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How would Adding Light-rail Acceleration and Deceleration Constraints for Passenger Comfort Affect Autonomous Car Use?

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Declaration

I declare that this thesis is my own work and has not been submitted in any form for another degree or diploma at any university or other institute of tertiary education. Information derived from the work of others has been acknowledged.

Signed by . . . .

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Abstract

Autonomous vehicles (AVs) are projected to become a reality in the near future, due to advancing technology and major incentives for manufacturers to pursue them. A notable incentive is the ability for travellers to free up their driving time, by allowing the car to drive itself. This enables travellers to perform other activities while travelling, which carries with it numerous considerations. Two key considerations are the increased potential for motion sickness, and the greater use of cars due to the appeal of being able to perform other activities while travelling. One way of addressing the former is through imposing acceleration and deceleration constraints, such as those used in light-rail trains to reduce the discomfort of passengers, improving comfort but potentially adding congestion. The ability to perform other activities while travelling can be understood as a reduction in the Value-Of-Travel-Time (VTT) of driving, which may lead to greater car use by reducing the utility cost of travelling. Both of these effects have been studied historically, but in isolation and through micro simulation. This study uses two modern agent-based transport simulation software MATSim and SUMO, to identify the contrasting effects of these two factors on car attractiveness and subsequently car use. Light-rail constraints are found to add 215 seconds on average to trips less than 10 km, but reduce travel time of trips greater than 10 km by 434 seconds. This change in travel times leads to a simulated increase in average car trip distance by 19%, and a reduction in public transport trip distance by 6%, due to part of the short-trip car users switching to public transport, and the reverse occurring for long-trip public transport users. The VTT reduction of performing other activities while travelling did not change the trip distributions of any travel mode. The overall proportion of car travellers changed by less than half a percent for both light-rail constraint and VTT reduction components, though was three times more significant for the VTT reduction than the light-rail constraints. The combined effect of light-rail constraints and VTT reduction could not be studied due to software issues, but was hypothesised to be no greater than less than half a percent. These findings suggest light-rail constrainted autonomous vehicle may be of benefit for long-distance travellers, but not short-distance travellers, due to added delays in trip times, where public transport is seen as more desirable, and may benefit from further investment should light-rail constrained AVs become a reality.

1 Introduction

Self-driving cars, also known as Autonomous vehicles (AV for short) are projected to enable an increase of $507 bn in financial revenue [1]. Autonomous vehicles utilise the existing technology of cameras, sensors and radars, in conjunction with intelligent driver support computer systems. Computer systems such as Nissan's Advanced Driver Assistance System [2] perform the function of driving themselves with little to no human intervention. Autonomous vehicles are typically defined as having Level 3 or higher automation, as per the SAE guidelines [3], whereby cars do not need human intervention to travel except as a fallback in emergency situations. Level 4 from the aforementioned guide is also commonly used, defined as an autonomous vehicle that can also self-manage emergency fallback procedures.

As of 2018-2019; Toyota, Volkswagen, Ford, Nissan, and Honda are the market leading automotive manufacturers [4], and all are currently developing their own versions of autonomous vehicles ([5], [6]) in an effort to acquire as much of this potential revenue as possible. Because of this, it is projected that ~25% of vehicles will possess a Level 4 or higher automation by 2045. Therefore it is imperative to understand the consequences of this technology before mainstream adoption occurs.

One of the potential consequences is a change in the way people travel, due to the unique characteristics that autonomous vehicles will possess. A major benefit of AVs is the ability to perform non-driving activities while travelling to a destination ([3], [7], [8], [9]). This would increase the attractiveness of driving [10], which can be measured by the value travellers place on travel time [8]. However, this involves travellers paying less attentionn to the road, making them more susceptible to motion sickness [11]. As a result, improving passenger comfort in order to reduce motion sickness is likely to be a key focus within vehicle design, and has been recommended in previous studies [12].

One way of tackling the issue of motion sickness within autonomous vehicles, is to add constraints to the maximum acceleration and deceleration of these vehicles ([12], [13]). This reduces the opportunity for jerks (sudden changes in acceleration) [14] to occur while driving. This has already been implemented in light-rail transit networks [15], and is currently being experimented with in autonomous vehicles ([12],[13]). However, this approach may increase congestion, by making cars slower, particularly in already congested areas that involve frequent starting and stopping. Because travelling is typically considered to be a cost or disutility ([16], [17]), this would detract travellers from using cars. This detraction is notably in contrast to the attraction of performing other activities while travelling, and may also be measured by its effect on traveller's value of travel time.

This suggests the appeal and subsequent use of autonomous vehicles, may depend on the product of the aforementioned two factors - the attractiveness of performing other activities while driving, and the detraction of constraining acceleration and deceleration. Both of these effects can be quantified in the universal metric of value of travel time. Therefore by understanding the net value of travel time of these two effects, it is possible to determine the appeal and subsequent use of autonomous vehicles in the future.

Understanding car use levels is an important aspect for planning future transport infrastructure, as it determines the amount and type of infrastructure that will be needed in the future. If car use levels are forecasted to increase as a result of the greater appeal of autonomous vehicles, this may necessitate further investment in infrastructure within affected areas. Conversely if car use is expected to decline as a result of increased congestion, such increases in spending may not be required. Separetely, the automotive industry writ large may benefit from knowing the appeal of autonomous cars in the future, as may other tangentially related industries such as the emergency services industry that cares for accident patients. This is the motivation for the study being conducted.

2 Objective

The goal of this research is to understand car use within an autonomous vehicle world – one where autonomous vehicles comprise a significant proportion of vehicle traffic. Doing so tells us whether car traffic volumes will become more or less prevalent through the advent of autonomous vehicles, and to what extent, which is vital for transport infrastructure planning among other areas. However this requires the notion of an autonomous vehicle to be defined and modelled.

Our definition of an autonomous vehicle focuses on passenger comfort, consisting of two opposing forces. These are the detracting congestion of imposing light-rail acceleration and deceleration constraints (LRCs), and the attracting opportunity to perform other activities while travelling.

These opposing forces are analysed through the unifying metric of Value-of-Travel-Time (VTT), which represents the relative worth of travelling as compared to other activities [18]. Light-rail constraints are expected to make travelling by car cost more in VTT for the user due to congestion. Conversely, the opportunity to perform non-driving activities reduces a car traveller's VTT by giving them back part of their free time. Using the simulation software MATSim and SUMO, it is possible to model both of these effects, and study the changes in travel mode choice by travellers that occurs as a result. This exercise is what will be undertaken as part of this study.

3 Literature Review

3.1 Acronyms

Below are acronyms used throughout the literature review

Acronym	Definition
AV	Autonomous Vehicle
HV	Human-driven Vehicle
LRC	Light-rail Accel. & Decel. Constraints
HSR	High-speed Rail
VOT	Value of Time
VTT	Value of Travel Time
VTTS	Value of Travel Time Savings
IVT	In Vehicle Time
OVT	Out of Vehicle Time
SP	Stated Preference
RP	Revealed Preference
OSM	Open Street Map

3.2 Value Of Time

The aggregate benefit or disadvantage of travelling is commonly quantified in the term 'value of travel time' (VTT). This represents the trade-off ratio between the in-vehicle time coefficient and the cost coefficient [18]. The value of travel time can thus be seen as the relative worth of travelling, by comparison to other activities, as a result of the utility (or disutility) it brings. In general the value-of-travel-time can be considered a net disutility rather than a utility, as drivers must sacrifice time they would otherwise spend in leisure for the purpose of travelling [19]. It is also important to note that value of time generally needs to be multiplied by the trip time itself to determine the trip's overall value. This is shown in [20], where the metric of dollars per hour per car was used, which in turn needs to be multiplied by the trip time. This is also shown in [21], where the value of time for the first hour may differ to the value of time for the second hour within a trip.

The notion of a value of time has within it the implicit goal of maximising utility and minimising disutility. Thus value of time and the maximisation of utility is a psychological concept, motivating in our case which travel mode one chooses, based on the utility of their choices. The components being studied are light-rail acceleration & deceleration constraints, and the increased productivity of using AV. Both the comfort that may be gained from light-rail acceleration & deceleration constraints, and the increased productivity are notable in being identifiable as first-order implications on value of time within a ripple effect model [7]. This ripple effect model is a means of categorising effects based on their relative distance from a triggering event.

These VTT components (light rail acceleration & deceleration constraints, and increased productivity potential) also work in opposite directions. Light-rail constraints on accelerating & decelerating vehicles that are currently under investigation as viable AV driving styles, as shown in ([12], [13]). These constraints add disutility to the car's VTT, by slowing the car's maneuverability down. Conversely, the productivity of passengers performing non-driving tasks while driving will add utility to their trip. This may ultimately lead to greater or fewer agents deciding to use AVs. If the productive activities utility when using an AV outweighs the light-rail constraint disutility, then we expect car usage to increase. On the other hand, if the added disutility of these light-rail constraints is greater than the productive activities utility of an AV, then we expect fewer car users. Both of these scenarios may have consequences on how we design the transport infrastructure of the future. Therefore there is an opportunity to research these two factors, to determine the ultimate effect on total car usage.

3.3 Impact of Higher Disutility from Light-Rail Acceleration & Deceleration Constraints

The first of the two value of time components being studied are the light-rail acceleration & deceleration constraints that increases the disutility of travel. This will be discussed here.

3.3.1 Motion Sickness in Vehicles

One significant problem with autonomous vehicles is motion sickness, due to many of the driving characteristics of autonomous vehicles (AVs) being linked to those which cause motion sickness [13]. Motion sickness can be defined as a sensory conflict between actual and expected vestibular, visual, and kinesthetic inputs [22], causing symptoms of nausea and vomiting. Other symptoms can be malaise, pallor, and cold sweating [23]. The word nausea itself originates from the Greek word 'naus' which relates to ships as in the word 'nautical' [22]. Driving characteristics that have been shown to contribute to motion sickness include having a compromised view of the road [11], acceleration and road surface ([13], [24]), as well as facing rearwards relative to the travel direction of the car ([13], [25]). These issues are unique to autonomous vehicles, because the ability for an AV to drive itself enables users to perform non-driving activities such as resting, or productive tasks [3] while travelling. This argument is naturally predicated on the assumption that most AV users will take advantage of this potential.

M. Turner and M. J. Griffin found 28% of passengers of coaches reported feeling ill, with the effect decreasing with age and travel experience [11]. However 79% of the ill passengers reported being only 'slightly unwell', while the mean sickness level was below that of sea travel. Yet even a mild discomfort may be a deterrent for frequent users such as those commuting to work.

Acceleration and road surface have been linked to motion sickness and discomfort ([13], [24]). [13] used twelve subjects split by driving style, while [24] used 115 subjects in real-world test scenarios. In both cases a driver was instructed to drive at varying levels of acceleration, while an accelerometer was used to both display and capture acceleration information. [13] studied both longitudinal and lateral acceleration, while [24] studied only lateral acceleration. Discomfort levels were obtained through surveys of the subjects. Both studies concluded that there was increased discomfort at higher acceleration levels both longitudinally and laterally.

One limitation to the existing literature on motion sickness is its high reliance on surveys, for example in studies [13], [11], [25], and [24], typically using a four or five-point scale from low to high levels of motion sickness. It is possible for example that travel users overstate or understate their sickness due to external factors impacting the objectivity of their perception, such as mood, appetite, or awareness of being observed (Hawthorne effect), that do not themselves affect one's motion sickness. This may lead to findings that motion sickness is a greater or less significant problem than it truly is, when compared to the user's real world travel decisions. More objective measures have been proposed, such as using sweat gland activity from a person's volar surface [26], or comparing stomach activity, blinking and breathing [27].

Thus far a link between auto-mobile travel and motion sickness has been established. To combat this motion sickness, users of AVs are likely to expect a comfortable riding experience [13], made available by the car's autonomy. Milakis et al. [7] in his literature review of potential AV effects suggests that "Motion sickness, ... could be included in path planning" systems, from the finding that travel comfort is a first-order implication within its ripple effect model. The ripple effect model as noted by the authors is a recognised describing tool for categorising effects based on their relative distance from the triggering event – in this case the introduction of AVs. A first- order implication therefore is one that is most causally linked to the introduction of AVs. The next section will describe the existing literature on how this comfort may be achieved.

3.3.2 Combining Light-rail Acceleration & Deceleration Constraints with AV Value-of-Time

Some of the ways motion sickness can be tackled include performing mental tasks and reducing head movements [11], yet it is unclear how effective or practical such exercises may be, particularly when such exercises interfere with a passenger's intended non-driving activities for the trip. Some studies show that on the contrary, passengers do not wish to perform mental tasks while being driven, instead opting for relaxation [9]. A similar argument could be perceived for why they may wish to not limit their head movements. Other approaches studied include improving the plushness of the ride, such as by introducing more comfortable seat cushions and backrests [28], or keeping passengers facing forward to the effect found in [25] of rearward facing seats causing motion sickness. These show some promise, and should be considered in conjunction with our approach.

A common approach to reduce discomfort is for vehicles to avoid where possible rapid accelerations or decelerations. Acceleration and road curvature have both been highly correlated with increased discomfort in previous studies [24], suggesting that reducing acceleration and deceleration will have a positive effect on rider comfort [3].

An existing example of reducing acceleration and deceleration for comfort purposes can be seen in light-rail transit systems [15]. Light-rail acceleration and deceleration is often constrained to values that ensure longitudinal and lateral g-forces do not exceed 0.07 [13]. This has resulted in light-rail vehicle specifications typically stipulating a maximum acceleration of 3mphps (1.34m/ s 2) and a minimum emergency deceleration of 4.5 mphps (2.01m/s 2) [15]. These constraints are often give the term LRT (light-rail transit) constraints or LRC (light-rail constraints). Research has already commenced on how to incorporate these constraints as driving styles for autonomous vehicles ([12], [13]). The first of these studies recommends further research in the area of comfort within AVs, and the effects of motion sickness.

3.3.3 Effect of Light-rail Acceleration & Deceleration Constraints on Congestion

It is hypothesised that adding light-rail acceleration & deceleration (i.e. braking) constraints to vehicles will lead to increased congestion. This is the intuitive assumption, since vehicles will take longer to reach their desired speeds, and will not be able to follow as closely safely, due to having less rapid deceleration or braking. Existing research supports this theory, as will be shown.

One area this has been researched is take-off time for a vehicle at an intersection. Taking off at an intersection necessarily requires acceleration. Existing acceleration constraints within vehicles appear to be a factor in take off time delays for vehicles waiting at an intersection. In [29] it was found that removing driver delays and vehicle acceleration constraints "would have resulted in a 24-s reduction in the total delay incurred during the simulated signal cycle". This study used a deterministic queuing model, further queue based models from the 1981 Australian Capacity Guide, shock wave theory, as well as delays estimated through the INTEGRATION microscopic traffic simulation software.

Le Vine et. al. in [8] discovered using the micro/mesoscopic simulation software VISSIM that light-rail acceleration & deceleration constrained (LRC) vehicles must approach an intersection at 29 kph, as compared to the 50 kph of non-LRC vehicles, due to the risk of a yellow light turning red, and its inability to stop in time due to the slower braking of an LRC vehicle. While the low- level impact of acceleration and deceleration constraints on individual intersections may be scalable, no existing studies have simulated the effects of such constraints within a complete transport network. Both [29] and [8] limited their study to individual intersections. This is not for lack of capability however; simulation of other acceleration & deceleration constraints has been proven possible in [30] and [31]. In [30] a proposed car following model that incorporates an acceleration and deceleration profile was implemented within the SUMO (Simulation of Urban Mobility) simulation software [32], and simulated on the Open Street Map (OSM) network of Fuzhou, China. Similarly, [31] simulated car following behaviour of autonomous vehicles, on a single 5 kilometre long lane using different communication methods between cars. The acceleration and deceleration profiles of the cars were implemented along with the communication controller using SUMO, and results were in line with expectations from prior analytical analysis. The existence of software such as SUMO that is capable of simulating acceleration & deceleration constraints, reveals an opportunity to study the macroscopic effects of the aforementioned LRC vehicles within a wider transport network. To date this has not been performed.

Apart from congestion, convenience and comfort may have other detrimental effects. For example, improving convenience and comfort of autonomous vehicles has the potential to "increase total vehicle travel and therefore crash exposure" [3]. This comment is based on a projected increase in vehicle miles travelled of 3-9%. However, this figure is taken using travel demand modelling of an assumed scenario occurring in the future, that is isolated to Germany. An activity based model was also shown to large increases vehicle miles travelled [33]. Still, the limited research in this area suggests further opportunity to validate this prediction.

3.4 Impact of Lower Disutility of Autonomous Vehicle travel

The second of the two value of time components being studied is the productivity gains that lower the disutility of travel. This will be discussed here.

3.4.1 Current Value-Of-Travel-Time Studies

Value of travel time (VTT) varies between travel modes, for reasons such as comfort [17] and the ability to perform non-driving activities while travelling [34]. These benefits (utilities) reduce the overall disutility of travel for these travel modes, enabling travellers to travel longer for the same relative cost. The importance of reducing the disutility of travel is so paramount, it is quantified as the 'value of travel time saving' or VTTS; where the saving is the reduction in disutility, and the value represents the relative worth of this saving. VTTS has been shown to be higher for long-distance trips, and vary by trip purpose, travel mode, country, as well as access and egress times in various meta-analyses ([35], [21], [36], [37]). First we will discuss VTT more generally through these meta-analyse, then identify the specific aspects of it that are pertinent to our question.

The main meta-analyse mentioned above on VTTS [35] used 77 studies across 28 countries, while [21] used 105 that were isolated to Britain, and was repeated for [36] and [37]. These meta-analysis all use stated preference (SP) methods, that employ regression models to estimate VTT coefficients from a series of studies. In these studies, SP methods are often coupled with Revealed preference (RP) methods, which rely on observed (revealed) data rather than opinion (stated) surveys. SP methods appear to be the de facto standard for choice modelling in transportation, in particular those that can be defined as 'Stated choice' experiments [38]. This is important for the case of AVs, as SP methods are the only way to measure the AV's VTT , until such time that AV travel exists within society and is observable. If there are shortcomings to SP methods, this will have ramifications for AV VTT findings.

While both [35] and [21] compared and combined SP and RP methods, their conclusions differed marginally, and neither have tackled the issue of autonomous vehicles. Both [35] and [21] found SP methods exhibit a lower VTTS than joint SP-RP methods ([21] specifies this as 15% lower), in particular around OVT (out of vehicle time) which is supported by numerous studies [39].

Despite this, [21] stated that SP and RP are "broadly comparable", and provided explanations in the form of the respondent's psychological rationalising process for why SP may differ, such as respondents using "simplified decision rules" and over-rating the variability of cost, thereby devaluing the cost and subsequent cost-savings. These limitations of SP models are important, since we have established that SP models are the only existing way to predict autonomous vehicle VTT. This suggests the eventual RP costs may be marginally greater than the SP data indicates.

While studies on AV VTT are limited, one can look at the characteristics that define existing VTT in existing travel modes, such as comfort, to infer part of the AV VTT, since it will have characteristics in common. In [17], the main and alternate modes of transport for 3945 respondents to a Danish VTT Survey are compared, to determine the relative VTT of each transport mode. It is found that – on average – non-autonomous car users have a higher VTT than other mode users, and are more likely to use high VTT travel modes. However this appears to be dependent on the driver's original mode, since car drivers also show high VTT within bus and train. Thus the author finds that "self-selection seems a credible explanation" for why travel modes differ in VTT, rather than the mode itself. When looking at mode effects, [17] found that the train travel mode has a higher VTT than non-autonomous cars for existing car and train users, due to the increased comfort level in non-autonomous cars. This contrasts with other studies that identify value of travel time within trains as lower than cars [40]. This may in part be explained by the difference in wage earnings of train users as compared to car users, as described in [41], where "VOTT is currently dependent not on the mode per se but on the associated wage rate of the 'average' traveller on that mode". This is supported by [17]'s finding that the driver's original travel mode is more indicative of their VTT than the mode itself. A limitation to [17] is the assumption of comfort being the determinant of any non-strategic travel mode choice, as well as no clear description of how comfort is defined.

We have shown above that both car and train users present an increase in VTT when using the train travel mode, relative to their original mode. We also showed that VTT for car users on average may be higher than those in trains. This highlights an important point, that VTT is dependant on specific subsets of the population. An example is Mokhtarian P and Salomon I, who note that some people prefer public transportation for its "opportunity to engage in other activities while traveling" [10], citing several studies that use circumstantial evidence of this. Though circumstantial evidence is not scientifically rigorous, due to the inability to extrapolate anecdotes towards large-scale effects, without elaborate justification for doing so. It is still plausible that this phenomenon can be extended to some of the population. [9] cites a paper stating that "commuters are more likely to consider their travel-time as wasted than people travelling for leisure or business reasons", which is partially supported by [37] that saw ~10% higher VTT in commuters, and [16] that sees VTT during peak hour times as higher than non- peak hour times. This higher VTT among commuters suggests that they would see the highest VTT benefit through the introduction of AVs, if AVs are able to provide VTT savings (VTTS).

More advanced VTT estimation methods include the creation of mixed logit models such as [18] and [42]. This approach goes beyond the simpler regression methods (simpler meaning fewer coefficients, steps required to calculate the result, and computational complexity) used in [35], [21],[36],[37]. The mixed logit model does not encounter some of the problems with other regression models such as the multinomial logistic regression model used in [43] - often referred to as multinomial logit. For example, multinomial logit models assume coefficients do not change between individuals ([18], [20]), that adding alternatives does not change the odds-ratio of existing alternatives (i.e. the odds ratios are independent) [18], and that repeated choices by the same respondent are independent of each-other [18]. One limitation with mixed logit models is the inability to quantify the effect of unobserved variables [20]. An example given is a traveller's wish to take a longer scenic walk over a shorter car trip for subjective reasons. Though this limitation is not unique to this method. This limitation may also not have any notable effect on VTT. If we assume that subjective reasons can be in part distinguished by demographics, then [16] supports this notion, as it finds no statistically significant effect for the unobserved heterogeneity of users.

While no clear consensus can be drawn, the above establishes car users as generally carrying a higher VTT than other transport users, with the user having more impact than the travel mode itself. It also shows that if given the choice, both car and train users show lower VTT in cars due to the car's added comfort. Commuters are found to have the highest VTTs, and therefore are the group that would benefit the most from VTTS, such as those born by AVs. Finally, we conclude finding that mixed logistic regression models are the most advanced and less susceptible of regression methods used for VTT calculation, but note that there is reason to suspect the improvement over simpler methods such as multinomial logit may not be statistically significant.

3.4.2 Reductions in Value-Of-Travel-Time of Autonomous Vehicles

With the advent of AVs, it is likely that the value of travel time for AVs will differ from that of HVs (human-driven vehicles). One of the major benefits of AV is the increased utility it may provide, by allowing drivers to perform other activities ([3], [7], [8], [9]). This will likely translate to a lowered value of travel time for AV users, due to part of the travel time being usable ([8], [40]). In [34] it is speculated that at 90% AV market penetration the economic benefits of AVs will reach $196 billion, 66% of which will be born by congestion benefits that include in part the "lowered burdens of in-vehicle travel time". In [9] it was found that those who spend-time working in public transport are most likely to consider working in autonomous vehicles as an advantage.

Gucwa has performed a "first-of-its-kind activity-based analysis of the prospective impacts of road vehicle automation on travel patterns in the San Francisco Bay Area" [8] citing [40]. This was achieved through various technologies, including CT-RAMP, Citilabs Cube, SAS, R, and Excel [40]. He finds that automation will lead to a short-run increase of 4-8% in daily vehicle miles travelled, as a result of the value-of-time being comparable to high-speed rail, or half that of a vehicle. The half-car VTT does not appear to be based on any reasoning; presumably it is calculated from the idea that half of the time in the vehicle is usable for performing other activities while driving. However this is not a rigorous approach, and therefore is not advisable to be used as a benchmark. The high quality rail figure is more understandable, as it is a real-world travel mode's value of time, has a high comfort level akin to non-autonomous cars that we previously saw decreases their VTT in [17], and provides passengers the ability to perform other activities that some people take advantage of [10], just as an AV would. For these reasons the high-speed rail figure of 4.0% – 5.2% greater vehicle miles travelled appears the more accurate of the two. This is approximately 1.587x of the amount of the half-car VTT, which is 6.7% – 7.9%. Unfortunately the VTT of high quality rail is not given, but if vehicle miles travelled scales linearly with the value of time, we can infer the high quality rail VTT presented in [40] as 1.587x higher than the half-car VTT, or 0.7935x that of a full-car VTT.

One recent working paper that attempts to define autonomous vehicle VTT is [43]. This study used the previously mentioned survey method that incorporates stated preferences (SP) and revealed preferences (RP) data within an analytical model. The model used is the multinomial logit model. This paper supports the earlier notion that commuters would benefit most from AVs, as they are found to perceive travel time in AVs less negatively when the car is driving itself than when it is being driven manually [43]. Riding autonomously to work is also perceived less negatively than all other travel modes, which confirms earlier VTT studies ([35], [21]). The study also aligns with earlier studies' findings that OVT (out of vehicle time) [38] is valued higher than IVT, resulting in more negative responses when it is exacerbated (e.g. waiting times). However it contradicts a previous study [41] that found passengers earning higher wages had higher VTTs on average, instead finding that low income earners were "perceiving travel cost more negatively than people with middle or high income". It also claims that these VTTS are in the range of public transport VTTS, contrary to [17] and [41], particularly because it controls for passenger's wage rate, which [41] claimed was the reason for public transport having a higher VTT.

Activities currently performed on existing light-rail transport vary widely. In London it has been found that they predominantly involve typing on a phone and interacting with technology [44], in a study comprising over 1700 passengers. These activities have shown to pose a safety risk if performed while driving, since they distract drivers from the road [45]. Since AVs mitigate this risk, it is likely that such activities will become prevalent within cars, adding to the utility of the AV.

This reduction in safety risk of performing activities within an AV will also have the side-effect of reducing the risk of existing users of phone within cars. In Melbourne, a recent study found that 3.4% of observed drivers at high-traffic intersections were using a hand-held phone [46]. This study observed 5813 drivers at six points of the day, noting the demographics and vehicle types. The amount using hand-held phones was as high as 7% for P1 plate drivers (first year of driver's license). Importantly this study was limited to intersections, and does not necessarily reflect the driver's phone usage habits while the driver's vehicle is in motion, where the majority of the safety risk resides. However this added safety is also likely to further reduce the VTT for cars, since risk-averse drivers will be more open to travelling, and travelling longer distances.

Therefore autonomous vehicles can be seen as likely to exhibit a VTT similar to existing high- speed rail services, and one that is lower than all other existing travel modes, yet closer to the existing public transport travel mode. As shown, the activities performed within these vehicles are likely to involve using a phone and interacting with technology. The ability to perform these activities safely will likely reduce the risk of those already using phones within their vehicles, improving the overall safety of car travel and further reducing the predicted AV's VTT. Collectively this forms the basis for understanding the VTT of AVs.

3.4.3 Incorporating Light-rail Constraints and Reduced value-of-time AVs within Travel Mode Choice

While a number of studies have been performed on the potential traffic effects of the introduction of AVs, only one ([8]) to date has incorporated the effects of light-rail acceleration & deceleration constraints that curb motion sickness, and none have incorporated both the light- rail constraints and VTT reduction. Nor has any study measured the effect of such light-rail constraints on existing VTT measures. The study mentioned ([8]) discusses the difference in VTT between an AV and a HV (human-driven vehicle) as part of its background, but did not account for this difference anywhere in its analysis. Therefore there is a gap in existing research, on understanding the combined effects of both light-rail acceleration & deceleration constraints, and the hypothesised reduced VTT of autonomous vehicles born by productivity gains.

In this vein a multitude of traffic effects can be studied: congestion, density of road traffic, distribution of vehicle types, or distribution of travel mode choice. As has been discussed and shown, the light-rail constraints mentioned would likely lead to increased congestion. Likewise the hypothesised reduced VTT of autonomous vehicles would lead to an increase in vehicle miles travelled [40], which is likely to further add congestion. However the combination of these two effects may convince car users – both AV and non-AV – to choose other forms of transport less affected by road traffic, such as trains and trams. Naturally this effect cannot be captured merely by measuring congestion or density of road traffic. Therefore it is proposed that the cumulative effect of both of these AV properties would be captured in the change in travel mode choice. This is because train travel mode is not - or in a very limited sense - affected by car congestion, it can be used as a baseline for whether autonomous vehicles improve or reduce the appeal of car travel. If the congestion drawbacks outweigh the productive benefits of AVs, then we expect the overall number of car trips to decline, as car users migrate to other forms of transport. Conversely if the productivity benefits of AVs outweigh the increase in congestion, then the reverse is expected, with more car users taking advantage of the extra time for non-driving activities.

This emphasis on understanding this potential change travel mode choice is also justified by the potential cost savings. One review [47] of existing literature on the monetary savings of public transport within Australia, found a saving of between \$0.044 and \$1.514 per marginal vehicle km travelled. The various economic models used for quantifying these economic costs are described in [48], and comprises their own area of research. Such considerations, while interesting, are beyond the scope of this review. It includes a study that predicted a 29% increase in delays if all public transport travel was switched to car. The converse was also included in this figure, in the form of decongestion, where \$0.305 to \$1.040 could be saved per car km that switched to public transport. The study also found these findings to be somewhat consistent with European and American studies, with Europe showing comparable figures while America showed a reduced figure of \$0.261 per km travelled. This suggests an increase or decrease in overall car users - as born by the introduction of AV - may increase or reduce economic costs respectively.

3.5 Understanding Travel Mode Choice

To understand the change in travel mode choices, as might be caused by the introduction of AVs, one needs to create a predictive model of travel mode choices, that contains parameters which can be altered for new scenarios. This can be done retrospectively, working backwards from the travel mode choice. An example of this is [49], where logistic regression was used on the characteristics of the persons making the travel choice, to determine to what extent (if any) each characteristic of the persons' influenced this decision, such as their age or income. Here a set of coefficients were initially chosen to represent trip and demographic characteristics. Then a stepwise regression was performed to determine the four most significant variables (coefficients) that determined the probability of an agent selecting a package tour. From these coefficients, one is able to predict new, previously unseen trips by knowing their characteristics alone. If, as a hypothetical example, a coefficient of in-vehicle productivity is a strong predictor for a trip being chosen, then trips which see greater in-vehicle productivity (such as those taken by AV) will be predicted as more likely to be chosen. While this approach may be taken with stepwise regression, stepwise regression has its own limitations, such as overfitting through capitalisation on sampling error [50], and being unable to accurately determine the order of significance within variables [51].

An alternative approach is to uncover the VTT of travel modes for each trip, then much as in the prior example, attempt to infer the VTT of a new travel mode by way of characteristics it shares with known travel modes. Once the VTT is known, if the trip times are also known, these can be multiplied by the trip mode's VTT, and the travel mode choice intuitively becomes the trip with the lowest cost (or highest utility if the value is positive). This is the approach taken in the multi- agent transport simulation software MATSim [52], which uses a multinomial logit model (MNL) in conjunction with its own VTTS formula, to determine the maximum utility plan for a select proportion of agents for each simulated day (see Chapter 3 of [52]). MATSim has been used to simulate numerous cities' travel networks around the world, including Berlin, Germany; Zurich, Sweden; San Fransisco, USA; Seoul, Korea; and many others [52]. Transport simulation accuracy appears to be high, with the Caracas scenario in [52] showing simulated traffic counts within 3% of a comparable study using an alternative method. Similarly, the Shanghai scenario found "Extensive simulation results indicate that most traffic simulation volumes matched quite well with observed counts". While research into choice of travel mode within a simulation is scarce, the San Francisco scenario extends MATSim's scoring function to include social influence factors, to determine the effect of social influence on travel mode choice. This relies on the multi-modal extension of MATSim, defined in 21.3.1 of [52], but shows the ability for simulation software to be used for predicting travel mode choice.

4 Methodology

4.1 Outline

The first property being analysed is the light-rail constrainted driving style that, as has been discussed in the Background and Literature Review sections, is likely to be adopted by autonomous vehicles. The second property is the reduced Value-of-Travel-Time by passengers (known as VTT) using autonomous vehicles, due to the opportunity provided to them to perform non-driving activities while travelling. The goal of our methodology is to represent both of these properties as detractors and attractors for car use respectively, in order to understand what the net attractiveness of car use will be. Using public transportation within our scenario (Trains and trams) as a control, it is possible to measure the change in car use by the relative increase or decrease in the use of trains and trams. This is made possible through the replanning module within the MATSim software, that allows travellers to change their travel mode based on the score of that travel mode. The score of the travel mode can be adjusted to take into account properties such as the two being analysed. By adjusting the score of car travel to account for the aforementioned two detracting and attracting properties, the simulation can be run to determine whether the adjustments lead to more or fewer car users. The following sections detail how these properties are identified and subsequently implemented within MATSim.

4.2 Software

Two pieces of transport simulation software are used – SUMO [53] and MATSim [52]. Both SUMO and MATSim are agent based modelling and simulation software. Agent Based Modelling and Simulation (ABMS) involves modelling individuals within a simulation independently, as self-contained, autonomous, and containing their own state, behaviours and goals [54]. This distributed approach produces emergent phenomenon not possible within a centralised system, such as patterns in congestion, travel mode and route choice.

The choice to use both software stem from limitations in both software, that prevent either from being used exclusively for the purpose of this study. SUMO is used for simulating the light-rail constraints imposed on our cars, as MATSim is not able to simulate acceleration or deceleration of agents. SUMO's capability for modelling light-rail constraints comes from its use of acceleration and deceleration to achieve agent velocity [32]. This enables microscopic simulation capability not possible in other simulation software such as MATSim. MATSim is used for simulating the VTT change born by travellers' ability to perform other activities while travelling [8], using its novel scoring function that does not exist within SUMO.

Alongside these software, python scripts are also developed and used to scale our car population and measure trip durations for subsets of the population. These were developed and ran through Jupyter Notebooks [55], an iPython GUI designed for developing reproducible workflows.

4.3 Melbourne Model

The analysis uses two existing MATSim models of the city of Melbourne. The main model used for running the final simulations is developed by the KPMG and ARUP companies for Infrastructure Victoria, an independent advisory board for Victoria, Australia's infrastructure. Importantly for this analysis, the model includes a linear regression on the Vista survey data [56], to produce travel mode utility functions (referred to as calibration parameters) for all travel modes that reflect current sentiment. The Vista survey is a public government survey conducted between 2012 and 2016, to understand Victorian household travel behaviours. This MATSim model is used within the final simulation. The words 'model' and 'scenario' may be used interchangeably, as the MATSim scenario is represented by a single model, and can only be referred to via its model.

A secondary model is used for discovering the effect of light-rail constraints, as the KPMG MATSim model was not available at the time. This model is for the city of Melbourne, Australia's Metropolitan Network, and is produced by RMIT University, University of Melbourne, CSIRO Data61, Swinburne University, and KPMG Australia [57]. This model will be referred to as the

'Vista' model, as it uses Vista survey data. It is used within all simulations. The words 'model' and 'scenario' may be used interchangeably, as the MATSim scenario is represented by a single model, and can only be referred to via its model.

The Vista model is converted to the SUMO format using SUMO's netconvert function. To improve running times, trips within the Inner East and CBD areas of Melbourne are isolated (see the results section 5.1 for details) and used exclusively for all SUMO simulations. All non-car population is removed (e.g. pedestrians), as these agents are simulated differently within SUMO or not at all, and are not required for our analysis. After converting the model to the SUMO format, trips are duplicated numerous times to achieve congestion levels in-line with expected values in Melbourne. These expected values are taken from an untouched version of this MATSim model.

The light-rail constraints are modelled using SUMO's "accel" and "decel" parameters within the config file, which set the upper bound metres-per-second acceleration and/or deceleration allowed by vehicles. The Melbourne model is run in SUMO with and without these constraints.

4.4 MATSim Scoring Function

The scoring function is a capability within MATSim, that enables the use of value of travel time models [52], by assigning utility and monetary value to trips and activities. This utility is generally provided in advance, but can scale with time and trip length, among other variables. It can also be adjusted higher or lower, such as to account for the added utility of performing other activities while travelling. Both components being analysed are represented as adjustments to the utility within MATSim's scoring function.

MATSim is used for determining the final attractiveness of car use. This is achieved through the scoring function, by inputting both the reduction in VTT from travellers being able to perform other activities while travelling, as well as the delay caused by adding light-rail constraints. This delay caused by adding light-rail constraints is framed as disutility, while the VTT reduction can be seen as adding utility. The scoring function and its terms are noted in Figures 1 and 2 below, and are taken from the MATSim manual [58]. The scoring function is used to determine the score of each trip, based on the utility or disutility it provides to the traveller. The terms that are to be adjusted have been highlighted in red and blue.

$$S_{trav,q} = C_{mode,q} + \beta_{trav,mode(q)} \cdot t_{trav,q} + \beta_m \cdot \Delta m_q + (\beta_{d,mode(q)} + \beta_m \cdot \gamma_{d,mode(q)}) \cdot d_{trav,q} + \beta_{transfer} \cdot x_{transfer,q} \quad (1)$$

Figure 1: The MATSim scoring equation, with terms used coloured

- $C_{mode(q)}$ is a mode-specific constant.
- $\beta_{trav,mode(q)}$ is the direct (see Section 3.2.4) marginal utility of time spent traveling by mode. Since MATSim uses and scores 24-hour episodes, this is in addition to the marginal utility of time as a resource (again, see Section 3.2.4).
- $t_{trav,q}$ is the travel time between activity locations q and q + 1.
- β_m is the marginal utility of money (normally positive).
- Δm_q is the change in monetary budget caused by fares, or tolls for the complete leg (normally negative or zero).
- $\beta_{d,mode(q)}$ is the marginal utility of distance (normally negative or zero).
- $\gamma_{d,mode(q)}$ is the mode-specific monetary distance rate (normally negative or zero).
- $d_{trav,q}$ is the distance traveled between activity locations q and q + 1.
- $\beta_{transfer}$ are public transport transfer penalties (normally negative).
- $x_{transfer,q}$ is a 0/1 variable signaling whether a transfer occurred between the previous and current leg.

Figure 2: Definitions of the terms used within the MATSim scoring equation, with terms used coloured

In the above equation, the VTT reduction of performing other activites while travelling is represented as a reduction in $\beta_{trav,car(q)}$, the marginal disutility* of travel time when travelling by car. This is achieved by scaling the existing car travel time disutility within MATSim by the VTT reduction identified. Similarly, the delay caused by adding light-rail constraints can be represented as a decrease in $\beta_{d,mode(q)}$, the marginal disutility of travel distance, whereby the further one travels the more delay one incurs (the decision to use distance here is explained further in this section). This is done by first identifying a linear function for the delay based on distance, then converting it into utility.

**NB: While the term is defined as marginal utility in the above table, travel time is defined within MATSim and the majority of literature as a disutility, due to the cost incurred to the traveller. Therefore to avoid confusion the term 'disutility' is used, rather than negative marginal utility, although both are interchangeable.*

4.5 Deriving Delay Function of Light-Rail Constraints

A linear function for the delay incurred by adding light-rail constraints (LRCs) is produced, by applying a simple linear regression on the results of running the SUMO simulation from section 4.2 twice, once with and without light-rail constraints. The trip duration difference ($\Delta t = t_{LRC} - t_{NonLRC}$) between the LRC and Non-LRC trip duration for each given trip is plotted against distance. This trip duration delta represents the delay incurred by using light-rail constraints. This time delta plot is used to develop a linear function through the use of linear regression with some manual adjustment. Separately, a logarithmic equation is found that fits the data better, but is not usable within MATSim.

Within this function the independent variable chosen is the length or distance of the trip, with the resulting coefficient on duration being the dependant variable. The rationale for making distance the independent variable rather than time, is that LRC delays are hypothesised to scale more with distance than with time. This is because the effect is likely to be more pronounced within start and stop traffic that occurs within short congested inner city trips, as opposed to long suburban or rural trips that require very little starting and stopping. While distances vary between these trip types, durations may be comparable, giving duration less explainability than distance with regard to trip type. This unreliability of trip durations makes trip distance a more suitable independent variable. Furthermore, as described in [59], part of the delay can be attributed to control delays, which are the delays caused by traffic control devices. Control delay "represents the time spent in queue plus the delay due to acceleration and deceleration"[59], and occurs at each traffic control. Since the probability of encountering a traffic control increases with distance travelled, distance can be treated as a rough proxy for the number of traffic controls encountered. It is true that traffic controls are more prevalent in inner cities, potentially causing an under-representation of the effect in cities and an over-representation in rural areas. Solving for this is beyond the scope of the study, however instructions on how to account for this are provided. A brief analysis is also performed on Inner City trips as compared to Suburban and Overall trips, to determine the significance of this effect. Acceleration and deceleration appear to be consistent independent of traffic conditions. This can be seen in acceleration and deceleration shockwaves, where wave speeds are independent of traffic conditions such as density and flow [60]. Therefore we have opted for applying a universal delay coefficient on metres travelled, rather than time travelled or other variables.

If a more accurate representation of the delay caused by light-rail constraints were required, it is possible to produce multiple of the aforementioned linear functions. This could be achieved by splitting the travelling population in both SUMO and MATSim by the characteristics of their journey, to create sets of travellers that each adopt their own linear function. Meaningful categories may include: number of traffic controls, number of intersections, number of turns, and average density of roads travelled, with categories defined as -1, 0, and 1 standard deviation away from the mean values. By creating additional modes in MATSim to represent each distinct category (e.g. $car1$, $car2$, ...), it would be possible to apply a different linear function to each mode. This approach has not been taken, but is documented here as a potential avenue for further research that was considered.

The goal of the delay function is to increase the perceived travel time among travellers, to account for the delay incurred by imposing light-rail constraints. To achieve this, the delay function must be inputted into the MATSim scoring function described in 4.4. This is done via the marginal disutility of distance term, $d_{trav,q}$. Since all inputs to the scoring function must be represented in terms of utility (or disutility), the travel time delay function is first converted into disutility using MATSim's default disutility per hour of travelling by car, by multiplying the delay by this disutility. Following this, the function is solved for one metre to get the disutility per metre travelled, which is required by MATSim. The resulting coefficient is then able to be placed within the configuration file.

4.6 Adding Utility For Performing Other Activities While Travelling

A further adjustment to the scoring function (4.4) is needed in order to account for the second property being studied, the ability to perform other activities while travelling. This takes the form of a reduction to the marginal disutility of travel time $\beta_{trav,car(q)}$, which is equivalent to a reduction in VTT (Value of Travel Time), as both definitions represent reductions in utility. Because existing research on the reduced Value of Travel Time (VTT) of travel modes that enable performing other activities (3.4.2) has found a usable coefficient, it was not necessary to discover this. Instead the existing research performed by Gucwa [40] was used to find the coefficient for the amount of reduction needed, in this case using the High Quality rail figures identified, due to the close match between the comfort and ability to perform other activities in High quality rail services, and those expected in autonomous vehicles. Unfortunately there were limitations in the precise values provided by Gucwa, and as a result several derivation and assumptions were needed to convert from miles travelled to VTT values, including converting half a car's VTT to a full car's VTT, since the full car VTT was not provided. The precise steps followed to find the VTT reduction amount and their values are outlined in the latter part of the Results section 5.3.

To convert the VTT of existing marginal disutility of travel time values by car, the MATSim marginal disutility of travel time term $\beta_{trav,car(q)}$ is solved for for one hour using the VTT reduction coefficient derived earlier, to obtain the new disutility per hour travelled. This parameter is then placed within the configuration file.

4.7 Execution

The final configuration for MATSim contains the new marginal disutility of distance travelled as a result of imposing light-rail constraints, and the new marginal disutility of time travelled after adding the VTT reduction of performing other activities while travelling. The simulation is run once with and once without these changes. The default proportion of travellers that have an opportunity to change their travel mode in MATSim is 10% per iteration; this is maintained and called *replanning* within MATSim. The term iteration here is defined as discrete simulation runs where some proportion of agents use information from a prior run to replan their trip, in this case 10%. This is documented within MATSim [52]. The default number of iterations is 10, however different amounts of iterations are experimented with as part of the analysis, until a convergence is identified. The resulting change in travel mode from first to last iteration is recorded, both in the original and adjusted model. This represents the net attractiveness of autonomous vehicles relative to ordinary vehicles, and subsequently the uplift or decrease one would see in overall car usage as a result.

The diagram below (3) outlines the process that has been followed.

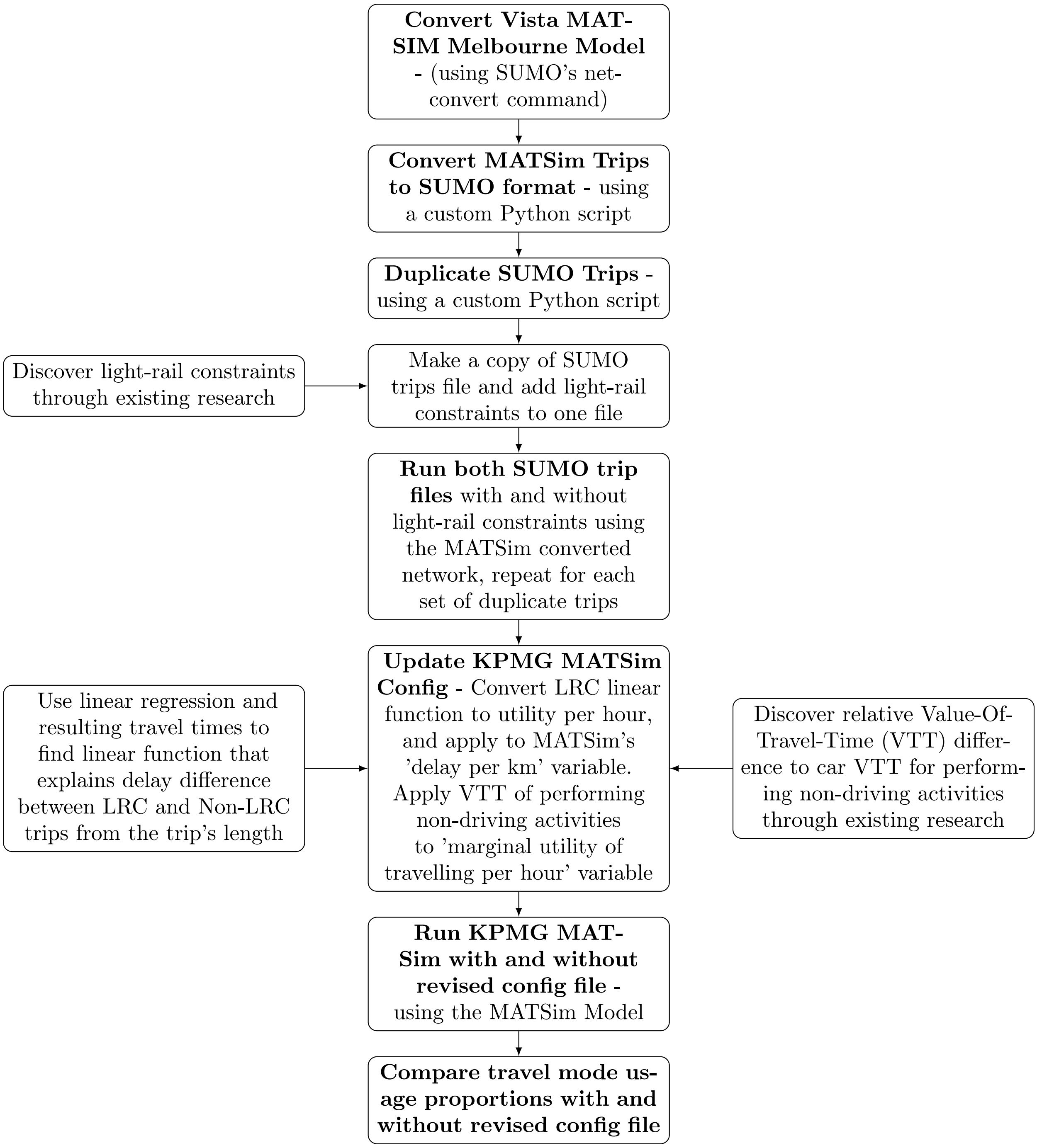


Figure 3: End to end process followed

5 Results

5.1 Vista MATSim Model

The Vista MATSim Model of the city of Melbourne was successfully converted to the SUMO format. Due to issues in converting traffic lights, these had to be generated using SUMO's traffic light guessing option. A custom python script was used to convert the MATSim format population trips to SUMO format trips. A second script was used to limit the trips counted to those within the Inner East and CBD of Melbourne. This removes all trips that don't originate or finish within the bounding box shown below. Note that persons and activities were not replicated, only the trips themselves and when they occurred.

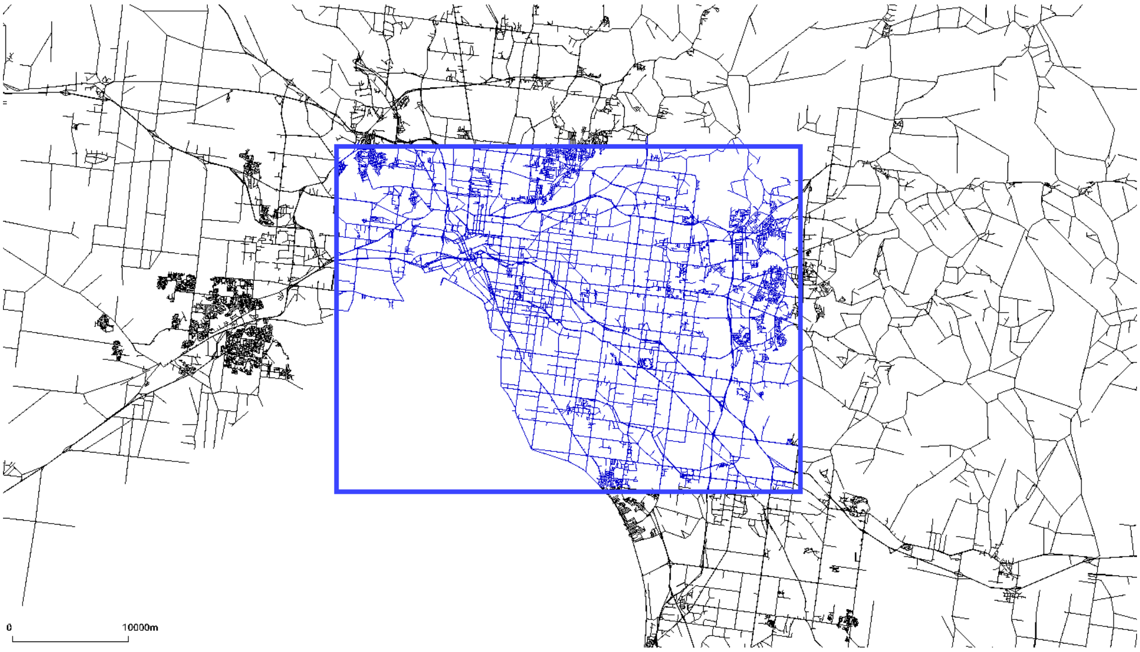


Figure 4: Maximum bounds for trip origin and destination

The original population of this scenario has 14,530 persons making 51,460 trips. Within these 51,460 trips there are 14,484 trips located within the Inner East Suburbs, as defined by the below map (4). These 14,484 are the trips used and duplicated within the study.

**NOTE: actual runs use 14,258 trips (98.4%) and 85,539 trips (98.4%) respectively due to 1.6% of trips having an error in conversion between MATSim and SUMO formats.*

Using the set car trips within Inner East and Melbourne CBD, the SUMO configuration file is duplicated, with one copy being adjusted to include the Light-rail acceleration and deceleration constraints (LRCs) of $1.34m^2$ and $2.01m^2$ respectively. These are found via the publicly available track design handbook [15] which is used within Washington D.C. This is higher than the typical passenger car's average acceleration of $1.34m^2$, but lower than a typical maximum acceleration of $3m^2$ and jerk acceleration of $2.13m^2$ as described in [59].

The trip population is run in SUMO for $n = 5, 10, 15, 20, 30, 40$ to determine the number of trips needed to mimic real-world average travelling speed of 42.73 km/h, which is obtained through the MATSim simulation. The average speed, road occupancy and density are noted. To understand the appropriate number of trips, the average trip speed in each simulation run is compared to the MATSim average speed of 42.73 km/h, and the ideal number of duplicates is chosen.

duplicates	no. of car trips	occupancy (%)	density (v/km)	speed (km/h)
1	14257	0.002	0.079	47.23
5	71283	0.019	0.459	45.44
10	**142459**	**0.061**	**1.506**	**44.13**
15	212679	0.153	4.235	39.15
20	278590	0.301	6.52	41.11
30	394937	0.813	14.13	37.74
40	486147	0.829	25.14	35.99

Figure 5: SUMO road occupancy, density, and speed by number of car trips

As can be seen in Figure 5, duplicating the trip population 10 times results in an average speed of 44.13 km/h, which closely matches the MATSim average speed of 42.73 km/h. Therefore the SUMO simulation is run with 10 duplicates, as this produces congestion levels in line with the existing MATSim network.

5.2 Light-Rail Constraints

5.2.1 Generating the Delay Function

The SUMO model is run with 10 duplicates, once with LRC applied in the configuration to all cars, and once without. The travel times of both LRC (t_{LRC})and Non-LRC (t_{NonLRC}) simulation runs are recorded, and the difference between the two trip durations for each trip ($\Delta t = t_{LRC} - t_{NonLRC}$) is analysed, in order to find a relationship with trip length. This relationship will be used to define the delay function that will be inputted into MATSim, using trip length as the independent variable.

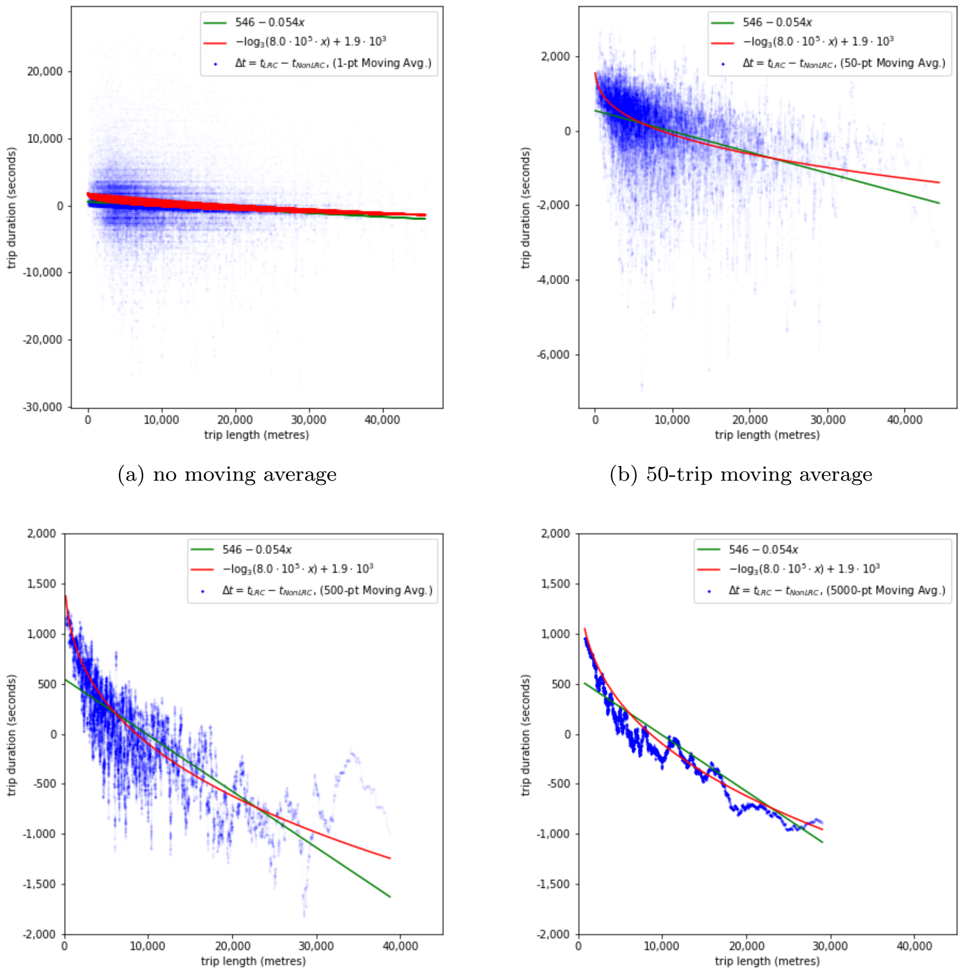
It is of note that while analysis is performed on individual trips, ultimately it is the *aggregate* duration for groups of trips that is used for deriving the delay function, rather than the duration of individual trips. This is because individual trips have a much higher volatility, due to the effect of applying LRCs being rather small, and subsequently not always occuring on any given trip. However while the LRC effect does not always occur on any given trip, it does always occur when at least a certain number of trips are made. The precise number of trips that need to occur to produce a reliable relationship can be identified using a moving average and pearson's correlation coefficient.

First the difference is taken for each trip duration between its LRC and Non-LRC run, to produce a time duration delta $\Delta t = t_{LRC} - t_{NonLRC}$. This delta Δt is plotted against trip length to test two hypothesise. One is to determine whether there is a relationship between the length of the trip and the amount of delay. The second is whether this relationship is linear and increasing with time as one would expect (the longer the trip, the more delay minutes are incurred), or not.

Secondly, trips are sorted by trip length, and a moving-average is used to group trips together. Moving averages of 1 (individual trips), 50, 500, and 5000 points are used. In Figure 6, graphs are generated showing the trip duration delta ($\Delta t = t_{LRC} - t_{NonLRC}$) against trip length, using 1, 50, 500, and 5000 point moving averages on the trip duration delta respectively (total population is 141,459 trips).

Finally, the delay function is defined using a linear regression with some manual adjustment of values to bring the trend closer to the data it represents. A logarthmic function is found that appears to correlate well with the grouped data. While the logarithmic function more closely follows the delay incurred, a linear function is necessary due to limitations in MATSim's utility function. While it may be possible to use logarithmic functions within MATSim, this requires development work that is beyond the scope of this study.

5.2.2 Analysing Findings



(a) no moving average

(b) 50-trip moving average

(c) 500-trip moving average

(d) 5000-trip moving average

Figure 6: Change in trip duration caused by Light-rail constraints ($\Delta t = t_{LRC} - t_{NonLRC}$) as a function of trip length

$$\Delta t_{trav,car(q)}(d_{trav,car(q)}) = 5.4 * 10^{(-2)} \cdot d_{trav,car(q)} - 5.46 \cdot 10^3 \tag{2}$$

Figure 7: Linear Delay function for the change in travel time when using LRC constraints ($\Delta t_{trav,car(q)}$) that can be explained by trip length ($d_{trav,car(q)}$)

$$\Delta t_{trav,car(q)}(d_{trav,car(q)}) = -\log_3(8.0 \cdot 10^5 \cdot d_{trav,car(q)}) + 1.9 \cdot 10^3 \tag{3}$$

Figure 8: Logarithmic Delay function for the change in travel time when using LRC constraints ($\Delta t_{trav,car(q)}$) that can be explained by trip length ($d_{trav,car(q)}$)

Note: For the above equations, the t terms' definitions reflect those described in the methodology section 4.4 and used in the MATSim manual [52].

It was originally hypothesised that imposing light-rail constraints would cause delays in trips, based on the understanding that less acceleration and deceleration would reduce a car's ability to react, due to phenomena such as control delay being exacerbated by delays in acceleration and deceleration [61]. While this is true for the 75% of trips that are under 10 km (9) that average 215 seconds (3.6 minutes), it is not for trips greater than 10 km, as can be seen in 6, that average 434 seconds (7.2 minutes) shorter trip times. This means light-rail constraints are likely to be a benefit rather than a hindrance for long distance commuters. It can be reasoned that the cause of the benefit is the reduction in traffic slowing phenomena such as phantom jams, that aretypically caused by over-acceleration or over-deceleration [62]. By reducing driver's ability to accelerate and decelerate, so too is their ability to over-accelerate and over-decelerate to cause such phenomena. This would not occur as often with shorter trips, as they typically involve lower average speeds, making them less likely to reach the acceleration and deceleration limits that were imposed.

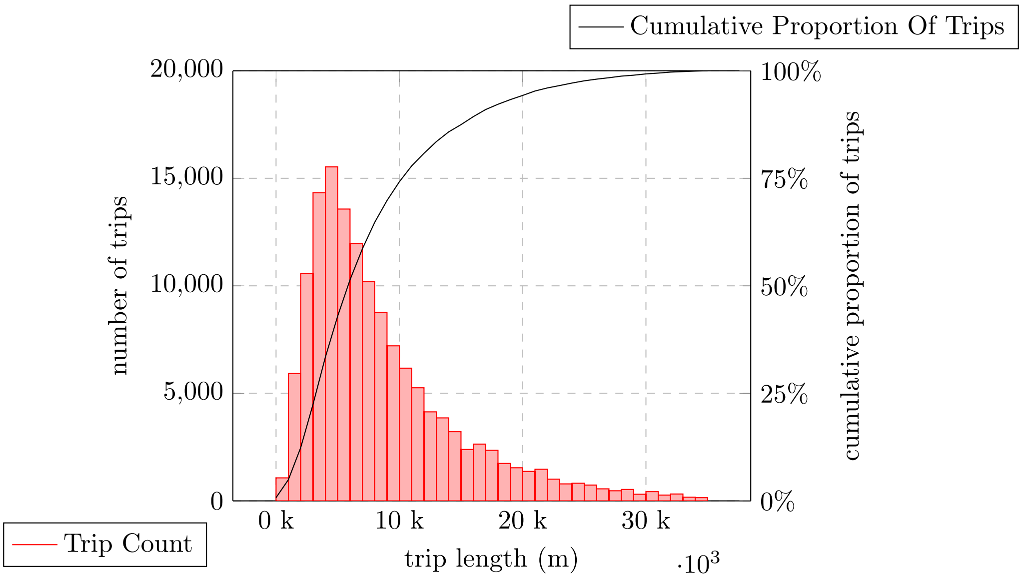


Figure 9: Trip Counts and Cumulative Distributive Function of Trip length

From the graphs in Figure 6, it can be seen that a 5000 point moving average produces the most reliable relationship between the trip duration delta Δt and trip length. This can be shown using the Pearson's Correlation coefficient, where a 500-point moving average results in a correlation of $r = -0.77$, while a 5000-point moving average results in a correlation of $r = -0.92$. Therefore the delay function being defined has been based on this finding.

The derived function suggests short trips initially incur on average a 546s penalty, but this reduces by 54 seconds per kilometre travelled. This means the delay is fully negated at 10km and a reduction of 54 seconds in travel time is achieved for every further kilometre travelled. This means a 20 km trip with LRCs imposed would result in a travel time saving of 600 seconds or 10 minutes. While it has been shown that the effect is most reliable for 5000 trips ($r = -0.92$), it is still strongly reliable for 500 trips ($r = -0.74$), which can be achieved in 1 year and 3 months of daily driving, assuming 200 workdays per year of driving to and from work ($200 workdays \times 1.25 years \times 2 trips = 500 trips$).

A summary of the correlation findings is shown below in Figure 10. Additional figures were produced for trips exclusively within the Monash University Clayton area, and trips exclusively within the Melbourne CBD area. The location of these areas is shown in Figure 11, and will be analysed separately.

N-point Moving Avg.	Bounded Area	Monash Clayton	CBD
1	-0.14	-0.08	-0.08
50	-0.40	-0.23	-0.28
500	-0.77	-0.54	-0.75
5000	-0.92	-0.91	-0.98

Figure 10: Pearson's Correlation Co-efficient between Trip Length and Change in trip duration caused by LRCs

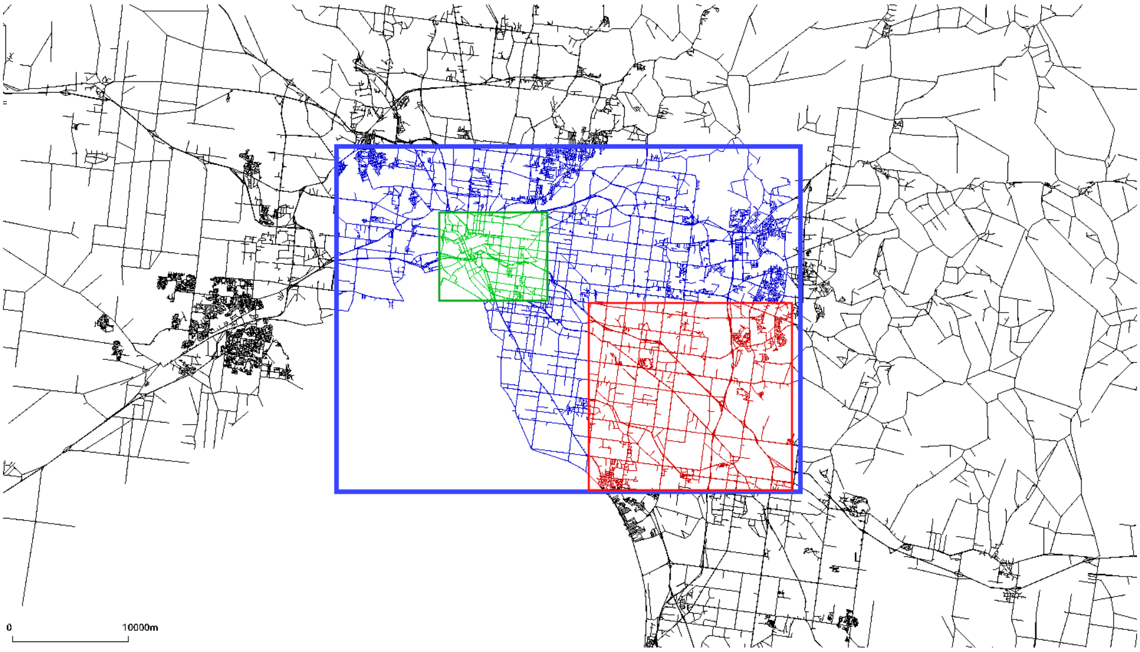
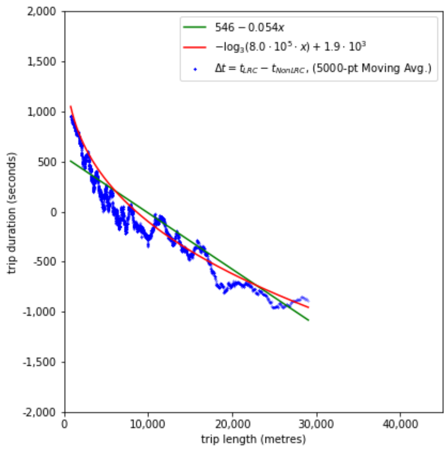


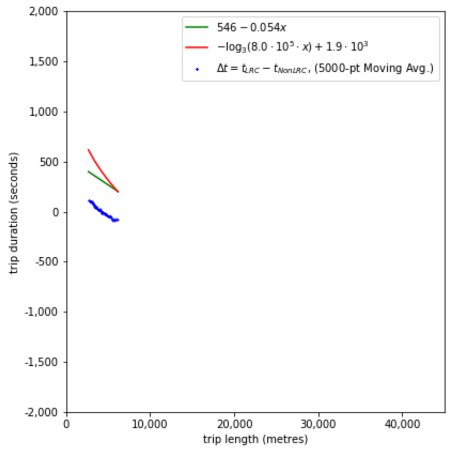
Figure 11: Monash Clayton (red), CBD (green), and Bounded Area (blue) bounds

5.2.3 Testing Universality of Delay Function

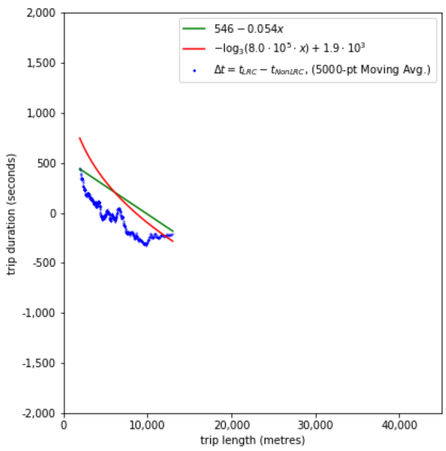
A further analysis is made on the CBD and Monash Clayton areas, to determine why the correlation coefficients may differ. The graphs in Figure 12 were produced in the same way as those in Figure 6, only in this case limited to a 5000-point moving average, as this grouping was found to have the highest correlation. The function derived from the overall data in 6 is carried over to test its universality. It can be seen that the Monash area's delay is over-represented by 200 seconds compared to the function overall, while the CBD area's delay is over-represented by 300 second variance. The delay data suggests that shorter, inner city trips are less likely to incur delays than suburban trips. However due to their short distance, CBD trips are also less likely to take advantage of the travel time savings caused by light-rail constraints in longer journeys that was identified earlier.



(a) Overall 5000-trip moving average



(b) CBD Area 5000-trip moving average



(c) Monash Area 5000-trip moving average

Figure 12: Change in trip duration caused by Light-rail constraints ($\Delta t = t_{LRC} - t_{NonLRC}$) as a function of trip length - Monash & CBD Areas. Truncation in the above graphs is due to maximum trip lengths being shorter within each area, as compared to the complete data set.

5.2.4 Converting Delay Function to a Utility Function

While the aforementioned function is useful for understanding travel delay in terms of travel time, in order for MATSim to make use of the function it must be converted to utility. This is because utility is the measure used within Value-of-Travel-Time (VTT) metrics, and is how MATSim derives its trip scores. MATSim by default uses a utility of -6 per hour for the car mode. As our delay is in seconds rather than hours, the travel time is divided twice by 60, then multipled by the -6 utility per hour currently used in MATSim for car travel (6). This provides us a marginal utility that can be used in turn to adjust the marginal utility of distance travelled by car in MATSim. which is desired since our delay function uses distance as its independent variable. The equation in (3) is repeated using the marginal utility term $\beta_{trav,car(q)}$ instead of the time term $t_{trav,car(q)}$.

$$\beta_{trav,car(q)} = t_{trav,car(q)}/60/60 * (-6) \tag{4}$$

Figure 13: Converting travel time by car ($t_{trav,car(q)}$) into MATSim marginal utility of travelling by car ($\beta_{trav,car(q)}$)

Now repeating the equation in (5), we arrive at the below equation, which has the following graph.

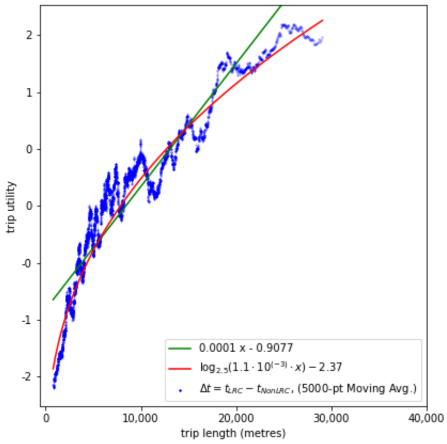


Figure 14: Change in marginal utility of travelling when using Light-rail constraints ($\Delta\beta_{trav,car(q)}$)

$$\Delta\beta_{trav,car(q)}(d_{trav,car(q)}) = 1.0 \cdot 10^{(-4)} * d_{trav,car(q)} - 9.077 \cdot 10^{(-1)} \tag{5}$$

Figure 15: Change in marginal utility of travelling when using Light-rail constraints ($\Delta\beta_{trav,car(q)}$) that can be explained by trip length ($d_{trav,car(q)}$)

This is then used to adjust the marginal utility of distance in MATSim. Since MATSim uses marginal utility per metre, we solve for 1 metre by inputting $d = 1$. Note that the constant $-9.077 \cdot 10^{(-1)}$ is not included here, as this is entered separately into the *constant* variable within MATSim.

$$\begin{gathered}
\beta_{d,car(q)} = \Delta\beta_{trav,car(q)}(d_{trav,car(q)}) \\
\beta_{1,car(q)} = \Delta\beta_{trav,car(q)}(1) \\
\beta_{1,car(q)} = 1.0 \cdot 10^{(-4)} \cdot 1
\end{gathered} \tag{6}$$

Figure 16: Adjusting marginal utility of distance ($\beta_{d,car(q)}$) using marginal utility of travelling ($\beta_{trav,car(q)}$), then finding the marginal utility for 1 metre ($d = 1$)

5.3 Value-Of-Travel-Time (VTT) Reduction from Performing Other Activities

To implement the second component of our passenger comfort model, the Value-Of-Travel-Time (VTT) of performing other activities while travelling is used. As performing other activities is while driving will be a function unique to autonomous vehicles, this feature has been referred to as the 'AV component' or 'AV VTT reduction' component from here on out.

5.3.1 Discovering the AV VTT Reduction Value

The precise reduction of Value-Of-Travel-Time will not be known until autonomous vehicles are a reality. However it has been hypothesised to be similar to existing high-speed rail services, at 79% of an existing car'[40]. The rationale and calculation behind this is described in 3.4.2. High quality rail has a VTT 1.587× higher than a 'half-car', which Gucwa uses as another possible VTT calculation, where the car's VTT is simply halved. As Gucwa does not provide the High quality rail VTT as a proportion of a full car's VTT, only a half car's VTT, we must calculate it based on the half-car's VTT. Also this VTT value itself must be derived from the increased proportion of miles travelled, since the value itself is not given. Here it is assumed that miles travelled is an inverse of VTT, since a decrease in VTT corresponds to an increase in miles travelled, as shown by Gucwa.

$$
\begin{aligned}
&v_{hqr} = \text{VTT of High Quality Rail}\\
&v_{hc} = \text{Half the VTT of a Car}\\
&v_c = \text{Full VTT of a Car}\\
&m_{hqr} = \text{Uplift in Vehicle Miles Travelled in High Quality Rail}\\
&m_{hc} = \text{Uplift in Vehicle Miles Travelled within a Half-Car VTT}\\
&m_r = \frac{m_{hqr}}{m_{hc}/2} = \text{High Quality Rail Miles Travelled uplift as proportion of Half car uplift halved}\\
&\text{Because VTT is inversely correlated with increase in miles travelled..}\\
&\text{we take the inverse of the ratio and multiply by half car VTT}\\
&v_{hqr} = v_{hc} * \frac{1}{m_r}\\
&\text{Which is the same as multiplying the full car VTT by half the uplift in miles travelled}\\
&v_{hqr} = (v_{hc} \cdot 2) \cdot (\tfrac{1}{m_r}/2)\\
&v_{hqr} = v_c \cdot (\tfrac{1}{m_r}/2)\\
&v_{hqr} = v_c \cdot (\tfrac{1}{0.6301}/2)\\
&v_{hqr} = v_c \cdot 0.7935\\
&= 20.65\%\ \text{reduction}
\end{aligned}
\tag{7}
$$

Figure 17: The Autonomous Vehicle VTT Reduction from performing other activities while travelling. Note that we multiply Half-Car VTT v_{hc} by two to get a Full Car VTT.

To incorporate the aforementioned VTT reduction of performing other activities while travelling, the existing marginal utility of time spent travelling by car is multipled by this VTT reduction, as shown in (18). Since MATSim uses marginality utility per hour, we solve for 1 hour by inputting $trav = 1$ in the below equation. MATSim sets a default marginal utility of -6 per hour for car travel, making this equation ultimately equal to -6 multiplied by our VTT reduction of 0.79.

$$\begin{gathered}\beta_{trav,car(q)} = \beta_{trav,car(q)} * \Delta\beta_{trav,car(q)} \\ \beta_{1,car(q)} = \beta_{1,car(q)} * 0.79 \\ \beta_{1,car(q)} = (-6) * 0.79 \\ \beta_{trav,car(q)} = -4.74\end{gathered} \tag{8}$$

Figure 18: Adjusting marginal utility of time spent travelling by car ($\beta_{trav,car(q)}$) using the VTT reduction ($\Delta\beta_{trav,car(q)}$), then solving for 1 hour ($trav = 1$)

5.4 Running the KPMG MATSim Model

5.4.1 Adjusting Initial Utility Values and Number of Iterations

For the execution of the simulation, the KPMG MATSim Model is used rather than the Vista MATSim Model. This is due to its improved travel mode utility functions discussed in 4.3. This model uses a default car utility of 0 per hour, which prevents the 21% VTT Reduction from being applied. To counteract this, all disutility per hour metrics have had 6 subtracted from them, making the initial car disutility per hour -6, the same as the default MATSim values, instead of 0. This changes travel mode usage as shown in the appendix Figure 27. However the validity of the conclusions remain if the new values are treated as baseline, and only the change that occurs when adding the LRC and AV VTT Reduction utility components is analysed. This is because the change is constant regardless of baseline.

The number of iterations needed for convergence is also analysed in the appendix Figure 27. Travel mode changes appear to stagnate after 25 iterations, converging to values that remain almost unchanged for a further 5 iterations. Because of this convergence, 30 iterations was deemed sufficient for this analysis.

5.4.2 Execution

The final LRC equation from Figure 6 is entered into the MATSim config variable $marginalUtilityOfDistance\_util\_m$. The final VTT reduction equation from Figure (18) is entered in the MATSim config variable $marginalUtilityofTraveling\_util\_hr$.

With the final MATSim config file including both the delay function from section 5.2.4, and the value-of-travel-time reduction from performing other activities in section 5.3, the simulation is run four times, once with these changes, once without as a control for comparison, and once with each change individually to assess its effect in isolation. The table in Figure 20 shows the average score of each of these runs.

Technical issues prevented the analysis of these effects together, where the simulation software was not able to complete the simulation run. However, hypothetical maximums and minimums were defined, depending on how mutually exclusive the effects are. The higher value would represent the effects being entirely independent, while the lower values assumes a dependency through increased congestion, which would limit car use to the highest value seen thus far. The equations in figure 19 describe these two hypotheticals.

$$\begin{gathered} max_{LRC+AV} = LRC + AV \\ min_{LRC+AV} = max(LRC, AV)\end{gathered} \tag{9}$$

Figure 19: Hypothetical minimum and maximum effect of applying LRC and AV components

5.4.3 Analysis of adding LRC and AV components

Travel Mode Attractiveness and Usage Changes

Travel Mode	Control	LRC	LRC Chg.	AV	AV Chg.	LRC AV Hmax	LRC AV Hmin
Car	25.67	26.08	0.41	26.56	0.89	26.97	26.56
PT	18.51	19.22	0.71	18.17	−0.34	18.88	19.22
School Bus	23.62	23.85	0.23	23.7	0.08	23.94	23.85
Transit Walk	27.04	30.95	3.91	28.55	1.52	32.46	30.95
Bike	10.86	11.56	0.69	11.61	0.75	12.31	11.61
Taxi	27.01	27.03	0.02	27.05	0.03	27.06	27.05
Walk	13.81	13.33	−0.48	13.91	0.1	13.43	13.91
Ride	34.35	34.34	−0.01	34.4	0.05	34.38	34.4
Other	34.67	34.68	0.01	34.71	0.04	34.72	34.71

Figure 20: Travel mode utility scores (attractiveness) after adding LRC and AV VTT reduction components. Note that Train, Tram and Bus are combined within the KPMG model to the single mode 'PT'

- **Control**: The model before adjusting for the two components being analysed.
- **LRC**: The model after it has been adjusted with the LRC component only
- **AV**: The model after it has been adjusted withthe AV component only (the reduction in VTT as a result of performing other activities while travelling)
- **LRC AV**: The model after it has been adjusted with both LRC and AV components
  - LRC AV Hmax: The hypothetical maximum of the LRC AV component, $max_{LRC+AV} = LRC + AV$.
  - LRC AV Hmin: The hypothetical minimum of the LRC AV component, $min_{LRC+AV} = max(LRC, AV)$.

Figure 21: Simulation run definitions

The average score for each travel mode describes its net attractiveness to travellers. On initial inspection it is evident that car attractiveness increases by 0.29 when LRCs are applied, rather than decreasing. This is surprising given that only 25% of trips were identified to have a saving in travel time in section 5.2.2 after LRCs were applied. However, the 25% of trips that had a travel time saving were all more than 10 km in length on average. By looking at the average car trip distances in Figure 22, it can be seen that while car trips were shown to be more attractive (have a higher score) in 20, total car trip distances also increase by 19% when LRCs are applied, compared to both AV and LRC components individually. Knowing that it is only trips greater than 10km that see a benefit from LRCs, it follows that the only way the average score for car users can increase, is if the proportion of long-distance (>10 km) travellers using cars increase, since an increase in short-distance (<10 km) travellers would reduce the average score. Therefore, the increase in average car score can be explained by more long-distance travellers (>10 km) opting for car travel over public transport. The reason for this is the decreased travel time (lowered disutility) that LRCs provide specifically to long-distance travellers. This means we are likely to see more car use from long-distance travellers as a result of imposing LRCs.

Travel Mode	Control	LRC	LRC Chg.	AV	AV Chg.	LRC AV Hmax	LRC AV Hmin
Car	41,996	49,062	7,067	41,791	−205	48,858	49,062
PT	24,878	23,592	−1,286	25,190	313	23,905	25,190

Figure 22: Average trip distance changes after adding LRC and AV VTT reduction components. Note that Train, Tram and Bus are combined within the KPMG model to the single mode 'PT'

Travel Mode	Control	LRC	LRC Chg.	AV	AV Chg.	LRC AV Hmax	LRC AV Hmin
Car	2,579	2,737	158	2,573	−6	2,731	2,737
PT	5,046	4,943	−103	5,121	75	5,018	5,121

Figure 23: Average trip time changes in seconds after adding LRC and AV VTT reduction components. Note that Train, Tram and Bus are combined within the KPMG model to the single mode 'PT'

Furthermore, after applying LRCs the average trip distance of public transport (PT) trips has decreased by 6%, which can be explained by the disutility of adding LRCs specifically for car trips less than 10 km. Because of this, short car trips are more likely to replaced by public transport trips after LRCs are applied. Interestingly, PT scores also improve by 0.71 as a result of LRCs, and Transit Walk scores improve by 3.91 or 14%. It is unclear why this behaviour occurs.

Applying the AV VTT reduction component also shows an increase in car attractiveness, by a greater 0.89. But unlike applying LRCs, the average trip distance does not change (22). This can be explained by the fact that the AV VTT reduction does not scale with distance, only with time. As has been discussed in section 4.5, short distance trips can take just as much time to complete as long distance trips due to congestion, particularly in heavily congested urban areas where average speeds are many times slower. Therefore, the 0.89 increase in average score is consistent across all trips, at least with regard to distance.

Travel Mode Split Changes

The change in average travel modes scores (and therefore greater utility) as a result of introducing the two components (LRC and AV) should in theory be reflected in a change in travel mode use, where more attractive travel modes are used more frequently, and less attractive travel modes less so. This is analysed in the table below 24.

Mode	Before Replanning	Control	LRC	LRC Chg.	AV	AV Chg.	LRC AV Hmax	LRC AV Hmin
Car	50.59%	58.19%	58.3%	0.11%	58.56%	0.37%	58.68%	58.56%
PT	14.49%	7.65%	7.53%	-0.12%	7.31%	-0.34%	7.19%	7.53%
Bike	1.38%	1.29%	1.28%	-0.01%	1.28%	-0.01%	1.27%	1.28%
Ride	18.96%	18.79%	18.79%	0.01%	18.77%	-0.02%	18.78%	18.79%
Walk	13.48%	12.99%	13.00%	0.01%	12.99%	-0.01%	12.99%	13.00%
Other	0.28%	0.28%	0.28%	0%	0.28%	0%	0.28%	0.28%

Figure 24: Travel mode usage changes after adding LRC and AV VTT reduction components - KPMG scenario. Note that Train, Tram and Bus are combined within the KPMG model to the single mode 'PT'

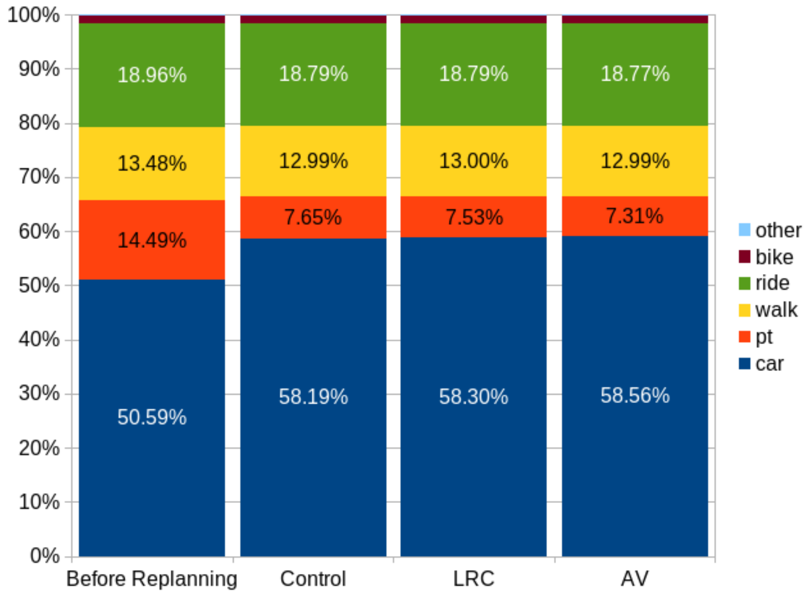


Figure 25: Travel mode split after adding LRC and AV VTT reduction components - KPMG scenario. Note that Train, Tram and Bus are combined within the KPMG model to the single mode 'PT'

- **Before Replanning:** The travel mode use before any traveller replanning occurs, and before adjusting for the two components being analysed.
- **Control:** The travel mode use after replanning, but before adjusting for the two components being analysed.
- **LRC:** The travel mode use after replanning, with the addition of the LRC component only.
- **AV:** The travel mode use after replanning, with the addition of the AV component only (the reduction in VTT as a result of performing other activities while travelling)
- **LRC AV:** The travel mode use after replanning, with the addition of both LRC and AV components.
- **LRC AV:** The travel mode use after replanning, with the addition of both LRC and AV components.
  - LRC AV Hmax: The hypothetical maximum of the LRC AV component, $max_{LRC+AV} = LRC + AV$.
  - LRC AV Hmin: The hypothetical minimum of the LRC AV component, $min_{LRC+AV} = max(LRC, AV)$.

Figure 26: Definitions used within the travel mode split

As expected from the improved average score of the car travel mode, car trips represent 0.11% more trips after the LRC component is applied, while public transport (PT) sees a 0.12% decrease. However, since it was identified in the beginning of 5.4.3 that car trips became 19% longer while PT trips became 6% shorter, this cannot be the same set of trips, and therefore is only explained by the fact that the shorter car trips that became PT trips were completely offset by the longer PT trips that became car trips. That is to say the negative attractiveness (disutility) seen by adding LRCs to trips less than 10 km, is completely offset by the positive attractiveness (utility) of adding LRCs to trips greater than 10 km. However, this effect can be identified as small, by comparing the LRC component's effect to the AV VTT reduction component's effect, which did not affect trip distances. The AV component led to an increase of 0.37% in car users, with a comparative 0.34% decrease in PT users. Since it is known that the AV component provides a constant utility increase across all trips, we can conclude that improving the average car attractiveness score by 0.89 leads to at most 0.37% increase in car use, all things being equal. This is further evidenced by looking at the consistency of average trip times in Figure 23, where there is a change of only 6 seconds between the Control and the AV applied run, as compared to a change of 158 seconds for when the LRC component is applied. This means the LRC component should have increased car use by

0.18% (half of the AV component) rather than 0.11%, yet didn't because of the aforementioned LRC's negative effect on short trips.

In spite of the change in trip distributions from the LRC component, and larger impact of the AV component, the overall effect on travel mode split can be considered negligible, as it is less than half of one percent. This includes the hypothetical maximum and minimum described in section 5.4.2. The reason for this is likely to be a combination of the smallness of the component's effects on average trip scores (2-4%), along with trip changes requiring a certain threshold to be reached before a change in travel mode occurs. The latter can be shown by the 7 point difference between the average score of Car and PT travel modes. In the vast majority of cases, a 2-4% increase in trip score would not be sufficient to broach this threshold.

6 Conclusions

The original hypothesis was that the introduction of light-rail constraints (LRCs) would add a net delay to all trips. While trips less than 10 km in distance saw an increase delay of 215 seconds on average, trips greater than 10 km in distance had reduced their trip time by 434 seconds through the introduction of LRCs. It was speculated that this may be due to the reduced ability for over-accelerating and over-decelerating in such scenarios, which has been known to cause traffic slowing phenomena such as phantom jams. Such over-acceleration and over-deceleration was believed to be less likely in shorter trips due to a lower average speed reducing the capability for high acceleration or deceleration. This suggests restrictions on acceleration and deceleration may be sought after in their own right for long journeys to improve traffic flow, and not simply for improving passenger comfort in autonomous vehicles as originally intended.

A further finding on the use of light-rail constraints was a dramatic change in car trip distance distributions, where car trips were on average 19% longer in distance after imposing light-rail constraints, while public transport trips were 6% shorter in distance. This was determined to be caused by the reduced travel time of longer trips as a result of imposing LRCs making car travel more appealing for long distances. Similarly, the delay in short-distance car trips caused by imposing LRCs was found to be responsible for reducing the average distance of public transport trips, as more short trip car travellers opted for public transport. The consequence of this are a potential greater emphasis on public transport use for short-distance urban travellers, along with a marginally reduced focus on long distance public transport. Though this would need to be considered against other factors such as parking, that may still prohibit some long distance travellers from driving in spite of reduced travel times.

The AV VTT reduction born by the ability for travellers to perform other activities while travelling was shown to have a more significant effect than light-rail constraints on the appeal of cars. However, it did not change the trip distribution across travel modes with regard to distance or time, as unlike the light-rail constraints component, average distances for travel modes did not change, nor did average travel times.

The intention of this analysis was to understand the effect of the LRC and AV (VTT Reduction) components on the appeal of car travel, and subsequently the number of car users on the road. While the LRC component added a delay for trips less than 10 km in distance, which comprised the majority of trips, both LRC and AV showed a net positive effect on the attractiveness of car use. Despite this, there appeared to be minimal to no change in travel mode as a result of implementing the LRC or AV components.

While technical issues prevented the successful simulation of the LRC and AV effects together, the use of rationalised hypothetical maximums and minimums showed this extra simulation run would not change the conclusion of the analysis.

7 Appendix

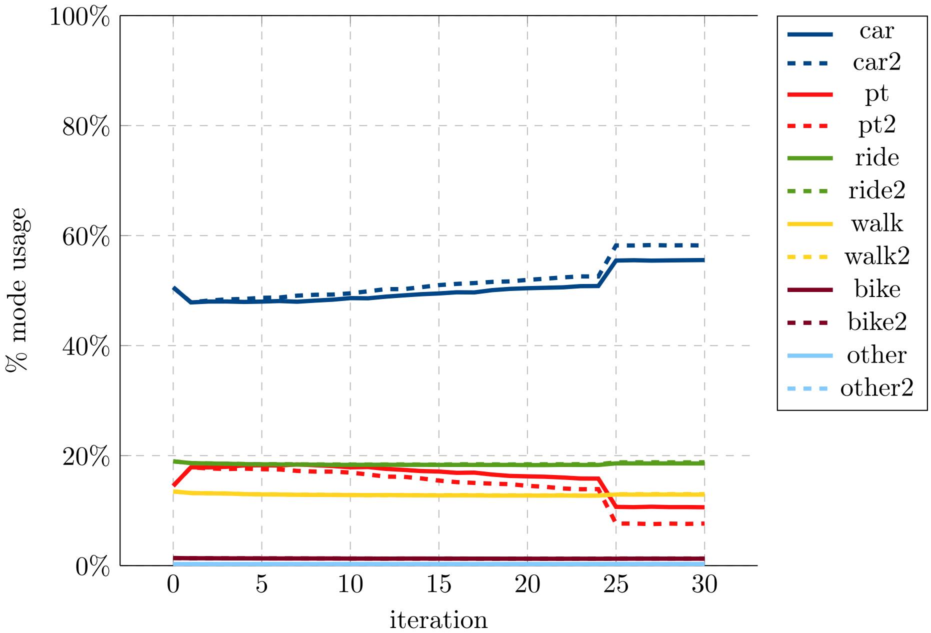


Figure 27: Old and New Utility values for travel modes within the KPMG MATSim model. Travel modes suffixed with '2' contain the new utility figures that subtract 6 utility (-6) per hour from all modes.

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