific models with proprietary functionality tend to provide similar results to each other. Based on this, it should be much easier to decide which models to use for our implementation, allowing us to include additional parameters with little risk of affecting the accuracy of the results.

### 2.3 The Science behind Traffic Congestion

#### 2.3.1 Critical Density

We considered earlier that the travel time on a particular road section can be compared to that of the same road section at its maximum flow as a method of measuring traffic congestion. This would indicate the existence of a point where the number of vehicles on the road is likely to increase the overall travel time; this is known as the ‘critical density’ of a road section in the world of traffic simulation, as described in Sugiyama’s paper (Sugiyama et al., 2008). His paper entitled “Traffic jams without bottlenecks” describes the first published experimental evidence that traffic jams can form without any kind of bottleneck (as defined earlier). Of particular interest is the explanation given for the build up of a congested state in this manner.
Observations of road occupancy in terms of vehicle density and flow rate allow us to locate the critical density of a road. For the time being we will simply state that the critical density for a section of road is the point at which the maximum flow rate is achieved, measured by the vehicle density at that moment. This point is approximately equal for any highway with similar attributes, such as the number of lanes and speed restrictions it imposes. Sugiyama’s paper includes a graph of observed road traffic on a Japanese highway, as shown in Figure 2.1. He plots $p$ as the vehicle density (vehicles/km) and $q$ as the flow rate (vehicles passed/5 mins).

We can see from the initial spike that the critical density is approximately 25 vehicles/km, as this is the point where a flow rate of about 200 vehicles over 5 minutes can be achieved. After this, the flow rate sharply drops off as the vehicle density increases, showing an increasingly random formation of data points that seem to represent the instability of a congested state.

![Figure 2.1: Vehicle densities and respective flow rates as observed on a Japanese highway from one month of data.](image)

To understand the importance of critical density, we first need a little more background on Sugiyama’s investigation. A new research concept was introduced in the 1990’s that tries to investigate traffic flow as a “dynamical phenomenon of a many-particle system” (Sugiyama et al., 2008). Sugiyama explains that “such a system drastically changes its macroscopic aspect owing to the effect of the collective motion of interacting particles”. Models of
many-particle systems are often used in the field of physics, giving each particle a set of ‘fuzzy’ behavioural values such that each is selected randomly between certain ranges. In terms of traffic flow, this suggests that uniform properties cannot be applied to the behaviour of vehicles interacting with each other due to basic individual differences between them and their drivers. Such behavioural factors could include driver reaction time and deceleration capabilities of the vehicle. Sugiyama tells us that phase transition, bifurcation of a dynamical system and pattern formation, among others, are all characteristic features of collective phenomena. Furthermore, the appearance of this physical mechanism should not be unexpected in socio-dynamical objects, such as the entities of traffic flow and congestion.

Bearing this in mind, Sugiyama successfully simulated a traffic jam in a system without a bottleneck. The crucial requirement for this experiment was the knowledge that “the effect of collective motion caused by the interaction among vehicles [...] is originated by drivers seeing other vehicles.” So as the critical density is passed, the amount of headway between vehicles decreases, allowing drivers to see and behave appropriately to each other’s vehicles, giving the effect of collective motion. Finally we see that “the effect [of collective motion] makes the free flow unstable and generates a traffic jam similar to phase transitions and pattern formation in non-equilibrium many-particle systems.” These cases of pattern formation are often referred to as ‘stop-and-go waves’ or ‘shockwave jams’. For the purposes of this project, we will be referring to these events as shockwave jams.

### 2.3.2 Shockwave Jams and Congestion Graphing

Carrying on from our discussion about critical density, it follows that we need to look at the way in which driver interaction behaviour corresponds to collective motion, and how this equates to the formation and sustainment of shockwave jams. Understanding how vehicles flow under congested circumstances may then help us differentiate between a road that is congested and one that is merely at maximum flow.

When a vehicle moves along a highway, one of the driver’s aims is to avoid colliding with the vehicle in front, meaning that he will slow down when there is a short headway between him and the vehicle in front (Sugiyama et al., 2008). It is this simple property of the motion of vehicles that paves the way for mathematical models of traffic flow, in particular car-following and lane-changing models. Based on this we can observe traffic flow as a non-equilibrium physical system, with two states (or solutions): free flow and jam flow. In a free flow state, cars travel at more or less the same high velocity with a large headway between them, whereas jam flow see cars moving and stopping in clusters at a low velocity.

An interesting way of explaining this is based around the idea that fluctuations continually occur between vehicles during traffic flow. Before critical density is reached (i.e., the vehicle density is low), these fluctuations are likely to dissipate due to large headways
between vehicles, maintaining the state of free flow. However, once we reach critical density, the fluctuations cannot disappear and instead grow larger until free flow is broken. The fluctuations effectively travel backwards through traffic in a jam state, causing ripple waves of slow or stopped traffic. The experiment described by Sugiyama in his paper effectively upholds these ideas, successfully creating a jam flow situation from an original state of free flow with no bottleneck. The experiment took place on a single lane circuit of 230m in circumference, with 22 drivers spaced evenly apart. The vehicle density was such that it satisfied “the condition for the onset of the instability of free flow”, with vehicles initially coordinated to travel at a consistent speed of approximately 30 kmh. As the experiment started, the drivers were only instructed to follow the car in front at a safe distance whilst still trying to maintain a speed of 30 kmh. A state of free flow was sustained initially, but fluctuations could be seen soon after in the headways between vehicles and slowly but surely the free flow was broken and a traffic jam could be observed as vehicles started to stop for periods of time. A shockwave jam could be seen as the wave of clustered traffic travelled upstream at a consistent velocity.

In an accompanying NewScientist article published in March 2008 (Glaskin, 2008), Sugiyama is quoted as saying “Although the emerging jam in our experiment is small, its behaviour is not different from large ones on highways”, making the experiment applicable to the aims of this project. The basic reason for the fluctuations occurring is likely due to human error. Tim Rees of Transport Research Laboratory in the UK commented that “[he suspects] that the trigger would either be a particular driver who was more nervous than the rest, or a particular location on the circle where the capacity was slightly lower”, adding that “If they had set up an experiment with robots driving in a perfect circle, flow breakdown would not have occurred”.

An interesting way of visualising the development of shockwave jams can be produced by graphing each vehicles distance travelled against time. Sugiyama shows a static example for this, calculated from the observations of the experiment from a 360-degree camera at the centre of the circuit. However, an applet developed by Cay Horstmann (Horstmann, 2008) graphs these properties progressively by scrolling the graph upwards, allowing us to modify the vehicle density and chance that cars will slow down and observe the outcome (a snapshot of this can be seen in Figure 2.2). The underlying simulation is based on the cellular automata approach, in that a freeway is broken up into a number of grid-points whereby each can be populated by a single vehicle at any one time. On top of this, a set of basic behavioural rules are applied to vehicles to determine their speed (in grid points per time interval) and the rate at which they accelerate and decelerate. The last rule (which is perhaps the most intriguing) states that at each time interval there is a chance of individual vehicles slowing down by one grid point for no good reason. This is based on the principle that humans are liable to make errors and cannot always consistently control a vehicle when they are distracted in some way, as we will discuss later.

When we set the chance of driver slowdown to zero, and increase the vehicle density to
the maximum (one vehicle per grid space) we notice that the road can still handle this level of occupancy. Referring to the comments made by Tim Rees earlier, this situation equates to that of robots driving at perfectly consistent speeds. As time follows the y axis, and distance on the x axis, each vehicle’s position at a given time is denoted by a dot, with every tenth vehicle shown in red for ease of visualising each vehicles progress. In the above scenario, each vehicle shows a straight progress path at about 30 degrees from the horizontal. If we now introduce a chance of vehicles slowing down, we see that cars start to cluster together, seen by thick black lines. If a shockwave jam occurs, we start to see vehicle paths of increasingly more vertical orientation, denoting that the vehicle stays in the same grid space for consecutive time intervals.

The model used for this visualisation is fairly simplistic in describing driver behaviour, but would be a useful way of providing output for our own simulation. The idea that distractions are a common cause for drivers slowing down is particularly interesting, especially in terms of explaining driver behaviour that is not a part of collective motion. Sugiyama’s work shows us that it is possible for shockwave jams to occur without a bottleneck which should allow us to simulate them fairly accurately. However, we have merely skimmed over the explanation for fluctuations occurring in the first place, simply attributing it to human error and driver distractions. In order to build an accurate simulation for the formation of shockwave jams, we really need to understand what behaviours cause drivers to slow down, otherwise we will be modelling a collective of robots that will never produce a congested
2.3.3 Why Do Drivers Slow Down Unnecessarily?

As we saw in the last section, there seems to be a belief that the onset of traffic jams can be at least partially attributed to drivers slowing down unnecessarily. Unfortunately neither of the examples can provide any clear evidence for this being the case, but common sense and personal experience would lead us to believe that any kind of distraction whilst driving would make it harder for the driver to control a vehicle consistently, as with any cognitive task.

A study by Baker and Spina questioned focus groups about their driving behaviour and awareness of distractions whilst driving (Baker and Spina, 2007). As a result, the survey determined that non hands-free mobile phones were considered to be the largest distraction, with 35% of participants claiming they slowed down when using one. Similarly, the same behaviour was claimed for other distractions within the vehicle such as tuning the radio or children in the back seats. Unfortunately this was not an observational study, so the results may not be entirely accurate. On the other hand, it does show us that it is not infeasible for a driver to slow down for reasons unrelated to the current driving conditions.

In chapter 4 of “The Psychology of Driving”, Hole presents a range of studies into driver distraction that look at additional resulting behaviours (Hole, 2006). A study by Alm and Nilsson (p. 74) involved asking participants to carry out a cognitive task using a mobile phone whilst driving in a simulator. When driving along a straight road (the ‘easy’ driving task) it was found that using a mobile phone increased the mean reaction time from 0.95 to 1.3 seconds. As an example, this means that drivers would be slower to notice a brake light ahead and decelerate accordingly, and are therefore deemed to be distracted by such an activity as conversing on a mobile phone. This is interesting, as in a stream of dense traffic where the second to front driver is distracted in such a way, if the leader of the stream brakes, the second to front driver is likely to amplify this braking effect due to the slower reaction time. This model of driver behaviour could also therefore be applied to the simulation we propose to develop.

2.3.4 Continuous vs. Discrete, Deterministic vs. Stochastic

We have already looked at types of simulation in terms of scale, whereby both micro- and macro- simulation can be used depending on the how coarse the results are required to be. However there are two other main ways in which simulations often differ; continuous versus discrete modelling, deterministic versus stochastic behavioural modelling (Lieberman and
The first looks at the way we represent time in the simulation. A true continuous model would update each entity’s state infinitely many times per second, something that is technically impossible in terms of computing. Although driving is a continuously changing event (the driver is always responding to new stimuli) we would be better off modelling it in a discrete fashion, whereby time is split up into ‘ticks’ and a new state is computed for each entity when on a tick. Furthermore, there are two forms of discrete modelling, time and event driven. Event driven modelling promotes computational efficiency, as certain entities do not change state and are ‘idle’ until a certain event occurs. For example, a traffic light changing to green would be an event that triggered vehicles to start moving, but until that event occurred the vehicles would not have had their state changed. Due to the nature of the scenario we wish to simulate, we will instead be using the discrete time method, whereby every entity has its state updated on every tick. For the majority of our simulation, vehicles will be updating their velocity continuously based on what they see ahead. Even for states of congestion, it would be impractical for a vehicle to send an event to the one behind it when it starts moving from stationary, when the velocity computation could just as easily be skipped if a vehicle notices that the one in front is not moving.

Deterministic versus stochastic describes the way that entity behaviours are computed. In a deterministic system, every entity would be seen to display the same behaviour when faced with the same condition or scenario. Although a simulation based on this model would be capable of developing states of congestion, it is rather simplistic in defining human behaviour. In actual fact, a more accurate model would apply a certain randomness to the chance of an entity displaying each of a given set of behaviours; this is known as a stochastic simulation. Although we may want a method of changing the chance each driver has a certain personality trait (that causes certain behaviours to prevail over others) this is still stochastic as we cannot accurately predict what any driver might do in a certain situation.

### 2.3.5 Car-Following Models

As we talked about earlier, car-following and lane-changing are the two main models that govern the movement of vehicles in a microscopic traffic simulation. There are a number of variations on both, some published in the early days when traffic modelling became a popular area of research, each with differing levels of complexity and variable consideration. First we will look at the range of car-following models available as this is the most basic form of behaviour for any driver travelling behind another vehicle.

One such model is the Intelligent Driver Model (IDM), based on the acceleration function below (Wikipedia, 2008a) (Kesting and Treiber, 2008):
\[
\dot{v}_\alpha = \frac{dv_\alpha}{dt} = a \left( 1 - \left( \frac{v_\alpha}{v_0} \right)^\delta - \left( \frac{s^* (v_\alpha, \Delta v_\alpha)}{s_\alpha} \right)^2 \right)
\]

where \( s^* (v_\alpha, \Delta v_\alpha) = s_0 + v_\alpha T + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{ab}} \)

The acceleration function incorporates two strategies, one for the free road condition where there is no other vehicle immediately ahead of the driver, and another for braking when the headway between the driver and the vehicle in front is less than the driver’s desired minimum headway. In the free road condition, the vehicle’s acceleration is at its maximum \( a \) for low velocities, and slowly diminishes as the vehicle’s velocity \( v_\alpha \) approaches the driver’s desired velocity \( v_0 \). This allows a single vehicle on the road to reach \( v_0 \) without any interruptions. The braking condition is dominant for situations where the vehicle is approaching another at a high rate or where there is a small distance between the two vehicles and speed is negligible in difference. At high approaching rates, the vehicle attempts to compensate for the difference in velocity without passing the comfortable braking deceleration \( b \). At small distances, the vehicle attempts to increase the headway between vehicles to that of the desired time headway \( T \).

An interesting effect of the IDM is that it does not allow vehicles to collide with each other. A minimum gap between vehicles \( s_0 \) is defined which forces the vehicle to decelerate at a rate higher than \( b \) if this restriction is compromised. This makes the model very attractive for use in our simulation as we do not want to factor in collisions as a cause of traffic congestion. Of additional note, this model is classified as time-continuous but can be used in a discrete manner.

Another main model is the Full Velocity and Acceleration Difference Model (FVADM) (Zhao and Gao, 2005). As the name suggests, when computing a vehicles velocity in respect to another, the difference in acceleration between the vehicles is taken into account as well as velocity. This model extends beyond many others developed before it that were deemed too simplistic, starting with the Optimal Velocity Model (OVM) first proposed by Bando et al (Bando and Hasebe, 1995). This calculated the optimal velocity for a vehicle based on the headway distance between itself and the vehicle in front. Although able to successfully model the jamming transition, comparison of empirical and field data suggested that “high acceleration and unrealistic deceleration occur in the OVM.” Helbing and Tilch then made an improvement to the OVM that took into account the velocity difference between vehicles when the leader’s velocity is lower (negative velocity difference): the Generalized Force Model (GFM). Unfortunately, neither the OVM nor GFM were capable of explaining the traffic phenomena described in Martin Treiber’s paper, such as stop-and-go waves. This
was due to vehicles not braking when the vehicle in front was travelling at a much larger velocity, despite the headway being less than the minimum. This meant that waves could not appear in traffic queues as they are commonly seen. This paved the way for another model, the Full Velocity Difference Model (FVDM) that also took into account positive velocity differences. The problem now was that the GFM and FVDM were both capable of avoiding a collision when modelling a vehicle slowing down on approach to a stationary vehicle, but not in the more urgent case where the vehicle in front was decelerating. Because of this, the Full Velocity and Acceleration Difference Model (FVADM) was finally created to take into account the acceleration difference between vehicles. This is based on the fact that a following driver can see the brake lights of the leading vehicle switching on and off, and therefore consider a course of action for slowing down appropriately. This indicates that acceleration difference plays an important part in traffic dynamics. Just like the IDM, the FVADM does not allow collisions to occur, unlike its predecessors.

Both the IDM and FVADM could realistically be used in our simulation, indicating that we may need to test both for their strengths and weaknesses during an initial stage of prototyping. Although possible to configure these models to allow for differences in vehicle acceleration and desired velocity (amongst other things), it effectively has the problem that the observed driver behaviour would be robotic and deterministic in nature. Differing desired velocities between vehicles could cause shockwave jams to form for a stretch of road that is above critical density, but not taken into account are the driver-specific behavioural traits such as slowing down without obvious cause. In order to attribute these behaviours to the likelihood of creating congestion, we could adapt the model to account for them, however it would probably be easier to define our own models for individual driver behaviour and compute them (along with the IDM or FVADM) in-line with each other.

2.3.6 Lane-Changing Models

Various models of lane-changing behaviour appear to agree on 2 general phases that describe the process from a driver’s point of view; choice of lane and gap acceptance (Toledo, 1997). Ahmed et al. also notes that there is a third phase that precedes the other two, which is the decision to make a lane change in the first place, based on the presence of some undesirable condition in the current lane (Ahmed, Ben-Akiva, Koutsopoulos and Mishalani, 1996). As this phase is based on a latent decision process, it is likely to be ignored in mathematical models given that the exact time that this phase occurs is unobservable when collecting data.

Ahmed et al. considers the lane choice and gap acceptance phases as a binary decision tree, shown in Figure 2.3. The situations in which a driver considers a lane change can be classified as either mandatory (MLC) or discretionary (DLC). Conditions that promote a MLC include the observation of the driver’s current lane closing at any point before
they intend to leave the road. Examples of a DLC being considered include situations where the driver’s current lane is travelling slower than his desired velocity or if there is an indication that vehicles ahead are decelerating. Toledo indicates an important additional situation where a DLC may be considered, whereby a lane to the driver’s nearside (normally considered to be a slower lane) is unobstructed for the immediate foreseeable future (Toledo, 1997). As we can see from the diagram below, despite a driver progressing down the MLC or DLC branches, the actual action of changing lanes will not actually occur if the conditions in the target lane are not acceptable, and will instead be delayed until the lane is evaluated to be acceptable. Because of this, a driver that is required to perform a MLC may find the action unacceptable, but instead choose to carry out a DLC in the meantime.

![Figure 2.3: A binary decision tree for lane change decisions.](image)

Ramanujam indicates that one drawback of this model and some of its predecessors is the lack of any trade-offs being considered between the two types of lane change, as they are considered separately from each other (Ramanujam, 2007). Also of note is the assumption that it is always known whether a MLC is required of a driver or not, whereas this is a typically unobservable part of driver behaviour.

Toledo presents a model that builds on Ahmed’s, but instead allows for trade-offs between mandatory and discretionary lane change (Toledo, Koutsopoulos and Ben-Akiva, 2007). Figure 2.4 shows vehicle A in the left lane with the intention of exiting the freeway, and the slow moving vehicle B in the right lane (note that the diagram depicts an American freeway whereby vehicles enter and exit from the right lane). Toledo states that “In current models once vehicle A enters an MLC state it will change to the right lane and stay there until the off-ramp. The presence of vehicle B does not affect this behaviour. The
proposed model [by Toledo] captures the trade-off between the utility of being in the correct lane (mandatory consideration) and the speed advantage of the left lane (discretionary consideration). Hence, the driver may choose to stay in the left lane until it passes vehicle B.

In considering Toledo’s model, Ramanujam notes that there is still an aspect of lane changing that is not considered; the choice of a target lane that is not adjacent to the current lane (Ramanujam, 2007). The assumption that drivers exhibit myopic behaviour in these models suggests that a driver in the far right lane of a 3 lane motorway would never desire to move to the far left lane without first switching to the middle lane and undergoing a second round of lane change consideration. To incorporate this, Choudhury developed the target lane model, whereby a driver chooses the lane with the highest utility, even if it is not directly next to the current lane (Choudhury, 2005).

Figure 2.4: A vehicle may consider trade offs between a MLC and a DLC.

Additional to the modelling of choosing a desirable lane, another factor of lane changing models is that of gap acceptance. This is the process whereby a driver evaluates a target lane for its ability to accommodate the vehicle in a suitable length of free space (not occupied by other vehicles) once the decision has been made to perform a lane change (either mandatory or discretionary).

Models of gap acceptance are based mainly around the lead and lag gaps visible in the target lane, calculated by the distance between the vehicle that is changing lanes and the adjacent leading vehicle (lead) and trailing vehicle (lag) in the target lane (Ramanujam, 2007). The gap that a driver will accept (the critical gap) generally varies between and within drivers, and can also be modelled to depend on additional factors such as driver cautiousness (being wary of the first gap the driver observes: ‘look before you leap’). Figure 2.5 shows the lead and lag gap positions, both of which must be acceptable for the critical gap to be acceptable and a lane change to occur.

Many of the state-of-the-art models used for lane changing are very complex in comparison to car following models such as the IDM. Some studies look to create increasingly accurate
extensions to the layered models, such as the impact of past decisions on gap acceptance behaviour. For example, critical gap measures may change for mandatory lane changes as the need to switch lanes becomes more urgent. It can be argued that the complexity of these models is beyond the scope of this project for two main reasons. Firstly, car following behaviour appears to be more important in modelling shockwave jams than lane changing behaviour, as seen earlier in the experiment by Sugiyama et al., in which only a single lane of vehicles allowed a traffic jam to develop. Secondly, whilst Choudhury’s target lane model would give us one of the most accurate representations of driver lane changing behaviour, there are still far too many factors that we cannot easily account for, such as courteous drivers allowing faster vehicles to pass before changing lanes or decelerating to allow drivers ahead to change lanes in front of them.

As a result of this, the level of accuracy required for lane-changing behaviour should be considered for the project implementation, once the feasibility of implementing a model such as Choudhury’s has been determined. Depending on time restrictions, this may require that a simple model is initially built that can be expanded on if needed.

### 2.4 Summary of Literature

In this section we have reviewed a range of literature that will help us to design and implement our own traffic simulation for modelling the causes of congestion.

The initial look at approaches of measuring congestion and the research into critical vehicle density has been insightful into the possibilities and problems of recognising states of congestion. It is clear that the simulation framework should test for certain extreme values such as low velocity and high vehicle density across the population in order to provide
feedback on the state of the system, yet the task of accurately defining congestion and asking the simulation to recognise the transition from free flow to a queuing state proves to be out of the scope of this project. The knowledge of fluctuations between vehicles could be utilised however, in such a way that the simulation could monitor headways between vehicles and provide some form of early warning system for the onset of congestion. Additionally, we have seen that output to the operator in the form of congestion and critical density graphing could be useful for determining the factors behind the breakdown of free flow.

Our analysis of the various types of simulation shows us that a microscopic model using a discrete time engine and stochastic driving behaviour would be most suitable for our needs, allowing us to focus on the individual vehicle interactions that can lead to congestion, based on a varying set of driver behaviours. This set of properties actually appear to be widely used in existing simulation software, as Lieberman’s traffic simulation manual indicates that six of the eleven models investigated use the exact same properties (Lieberman and Rathi, 1992).

We have seen how certain driving factors can cause drivers to lose the ability to control a vehicle consistently, such as distractions within the car. As we saw from the experiment by Sugiyama et al., drivers can find it hard to keep a steady following speed, which was effectively the only reason why congestion formed on the road (Sugiyama et al., 2008). Based on this knowledge, we may want to include user-adjustable variability into the simulation, effectively allowing the user to change the distribution of reaction speeds and chance of slowdown across the driver population. Using extreme values of these may affect the accuracy of the simulation, but it will be useful for analysing which factors cause the largest affect to the process of congestion forming.

Finally, research into the various scientific models of traffic flow that are available has turned up a number of acceleration and lane changing functions that can describe driver interaction with respect to other vehicles and the current driving environment. In order to assess each for its appropriateness we can use a prototyping stage to monitor any large differences in performance between the models in order to decide on the best ones for use in the simulation.
Chapter 3

Requirements Specification

Based on our research of traffic simulation carried out in the literature survey, we now have a good idea of the direction we wish to take the project, with a clear understanding of our aims and objectives. This chapter will analyse the basic requirements for our proposed simulation, as well as our experimental hypothesis and any further considerations that must be kept in mind.

3.1 Character of work

Following on from our findings throughout the literature survey, we propose the development of investigative simulation software to reinforce and build upon current explanations for traffic congestion. We use the term ‘investigative’ to describe an evolutionary software development process that is likely to raise additional insight into the problem as we build the simulation software. Due to the nature of the problem, it is perhaps naive to consider that an accurate simulation will be developed seamlessly from an early design process. It is quite likely that a higher degree of trial and error will be required compared to that of a more traditional software development whose requirements are fully known and understood from the start.

We look to evaluate the strengths and weaknesses of individual features as they are developed, so that we may progress through the software lifecycle in a constructive fashion, modifying the requirements as we gain a greater understanding of the problem. An initial set of requirements are proposed, but changes should be expected as the project develops.
3.2 Experimental Hypotheses

Our findings from the literature survey suggest that previous attempts to accurately model traffic flow rely rather heavily on highly evolved car-following and lane-changing models, with little consideration for additional behavioural characteristics of drivers. The data presented by Sugiyama for motorway flow rate observations can be used in comparison to data collected from our own simulation, in order to show that consideration for behavioural characteristics is an important stage of the modelling process. We therefore present the following hypotheses:

- **Hypothesis 1:** The modelling of only car-following and lane-changing models in our simulation will produce higher rates of traffic flow in comparison to the real observed data.

- **Hypothesis 2:** The modelling of behavioural characteristics for drivers in addition to car-following and lane-changing models will produce lower rates of traffic flow and a higher correlation to the real observed data than that of using only the car-following and lane-changing models.

Additionally, we look to extend Sugiyama’s work on shockwave jams by observing their occurrence on a multi-lane road in our simulation, proving that they are not only restricted to single lane traffic. We therefore state our final hypothesis as follows:

- **Hypothesis 3:** Behavioural characteristics will cause shockwave jams to occur in the simulation for both single lane and multi-lane scenarios, showing a positive linear correlation between the number of shockwave jams that occur and the vehicle density of the road.

3.3 Requirements Analysis

To allow us to investigate the hypotheses outlined above, we need to analyse how the simulation should be structured, and which behavioural characteristics should be developed. Here we will form a brief outline of the problem to facilitate the collection of our project requirements. We will be looking at the design and implementation of specific functionality in more depth in Chapter 4.
3.3.1 Hypothesis 1

We require an initial basic implementation consisting of only the car-following and lane-changing models that is capable of modelling traffic ‘robotically’. A basic engine will be needed to provide an inflow of vehicles and update their positions over time. Additionally, we will require a way to quantitatively measure the flow rate of traffic past a particular point in order to compare likewise vehicle densities in our simulation and the real observed data.

3.3.2 Hypothesis 2

For the second hypothesis, we need to decide on the behavioural characteristics we will implement. The most obvious and commonly seen difference between drivers is the choice of a comfortable or desired velocity. In our literature survey we also found that reaction times and random slowdown due to distractions are likely to have a detrimental effect on traffic flow. Furthermore, the experiment by Sugiyama suggests that human drivers can make inaccurate judgements when braking to avoid collisions, so we will also attempt to model this form of behaviour in the simulation.

3.3.3 Hypothesis 3

Our last hypothesis calls for a visual form of congestion graphing, in order to locate areas of queued traffic on a stretch of road over time. In the literature survey we looked at the time-distance graphing technique. This is one possible solution, but we will also consider a new form of congestion graphing if it is more suitable for this hypothesis. In order to support this, we will also look at the possibility of measuring the fluctuations in distance between vehicles as a supplementary measure of congestion.

3.4 Requirements Outline

Due to the investigative aspect of this work, certain requirements may be beyond the scope of the project in terms of complexity. Unfortunately, this will likely remain unknown until some basic aspects of the simulation have been achieved. To accommodate for this, we will split the requirements up into separate categories. The ‘primary’ category will represent the functionality which we can confidently implement successfully, including features that are similar to earlier research projects. The ‘secondary’ category will mostly consist of
those requirements that look to build upon previous research, such that we are less certain of how successful or accurate any such solution may turn out to be. Although there is no correlation to the sets of requirements and our hypotheses, we are confident that we can implement the majority of the secondary requirements successfully in order to draw useful conclusions from the project.

3.4.1 Primary Requirements

- Implement a simulation to model up to 3 lanes of traffic, whereby vehicles may change lanes as desired (thus simulating a typical British motorway).
- Develop car-following and lane-changing algorithms to govern vehicle movements and interactions, based on previous research and existing models.
- Implement a suitable quantitative measure of vehicle flow rate.
- Create a visual bird’s eye view representation of the simulation to aid user interpretation and results gathering.

3.4.2 Secondary Requirements

- Develop algorithms to reflect between-vehicle driving inconsistencies based on the following human behavioural characteristics:
  - Choosing a desired (or comfortable) travelling velocity.
  - Ratings of aggressiveness and the desired minimum gap to other vehicles.
  - Undesired/unnecessary vehicle slowdown.
  - Reaction time to stimuli when changing lanes and following vehicles.
  - Over-cautious braking.
- Develop a form of congestion identification based on average vehicle velocities and flow rate.
- Explore the possibility of visualising fluctuations between vehicles, and thus predicting the onset of congestion.

3.5 Development Tools

The entire simulation will be developed in C# using the .Net Framework 2.0 and Visual Studio Tools. Due to the scientific emphasis of the project, this decision allows us to focus
on developing the appropriate algorithms in a familiar language, also reducing the overhead required to build a user interface for the simulation. Unfortunately this means that the simulation will only run on Windows operating systems, however as a research project it is not intended to be distributed to end users once completed.
Chapter 4

Design and Implementation

4.1 Initial Considerations

Before we continue with the main implementation, we must make certain decisions that govern the overall development process. We also acknowledge the research of common vehicle properties and statistics to ensure that the simulation accurately represents real traffic.

4.1.1 Simulation Metrics

In the simulation, all distance and vehicle positions, velocities, acceleration and deceleration speeds will be calculated in the appropriate metre metrics. Although many such measurements are often defined using mile or kilometre metrics, the metre standard will help to facilitate the development of a simple graphical representation.

4.1.2 Vehicle Properties

In order to simulate vehicles as accurately as possible, we need to define certain properties that are representative of vehicles in the real world, such as their dimensions and speed capabilities. Although this may at first appear insignificant, it is directly relevant, but not limited, to calculations of critical vehicle density and the rate at which congestion travels upstream of traffic.
For vehicle dimensions, we refer to Parkers, an online database for vehicle facts and figures (Parker’s, 2009). By selecting fairly common small and large cars, we can calculate a range for car length. It should be noted that we use a constant width for all vehicles as this will have no effect on the simulation. For our small car, we select the Citroen Saxo (∼3.7m length) and for our large car the BMW 5 Series estate (∼4.9m length). Based on these, we choose lengths of 3.5m, 4.5m and 5m for small, medium and large cars respectively. Additionally we require the inclusion of HGVs in the simulation. Although these vary wildly in length, they account for only a small portion of motorway traffic, so we take an average length of 10m based on various sources.

For acceleration capabilities, a range of car models from the last 20 years were reviewed at Car Specs Directory (Directory, 2009). Acceleration speeds of between 2m/s\(^2\) and 6.5m/s\(^2\) appear to be reasonable, where the higher bounds will be applied only to a very small minority of vehicles in the simulation. In reality, acceleration differs for a certain vehicle depending on its current velocity. We instead use an averaged value based on timings for vehicles to accelerate from 0-60mph to avoid complication. Values for HGVs were obtained from a paper by Short et al., ranging between 1m/s\(^2\) and 1.9m/s\(^2\) (Short, Pont and Huang, 2004). For now we will simply designate a deceleration speed that is double the vehicle’s acceleration, based on an averaging of the graphs in the above paper.

The last main property we require is vehicle velocity. Although this is not a fixed attribute of the car (except for limitations of the engine; due to speed limits most drivers would never reach this point), it is understandable that there will be differing desired maximum velocities between drivers. Based on a motorway traffic survey carried out by the Department for Transport we believe we have created a fairly accurate table for the distribution of desired velocities, both for cars and HGVs (DfT, 2008). This will be our first human characteristic that can be enabled from the user interface.

No correlation will be made in the simulation between the desired velocity of a driver, their vehicle size and possible acceleration speed.

### 4.1.3 Vehicle Distribution

We will use basic user interface sliders to manipulate the flow of traffic in the simulation and the percentage of vehicles that are cars and HGVs. This will be the first way of altering the traffic scenario, as using fixed values wouldn’t help for investigating the critical density. Statistics compiled by the Department for Transport show that on average, cars will make up 85% of the traffic population on a motorway, compared to HGVs 15% (when considering only these two classes of vehicle) (DfT, 2008). These values will therefore be set as the default in our simulation.
4.2 Simulation Development: Phase I

Here we will review details regarding the implementation of the main simulation features, and any problems that are overcome in the process.

4.2.1 Basic Simulation Engine

As mentioned earlier there are many choices to be made about the style of the simulation, many of which affect both the level of accuracy that can be achieved and the relative computing power required to run. We will be using a microscopic approach as we are interested in modelling the differences and individual interactions between vehicles. Were we to take a macroscopic approach, we would not be able to obtain such a low level of measurement or be able to accurately speculate on the critical vehicle density. There is a trade-off however, in that simulating such fine grained interactions means we may be restricted in the number of vehicles that can be efficiently simulated simultaneously.

The next decision is that of continuous versus discrete time stepping. As we noted before, a true continuous simulation is impossible based on the mechanics of current day computers, but we can get very close to this. Although a moving vehicle can have infinitely many states per second, it is logical to assume that a driver’s viewpoint of his position is only updated a few times a second. In comparison to a computer, a human driver’s relatively slow decision making processes will restrict him from making changes to the input of the vehicle very often. We can use this idea to mitigate against inaccuracies in a discrete time simulation as long as we select an update delay that is faster than a human’s approximate thinking speed. To achieve this, we have chosen an initial engine tick time of 50 milliseconds, where ‘tick’ refers to the amount of time between updates of the entire simulation. This allows us to update the state of all car positions, velocities and accelerations approximately 20 times per second, which should give a visibly smooth flow of traffic. Additionally, as each vehicle will have its properties changed very frequently, there is little risk of vehicles making mistakes, such as getting too close to each other before realising that they need to slow down. We will not be using an event-driven update process for any part of the simulation for reasons explained earlier, mainly the lack of any driving situation where the driver is not required to respond to stimuli.

Our final decision is that of deterministic versus stochastic modelling. As we wish to consider human driving characteristics, the simulation will be stochastic in the sense that behaviour displayed will be different between vehicles. Despite the fact that a single driver will act similarly in all situations based on the chosen properties of the vehicle and themselves, these will be selected at random using our distributed velocity and acceleration table, for example. Also, certain characteristics such as the random chance of a driver un-
knowingly slowing down are what will cause the largest amount of unpredictable behaviour, though we will develop controls that will allow these to be turned off for scenarios that are more deterministic in their approach.

4.2.2 Car-Following Model

The simulation allows the user to select from a list of road lengths in the range of 150-2000m. Using a flow rate control that allows the user to determine the number of vehicles that enter the simulation per minute, the corresponding timer instantiates a new vehicle (based on the car to HGV ratio) with randomly selected attributes and inserts it into one of the 3 lanes at either the 0 metre or the half way mark, depending on the chosen point of inflow. The decision to allow traffic to enter at the half way mark is based on the ability to see congestion forming upstream from the inflow point in this mode. If there is no other vehicle at or behind this mark, the vehicle accepts this starting point, otherwise it positions itself behind the trailing vehicle in that lane at an appropriate following distance in relation to its velocity. From this point onwards it moves forward with traffic until it reaches the length of the simulated road section, at which point it is simply removed from the simulation.

In order to ensure that vehicles travel at the correct speed and do not collide with each other, we require a car-following model, as discussed in our literature survey. We have chosen the Intelligent Driver Model (IDM) for its relative ease of implementation compared to other models and the capability to extract a free road term from the overall equation, such that the computational complexity is significantly less for vehicles that are not following closely behind another. Additionally, this model is used in Martin Treiber’s work, our main focus for extending to a 3-lane model. Shown below are the two terms we will use for free road behaviour and interaction behaviour. It should be noted that we use a slightly altered interaction term to our source as we use a more generalised definition of vehicle interaction (Wikipedia, 2008a).

\[
\dot{v}_\alpha^{\text{free}} = a \left( 1 - \left( \frac{v_\alpha}{v_0} \right) ^\delta \right)
\]

\[
\dot{v}_\alpha^{\text{interaction}} = a \left( 1 - \left( \frac{v_\alpha}{v_0} \right) ^\delta - \left( \frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha} \right) ^2 \right)
\]

The IDM works on the principle that each driver has the desire to keep a certain time distance between his vehicle and the leading vehicle (i.e. a desired time distance of 2
seconds at \( 27 \text{m/s} = 2 \times 27 \text{m} = 54 \text{m headway} \). At slower velocities, this gap will be reduced as the driver will be forced to travel at the leading vehicle’s velocity if he cannot change lanes to overtake. This is true until the point at which the velocity of the leading vehicle is so slow that the following vehicle would be forced to leave an unrealistic distance between them. To avoid this, the IDM accounts for a minimum standing distance, i.e. the distance left between vehicles in a stationary jam; we define this as 2 metres.

This is where our second human characteristic comes into play. It has been hinted by various people such as Ahmed et al that drivers can be separated into similar behavioural groups based on an aggression rating given to them (Ahmed et al., 1996). Drivers with high aggression ratings are expected to show very erratic behaviour, such as tailgating vehicles to bully them out of the way and performing illegal undertaking manoeuvres; your typical road hog perhaps. On the opposite side of the spectrum are the relaxed drivers who will happily follow a leading vehicle at a slower speed than they wish to be travelling, yet lack the urgent desire to overtake; the conservative driver.

We therefore link a driver’s desired velocity to their desired following distance, as it seems reasonable to suggest that the aggressive drivers are those likely to travel fastest, whereas the conservative drivers wish to save fuel and drive at a speed that can realistically be kept consistent. A study of aggressive driving behaviour by Leon James would appear to support this idea, with the finding that those [drivers who] drive the "soft" cars (family and economy) tailgate less than those who drive the "hard" cars (sports and SUV) with a ratio of two to one (James and Nahl, 2009). We therefore give each driver a random value for aggressiveness between 0 (least aggressive) and 1 (most aggressive), which dictates their desired velocity (based on the distribution tables) and their minimum desired following distance. Our smallest following distance is set as 0.25 seconds (for very aggressive drivers), with the largest being 2.25 seconds. These are based on prior experience and our own observations of motorway traffic, and are therefore very experimental in nature and subject to be modified later on. These values are calculated using the following expression:

\[
\text{MinimumFollowingDistance} = 0.25 + (2 \times (1 - \text{Aggression}))
\]

4.2.3 Simple and Efficient Vehicle Tracking

In order to update each vehicle over the stretch of road being simulated, we need a mechanism for tracking each vehicle’s position relative to others. Unfortunately there is little evidence as to how this is actually done in similar implementations, although we did consider in the literature survey that a multi-agent based engine could be used. Erol’s was one such paper explaining the benefits of multi agent based systems, but in general these only seem appropriate for complex traffic networks with numerous intersections (Erol et al., 1999). For our simulation we argue the use of an array based storage and update mechanism for
vehicles.

Let us first consider a multi agent based architecture. Vehicles could be instantiated such that they only have knowledge of their local surroundings, which is generally the only information required for them to select an appropriate speed. Vehicles could report their positions if required, such that other vehicles can update their understanding of their surroundings. But is it really required that each vehicle have its own intelligence, when the same basic principles of car-following and lane-changing will be applied to them all? After all, we are not simulating any change in intelligence for drivers, although this could be an interesting area to look at in future work around the subject.

Instead we look to build the engine in a monolithic fashion. As we are modelling a straight stretch of road with no intersections, we can realistically store all vehicles inside an array structure in the order that they appear in the lane. As long as we update the entire set of vehicles simultaneously (and, with such a fast engine tick being used, there’s no reason why we wouldn’t), this approach requires no more retrieval complexity for finding vehicles and calculating distances between them than a multi agent approach might. This also allows for easy retrieval of nearby vehicles in an adjacent lane by traversing the array and matching distance bounds to the position of each vehicle. Based on our maximum road length, average vehicle length and minimum spacing gap, we would expect an average look up in the worst case of:

\[
\frac{\text{Max Road Length}}{\left(\frac{\text{Average Vehicle Length} + \text{Minimum Spacing Gap}}{2}\right)} / 2 = \frac{2000\text{m}}{\left(\frac{(3.5\text{m} + 5\text{m})}{2}\right) + 2\text{m}} / 2 = 160 \text{ vehicles per lane change}
\]

Taking into account the infrequency of lane changes, by today’s processing standards this should prove little problem for the simulation engine. Additionally, if slowdown is experienced, we can look at using a sorting method to significantly reduce this value.

As we are using such a fast engine tick, the accuracy lost from updating each vehicle one after the other will be minimal, as there will be very little difference in position and velocity each time they update. We will however need to ensure that we don’t allow any vehicles to change lanes until each vehicle’s position has been updated, to avoid updating any vehicle twice.

4.2.4 Developing a Suitable Lane-Changing Model

Our previous research looked at various models for lane changing, most of which consist of a two stage decision process; lane choice and gap acceptance. We will be building our own model based on this process as many existing models are over-complicated for our needs.
In the lane choice stage we check for both the availability of a left hand lane for vehicles at their driver’s desired velocity, and the availability of a right hand lane for vehicles where the headway to the leading vehicle is that of the driver’s minimum desired gap and the vehicle’s velocity is less than the driver’s desired velocity. We say that a driver will only consider a change down (to the left) if they will not catch up to a slower vehicle within 10 seconds. To calculate this, we check for the closest leading vehicle in the current lane or left hand lane and project positions for them 10 seconds into the future based on their current positions and velocities, including the target vehicle. We then compare the projected gap between these vehicles and the target vehicle to the target vehicle driver’s desired minimum gap. It should be noted that we check the current lane as well as the left hand lane as we must check that the driver would not need to change back up again to overtake the vehicle in his current lane to avoid illegal undertaking. Figure 4.1 displays the gap calculations required. The red vehicle denotes the target, while the purple vehicles denote the leading vehicles of the current and left hand lanes.

For changing up lanes (to the right) we must simply check that there is a large enough gap in the right lane for the vehicle to move into, based on the driver’s minimum desired gap, in the same way that figure 4.1 shows the driver checking for an acceptable gap in the left lane.

In the simulation, we have chosen to make lane change manoeuvres instantaneous, instead of a gradual changing approach. To this effect, when a vehicle commits to changing lanes (chooses a lane and finds a suitable gap) it is removed from the array for its current lane and inserted at the correct point in the array for the target lane. In effect, this means that on the next engine tick, vehicles will now calculate their position based on the new order of vehicles.

We can justify this by considering a human response to a vehicle changing lane. If a vehicle is indicating to change lane and they start moving over (the point at which they change
lanes in our simulation), the vehicle following behind will start acting as if the vehicle is no longer in that lane. Conversely, the driver of the new trailing vehicle in the target lane will also immediately start adjusting his velocity based upon the vehicle that is changing lanes.

One last point of note is the decision to continue simulating vehicles past the end of the road. With lane changing implemented, we saw a great deal of unnatural behaviour where vehicles disappearing would cause their trailing vehicles to switch down lanes near to the end of the road. We therefore simulate the road for 250m past the selected length in order to reduce the visual signs of this occurrence, such that it will not be considered when we come to implement a way of measuring congestion.

4.2.5 Considering Human Reaction Times

Using Visual Expert as a reference, we can define a set of rules that determine the reaction times of individual drivers in the simulation (Expert, 2009). This is our third human characteristic, based on the idea that stimuli while driving can take longer to register in a human than in a computer and as such earlier information about the position and velocity of a vehicle may be used to calculate a driver’s own position instead of current data. The article suggests that reaction time tends to range from between 0.7 and 1.5 seconds, based on the state of awareness of the driver. For ease of computation, it would make sense to take values between 0.75 and 1.5 if we choose to make it random. It should be noted that driver reaction values should ideally be multiples of the time between engine ticks, otherwise inconsistencies will arise from discrete data boundary conflicts. Further limitations may also be necessary depending on how frequent the engine ticks occur, else we may end up holding an overly large number of values for each vehicle, thus slowing down the simulation.

An initial analysis of the reaction time problem would suggest that each driver should adjust his acceleration to be at an optimal distance from the leading vehicle based on that leading vehicle’s position at the current time minus the following driver’s reaction time. However, this will cause problems with keeping the following gap, as the driver would actually keep a gap equal to their desired gap plus the distance they would travel over their reaction time. Instead, our initial algorithm will base the following driver’s velocity and acceleration change on a projection of the leading vehicles position at the current time, based on the leading vehicle’s position and velocity at the current time minus the following vehicle’s driver’s reaction time. This effectively means that when the leading vehicle starts braking sharply, the following vehicle will continue to accelerate or maintain a steady speed for the duration of their reaction time, and then start braking once they have seen’ the deceleration occur. Because of this, we will still enforce a policy in our model of the IDM to avoid collisions by adjusting deceleration values no matter how unreasonable they are.
This is very much an experimental behavioural characteristic, as there is little concrete proof to suggest exactly how reaction times change while driving. We will investigate how this characteristic appears to affect traffic flow in Chapter 5.

4.2.6 Extending Reaction Time Behaviour to Lane-Changing

We assume that reaction times also lend themselves to changing lanes, such that when a driver first makes a decision to change up or down, he waits a period of time to check that the target lane is actually safe. As discussed earlier, Ahmed states that the decision to change lanes is a latent and unobservable step prior to the two stage process, so we have no idea how long a driver waits before changing (Ahmed et al., 1996). We therefore choose not to implement a longer waiting time before changing lanes as this would mainly be based on guesswork and very hard to prove the accuracy of.

The implementation of this reaction time at all is actually aimed at fixing a problem with the car following model. Currently, the IDM causes fluctuations in a vehicle’s velocity when they are at the minimum gap and have a higher desired velocity than the leading vehicle. This can cause a vehicle to switch lanes back and forth repeatedly based on the continually decision that the other’ lane has best utility. By requiring a vehicle to commit to the lane change for the full duration of their reaction time, we have limited the occurrence of this erratic behaviour to a few very rare cases.

4.2.7 Random Slowdown and Over-Braking

The last two human characteristics that we wish to simulate are the chance of a vehicle randomly slowing down for a period of time, and the tendency for driver’s to apply the brakes over-cautiously.

It is considered that random slowdown is a possible outcome of drivers being distracted in some way, such as talking to passengers or tuning the radio. The study we looked at earlier by Baker and Spina (Baker and Spina, 2007) suggests that participants of focus groups admitted to slowing down whilst being distracted, but were unable to say exactly how large this effect is. Although no evidence has been shown, it seems likely that slowing down could also be a result of complacency while being in a relaxed driving state, travelling at your desired velocity with no stimulus immediately ahead.

Although there is no evidence of the extent to which such a situation slows a vehicle down, we suggest experimentation with this behaviour to see what effect it would have in small amounts. We implement the chance of slowdown in any vehicle to be selected randomly at
a probabilistic rate of 2.5% per second. Once in this state, the driver will progressively lose 0.45m/s (1mph) from his velocity each second for 5 seconds. This applies to any vehicle no matter the speed, allowing for both complacency at the desired velocity and the possibility of distractions occurring at any velocity. Based on this initial configuration, we would expect each vehicle to be in a state of slowdown for approximately 12.5% of their travel duration, or 5 out every 40 seconds travelled.

There are also a number of suggestions that applying the brakes more than is necessary could be a large factor in the development of shockwave jams, especially when the road is close to vehicle density. This is based on the idea that humans cannot always make accurate judgements, especially if they have little time to react to an incident developing in front of them whilst driving. In this case, it is expected that (at least the majority of) humans would rather leave more than enough space between them and the leading vehicle than not enough, such that the situation results in a vehicle collision.

Much like the random chance of slowdown, we look to experiment with over cautious braking as a simulation modifier to see if even a small amount of excess braking displays any differences in congestion build up. Our initial configuration will simply promote a universal braking modifier to every vehicle, at a rate of 1.5 times the required deceleration at any time the vehicle attempts to slow down.

### 4.2.8 Congestion Identification and Graphing

In the literature survey, we considered that congestion must be identified before it can be measured, a fairly straightforward task for a human observer, but perhaps more difficult to judge computationally in our simulation. One interesting approach that we already looked at is the representation of vehicles graphically such that their distance along a finite stretch of road is plotted against time. This allows us to visually identify areas where vehicles are clustered together at slow velocities, as well as track the individual progress of unrestricted vehicles.

One drawback with this idea is that it does not work particularly well for a multi-lane road. When congestion occurs on a motorway, it can generally be seen in equal measures across all lanes, at the same locations. If it were not, congestion would not occur as the slow vehicles would be able to utilise the free lanes. Trying to map the data of all lanes onto a single graph can lead to a cluttered and ambiguous view of vehicles and their paths, as vehicles are adjacent to each other, displaying similar distances. The reason that this graphing works so well on a single lane is due to the fact that no two vehicles can physically occupy the same space, distance wise. In reality, each lane of the road can be distinguished using a separate graph, however this can make it harder to identify general patterns of congestion.
We propose a new graphing model that can support multiple lanes on a single graph, and as such can later be used to analyse separate scenarios in our simulation. Recalling our definition of congestion, we understand that “Traffic congestion is a condition on any network as use increases and is characterized by slower speeds, longer trip times, and increased queuing”. We therefore believe that the key here is to take a measure of vehicle velocity against desired velocity, as a percentage. By averaging these values for all vehicles over a 50m section of road, we can distinguish between one vehicle being locked in behind a slower vehicle and a full blown traffic jam. In Figure 4.2 we show an example of both graphing systems for a single lane road simulation (the average-velocity graph has been resized to more closely match the time-distance graph).

Figure 4.2: Comparison of graphing methods: time-distance (left), average-velocity (right).

In order to understand this new graphing system, it is important to realise that we still measure time on the y axis, and distance along the x axis (in terms of road sections). Each 50m road section displays its averaged vehicle velocities as a thin vertical strip over time. In the sample graph, it can be seen how the road sections are split up by the ‘pixelated’ appearance. For sections where the average vehicle velocity is close to 0% (stationary traffic), a red square is drawn. The scale progressively follows through to orange, to yellow and finally to green to denote average vehicle velocities of 100% (travelling at the desired velocity). This colour scale helps us determine where traffic starts dispersing and eventually returns back to freeflow. One final note on this graphing system is that any section not populated by any vehicles will also display in green, denoting an area of no congestion. Because of the midpoint inflow of the graph, the upper left and right corners are solid green because at the starting time there are no vehicles in those sections.

It can clearly be seen from both graphs that a wave of congestion sweeps backwards from the centre point, as the simulation was set up to allow vehicles to enter at the midpoint of the road. The time-distance graph helps us visualise an average journey for a vehicle in the simulation by looking at every tenth car, denoted in red. However, we believe there are more visual clues as to where the traffic starts to disperse, and more definition of clear patches in the average-velocity graph.
4.3 Further Development: Phase II

In our initial consideration of the problem, we paid little attention to the problem of accurately modelling traffic flow into the simulation. As discussed, we have developed a simplistic algorithm to randomly instantiate vehicles and insert them into the lane that best fits the vehicle properties. Unfortunately, this method is based on a rate of flow per minute, and is not suitable for sustaining a particular vehicle density over the length of road.

This poses a problem in that it limits the accuracy of any tests we carry out to support our first two hypostheses, and any attempts to identify the critical density in our simulation. Such tests require that a measurement of vehicle density be taken, and the corresponding flow rate counted over a period of time. However with our current implementation of traffic inflow, the occurrence of shockwave jams and light congestion can cause the vehicle density to fluctuate wildly over time, making it hard to know which vehicle density each flow rate observation should be mapped to.

To overcome this problems, we propose the following additional requirement for a new phase of development:

- Design and build a new model for traffic inflow to allow for specific vehicle densities to be sustained.

4.3.1 Accurate Traffic Inflow

The idea for a new model of traffic inflow comes from the experiment discussed in the literature survey by Sugiyama (Sugiyama et al., 2008). The idea was to maintain vehicle critical density to show the occurrence of shockwave jams, using an infinite loop of traffic. This idea of using wrap around traffic means that only a small number of vehicles were required for the experiment to take place, and allowed the shockwave jams to continue travelling upstream of traffic for an infinite length of time.

By using a similar model, we can ensure that we also maintain a steady vehicle density. Although the road in our simulation is not a loop, we can replicate this behaviour by inserting vehicles back into the simulation once they have been removed. However, we believe that Sugiyama’s experiment is not entirely accurate of real life traffic. With the wrap around effect, fluctuations between vehicles will continue to grow indefinitely as they flow back around traffic, such that a vehicle can be affected by the fluctuation it caused when it comes back around again. Additionally, simulating traffic flow in the way shown
CHAPTER 4. DESIGN AND IMPLEMENTATION

by Sugiyama throws a few computational difficulties into the equation. For example, if a
driver nearing the end of the road wishes to change lane, he must check the positions of
vehicles within a certain distance in front of him. This means we must also wrap around
calculations for vehicle movement which seems very counter-intuitive given the structure of
our simulation engine. For simulating small distances, this could also cause problems with
vehicles basing their movements on themselves.

To overcome these problems, we propose a model which simply duplicates a vehicle and
inserts it at the start of the lane it was in when it left the simulation. Vehicles will not
wrap around their movement calculations, so their velocity may need to be overridden when
reinserted into the lane if the new leading vehicle is travelling slowly. We believe this will
provide a more realistic traffic flow with fewer complications than full wrap around traffic.
Due to the nature of this model, we refer to it in the simulation as the constant density or
partial wrap around mode.

4.3.2 Flow Measurement Adaptation

When using the partial wrap around mode for traffic flow, we need to make sure that
our method of measuring flow rate accurately represents the selected vehicle density. In
theory, it should no longer matter at which point we measure from, so for simplicity we
continue to increment a counter every time a vehicle leaves the simulation, as was originally
implemented. Of course, this will then cause the vehicle to be reinserted back at the start
of the road. At the start of a partial wrap around simulation, the road will initially be
populated with vehicles at the minimum level of congestion possible, so measuring from
the end could cause inaccuracies. Because of this, measurements are only taken after the
traffic has had a suitable length of time to settle into an appropriate pattern.

4.4 Development Summary

We have successfully implemented an application capable of basic traffic simulation across a
multi-lane road using appropriate car-following and lane-changing models. Furthermore, we
have extended upon this functionality with the ability to optionally include consideration
for a variety of human behaviours that are believed to affect driving efficiency and the rate
at which congestion and shockwaves jams occur and develop. To understand the impact of
these behaviours, we have proposed and developed the functionality to obtain data for flow
rate and congestion over time. Example screenshots of the completed Traffic Simulator
program can be seen in Appendix A and example code is presented in Appendix C.

For the most part, we have included the ability to configure the simulation for running
particular scenarios from the user interface, which will be used for our end testing. Additional to this there are many ways of tweaking performance from within the source code, an activity that was carried out frequently throughout development. Before we look at simulating and measuring individual scenarios, we will first take an in depth look at the experimental findings of configuring and evolving the human behavioural functionality, and how it has furthered our understanding of such behaviours.
Chapter 5

Behavioural Findings

Prior to testing the effect of our human behavioural characteristics on traffic flow, we will discuss our findings throughout the development stage. In keeping with the investigatory approach to the project, we discovered and built solutions to many issues that arose as behaviours became intertwined with each other. Many of these issues were unforeseen at the start of development and only came to light as our understanding of the problem evolved.

In this section we will review some of our key findings on various behavioural characteristics and the effect we believe they have on the accuracy of the simulation. In particular we will only be looking at three of these; reaction times, slowdown and over-braking. We will not be looking at desired velocity and aggression ratings as they are both closely linked to real data collected for motorway traffic, and are therefore less open to experimentation.

5.1 Reaction Times

Our initial implementation of human reaction behaviour used a constant standard reaction time of 1 second for all drivers to aid in debugging problems with our model. Although we can see some major differences in the simulation simply by implementing this uniform behaviour, there are also many limitations which we’ll look at shortly.

We believe human reaction times to be one of the largest contributors to the build up of congestion and shockwave jams. As mentioned in our literature survey, Sugiyama’s experiment in the breakdown of free flow traffic would not have seen congestion forming if the drivers were robots, capable of extremely accurate rational thinking (Sugiyama
et al., 2008)(Glaskin, 2008). Obviously there were more factors to the congestion formation than just reaction times, but the lack of such a behavioural trait means that should a driver inadvertently slow down, all drivers would be able to immediately adjust their speed accordingly to avoid stopping until the driver could make up the speed again.

This is something we have seen in our simulation, in a comparison of drivers with reaction times turned on versus drivers without. We tailored the simulation to allow only one lane of traffic, but with a flow rate that caused a vehicle density far beyond the critical point (90 vehicles/min). In the simulation with reaction times turned on, we saw that vehicles would queue as expected, slowing down enough to stop for the majority of their time in the queue. At the front of the queue, we saw a delay between the front vehicle and its trailing vehicle start accelerating. This is what we would expect, as the following vehicle takes that second to realise he can move again.

In the simulation without reaction times turned on, we saw that vehicles displayed regular patterns of traffic queuing, but never actually stopped. Because they were able to immediately identify movement in the vehicle in front, we saw the congestion dispersing gradually between the front 10+ vehicles. This is unrealistic for human drivers, with the effect of clearing patches of congestion faster than can be seen on our motorways. Additionally, the occurrence of shockwave jams is impossible with such behaviour. Figure 5.1 shows a comparison of the two scenarios where congestion starts the transition back to free flow.

![Figure 5.1: Vehicle queueing: without reaction time (top), with reaction time (bottom).](image)

Using the debugging capabilities of the language, we can see this detrimental effect of reaction times on the speed at which drivers can re-establish velocity after being stopped in a traffic jam. From standstill, we plot the distance between the two vehicles at the front of a traffic jam in the two scenarios. In both scenarios, the two vehicles shared identical values for acceleration and desired velocity.

The results of this experiment can be seen in Figure 5.2. In order to understand the results, we need to think about the gap that the following vehicle will attempt to keep. Both vehicles shared a desired velocity of 31.5m/s (70mph), acceleration of 2m/s/s and a minimum time gap of 1 second. We therefore expect the following vehicle to have a desired distance gap of 31.5m when at his desired velocity. Now consider that the gap between the vehicles can never be closed up due to their identical acceleration and desired velocity. In the scenario with no reaction time, we see that the vehicles maintain a gap of 30.7m/s at their desired velocity. This is essentially 31.5m, the minimum gap, but due to the discrete time limitations of the simulation we lose 1 tick of accuracy when updating
vehicles, therefore losing us approximately:

\[(31.5m / (1000 / 25)) = 0.8m\]

However when we include a reaction time, we find that the vehicles have a gap larger than the minimum at desired velocity, 32.7m. With the same justification as above, this gives us a gap 2m larger than the minimum at desired velocity, i.e. the minimum distance left between vehicles when stopped.

![Comparison of following distances with reaction time on/off](image.png)

**Figure 5.2:** A comparison of vehicle following distance and reaction time.

In terms of the effect on the simulation of 3 lanes of traffic, this behaviour characteristic will cause some vehicles to be more spaced apart, therefore reducing the critical density. Vehicles with slow acceleration will cause longer congestion delays, though we will see very little effect in areas of congestion on vehicles that have a faster acceleration than the vehicle in front as they will be able to make up the gap easily. Of course, we must remember that a domino effect occurs in such a situation, so vehicles with a slower acceleration will continue to hold up traffic longer than if they had no reaction time.

Unfortunately, one problem we have with reaction times is that we cannot vouch for the accuracy of our modelling. As stated by our source, Visual Expert, reaction times are liable to differ between and within drivers, often depending on their state of alertness (Expert, 2009). Our main concern with this is the modelling of drivers slowing down to avoid colliding with a following vehicle. We implemented reaction times for car following
in such a way that a driver projects the leading vehicle’s position based on that vehicle's past values for velocity and position. We thought this would cause the following driver to brake harder to avoid colliding with the leading vehicle as it slowed down, due to the delay in information that the leading vehicle is slowing down. However, further thought on this model would suggest that this is not actually the case as the following driver’s view of the leading vehicle is always delayed by the reaction time. So in effect the only real change this provides is that for extreme slowdown, the IDM may have to override the following vehicle, causing it to stop behind the leading vehicle when it could instead have approached slower if the reaction time had lowered.

As we are unsure how and when a driver’s state of alertness changes, it is hard to model this any more accurately. We have experimented with reducing reaction time when there is an immediate need to slowdown, and increase it when in a more relaxed state, such as driving at desired velocity. Unfortunately it is very hard to obtain evidence for the effect this has on the simulation, so we eventually opted to leave the model as it originally stood to avoid over complexity and extended computational requirements.

Research appears to be fairly sparse in this area, so the implementation of reaction times perhaps lends itself better to further investigation in a separate project. We still believe that our model of reaction times is relevant to the simulation, at the very least displaying evidence that the IDM appears to be calculating car-following distances correctly.

5.2 Slowdown

When we first implemented a random chance of slowdown, the model was based on the simple theory that distractions can cause drivers to slow down, as discussed in Baker and Spina’s paper (Baker and Spina, 2007). Unfortunately we could not find any evidence to show exactly how much they slow down by. This characteristic therefore stands as a proof of concept rather than the implementation of observed behaviour.

Our process of choosing an appropriate likelihood and corresponding rate of slowdown was based on basic trial and error to find a realistic level of effect on traffic flow. These values are required to be small enough that they would have little effect on free flowing traffic below the critical density, but large enough to cause ripple effects in congested traffic, such that the fluctuations cannot dissipate and therefore aggravate the build up of congestion.

The initial model used is encouraging based on an analysis of single lane traffic in our simulation. We set up a scenario with uniform vehicle acceleration and desired speed, with minimum gap time of 1 second between vehicles. This led us to choose a flow rate of 53 vehicles/min, which due to the uniform vehicle properties was slightly above the critical
rate (logic may suggest that with a minimum gap of 1 second, the critical density would be 60 vehicles/min based on flow rate, but we have to account for vehicle length in the IDM). In Figure 5.3 we show the results of running the above scenario first without slowdown enabled and then using a slowdown likelihood of 2.5% per second, at a deceleration rate of 0.45m/s\(^2\) for 5 seconds, as discussed earlier. As a further comparison, we doubled the rate of slowdown to 0.9m/s\(^2\) and ran the simulation again with this new value. The comparison is based on our average-velocity graphing to show areas of slowdown, however each graph has had its colours inverted to give a clearer representation; the actual slowdown is minimal, showing very small differences in colour on the original graphs. It should also be noted that vehicles were set to enter the simulation at the midpoint of the road.

![Average-velocity graphing for differing levels of slowdown.](image)

As we can see there is very little congestion in the scenario where slowdown was not enabled. The small patch that is visible was due to differences in vehicle length, but can be seen to dissipate back to full free-flow. In comparison, our scenario with slowdown enabled shows a more widespread effect on vehicles across the simulation, indicating that the gap between vehicles left little room for error such that a domino effect of braking occurs downstream of traffic. We believe the average velocity graph shows that this behaviour actually had very little effect in this scenario on its own, but it is easy to see how the slowdown could be aggravated in congested traffic where vehicles have little time to notice the leader slowing down. This would especially be true if other behavioural characteristics were involved, such as non uniform spacing as a result of aggression ratings.

For the final comparison, we can see that increasing the rate of deceleration shows a much more pronounced area of slowdown, to the point of perhaps exaggerating the effect that this behaviour would have on traffic. If the effect of one vehicle slowing down was so large, it would be a miracle to ever find an uncongested patch of traffic on the motorway, or even a single carriageway road.

One final observation is that there are no signs in the slowdown scenarios of the traffic
flow completely breaking down and causing a tailback of vehicles. This suggests that the lack of any other behavioural characteristics allows vehicles to recover from slowdown as quickly as they were originally affected by it. There is also a fair likelihood that the random nature of our slowdown model gave periods of relief to the traffic flow when slowdown was not applied to vehicles at the inflow. To show this, we ran another two scenarios with and without slowdown enabled. Additionally, we enabled one behaviour characteristic, aggression ratings, in both scenarios. We can see a sharp contrast in the results, as just enabling aggression ratings causes instability in the traffic flow which results in tailbacks. Furthermore, a comparison of the difference in the time to the build up of congestion supports our belief that our slowdown characteristic will have only very little effect on traffic flow.

Figure 5.4: The effect of aggression on traffic flow with and without slowdown enabled.

We ran the two scenarios multiple times with similar results, an example of which can be seen in Figure 5.4 (with the regular colouring scheme). We have marked each area where traffic can be seen to be queuing a further 50m section behind the inflow point, starting with the section immediately after the point of inflow marked A’. In this instance, we see that slowdown only decreases the tailback formation time by approximately 15%, based on figures for vehicles reaching section C’ (62 seconds without slowdown, 52 seconds with slowdown). This seems reasonable given that each vehicle is expected to spend an average of 12.5% of travel time in a state of slowdown.

Overall we feel that the slowdown characteristic has been configured to reasonably modify the rate at which congestion builds up, although we may be able to further measure the effect of this in our overall testing in Chapter 6.
5.2.1 Over-braking

During the initial phase of development, the implementation of the over-braking characteristic was fairly straightforward. Based on the theory that drivers often misjudge velocities and distances, we simply used a deceleration multiplier to exaggerate braking force whenever a vehicle was forced into decelerating by the IDM. We now know that despite sounding foolproof, this method actually had very little (if any) effect on traffic flow due to the nature of the simulation engine.

The basic idea behind the deceleration multiplier was such that for the duration of the actual required braking time for a vehicle to maintain the minimum time gap, the multiplier would be invoked to slow down the vehicle more than necessary. Our implementation used a fairly modest multiplier of 1.5, but until we tested the behaviour characteristic on its own we did not realise that the multiplier is irrelevant when used in this way.

Although our model was causing vehicles to brake harder, it was not causing them to brake longer than necessary. As we limit the deceleration rate anyway, one extreme caused vehicles that already wanted to brake as hard as possible be completely unaffected by the multiplier. At the other extreme where vehicles only wished to undergo minimal deceleration, the multiplier would affect the braking rate, but the time until a constant velocity could be maintained was shortened. This therefore led to vehicles in the simulation braking in a far more urgent yet still accurate fashion, such that vehicle movement was actually more efficient instead of less.

Our new model of over-braking is based on the realisation that this behaviour characteristic is actually closely related to the minimum time gap that a driver attempts to maintain between him and the leading vehicle. When a driver misjudges the braking force required to avoid a collision, they are effectively extending the minimum time gap for the duration of the braking period. Upon realising that they have been braking too hard, they will start accelerating again and revert back to their default minimum time gap. Based on this, we now store a value to indicate whether the vehicle was decelerating on the last tick, and if so we apply the multiplier to the driver’s minimum time gap.

When we tested the original implementation of this characteristic, we saw no visible signs of congestion or slowdown from the average velocity graphing. This was based on a single lane of traffic, with uniform acceleration and desired velocities at 53 vehicles/min flow rate, as used for our testing of the other behavioural characteristics for its proximity to the critical density. However, with the new implementation we can see more promising results, whereby tiny fluctuations grow steadily in size until a congestion shockwave occurs. Figure 5.5 shows an example average velocity graph for this scenario with multipliers of 1.1, 1.2 and 1.3.
CHAPTER 5. BEHAVIOURAL FINDINGS

Figure 5.5: A comparison of levels of over-braking on traffic flow.

These results suggest that our original multiplier of 1.5 was far too high, based on the comparison of these 3 test scenarios. Our multipliers of 1.1 and 1.2 show a visible effect on traffic flow, but do not cause major congestion alone. However, the jump to 1.3 causes vehicles to start queuing, causing a major tailback. On reflection, our original multiplier suggested that humans over-brake by 50%, which seems somewhat inconceivable considering the frequency at which a driver would have to carry out this manoeuvre. We will therefore adopt a multiplier of 1.1 instead, as we assume that it would be possible for a 10% error to creep in when a driver calculates braking requirements.

As with the other behavioural characteristics we have discussed in this chapter, it must be stressed that developing an accurate model of over-braking that reflects the real life detrimental effects on traffic flow is very difficult and subject to trial and error. Although we had little understanding of this problem initially, the evolution of the simulation allowed us to understand how better to implement the characteristic based on the limitations of the IDM.
Chapter 6

Testing and Analysis

The testing and analysis of the simulation will look at running a range of scenarios to determine the effects that vehicle density and our human behaviour characteristics have on traffic flow. We will investigate and hopefully validate our simulation in terms of the hypotheses presented earlier regarding the relationship between critical density and flow rate and the occurrence of shockwave jams.

6.1 Critical Density

6.1.1 Test Summary

In our literature survey we discussed Sugiyama’s presentation of the relationship between vehicle density and flow rate on a motorway (Sugiyama et al., 2008). Looking at the evidence provided in Figure 2.1 it can be seen as somewhat ambiguous and open to misinterpretation. Based on initial testing within the simulation, it would appear that the vehicle density is measured over 1km over only a single lane, which makes sense given the metric of vehicles/km. What is not entirely clear on first impressions is that flow rate is also only based over one lane of traffic, with a survey duration of 5 minutes. We assume that the data for flow rate and density were based on an averaging of all 3 lanes and thus replicate our testing procedure as such.

In our implementation, we noted that the inclusion of a partial wrap around mode of vehicle flow allows us to maintain a steady vehicle density throughout the duration of the simulation. This is crucial to measuring the critical density as our model of inflow based
on a flow rate would not give us an accurate measure of density. Our partial wrap around mode is therefore perhaps the most realistic representation of traffic flow for this area of testing.

The real data that we wish to compare against was collected over a period of 1 month and as such allowed observations of a range of vehicle densities. To ensure we get a fair data spread for our comparison, we will be using a test harness to run the simulation across a range of vehicle densities and iterating over each multiple times. The harness was initially setup to run at each vehicle density between 15 and 50 vehicle/km. Based on preliminary testing and our expectations from the real data it seemed unlikely that values below 15 would be non-linear, as little interaction would occur between vehicles due to the large spacing between them. The upper bound of 50 was based on assumptions that we would see the flow rate trail off before this point due to the occurrence of shockwaves jams with small gaps between vehicles. This should then cause a similar bottleneck no matter the value for vehicle density, thus limiting the flow rate fairly uniformly.

Consideration of road length and survey duration was required to ensure we obtained accurate results from the test harness. Based on our understanding of shockwave jams, the longer the length of road being simulated, the longer the survey window needs to be. This is due to shockwave patches of both clear and congested space occurring in the simulation, which due to our use of partial wrap around traffic would be upheld for an infinite length of time. Thus, taking a very small survey window and multiplying it to get the flow rate over 5 minutes could result in an unrealistically high measurement if the window happened to fall over a patch of free flow traffic. Additionally, the reverse can be said for the window landing on a patch of high congestion.

Our simulation used a road length of 1km (or 750m due to the overflow of 250m) with a survey window of 3 minutes. Furthermore, the survey window would not start until 1 minute after the simulation was started to allow traffic to settle into the likely pattern for that vehicle density, otherwise a high flow rate at the very start could cause a loss of accuracy. Iterating three times over each vehicle density in our range of 1 - 50 vehicles/km, the test harness took approximately 12 hours to complete, factoring in extended simulation times for the higher vehicle densities due to the limitations in available computational power. This process was carried out twice for comparison within the simulation, initially running with all behavioural characteristics off and then again with them all on. Both sets of data will be used for the comparison against the real data, with the comparison between them giving a good indication of the extent to which the behavioural characteristics affect traffic flow.
6.1.2 Initial Density Observations

As we are using the partial wrap around mode in our simulation, setting up the scenario for each vehicle density requires the road to be initially populated with vehicles. We mentioned before that in an attempt to maximise the accuracy of this initial positioning, each vehicle’s desired velocity and minimum time gap are taken into account when assigning the gap between the vehicle and the one in front. We can therefore make an initial observation of each vehicle density as we know the percentage of each vehicle’s velocity in terms of their desired velocities. This shows us an early indication of the point at which critical density may occur, whereby if the gaps are large enough to allow each vehicle to have an initial velocity equal to its desired velocity, it follows that slowdown is less likely to occur as there should be enough room for vehicles to arrange themselves in an optimal pattern. Once velocities start to be restricted, we would expect a higher chance of congestion forming, thus causing the bottleneck to traffic flow.

Figure 6.1 shows the relative velocity percentages measured for vehicle densities in the range of 20 - 30 (additional densities are omitted for clarity due to the uniform data pattern they represent). The data was collected with all behavioural characteristics turned on, however only aggression ratings and desired velocity contribute to the process of population. The simulation was populated 10 times for each vehicle density to reduce the influence of anomalies caused by the random factors of vehicle generation. For a listing of the raw data for this graph, see Appendix B.1.

![Effect of vehicle density on average vehicle velocities](image)

Figure 6.1: Effect of vehicle density on average vehicle velocities.

As we can see from the results, the available gaps are large enough for every vehicle to
start at their desired velocity for vehicle densities up to 23 vehicles/km. However, as soon as we pass a vehicle density of 24 vehicles/km, depending on the combined vehicle length (based on random population factors) we start to see restricted velocities. The decline is visibly linear, with tests on a very high vehicle density of 90 vehicles/km showing that vehicle velocities are restricted to approximately 15% of their desired velocity with visible widespread congestion.

These results should not be directly compared to the real data shown by Sugiyama as it is measuring something entirely different. However, it is interesting to note that the decline in optimal service displayed here occurs at approximately the same vehicle density as in the real data, in the region of 24/25 vehicles/km. Therefore we would expect that with velocities at 100% of desired velocities, the more vehicles there are on the road, the higher the flow rate will be. But after 24 vehicles/km, although we have more vehicles on the road, the restriction in their velocity means that the flow rate will neither increase nor decrease, but stay fairly constant. We will now look to our main surveying of flow rates over time to see if this prediction is supported in the simulation.

6.1.3 Test Harness Results

The results obtained from the test harness provide a good indication of the effect that our behavioural characteristics have on traffic flow. We found that each iteration of the simulation at any given vehicle density gave a flow rate result within a small range of each other. However, running the test harness showed a large difference in results between the scenario with behavioural characteristics and the scenario without. We plot both sets of data on a single scatter graph, shown in Figure 6.2. It should be noted that we follow the graphing style displayed in Sugiyama’s work. Our flow rate (y axis) is based on vehicles observed over 5 minutes past a particular point for a single lane of traffic (on average). Our scale of vehicle density (x axis) also remains identical on a per lane basis using a measure of vehicles positioned over 1km. For a listing of the raw data for this graph, see Appendix B.2.

In a side by side comparison, the data shows very little difference in the ratio of flow rate to vehicle densities in the range of 0 - 15 vehicles/km, regardless of whether behavioural characteristics are enabled or not. This was expected, as the gaps between vehicles are large enough such that the minimum time gap can be kept for the majority of time. This leaves little room for behavioural characteristics to take effect even if they are enabled. We speculate that the slight difference between the two sets of data in this range is most likely due to our slowdown characteristic, as this increases the travel time of vehicles that are optimally able to travel at the desired velocity, therefore reducing flow rate.

We continue to see a linear increase in flow rate as vehicle density also increases, up to
approximately 25 vehicles/km for the scenario with behavioural characteristics and 30 vehicles/km without. Past these densities we see that any increase in vehicle density no longer has the effect of increasing flow rate. Instead, we see fairly uniform maximum achievable flow rates of around 180 vehicles/5 min with behavioural characteristics, compared to 265 vehicles/5 min without.

These maximum flow rates support our expectations about behavioural characteristics, in that they cause a breakdown of free flow much faster when enabled, leading to high levels of congestion and creating a bottleneck to traffic flow. Although this shows more than a 30% decrease in flow rate when behavioural characteristics are used, we need to compare our results with the data shown by Sugiyama to make judgements on the accuracy of our simulation.

In our comparison, we will be focusing only on the data with behavioural characteristics enabled. The first point of interest is the similarity in an estimation of the critical density. In the real observed data, we see that the critical density occurs at around 25 vehicles/km, which is very close to the point at which our data diverges from the pattern of linear growth at around 22 - 27 vehicles/km. It is hard to pinpoint this as our data actually shows the flow rate continuing to slightly increase at high vehicle densities, but this is likely to be the effect of a low sample size.

One major observation from our data is that once critical density is reached, there isn’t a randomly distributed decline in flow rate. In fact, the flow rate seems to stay fairly
consistent for any vehicle density above 30 vehicles/km. In the real data, we see that flow rate is entirely unpredictable past the critical density, and likely depends on large differences in driver behaviour. Our testing shows that congestion and shockwave jams frequently occur at high vehicle densities so we would expect a decline in performance, but this does not seem to be happening. This suggests that our models of behaviour are actually inaccurate to the point where traffic can always recover from congestion at a uniform rate.

So what problems could be contributing to this lack of decline in flow rate? The most obvious explanation would be that our drivers do not display adequately cautious behaviour when leaving a traffic jam. In real life we would expect a driver to refrain from accelerating as fast as possible in case there is still congestion ahead. This is one factor that is not considered in our simulation, but without any research into this sort of behaviour we would not know how to implement it effectively. Furthermore, there is nothing to suggest this would necessarily cause a random distribution in flow rates as seen in the real data as queued traffic may just recover from this in the same way that it recovers from the congestion itself.

Overall we are pleased with these results as they show a fair likeness to the real data, although our simulation doesn’t seem to allow flow rates quite as high as the real data shows. Again, this could be due to the low sample size, but it is more likely that this is a direct result of not understanding the full complexity of driver behaviour.

6.2 Shockwave Jams

One of the main aims of the project was to support and evaluate Sugiyama’s findings in his experiment to replicate shockwave jams in a wrap around model of traffic flow. Explanation for the cause of the shockwave jam placed a lot of emphasis on driving characteristics that limited a driver’s ability to maintain a consistent speed. As the vehicles were placed on the road at critical densities, these fluctuations in each vehicle’s velocity could not disappear and so caused a shockwave jam to travel upstream of traffic.

We are able to replicate this experiment in our simulation using the partial wrap around mode to set traffic flowing initially. We believe that our method is in some ways fairer than Sugiyama’s as we were able to start each vehicle moving at the same speed, whereas the initial period of acceleration in Sugiyama’s experiment could have initially caused gap fluctuations. For the experiment, we gave each vehicle uniform acceleration and disabled desired velocities, as all drivers were asked to maintain the same velocity as each other. We also enabled the reaction times, slowdown and over-braking behavioural characteristics as these are the factors that were believed to cause fluctuations in the experiment. We did not enable aggression ratings as each driver in the experiment was asked to keep a given distance between him and the vehicle ahead.
We show sample average-velocity graphs for three different vehicle densities in Figure 6.3 and Figure 6.4 for 1 lane and 3 lanes respectively. Each graph covers a duration of 80 seconds, but not necessarily from the start of the simulation; we are more interested in observing traffic patterns that may take a minute or so to develop. It should be noted that we also ran the simulation without the behavioural characteristics for all three vehicle densities, producing a robotic driving effect. In these cases, the average velocity graphs showed no fluctuations or heavy areas of congestion, only a uniform colouring based on the velocity required to travel at the minimum gap with the corresponding vehicle density.

Figure 6.3: Observations of shockwave jams over 1 lane at various vehicle densities.

Figure 6.4: Observations of shockwave jams over 3 lanes at various vehicle densities.

For the single lane simulation, our first setup used a vehicle density that we believe to be close to the critical density based on our earlier testing, 25 vehicles/km. Here we observed a single shockwave rippling back through traffic. Despite the appearance of slow movement upstream, the low vehicle density and large road length caused a minimal representation of queuing. As such, we measured the shockwave movement at approximately 2m/s upstream
of traffic. This vehicle density showed some interesting behaviour, in that occasionally the shockwave jam would get close to clearing before forming again further upstream of traffic.

Our experiments with vehicle densities of 30 and 40 vehicles/km displayed a far greater area of congestion spread over multiple separate queues. The graph for vehicle density of 40 vehicles/km displays the first 80 seconds of the simulation, showing that traffic which is originally spaced within close proximity (the yellow area) splits up into separate traffic jams that develop around the vehicles most affected by the behavioural characteristics.

In comparison, our multi-lane simulation results show a greater number of shockwave jams than in the single lane results. Additionally, the time required for shockwave jams to develop was much less for multi-lane than single lane. Although the shockwave jams look far less intense, this is due to a slight inaccuracy in our average-velocity model of graphing for multiple lanes. If shockwave jams in each lane are slightly staggered, the average-velocity graph will average closer to a yellow value than a red one.
Chapter 7

Findings

In this chapter we look to compare the results of our testing with our experimental hypotheses to see if our predictions were accurate.

7.1 Hypothesis 1

- The modelling of only car-following and lane-changing models in our simulation will produce higher rates of traffic flow in comparison to the real observed data.

In the real data presented by Sugiyama, the highest flow rate seen over a one month period was approximately 205 vehicles/5 mins. This value occurred at a vehicle density of around 25 vehicles/km. At the same vehicle density, our own simulation gave a flow rate of approximately 220 vehicles/5 mins. Although this value is higher (as we predicted in our hypothesis), it is perhaps not quite as high as expected.

However, we can argue that as this was the observed critical density for the real data, there should not have been much difference between the flow rates until past this density. In fact, we actually see that the flow rate continues to increase linearly until it tops out at about 265 vehicles/5 mins when behavioural characteristics are disabled. We therefore conclude that this hypothesis holds true as we had hoped.
7.2 Hypothesis 2

- The modelling of behavioural characteristics for drivers in addition to car-following and lane-changing models will produce lower rates of traffic flow and a higher correlation to the real observed data than that of using only the car-following and lane changing models.

Our second hypothesis is somewhat harder to confirm than our first, but there are two key points that should be considered here. Firstly, an initial look at the data would suggest that our modelling of behavioural characteristics is slightly over-enthusiastic, as we never reach a flow rate of 200 vehicles/5 mins like we see in the real data. Secondly, however, similar to the data for no behavioural characteristics, we see that the flow rate does not drop off after the critical density. It is promising to see that the critical density matches that of the real data, but unclear whether the drop off is due to inaccuracies with the behavioural modelling or not; if it was, why does the data for no behavioural characteristics also show no sign of drop off?

Based purely on both sets of flow rate data collected from our simulation, we could simply state that our second hypothesis holds true, but this is dependant on how you interpret the hypothesis. It’s clear to see that lower flow rates are seen when behavioural characteristics are enabled, but we were perhaps unclear in terms of our definition for “higher correlation to the real observed data”. For the behavioural characteristics, the maximum achievable flow rate is closer to the real data than for behavioural characteristics disabled. Overall we feel there is not enough justification to conclude that the hypothesis is true, yet too much ambiguity to invalidate it either.

7.3 Hypothesis 3

- Behavioural characteristics will cause shockwave jams to occur in the simulation for both single lane and multi-lane scenarios, showing a positive linear correlation between the number of shockwave jams that occur and the vehicle density of the road.

The observations of shockwave jams from average-velocity graphing support this hypothesis for both single lane and multi-lane scenarios. Of particular note is that shockwave jams were not visible when behavioural characteristics were turned off, as predicted by Tim Rees in the NewScientist article relating to Sugiyama’s work (Glaskin, 2008).

Furthermore, we noticed that reaction times were the largest contributing factor to the breakdown of free flow into shockwave jams, as identical tests run with this behavioural
characteristic turned off produced very similar results as the testing carried out with all behavioural characteristics off.
Chapter 8

Conclusions

In this final chapter we will evaluate the project based on our results and findings, discussing the strengths and weaknesses of the simulation software and how our understanding of the initial problem has changed over the course of development.

8.1 Investigative Findings

In our findings, we have concluded that hypotheses one and three have been validated based on data returned from the simulation, while we remain unsure about hypothesis two. Overall, we are pleased with the results shown, not only supporting and validating the work carried out by Sugiyama, but also indicating that behavioural characteristics are capable of affecting traffic simulation to such a large extent (upwards of 30% difference in flow rate as shown by our data) that they should not be ignored in future modelling techniques.

One interesting finding was the similarity of data for traffic flow at vehicle densities below the critical point, when both enabling and disabling the behavioural characteristics. This would indicate that the sole implementation of car-following and lane-changing models is enough to accurately model traffic flow at very low densities, due to the limited interaction between vehicles. But as the density progresses further and further past the critical point, the larger the potential for error will creep in.

Interestingly, the results from the simulation allow us to speculate as to the congestion-reducing potential behind the variable speed limits introduced on the M25 motorway in Britain (Harbord and Jones, 1996). We have seen that the reaction time characteristic contributes greatly to the build up of congestion and shockwave jams, more so than any
of the other behaviours. It seems that the idea behind variable speed limits on the M25 could be to reduce vehicle velocities for times when the vehicle density is at or above the critical point. Although this does nothing to lower the vehicle density, this is realistically unachievable anyway based on the basic principles of motorway design. However, if the lower speed limits are successfully adhered to, the time gap between vehicles will increase, causing reaction times to have less effect on the fluctuations between vehicles. Unfortunately, the highly aggressive drivers will never wish to travel at such slow velocities and will eventually ruin the daily commute for everyone!

Additionally, many motorway drivers will have noticed that in the event of lane closures decreasing the number of utilisable lanes, there are often roadway signs that ask you to stay in one lane. Although we were not looking at traffic systems with physical bottlenecks, our research supports the reasoning behind these signs. It was noted in our testing that identical simulations with behavioural characteristics enabled showed a longer time to shockwave jam formation for single lane scenarios compared to their multi-lane equivalents. As the simulations were carried out with an initially identical vehicle density in each lane, this would suggest that the act of drivers switching lanes can have a large impact on the flow rate. Therefore, if drivers are able to stick to the lane they started in during lane closures, it is probably far less likely that the free flow will break down into congestion.

8.2 Research Limitations

8.2.1 Validity of Reaction Time Modelling

Although we already discussed the validity of the reaction time characteristic, it cannot be stressed enough how limited we were in this area of behaviour modelling. A basic analysis of the problem indicates that this is probably the most complicated of all the behavioural characteristics, but without hard evidence to show how reactions change based on stimuli, we chose to adopt a fairly simplistic model.

Unfortunately, as with the initial decision to make a lane change, the fluctuations in an individual’s reaction time would appear to be unobservable. The likelihood that a psychological study could be developed that is capable of measuring this change seems fairly low. Further analysis of the problem suggests that the reduction in reaction time of observing successive stimuli would actually tell us very little. In actual fact, we are probably more interested in the rate that a driver can update their understanding of their surroundings after the initial stimulus. We hope that this aspect of driving can one day be explained further to help increase the accuracy of such a behavioural model.
8.2.2 Congestion Graphing

Overall, we feel our new method of graphing areas of congestion based on average velocity allows for easy analysis of the traffic flow across multiple lanes. However after a review of our testing, it’s clear that this method could be improved by increasing the accuracy of the calculations. Currently, the average-velocity graph sums and averages the velocities of all vehicles in comparison to desired velocities over 50m sections. Our results show that this is perhaps too large an area to average over, as the existence of a single stationary vehicle can be masked by other vehicles travelling at their desired velocities.

To increase the benefit of this graphing system, we could reduce the sections that we average over to a much smaller section of the road, such as 10m. However, this could also show slightly exaggerated data either way, as it is likely that vehicles on the boundary of two areas would need to be included in the averaging of both in order to get a clear picture of congestion given the small sample size of each area. Another option would be to err on the side of congestion, overriding an otherwise free flowing area with a red dot for times when there is only one stationary vehicle.

8.2.3 Undertaking

Throughout the development of the simulation, we noticed that the car-following and lane-changing models did not restrict vehicles from undertaking other vehicles as we had hoped. Many attempts were made to rectify this with adaptations to these models, but this often caused undesirable behaviour to be shown due to the discrete time updates in the simulation.

Overall, we believe that this behaviour will have had only a very small detrimental effect on our findings, as it was only really observable at low frequency, regardless of vehicle density. Unfortunately, we believe this behaviour stemmed from the lack of sympathetic human behaviour often observed on our roads, whereby drivers may slow down to let a vehicle ahead join their lane, for example. Although there are rare cases of overly-aggressive drivers undertaking with little due respect for other road users, this area of human behaviour would require more research before such feelings towards other drivers could be considered.

8.3 Future Work

The overall investigative approach to this project has helped us discover many areas where the simulation could be extended to enhance the accuracy and range of data drawn from
the simulation. There is no question that we have only touched upon the wide range of human behaviours that contribute towards driving style, some of which have already been discussed.

As further consideration for future work, it would be interesting to look at the behaviour of drivers in a multi-agent system, whereby each could hold memories of previous interactions with other vehicles that would essentially dictate how they make allowances for new drivers in the future. This is a topic we touched upon briefly during the design of the simulation, and would allow us to show the more sympathetic nature of human drivers.

Although we have only touched on the idea of variable speed limits as a way to reduce congestion, a new direction of research could look at modelling the range of effects this could have on traffic flow depending on the level of driver conformance. Similarly, the consideration of such alarming stimulus as speed cameras could also allow us to determine whether such attempts to slow drivers down are successful, or just result in less efficient traffic flow.

Finally, our initial analysis of the problem resulted in a secondary requirement to investigate the possibility of visualising fluctuations between traffic, in order to predict the onset of congestion. As the development of the project progressed, we realised that this represented enough work to warrant a whole new research project. Although this seemed to be one of the most intriguing ideas in the area of traffic modelling, it was simply out of the scope of the project, and would also be a consideration for future work.

8.4 Final Comments

This project has proved that the research behind traffic flow and causes of congestion is very much incomplete, and could continue to advance for the unforeseeable future. Every aspect of this project has opened our eyes to the relatively unexplored factors that account for both the stochastic and deterministic nature of vehicle interaction and traffic flow, such that we hope to further contribute to this area of traffic simulation in the future.
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Appendix A

Example Screenshots

The following page contains sample screenshots taken from the Traffic Simulator program.
Appendix B

Raw results output

B.1 Data: Effect of vehicle density on average vehicle velocities

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### B.2 Data: The effect of vehicle density on the achievable flow rate

#### B.2.1 With Behavioural Characteristics

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<td>165 / 170 / 175</td>
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<td>165 / 165 / 175</td>
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<td>34</td>
<td>170 / 170 / 180</td>
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<tr>
<td>35</td>
<td>165 / 170 / 170</td>
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</tbody>
</table>
### APPENDIX B. RAW RESULTS OUTPUT

<table>
<thead>
<tr>
<th>Veh. Density (veh/km)</th>
<th>Flow Rate (veh/5 min)</th>
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<tbody>
<tr>
<td>36</td>
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</tr>
<tr>
<td>37</td>
<td>165 / 175 / 180</td>
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<td>38</td>
<td>170 / 170 / 175</td>
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<td>39</td>
<td>160 / 170 / 180</td>
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<td>170 / 175 / 175</td>
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<td>41</td>
<td>165 / 170 / 170</td>
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<td>42</td>
<td>175 / 175 / 180</td>
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<td>170 / 170 / 175</td>
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<td>44</td>
<td>170 / 175 / 185</td>
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<td>170 / 175 / 185</td>
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<td>175 / 175 / 180</td>
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<td>47</td>
<td>175 / 175 / 185</td>
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<td>49</td>
<td>175 / 180 / 180</td>
</tr>
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<td>50</td>
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</tbody>
</table>
### Without Behavioural Characteristics

<table>
<thead>
<tr>
<th>Veh. Density (veh/km)</th>
<th>Flow Rate (veh/5 min)</th>
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<tbody>
<tr>
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<td>245 / 250 / 250</td>
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<tr>
<td>39</td>
<td>250 / 255 / 255</td>
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<tr>
<td>Veh. Density (veh/km)</td>
<td>Flow Rate (veh/5 min)</td>
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<td>260 / 260 / 265</td>
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</tbody>
</table>
Appendix C

Sample Code

Included here are two sample source code files:

- Vehicle.cs - class structure for storing and managing individual vehicle properties.
- Globals.cs - globally available variables and functions used throughout the program.

A full source code listing can be found on the accompanying CD-ROM.
C.1 File: Vehicle.cs

```csharp
using System;
using System.Collections;
using System.Collections.Generic;
using System.Text;

namespace TrafficSimulator
{
    /// holds properties of individual vehicles
    class Vehicle
    {
        private static int next_id = 0;

        private int id;
        public int ID
        {
            get { return id; }
        }

        /// vehicle type
        private Globals.VType type;
        public Globals.VType Type
        {
            get { return type; }
        }

        /// position (m)
        private float pos;
        public float Pos
        {
            get { return pos; }
            set { pos = value; }
        }

        /// length (m)
        private float len;
        public float Len
        {
            get { return len; }
        }

        /// desired velocity (m/s)
        private float dVel;
        public float DVel
        {
            get { return dVel; }
        }

        /// max desired velocity (m/s)
        private float mDVel;
        public float MDVel
        {
            get { return mDVel; }
        }

        /// current velocity (m/s)
        private float cVel;
        public float CVel
        {
            get { return cVel; }
            set { cVel = Math.Min(value, dVel); }
        }

        /// acceleration (m/s²)
        private float acc;
        public float Acc
        {
            get { return acc; }
        }

        /// deceleration (m/s²)
        private float dec;
        public float Dec
        {
            get { return dec; }
        }

        /// velocity change (m/s)
        private float vChange = 0;
        public float VChange
        {
            get { return vChange; }
            set { vChange = value; }  // decel = (value < 0);
        }
    }
}
```
APPENDIX C. SAMPLE CODE

private float aggr;
public float Aggr
{
    get { return aggr; }
}

private float relaxTime = 0;
private bool slowdown = false;
public bool Slowdown
{
    get { return slowdown; }
}

private ArrayList pastAtts;

private float react;
public float React
{
    get { return react; }
}

private float minTimeSpac;
public float MinTimeSpac
{
    get
    {
        if (Globals.allow_aggr) return minTimeSpac;
        else return Globals.std_min_time_spacing;
    }
}

private int targetLane = -1;
private int targetForTime = 0;

private bool deccel = false;
public bool Deccel
{
    get
    {
        return deccel;
    }
}

private Vehicle()
{
}

public Vehicle(Globals.VType type)
{
    this.id = Vehicle.next_id++;
    if (Vehicle.next_id == 10000) Vehicle.next_id = 0;
    this.type = type;
    Globals.get_veh_attributes(type, out acc, out mDVel, out len, out aggr);
    dVel = mDVel;
    cVel = mDVel;
    dec = acc * 2;
    pos = Globals.road_entry;

    react = 1;

    if (Globals.allow_aggr) return minTimeSpac;
    else return Globals.std_min_time_spacing;
minTimeSpac = Globals.agr_min_time_spacing +
(2 * (1 - aggr));

pastAtts = new ArrayList();
PAST ATT is the array of past attributes
with duplicate
* entries, just to be safe */

string def = String.Format("{0}::{1}", pos.ToString(), cVel.ToString());

for (int i = 0; i * Globals.engine_tick <=
Globals.max_react; i++)
{
pastAtts.Add(def);
}

/*
Globals.addToDebug(String.Format("{0}::dVel={1}m/s", type.ToString(), dVel)); */

/* returns true if change is allowed */
public bool desiredChange(int targetLane)
{
/* if we aren’t using reaction times, * bypass this */
if (!Globals.allow_react)
return true;

if (this.targetLane != targetLane)
{
this.targetLane = targetLane;
targetForTime = 0;
}

else if (targetLane != -1)
{
targetForTime += Globals.engine_tick;
}
/* slight loss of accuracy for
* reaction times not on tick
* multiples, but not really a
* big problem */

if (targetForTime >= (react * 1000))
{
targetLane = -1;
targetForTime = 0;
return true;
}

else
return false;

}

public void adjustVelocity()
{
if (!Globals.allow_slow)
{
dVel = mDVel;
return;
}

/* apply velocity modifiers here (slowdown)
* */

if (!slowdown)
{
/* see if we should enter slowdown */
int chance = Globals.rand.Next(0, 100000);
if ((float)chance / 1000F <=
Globals.slow_chance)
slowdown = true;
}

if (slowdown)
{
/* add to slowdown time */
relaxTime += ((float)Globals.engine_tick
/ (float)Globals.sec_in_ms);
}
/* if still in slowdown, reduce velocity */
if (relaxTime <
    Globals.slow_rate_duration)
{
    dVel -= Globals.slow_rate_ms;
    cVel = Math.Max(0, cVel -
        Globals.slow_rate_ms);
}
/* else reset */
if (relaxTime >=
    Globals.slow_total_duration)
{
    slowdown = false;
    relaxTime = 0;
    dVel = mDVel;
}
*/

/* save position and velocity to attributes for
 * lookup by other vehicles */
public void savePosition()
{
    pastAtts.Insert(0, (String.Format("0:{1}",
        pos.ToString(), cVel.ToString())));

    /* check if we have too many values */
    int count =
        Convert.ToInt32(Math.Ceiling((double)(Globals.max_react
            / Globals.engine_tick))) + 1;
    if (pastAtts.Count > count)
        pastAtts.RemoveAt(pastAtts.Count - 1);
}

/* get past position and velocity attributes for
 * this vehicle */
public void getPosition(float time, out float pos, out float vel)
{
    /* complicated (and probably slightly
     * redundant)
     * but works */
    int index = Convert.ToInt32((time *
        Globals.sec_in_ms) /
        (Globals.engine_tick *
            (Globals.sec_in_ms /
                Globals.sim_second)));

    string atts =
        (string)pastAtts[Math.Max(index - 1, 0)];

    /* find delimiter */
    int divIndex = atts.IndexOf(':');
    pos =
        (float)Convert.ToDouble(atts.Substring(0,
            divIndex));
    vel =
        (float)Convert.ToDouble(atts.Substring(divIndex
            + 1));
}

/* replicate this vehicle for
 * reinsertion at the start */
public Vehicle Clone()
{
    Vehicle v = new Vehicle();
    v.id = Vehicle.next_id++;
    v.pos =Globals.road_entry;

    /* clone properties */
    v.acc = this.acc;
    v.aggr = this.aggr;
    v.cVel = this.cVel;
    v.dec = this.dec;
    v.dVel = this.dVel;
    v.len = this.len;
    v.mDVel = this.mDVel;
    v.minTimeSpac = this.minTimeSpac;
    v.react = this.react;
    v.type = this.type;
```csharp
v.pastAtts = new ArrayList();

/* initialise the array of past attributes with duplicate entries, just to be safe */
string def = String.Format("{0}:{1}", v.pos.ToString(), v.cVel.ToString());

for (int i = 0; (i * Globals.engine_tick) <= Globals.max_react; i++)
{
    v.pastAtts.Add(def);
}

return v;
}
}

C.2 File: Globals.cs

using System;
using System.Collections;
using System.Collections.Generic;
using System.Drawing;
using System.Text;

namespace TrafficSimulator
{
    /* variables and functions used */
    public static class Globals
    {
        public static int engine_tick = 25; /* ms */
        public static int sec_in_ms = 1000;

        public static bool sim_running = false;
        public static int sim_second = 1000; /* ms */
        public static int flow_interval; /* ms */

        public static int graph_refresh = 2000; /* ms */
        public static float graph_unit;

        public static Color btn_on_colour = Color.FromArgb(153, 180, 209);

        public static int road_entry = 0; /* m */
        public static int road_length;
        public static int road_overflow = 250; /* m */
        public static int road_seg_len = 200; /* m */
        public static int road_offset = 57; /* m */
        public static int flow_rate = 0; /* veh/mm */
        public static int car_perc = 85; /* based on dft stats */

        public static int lane_count; /* 1/2/3 */
        public static float min_dist_spacing = 2; /* m */
        public static float agr_min_time_spacing = 0.25F; /* s */
        public static float std_min_time_spacing = 1; /* s */
        public static float change_down_time = 10; /* s */
        public static float change_down_lookahead = 150; /* m */

        public static bool const_den = false;

        public static bool allow_react;
        public static bool allow_aggr;
        public static bool allow_slow;
        public static bool allow_obrake;
        public static bool allow_desiredv;
        public static bool allow_diffacce;

        public static float slow_chance;
        public static float slow_rate_ms; /* ms */
        public static float slow_rate_duration; /* ms */
        public static float slow_total_duration; /* ms */

        public static float obrake_multiplier = 1.3F;
        public static float max_react = 2000; /* ms */
    }
```
public delegate void OnDebugDelegate(string text);

public static event OnDebugDelegate debug;

/* our random generator for all things */
public static Random rand = new Random();

/* vehicle types */
public enum VType
{
    car,
    hgv,
}

/* conversions (using 1/x for the reverse) */
public static float mph_in_ms = 0.45F;
public static float kph_in_ms = 0.28F;

/* car/hgv lengths in metres */
private static float sma_car_len = 3.5F;
private static float med_car_len = 4.5F;
private static float lar_car_len = 5;
private static float hgv_len = 10F;

/* min/max/interval for car acceleration */
private static float car_acc_min = 2;
private static float car_acc_max = 6.5F;
private static float car_acc_int = 0.5F;

/* min/max/interval for hgv acceleration */
private static float hgv_acc_min = 1;
private static float hgv_acc_max = 1.9F;
private static float hgv_acc_int = 0.1F;

/* min/max/interval for vehicle velocity */
in mph, calculate m/s after assignment */
private static int veh_vel_min = 45;
private static int veh_vel_max = 90;
private static int veh_vel_int = 5;

/* used for cars and hgv currently but with */
/* different interval/max/min values */
/* based roughly on halves i.e. 0:50, 50:75 etc */
private static int[] veh_acc_devs = new int[]
{ 50, 75, 85, 90, 93, 95, 97, 99, 100};
/* based on stats from dft.gov.uk for motorway */
/* car speeds, 2006 */
/* i.e. 0.5 = 45.50mph, 5:16 = 50.55mph */
private static int[] car_vel_devs = new int[]
{ 4, 10, 16, 28, 46, 66, 82, 97, 100};
/* based on stats from dft.gov.uk for motorway */
/* hgv/bus speeds, 2006 */
/* i.e. 0.5 = 45:50mph, 5:27 = 50:55mph */
private static int[] hgv_vel_devs = new int[]
{ 8, 45, 82, 92, 95, 97, 98, 99, 100};

public static void get_veh_attributes(VType type, out float acc, out float mDVel, out float len, out float aggr)
{
    /* assign mins as default */
    acc = (type == VType.car ?
        car_acc_min :
        hgv_acc_min);
    mDVel = veh_vel_min;

    /* get vehicle length */
    if (type == VType.hgv)
        len = hgv_len;
    else
    {
        int len_rand = rand.Next(0, 2);
        if (len_rand == 0)
            len = sma_car_len;
        else if (len_rand == 1)
            len = med_car_len;
        else
            len = lar_car_len;
    }
/* get random acc and vel factors (0;100) */
/* use vel_index as our basis for aggression */
int acc_index = rand.Next(0, 100);
int vel_index = rand.Next(0, 100);
aggr = Math.Min(1, (float)vel_index / 100);

/* get actual acc deviation */
if (allow_diffacc)
{
    for (int i = 0; i < 10; i++)
    {
        if (acc_index <= veh_acc_devs[i])
        {
            acc += (type == VType.car?
                (i * car_acc_int) : (i * hgv_acc_int));
            break;
        }
    }
}
else
{
    if (type == VType.car)
        acc = 4P;
    else
        acc = 1.5P;
}

/* get actual vel deviation */
if (allow_desiredv)
{
    for (int j = 0; j < 9; j++)
    {
        if (vel_index <= (type == VType.car?
            car_vel_devs[j] : hgv_vel_devs[j]))
        {
            /* get extra velocity */
            mDVel += j * veh_vel_int;
            /* now convert to m/s */
            mDVel = mDVel * mph_in_ms;
            break;
        }
    }
    else
    {
        if (type == VType.car)
            mDVel = 70 * mph_in_ms;
        else
            mDVel = 60 * mph_in_ms;
    }
}

public static void addToDebug(string text) {
    debug(text);
}