THE IMPACT OF PLANED SPECIAL EVENTS (PSE's) ON URBAN TRAFFIC CONGESTION

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ABSTRACT

THE IMPACT OF PLANED SPECIAL EVENTS (PSE's) ON URBAN TRAFFIC CONGESTION

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Traffic congestion has been on the rise in much of the world, and all indications are that it will continue to worsen, posing a danger to the quality of life in the city. Its main manifestation is the progressive reduction of traffic speeds, which translates into increases in travel times, less reliable travel times, increased fuel consumption, and other operating costs and air pollution. There are two types of congestion: recurrent congestion and non-recurrent congestion.

Non-recurring congestion refers to a type of congestion that occurs irregularly, usually associated with events such as traffic accidents, road repairs, bad driving practices, etc. In general, these events reduce the capacity of the transport system and happen independently of the increase in demand associated with peak hours (recurrent congestion).

Unlike recurrent congestion, the characteristics of non-recurrent congestion, that is, frequency, duration and severity, have not been addressed in the local environment, and therefore there is not enough background to estimate the cost of these externalities in the operation of the transport system. Given the above, it is possible to reason that there will be certain thresholds from which it is possible to propose incident management plans such that the cost of their implementation is lower than the savings obtained from the operation of such plans, and in this way justify traffic management plans that can mitigate the effects of non-recurring congestion.

Past research has shown that PSEs such as concerts or sports games, festivals, and conventions significantly impact everyday urban transportation. Therefore, the doctoral thesis investigates the impact of PSEs on urban traffic congestion. This research utilises event characterise, mobility behaviour and urban traffic accidents to examine the impact of PSEs on urban road traffic congestion by applying spatial-temporal data mining methods. This research will contribute to the gap in the existing literature on event-driven traffic predictions, allowing more precise planning of urban mobility services in the presence of PSEs.

DOCTOR OF PHILOSOPHY DECLARATION

I, RPF Fernando, declare that the PhD thesis entitled *The Impact of Planed Special Events (PSE's) on urban traffic congestion* is no more than 100,000 words in length, including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, thisthesis is my own work.

Signature [redacted] Date 30/07/2021

This thesis is dedicated to my late father, mother, husband, sister, and brother-in-law for their love, endless support, and encouragement, especially my Lord Jesus Christ, who is always by my side and has carried me through my darkest hours.

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ACHIVEMENTS SUMMARY

Publications

The following articles have been published or submitted in International Journals and Conferences based on this research work.

- **Journal Articles**

Fernando, R., 2019. The impact of Planned Special Events (PSEs) on urban traffic congestion. EAI Endorsed Transactions on Scalable Information Systems, 6(23).

- **International Conference Articles**

Fernando, R., Wang, H., Zhang, Y., Prakash, M. and Debnath, A., 2020, September. The effects of travel containment measures within COVID-19. In 2020 24th International Conference Information Visualisation (IV) (pp. 403-408). IEEE.

Industry Internship

Successful completion of a five-month APR internship at the Victorian Department of Transport investigating motorist behaviors during a planned disruption – reference letter attached in the appendix section.

Other Presentations

1. Impact of Planned Disruptions - presentation to the Demand Forecasting division at the Victoria Department of Transport in 2020
2. Presented at the National Roads and Traffic Expo 2019 at the Melbourne Convention and Exhibition Centre.
3. Research Presentation during VU Open Day Program 2018.

Awards

1. Graduate Research Scholarship (PhD) awarded by Data 61, CSIRO
2. Winner of the VU's ISLIC HDR Conference 3MT competition 2020
3. Runner-up International Student of the Year (Research) 2020 at Victorian International Education Awards
4. Winner of VU's Visualise Thesis 2019 Competition, Finalist of International VTC in 2019
5. Runner-up of the VU's 3 Minute Thesis' 2018 Competition

Featured In

1. Celebrating the Impact of Graduate Research video by Australian Council of Graduate Research

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CHAPTER 1

INTRODUCTION

This chapter introduces the doctoral thesis, starting with the background and motivation, then formulating the research problem and the sub-questions, followed through to the research contribution significance, and lastly, the structure of this doctoral thesis.

1.1 Background and Motivation

In recent years, the increase in transport demand has caused significant increases in congestion [1]. All the indications are that this problem will continue to worsen. Its primary manifestation is reducing traffic speeds, which translates into increased travel times, less reliable travel times, increased fuel consumption and air pollution [2]. In addition, slow travel increases drivers' frustration and encourages their aggressive behaviour [3].

Depending on the source of traffic congestion, traffic congestion is classified into two, recurring congestion and non-recurring congestion [4]. Recurrent congestion refers mainly to the fact that the demand for using the transport infrastructure exceeds the same capacity and therefore is often considered a sizing problem that is logically combated by increasing the system's capacity. In general, this type of congestion tends to be concentrated in short periods, typically known as "rush hour." Therefore, recurrent congestion refers to a phenomenon of repetitive and predictable character. Consequently, the associated impact has been investigated thoroughly, and a wide range of studies quantified its impact on transport systems throughout the world and therefore analysed with proven and well-known methodologies.

On the other hand, non-recurring congestion refers to a type of congestion that occurs irregularly, usually associated with events that reduce the capacity of the transport system [5] and that happen independently of the increase in demand at peak times. The non-recurring congestion is the result of traffic accidents, lousy driving practices, bad adverse weather conditions, presence of planned special events, maintenance activities of the transport system (road construction, maintenance of traffic lights, etc.), construction sites, police activity, and in general, any other non-routine activity in the transport system [6].

The causes mentioned above are generally referred to as traffic incidents and are further grouped into planned and unplanned traffic incidents. Previous studies have indicated that incidents are one of the leading causes of time wasted and cost increases on transportation networks.

Unlike recurrent congestion, the characteristics of non-recurrent congestion, i.e. severity (number of tracks affected), frequency (periodicity of occurrence of incidents) and duration (time in which the capacity of the road being affected), have not been addressed in the local environment [7] [8]. Therefore there is not enough background to estimate the impact of these externalities in the operation of the transport system.

More and more cities organise PSEs as these events attract tourists, promoting their economy [9]. These PSEs include cultural and sports activities, conventions and exhibitions, and commercial and promotional activities [10]. One of the critical elements of the success of these activities is transportation. PSEs are often held in short periods. Therefore, traffic impacts caused is temporary (or a few days), and solving transportation problems caused by PSEs will not require a permanent increase of road capacity [11] but needed to find better ways to mitigate congestion [12]. As PSEs are planned and by predicting the congestion, we can use the insights to minimise congestion.

Researchers have paid much attention to how PSEs have positive and negative impacts on fast-track urban development; however, scholars have devoted less attention to the equity implications of the transport issues of PSEs. The literature on PSEs and urban transport has focused primarily on traffic management and contingency plans to address peak demand and congestion. Currie and Shalaby [13]; Silva and Portugal [14]; Malhado [15]; Han, et al. [16]; Pereira [17] only a handful of studies have focused on traffic accidents or crashers influenced by PSEs. This contributes to the overall congestion influenced by PSEs.

The last few years have been marked as the beginning of exploring Big data in all industries. This had an enormous impact on the transport sector, contributing to the development of ITS (Intelligent Transportation System). Previous researchers have used data mining techniques on traffic congestion data to measure parameters such as the travel time [18], the average speed of the road section [19], the congestion degree [20], the best route selection [21], provide real-time urban traffic flow distribution [22] are some other topics used big data mining approaches. These studies were possible due to evolved transportation data collection methods such as access to real-time traffic information using the traffic sensors and GPS (Global Positioning System) devisers that capture urban activity evolution in real-time [18]. Most traffic sensors are installed directly in the roadway (e.g. magnetic loops, cameras) to collect data necessary and inherent limitations such as partial coverage of a road network and high installation and maintenance costs. Alternatively, GPS data, also referred to as Floating Car Data received from GPS embedded vehicles or smartphones, is considered as the most suitable solution to overcome the limitations of fixed sensors [22]. The significant growth of GPS data collection methods has allowed many helpful research and practical insights on urban traffic congestions, such as automatic detection of road events in real-time [23], evaluating the duration of future congestions, and predicting road events.

Given the above, it is possible to investigate the impact of planned special events on non-recurrent urban traffic congestion.

1.2 Research Problems

The primary research question is divided into three related sub-questions, and each is detailed below.

Research Question: What's the impact of Planned Special Events on urban non-recurrent traffic congestion?

The main research objective of the task is to develop a short-term traffic flow density forecasting model that reliably, accurately, flexibly and validly forecasts a particular situation shortly in such a way that the proposed method will be more efficient than the known and part of the models under consideration.

Assuming using such a model in a natural road environment, the latter would significantly contribute to developing the road transport system or increasing its efficiency.

There are differences between urban arterial roads and urban freeways traffic; even both are considered network structures. The freeways are relatively closed environments; an urban road network has many variabilities and more complex traffic habits. Includes other users than the automobilists (pedestrians, cyclists, scooters) and need to share with them as part of the public space. Therefore their behaviour is less predictable and challenging to measure the impact on road traffic. Consequently, sub-questions 1 and 2 concentrates on the short-term traffic flow density forecasting model separately for urban arterial roads and freeways. Finally, a comprehensive evaluation of the relationship between planned special events and the urban traffic accidents as the sub question 3.

Sub-Research Question 1: What methods are appropriate to quantify and predict this influence of PSEs on an urban freeway?

A variety of factors overlays the PSEs influence on traffic volume and traffic situation. Therefore, it is another goal to identify these inflow variables, structure them, and statements based on how these influencing variables are integrated into the modelling process. Finally, prerequisites for applicability and recommendations for the use of the presented model approaches will be formulated. For this purpose, an evaluation procedure for the model approaches is developed.

Sub-Research Question 2: What methods are appropriate to quantify and predict this influence of PSEs on an urban arterial?

Since the model results are primarily intended to improve traffic information for transport participants and provide a basis for PSEs dependent traffic influence, the focus is on model applications for short-term forecasting. The traffic volume at the daily and hourly level and the traffic situation on the city of Melbourne urban road network intersection of Flinders Street and Exhibition Street is examined.

Sub-Research Question 3: What is the relationship between PSEs and urban traffic accidents in presence of both recurrent and non-recurrent congestion?

Planned special events lead to other engagements in specific urban locations and increase traffic volume on the road network. Consequently, the capacity and travel time of a road are affected by the PSEs. On the other hand, due to the increase in traffic volume, there is a higher risk of accidents by those drivers who do not adjust their driving behaviour. An accident, in turn, directly affects the existing capacity through possible lane closures. Despite these well-known and everyday relationships, the PSEs influence on urban traffic accidents has rarely been considered. Therefore, it is desirable to quantify the presumed impact of the PSEs on urban traffic accidents that influence urban congestion both recurrent and non-recurrent.

1.3 Contributions and Significance

The doctoral thesis of the complexity of the problem represents a theoretical and practical contribution in research and development of short-term forecasting of traffic flow hashing with an emphasis on producing a faster and more accurate forecasting process. The selected different Machine learning model of identification and predicting traffic flow analysis in a non-linear dynamic system represents a novelty in the field of short-term traffic flow forecasting, which has proved more appropriate in medicine, physics, and economics.

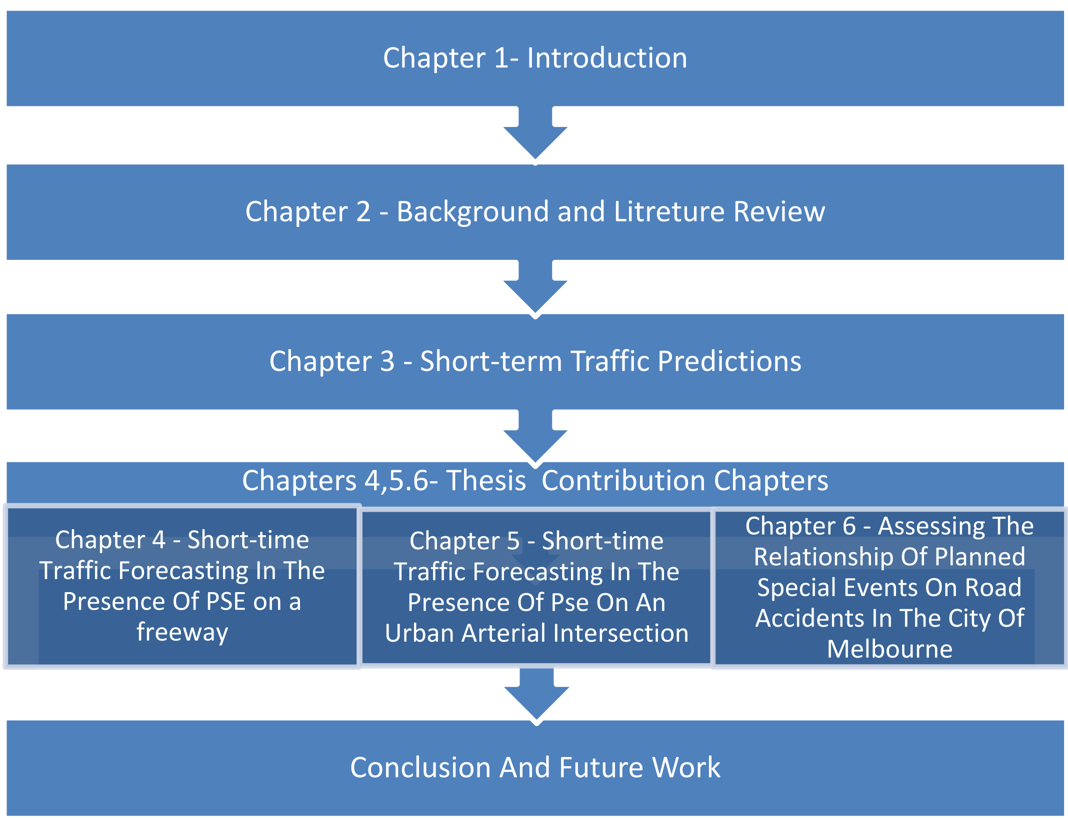
Based on an in-depth study of the theoretical basics of analysing and identifying chaotic parameters for short-term traffic flow forecasting in the presence of PSEs, large-scale experimental research examines the effectiveness of the proposed model with the new proposed system for short-term traffic flow density forecasting.

The usefulness and verification of the proposed model are proven experimental, in the real case on both freeway and arterial road networks using ML models and algorithms for the frequency of traffic flow forecasting, written and calculated using appropriate machine learning algorithms. In the doctoral thesis research it is possible to identify the original contributions that will help to understand better and address the impact of PSEs on urban traffic congestion and short-term predictive of traffic flow. Scientific research has also had practical effects in solving the problem.

The resources available to a society are always limited. It is therefore desirable that the use of limited resources should be based on sound decisions. The contribution of the doctoral work the impacts of PSEs can be determined to provide such a sound basis for decision-making using an adequate and realistic forecast of traffic parameters. Building on this, current and future planned special events can be optimised utilising traffic planning measures, traffic management measures and information for road users. In particular, the provision of this information to road users is playing an increasingly important role, as this will improve the use of the existing transport network.

1.4 Thesis Structure

The following illustrate the structurer of the thesis and the detailed description of each chapter is provided under thesis outline section 1.5



1.5 Thesis Outline

The rest of the thesis is organised as follows:

Chapter two is divided into three sections, The first sections, a literature analysis of the current state of research on Traffic Congestion, provides literature dealing with congestion to identify a definition of congestion and the relevant variables. It deals with definitions, thresholds of acceptability, causes, impacts and methods of measuring traffic congestion. Next, "Planned Special Events", analyses literature by various authors and various classifications will be reviewed according to their different PSEs characteristics and the impacts of PSEs. The Third section will introduce all the different data sources and the technologies used to analyse the data in the chapters four, five and six.

Chapter 3 is divided into two sections; The first section covers the definitions of key terms and the basic description of the methods used for analysis and forecasting. In addition, the chapter contains a literature analysis of currently available approaches and methods for short-term traffic forecasting and discuss their potential and shortcomings. These methods currently offer the most promising potential for the second estimation and forecasting of transport variables. The second section will introduce all the different data sources and the technologies used to analyse the data in chapters four, five and six.

Chapter 4. Ensuring that cities have access to a sustainable standard of living and economic development is one of the necessary conditions for establishing a highway road connecting the living spaces and a traffic network flowing with the least possible problems in this order.

Planned special events are one of the factors that cause congestion on highways which reduces vehicle speed. The speed of the vehicles may be more or less, both as a result of driver preferences or due to traffic rules or other factors. This excess or less speed affects the flow of traffic, which causes a change in density and the level of intensity. In addition, to density; the number of accidents, the vehicles in traffic; meteorological events such as temperature, precipitation, weather; infrastructure features of the road; the day and time when traffic demand is increasing, whether it is a holiday period or not and also impact factors that contribute to the experience of the drivers as they travel in freeways.

In this chapter, we use the city of Melbourne; PSEs factors such as event occurrence, event time and duration, event type, event location, expected attendance and event market area; due to its effects on traffic demand. With the arguments included in the study, the speed of the vehicles was estimated, and the density evaluation was made on these speed values.

Chapter 5 In this chapter, the short-term traffic forecasting performance of parametric and non-parametric forecasting methods for intelligent transportation systems was examined, and the effect of forecast values on the circuit time and performance of signalled urban intersections during PSE was investigated. It aims to improve latency and reduce intersection waiting times depending on the traffic data observed at the intersection and improve the intersection's performance. The intersection of Flinders Street and Exhibition Street, the city of Melbourne, Victoria, has been selected as the case area. The data obtained with the help of sensors located in the approach arms of the intersection are arranged as data sets. This chapter made short-term traffic estimates with auto-regressive integrated moving average (ARIMA) and artificial neural networks (ANN) methods. Prediction results were optimized for intersection circuit time using the Webster method. After calculating the optimum circuit time and green times, the webster delay method and the delay values of the intersection approach arms (road segments) and the intersection as a whole were compared with the estimate results obtained from both the ARIMA method and the ANN method. In short-term traffic estimation for a selected intersection, the ANN method was more successful than the ARIMA method.

Chapter 6 analyse the relationship between PSEs and road accidents, a space-time analysis is carried out for PSEs and traffic accidents using various geostatistical techniques using a geographic information system (GIS) and a spatial database. Among the results obtained is the variety of accidents in terms of the presence or absence of PSEs. The different analyses consider the time slot of the even features and the distance between the accident and the place of occurrence of the PSEs. Some spatial grouping techniques such as the Moran's index, the Nearest Neighbour index for analysis of concentration or dispersion pattern identifications, and statistical methods that characterise accident behaviour were analysed in the results.

Chapter 7 Summarizes the main statements of the work and provides an outlook on the necessary and possible future developments of the connection to the net-second short-term forecast.

CHAPTER 2

BACKGROUND AND ITERATURE REVIEW

This chapter is divided into three sections, each of which responds to a specific objective. The first section, entitled "Traffic Congestion", provides a portrait of the literature dealing with congestion to identify a definition of congestion and the relevant variables. It deals with definitions, thresholds of acceptability, causes, impacts and methods of measuring traffic congestion. The second section, titled "Planned Special Events", analyses literature by various authors and various classifications will be reviewed according to their different PSEs characteristics. Next, the impacts of PSEs are discussed. The Third section will introduce all the different data sources and the technologies used to analyse the data in the next three chapters.

2.1 Traffic Congestion

Traffic congestion is a phenomenon that has received a great deal of attention in the literature. We even trace findings concerning traffic congestion as far as Ancient Rome, where the narrow porticoes of entrances to cities caused significant delays [24]. This section provides a literature portrait on the different parameters and variables that define it to understand traffic congestion better.

2.1.1 Vehicular traffic theory

The theory of vehicular traffic helps us to understand the phenomenon caused by the flow of vehicles on a road, street, or highway by analyzing the elements of the vehicular flow can understand the characteristics and behaviour of the site, essential requirements for the planning, project and operation of roads, streets, and their complementary works within the transport system. With the application of the laws of physics and mathematics, the analysis of vehicular flow describes the way vehicles circulate on any road, which allows determining the level of efficiency of the operation.

One of the most valuable results of vehicular flow analysis is the development of macroscopic and microscopic models that relate their different variables such as volume, speed, density, interval and spacing. These models have been the basis for developing the concept of capacity and service levels applied to different road elements [25].

- Macroscopic models focus on capturing global traffic flow relationships, such as vehicle speed, vehicular flow, and traffic density. By their nature, they are continuous models, which make extensive use of differential equations.

- Microscopic models focus on describing the behaviour of vehicular traffic flow by representing the individual and discrete atomic entities that interact with each other (in this case, each vehicle).

- Microscopic models define a function that expresses the probability that a vehicle at a certain speed will be in a particular position at a specific time. They usually use statistical methods.

When addressing vehicular traffic theory, it is intended to emphasise the aspects that relate the variables of vehicular flow to the probabilistic or casual description of the traffic flow, the distribution of vehicles on the road, and the statistical distributions used in project and traffic control.

2.1.2 Supervision of the road network

Traffic congestion is a state of the network when traffic demands exceed available capacity. The state when traffic demand equals capacity is known as ‘saturation’. This state results in lengthy delays and queue formation until demands reduce to below capacity [26]. The capacity of a network is not static but variable. It depends on many factors, including traffic volumes and flow conditions on each network component, road link conditions, traffic signal phasing and cycle times, parking activity, and other factors [22]. During periods of traffic congestion, minor disruptions to traffic flow can result in dramatic reductions in vehicle speeds with stop/ start conditions propagating back into the traffic flow [26] .

The dynamics of vehicle flows spreading on the road network is the real object of study of infrastructure managers. This dynamic is understood in various locations of the network via well-defined traffic characteristics in the field. Since they are interested in the flow of traffic and not in the vehicles (microscopic particles) that make up the traffic, these traffic characteristics are described as macroscopic. Traffic states are usually determined by four macroscopic characteristics:

- The flow rate(Qd) defines the number of vehicles crossing a point of the network during a specific period T. The flow rate is expressed in vehicles per hour (veh/h). It characterizes the intensity of the flow crossing a portion of the network during a specific period T.

- The speed (V) characterizes the velocity of the moving flow on the network in kilometers per hour (km/h) and distinguishes 3 definitions:

  the average speed of vehicles crossing a fixed position of the network. We talk about of **time average speed** . It is defined by $V_T(x) = \frac{1}{N_T}\sum_{i=1}^{N_T} v_i(x)$ where N_T is the number of vehicles that have passed through the position during a period T

the average speed of the vehicles at a time t on a stretch of road of length L specified. This is the **average spatial velocity**. It is defined by $V_L(t) = \frac{1}{N_L}\sum_{i=1}^{N_L} v_i(t)$ *N* is the number of vehicles within the zone of length *L*.

the stream speed of vehicles, defined in an equivalent way by the average speed Space some Vehicles or the speed average Time harmonic Expressed by $\frac{1}{V_T^{\text{harmonique}}} = \frac{1}{N_T}\sum_{i=1}^{N_T} \frac{1}{v_i}$

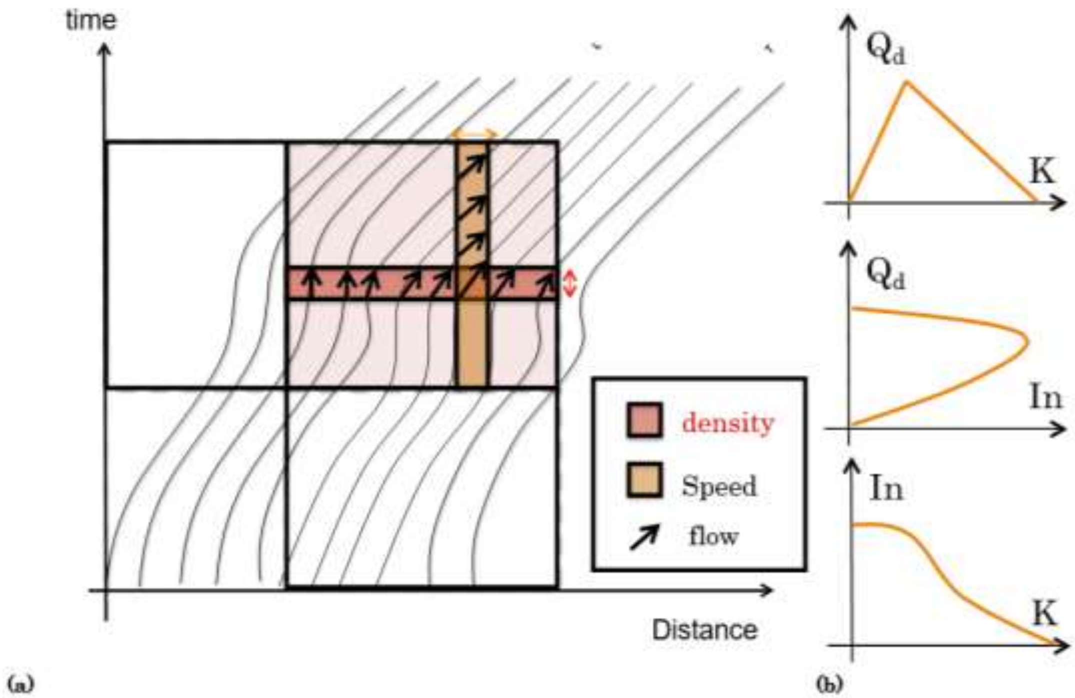
- Travel time (*TT*) defines the time it takes by a vehicle in the flow for join two separate points of the network. The individual journey time is defined for any vehicle by the difference in transit times between the points A and B of the network: $TT = t_B - t_A$ for one section *l* of length *L* of the network the time of route Medium *NL* at a given time is provided by: $TT_l(t) = \frac{1}{N_L}\sum_{i=1}^{N_L} TT_i(t)$, where *N* is the number of N_L and=1 vehicles on the section of length *L*. The division of this expression by *L* results in directly to the expression of harmonic velocity.

- Density (K_d) or concentration defines the number of vehicles over a length specific of route. this density east Characterized by the relation : $K_d = \frac{Q_d}{V_L}$ the binder at debit and à the speed average Space. in practice the density K_d is not step directly measurable. Only the measure of occupancy rate *TO* at a point in the network allows you to estimate it.

These characteristics of the traffic flow are linked by a phenomenological relationship, identified by Greenshields as early as 1934 [7] and called fundamental diagram. Adopting various forms (Figure 1.1(b)), these models reflect certain logical links relating to traffic. The linear relationship linking, in fluid mode, the density to the flow rate, due to the low variability of the average spatial velocity of this regime, is an example.

A graphical tool makes it possible to reproduce the dynamics of a portion of road (length L) over a given period T from the trajectories of the vehicles. This is the space-time diagram shown in Figure 1.1(a).

Figure 1 Classical representations of macroscopic traffic variables: a) Spatio-temporal representation of vehicle flow (Space-Time diagram) b) Fundamental diagrams linking macroscopic traffic variables, according to the Greenshield model.



The supervision of the road network consists in the observation of the characteristics defined in section 1.1.3 on each of the arcs of the road network in question. The objective of the manager is to have as much information as possible on the state of operation of the network and to centralise it for interpretation. However, these traffic variables cannot be known at all points and require sensor measurements. In this perspective, various technologies were born. On the initiative of the managers, they now populate the road infrastructure and specifically the expressways and freeways.

Traffic congestion within an element of the network is simplified in the speed flow diagram. As the network demand flow increases, vehicle speeds reduce until they reach a maximum volume. As traffic demands increase beyond this point, vehicle speeds reduce further, thus causing reduced flow [22]. This results in unstable queue formation and lengthy delays within the network. It is also essential to understand that due to the non-learner nature of this relationship of volume and speed, the congestion can be well managed by reducing the volume somewhat. Further congestion is distinguished between two forms of this phenomenon, recurrent congestion and non-recurring congestion [27].

Recurrent congestion

Recurrent congestion occurs in time intervals associated with peak hours where the demand for traffic is very close or even exceeds the available road capacity. Therefore, recurrent congestion tends to be predictable and repetitive. Many studies have proven its predictable nature using time series analysis.

Non-recurring congestion

According to Anbaroğlu, et al. [28], this type of congestion results from random events or predictable difficulty variations from one road segment to another. The main events at the origin of the non-recurring congestion are traffic accidents (accidents, breakdowns, etc.), weather conditions, road maintenance, and PSEs. Non-recurring congestion is sometimes associated with the reduction in road capacity due to accidents, road maintenance but also, associated with high demand due to Planned Special Events.

Traffic incidents can be defined as any event that disrupts the normal operation of the transportation infrastructure, degrading safety and reducing capacity. These events include damaged vehicles, traffic accidents, road maintenance activities, adverse weather conditions, protests, road debris, etc. Traffic congestion related to the incident (including side impacts) has detrimental effects on public safety, the local economy and the environment. So

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Both the quantification and characterisation of these events are essential when implementing management plans for these incidents and, consequently, reducing their effects. Incident handling brings critical benefits, such as reducing delays in vehicle travel times due to incidents by reducing the frequency of incidents and improving the response and dispatch time of incident assistance units.

Traffic incidents reduce the available capacity or degrade its performance, expressed in lower operating speeds and more significant congestion. They can also increase the likelihood of secondary incidents and performance degradation on streets that are not even directly influenced by the incident through circumstances such as the well-known rubbernecking phenomenon (Cambridge Sys Inc. et al., 1998).

2.1.3 Vehicular traffic solution strategies

Efficient traffic management requires recording and analysing traffic conditions, which provide appropriate information for traffic control centres and road users. This information must be produced promptly (current) and predictive (forecast) and as comprehensively as possible, which then can be translated into user-adapted information.

An important basis of such systems is recording current traffic conditions and relevant variables through suitable detection devices and sensor measurements. From this perspective, various technologies were born, and they now populate in road infrastructure. These detection devices are further categorised as Infrastructure-related collection methods, including loop detectors and laser or infrared sensors, Infrastructure-related and onboard collection methods including blue tooth or Wi-Fi sensors and Onboard collection methods that crowdsource users on-board equipment, which includes social media sensors.

2.1.4 Harmful effects of congestion

The above discussed traffic sensors provides insights about traffic conditions but is not free of imprecisions or errors. Three well-identifiable such issues are:

Economic consequences

Road congestion causes extra time to move from the point of origin to the end of the destination. This additional time influences the delivery times of goods as well as the travel time. In addition, traffic congestion reduces labour hours and accessibility to economic activities [29]. Melbourne congestion was $4.6 billion in 2015, and it's estimated to increase up to $10.2 billion by 2030 [30].

Ecological consequences

When the number of vehicles (density) increases on the road, the speed decreases, and the time of displacement is prolonged. This results in an additional emission of air pollution and noise pollution [31]. The residents of the road and the motorists are most affected by these emissions. In this context, several studies have been conducted by Hu, et al. [32], who showed that air quality deteriorates due to traffic.

Social consequences

In addition to the ecological and economic consequences, congestion has a detrimental effect on society. Speed reduction can decrease social contact between people significantly when the tolerated travel time is exceeded because of congestion

[32]. In addition to the ecological consequences, atmospheric pollution additional increase due to this phenomenon has negative impacts on health, for example, the effect of some gases on the respiratory capacity. In addition, noise pollution affects people's physical state (stress, quality of sleep, etc.) [31, 32].

2.1.5 Measures and indicators of traffic congestion

Congestion indicators have an essential role in the decision-making process. They aim to simplify and better understand the phenomenon of congestion and detect failures in the road transport system. Several research projects have been undertaken on this subject, including the Weisbrod, et al. [33] tittled "Economic implication of congestion", published by the Transportation Research Board (TRB) in 2001. This report proposes a comprehensive classification of measures and indicators of road congestion.

Time-based measures

The time-based measures are used to assess congestion. The advantages of these measures are that they can be carried out at any time and involve all modes of transport. In addition, they are being found in intelligent systems, particularly real-time information systems. The Weisbrod, et al. [33] cites other indicators that arise from such measures, such as:

- Travel time on a road is the most well-known measure and serves as a reference for road users to assess congestion.
- The origin-destination journey temps are estimated to move from an origin area to a destination area for a given road network.

Flow-based measurements

Flow-based measures are more attractive because of the wide availability of data on traffic throughput and the number of Vehicle Miles Traveled (VMT) [33]. The latter is also used in studies conducted on air quality. The observed throughput is often compared to the available supply, and this relationship is expressed in terms of the throughput-to-capacity ratio. As illustrated in Figure 1, flow is used with density and density to define the state of traffic.

Congestion indices

These indices describe the state of congestion with a high level of aggregation [33]. Indeed, they are tools capable of estimating global congestion on a road network. Among these indices, we cite the RCI (Roadway congestion Index) which is developed by Hanks and Lomax (1992) in a study on urban mobility. In this study, the latter used data from "vehicle-miles of travel" (VMT) and lane-mile length simultaneously to assess the level of urban mobility in fifty regions of the United States.

Delay measures

This indicator is used to describe the state of congestion and illustrate the transmission network's performance. The delay is the difference between the observed journey time and the free flow journey time [34]. In addition, to delay time, Lomax [35] titled "Quantifying Congestion", published by the Transportation Research Board (TRB) in 1997, highlights other delay measures, which are as follows:

- Travel rate—Is the ratio of travel time to the length of the segment travelled (expressed in minutes per mile)
- Delay rate—Represents the lost travel rate created by congestion equal to the difference between the actual travel rate and the acceptable placement rate (expressed in minutes per mile). It is noted that the acceptable displacement rate is the ratio between the travel time in a free flow and the length of the segment traversed.
- Total delay—Represents the product of the number of vehicles on the

congested road segment and the delay rate (expressed as a minute vehicle).

The purpose of an indicator is to assess a phenomenon using its measurable parameters. The doctoral research uses temporal indicators based on the travel time or delays for urban arterials and speed indicators for the freeway.

The delay for arterial and reduction of freeway speed may be caused by recurrent or Non-recurrent congestion. The Recurring delays or decrease speed are encountered daily during rush hour travel and can be predicted from historical data. Non-recurring delays or speed reductions are caused by events, incidents, or accident congestion prediction that is a changeling and addressed by this doctoral thesis.

2.1.6 Road characteristics factors related to traffic congestion

Multiple studies have been done in the literature to explain the relationship between congestion and road characteristics either implicitly or explicitly. As mentioned in the second part of this chapter, recurrent congestion is the result of an excess of transport demand over the remaining road capacity [34]. The demand for transport depends on the reason for the displacement and the area's characteristics (commercial, residential, industrial, etc.). In addition, the capacity of the road, which itself represents a characteristic of the road, is calculated according to the formula derived from the HCM (1997):

$$C_f = C_i * \left(\frac{V}{C}\right) * f_d * f_m$$

Where:

Ci: hourly capacity under ideal conditions

Cf: hourly capacity

V/C: the volume/capacity ratio

fd : capacity reduction factor for directional imbalance

fm: reduction factor for track and narrow shoulders.

From this formula, it can be concluded that capacity depends on four physical factors of the road: the width of the shoulder, the number of lanes, the direction of traffic and the width of the lane. The HCM proposed in 2000 a new formula for calculating capacity by adding other factors, in addition to those presented in 1997, such as factors of traffic composition and traffic conflict, presence of parking, etc.

In addition, some congestion indicators are calculated based on physical factors in the road segments, including the RCI "Road Congestion Index" from [36]. Indeed, the latter expressed this indicator in terms of the length and type of lane, distinguishing between the flow of traffic on a motorway and that on the main artery.

In addition, the characteristics of roads have been highlighted in accident studies that represent one of the causes of non-recurrent congestion. These studies include [37] on the effects of congestion on PSEs. The physical factors that have been mentioned are the length of the road, the direction of travel, the no of lanes and the geometry of the road.

The speed limit is also a factor in the characteristics of congestion. In some studies, congestion would occur when the (observed) speed does not exceed a certain threshold of the authorized speed. In the report "Congestion and Accident Risk", published by the Department for Transport (2003), an urban road segment is considered congested if the average speed is less than 50% of the authorized speed. On the urban road network, drivers are, in some cases, forced to reduce their speed and consequently, the journey time increases. They must stop or decrease their speed at intersections or in speed-limited areas, especially next to schools and the commercial regions [38].

In Australia, National guidelines for transport system management [39] specifiesthat congestion on some sections of the motorway stems from the geometrical characteristics of the road, namely:

- The number of lanes
- The presence of complex interchanges that promote the use of the left lane for movements between highways
- The absence of shoulders on some motorway sections ise very usefully when an incident occurs on the road (accidents, breakdown, etc.)
- The high number of inlets and exits can result in many vehicle interlocking movements on high-flow motorway segments.

The same report points out that traffic increases on bridges during the morning and evening peak periods, particularly motorway bridges.

2.1.7 Issues of traffic supervision

The above-discussed traffic sensors provide insights about traffic conditions but are not free of imprecisions or errors. Three well-identifiable such issues are:

- The adequacy between sections of the road network and the location of traffic sensors. A latent difficulty in monitoring is the network's coverage by the sensors. A small number of sensors and their poor positioning inexorably cause the information on the network graph to break. These constraints have long restricted the study of the road network to highly localised approaches on isolated sections or well-defined corridors. The use of historical survey processes alone (infrastructure-related) contributes to such difficulties. The insertion of the sensors and the technology used is expensive, restricting their coverage of the network. They often require a pair of sensors (measurement of speed from electromagnetic loops) and provide point information. In addition, these sensors are characterised by the high cost of materials and thefts Frequent. The appearance of alternative collection typologies and the dematerialisation of sensors limits these inconveniences. Better network coverage is obtained, of course, at present, at the expense of the number of vehicles detected.

- Management of outliers or missing measures captures Faulty, unregulated sensors, or even parasitic physical phenomena are all likely causes of erroneous or absent detections. Processes for filtering and completing noise data have emerged in recent decades. Travel time or individual speed measurements are the components of traffic conducive to such filtering. Operations are based on the analysis of individual velocity distributions. Slippery deviation-type algorithms [10], speed thresholds [11, 12], comparison to smoothed normal distributions [13] and modelling of distributions are all processes developed in the literature.

  Data estimation and assimilation is also an observed process applicable to any traffic characteristic. Kalman's filter is the most common example [14, 15, 16, 17]. This recursive estimator is based on a predictive model based on assumptions of stationarity of traffic flow. Practised when data are particularly noisy or absent, estimates will be incorrect in the face of incidents.

- Estimated time for traffic conditions. Depending on the technology used and the effort required to eliminate data noise, traffic features may be available quickly. Real-time interventions by managers require a short estimate time for the entire network processed.

2.2 Planned Special Events (PSEs)

An extensive review of the impacts of the planned special events in the host locations is carried out.

2.2.1 Conceptualization of planned special events

Events are a planned or unplanned transient space-time phenomenon. Each event is unique because of the relationships between the environment, people and organisational or management systems [40, 41]. Planned events are those created to have gone beyond the scope of individual initiatives and community in professionals and entrepreneurs [41]. Some authors refer to them as special events [40]; Shone and Parry, 2004; Allen et al., 2005). In this sense, Masterman (2014) tells us that the terminology differs. As mentioned by various authors, there are events of great relevance, hallmark events, mega-events, main events, and major events. Thus, for Goldblatt (1997) and Hall (1992a) the Olympic Games would be an event of great relevance. However, for Getz [40] and Allen et al. (2005), they would be a mega-event and, in turn, describe the events of great relevance or "hallmark events" as those that are repeated in a particular place in which the city and the event are inseparable, such as Wimbledon (London) for tennis.

2.2.2 Conceptualization of planned special events

In recent years, the success of various kinds of events has meant that more and more cities or communities have organised events to benefit as many of them as possible. Dynamising organisations that, through the event, try to keep alive the culture and traditions of a community; other organisers, on the other hand, could decide to host an event to change the identity of a place trying to transmit and spread a different image. Very often, events can be used as a marketing strategy to promote the area and to make it known in such a way as to increase the influx of tourists and thus generate new economies or strengthen existing ones. The considerable quantity and diversity of events that have spread make classification difficult; some events may be similar for some characters but different for others. The same criteria that previously attached them can change over time, giving rise to differences.

Attempts to classify events were made by Hall [42], Roche [43] and Müller [44] according to size criterion. They considered: the market breadth that an event manages to cover, i.e. the size of the audience that it can reach, thanks to the type of media that cares and talks about it and the type of leadership involved in its design and implementation. Specifically, Hall [42] divided the events into three macro-categories according to the target market, public financing and the organisation behind them. As a first category, it identifies "Mega events", identifying them with those events that can attract an international audience, which requires management and planning at the government level and funding at the national level. Examples include the Olympic Games, universal exhibitions, and the Australian bicentennial. The second category concerns “Special Events" and within it, depending on the slight nuances that distinguish them, recognizes four types: 1) special events which have an international and national audience, which are subsidized by the nation and/or the region and which require coordination between central and regional government for their management. These events, according to Hall [42], can be identified with events within reach of the Grand Prix or America's Cup; (2) special cases of interest to a more national than an international audience involving regional and partly national funding and which are managed at the regional and national level with the limited participation of local organisations (e.g. international art exhibitions); 3) special events which have an impact and require funding at both national and regional level (Coast to Coast Race or national exhibitions of an artistic, zootechnical or nursery nature); 4) special events involving participants at the local level and receiving funding and being managed by the region (such as artistic or cultural events).

The last category is that of community-wide events, from Hall called

"Community events" which can attract tourists from the region or only at the local level, the funding of which is mainly local and the organisations that deal with them (e.g. country celebrations or fairs).

The breakdown carried out by [43] is slightly different, dividing events into three but four categories. The criteria for classification are based only on the size of the audience they reach and the degree of interest they arouse in the media by not referring to the types of funding they receive or the organisations in charge of them. Like Hall [42], Roche [43] also recognises the category of "Mega events", which can attract a global target and media interest (Olympics and the Expo), and of the "Special Events" by including in this definition only those events with an audience and media attention at the national level. Unlike [42], to identify festivals and major city festivals that affect a purely national and regional audience, and the same for the media creates the category of "Hallmark events". Finally, there are the "Community events"(also this definition taken up by [42], which look at a much smaller audience and purely local publicity. Müller [44], on the other hand, in his analysis, neglects smaller manifestations to focus only on the classification of major events. It identifies: "Mega events", "special events", and "great works". In the first category, the "Mega events" include the Olympics, the World Cups of Football and The Expo, which entire lycopene up a global market and have as much media coverage with live television performance. The "special events" divide them into special sporting events (world skiing and athletics, motorcycling, etc.), special religious events (jubilee or the ostension of the Shroud) and special political events (international summits) with global and macro-regional targets and special economic events (specialist fairs such as the boat or book show, etc.) and special cultural events (festivals, major exhibitions, capitals of culture) which have both a national and international impact. The scholar identifies how these special events are broadcast not live but mainly through TV services. And finally, "great works" such as the inaugurations of squares, museums or public projects around which real national and regional impact events are created. These two enjoy television visibility thanks to the services, even if not live.

Other criteria for trying to classify events and grasp their differences and similarities are [44]: the season, duration, target audience, location, number of visitors, type of access, media attention, reference target, schedule of activities, services, type, main purpose or theme, financial resources, initiative and ownership of organisations and stakeholders. As far as concerns, the first criterion, the season, refers to the time of year to carry out the event. It is a critical choice since, depending on the period chosen, you can impact the influx of tourists in different ways. If it is scheduled before the start or end of the season, it is possible to extend the duration of the season instead of the organizes during the low season, it can be aimed at an increase in the level of attendance at that time. The duration of an event, on the other hand, indicates the length of time it is held. The latter can vary greatly, ranging from a few hours to a week or even a month or more. The target audience indicates the vastness of people whose interest is captured by the event as the event can be of interest to an international, national, regional or local audience. Making predictions about the number of participants is essential to decide transportation and logistic free entry to the event or using mixed access methods. In addition, some tickets, depending on the categories to which they refer, may provide discounts: the elderly, minors, students, groups exceeding a certain number of people or those enrolled in specific associations may enjoy some decreases from the initial price. As previously seen by [42], [43] and [44], media attention can also serve as a criterion for classification depending on whether it involves global, national or regional-local averages. Another important consideration that event organisers must make is the choice of the target group. The more precise the definition of the group or groups to which you want to refer, the more the organisation will know what specific expectations potential visitors will want to see met. In this way, the organisers will learn how to direct their efforts to realise an event that may be of interest to the identified segments and which type of communication is best suited to reach them. The location criterion concerns the choice of the place to hold the event. Many factors can influence this decision. Such as technical and organisational requirements. If many visitor flows are expected, then the organisation must orient itself towards a prominent enough place, or if there is a need for specific equipment, you choose a suitably equipped place. Once you have selected where to carry out the event, you must identify the venue or venues. These must be suitable to welcome responsibly (i.e. in accordance with safety regulations) an adequate number of tourists, must be as accessible as possible to meet the needs of the most sensitive categories and must have all the equipment necessary for the proper conduct of the event. As for the schedule of attractions offered, these vary depending on the conformation of the event that can consist of a single moment (as in the case of concerts) or multiple (think of the opening ceremony or inauguration, the presence of different activities or shows planned during the day, etc.). The services offered concern all the ancillary functions that enrich the participant's experience in the event: these can range from the stands that provide food or drink to the types of parking and transport and the presence of other commercial stands or info-points.

The type of event can very often depend on the area in which you decide to organise it. For example, in a city of art or rich in history and traditions, the typology that best suits it is cultural or celebratory. In contrast, the most modern and equipped cities lend themselves to commercial or sporting events. Depending on the type, the type of event depends; those with a cultural background are organised as festivals, exhibitions and exhibitions if they concern art or in fairs and re-enactments if you refer to the traditions and history of a place. On the other hand, commercial events take the form of meetings, conventions, or exhibitions of various kinds.

Each event then, regardless of type, can be developed around a single main theme or purpose that deal with a specific topic. Such events can be designed to raise funds for associations or research institutes, raise people's awareness of specific issues, and enhance consequences. Environmental aspects or attractions aim to promote the destination and spread a positive image. Another purpose for which an event is organised and hosted is to generate more revenue by attracting more visitor flows. The economic need often merges with the socio-cultural one. When we talk about the economic and financial aspects surrounding an event, it can be said that for an event to take place, funding or public funding is used, which may come from the central government, the region or the municipality, or private if they come from organisations or associations that make a donation or sponsorship. The ownership criterion includes the event's creators, i.e. those who have the initial idea, who identify the type and theme, and promoters, i.e. those who approve of the idea and apply for it to be confirmed.

But financiers, creators and promoters are only part of the dense and complex network of actors involved in the realisation and success of an event. In fact, the network of relationships that are created also includes different types of workers who collaborate and make their knowledge available for the success of the event. These can be the direct employees of the promoting organisation, and external collaborators called to perform specific tasks that, depending on the event, can range from technicians specialising in fittings, light technicians, sound engineers, security personnel, etc. Also essential are the volunteers who lend themselves to carrying out services right away (such as civil protection, art enthusiasts within exhibitions or inhabitants who want to feel an active part of that event). Other players inevitably gravitate around creating an event or are suppliers at both local and regional levels. Another critical role is played by advertisers who use various channels as a sounding board for the event. An important channel is the media that can reach the public widely; another disclosure system is the paper system that ranges from advertisements in newspapers, brochures and posters. In addition, there are more and more telematic communications that can be accessed by mobile phone or computer. All these types of communication contribute to the knowledge of the event by informing potential tourists and spreading the name of the event and the host city. Finally, the presence of event participants and visitors is fundamental in the network of stakeholders. A positive response to what is proposed to you creates a large influx of satisfied tourists who tell their experience to friends and relatives, thus expanding the future catchment area by word of mouth. But some of the visitors can also negatively judge the distance event, thus judging, with their opinion, the potential participation of other people [45]. Both positive and negative effects can be amplified by critics holding a prominent role as opinion leader has considerable weight in conditioning individual ratings and generating further publicity. If, on the other hand, individuals did not participate or were only slightly present at the event, this would not succeed; without the public, its function of transmitting messages, spreading culture or innovation or increasing tourist flows would be lost; thus also missing the whole series of revenues that would result.

Xing-zhu and Lin [46] stress the need for this dense network of stakeholders to carry out an event by arguing that the level of interdependence between the partners involved is as remarkable as the degree of sharing of resources and skills. These two studies identify how at the centre of the network of relationships there is a diade composed of the owners of the structures and the promoters of an event. These two parties have complementary interests because the former needs the latter to exploit their structure as much as possible while the latter need a place to carry out their events. This first core of relationships is called by Erikson and Kushner a "focal relationship", but by connecting their respective parties, they also involve their micro-network of relationships. This creates a series of new connections that the authors break down into three groups. They identify the "primary connections" generated between a member of the diade and an individual not part of the focal relationship but belong to the network of relationships of the other elements of the diade. For example, if a promoter calls a sponsor who knows this, it will establish relationships with the owner of the property or vice versa. If the property uses a type of mass media, this will also tie with the promoters of the event. Then there are the "secondary connections" made up of individuals involved in the event who establish relationships with each other but not with the subjects of the initial diade. Finally, they identify the "tertiary connections" created by a participant outside the diade that weaves and maintains ties only with a member of the focal relationship.

However, the two authors acknowledge that these three levels of connection may vary and depend on the type and strength with which a link is established between the various actors involved.

2.2.3 Definition and Characteristics of a Megaevent

According to Varrel and Kennedy [47] Mega-events, it is defined as events with global audiences that can vary in type and organisation but have in common the itinerant character, which occurs regularly in different places. This definition is inserted the World Fairs, World Cups of various sports, regional athletic competitions such as the Euro Cup, or the Asian Games, such as the Olympic Games.

Paiva [48] defines events that are specifically targeted at the international tourism market and can be described as 'mega' in the future of its grandeur in terms of audience, target market, level of financial involvement, the public sector, political effects, the extension of television coverage, construction of facilities and impact on the economic and social system of the host community." According to Tzanelli [49], events are classified according to their nature: sports (games and competitions), cultural (shows, exhibitions, art shows, seminars etc.). Ecological (tours, cleaning task forces), linked to entertainment and leisure (games), in the commercial area (conventions, product launches, business fairs), special (commemorative dates, historical facts), and relationship events (parties, family meetings, meetings).

Varrel and Kennedy [47] analyses how governments and citizens in cities with different patterns of economic growth use participatory spatial knowledge management to or enable urban governance towards more sustainable development. Participatory spatial knowledge management is the central concept used to study this issue; it is a strategic resource. All stakeholders can contribute to participatory governance processes oriented towards sustainable development.

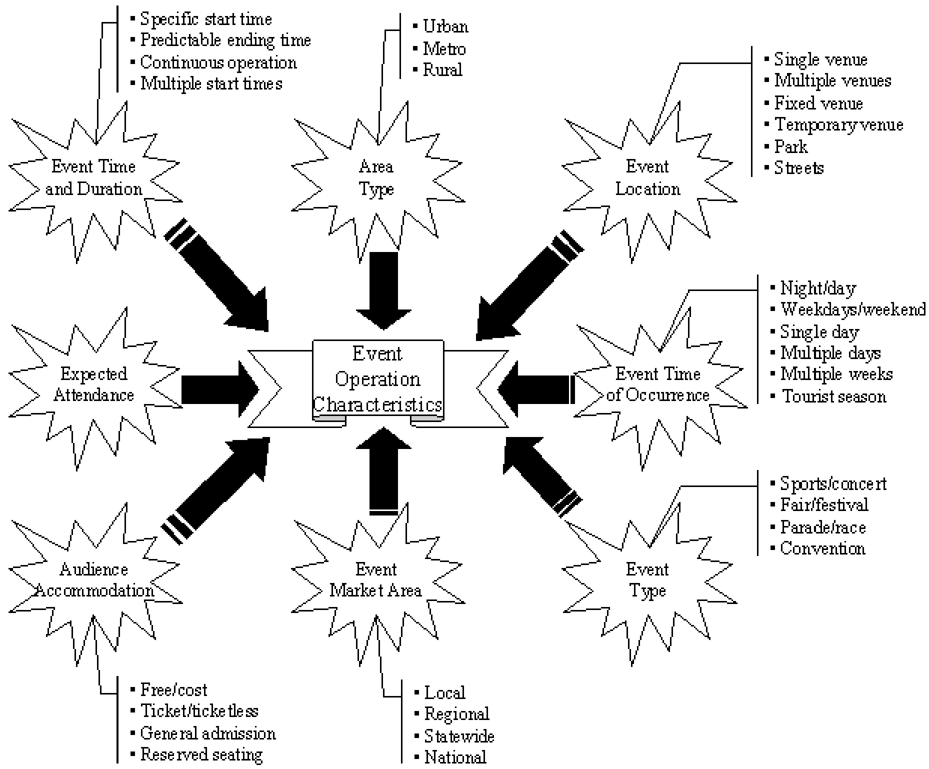
However, mega-events can be considered PSEs – Planned Special Events. According to Chirieleison and Scrucca [50], public activities with a predefined agenda, location and duration; impact the ordinary transport system. EEP's can be classified by their nature as well as by their operating characteristics. Figure 02 shows the typical functional features of a planned special event. Each character represents a variable that influences the scope of action of the event and its potential impact on the transportation system. These variables include:

- Event occurrence time: Sets the time of the (s) day(s). Events during the week may face restrictions on the track, traffic and parking capacity.

- Event time and duration: defines whether the event will take place at a start time, which will likely condense the arrival of the event, or whether it will work continuously throughout the day where customers can come freely and leave.
- Event location: The location definition will involve connecting to the existing transport infrastructure. Fixed locations, such as stadiums or arenas, will need parking areas, good access to freeways and the urban arterial streets. Temporary facilities may not have these resources, thus requiring the development of a local access plan and detailed parking.
- Area type: defines the available transport services, the characteristics of the area's traffic, and the various stakeholders that can engage in event planning and management. These characteristics influence event, process, and travel management operations but vary significantly between rural, urban and metropolitan areas.
- Event market area: defines the size and scope of the event—the potential to attract people from other regions.
- Expected attendance defines the maximum estimated number of participants of the event. Estimates may include the expected number of VIPs with advance tickets, customers with an assigned parking pass and customers in need of special assistance.
- Public Hosting: Knowing the origin of potential participants can help predict the number and origin of the trips generated by the event and the type of trip participants can make to the venue.
- Event type: Defines the type of event subject to special regulations and licensing requirements. The event type includes many characteristics of the planned special events that influence trips generated by the event, demand, and impact on the transportation system.

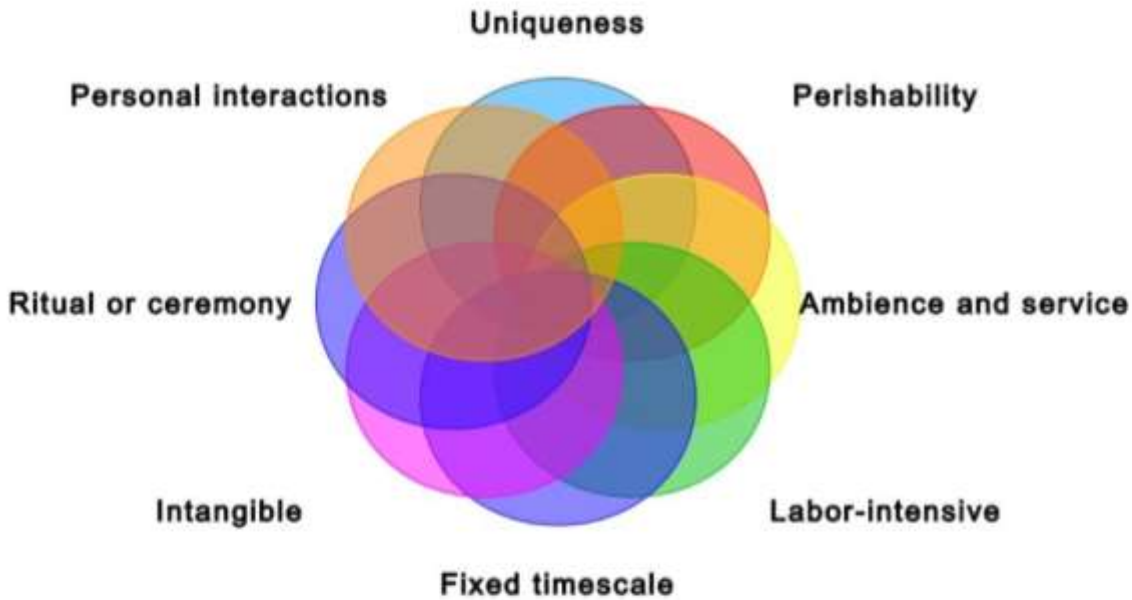
Figure 2 a. the operational characteristics of a Special Event

Cast: Lastoski et al (2003)



The success of an event is strongly connected to the objectives of the event and how those are met. Further to the operational characteristics of a Special Event suggested by Latoski, et al. [51] in 2003, in order to create a successful special event, Parry and Shone [52] in 2019 suggested the use of uniqueness, perishability, labour-intensiveness, fixed timescales, intangibility, personal interaction, ambience, and ritual or ceremony as characteristics of special events. These eight characteristics shown in Figure 2 b. were studied to identified as the key characteristics of a special event.

Figure 2 b. Characteristics of special events, by Parry & Shone 2019



2.2.4 Planned Special Event Characteristics

The operational characteristics of the Latoski, et al. [51] list five categories:

- A recurring event in a permanent location - It happens regularly in the same place; has a set duration—the peaks of arrival and departures more predictable concerning the other categories. Spectators arrive at the stipulated time and depart from the venue shortly after the end of the event. Examples of this category are sporting events and concerts.
- Ongoing event - It can happen in a single day or several days. Spectators arrive and leave throughout the event, are usually held in temporary spaces such as parks or other open spaces. Conventions and fairs can be cited as an example of this type of event.
- Street event - This is the case of marathons and bicycle races, which may require temporary closure of roads and usually occur in urban areas and business centres.

- Regional and multi-local events - Refers to several planned special events in a region simultaneously or in a period. Events in this set can have different start times and can be different in sorting. For example, the Olympics holds several other sporting events simultaneously and in the same city.
- Rural event - This type encompasses any recurring or continuous event in a rural area. This has differentiated classification by present access difficulties, lack of parking and limited monitoring infrastructure.

An event can be inserted in more than one category of Planned Special Event, as occurs with the Olympic Games, which can be considered a recurring, continuous, street and multi-venue event. It is worth noting that not all significant events are considered mega-events.

The definition give by Pereira, et al. [53], where a megaevent involves significant temporary changes in the city’s daily life that hosts it, in its logistics, transport organisation and travel behaviours.

2.2.5 The Impacts of Events

The studies carried out by Hall [42], Getz [40], and Brent Ritchie and Aitken [54] has tried aspects, which events generate on the communities (and towards the inhabitants of the environment) that host them. Six types of impact have been identified: economic, commercial, physical-environmental, social-cultural, psychological, and political-administrative.

- **The economic impact**

The researchers, Brent Ritchie and Aitken [54], Getz [40] and Hall [42], observed that both in the run-up to the event and during its conduct, there are significant changes in the economy of the host community. In the initial phase, this is due to the start of the organisational machine, to the involvement of different personalities in its planning. Still, it is above all during its preparation that the collaboration of companies and specialised people is required. This, therefore, involves both an increase in the organisation's efficiency and the creation of new jobs and job opportunities. The rise in employment and the entry of cash flows from visitors thus contribute to a greater circulation of capital and a consequent increase in living standards. The new circle of money brought about by tourists has direct, indirect and induced effects. The immediate results relate to the expenditure made by visitors directly at the facilities they use during their stay at the destination. On the other hand, indirect effects are generated by businesses in the tourism sector using other local companies related to them, such as hotel or restaurant providers, maintenance services, etc. Finally, the induced effects are generated by spending part of the income accumulated by residents through wages or annuities derived from the event.

However, there are also negative changes such as, for example, the temporary increase in the prices of necessities, transport, parking or housing, for the duration of the event, to have a more significant profit margin on tourist expenditure, but this inevitably undermines the purchasing power of the population. What is more, high costs are likely to act as a disincentive to potential tourists. Another important aspect, during the planning of the event, is that the responsible body conducts an adequate analysis of the available budgets in such a way as to have full knowledge of the capital that can be used to avoid being, once the event is over, with a total of revenue less than the costs incurred. A final economic and negative impact, which can occur, is the possible loss for the organisation of resources from potential lenders if, contrary to expectations, they are more interested in subsidising another type of event.

- **The tourist-commercial impact**

The high echo that an event generates helps the city spread its image and advertise its tourist offer, making it more attractive to travellers and entering new markets. Organising an event is helpful to attract different types of tourists. There are, for example, people visiting the city who have been affected by the event who decide to extend their stay or those who go to a particular destination solely because they are interested in the event. If it had not taken place, they would probably never have gone there. Or there is that segment that has already had the opportunity to get to know the city and spend time there and that without the event would not return a second time. An event is attractive to tourists and residents of the area where it takes place because, thanks to the event, they could be driven to go to places that previously did not attract their interest (or even their existence) or increase their expenditure in some sectors. Therefore, there is beginning to be greater awareness of the region as a travel destination, and the growing interest generated towards that particular place makes it attractive to potential investors or to new businesses that want to expand and expand their scope. But hosting an event also becomes a strategic move to change the tourist season. An aim can be made to extend the duration of the latter by planning and carrying out one or more events before the start of the season or just after its end. In this way, the aim can be to achieve a wider time frame in which tourists can enter. This creates more job opportunities for those working in the sector and thus increases economic revenues. In addition to anticipating or prolonging the season, it is possible to try to create a new one, thus avoiding or limiting the phenomenon of the low season. The latter occurs when, in a destination, the flow of visitors decreases due to the weather conditions not favourable to the performance of tourist activities. By planning a series of events, the place can return and arouse other interests and generate new arrivals that revitalise the economy in that period of low turnout. An event can also be scheduled in the high season if the number of attendances has not yet reached the highest level. However, attention must be paid to the negative effects that this strategy can generate if the degree of attendance becomes unmanageable. The high degree of crowding, traffic and dirt could disfigure the destination and make tourists live pleasant experiences that could be discouraged from repeating the visit in the following years.

The increase in attendance can create new facilities aimed at welcoming tourists or additional attractions to make the destination more attractive and exciting. Another positive aspect is the growing attention and awareness of all types of visitors, which leads to greater attention being paid to the problems of accessibility, thus modernising the structures no longer able to accommodate the most sensitive categories adequately.

However, a destination must pay attention to the type of facilities and services it can offer because if these are perceived as inadequate or insufficient by visitors, it risks acquiring a bad reputation that, in the long run, could lead to the loss of tourists. Other aspects that can cause a drastic decrease in tourist-commercial flows are the offer of attractions that differs from the one advertised, or a lack of funds due to an incorrect calculation of available resources or any building speculation, or the price increase implemented by traders to obtain more margin from sales but which can discourage especially the less well-off groups of tourists. Another disadvantage could be the emergence of unreeling favourable reactions from local businesses as they feel threatened and competing with new companies entering the market attracted by the new opportunities offered by the destination.

- **The physical-environmental impact**

Due to the tourist expansion that can occur in a destination, the physical and environmental impact concerns all those positive or negative changes affecting the architectural structures or ecosystems of a place. A positive result is the construction of new buildings or the improvement of existing local structures and transport. In this way, it is possible to ensure the correct and safe conduct of tourist activities or demonstrations and to avoid the disfigurement of the image of the city, which could be caused by a building no longer in excellent condition, even from the point of view of safety, or even dilapidated. Depending on whether the event is of great importance (and therefore needs new facilities to adequately accommodate both the functional aspects of its development and visitors) or of medium to small importance, the redevelopment of a city or its redesign as well as offering benefits to visiting people and the inhabitants themselves can also make positive changes to the environment. The refurbishment of an area, its partial or total renovation, or cleaning of a historic centre help keep the city more welcoming and preserve its cultural and landscape heritage.

On the other hand, there is the damage that an erroneous plan to change the city can cause. When we talk about the design of new buildings, if not thought in harmony with the architecture and the type of environment in which the work would be placed, there is a risk of ecological damage, what scholars call " architectural pollution" that is, architectural pollution: structures that undermine aesthetics but also the functions of natural and urban so-called systems. A final negative aspect concerns the damage caused by the overpopulation of the city. If the amount of tourists arriving in a place exceeds the load capacity of the destination, that is, the ability of a given environment to support a given number of individuals, there is a risk of compromising, as indicated by Ferroni (2017), in the long term, "the endogenous resources, the social fabric, the economy and the cultural identity of a given territory". In addition, uncontrolled and irresponsible tourism risks producing both serious physical damage to historical centres (as happened in Rome, for example, when they scarred the Colosseum or the Barcaccia fountain was chipped) and environmental damage (think of the dispersion of waste in mountain or seaside areas or the "sand thefts" in the latter).

- **Carrying capacity**

According to the definition given by the World Tourism Organization in 2000, the Tourist Load Capacity corresponds to the maximum number of people who can visit a destination at the same time, without damaging its physical, economic and socio-cultural aspects and without reducing visitor satisfaction. However, it must be borne in hand that each destination, because of its ecosystem, needs a different calculation model. Depending on how the tourist load capacity is investigated, the emphasis is on several aspects: if we look at the social sphere, we aim to perceive the degree of satisfaction of residents with the tourist flow. If we focus on the economic aspect, we aim to maximise profit while taking into account the environmental limits, and if we take into account the ecological one, as for protected areas, attention is paid to the permissible number of tourists depending on the area of the destination.

Concerning the economic dimension of the ancestrally and Costa [55], in their study to try to determine an acceptable number of tourists who do not adversely impact residents and the area of the historic centre of Venice, they resume the research of Fisher and Krutilla [56], highlighting how the criterion for an excuse of the resources of a tourist attraction is: $\pi(q) = B(q) - C(q)$. Where π indicates the net benefits of subtraction between benefits (B) according to the level of use of recreational attractions (q) and costs (C) (those resulting from environmental damage, current expenditure, capital expenditure) in turn as a function of q.

Another interesting approach is used by Mansfeld and Jonas [57] in their study of perceptions by the Kibbutz Yiron community (in northern Israel) about tourist flows in their area. The two scholars were able to observe how each resident perceives the tourist flow differently. They categorise individuals' sensations according to three degrees: one of tolerance (which, if overcome, indicates a negative perception), one related to the current situation (the impressions generated by the tourist flow as it unfolds) and one concerning future expectations. These opinions are collected through moments of a discussion carried out by ingroups. In this way, it is possible to identify the most significant concern to residents to take them into account later when planning and managing tourist flows or future events. If it is possible to ease the tensions perceived by the population, it could prove more favourable in accepting the next flows of visitors.

- **The social-cultural impact**

The realisation of an event is also essential to awaken the interest of the population, which can be valuable for participation in types of activities associated with the event; if the inhabitants are aware of the potential that their city can offer, they are also able to transmit these values better and in doing so strengthen and pass on traditions over time.

It is also up to the loyalty of the residents to take advantage of it by marketing activities that may be of a personal or private nature, by charging for a service that is normally free but that visitors are not given to know or modify traditional production aspects to increase revenues, or to change the essence of the event only to meet the needs of tourists. Another problem that can occur because of overcrowding of people in one place is the increase in crime incidents, due both to the reckless action of visitors (who may not respect the customs and customs of a community or disfigure ecosystems by polluting with poor waste management) and to the protest behaviour of members of the host community. In addition, some citizens who are particularly intolerant and disturbed by tourist flows may decide to leave the city temporarily, anticipating their holiday period or, in the most drastic cases leaving the city to move to neighbouring areas but less frequented by tourists.

- **The psychological impact**

Once the population is aware of the peculiarities and rarities that their region can offer, and of the interest it arouses at the national and international level, there is an increase in local pride: greater participation and interest in the activities that develop within the community that leads to a rise in collaboration between individuals and in the community spirit. Thus sensitised, they realise the treasures they can make known, they become more aware of what they must transmit and the attention they must pour into their attitudes towards the tourist; a visitor who finds a welcoming and participated climate is more driven to repeat the experience or advertise it by word of mouth.

However, contrary attitudes can also occur; that is, the population becomes protective towards its traditions, thus activating defensive behaviours and giving rise to some misunderstandings in the host-visitor dialectic, leading to various degrees of hostility. A final factor is a cultural shock: the arrival of tourists is not always considered as a possibility to promote intercultural contacts, make new friends, and develop networks. Sometimes a large number of visitors is seen as a possible threat, a kind of pollution of the lifestyles and customs of their country, since they irresponsibly do not move in accordance with local businesses.
The political and administrative impact.

The more the event can attract media attention, the greater the international recognition of the region and the values it has to offer. In addition, its design and implementation is an excellent springboard for the development of the skills and competencies of the network of individuals involved in its creation and management.

If, however, there is opportunism on the part of the political elite at the head of management, there is a risk that it will act to meet its ambitions, thus ignoring the needs of its region to the point of economic exploitation of the local population. It can also happen that to transmit its values, the organisation that deals with it distort the event's true nature by spreading messages that differ from the original ones. The event can then be used to legitimise unpopular decisions or capture assaults on their activities that may be of an administrative or political nature. Another type of opposing political and administrative impact is the inability of the responsible body to achieve its objectives due to an erroneous strategy that leads to the provision of a type of event other than that promised by not meeting the expectations of participants who can discredit its competence at regional or even national level.

Another problem that occurs in the design of an event is the increase in administrative costs: the mobilisation of different competencies and actions on the territory lead in fact, to the rise in average public expenditure that can only be supported following an adequate analysis of the costs to be incurred to obtain the benefits that the realisation of the event and the advertising that this generates can bring.

Subsequently, Hall (1992) focuses mainly on the socio-economic aspect of the environment in which an event occurs, identifying it as decisive for the development of events and the consequent impacts that an event generates at the social, political and economic level. It argues that there can be an interdependent relationship between the economy, society, politics, and the event's nature. The realisation of an event depends both on the political, social and cultural aspects present in a tourist destination (a certain event is organised according to traditions that a place has to transmit either according to the ideas and will of the political elite) but also on its economic situation: if there is a lack of capital or funding, even though there is an idea or value to share, the event is not organised. However, once the event is aware of its implementation, it impacts culture and society, as seen above, and on the economic aspects, increasing or damaging the local economy.

The stories and traditions that an event can transmit are inextricably linked to the social fabric, the political and economic cultural context of the region in which they are carried out, and the events that have a more recent history disseveration that culture and enrich it. The significance of an event depends on the perspective with which it is considered: organisers and the host community can see it as a source of pride, affirmation at the regional or national level (for mega-events also at international level) of the qualities of their city while financiers or companies can consider it purely as a profitable economic and advertising outlet and visitors both as a recreational moment and as a source of personal enrichment.

There are several aims that a political elite, organisation or community wants to achieve through the organisation of an event and the benefits that visitors and financiers seek. For example, religious events are fundamental to telling and consolidating the millennial tradition of the faith, such as the pastoral visits of the Pope or Dalai-Lama, who with their aura of sacredness attract faithful from all over the world and simply curious. Cultural events, which concern the nature, folklore and artistic production of a place, are events that since the mid-1900s have increased following the wave of a growing push in demand for cultural heritage: greater awareness of tangible and intangible heritage has increased their consumption but also the awareness of their prestige that makes them a source of pride and intellectual wealth for citizens living in that area. Commercial events, such as trade fairs dedicated to certain products and excellences or conventions, are of interest especially for the administration because, in addition to contributing to a change in the production sector, dictating the new guidelines, they become fundamental to increase sales and exports more. Being at the forefront of a specific production or for a given exhibition generates an echo at different levels, leading the city to be recognised more even abroad. Its geographical location, if previously ignored, begins to be known. Sporting events help to increase the sense of belonging and represent the city during competitions; think only of sports teams that become part of the culture and social fabric. Mega-events, on the other hand, such as the Olympics, generate a greater sense of honour and pride for having been chosen as the host country among all the other candidates and for the possibility especially during the opening ceremony and with commercials to broadcast globally the traditions, the cultural and natural heritage that the region has to offer. The success of an event, in addition, highlights the organisational skills of the host government and the climate of tranquillity it manages to ensure. Political events, which may be set up during representative trips or conferences of Heads of State, rulers or government representatives, are intended to celebrate the importance of this figure.

Therefore, it can be said that an event is conditioned by the environment and the society that hosts it and impacts at the political, economic, and social levels. These are the three dimensions of most significant interest and are present in the studies dealt with in lettering, which will be examined in more depth in the next chapter.

2.3 Data

In this section, the details of the datasets used in the experiments are discussed. The dataset related to the urban traffic networks, both freeways and urban arterial road networks of Melbourne, Victoria, used in this thesis.

2.3.1 Melbourne Victoria PSEs dataset

Planned Special event details weren't available as a resource; therefore, using the web scraping technique, the event details were captured for Melbourne, Victoria for 2019.

The method designed to extract web information is divided into three main modules, primary extractor, extractor link and selection. The modules provide the processing of the web pages for the extraction of planned events.

Main extractor. This module is dedicated to finding, given a home page, pages named above, the second pages, suitable to be the incoming links to the next module. That is all pages that link to the home page. The link extractor collects the incoming links from the main page to extract the links from each of the events they contain. Subpages typically group events by a specific category.

The link extractor outputs the list of pages of extracted events processed by the selection module to extract relevant information from PSEs.

The selection module is intended for extracting fields and labels from PSEs pages individually. A process that depends on Scraping Web refers to a set of techniques used to obtain information from a web page automatically and not manually. In particular, the scraping method is adopted to access data belonging to sections or objects; search for tag, content, or attribute names that match selection criteria; and access attributes using reference id. Scraping is done by using Python libraries provided by HTML Parser and Beautiful Soap.

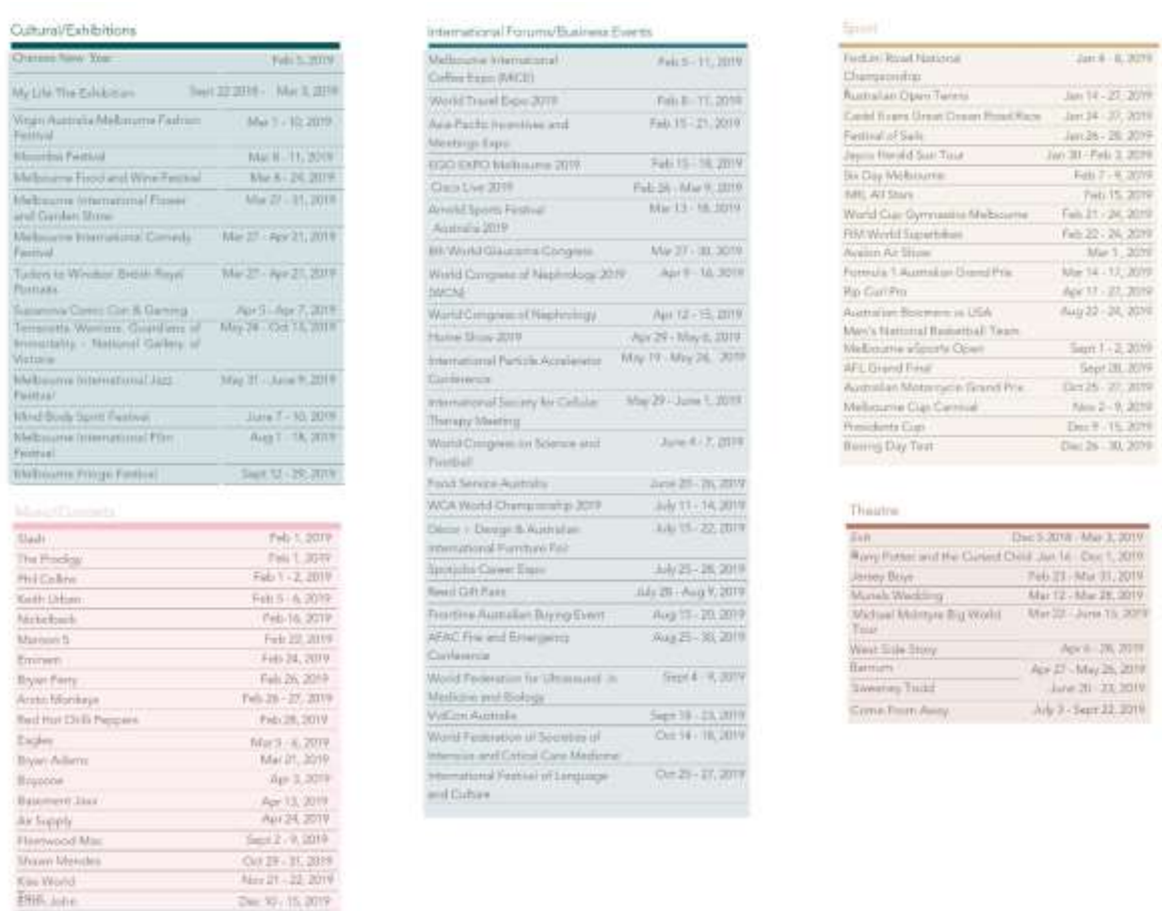
The selection module outputs as an ordered dataset, belonging to the attributes of the extracted events along with the corresponding URL and its descriptions. This dataset will be stored in a spatial database for data processing, cleansing, and standardization.

The execution of the information extraction process is carried out daily to capture the events with multiple presentations, covering PSEs with daily presentations and with specific characteristic periods.

Aligned with the data extraction process and the proposed modules, it integrates with the query of the geographical locations of the events. The method involves querying and extracting the lengths and latitudes of PSEs, based on the captured direction of each event. In Annex 1, the logic with which the method is developed.

After the process of extracting information from PSEs, the data is saved in CSV-formatted files, in which commas and rows per line break separate columns. When daily extraction is performed, the files are named with the name of the extraction page plus the day's date. As you get to download the files, the information is stored in a PostgreSQL spatial database. Figure 3-3illustrates a section of data extracted for 2019.

Figure 3 PSEs details for 2019 extracted by web scraping



Planned Special event details weren't available as a resource; therefore, using the web scraping technique, the event details were captured for Melbourne, Victoria for 2019.

2.3.2 Melbourne Victoria SCATS dataset

Sydney Coordinated Adaptive Traffic System (SCATS) is a fully adaptive urban traffic control system used in 27 countries to capture and (potentially) augment the decision-making related to traffic flows. The SCATS system utilizes a wide coverage sensor network on major roads and intersections to monitor the traffic flow status in Australia. It is an official public urban traffic data source provided by the Australian government agency. In Victoria, the SCATS data is supported by VicRoads. SCATS data can be directly used for detecting traffic issues. However, it has its limitations:

- Cost: The installation and maintenance of the SCATS sensor network are expensive, and devices are only deployed on major roads and predominantly in cities.

- Lack of real-time support: There is no live stream of the SCATS data open to the public. Information about urban traffic is typical, very time-sensitive. It is almost impossible to provide real-time traffic analysis.

- Nature of the data- As categorised as Big data, its obvious challenges are storing and analysing all the information. Therefore, identifying appropriate hardware and software is crucial for success in SCATS data processing.

In this project, the SCATS volume data was collected from the Victorian Government Data Directory (https://www.data.vic.gov.au). The SCATS volumes provide structured data with fields such as the UID (unique identifier) of the sensor site, the name of the street section, the volume of passing vehicles every 15 minutes and the timestamps for the signals. A supportive data set to the SCATS volume data provides geographic information, e.g. latitudes and longitudes of the sensor sites.

Geospatial data describe any data related to or contain information about a specific location on the earth’s surface. Since the SCATS volume data and its supportive data set share the exact nature of data, traffic sensor/device sites, the SCATS volume data set can be converted into a structured geospatial data set with points and road lines using spatial join operation.

SCATS TRAFFIC VOLUME – VICTORIA, AUSTRALIA

A typical example of a SCATS enabled sensor network is shown in Figure 1, in which each red dot is a SCATS sensor. This sensor network is for the area around Melbourne Central Business District (CBD). Figure 2 shows the whole SCATS sensor network installed in Victoria.

To monitor traffic, the principal intersections are equipped with sensors (inductive loop) that detect the passage of vehicles. Therefore, it is possible to count the number of vehicles that have travelled through a section during a given period and to deduct a vehicle flow per hour. Sensors measure this value with a time aggregation step of 6 minutes, i.e. a measurement corresponds to the average flow observed over the last 6 minutes.

Figure 4 Flow measurements on a traffic sensor for a week (Monday to Sunday)

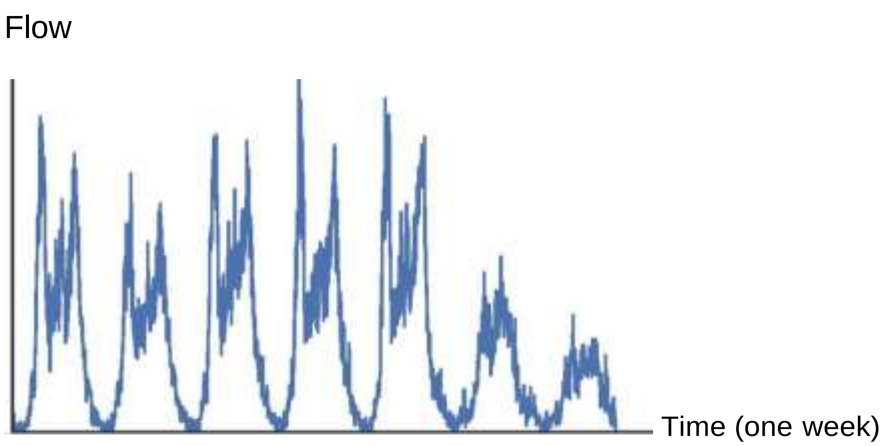


Figure 6.1 shows the flow rate curve for a network sensor over one week (Monday to Sunday). There is a trend on weekdays (Monday to Friday) with a peak inflow in the mornings and late afternoons, corresponding to the movements of motorists to their place of work. It can also be seen that Saturday and Sunday are very different, corresponding to the difference in users' activities during the days not worked. Finally, we observe the more significant fluctuations

at high frequency, of which the modelling is an essential issue for the forecast.

We have the history of nearly 600 sensors whose positions are given in Figure 6.2, for a period ranging from a few months for the most recent to two years for the oldest. However, the dataset contains many missing values, sometimes over long time ranges. These missing values can be caused by a sensor failure, a maintenance intervention, or work on the road. It can also contain outliers, for example, when a vehicle is parked on a sensor. This poses a problem for many forecasting methods, which require a cleaned dataset.

Figure 5 SCATS Sensors Installed in the Melbourne CBD

Cleaning the dataset: We have chosen to exclude sensors with too long a range of missing values (more than five consecutive time steps) and attribute the remaining missing values by linear interpolation. One possibility for imputation of long spans of data would have been to use mean or median values on the history (for the same time of day). However, we wanted to avoid biasing the evaluation of forecasting methods and their comparison by the imputation choices made before the apprenticeship. Thus, we preferred to restrict ourselves to a set of sensors with few missing values.

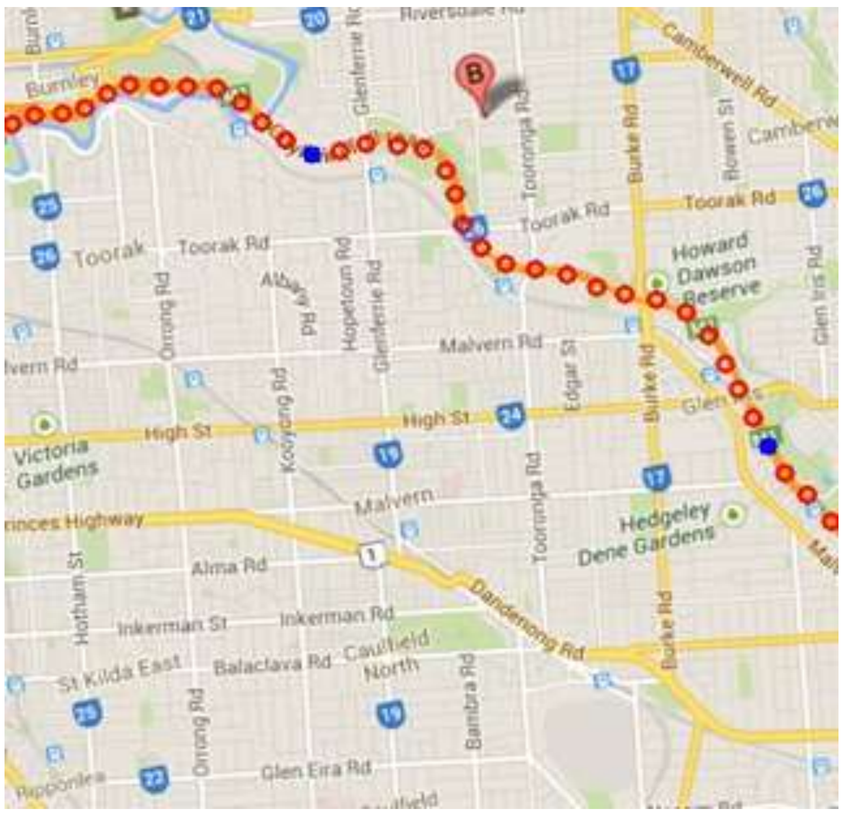
Figure 6 SCATS Sensors Installed in the city of Melbourne

When investigating a specific intersection to access the PSEs impact on urban roads discussed in chapter 5, information about the configuration of the selected intersection is required. VicRoads provides open access to signal configurations to all intersections in Victoria.

2.6.2 Monash Freeway dataset

In addition to the SCATS data on Melbourne CBD, we also have data for the Monash freeway of a slightly different nature. While the CBD sensors are installed mainly on the urban network, the data are collected here on the freeway immediate outskirts of the city of Melbourne.

Figure 7 Sensor layout of Monash Freeway



The sensors are installed for both directions of circulations. There are 24 sensors on the freeway of 15 km shown in Figure 7. During the collection, the passage of each vehicle is recorded with the associated timestamp. From these records, it is possible to reconstruct flow measurements and choose the time aggregation step.

2.4 Chapter Summary

Although transport plays a decisive role in the well-being of individuals and in the economic development of a country, it is a sign of "poor development", when the planned events develop significant increase in urban traffic congestion. Urban congestion has adverse effects on society, the environment, and the economy. The relationship between planned special events and urban traffic congestion has been implicitly mentioned in several research by different authors. This chapters the main focus is on the presenting the literature and analysing on the topics of urban traffic congestion and planned special events.

CHAPTER 3

SHORT-TERM TRAFFIC PREDICTIONS

Since the early eighties, short-term traffic predictions have been a fundamental part of integrated transportation systems (ITS) and related research. Moreover, during this last decade, a particular emphasis has been placed by researchers on the development and application of mathematical models for the most accurate traffic prediction. The literature review research by Ermagun and Levinson [58] shows that the number of related publications has increased over the past decade. It is believed that this increase occurs mainly due to significant advances in technology, which has allowed to improve the capabilities of collecting and handling large amounts of data.

The modelling can be categorised generally based on two primary factors: the type of variable and the methodological approach. These different categories and their respective literature will be presented in this chapter.

3.1 According to variable type

Researchers have made efforts to analyse and predict travel times and instantaneous speeds, spatial velocities, volume, and flow. Given the fundamental relationships between these variables, it is sometimes possible to obtain the values sought by calculations of the others.

Additionally, researchers need to correctly define the predictive horizon they need to meet their goals. The prediction horizon defines the temporal resolution of the information used as input data in time intervals. In the literature, values between 0-30 minutes are generally defined (and applied) as a short-term interval. It is possible to find dissenting positions about how much would be an appropriate time for predictions; On the one hand, Tian and Pan [59] and Ishak and Al-Deek [60] concluded that the predictive accuracy of the models decreases considerably as the predictive horizon increases, and on the other hand, Zhang, et al. [61] argue that there is a considerable decrease in the accuracy of their models when examined at time intervals of less than one minute due to large fluctuations in traffic parameters, where the variations decrease as the data aggregation interval increases. Given this trade-off between how large or small the prediction horizon must be, properly defining this aggregation interval is a crucial factor that determines the quality of the information used in predictive models.

3.2 According to the methodological approach

Vlahogianni, et al. [62] compiled a comprehensive literature review of short-term prediction techniques, categorising predictions of speeds and travel times into two main approaches: parametric and nonparametric methods. Similarly, Guo, et al. [63] and Meng, et al. [64] consider in addition to statistical and data-driven models (analogous to those of parametric and non-parametric type, respectively) the existence of a third category: methods based on traffic models. These definitions will be used and described below:

3.2.1 Parametric methods

Statistical methods usually predict future traffic conditions by applying theoretical knowledge to a database to estimate the optimal parameters that can explain the relationships between dependent and independent variables or the theory of spatial states.

The most basic model used by researchers is the historical average. They are generally not investigated in themselves. Still, they are compared against others with greater predictive power, as Smith and Demetsky [65], among others, have done.

Based on the family of autoregressive linear models of historical averages (ARIMA) initially used by Ahmed and Cook [66], a variety of researchers have conducted similar studies, including Hamed, et al. [67] using an ARIMA (0,1,1) and Williams and Hoel [68] adding the covariance managed to use an ARIMAX model. Similarly, Miller and Williams [69] and Williams and Hoel [68] developed and compared a self-aggressive linear model of historical averages with statistical modification (SARIMA) with better results than those obtained by previous ARIMA models. These studies showed a clear problem in this family of models since these tended to concentrate on values close to the mean and have great difficulty in predicting extreme fluctuations, such as those that occur in traffic.

Ishak and Al-Deek [60] used nonlinear time series for predicting highway travel times. The last of these highlights the fact that the model's predictive capacity increases considerably when it is in a non-congested state instead of a congested one.

On the other hand, both Kwon, et al. [70] and Sun, et al. [71] used linear regressions to predict flow, where it is concluded that this type of model works quite accurately for short times while using historical information provides a better prediction for longer prediction horizons. These conclusions were also obtained in the analysis of Ishak and Al-Deek [60] for nonlinear time series. Both Kwon and Sun consider their studies successful by comparing a feed-forward neural network and a K-nearest neighbour model, respectively. Despite the above, both researchers highlight the future opportunities of the latter, where they conclude that through development and research, they could overcome their methods.

Finally, the Kalman filters used by Chen and Chien [72], Lu, et al. [73] and Guo and Williams [74] can also be considered as time series, where, similar to the rest of the statistical methods, the main obstacle is the low predictive capacity when there are considerable fluctuations, such as the passage from a decongested state to one with congestion.

3.2.2 Non-Parametric methods

Data-driven or non-parametric models attempt to find relationships and patterns without the data being explicitly delivered to the model. This classification includes support vector machines, neural networks, nonparametric regressions and hybrid approaches that combine different algorithms to reduce dimensionality and efficiently perform work.

Support Vector Machine (SVM) is a supervised learning algorithm that works under the idea of finding hyperplanes that optimally separate the points of one class from another. Wu and Dietterich [75] successfully compared an SVM model to a historical average and the algorithm used by the highway power station studied. Vanajakshi and Rilett [76], conducting a similar study, concluded that the SVM predicts better than a neural network in a scenario with a limited amount of data. Castro-Neto, et al. [77] present that their SVM model predicts more accurately in atypical events than a neural network. On the other hand, Haq, et al. [78] used k-means clustering, principal component analysis, and self-organising maps to find space-time relationships and thus pass them to an SVM model, with successful results. Yu, et al. [79] have shown that SVM is a method comparable to neural networks in terms of predictive capabilities.

Similarly, Random Forest (RF) has also been used by researchers to predict operating conditions. Hamner [80] successfully developed and implemented a methodology with Random Forest that improved by more than 60% of the study highway methods.

The K-Nearest Neighbor (KNN) method is a supervised classification method based on estimating the value of the probability density function or directly the a posteriori probability that an element belongs to a particular class. In the last three decades, great strides have been made in this area since the first attempts of Davis and Nihan [81]. These include Gangopadhyay, et al. [82], who predicted traffic on London's M25 motorway using a KNN method by observations of the operating conditions of the road (mainly occupation and flow), which allowed him to forecast these values to obtain an accurate prediction of the future speed of each state. However, since the method was only tested for three weeks, it does not clarify how generalisable the application of KNN can be given the small amount of information trained. For its part, Yu, et al. [83] compare the results obtained by the KNN method with a Support Vector Machine and an Artificial Neural Network, concluding that although it is not strictly better than these methods, it is an effective and viable alternative for short-term traffic predictions.

The applications of artificial neural networks or artificial neural networks (ANN) in short-term traffic predictions range from the configuration of a Multilayer Perceptron used by Clark, et al. [84] and Smith and Demetsky [65] to more complex structures such as Modular Neural Network, Time-Delayed Neural Networks (TDNN); Recurrent Neural Network (RNN); Dynamic Neural Networks and Bayesian Combined Neural Network Approach [85].

Recently, advances in research related to neural networks and Deep Learning have made the classification of these models a little more diffuse, where Huang, et al. [86] proposed an architecture that depends on two parts: a Deep Belief

Network and a Multitask Regression. Fu, et al. [87] and Tian, et al. [88] made predictions using Long-Short-Term Memory Recurrent Neural Network (LSTM) with promising results compared to models with less complex neural networks, where Cortez, et al. [89] compared an LSTM with a Hierarchical Temporal Memory Neural Network. Yang, et al. [90] used an architecture based on Feed-Foward Neural Network to predict behaviours at two unusual moments: at the exit of an American football game and in a snowstorm. Finally, Ma, et al. [91] tested a Deep Convolutional Neural Network with the idea of converting the space-time dynamics of traffic into images that would describe the time-space relationships using a two-dimensional matrix, comparing his method with four classical methods: square minimos, KNN, ANN, Random Forest and three deep learning methods: stacked autoencoder, RNN and LSTNN, with successful results.

3.2.3 Methods based on traffic models

These models are fundamentally based on knowledge of traffic theory, intentando describe and functionally represent the interactions between physical variables, which describe the transit phenomena in a macroscopic and microscopic way. Most microscopic models concentrate on predicting traffic behaviours based on analogies of vehicular traffic with gas and fluid dynamics. In contrast, microscopic models consider individual behaviour in great detail to analyse interactions between vehicles on the network. Knowledge obtained through theory, simulations or practice in real life.

Generally, it is necessary to relate this knowledge to the methods mentioned above since the nature of these investigations requires evaluation with data. The macroscopic model of Liu, et al. [92] associates operational states with a State-Space Neural Network to make predictions. Stathopoulos and Karlaftis

[93], using time series, captured a wide variety of transit flow dynamics through the interactions of their variables.

Given the complexity of establishing models that explain and understand the totality of interactions in traffic [94], recent research has required that these studies are not conducted in a pure way, that is, that they work in a hybrid way with either of the two named approaches.

3.3 Methodology and development

The three types of approaches mentioned in the previous chapter (parametric, non-parametric, and traffic-based) have been used on several occasions to estimate both travel times and speeds. It is possible to see a change in the method used in this last decade, where parametric methods have been left aside. There has been a constant increase in non-parametric methods, particularly Machine Learning [95]. It is proposed that this is due to various factors, including the improvement in the ability to obtain and store a large amount of data and the considerable advances of the latter, since, in a large majority of recent studies, these methods far exceed their statistical counterparts.

While it is understood that parametric and traffic model-based models have a greater capacity for interpretation compared to non-parametric ones, significant efforts have been made to calibrate and improve the latter. Furthermore, given the significant advances in information technologies and data collection and processing capabilities, these implicit models have become a rather attractive alternative.

For data-based models, both parametric and non-parametric, the type of method used, the quality of the information, and the parameters used in development and implementation are vital for predictive quality.

3.4 Statistical Models Overview

3.4.1 Regression models

When the rules governing a phenomenon are unknown, regression models are typical for seeking a relationship between dependent and independent variables. In this model type, a mathematical relationship is established between the independent and dependent variables according to the logic established from a set of historical data. These models must be calibrated considering the historical data so that the chosen parameters minimize some error function between the actual value, the dependent variable and the estimated from the independent variables. These models have also been considered to predict bus travel time (PATNAIK, 2004; RAMAKRISHNA et al., 2006). The advantage of such models is that they can include all variables that influence the travel time of a bus through a system of linear or nonlinear equations. In this field, they have generally been used as models to compare the results with other proposed models, such as Neural Networks or Kalman Filter (CHEN et al., 2004). The main disadvantage is that they require that the variables that affect the vehicle's travel time be independent of each other. In transport, all variables are highly correlated (GURMU & FAN, 2014; AMITA et al., 2015). This problem can be partially resolved with nonparametric regression models.

Non-parametric regression models that have been considered for predicting bus travel time do not require prior estimation of parameters and are therefore more appropriate in real-world applications. So Chang et al. (2010) and Park et al. (2007) developed an algorithm to predict travel time using the Nearest Neighbor k (k-VP) method. This is a very simple method that analyzes the new point in relation to the neighbouring points that are in the dataset (GOODFELLOW et al., 2015). On the other hand, Sinn et al. (2012) used the Kernel Regression method to predict the travel time for the buses, considering measures in real-time and obtained a forecast level of up to five minutes in a total interval of 50 minutes. In addition, the authors showed their efficiency in relation to the implementations of the world by linear regression and a k-VP algorithm.

Logistic Regression

Logistic regression is a method for binary classification, and it is based on the lo- gistic function (also called sigmoid). The two characteristic features of that func- tion make it particularly convenient for modelling probabilities. These are: 1) it is monotonically increasing 2) its range is between 0-1. As stated before, logistic regression is a probabilistic function, which means that the conditional proba- bility of a data point belonging to a class of interest using the sigmoid function must be fit. The probability of assignment to the opposite class is simply its complement. There are many ways for fitting the best coefficients. In the logis- tic regression model, the coefficient vector that maximises the joint likelihood of the input data points in the training set having their corresponding label is favoured. As an optimisation technique, gradient descent is most frequently used. What makes logistic regression classifier convenient in text-related tasks is the inspection of its coefficients generated from the training set. Given the high level of ambiguity present in all-natural language processing tasks (short messages such as tweets in particular), the insight into the classification criteria allows for further algorithm refinement to better fit its purpose. This feature is especially advantageous when the goal is the extraction of relevant data on a particular topic given user-defined criteria (e.g. posts using specified key- words). In that case, both features determination, as well as classifier selection and tuning, contribute towards overall systems sensitivity

Models based on Kalman Filter (FK)

Other bus travel weather forecast studies consider Kalman filter equations to predict travel time. It is a model designed to establish the state variables of a phenomenon that occurs over time, such as fluid or current flows in general. They are phenomena that dynamically evolve and change their state. The input data contains a noise that propagates from the input to the system output, and its value is backed back to be considered at the next moment. In its discrete version, the Kalman Filter has been used to correct a vehicle's travel time according to the latest information [96]. In other cases, Kalman's filter is applied to travel time forecasting, evidencing better performance than regression models and even a neural network model [97]. Chen, et al. [96] also individually apply Kalman's Filter for travel time forecasting on a BRT line with GPS-equipped vehicles.

3.4.2 ARIMA family of models

The ARIMA model was introduced in 1970 by Box and Jenkins [98]. It is used to predict the future values of a univariate time series. This model consists of: a self-regressive part (AR) which describes the dependence between a moment and the past moments, and a moving average (MA) part, which captures the error of predicting the past moments. The concept of integration

(I) means that the differentiated version of the series is sometimes modelled. This methodology was quickly used to forecast traffic in the short term and quickly established itself as an essential basis to compare.

Many extensions of this method were proposed subsequently. The AX-ARIM method is used to integrate exogenous variables into the model. It is used in particular to incorporate meteorological data into the forecast [99], but also information from a data participation algorithm (clustering) [100]. The Seasonal ARIMA (SA-RIMA) model is used to model the seasonality of traffic data [101].

To meet the objective of predicting several sections of the network with the same model, the work was oriented towards multivariate versions of ARIMA. The ARIMA Space-Time model (STARIMA) [102] makes it possible to pre-tell several time series by integrating a priori knowledge about their spatial and temporal dependence. In traffic, this model was used to integrate the knowledge of the physical network into the prevision [102]. The parameters estimated in this model are global: they are common to all sensors. The Generalized STARIMA (GSTARIMA) model integrates the a priori on the dependency in the same way and allows learning different parameters for each sensor [103]. In the end, the Autoregressive Vector (VAR) [102] and Autoregressive Vector and Moving Average (VARMA) models [104] make it possible to learn Spatio-temporal dependence rather than integrating it a priori.

The ARIMA model is a reference model for describing a stationary process's behaviour or that can be made static by an operation called differentiation. This model is a generalization of the ARMA model, which combines the autoregressive model (AR) and the moving average (MA) model. The letter "I" for integrated refers to the series being differentiated to be made stationary.

Autoregressive model AR(p)

The autoregressive model assumes that the current value of the series can be regressed from its past p-values. This is called an autoregressive model of order p. It is formulated as follows:

$$\begin{aligned} z(t) &= c + \phi_1 z(t-1) + \cdots + \phi_p z(t-p) + \epsilon(t) \\ &= c + \sum_{i=1}^{p} \phi_i z(t-i) + \epsilon(t) \end{aligned}$$

With c a constant playing the same role as the intercept in a classical regression model.

Ma(q) moving average model

The moving average model expresses the error term as a linear combination of past error terms. This makes it possible to model the impact of an unforeseen shock on the evolution of the system.

This model is expressed as follows:

$$\begin{aligned} z(t) &= \mu + \epsilon(t) + \theta_1 \epsilon(t-1) + \cdots + \theta_q + \epsilon(t-q) \\ &= \mu + \epsilon(t) + \sum_{i=1}^{q} \theta_q \epsilon(t-i) \end{aligned}$$

ARMA(p,q)

There is a theoretical equivalence between autoregressive models and moving average models. Indeed, for an autoregressive model of finite order p, there is an equivalent formulation of this model in the form of a moving average model of order infini. Similarly, for any moving average model of finite order q, there is an equivalent formulation in the form of an autoregressive model of infinite order.

In practice, we want to learn a model with a weak order to limit the number of parameters to be estimated and thus respect the principle of parsimony. Sometimes it is difficult to find a weak-order AR(p) or MA(q) model that correctly describes the data. But by combining the two approaches, it is possible to learn a more parsimostical ARMA(p,q) model, which is very useful in practice. The ARMA(p,q) model is formulated as follows:

$$\boldsymbol{z(t) = c + \epsilon(t) + \sum_{i=1}^{p} \phi_i z(t-i) + \sum_{i=1}^{q} \theta_q \epsilon(t-i)}$$

Delay operator To facilitate the writing and combination of models belonging to the ARIMA family, it is common to use the delay operator L. This operator associate each element of a time series with the previous observation. We will therefore have:

$$Lz(t) = z(t-1)$$

The delay operator can be applied multiple times:

$$L(Lz(t)) = L^2 z(t) = z(t-2)$$

We can thus rewrite the ARMA model with this operator:

$$z(t) = c + \epsilon(t) + \sum_{i=1}^{p} \phi_i L^i z(t) + \sum_{i=1}^{q} \theta_q L^i \epsilon(t)$$

or, in a factorized form that reveals polynomials:

$$\left(1 - \phi_1 L - \cdots - \phi_p L^p\right) z(t) = c + \left(1 + \theta_1 L + \cdots + \theta_q L^q\right) \epsilon(t)$$

ARIMA(p,q,d)

Difference When the series is not stationary, it is sometimes possible to apply a transformation to it to make it stationary. An often-used operation is to affix the Δ difference operator, which returns the difference between two successive values of the series:

$$\Delta z(t) = z(t) - z(t-1)$$

which can be rewritten with the delay operator:

$$\Delta z(t) = (1 - L) z(t)$$

As for the delay operator, it can be applied several times:

$$\begin{aligned}\Delta^2 z(t) &= \Delta(\Delta z(t)) \\ &= (1-L)(1-L)z(t) \\ &= (1-2L+L^2)z(t) \\ &= z(t)-2z(t-1)+z(t-2)\end{aligned}$$

ARIMA(p,d,q) The ARIMA model consists of applying the difference operator one or more times to the original series (in practice, rarely more than twice) to make it stationary and then learning an ARMA(p, q) model for this new series. The d parameter determines the number of times the original series is differentiated. The model is therefore stated as an ARMA model by replacing $z(t)$with $\Delta^d z(t)$

$$\left(1-\phi_1 L-\cdots-\phi_p L^p\right)\Delta^d z(t)=c+\left(1+\theta_1 L+\cdots+\theta_q L^q\right)\epsilon(t)$$

Model estimation If the hyperparameters (p, q) are fixed, then the series $\Delta^d z(t)$ If calculated, then the ARMA(p, d, q) model is learned, most often, by an exact estimate of the maximum likelihood by the Kalman filter.

Initially, the choice of hyperparameters (p, d, q) was made by observing the curves of the temporal series, its functions of autocorrelation and partial autocorrelation and, if necessary, of the differentiated series one or more times. This methodology proposed by Box and Jenkins [8] has the disadvantage of involving a lot the subjectivity of the modeller and of being poorly adapted when the number of series to be modelled is large. A procedure for machine learning of hyperparameters is proposed by Hyndman and Khandakar [46, 45]. First of all, the number of differences d is estimated by a sequence of KPPS root-unit tests [58]. If the first test is positive, the series is differentiated, and a new examination is performed on the series obtained. We stop determining when the test is negative. To choose the number of autoregressive terms p and moving averages q, an iterative approach is proposed to select the best model according to the corrected Akaike information criterion (AICc) [11]. Several simple models are evaluated, then the best is preserved. Several variations of this model are evaluated again (by adding or subtracting one from the p or q parameter; by adding or removing a constant terme c), and the best variation is preserved. The search stops when no variation improves the AICc.

3.4.2 State-space model

A space-state model is a mathematical representation of a physical system composed of input, output, and state variables. State variables are chosen to represent the "internal" behaviour of the system how state variables change over time depending on their past values and the exogenous input variables. The importance of the output variables depends only on the state variables.

The input, output, and state variables are connected by first-order differential equations (difference equations in the discrete case). The estimation of these quantities requires the system of equations, most often by a Kalman filter approach.

The space-state models have several advantages: they make it possible to analyze the structure of the series (trend, seasonality), the transition from a univariate version to multivariate is direct, unlike the models of the ARIMA family, which requires to propose new theoretical tools [93, 33]. These models have good prediction performance in usual traffic situations, superior to the ARIMA [93] and SARIMA [33] models. However, the configuration of these models remains time-consuming, which complicates their application to a complex and large system such as an urban network.

3.5 Machine Learning Algorithms Overview

One of the relevant points to consider in this thesis is the comparison of four models used recurrently by researchers, which are an Artificial Neural Network (ANN), a Support Vector Machine (SVM), a Random Forest (RF) and a Long ShortTerm Memory Recurrent Neural Network (LSTM). These models are used for comparison with the proposed architectures due to their ability to obtain accurate results even on large bases.

In addition, two modifications are proposed on the architecture of the models, where knowledge about traffic phenomena applied to the models is taken advantage of. The explanation and development of these algorithms will be presented later in this chapter.

3.4.1 Random Forest

The Random Forest model is a supervised learning model proposed by L. Brieman (2001), which is based on the idea of using the 'Bootstrap Aggregation' or 'Bagging' procedure on a large number of decision trees. This procedure states that the combination of several learning models increases the accuracy of predictions, reducing variance by averaging noisy or biased models. So it has no problems with large databases.

Each of the trees in a Random Forest depends on an independently sampled random vector whose attribution is entirely identical for the vectors of each of the trees. Trees estimate characteristics of the values entered by identifying data areas with similar parameters or characteristics. By analysing the performance of the training data of each tree separately, it is possible to detect the trees that are more efficient in predicting the required values and consequently give more relevance to these by weighing them by higher values in the final result, while at the same time discarding those that achieve the worst results, thus obtaining the best possible estimates.

The most generally used classifier for text classification. The basic idea behind this classifier is to estimate the probability to which class the document belongs. Depending on the precise nature of the probability model, the naive Bayes classifiers can be trained very efficiently by a relatively small amount of training data to estimate the parameters necessary for classification. As the independent variables are assumed, only the variances of the variables for each class need to be determined, not the entire covariance matrix. Due to its over-simplified assumptions, the naive Bayes classifiers often work much better in many complex real-world situations than one might expect. It has been reported to perform surprisingly well for many real-world classification applications un-der specific conditions [133], [201]. An advantage of the naive bayes classifier is that it requires a small amount of training data to estimate the parameters necessary for classification.

3.4.2 Support Vector Regressor

The Support Vector Machine has also been used to predict bus travel time. It is an algorithm specific to machine learning and can be used both to classify the data and perform a regression. The optimisation problem corresponds to the minimization ofstandard1 of support vectors, and the use of Kernels 2 functions allows you to perform nonlinear regressions. Yu et al. (2006, 2010) have addressed weather forecasting travel on two itineraries in Dalian, China. The authors defined itinerary segments and based on the average characteristics of the previous stretches, the following section is expected. In their most recent work, the authors compared their results with a neural network and a model based on the historical average of the data series. MVS was numerically more efficient.

Used a combination of an MVS with an FK (hybrid modelling) based model. In the first stage, they determined the time forecast of arrival at the next stop; with the second model, the average speed of the following segments. The generation of new information that occurs with the advance of the bus constitutes the entrance to the Kalman Filter, which, in turn, allows for correcting the forecast. Likely, Chen and al. (2012) proposed a hybrid model with the integration of MVS with FK to estimate travel time with data from a BRT line from Chaoyang District, Pequin, China. The authors note that this model was superior to the model that uses the Kalman Filter alone. When considering the data from the city of Shenyang in China, Zhong et al. (2015) also used error-handling techniques both for data filtering and to correct results after forecasting travel time. The error found is higher at peak times than in those between peak (valley time) in some of the 19 intermediate stops of the line that is approximately 11 (eleven) kilometres long. In general terms, the model achieves 10.7% average error when considering all intermediate stops of the line. A similar approach taken for the city of Shenzen, also in China, considers several Kernels and compared mvs with a pure neural network and a neural network corrected by a Kalman filter (BAI et al., 2015). Absolute errors are very close to each other and for the different cases studied, they range between 4.3% and 7.0%.Based on combinations of MVS and other techniques, hybrid models present better results than when MVS is applied individually. Zheng et al. (2012)

Support Vector Regression is an unsupervised learning model proposed by V. Vapnik and H. Drucker (1997). It is a modification of the Support Vector Machine model. It is suggested to represent the observations as points in space, placed so that it is possible to separate with a separator hyperplane that allows categorising the variables of one type or another.

The Support Vector Regressor algorithm aims to solve the following problem:

$$\min_{w} \ \frac{1}{2} \| w \|$$
$$\text{s.a} \ \ y_i - < w, x_i > - b \leq \varepsilon$$
$$\text{s.a} \ \ < w, x_i > + b - y_i \leq \varepsilon$$

Where xi corresponds to the observation associated with y_i the inner product plus the intercept $< w, x_i > + b$ is the prediction of the sample. Finally, ε corresponds to a free parameter that serves as a limit: all prophecies must be between the ε range of observations. Slack variables are added to allow errors and approximations in case the problem is infectible.

3.4.3 Neural Network-based models

This type of model is the one that has received the most attention in the literature. One of the pioneering works in this line of research was proposed by Chien et al. (2002), considering two models of Neural Networks capable of predicting the travel times of buses on a simulated transport line by computer. In 2002, when this work was published, it wasn't easy to rely on information from GPS devices to be able to analyze and train any technique in the field of artificial intelligence. The authors chose to avoid such difficulty to simulate the route of buses using software explicitly designed for this purpose. Thus, CORSIM 3 software was used to simulate a bus line in New Jersey, USA, completely. With simulation, many variables were obtained, and, therefore, two neural networks were designed with great detail of information that is generally not available in real-time in practice. The first network considers the information between each pair of intersections, such as traffic volume, speed, and travel time. The second considers aggregate information with average data, such as the average traffic volume, the average bus speed, the standard deviation of speed, etc. From all input variables, different scenarios were analysed, resulting in 10 various networks for training, the largest of them with seven nodes, and only one intermediate layer was taken into account in all of them. In all, 380 examples of termination were considered. The low forecasting errors obtained allowed establishing the potential use of neural networks to predict travel time in urban public transport.

Chen et al. (2004) devised a neural network to predict the travel time of a 4-bus line that passes through several jurisdictions in New Jersey. The implemented network considers a layer with up to six nodes and is fed with variables such as the day of the week, the daytime, the weather, and an identifier of the route segment. The dependent variable is the travel time between adjacent bus stops. The data considered were only the working days from Monday to Friday. A Kalman Filter has been used to correct arrival times at bus stops, considering the travel time information you have so far. The network is trained from the square root of the average quadratic error, and as a result, are produced predictions for travel time of up to 150 seconds approximately. The hybrid algorithm, which combines both techniques used in the dynamic process, shows clear supremacy over the neural network working individually. This is because the network's forecasts are corrected by the filter each time new information is obtained, which happens at each new vehicle stop. For this reason, the authors call this approach dynamic.

Establishing a neural network model for a problem requires several definitions that must be studied for each case. Such definitions identify appropriate activation functions, the number of nodes, the number of layers, and the objective function that will be used to minimize the error in the optimization problem. In one of the classic works in the area, Jeong and Rillet (2005) show that using a neural network with a single intermediate layer of up to 15 nodes can achieve significantly better results than those found by a regression model and those based on historical data. We considered a neural network with 13 learning models and two different activation functions to conclude that the best learning algorithm is Levenberg-Marquardt4. It is desired to predict the travel time required for a bus to move between the current stop and a future stop. A relationship is established between this time, the time of arrival of the bus at the current stop, the time of embarkation and disembarkation of passengers at that same stop and the interval between the present time and the time previously scheduled for the bus. To determine the number of nodes in the inner layer of the network, different tests were performed, concluding that the best performance is obtained with the highest values of a number of nodes. The results were evaluated with a set of data from the city of Houston, Texas. There is no significant difference between the evolution of the two learning functions in any of the periods of the day.

Recently, data availability from GPS devices has been to incorporate the first level of improvement in neural network-based models. Thus, using a conventional Neural Network with a single intermediate layer and with data from GPS, one can efficiently predict the time left for a bus to reach any point. Gurmu and Fan (2014) model the problem of forecasting travel time from the current position of a bus to a future stop to an intercity public transportation line. As independent variables, the time interval of the day, an identifier code for the current bus stop, and an identifier code for the stop to calculate the arrival time is considered. The case study considers GPS data obtained with trips between 2008 and 2009 that come from the route between Macaé and Rio de Janeiro, two cities in Brazil, among which there are 35 stops. To perform a comparative analysis, the authors separate d'ori the original itinerary into three subsections. It is observed that for the two mirrored its used; the network produces better results than analysis based on historical data. With a similar model that considers a single intermediate layer, Amita et al. (2015) also determine the arrival time of buses to inform both passengers and the public agency in real-time so that strategies to improve the service are implemented. Auto reuse an intermediate layer in the conventional neural network with up to 15 nodes. The data corresponds to two bus lines in Delhi, India, with 33 and 53 stops. The same situation also used is the multiple linear regression model. The most important result found by the authors is the better performance of the neural network over the regression model for the same data set. The errors and nods are low, and therefore the prediction error is only a few seconds long.

The second level of improvement of neural network models for predicting travel time is due to these models' evolution in machine learning (Machine Learning). Models of deep neural networks have recently been used to predict bus travel time to reach a traffic light. For this, a control sensor is installed before the semaphored intersection. The objective is to adjust the semaphoric cycle according to the size of the bus queue to facilitate traffic on the stretch under study (XIONG et al., 2015). A neural network addresses the problem with several intermediate layers that are gradually trained using the concept of an auto-encoder. The authors define an auto-encoder as a conventional neural network (feedforward) of a single middle layer fed from a network input that is the same size as the output. The advantage of using the auto-encoder is that training can be done gradually and sequentially. Each of the self-encoders uses the production of the training network as the input to train the next auto-encoder. Thus, the networks used considered five intermediate layers with a maximum of 20 knots for canto one. An intersection was simulated using software to generate the network input data to evaluate network performance, which led the authors to find a four-second error in the forecast.

The potential of using recurrent neural networks for urban public transport applications was evident in a recent international competition held to discover the destination of taxis in a city-based only on information from the beginning of its trajectory. Among 381 participating groups, the winning team presented a recurrent neural network and a two-way network to predict the destination of taxis (BRÉBISSON et al., 2015). The data set contains complete itineraries of 442 taxi trips made in the city of Porto, Portugal. Although the winning architecture considers a fixed trajectory of the GPS points for each trip, very similar results were obtained by a recurrent neural network with an LSTM layer and by a bidirectional re-neural recurrent. The authors performed additional tests with their data, showing that the bidirectional network was significantly more reliable for this case.

3.4.4 Artificial Neural Network

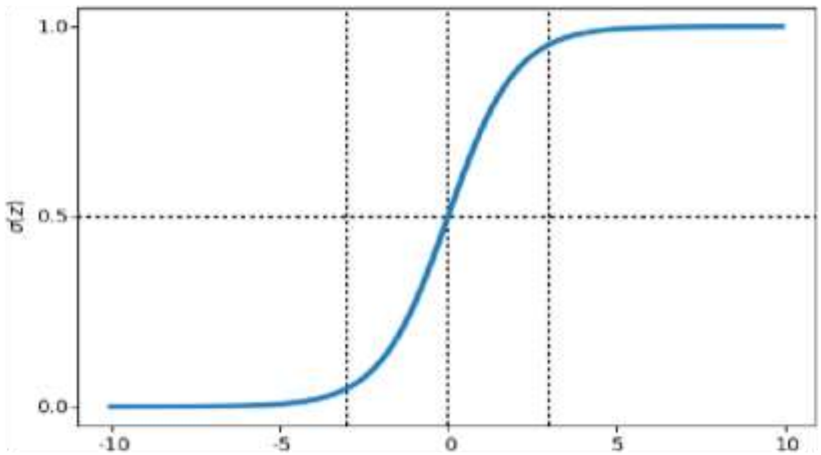
Artificial Neural Networks (ANN) correspond to computational systems inspired by the interconnectivity of biological neural networks (Zurada 1992). These neural networks can learn characteristics or similar behaviours by considering examples without being explicitly told their goals. The essential elements of neural networks and the back-propagation learning rule will be laid out below:

- Node: The essential element corresponds to the neuron, also known as a node. A node takes a series of inputs and computes a normalised output according to a function of transfer.
- Pesos of connection: one red neuronal this Composed of several Nodes United between them through connections, where some of the outputs of these nodes correspond to inputs of others, all these connections have different forces, with a weight (between zero and one) associate at every connexon.
- Transfer function: Generally, the output state of a neuron can be characterised as turned on or off. Switching from one state to another is triggered when the weighted sum of inputs and weights passes a specific limit generated by this function. As an example, an activation or transfer function type corresponds to the process sigmoid the Which one this Set

of the following way:

$$\sigma_{(z)} = \frac{1}{1 + \mathrm{e}^{-z}}$$

Figure 8: Sigmoid function

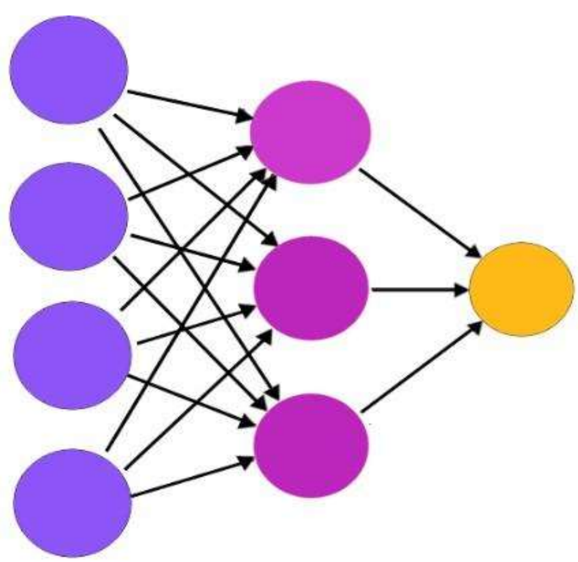


- Topological structure: Really, any type of topological structure can be used to facilitate analysis and visualisation problems, with layered neurons, with layered nodes adjacent to one another. A network neural has an input layer and one or more hidden layers, so-called because all its connections are internal to the network. Each node belonging to a hidden layer takes how input all the Nodes of the previous cloak y Propagates his value the cloak following. Figure 3.2, a continuation, Presents the architecture basic of one red neuronal.

The Backpropagation paradigm is used to calculate the gradient necessary for calculating the Pesos Used in the red. The idea basic it adjust the weight of the Neurons. Computing the gradient of the Function of error y, this error is propagated to the rest of the network layers. To carry out the training of form effective herself Need one great number of Examples of the behaviour desired. one summary of the steps Iterative Involved with the training it the if someone too:

1. *Present an observation of the data used by normalising between* $0y1y$ *between the network's input layer.*
2. *Using the current connection weights of the network, compute the output of the input object.*
3. *Compare the output obtained with the desired output.*
4. *Calculate an error measure as a function of the weight vector w of the following* $E(w) = \frac{1}{2}\sum_{\mathrm{d} \in D} \left(y^{(\mathrm{d})} - o^{(\mathrm{d})}\right)^2$ *, this error defines a surface on the direction in which the weights should be modified to reduce this error.*
5. *Modify the connection weights by a small amount with the idea of approaching the desired output.*

Figure 9 Basic architecture of an artificial neural network



Given the nature of the algorithm, which prevents researchers from knowing what characteristics each of their neurons considers, the number of layers and neurons per layer y, as well as the initialisation of the weights and the transfer function is chosen depending on each particular case study, these parameters being chosen through experimentation.

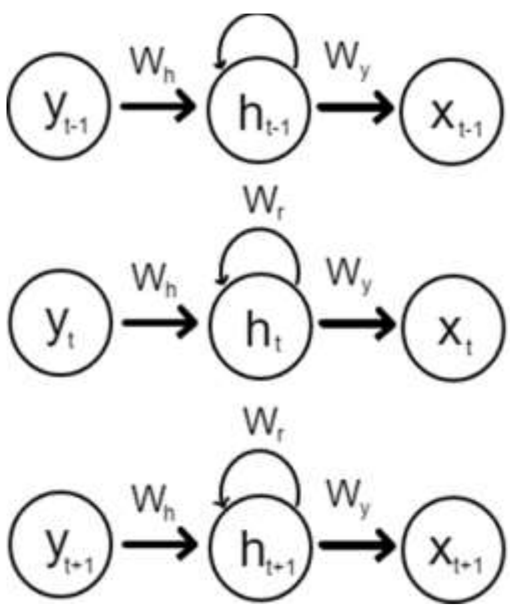
3.5.1 Long Short Term Memory Recurrent Neural Network

A recurrent neural network (RNN) is a class of neural networks whose connections form a cycle, working with temporal data. The adjective recurrent refers to the existence of connections that allow a node to return to itself. The simplest expression for a recurrent neural network is denoted as follows:

$$h_t = \sigma(W_h X_t + W_r h_{t-1})$$
$$y_t = \sigma\left(W_y h_t\right)$$

Where X_t corresponds to the input data at time t, σ the activation function used, W_h corresponds to the weight matrix of the input layer to the hidden layer, W_r Denotes the weights of the hidden layer to the output layer, h_t It corresponds to the weights of the hidden nodes at time t and corresponds to the output node value at time t. Figure 3.3 illustrates the characteristic architecture of recurring neural networks:

Figure 9 Iterations over an RNN



Iteration t-1

Iteration t

Iteration t+1

Because this recurring architecture makes the Backpropagation algorithm in-feasible due to the fading gradient problem (Hochreiter (1991)) and it never finished iterating, Backpropagation Through Time (BPTT) is introduced to expand the current architecture so that the weights of the current iteration are optimized in conjunction with the previous iteration. The error function is implemented as the square of the error given by the following equation:

$$E_t = \sum(y_t - y)^2$$

WhereE_t Is the recursive error and t represents the predicted value of time in t e and denotes the searched value.

The architecture of the Long Short-Term Memory Recurrent Neural Network (Hochreiter and Schmidhuber (1997)) is similar to that used in the architecture of artificial neural networks, but the hidden layers of the LSTM contain additional connections, which use the classical architecture of recurrent neural networks, which also allows them to have the ability to learn or forget patterns.

Each node of the LSTM is composed of four connections or gates: called general mente input gate, output gate, forget gate and memory cell, which are used to control the flow of information.

The first step for the LSTM is to decide what type of information will be retained or forgotten by each node. This decision is made by the 'forget gate' using the sigmoid function, it analyzes the values of ht−1 and xt and delivers a number ft between 0 and 1, where 1 represents 're have completely' while 0 means ' completely forget ', while values intermediates represent learning limited amounts of information. The next step is to decide which new information is considered necessary to be stored in the cell state. This has two parts, the first layer, called the input gate that uses the sigmoid function to deliver a value that decides which values will be updated in the current iteration and second a layer that, by using the hyperbolic tangent function, creates a new vector of possible values Ctt that are candidates to be added to the node state. These values are combined by multiplying the previous state of the cell by ft and summing the value obtained from it by the possible values to update C_t to update the value of the state of the cell. Finally, the fact is chosen whether the final state will be propagated to the next cell or not; the output gate makes this decision. Both the formulas corresponding to the various connections as well as an illustration of a typical LSTM node, are presented below.

Forget gate:

$$f_t = \sigma\left(W_f * [h_{t-1}, x_t] + b_f\right)$$

Input gate:

$$\mathrm{i}_t = \sigma(W_\mathrm{i} * [h_{t-1}, x_t] + b_\mathrm{i})$$
$$C_t' = \tanh\,(W_c * [h_{t-1}, x_t] + b_c)$$
$$C_t = f_t * C_{t-1} + \mathrm{i}_t * C_t'$$

Output gate

$$o_t = \sigma(W_o * [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t * \tanh\,(C_t)$$

Where x_t represents the observation entered in time t. The values of i i_t, f_t , o_t, C_t, h_t represent the values of the input gate, forget gate, the activation vector of the output gate, the state of the cell, and the output vector of the node at time t, respectively. The values of W_i, W_f, Wo correspond to the weight matrices of the input gate, forget gate and output gate, bi, bf , bc and bo representant the bias layer to minimize and σ corresponds to the sigmoid function .

The Long Short-Term Memory networks (LSTMs) model [84] is an improvement of the RNNs model by adding a memory component, to add a delay between the input and output. The LSTMs unit adds contextual information to the net work and learns long-term dependencies without redundant information. This works remarkably well on Natural Language Processing tasks and sentiment classification in addition to image processing. The LSTMs unit can store the history information by it’s memory unit. Thus, the input gate, the output gate and the forget gate can be updated by utilizing historical Information. The structure of LSTMs unit for our task is as follows. First, we compute thevalues for i_t, the input gate at time t.

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

3.4.5 K-Nearest Neighbours

The k-nearest neighbours' algorithm [88] works on the principle that the documentsthat are close in the space belong to the same class. It is an instant-based learning algorithm used to test the degree of similarity between documents and k training data and store a certain amount of classification data, thereby determining the category of test documents. The key element of this method is the availability of a similarity measure for identifying neighbours of a particular document, and it is based on a distance or similarity function for pairs of observations, such as the Euclidean distance or Cosine similarity measures. Theadvantage of this method is its effectiveness, non-parametric property as well.

As an easy implementation, however, the disadvantage is the long classification time, and it is difficult to find an optimal value of k. It uses all features in distance computation and causes the method computationally intensive, especially when the training set grows. Besides, the accuracy of k-nearest neighbours is severely degraded by the presence of noisy or irrelevant features.

3.5 Performance Measures

RMSE The root mean squared error (RMSE)is a classic c-measure in prediction. For a prevision at the horizon h, it is given by the following formula:

$$\mathrm{RMSE} = \sqrt{\frac{1}{T_{\text{test}} - h} \sum_{t=1}^{T_{\text{test}} - h} (\hat{x}(t+h) - x(t+h))^2}$$

With Tests, the number of examples in the test set. The square root is used to obtain a measure in the same unit as the predicted variable. However, minimizing this error is equivalent to minimising the root mean square error, which is often simpler to manipulate. Each error is squared means that big mistakes will be penalised more heavily than small ones.

MAE (Mean Absolute Error) is another frequently used measure. For a forecast at horizon h, it is given by the following formula:

$$\mathrm{MAE} = \frac{1}{T_{\text{test}} - h} \sum_{t=1}^{T_{\text{test}} - h} |\hat{x}(t+h) - x(t+h)|$$

This measure differs from the RMSE mainly by the use of the absolute value instead of the square. This means that it penalises significant errors less than the RMSE. This means that it is less sensitive to the presence of outliers.

MASE The flow time series measured by the sensors can have very different amplitudes caused by differences in traffic volume between different routes. This is especially true for an urban traffic dataset, with different types of streets, from the small street to the main avenues, sometimes even the ring road. Suppose one wishes to obtain a network-wide performance measurement. In that case, it is not possible to use a conventional measurement such as the RMSE (or the MAW) by using it on all the sensors because the differences in traffic volumes will influence the amplitude of the RMSE for the prediction of a sensor. That is why we are interested in a measure that does not have this particularity.

The MASE (MeanAbsolute Scaled Error), proposed by Hyndman and Koeh- ler [44], is a standardized version of the MAW. It is given by the ratio between the MATE of the evaluated method (on the test set) and the MVA of the naïve forecasting method consisting in answering the last observed value (evaluated, for greater robustness, on the training game, which often has more examples). This measurement is therefore unitless and does not depend on the amplitude of the predicted series. The coefficient of normalization is defined as follows:

$$Q = \frac{1}{T_{\text{train}} - 1} \sum_{t=2}^{T_{\text{train}}} |x(t) - x(t-1)|$$

Where T train is the number of examples in the training game, for a pre-vision on the horizon h, the MASE is given by the following formula:

$$\text{MASE} = \frac{1}{T_{\text{test}} - h} \sum_{t=1}^{T_{\text{test}} - h} \frac{|\hat{x}(t+h) - x(t+h)|}{Q}$$

Using the same normalization coefficient Q for each forecast horizon makes it possible to evaluate the evolution of the performance of a method about the forecast horizon. For a one-step forecast (h = 1), the MASE can be seen to compare the evaluated method and the naïve method. A value greater than one indicates that the method is worse than the naïve method. A lower value represents better performance. This is an approximation because Q is calculated on the learning set and not on the test. For the other forecast horizons, one cannot directly interpret an ane-value of MASE but simply compare values between them.

Standardized RMSE, The use of the RMSE, may be preferred to that of the MAW in evaluating the forecast of a series, for example, when it is desired to penalize large errors heavily. In this case, we propose to adopt an approach similar to mase. We will then have the following coefficient of normalization:

$$Q = \frac{1}{T_{\text{train}} - 1} \sum_{t=2}^{T_{\text{train}}} (x(t) - x(t-1))^2$$

and the standard RMSE formula:

$$\text{RMSEN} = \frac{1}{T_{\text{test}} - h} \sum_{t=1}^{T_{\text{test}} - h} \frac{(\hat{x}(t+h) - x(t+h))^2}{Q}$$

The measure presented The performance measure used for the results presented in this section is the MASE. The figures shown were also generated for the RMSEN. The behaviour observed for these two measurements is almost identical, and the order of the methods is preserved. The enormous benefit of Social Media is the short period that the messages

3.6 Chapter Summery

This chapter provides the high-level overview of parametric, non-parametric and traffic models which are traffic congestion analysis and prediction methods used in the transportation research. Further chapter provided various Statistical and Machine Learning algorithms popular in traffic prediction as well as the application of these techniques in the analysis of traffic congestion data. The brief summary allowed to obtain a good understanding of the available techniques on working with traffic congestion big data, and the three upcoming contributing chapters four, five and six explains the specific literature and what exact methods are used to address the specific research contribution along with justification to why the suggested methods are proper is discussed .This chapter also discuss the performance measures used in the upcoming chapters.

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CHAPTER 4

SHORT-TIME TRAFFIC FORECASTING IN THE PRESENCE OF PSE ON A FREEWAY

Congestion is mainly caused by a flow of vehicles more significant than the road network's capacity, either because of an increase in demand or reduced road capacity. Causes are typically categorised as recurrent or incidental. Recurrent congestion is mainly due to a permanent or geometric bottleneck (reducing lanes, entrance ramp). In contrast, incident congestion is somewhat due to a temporary or unexpected bottleneck (weather, accidents, works, signage, special events, etc.). However, the literature shows that it is not easy to assess the causes of congestion, especially since they are often combined [105]. The FHWA published an estimate of the distribution of the average causes of congestion in the United States in 2004 but maintains that local conditions vary widely, from city to city and between highways and urban roads [106]. In addition to causing significant delays, incidents of congestion also increase the variability of traffic conditions. Even though most past researchers have focused on recurrent congestion, there is more public interest in the reliability of nonrecurrent traffic conditions such as PSEs, to "arrive on time" as unpredictable delay is more irritating than a recurring delay [107].

4.1 Introduction

Ensuring that cities have access to a sustainable standard of living and economic development is one of the necessary conditions for establishing a highway road connecting the living spaces and a traffic network flowing with the least possible problems in this order.

Planned special events are one of the factors that cause congestion on highways which reduces vehicle speed. The speed of the vehicles may be more or less, both as a result of driver preferences or due to traffic rules or other factors. This excess or less speed affects the flow of traffic, which causes a change in density and the level of intensity. In addition, to density; the number of accidents, the vehicles in traffic; meteorological events such as temperature, precipitation, weather; infrastructure features of the road; the day and time when traffic demand is increasing, whether it is a holiday period or not and also impact factors that contribute to the experience of the drivers as they travel in freeways.

When the reasons and the consequences are taken into account, the importance of controlling vehicle traffic increases, especially in metropolitan areas such as Melbourne, where large crowds of people live, the level to be determined by determining the current congestion level should be controlled. The main reasons that cause it and current and possible measures should be implemented to prevent this condensation.

In this chapter, we use the city of Melbourne; PSEs factors such as event occurrence, event time and duration, event type, event location, expected attendance and event market area; due to its effects on traffic demand. With the arguments included in the study, the speed of the vehicles was estimated, and the density evaluation was made on these speed values.

4.2 Literature Survey

Andrey et al. in their study, in which they investigated drivers' adaptation to planned special events, stated that driver behaviour was particularly problematic based on the event type [108]. Grimm, et al. [109] investigated if the planned special events influence road accidents using special analytic techniques. Compared to collisions in clear visibility conditions, collisions in

PSEs conditions tended to cause more severe injuries. The study by Chang and Lu [110] found that drivers at different levels of risk reduced their speed and travel time increase due to special events. Pulugurtha, et al. [111] stated that the effect of PSEs on traffic volume varies by day, time and event type. Kwoczek, et al. [9] proposed an integrated solution to predict and visualize non-recurring traffic congestion due to planned special events in urban environments. Cools, et al. [112] found that the differentiation of the number of daily vehicles can be explained by weekly periods and that the density decreases significantly during the holiday periods [112]. Yuan, et al. [37] found that PSEs caused an increase in the average number of accidents for the day and night [37]. Unrau and Andrey stated that volume-occupancy and speed-volume relations are affected by precipitation and that the speed is strongly dependent on volume (Unrau & Andrey, 2006).

4.2.1 PSEs Variables

- Event occurrence time: Sets the time of the (s) day(s). Events during the week may face restrictions on the track, traffic and parking capacity.
- Event time and duration: defines whether the event will take place at a start time, which will likely condense the arrival of the event, or whether it will work continuously throughout the day where customers can come freely and leave.
- Event location: The location definition will involve connecting to the existing transport infrastructure. Fixed locations, such as stadiums or arenas, will need parking areas, good access to highways and the main Freeway streets. Temporary facilities may not have these resources, thus requiring the development of a local access plan and detailed parking.
- Event market area: defines the extent and scope of the event—the

potential to attract people from other regions.

- Expected attendance defines the maximum estimated number of participants of the event. Estimates may include the expected number of VIPs with advance tickets, customers with an assigned parking pass, and customers needing special assistance.
- Event type: Defines the type of event subject to special regulations and licensing requirements. The event type includes many characteristics of the planned special events that influence trips generated by the event, demand, and impact on the transportation system.

4.2.2 Service Levels

The level of service of a road, speed, journey time, the manoeuvrability of vehicles and pausing are evaluated based on performance criteria. Service levels range from A to F, rather than congestion. Level-based definitions are shown in Table 1, and speed-based Service Levels are shown in Table 2 (HCM, 2000):

Table 1 Service levels

level	Flow Status
A	Free flow
B	Reasonably free flow
C	Near free flow
D	Approaching unstable flow
E	Unstable flow
F	Force or Break

While the minimum density is seen at A-level service levels, density increases at levels B, C, D, E, and F. Since it is challenging to predict stop-and-go conditions at level F, the F level was excluded from the evaluation and a speed-based assessment was carried out on 5 service levels.

Service flow rate is the reasonable hourly speed level of vehicles expected to pass through a nocthle or part of the road at a unit time. Service flow rates in C or D are typically used to provide satisfactory operating service for road users. In the table, in addition, the maximum density, average speed, maximum volume and capacity ratio and several lane-based hourly vehicles are provided for various free-flow speed levels.

Table 2 Service levels on multi-lane roads

Free Flow Speed	Criteria	A	B	C	D	E
100	Maximum density (vehicle / km / lane)	7	11	16	22	25
	Average speed (km / h)	100	100	98.4	91.5	88
	Maximum volume /capacity ratio (v/c)	0.32	0.50	0.72	0.92	1.00
	Maximum service flow rate (vehicle/ sa/lane)	700	1100	1575	2015	2200
90	Maximum density (vehicle / km / lane)	7	11	16	22	26
	Average speed (km /h)	90	90	89.8	84.7	80.8
	Maximum volume /capacity ratio (v/c)	0.30	0.47	0.68	0.89	1.00
	Maximum service flow rate (vehicle/sa/lane)	630	990	1435	1860	2100
80	Maximum density (vehicle / km / lane)	7	11	16	22	27
	Average speed (km /h)	80	80	80	77.6	74.1
	Maximum volume /capacity ratio (v/c)	0.28	0.44	0.64	0.85	1.00
	Maximum service flow rate (vehicle/sa/ lane)	560	880	1280	1705	2000
70	Maximum density (vehicle / km / lane)	7	11	16	22	28
	Average speed (km /h)	70	70	70	69.6	67.9
	Maximum volume /capacity ratio (v/c)	0.26	0.41	0.59	0.81	1.00
	Maximum service flow rate (vehicle/ sa/ lane)	490	770	1120	1530	1900

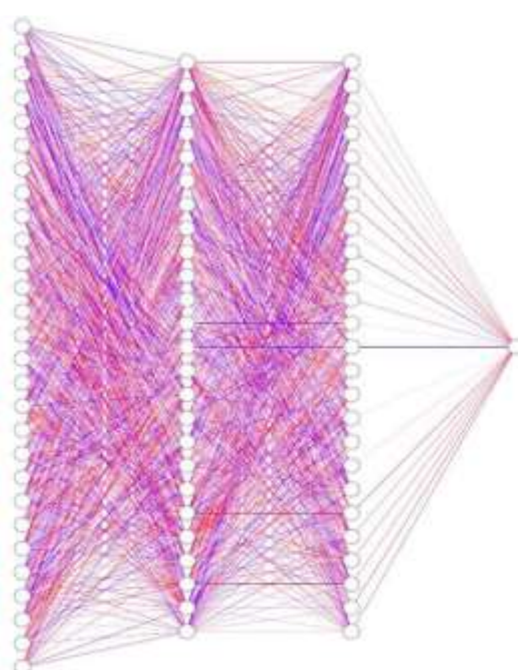
4.3 Methodology

Following the first artificial neurons produced by Walter Pits and Warren McCulloch in 1943, artificial neural networks, which made significant improvements in the 1970s, have been used more and more in daily life.

Artificial Neural Networks (ANN); the input layer consists of 3 layers parallel to each other: the intermediate and output layers. ANN is similar to the human brain in obtaining outside information through networks and changing its weight in periodic cycles until the learning process becomes accurate with the algorithm called the 'learning algorithm' [113]. Neural Networks collects data that comes to cells with different weightings from the outside in a collection function and then passes it through activation to other cells [114-116].

This chapter aims to determine the possible traffic congestion on the relevant road by estimating the speed on a highway with a high number of vehicle crossings. While the dependent variable is speed, as arguments, event occurrence, event time and duration, event type, event location, expected attendance and event market area, PSEs conditions variables were used. Categorical variables of day, time and PSEs condition; dummy variable was determined as a total of 28 arguments. The model is thought to be two hidden layers. Thus, the model has 28 input layers consisting of arguments, two hidden layers with 25, and 1 output layer. The designed model is shown in Figure 10.

Figure 10 Artificial Neural Network model



4.4 Research Finding

Table 3 Correlation matrix

		speed	event time	Event day	event time	event occurrence	event location	event market area
speed	Pearson Correlation	1						
	itself. (2-tailed)							
	n	1760						
event time	Pearson Correlation	.205**	1					
	itself. (2-tailed)	.000						
	n	1760	1760					
Event day	Pearson Correlation	-.069**	-.008	1				
	itself. (2-tailed)	.004	.746					
	n	1760	1760	1760				
event type	Pearson Correlation	.307**	.022	.000	1			
	itself. (2-tailed)	.000	.354	1.000				
	n	1760	1760	1760	1760			
event occurrence	Pearson Correlation	-.714**	-.246**	.026	.287**	1		
	itself. (2-tailed)	.000	.000	.271	.000			
	n	1760	1760	1760	1760	1760		
event location	Pearson Correlation	.308**	.123**	.127**	-.437**	-.568**	1	
	itself. (2-tailed)	.000	.000	.000	.000	.000		
	n	1760	1760	1760	1760	1760	1760	
event market area	Pearson Correlation	-.645**	-.085**	.055*	.355**	.447**	-.188**	1
	itself. (2-tailed)	.000	.000	.021	.000	.000	.000	
	n	1760	1760	1760	1760	1760	1760	1760

Regression analysis was performed with OLS (Ordinary Least Squared), the Ordinary Smallest Squared Method. R-Squared (R2) was 0.85 and had a general acceptance value of above 0.70 and was a good result. The adjusted

R-Squared value is 0.853 and is close to R2 and a good result. The P-value is less than .05, and the coefficients of the arguments are statistically significant. Coefficients in Table 6 show the number of regression multiples. The value of each variable indicates how much the predicted rate will change if there is a one-unit change in that variable.

Table 4 Regression coefficients

Argument	Coefficients	Argument	Coefficients
Occurance	-0.8199	Time - 11:20:00	158.690
Event location	0.0579	Time - 11:50:00	114.890
Market Area	-0.2441	Time - 13:20:00	107.070
Day- Monday	383.573	Time - 13:50:00	159.488
Day- Tuesday	389.553	Time - 14:20:00	159.029
Day- Wednesday	390.235	Time - 14:50:00	160.138
Day-Thursday	383.877	Time - 15:20:00	112.492
Day- Friday	388.293	Time - 15:50:00	111.028
Time - 08:20:00	81.643	Time - 16:20:00	111.165
Time - 08:50:00	79.881	Time - 16:50:00	62.061
Time - 09:20:00	121.480	Event type- Concert	476.154
Time - 09:50:00	119.326	Event type- Sporting Game	521.600
Time -10:20:00	117.062	Event type- protests /rally	491.442
Time - 10:50:00	160.089	Event type- festivals	446.336

80% of the data in the study is divided into learning data, and 20% is divided into test data. Root Mean Square Logical Error (RMSLE), the ratio between actual and estimated value; Root Average Frame Error (RMSE) measures the performance of the model, and the proximity of these levels to zero indicates how well the model works (Janik et al, 2018). The RMSE value for the model is 3.34, and the RMSLE value is 0.04.

4.4.1 Event time-Based Speed Forecast

Among the arguments, type, date and location values were taken as fixed assumptions based on the event day, Monday as a day and event type as sports Table 7 shows the highest speed estimate; The lowest speed estimate was at 71.76 at 2:20 AEST and 4:50 a.m. Based on estimates; It is seen that speed estimates increased compared to the previous hour at 9:20 PM, 10:20 PM, 11:20 PM, 1:50 AM and 2:20 AM, and decreased by the earlier measurement of other hours.

Table 5 Speed estimation based on event time

Assumptions		time	speed estimated	time	speed estimated	time	speed estimated
Occurance	Annually	8:20 PM	73.39	10:50 PM	81.59	2:20 AM	82.09
event location	MCG	8:50 PM	72.84	11:20 PM	81.84	2:50 AM	81.70
Market Area	Victoria	9:20 PM	77.32	11:50 PM	76.85	3:20 AM	76.92
Day	Monday	9:50 PM	77.10	1:20 AM	76.26	3:50 AM	76.68
Event Type	Sport	10:20 PM	77.81	1:50 AM	82.07	4:20 AM	76.33
						4:50 AM	71.76

4.4.2 Weekday Based Speed Forecast

Table 6 takes the measurement made at 08:20 event time and the sports option as event type as fixed assumptions based.

Table 6 Weekday-based speed forecast

Assumptions		Day	Speed Prediction
Occurrence	Annually	Monday	73.39
event location	MCG	Tuesday	73.92
Market Area	Victoria	Wednesday	73.15
Time	08:20	Thursday	73.57
Type	Sports	Friday	73.68

The highest speed estimate and the lowest speed forecast was at 73.92 on Tuesday and 73.15 on Wednesday. Based on estimates; Speed estimates on Tuesdays, Thursdays and Fridays increased compared to the previous day, while on other days, there was a decrease compared to the last measurement.

4.4.3 Event Occurrence Based Speed Forecast

Among the arguments, the event occurrence values were taken as constant assumptions based on the events independent variables, at 08:20 on Monday, like event time. The cloudy option as weather is taken as fixed assumptions.

It is seen that the highest speed forecast is made with 86.92 for the One off events, and the lowest speed forecast is 81.47 for the Annual events.

Table 7 Event Occurrence -based speed prediction

Assumptions		Occurrence	speed estimated
event location	63	One off	86.92
Market area	Vic	Seasonal	84.16
day	Monday	Annual	81.47
time	08:20		
Event type	Sport		

4.4.4 Event Location-Based Speed Prediction

Among the arguments, the event location values were taken as constant assumptions based on the events independent variables, the measurement made on Monday as a day, at 08:20 event time, and the sports option as the event type.

Table 8 Event Location-based speed estimation

Assumptions		event location	Speed Prediction
type	Sports	1 km radius	73.02
Markrt Area	Vic	3 km radius	74.26
Occurance	Annually	5 km radius	75.49
day	Monday	10 km radius	77.03
Time	08:20		

4.4.5 Markert Area Based Speed Forecast

Among the arguments, the market area values were taken as constant assumptions based on the events independent variables, the measurement made on Monday as a day, at 08:20 event time, and the sports option as the event type.

Table 9 Market Area-based speed forecast

Assumptions		Market Area	speed estimated
type	Sports	Mel	78.50
event location	MCG	Vic	77.86
Occurrence	Annually	Other states	76.20
day	Monday	International	74.12
Time	08:20		

Table 9 shows; the highest speed forecast is 78.50 at 50 when the market area is Mell, and the lowest speed forecast is 74.12 when the event is marketed internationally.

4.4.6 Event type -base Speed Forecast

As shown in Table 10, event types values are taken as constant assumptions based on the incidence of independent variables, on Monday as a day and at 08:20 as event time. It is seen that the highest speed forecast is 78.37 in open different event types, and the lowest speed forecast is 68.83 in rallys. Based on estimates, the speed estimates obtained in event type conditions increase compared to the previous day, and on other days, there is a decrease compared to the last measurement.

Table 10 Event type-based speed forecast

Assumptions		Type	Speed Prediction
Market Area	Vic	Sports	73.39
event location	MCG	Concerts	78.37
Occurance	Annually	Festevals	72.64
day	Monday	Rallys	68.83
Time	08:20		

4.5 Summary of Finding

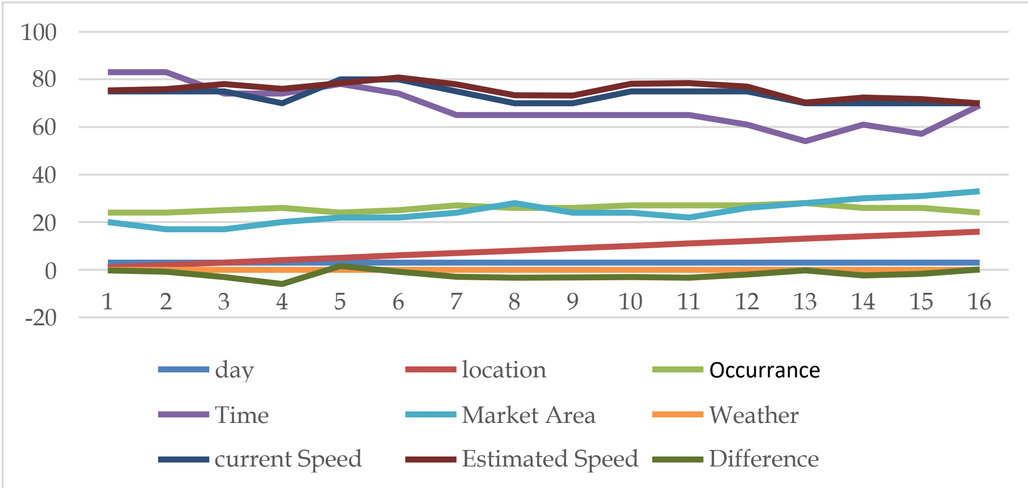
In this chapter, we presented an approach to analysing the impact of PSE on urban congestion on a highway. To analysis, the impact of PSEs characteristics on road traffic congestion, the effect of these characteristics should be measured [37].

Table 11 The difference between the first day variables, the actual and estimated speed value

day	Event Time	Occurrence	Event location	Market Area	Event Type	Speed (Real Value)	Speed (Forecast Value)	difference
2019-07-10	8:20 A.M.	annually	MCG	Vic	Sports	75	75,29	-0,29
2019-07-10	8:50 A.M.	annually	MCG	Vic	Sports	75	75,83	-0,83
2019-07-10	9:20 A.M.	annually	MCG	Vic	Sports	75	78,05	-3,05
2019-07-10	9:50 A.M.	annually	MCG	Vic	Sports	70	75,98	-5,98
2019-07-10	10:20 A.M.	annually	MCG	Vic	Sports	80	78,40	1,60
2019-07-10	10:50 A.M.	annually	MCG	Vic	Sports	80	80,79	-0,79
2019-07-10	11:20 A.M.	annually	MCG	Vic	Sports	75	77,89	-2,89
2019-07-10	11:50 A.M.	annually	MCG	Vic	Sports	70	73,32	-3,32
2019-07-10	1:20 P.M.	annually	MCG	Vic	Sports	70	73,21	-3,21
2019-07-10	1:50 P.M.	annually	MCG	Vic	Sports	75	78,39	-3,39
2019-07-10	2:20 P.M.	annually	MCG	Vic	Sports	70	70,23	-0,23
2019-07-10	2:50 P.M.	annually	MCG	Vic	Sports	70	71,73	-1,73
2019-07-10	3:20 P.M.	annually	MCG	Vic	Sports	70	69,91	0,09
2019-07-10	3:50 P.M.	annually	MCG	Vic	Sports	75	78,12	-3,12
2019-07-10	4:20 P.M.	annually	MCG	Vic	Sports	75	77,01	-2,01
2019-07-10	4 :50 P.M.	annually	MCG	Vic	Sports	70	72,41	-2,41

Table 11 and Figure 11 illustrate the measurement values of the variables, the speed estimated value based on these values, and the difference between the actual and the estimated speed value. As a result of the estimate of 16 observation values on the PSEs day, it was observed that 10 of the estimated speed values were in the range of 75-80.

Figure 11 Variable-based speed estimates and difference value



In this study, on the road with a high density of vehicles, the relationship between planned special event characteristics. Fore event days and nonevent days with the speed of vehicles and therefore, traffic density were examined.

CHAPTER 5

SHORT-TERM TRAFFIC FORECASTING IN THE PRESENCE OF PSE ON AN URBAN ARTERIAL INTERSECTION

In this chapter, the short-term traffic forecasting performance of parametric and non-parametric forecasting methods for intelligent transportation systems was examined, and the effect of forecast values on the circuit time and performance of signalled urban intersections during PSE was investigated. It aims to improve latency and reduce intersection waiting times depending on the traffic data observed at the intersection and improve the intersection's performance. The intersection of Flinders Street and Exhibition Street, the city of Melbourne, Victoria, has been selected as the case area. The data obtained with the help of sensors located in the approach arms of the intersection are arranged as data sets. This chapter made short-term traffic estimates with auto-regressive integrated moving average (ARIMA) and artificial neural networks (ANN) methods. Prediction results were optimized for intersection circuit time using the Webster method. After calculating the optimum circuit time and green times, the webster delay method and the delay values of the intersection approach arms (road segments) and the intersection as a whole were compared with the estimate results obtained from both the ARIMA method and the ANN method. In short-term traffic estimation for a selected intersection, the ANN method was found to be more successful than the ARIMA method.

5.1 Introduction

As discussed in Chapter 2, high levels of urban traffic congestion are experienced during planned special events in Melbourne, Australia and other major cities in the world. Limited resources and an expected but significant increase in demand increases the waiting times at intersections in the presence of PSEs. Increasing waiting times affects people psychologically and economically; also, the contribution to air pollution and global warming poses serious threats [117-119].

Technological developments have been used to reduce traffic congestion, increase safety, minimize delays, use road capacities efficiently and minimise travel time. The use of technologies produced in different areas thanks to today's scientific developments for a safe, efficient, and sustainable transportation system is generally defined as Intelligent Transportation Systems (ITS) [120]. One of the key components for ITS is short-term traffic forecasting. Short-term traffic forecasting can be defined as the immediate future forecasting process, with historical and current data of the expected traffic conditions [121]. In the last decade, there has been an increase in traffic forecasting methods developed primarily to predict traffic conditions on short-term horizons (usually 5 to 15 minutes). The dissemination of predicted traffic conditions information will mainly affect the travel time in daily life and their decisions on the chosen route. The accuracy and reliability of the information envisaged are crucial for better distribution of demand and maximum use of its existing capacity. Short-term traffic estimation can be defined as the process of estimating the traffic conditions foreseen in the short-term future, considering past and current traffic information [122].

In this chapter, circuit time optimisation was made with short-term traffic forecasting to effectively and efficiently reduce waiting times. The Intersection of Flinders Street and Exhibition Street, one of the busy urban intersections of the city of Melbourne. The intersection is on the axle, where home and business travel are used extensively due to its location. On the other hand, the intersection is presented with its censored data (SCATS data). For these reasons, the Intersection of Flinders Street and Exhibition Street was selected in the study. This chapter aims to improve intersection delay performance by comparing the results by making short-term predictions of volumes in the intersection approach arms with the help of parametric and non-parametric methods and optimizing circuit time according to the calculated forecast results. The study will include auto-regressive integrated moving mean (ARIMA) from short-time traffic estimated parametric methods, comparison of results from non-parametric methods using artificial neural networks (ANN) method, and late performance analysis with intersection circuit time optimisation.

5.2 Literature Survey

Literature includes many artificial intelligence models that predict vehicle delays at signalled intersections. Vlahogianni [123] predicts vehicle delays at signalled intersections with Fuzzy Logic (BM) from artificial intelligence methods. Olayode, et al. [124] and Dogan, et al. [125], Singh, et al. [126], who predicted using the forward-feed ANN, Murat and Ceylan [127] predicted with both analytical and ANN models, produced estimates closer to actual latency values compared to analytical models. Murat [128] and Korkmaz and Akgüngör [129] better-predicted vehicle delays at signalled intersections with the Adaptive network-based fuzzy inference system (ANFIS) model than analytical models. Korkmaz and AKGÜNGÖR [130] has developed a time-dependent mathematical model that predicts latency at signaled intersections. Other models in the literature are shown in Table 1 in chronological order with their findings.

Table 12 AI models that predict vehicle delays at signalled intersections.

Article	Model/Application	Results
Dogan, et al. [125]	ANN	Two models that estimate the number of vehicles delays and stop at signalled intersections have been developed with ANN. ANN-latency model performs better than ANN-stop model is specified.
Korkmaz and AKGÜNGÖR [130]	Differential development algorithm (DGA), Artificial bee colony algorithm (YAKA)	The delay models created in different forms were optimised with DGA and YAKA. Created in semi-quadratic form and optimized according to DGA, the model predicts latency values detected
Olayode, et al. [124]	Artificial Model, ANN	They modelled for three separate traffic situations with ANN. It has been shown that the ANN model predicts better latency than analytical models.
Zarinbal Masouleh [131]	Bluetooth technology	With Bluetooth technology, latency and travel time are estimated. The method's control delay at signalled intersections has been found to be close to latency values.
Garshasebi [132]	Linear regression (LR) Support vector regression (SVR) Random Forest regression (RF)	Models created with LR and RF have been found to predict vehicle delays more accurately.
Balta and Özçelik [133]	Software-defined networks (SDN) Ant colony algorithm (PPE)	SDN-based PPE was found to estimate average latency 7-12% better than conventional techniques and 15-22% better than computational techniques.
Clara Fang and Pham [134]	Fuzzy logic (UN)	The UN method has allowed more vehicles to pass through the intersection in the same green time and is superior to constant time inspection.

Forecasting methods are mainly examined in 3 categories. These are statistical methods, AI-based methods, and hybrid prediction methods. Statistical methods: exponential correction, ARIMA, linear regression and Kalman filtration, etc. AI-based methods; fuzzy logic, ANN and k-nearest neighbour (k-NN) etc. Hybrid methods consist of a combination of two different predictive methods selected.

Previous studies have found that the ARIMA method results more accurately under certain conditions than other parametric prediction methods. Likewise, the ANN method from non-parametric methods has been shown to produce successful results in short-term predictions. For this reason, the ARIMA method has been compared with the ANN method, which is one of the non-parametric methods, to compare improvements in intersection performance.

5.3 Methodology

Forecasting methods are mainly examined in 3 categories. These are statistical methods, AI-based methods and hybrid prediction methods. Statistical methods, exponential correction, ARIMA, linear regression and Kalman filtration, etc., are separated. AI-based methods; fuzzy logic, ANN and k-nearest neighbour (k-NN) etc. Hybrid methods consist of a combination of two different predictive ways selected.

Previous studies have found that the ARIMA method results more accurately under certain conditions than other parametric prediction methods. Likewise, the ANN method from non-parametric methods has been shown to produce successful results in short-term predictions. For this reason, the ARIMA method has been compared with the ANN method, which is one of the non-parametric methods, to compare improvements in the performance of the intersection. Chapter 2 elaborate both ARIMA and ANN methods in detail.

5.3.1 Training and Testing of Artificial Neural Networks

In ANN, the process of determining the weight values of the connections of neurons is called " training the network ". Networks change these weight values. During the ANN setup phase, the sample data set is divided into two data sets for the training and testing of the network. There is no general rule for separating data. However, data type, amount of data, and problem are essential factors in separating the data set. Errors in the selection of the training and test data set will affect the performance of the network. Training samples from the allocated data are used to develop the artificial neural network model, while test samples are used to evaluate the predictive capability of the developed model. In the learning process, weights are randomly assigned at startup, and weight values are updated as samples are shown to the network according to the selected learning algorithm. The goal is to find weight values that will produce the correct outputs for the instances shown to the network. The network, which has reached the correct weight values, has been able to generalise the event represented by the instances and has completed network learning.

5.3.2 Delay and capacity calculations at signalized intersections

The three most used methods for delay calculations at signalized intersections are Webster (British), The Capacity of Roads Manual (HCM) and the Australian method by Dr. Rahmi Akçalik. This chapter selected the Webster method, which is widely used in the literature for delay calculation.

Saturation Current

Saturation current is the maximum number of vehicles allowed to pass through a signalled intersection by turning the light green. In other words, it can be explained as the constant presence of vehicles in the intersection approach arm and the constant green light of the light. In determining the saturation current, many research use different approaches and mathematical models.

From the moment the green light is given on the intersection approach arm to the start of the movement of the vehicles, the initial loss occurs. In addition, during the transition of phases during the circuit period, the time between the greens and the protection times are added to the lost times. For this reason, intersection capacities are linked to adequate green time and loss times. The saturation current value is calculated by equation, depending on the saturation tracking interval.

$$S = 3600/h_n$$

Here h_n shows the volume/capacity ratio of the approach arm.

Vehicle Composition

One of the critical factors affecting the delay at intersections is the number of heavy vehicles. It is possible to collect motor vehicles, light vehicles, and heavy vehicles in two general classes. It represents light vehicles consisting of single-destruct vehicles, cars, minibuses and vans, and smaller vehicles. Large vehicles such as buses and trucks are classified as heavy vehicles. There may be more than one axle on the back of these vehicles, or there are two wheels at both ends of these axles. After the traffic volumes and vehicle type distributions are determined, the intersections are converted into unit cars for calculations.

Volume/Capacity Ratio

Capacity at signalled intersections depends on saturated current (s_i). The volume /capacity ratio is determined by dividing the volume(v) of traffic in any approach arm of the intersection by saturated current. The volume/capacity ratio at intersections is calculated by equation.

$$X_i = (v/c) = \left(v_i / \left(s_i \cdot \left(\frac{g_i}{c}\right)\right)\right)$$

Here Xi shows the volume/capacity ratio of the approach arm, v_i traffic volume (ta/sa), Ci, capacity (ta/sa), s_i, saturated current value, g_i, active green time and c, circuit time.

The active green time is calculated by equation

$$g = G - l$$

Here is G, the green time that appears, i, lost time. According to the Webster method, the capacity of the intersection depends on the sum of lost times (L) in the circuit.

Optimum Circuit Time

According to the Webster method, the total lost time in one phase is obtained by collecting the lost time in one phase by taking the yellow light time from the green time. Lost time in a phase (l) is the sum of the initial loss and the second half of the yellow duration of the phase. The rest of the circuit is called useful time. This useful time is shared between surpluses. In this share, the ratio of the weighted current volume of each phase to the saturation current is calculated. In the Webster method, this ratio indicates the degree of saturation. If the saturation rating is indicated by "y", the optimum circuit time to cauterise the best latency from the intersection is calculated by equation.

$$D_0 = \emptyset . L + 5/1 - Y$$

Where D_0, optimum circuit time, L, total lost time in a circuit, Y, the sum of saturation degrees of currents for each phase and ∅is the multiple numbers, which varies between 1,2-1,8.

Delay Account

The total delay at a signalled intersection is defined as the time difference between the time a vehicle unloads the intersection without waiting at a supervised intersection and the time it waits at the intersection (the time it is subjected to a stop delay). According to the Webster (British) method, the average latency value for a current in fixed time signalling can be expressed. Saturation rating: is the ratio of the current passing through an intersection arm to the maximum current that can pass through that intersection and is calculated with the help of the equation.

$$w = \left(\frac{D \cdot (1-\lambda)^2}{2 \cdot (1-\lambda \cdot x)}\right) + \left(\frac{x^2}{2 \cdot q \cdot (1-x)}\right) - \left(0{,}65.\left(\frac{D}{q^2}\right)^{\frac{1}{8}} \cdot x^{(2+5.\lambda)}\right)$$

Where, w, the average delay per vehicle on a junction arm (sec), ε, green time ratio (ε = g/D) *g*, green time, *D*, circuit time, *x*, Saturation rating; is the ratio of the current passing through an intersection arm to the maximum current that can pass through that junction (x = q / λ.s) *q*, traffic volume (b.o/sa) ve *s*, saturated current.

5.4 Experiment and Analysis

The intersection of Flinders Street and Exhibition Street has been selected as the study intersection. This chapter provides circuit time optimization and latency performance analysis with the Webster method because of short-time traffic estimation using artificial neural networks (ANN), which is one of the non-parametric methods, and ARIMA methods, which are one of the parametric methods. The number of vehicles obtained from loop detectors is divided into 5-, 10- and 15-minute data sets to measure the impact of the forecast horizon on performance.

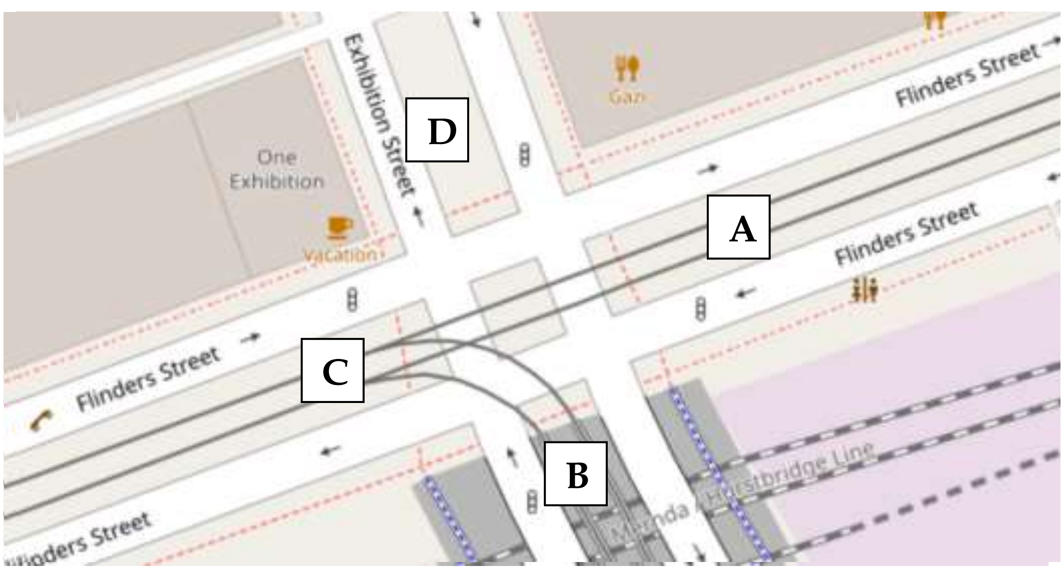
This stage presents the proposed approach for automatic identification of ATHI mentions from DV posts. We adopted two popular states of the art Deep Learning architectures for ATHI extraction task. The Deep Learning algorithms rely on the feature extra

5.4.1 Traffic Study and Network Design

In this section, traffic analyses were carried out one day to cover the peak and non-peak hours of the selected intersection. VicRoads provided traffic analysis and signal plan information of the intersection. The SCATS counts were carried out through loop sensors located in the approach arms of the intersection. In addition, phase plans of the intersection have been removed, geometric characteristics such as signal times and strip numbers and approach arm widths have been determined.

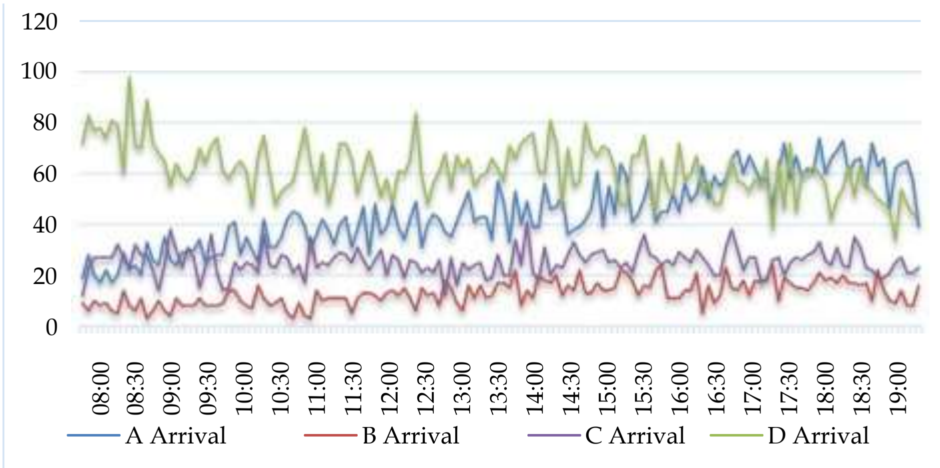
Within the scope of the study, A 12-hour traffic study was carried out on a weekday at the Intersection of Flinders Street and Exhibition Streeton Street. It's one of the busiest intersections in the heart of the city of Melbourne. The intersection of Flinders Street and Exhibition Streeton Street position and approach arms of In Flinders Street and Exhibition Street is shown in Figure 13.

Figure 13 Intersection of Flinders Street and Exhibition Street signal groups and phase plan



The morning peak time and non-peak time signal configuration data (OP SHEETS) are provided by VicRoads is extracted.

Figure 114 elaborates the daily traffic volume values of the intersection Flinders



Street and Exhibition Streeton Street. As can be seen, the traffic volume of A arrival and arrival arms is higher than the arrival arms of B and C.

In figure 14 the daily traffic volume values are shown in 5-minute periods. As can be seen, the traffic volume of A arrival and D arrival arms is higher than the arrival arms of B and C.

5.4.2 Current Status Analysis

The intersection delays were calculated by the Webster method. The delay analyses are based on the 5, 10 and 15-minute data sets of the intersection arrival arms; the delay values of the B and C arms are calculated more according to the delay values of A and D arms. The main reasons for this the intersection are given more green times (B and C). The following section shows short-term traffic estimates based on data sets and a comparison of forecast results.

Table 13 Table Average delay analysis values of the current situation at the intersection

Time	Morning Peak	Out of Peak	Evening Peak
5 minutes.	49,4	49	51,6
10 minutes.	51	48,8	51,7
15 minutes.	52,3	48,8	51,5

5.5 Short-Term Traffic Forecasts

5.5.1 ARIMA Method

To determine the ARIMA model, it is first checked whether the time series is stable. 5, 10 and 15 minutes of data obtained from the approach arms were determined by unit root test. KPSS test and Dickey-Fuller test were used for unit root test and statistical analysis. In the KPSS test, evidence was investigated that the zero-hypothesis data was stable and that the zero hypotheses were incorrect. If the p-value calculated in the KPSS test is less than alpha (0.05), the time series alternative hypothesis is considered; the series is not static. If the P-value is greater than zero hypotheses is accepted, the series is static. In the Dickey-Fuller test, the zero hypotheses indicate that the time series is not static, and the alternative hypothesis indicates that the time series is static. The calculated p-value is greater than the specified alpha (0.05) signability level zero hypothesis is accepted; the series is not static. In the case of small, the alternative hypothesis is accepted; the series is static. As a result of the unit root test analysis, it was observed that the data obtained from the intersection approach arms were not stable. In Table 11, the p values of the Dickey-Fuller and KPSS tests of the approach arms are given, and their stasis is determined according to the p values.

Table 14 - Unit root analysis results of the approach arms

	Dickey-Fuller(p value)	KPSS (p value)
A arm 5 min.	0,174	< 0.0001
A arm 10 min.	0,289	< 0.0001
A arm 15 min.	0,219	< 0.0001
B arm 5 min.	0,185	< 0.0001
B arm 10 min.	0,390	< 0.0001
B arm 15 mins.	0,394	< 0.0001
D arm 5 min.	0,124	< 0.0001
D arm 10min.	0,221	< 0.0001
D arm 15 min.	0,260	< 0.0001
C arm 5 mins	0,156	< 0.0001
C arm 10 min	0,183	< 0.0001

Within the theoretical framework, the most appropriate ARIMA models were tried to be determined for the time-series data, and the parameters of the forecast model were calculated. Choosing the proper model requires the testing of many models. ACF and PACF graphics were also used in the determination of the model; different ARIMA models were calculated for each approach arm. The criteria for Comparison between Root Mean Squared Error (RMSE), Mean Absolute Percent Error (MAPE) and Akaike Information Criterion (AIC) were looked at. The values p,d,q determined according to the autocorrelation and partial autocorrelation values are shown in Table 15

Table 15 - p,d,q values of junction approach arms

	ARIMA (p,d,q)
A arm 5 min.	(3,2,3)
A arm 10 min.	(3,2,3)
A arm 15 min.	(3,2,3)
B arm 5 min.	(3,2,3)
B arm 10 min.	(3,2,3)
B arm 15 mins.	(3,2,3)
D arm 5 min.	(3,1,3)
D arm 10min.	(3,1,3)
D arm 15 min.	(3,1,3)
C arm 5 mins	(3,1,1)
C arm 10 min	(3,1,1)
C arm 15 mins	(3,1,1)

ARIMA Model 5, 10, and 15min observed and predicted results are demonstrated in the following Figure 15 – Figure 20

Figure 12 - A and C arrival arm 5 Minute, observed and predicted (ARIMA)

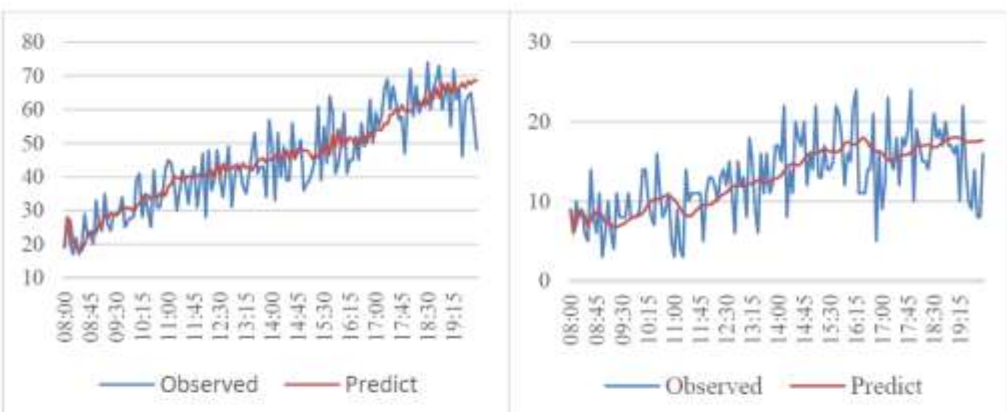


Figure 16 - B and D arrival arm 5minute, observed and predicted (ARIMA)

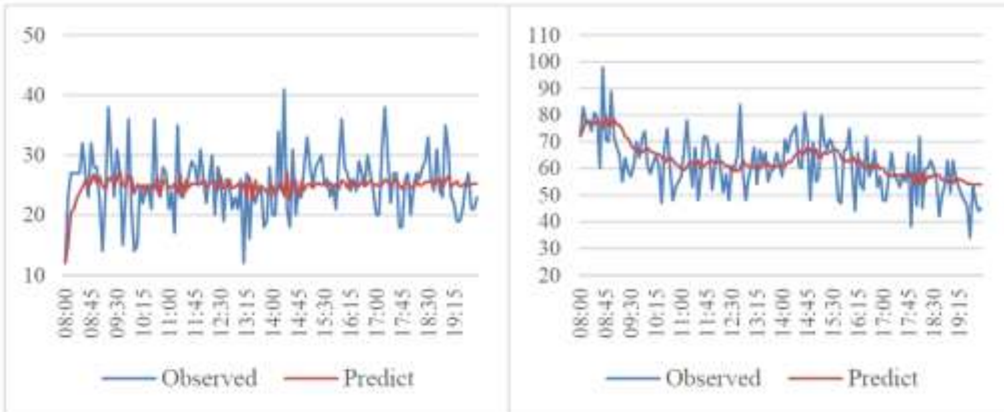


Figure 13 - A and C arrival arm 10 Minute, observed and predicted (ARIMA)

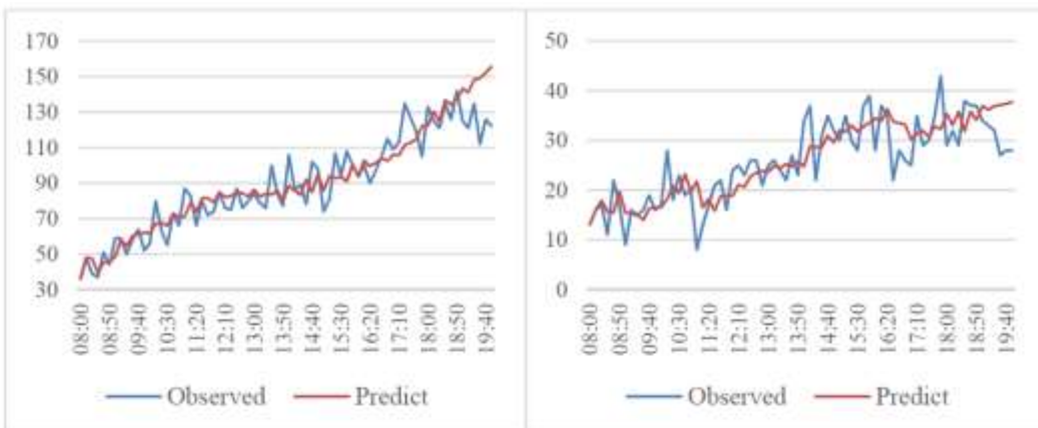


Figure 18 - B and D arrival arm 10 minute, observed and predicted (ARIMA)

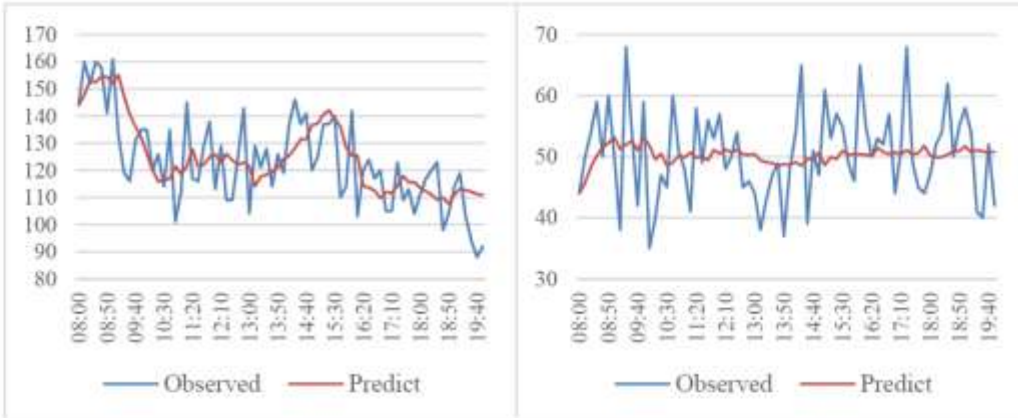


Figure 19 A and C arrival arm 15 Minute, observed and predicted (ARIMA)

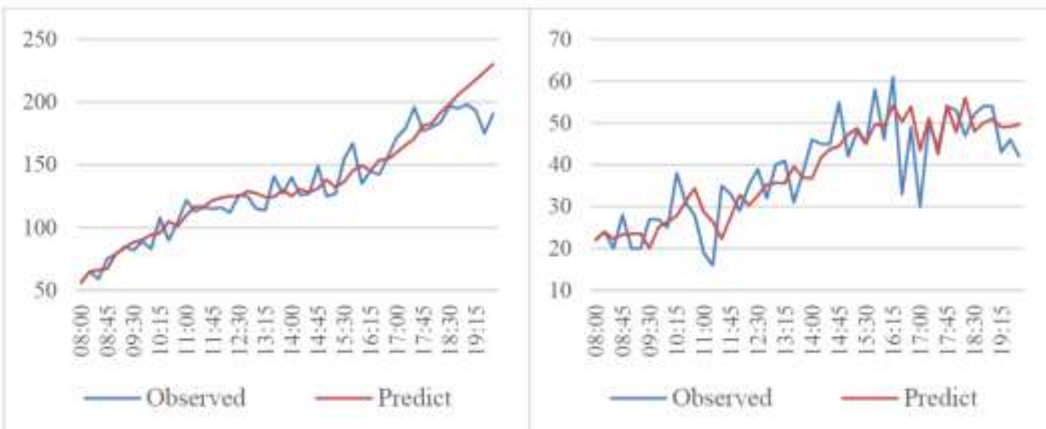
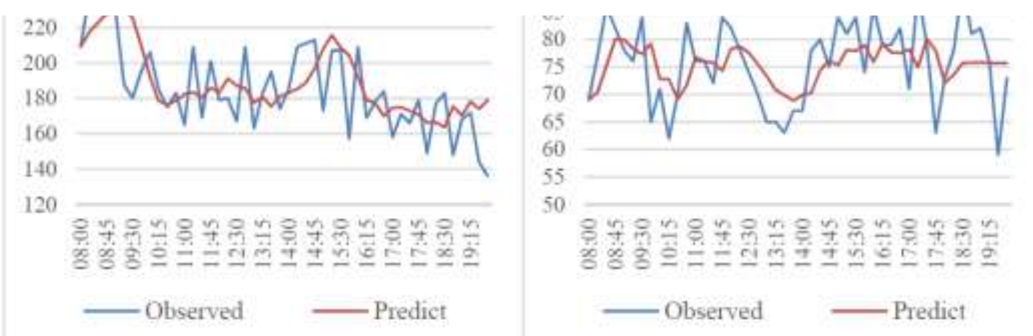


Figure 20 B and D arrival arm 10minute, observed and predicted (ARIMA)



5.5.2 ANN Method

The nonlinear auto-regulatory external input (NARX) algorithm for data sets has been approved. Data sets are divided into 70% training, 15% verification, and 15% testing. The data set is trained with the Levenberg-Marquardt resurbe algorithm. The reason for choosing the Levenberg-Marquardt repatriation algorithm, which is often preferred among optimization algorithms, is due to the fact that it helps achieve a fast, stable and consistent result in short-term or medium-term data sets. During the application, the number of hidden layers of the network is determined by the user. The number of hidden layers applied in the study, the number of neurons in these layers and the activation function used are also found by trial and error. After the trials, it was evaluated that it would be appropriate to take the number of hidden layers as 10 and the number of delays as 6. If a small number of hidden layers are selected, the ability to generalize on the network appears to be increased. If a large number of neurons are selected, an increase in the educational ability of the network is observed. However, adding many hidden layers to the network leads to an increase in the number of calculations. The same training was carried out for each data set, and the adaptation graphs of regression analyses were examined. The forecast results of the data sets of the ANN model are calculated for each approach arm and shown between Figure 21 and Figure 26.

Figure 21 - A and C arrival arm 5 Minute, observed and predicted (ANN)

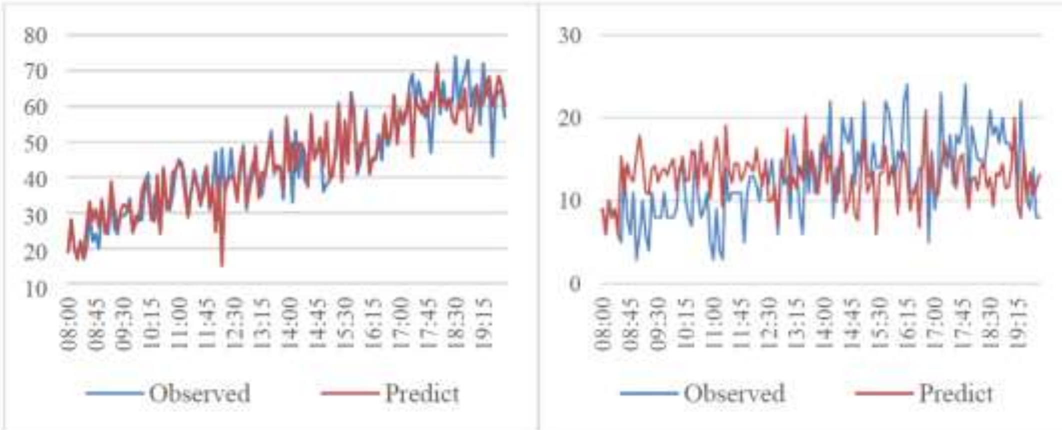


Figure 22 B and D arrival arm 5 Minute, observed and predicted (ANN)

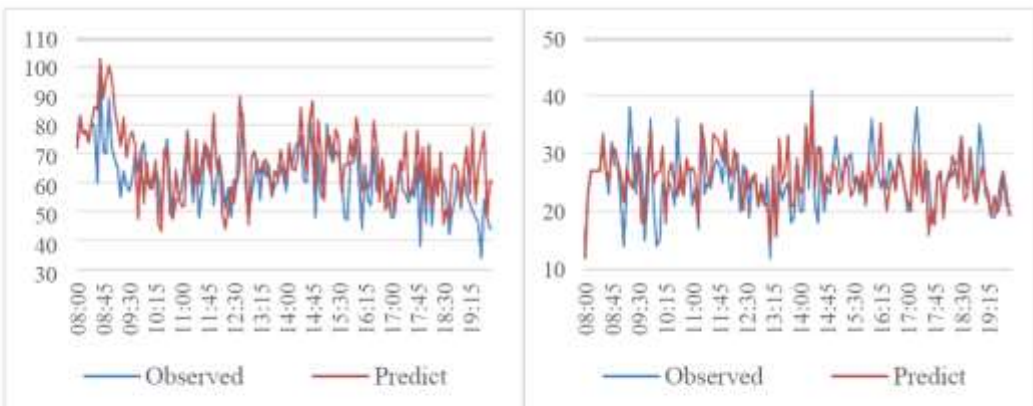


Figure 23 - A and C arrival arm 10 Minute, observed and predicted (ANN)

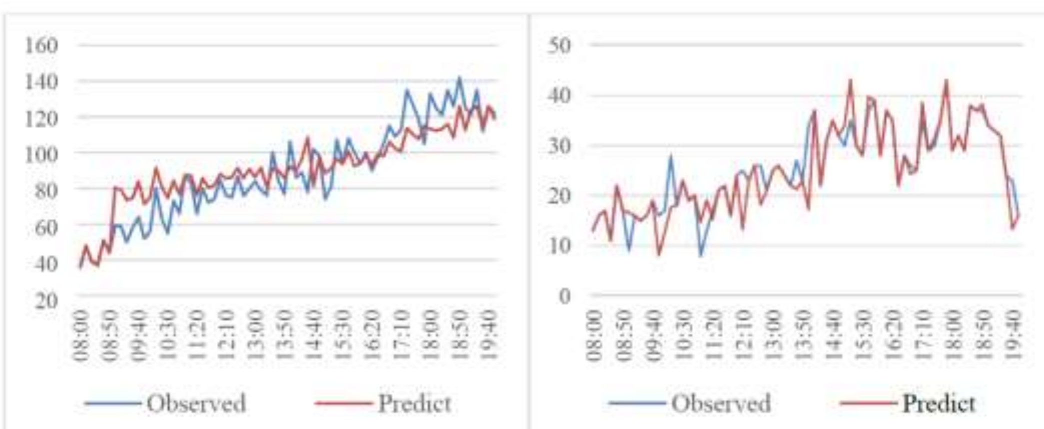


Figure 24 - B and D arrival arm 10minute, observed and predicted (ANN)

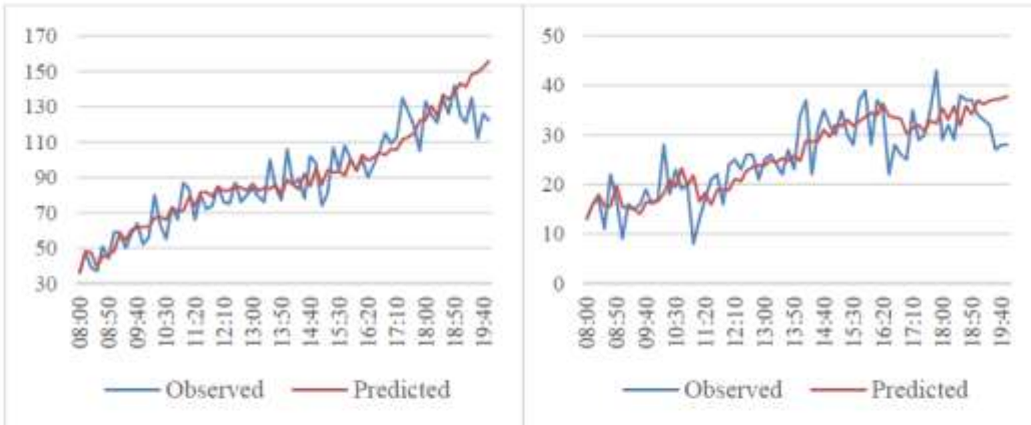


Figure 25 A and C arrival arm 15 Minute, observed and predicted (ANN)

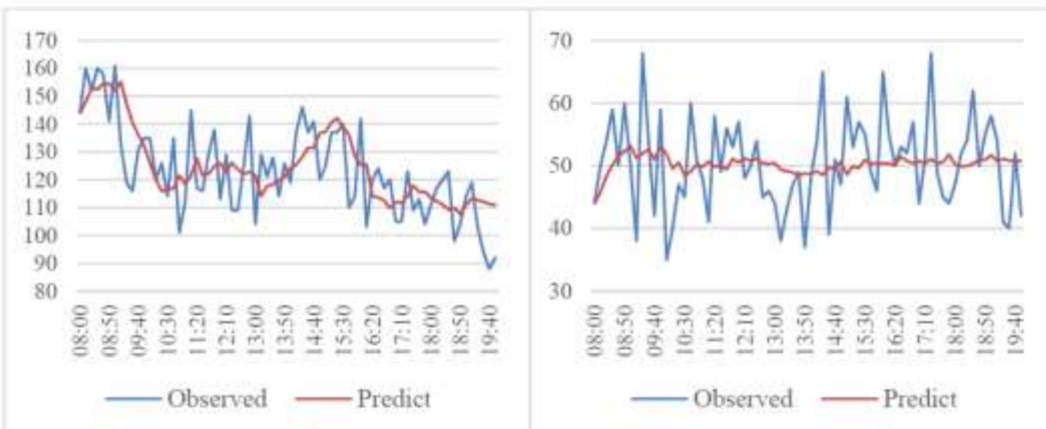
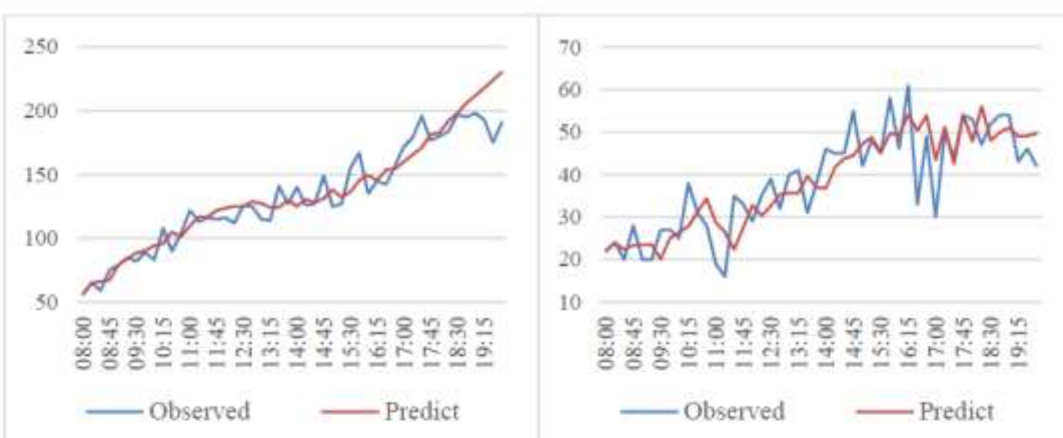


Figure 14- B and D arrival arm 15minute, observed and predicted



5.6 Forecast Results

MAPE and RMSE error values will be compared to compare the forecast results of the ANN and ARIMA models. Absolute average percentage error (MAPE) equation and the square root (RMSE) equation of the mean of the error frames.

$$MAPE = \frac{1}{p} \cdot \left(\sum_{j} \left[\left(t_j - o_j \right) / t_j \right] \right) \cdot 100$$

$$RMSE = \sqrt{\frac{1}{p} \cdot \sum_{j} \left[\left(t_j - o_j \right)^2 \right] \Bigg)}$$

The "*t*" in the equations refers to the real-time data, "*o*" refers to the forecast data, and "*p*" refers to the total amount of data.

In short-term traffic estimates made by ARIMA and ANN methods, it is observed that the ARIMA model caught the series late and responded late to the reactions of the series. Therefore, in short-term forecast stages, error levels make a difference with the realized values. However, when looking at the model with ANN, the model's complex movements are observed to catch the series and try to calculate the short-term movements made by the series as if they were long-term movements. Therefore, the difference between the realized values and the ANN model was also observed.

Table 13 shows the error comparison values for the ARIMA and ANN models. In table 6, the error rates of the ANN and ARIMA method in the 5-minute data set do not outperform each other, while in the10- and 15-minute data sets, ANN error rates are more successful than ARIMA error rates.

Table 16 - Comparison of error values for ARIMA and ANN models

	ARIMA	ARIMA	ANN	ANN
	MAPE (%)	*RMSE*	*MAPE (%)*	*RMSE*
A Arrival (5 min)	41	6	9	7
B Arrival (5 min)	30	4	43	5
D Arrival (5 min)	12	9	15	12
C Arrival (5 min)	17	5	13	5
A Arrival (10 min)	8	9	13	12
B Arrival (10 min)	17	5	9	4
D Arrival (10 min)	8	12	6	10
C Arrival (10 min)	11	7	11	7
A Arrival (15 min)	7	11	6	11
B Arrival (15 min)	16	7	15	7
D Arrival (15 min)	8	19	2	10
C Arrival (15 min)	11	7	4	7

5.7 Intersection Delay Improvement

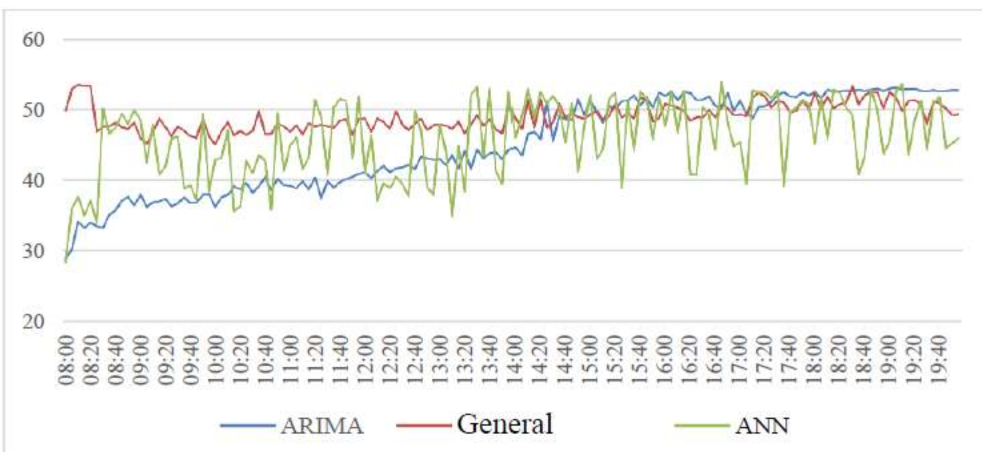
There are many methods for optimizing the signal times of intersections. Circuit time optimization in this study is the equation found by Webster and Cobbe [15] used. Short-term traffic estimates made by ANN and ARIMA methods are arm based, and vehicle delay values are subtracted from intersections. Forecasts of 5, 10 and 15 minutes were converted into hourly volumes, and optimum circuit and green times were calculated in the optimisation study. Thus, if the intersection is converted from an isolated system to an adaptive system, the vehicle delay values are generally calculated of the intersection provided in the ANN and ARIMA models. 7-step optimization technique has been applied for delay improvement at the intersection.

- Conversion of traffic volumes (5, 10 and 15 minutes) resulting from forecasting to hourly traffic volume
- Determination of strip numbers and saturated current values
- Finding volume/capacity ratios

- Determination of phase number and lost durations
- Determination of optimum circuit time by Webster method
- Distribution of green time according to the approach arms
- Arm-based and intersection-wide delay analysis with Webster method

5 Minute predicted with data calculated in an intersection of an urban road in PSEs day delay values is illustrated by Figure 27. morning peak from hours a day inside to hours until ARIMA model Forecasts better result while showing, ANN 5 Minute predicted achieved made to delay Values instability Shows. However, evening hours and evening peak hours for traffic Density her one Approach Round inside Increase, yan your arms (C D arrival) single ribbon because of predicted values Achieved made to delay Results existent delay values is close.

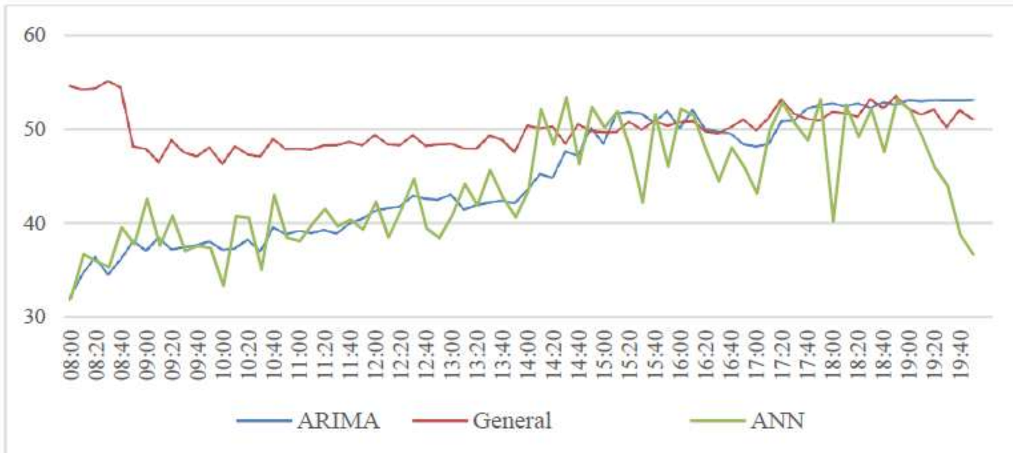
Figure 27 5 Minute predicted with data Calculated in general delay Values



10 Minute predicted with Calculated data crossroads in general delay Values figures 6. is given. Morning peak from hours a day inside to hours until ARIMA model Forecasts better result while showing that ANN 5 Minute predicted their analysis according to better result exhibits. However, evening peak during the hours according to ANN forecasts calculated delay values more successful is morning peak in the hours of like one Healing Observed. However, ARIMA

achieved made to delay Values existent with same levels is seen.

Figure 28 10 Minute predicted with data Calculated in general delay Values



Intersection-wide delay values calculated with 15-minute forecast data are given in Figure 28. ARIMA model forecasts show a better result from morning peak hours to intraday hours, while ANN shows better than a 5-minute forecast analysis. However, since the delay values calculated according to ANN estimates during the evening peak hours are more successful, an improvement is observed in the morning peak hours. However, the latency values obtained from ARIMA estimates are seen at the same levels as available.

As a result, the 5, 10 and 15-minute vehicle counts of Intersection of Flinders Street and Exhibition Street between 08:00 and 20:00 one day were estimated in short time by ARIMA and ANN methods; circuit time optimization was made by Webster method and delay performance analysis was observed with Webster latency method.

The forecast results show latency improvements for the 5-minute data set, taking into account the success of data sets by day, in Figure 29. Between 12:00 and 13:00, ARIMA and ANN show improvements of 10%-25%. However, the

ARIMA method for the 5-minute data set shows a more stable result than ANN. However, after 14:00 and during the evening peak hours, ARIMA does not perform more than 5%, while ANN performs between 6% deterioration and 25% improvement. Morning peak in 5-minute data set and from noon before during the hours ARIMA and ANN is also successful Improvement Rates when appearing, from noon after peak moment apart from and evening peak in the hours of delay fall Reason evening during the hours traffic Density increase, Models predicted Results negative Affected, therefore delay Improvement observed.

Figure 29 -15 Minute predicted with data Calculated crossroads in general delay Values

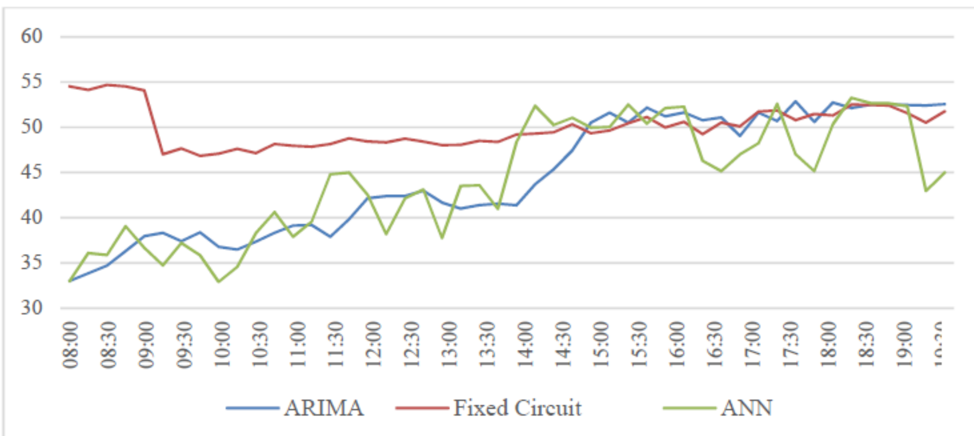
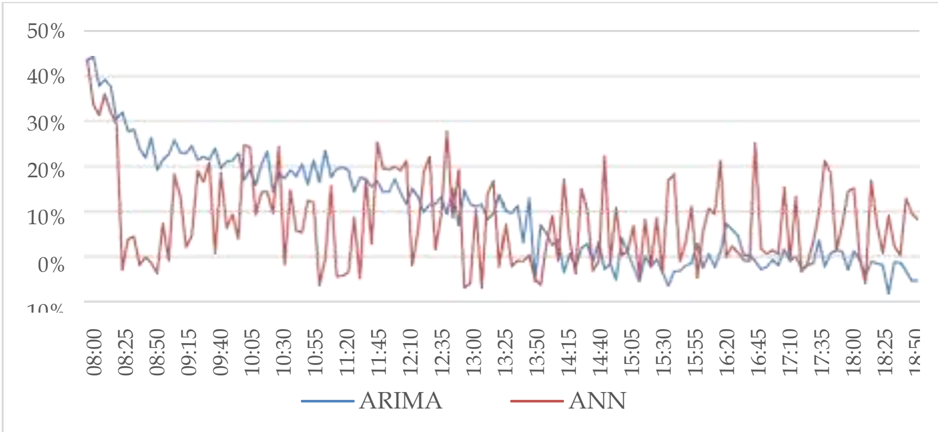
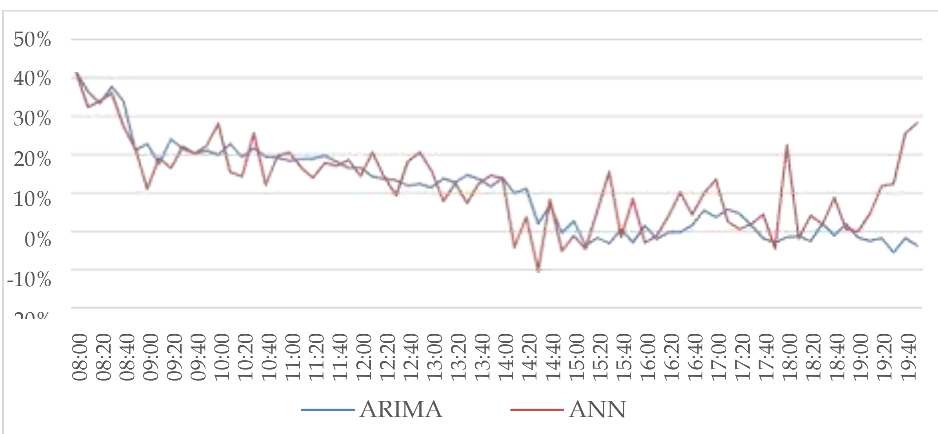


Figure 30 - 5 Minute crossroads in general delay Improvement Percentages



Latency improvements for the 10-minute data set are shown in Figure 30. In the afternoon and evening, the ARIMA model exhibits worsening. ANN model is 10% declining with 25% Healing between performance exhibits. However, ANN's 10 Minute Real Results ARIMA'S, according to more successful is delay improvements moment 19:00 Then successful Results Shows.

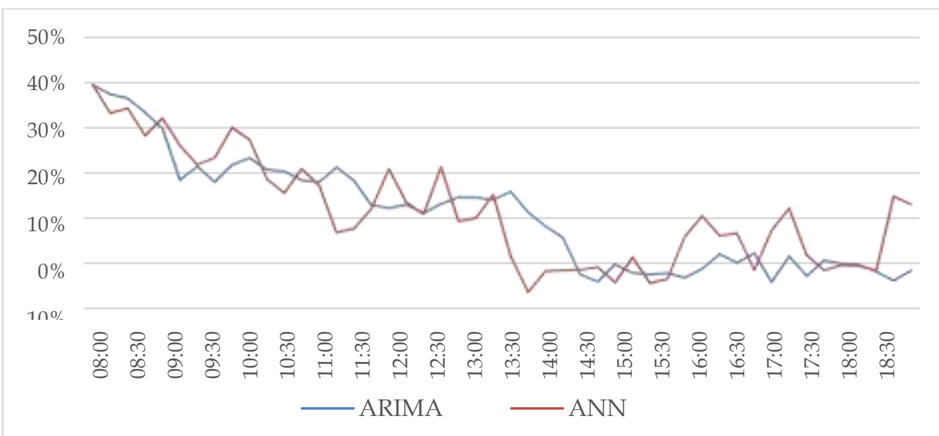
Figure 31 -10 Minute crossroads in general delay Improvement Percentages



15 Minute Real result for Made delay Improvement’s figure 32 Shows. 15 Minute Results in line with morning peak Hours and noon Hours for ARIMA models

delay Improvements %11 with %35 between when ANN models delay Improvements %10 with %33 between performance exhibits. Evening peak Hours for ANN Models %10 Worsening with %25 Healing between performance exhibits. Her two Model evening peak hours true Healing rates Fall to be seen Reason if crossroads Density Increase and yan your arms (C and d streets) because it's, is caused by. However, ANN predicted Results successful because of delay improvements evening peak Watches of successful Results Shows.

Figure 32 15 Minute crossroads in general delay Improvement Percentages



5.8 Summary of Findings

In this chapter, the performance of short-term traffic estimation algorithms was tested in order to determine the signalling system parameters that can be operated at variable circuit time within the scope of intelligent transportation systems at the Intersection of Flinders Street and Exhibition Street OF City of Melbourne, which was selected as an application zone. The forecast performance of the ARIMA and ANN models chosen for this purpose was evaluated, taking into account improvements in optimized circuit time and latency calculated based on the estimated traffic values. The practical implementation of these models required real-time data and historical traffic data such as traffic flow from urban networks. This traffic data must be stored in a database. For practical application, a few weeks, preferably during a season, historical data is needed. Historical data must be collected for several weeks before the proposed methods can be implemented and to create a new database.

The results from the study are as follows;

From short-term traffic forecasting models, the ANN model usually achieves more responsive results than the ARIMA model. When the ANN model was analyzed, it was observed that the forecast results achieved more successful results in 10 and 15 minutes of data according to the error values (See. Table 17).

Table 17 - Comparison of RMSE error values for ARIMA and ANN models

	ARIMA	ANN
A Arrival (5 min)	6	7
B Arrival (5 min)	4	5
D Arrival (5 min)	9	12
C Arrival (5 min)	5	5
A Arrival (10 min)	9	12
B Arrival (10 min)	5	4
D Arrival (10 min)	12	10
C Arrival (10 min)	7	7
A Arrival (15 min)	11	11
B Gel (15 min)	7	7
D Arrival (15 min)	19	10
C Arrival (15 min)	7	7

The Webster method, which is widely used worldwide when calculating delays in the current and forecast results of the intersection, has been selected. At present, no optimization has been made as the intersection is played with fixed circuit time. With 5, 10 and 15 minute periods when making delay calculations with forecast results, traffic data received was converted into hourly volumes, and latency calculations were made. (see Table 18)

Table 18 - Latency improvement rates (%) by 5, 10 and 15 minute traffic volumes of ARIMA and ANN models

	Five minutes.		Ten minutes.		Fifteen minutes.	
	ARIMA	ANN	ARIMA	ANN	ARIMA	ANN
08:00-09:00	33	17	34	32	37	34
09:00-10:00	22	10	21	18	22	26
10:00-11:00	19	13	20	19	22	23
11:00-12:00	18	3	18	17	19	13
12:00-13:00	14	16	13	16	12	14
13:00-14:00	11	7	13	12	14	14
14:00-15:00	5	2	7	1	10	-2
15:00-16:00	-1	4	-2	3	-2	-1
16:00-17:00	-2	6	1	4	-2	2
17:00-18:00	1	5	2	3	0	5
18:00-19:00	0	8	-1	6	0	3
19:00-20:00	-3	6	-3	13	-2	6

Circuit time optimization and delay analysis with forecast data from ANN and ARIMA models showed improvements in both models during the peak hours of the morning, increased traffic density during the evening peak hours and increased traffic volume, especially in the main artery and the single lane of the side arms causes delay improvements to be low or even worsened.

Delay improvement rates of the results obtained from the ANN method during off-peak hours and evening peak hours were more successful than the ARIMA method. Arima and ANN draw close results for morning peak hours.

When the prediction results of ARIMA and ANN methods and latency improvement analyses obtained from the results were examined, it was observed that the ANN method was more successful than ARIMA.

CHAPTER 6

ASSESSING THE RELATIONSHIP OF PLANNED SPECIAL EVENTS ON ROAD ACCIDENTS IN THE CITY OF MELBOURNE

6.1 Introduction

As previous chapters 4 and 5, it's evident that Planned Special Events impact urban congestion. Further, its observed, PSEs increase the risk of accidents in public crowds. This chapter seeks to identify the relationship between PSEs and traffic accidents analytically, using PSEs held in the city of Melbourne between January 2019 and December 2019. The traffic accidents data was obtained from the VicRoads (Victoria Department of Transport) and PSEs data from wed scraping as elaborated in chapter 2.

To analyse the relationship between PSEs and road accidents, a space-time analysis is carried out for PSEs and traffic accidents using various geostatistical techniques using a geographic information system (GIS) and a spatial database. Among the results obtained is the variety of accidents in terms of the presence or absence of PSEs. The different analyses consider the time slot of the even features and the distance between the accident and the place of occurrence of the PSEs. Some spatial grouping techniques such as the Moran’s index, the Nearest Neighbour index for analysis of concentration or dispersion pattern identifications, and statistical methods that characterise accident behaviour were analysed in the results.

The quantitative approach was used in this research to analyse the relationship of PSEs with road traffic accidents, which would establish the relationship between these two variables, which uses geostatistics and quantitative data analysis techniques. With a research design of explanatory type, since it will be inferred the modification of variables or elements but is based on obtaining geospatial data that underscores the relationship between PSEs and vehicle accidents.

The spatial distribution of traffic accidents and PSEs allows identifying patterns, concentration, or dispersion of events, as know the frequency and occurrences of these events in the different urban areas, and an impact on accidents in urban roads [7]. To understand the relationship between PSEs and accidents, Grimm et al. [109] propose spatial analysis using statistical techniques and mathematical methods to analyse spatial relationships of such planned special events on urban road accidents. Bailey and Gatrell [135] broadly define spatial analysis as the quantitative study of phenomena in geographical space. Similarly, Legendre and Fortin [136] indicate that spatial analysis involves quantitatively studying spatial data or data containing location information. Therefore, traffic accidents and PSEs, occurring in space and time are geographically located and can be analysed spatially. This chapter presents the background to studies analysing road accidents and the computational techniques used for such analysis to have as its basis the approach and results obtained to impart on the problems presented and present alternatives in the development of research.

6.2 Literature Survey

Traffic accidents involve the interaction of various components, such as the driver, vehicle, and road complemented by other essential elements, causing a shortfall in road safety. Some researchers, such as Martín, et al. [137], focus on identifying dangerous points and road network elements as causal accidents. For their part, Xi, et al. [138], Wang, et al. [139] established an analysis of the causal elements with the most significant influence on traffic accidents, in which they identify the likelihood of the accident based on the operational state in which these accidents are located. Above mentioned and some other studies have only focused on quantifying the impact of some factors that impact road accidents as the leading cause, such as mechanical or drivers' failures, and no external factors, such as road signs and road status. For example, researchers Novkovic, et al. [140] have associated climate as a significant causality of accidents. Weather conditions increase the likelihood of accidents with the seriousness of high injuries. However, these studies do not apply to all cities, as the characteristics of the climate state are different.

Some research aimed at characterising and predicting accidents possible causal patterns and trends [141, 142]. The different approaches to use and the objectives of each of the studies extracted from the literature are presented in Table 19.

Table 19 Studies treated in road accidents over the past 10 years

Approach	Objective	Authors
Characterisation	Describe the variables involved in traffic accidents	Zhang, et al. [143] .
		Liu, et al. [144]
		Jha, et al. [145]
		Serna, et al. [146]
		Akomolafe and Olutayo [147]
	Identify critical points and elements likely to improve the tracks	Martín, et al. [137]
		Akomolafe and Olutayo [147]
Severity of injuries	Identify the degree of severity of injuries caused by vehicle	Sameen and Pradhan [148]
		Singhal, et al. [149]
		Shanthi and Ramani [150]
		Tavakoli Kashani, et al. [151]

	accidents	Chong, et al. [152]
Causality	Identify the relationship between weather factors and road accidents	Novkovic, et al. [140]
		Ren, et al. [153]
	Identify the relationship between social events and traffic accidents	Grimm, et al. [109]
		Shekhar, et al. [142]
		Cerquera Escobar [154]
		Sastre, et al. [155]
	Determining the influence of the state of different components involved in traffic accidents	Bayam, et al. [156]
		Jain, et al. [157]

Different algorithms and data mining techniques have been used for studies carried out on the characterization and problems of traffic accidents. In most cases, the authors employ supervised learning and unsupervised learning according to the research objectives. The following section mentions some of the different techniques used in studies on road accidents.

6.2.1 Data mining techniques in traffic accident studies

In the different investigations (see table 1), they have applied several machine learning techniques, for example, in the analysis to determine the severity of injuries as a result of traffic accidents, Sameen and Pradhan [148] employed neural network algorithms, where they compared recurrent neural network (RNN), Perceptron multilayer (MLP) models and Bayesian Regression Logistic (BLR) models. As a result, the RNN model outperformed MLP and BLR, with validation accuracy of 71.77% and 10% greater effectiveness than other algorithms. Despite the results, the RNN model had some limitations, such as the difficulty with estimating the probabilities of output, due to the lack of factors, since these are a prerequisite of input of the proposed model. Chong, et al. [158], in their study, employed neural network and decision-making tree techniques. They achieved better results using decision trees model than with neural networks, which exceeded the number of correctly classified cases.

Although other researchers emphasize the artificial neural network decision tree (ANN-DT) algorithm, which extracts trees of binary decisions of a trained neural network, as do Chong, et al. [152], to study the severity of injuries, where this hybrid approach gets better results than Support Vector Machines (SVM), neural networks and decision trees independently.

Based on other studies and techniques, Zhang, et al. [143] apply stain to learning techniques such as a Deep Belief Network (DBN) to analyse social media data in the detection of traffic accidents. These researchers show the significant advantages of DBN since, in their studies, DBN outperforms the artificial neural network (ANN) with a hidden layer, sequence labelling with long short-term LSTM memory units, and support vector machines (SVMs). Other techniques used are association rules to identify the main factors associated with a traffic accident which implement cluster for data pooling, and the apriori algorithm to generate these rules [159]. Although these techniques produce good results, some rules generated for datasets show that association rules do not reveal appropriate information, which may be related to an accident [159, 160]. In the study for the correlation between the different climatic factors and occurrences of traffic accidents, Novkovic, et al. [140] used set techniques, decision trees and SVM such as Random Forest, K-nearest neighbour (KNN), Naïve Bayes and J48, in addition to proposing the use of Random Forest given the most successful rate in predicting positive events.

A study conducted in Chicago, the USA, on traffic accidents and PSEs, was based on SVM techniques and neural networks for data analysis, and like some studies already mentioned under these techniques, the results were not as expected; the SVM model was a poor predictor of traffic incidents. In addition, like most case studies, it precedes problems with data efficiency. The researchers used a program to equilibria the training data set, supplementing the issue of the data, where neural networks obtained better results. However, the proposed neural network was not the most effective [109].

One of the problems that have arised in data analysis is the heterogeneity of traffic accident data. Kumar and Toshniwal [159] proposed that grouping before analysis is convenient for heterogeneity in accident data. For their part, Kumar and Toshniwal [161] used the latent class grouping (LCC) technique to eliminate the heterogeneity of the data in which it provides different cluster selection criteria to be used in identifying the number of groups present in the dataset. Table 17 shows a comparative analysis of the other techniques used for traffic accident analysis, showing that decision trees are the most commonly used technique, followed by SVM and ANN techniques. The decision rules and the hierarchical analytical process (AHP) were the least used techniques with the minor performance. As in the case of a study conducted by Gupta, et al. [162], the algorithm showed the fewest incidents compared to algorithms such as Naive Bayes and J48 decision trees. SVM is among the most commonly used algorithms, where less accuracy has been obtained than decision trees and neural networks. The latter outperforms the other techniques in predicting traffic accidents more accurately [109, 158, 163].

Many academics analysed and explored the characteristics and causalities of traffic accidents as mentioned above. Due to the difference in traffic conditions and the environment, the features were not the same in previous research. Nevertheless, there is only very few studies which analysis the features of PSEs as an influential external factor in traffic accidents.

Table 20 Table. Data analysis techniques used in traffic accident study

Author	Decision trees	Sorting trees	Regression trees	AdaBoost	Clustering	Support vector	Naive Bayes	Hierarchical analytical	Random Forest	Recurrent neural	Artificial neural	Association rules	Decision rules
Zhang, et al. [143]						X				X			
Novkovic, et al. [140]	X			X		X			X				
Grimm, et al. [109]						X					X		
Sameen and Pradhan [148]										X			
Tiwari, et al. [164]	X				X	X	X						
Ren, et al. [165]								X				X	
Suganya and Vijayarani [166]	X												
Kumar and Raubal [167]	X						X						X
Kumar and Toshniwal [168]					X							X	
Hazaa, et al. [169]	X										X		
Martín, et al. [137]	X											X	
Akomolafe and Olutayo [147]	X												
Shanthi and Ramani [170]	X								X		X		
Krishnaveni and Hemalatha [171]	X			X			X		X				
Tavakoli Kashani, et al. [151]	X		X										
Beshah and Hill [172]	X		X										
Guan, et al. [173]											X		
Hui, et al. [174]									X				
Tseng, et al. [175]	X									X			
Chong, et al. [176]	X					X					X		

6.3 Space-time analysis

This section discusses the processes and techniques used in spatial and temporal data analysis. This with the aim of determining the degree of association between the occurrence of PSEs and traffic accidents in the city of

Melbourne. From the information collected about PSEs according to chapter 2, places of occurrence were identified. Events are covered in places such as stadiums, conventional centres, theatres, bars, hotels and restaurants, parks and some large spaces for gatherings and festivities. Figure 35 shows the PSEs for the year 2019 in the city of Melbourne.

Figure 15 List of PSEs for the year 2019 in city of Melbourne.

Cultural/Exhibitions

Chinese New Year	Feb 5, 2019
My Life The Exhibition	Sept 22 2018 - Mar 3, 2019
Virgin Australia Melbourne Fashion Festival	Mar 1 - 10, 2019
Moomba Festival	Mar 8 - 11, 2019
Melbourne Food and Wine Festival	Mar 8 - 24, 2019
Melbourne International Flower and Garden Show	Mar 27 - 31, 2019
Melbourne International Comedy Festival	Mar 27 - Apr 21, 2019
Tudors to Windsor: British Royal Portraits	Mar 27 - Apr 21, 2019
Supanova Comic Con & Gaming	Apr 5 - Apr 7, 2019
Terracotta Warriors: Guardians of Immortality - National Gallery of Victoria	May 24 - Oct 13, 2019
Melbourne International Jazz Festival	May 31 - June 9, 2019
Mind Body Spirit Festival	June 7 - 10, 2019
Melbourne International Film Festival	Aug 1 - 18, 2019
Melbourne Fringe Festival	Sept 12 - 29, 2019

Music/Concerts

Slash	Feb 1, 2019
The Prodigy	Feb 1, 2019
Phil Collins	Feb 1 - 2, 2019
Keith Urban	Feb 5 - 6, 2019
Nickelback	Feb 16, 2019
Maroon 5	Feb 22, 2019
Eminem	Feb 24, 2019
Bryan Ferry	Feb 26, 2019
Arctic Monkeys	Feb 26 - 27, 2019
Red Hot Chili Peppers	Feb 28, 2019
Eagles	Mar 5 - 6, 2019
Bryan Adams	Mar 21, 2019
Boyzone	Apr 3, 2019
Basement Jaxx	Apr 13, 2019
Air Supply	Apr 24, 2019
Fleetwood Mac	Sept 2 - 9, 2019
Shawn Mendes	Oct 29 - 31, 2019
Kiss World	Nov 21 - 22, 2019
Elton John	Dec 10 - 15, 2019

International Forums/Business Events

Melbourne International Coffee Expo (MICE)	Feb 5 - 11, 2019
World Travel Expo 2019	Feb 8 - 11, 2019
Asia-Pacific Incentives and Meetings Expo	Feb 15 - 21, 2019
EGO EXPO Melbourne 2019	Feb 15 - 18, 2019
Cisco Live 2019	Feb 26 - Mar 9, 2019
Arnold Sports Festival Australia 2019	Mar 13 - 18, 2019
8th World Glaucoma Congress	Mar 27 - 30, 2019
World Congress of Nephrology 2019 (WCN)	Apr 9 - 16, 2019
World Congress of Nephrology	Apr 12 - 15, 2019
Home Show 2019	Apr 29 - May 6, 2019
International Particle Accelerator Conference	May 19 - May 24, 2019
International Society for Cellular Therapy Meeting	May 29 - June 1, 2019
World Congress on Science and Football	June 4 - 7, 2019
Food Service Australia	June 25 - 26, 2019
WCA World Championship 2019	July 11 - 14, 2019
Decor + Design & Australian International Furniture Fair	July 15 - 22, 2019
Sportsbiz Career Expo	July 25 - 26, 2019
Reed Gift Fairs	July 28 - Aug 9, 2019
Frontline Australian Buying Event	Aug 13 - 20, 2019
AFAC Fire and Emergency Conference	Aug 25 - 30, 2019
World Federation for Ultrasound in Medicine and Biology	Sept 4 - 9, 2019
VidCon Australia	Sept 18 - 23, 2019
World Federation of Societies of Intensive and Critical Care Medicine	Oct 14 - 18, 2019
International Festival of Language and Culture	Oct 23 - 27, 2019

Sport

Fedun Road National Championship	Jan 4 - 8, 2019
Australian Open Tennis	Jan 14 - 27, 2019
Cadel Evans Great Ocean Road Race	Jan 24 - 27, 2019
Festival of Sails	Jan 26 - 28, 2019
Jayco Herald Sun Tour	Jan 30 - Feb 3, 2019
Six Day Melbourne	Feb 7 - 9, 2019
NRL All Stars	Feb 15, 2019
World Cup Gymnastics Melbourne	Feb 21 - 24, 2019
FIM World Superbikes	Feb 22 - 24, 2019
Avalon Air Show	Mar 1, 2019
Formula 1 Australian Grand Prix	Mar 14 - 17, 2019
Rip Curl Pro	Apr 17 - 27, 2019
Australian Boomers vs USA Men's National Basketball Team	Aug 22 - 24, 2019
Melbourne eSports Open	Sept 1 - 2, 2019
AFL Grand Final	Sept 28, 2019
Australian Motorcycle Grand Prix	Oct 25 - 27, 2019
Melbourne Cup Carnival	Nov 2 - 9, 2019
Presidents Cup	Dec 9 - 15, 2019
Boxing Day Test	Dec 26 - 30, 2019

Theatre

Evil	Dec 5 2018 - Mar 3, 2019
Harry Potter and the Cursed Child	Jan 16 - Dec 1, 2019
Jersey Boys	Feb 23 - Mar 31, 2019
Muriel's Wedding	Mar 12 - Mar 28, 2019
Michael McIntyre Big World Tour	Mar 22 - June 15, 2019
West Side Story	Apr 6 - 28, 2019
Barnum	Apr 27 - May 26, 2019
Sweeney Todd	June 21 - 23, 2019
Come From Away	July 3 - Sept 22, 2019

The spatial distribution of the different locations of the accidents between 2019 Jan to 2019 Dec is mostly concentrated in the inner city. Unlike road accidents the sample covering all areas of the city as illustrated in Figure 36

Figure 16 Traffic accidents between the period of January 2019 and December 2019.

6.3.1 Creating Buffers

The buffer is a spatial analysis technique that is typically used in GIS for inter-layer operations. The buffer zones denote the areas of influence of events. To analyse the region from traffic accidents that may be related to the presence of PSEs. The buffer generates two areas, one that is within a specified distance to a spatial object and another outside area. The internal area demarcated by the specified distance is named as the buffer zone [49]. In geographic information systems, buffer zones are represented as vector polygons, surrounding a punto, line, or another polygon. An object can also have more than one buffer zone [50]. Consider that in the visualisation of the spatial distribution of points of the event's location, this does not include the magnitude of establishment or area in which the event is presented. For this reason, the need to generate buffer zones that cover both the area of the PSEs venue and that of traffic accidents around it is created. Contemplating the places' capacity, which mobility may be affected, either by a reduction by the speed at which it is handled or an increase due to the influence of vehicles in the area. To cover the buffers where they are at risk of congestion or increased accidentality.

6.3.2 Multiple buffer zones

There are several alternatives when generating a buffer. The buffer distance or buffer size may vary depending on vector layer attribute values for each feature. Numeric values must be defined in units on the map based on the Coordinate Reference System (CRS) used with the data.

Table 21 Degree equivalences with meters of buffer zones.

Degrees	***Meters***
0.000898	100
0.00179	200
0.00269	300
0.00359	400
0.00449	500
0.00628	700
0.00898	1000
0.01347	1500

For buffer generation, zones with different distances were created, ranging from 100 to 1500 meters from the centre or location of the site. Table 21 names the different distances of the buffers created and their equivalence in degrees for generation under the CRS. Figure 6.3 illustrates buffer zones created around PSEss as an area of influence for vehicle accidents.

Figure 17 Multiple buffers around PSEs venues

6.3.3 Analysis by buffer

To observe the behavior of accidents, a temporary analysis is performed in the areas of influence, when there is and not the presence of events. Considering captured events and places of occurrence, four locations were selected (Figure 38 to 41), capacity and type of event. Based on the above, the following locations were selected: Marvel Stadium, Federation Square, Melbourne Convention and Exhibition Centre and the Melbourne Cricket Ground (MCG)

For the respective analysis, the number of accidents per hour was counted, for each of the datasets in the areas of influence. After measuring, the average number of accidents per hour was calculated when there is a presence or absence of PSEs. Figure 36 to 39 shows the behaviour of the average accidentality per hour when the buffer distance increases from the place of occurrence. The analysis is carried out in each of the sites.

Figure 18 Average accidents per hour according to the distance of influence in the Melbourne Cricket Grounds

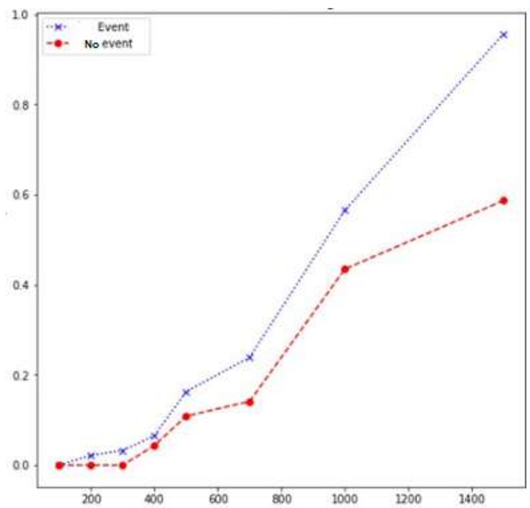


Figure 19 Average accidents per hour according to the distance of influence in the Federation square.

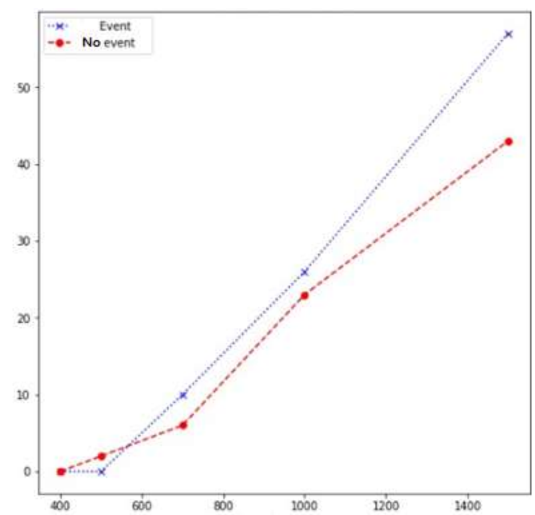


Figure 20 Average accidents per hour according to the distance of influence in the Marvel Stadium.

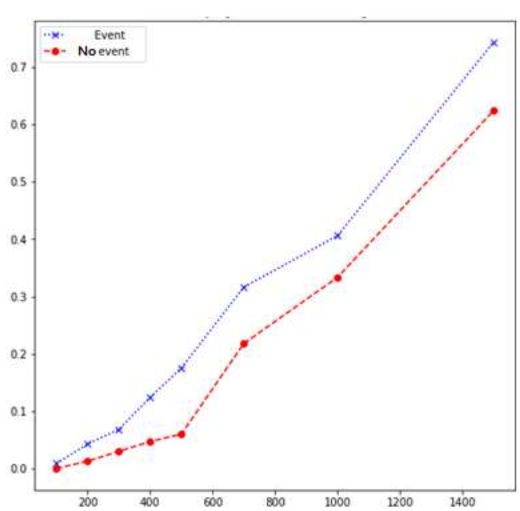
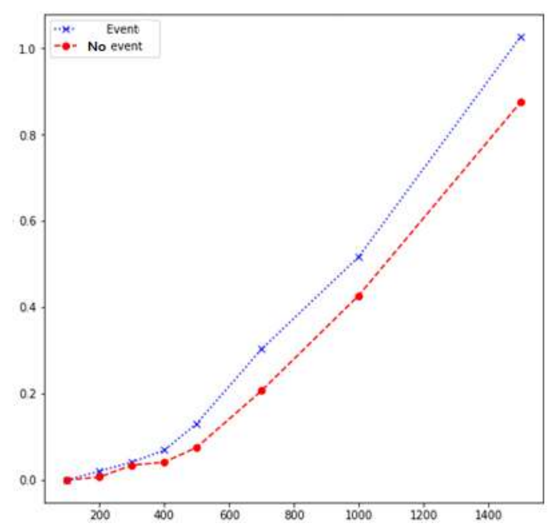


Figure 21 Average accidents per hour according to the distance of influence in the Melbourne Convention and Exhibition Centre



6.4 Statistical analysis

This section describes the statistical methods used for analyzing the correlation between PSEs and traffic accidents. Like the results that were obtained. Among the methods applied are the hypothesis test, Kendall Tau or Kendall rank correlation coefficient and Wilcoxon signed rank tests expressing the results using graphs and tables [177].

6.4.1 Hypothesis test

A statistical method used to compare two groups of experimental data is called hypothesis tests. This part of the assumption about a population parameter (mean and/or variance) thus generating the hypothesis that is tested (may or may not be true) [178].

The test contains a hypothesis system that includes the null hypothesis and the alternative. The null hypothesis is a statistical statement that these populations being compared are the same according to the reference population parameter. The alternative hypothesis responds to contradict the null hypothesis. The formula bellow shows the hypothesis system when the mean is taken as a reference to the population parameter.

Null hypothesis- is $H_0\colon \mu_A = \mu_B$

Alternative hypothesis is $H_1\colon \mu_A \neq \mu_B$

Where A and B refer to the two populations of interest.

If you work with a single dataset. μB can be replaced with a specific value when what is sought is not to compare two populations but a population against an expertly given value. The null hypothesis refers to the parameter being equal to a given value. Therefore, the alternative hypothesis refers to the population parameter is different from the given value.

Continuing the case of comparison of two populations, which is the one that applies in this case, the null hypothesis as specified in the above equation, which sums up is that there is no difference between the two population means. The observations of both datasets are purely random. The alternative hypothesis refers to the average observations of each of the datasets of interest being the result of an actual effect, influenced by the variable specified by population A of B.

However, the possibility of accepting or rejecting a hypothesis does not include 100% accuracy as it results in the level of significance, which refers to the probability that the test is a null hypothesis. When it is true, the test is denoted as α and is technically called type I error. The method also contemplates type II error (β.) which is the mistake of accepting the null hypothesis when it is false; however, for this analysis, it is considered to prove that it handles the type I error. This implies that the p-value of each test will be compared with a tolerable significance level for the test, and being less, the null hypothesis is rejected. The tolerable significance for this case is 10%.

For the application of the hypothesis tests, it is necessary to comply with the normality of the data, so in this case in particular, The Kolmogorov-Smirnov test to confirm the assumption and be able to analyse the results produced by the hypothesis tests.

6.4.2 Kendall's rank correlation

A non-parametric test measures the dependency force between two variables, evaluating statistical associations based on the data ranges. Kendall's correlation coefficient uses pairs of observations and determines the association force based on the match or mismatch pattern between the data pairs. Being insensitive to error, P values are more accurate with smaller sample sizes [177]. The following formula is used to calculate the value of the Kendall range correlation:

$$\tau = \frac{n_c - n_d}{\frac{1}{2}n(n-1)}$$

Where n_c the numberof concordants and nd the number of discordants. Defining concordant as a pair of observations (x_2 -x_1) y (y_2-y_1) that have the same and discordant sign when they have opposite signs.

6.4.3 Wilcoxon signed rank tests

It is another non-parametric test of comparison of two related samples (in this case, there are two populations that match at the place of occurrence and differ by the topic of PSEs). This allows you to test the randomness of a sequence of data. The test compares two (medium) centre measurements and determines that the difference is not randomly caused (that the difference is statistically significant). The model assumes that the data comes from the same population over time or place. Because the test is non-parametric, it does not require a particular probability distribution of the dependent variable [178]

The test essentially calculates the difference between each dataset and analyses these differences. The null hypothesis of interest is:

H_0 – The difference between the medians in both datasets is equal to zero.

H_1 – The difference between the medians in both datasets is not equal to zero.

Under the alternative hypothesis, the differences will tend to be positive or negative. If H_0 is true, it would tend to make half the differences positive and about half of the differences negative. Assuming, the sum of the positive ranks would be approximately equal to the sum of the negative ranks:

$$(T+) \approx (T-) = \frac{1}{2} * n(n+1)/2\text{y}$$

and this does not reject the null hypothesis raised by the method.

In this same case, the decision is made based on the p-value of each test that is compared with a tolerable significance level for research and being less, the null hypothesis is rejected. Tolerable significance for this case is 10%

6.5 Description of the results

Having clear the intention of each of the most relevant statistical methodologies to respond to Objective 2 of the investigation. In other words, they are methodologies that are intended to deliver results on the relationship that may have the existence of PSEs and road accident. Then the results yielded for each of the sites of interest are assumed.

It should be clarified that the data set for each of the sites respond to comments made between 01/01/2019 and 31/12/2019; the records are divided into two subpopulations of interest that are:

- Records that are taken at times when there is no presence of PSEs.
- Records that are taken before, during, or after the development of one or more PSEs.

Each of the sites describes the results since the particularities of them at the location, capacity, and event types, among others, do not compare results between the places of interest feasible.

For each site, an overview of the worked dataset has been given, and then the Tau-Kendall match coefficient is applied first to have an idea about the behaviour of road accidentality reported in the data set when there is no presence of PSEs and in the dataset when there is an event or more.

Since there are other methodologies for analyzing the behaviour of road accidents in each of the subpopulations of interest, the Kolmogorov-Smirnov normality test is applied to confirm this assumption and have feasibility for the application of hypothesis tests and other parametric correlation coefficients such as Pearson's. For cases where the assumption of normality in the data is not met, a non-parametric hypothesis testing methodology will be applied (no distribution assumptions are required in the data). The above seeks to have statistical support to analyze the difference between the medians of each subpopulation; the median is a more robust centre statistic, and extreme values do not influence that.

It is important to clarify that the dataset initially extracted includes records without PSEs simply because they are times of the day when such events will hardly take place, implying that accidental consideration is being made that they will have no point of comparison in a scenario with a PSE, and the time slot is being contemplated. This means that, within the analysis, the dataset should be reduced to records where a PSEs has been presented independently or not, whether it is a time when the PSEs; from the statistical approach, the comparison of variables must seek the measurement of these in scenarios without bias or with the least possible bias so that the results are the product of the variable's variability and do not respond to predictable behaviours by the exact nature in which the data was generated.

This involves working with the following datasets:

- Initially extracted records - Work with the data initially extracted, and spatial and temporal analyses have been developed. This is called the original dataset.
- Logs only generated when PSEs take place - Work with data that can analyse the behaviour of road accidents in the scenario where research's interest is most concentrated: the presence of PSEs (with at least one PSE in development). This means having the most specific inputs to be able to respond to the following concern: what happens to accidentality in the presence of PSEs?, Does it increase, does it decrease, there's no

relationship, the more PSEs, the more road accidents, the less, there's no specific behaviour? It is called an acidic dataset because it is the set with the minimum records that must answer the question of this investigation.

- Aggregate records per day- Day-level registrations where you can have days without a PSE or with a PSE or more. This is intended to mitigate the risk of analysing sessed data. On the one hand, a dataset only has recorded in a single scenario: only under the presence of PSEs, (data set No. 2). On the other hand, data in which there is an increase of records without PSEs since it is unworkable hours for events of thisindole to take place. This is called a day-level dataset.

The statistical model described above was applied for the three datasets; the most relevant and conclusive results are highlighted in their description.

6.5.1 Case Study- Melbourne Cricket Ground Stadium

As mentioned in previous sections, 2.5% the total observations held for this place are are event records, and the remaining 97.5% refer to observations where no PSEs was identified.

Table 22 Summary of the original data MCG.Due to wide popularity and extensive engagement of sharers and supporters on..

		Number of accidents that occurred					
		Count	***%***	***Media***	***Medium***	***Max.***	***Standard deviation***
Existence of Events	***There were no events***	7054	97,5%	0,4716472	0	11	1
	If there were events	181	2,5%	0,3812154	0	4	1
	Total	7235	100%	0,4693849	0	11	0,99180836

Table 22 concludes that there is an imbalance of information as the number of reports of times when there is no event is considerably higher than the number of reports at previous times. When analysing only the plant measurements within each set, it is necessary that, for each observed hour, there is between zero (0) and maximum one (1) road accident on average, there is or is no presence of a PSEs; the median in both subpopulations is zero (0) which means that at least 50% of the data reports zero (accidents).

Taking into account the result of the standard deviation, this reference can be extended to maximum two (2) accidents per hour in both cases. It should be noted that at the time when road accidents (11 accidents) were most present, it was at a time of day that no PSEs was reported.

The maximum number of road accidents that occur when there was a PSEs were four (4). This provides a preliminary conclusion on two datasets that do not have a marked difference in road accidents. In addition, it justifies working with other datasets that make the comparison fairer.

Table 23 Proof of correlation by Tau de Kendall in the MCG.

		Number of events that occurred	Number of accidents that occurred
Number of Events that occurred	***Correlation coefficient***	1,000	-0,006
	Sig. (bilateral)	.	0,593
	N	7235	7235
Number of accidents that occurred	***Correlation coefficient***	-0,006	1,000
	Sig. (bilateral)	0,593	.
	N	7235	7235

However, by applying a non-parametric correlation coefficient that allows us to identify whether the road accident quantity data and the number of events occurred; the number of accidents is expected to be similar, on the one hand, in the dataset when there is no event, and on the other, in the dataset when there is an event, but that the number of accidents differs between one subpopulation and another.

Having the coefficient is -0.006, it is concluded that there is no agreement between accidents occurring and PSEs developed. This result cannot be compared to the analyses done above as what is intended with Kendall Tau is to identify whether there is a match between the number of road accidents and the number of events. The above analyses focused on verifying the behaviour of road accidents according to proximity to the influence site (Figure 38 - 41), and road accidents in a particular day and time when the difference could be seen with and without PSEs (Figure 38-41); the variable PSEs in the previous analyses was worked as a nominal variable (there is or no event), in Kendall tau is taken as a discrete variable (there is an event, two, three, those that are recorded).

Kendall's Tau coefficient was applied in the dataset that contains only records under the development of PSEs (acid dataset). The conclusion does not differ from that already obtained by having a correlation coefficient of 0.012. Gives the above insists on applying the other methodologies to be researched on the behaviour of accidentality in both datasets.

The Kolmogorov test is applied to confirm the null hypothesis about the distribution of the data worked and its correspondence with the normal distribution. However, according to Table 19, there is no significance and statistics to confirm this hypothesis test in the acidic data set and therefore, the conclusion is to reject it; the p-value tested (0) is less than the threshold defined by the researcher (10% or 0.1)so theis null hypothesis is rejected on normality in the distribution of road accidentality data at the Nemesio Camacho el Campín Stadium

Table 24 Results of the contrast of hypotheses against the distribution of normality in the data recorded in the MCG.

Null hypothesis	***Test***	***That's it, that's***	***Decision***
The Distribution of the Number of Accidents Occurred is normal, with a mean 0 and standard deviation 992.	Kolmogorov-Smirnov test for a sample	0	Reject the null hypothesis.

By doing a graphical analysis of the data, there is no similarity to a normal distribution since there is the concentration of data at the lowest accidentality values; there is a bias to high amounts of road accidents. It is remembered that normal distribution is where the lowest or highest values of the variable are the most frequently. The concentration of the data is given in the average values.

The normality test was also applied to the original dataset, and given the conclusion for the acid dataset, there is also rejected Gaussian distribution in the data.

However, having rejected the case of normality, it is statistically unworkable to apply parametric hypothesis tests that discuss parameter equality such as mean and or variance; it is also ineffective to calculate correlation coefficients such as Pearson's. The last option you have is to apply a non-parametric test that compares the medians and lets you know whether or not the difference between those medians is zero; if it is zero, it implies that the behaviour of road accidents is similar whether or not there are PSEs. In this case, it is applied for the aggregated dataset per day to smooth the bias of records without PSEs because of the development of such events at appropriate times.

Table 25 Wilcoxon Rank sum test of continuity correlation with the MCG stadium.

In	***p-value***	***Alternative hypothesis***
6551,5	0.01968	Decision: to reject the fact that the medians of both datasets they're the same.

6.6 Spatial Analysis

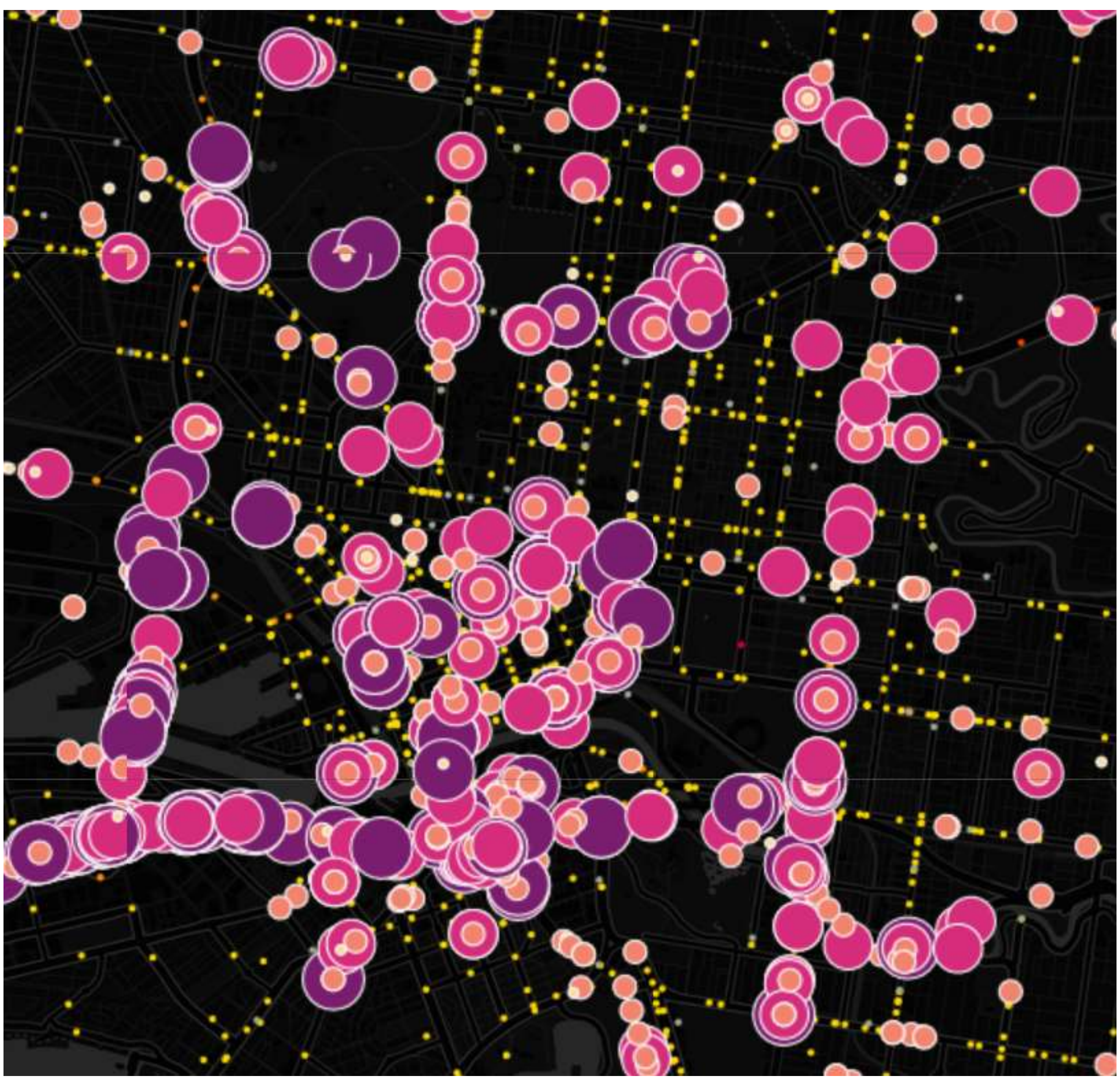
This section performs a geostatistical spatial analysis of PSEs and traffic accidents. Grouping techniques are used, as well as counting points in polygons for the analysis of patterns and autocorrelation indexes space. With the aim of identifying patterns of grouping or dispersion of accidental and PSEs in the different areas and critical points of the city of Melbourne.

6.6.1 Grouping of spatial points

When you have a vector layer with thousands of points, it is useful to use markers that group the points, allowing you to visualize elements of interest. In this section, see that the points are grouped into clusters in conglomerate areas of space. The conglomerate analysis of hierarchical

grouping spatial points (traffic accidents) is based on the distance between them. Figure 5-1shows the clusters obtained through the DBSCAN Clustering algorithm, with the respective number of accidents in each cluster during the period September Jan 2019 to Dec 2019. The DBSCAN clustering algorithm groups dots into a certain number of clusters. Each point feature is assigned to the cluster whose centroid is closest to it. Cluster identification is not based on a range of distances or spatial proximity but rather on their statistical proximity, allowing clusters to be identified with a particular statistical significance.

Figure 22 Traffic accident grouping



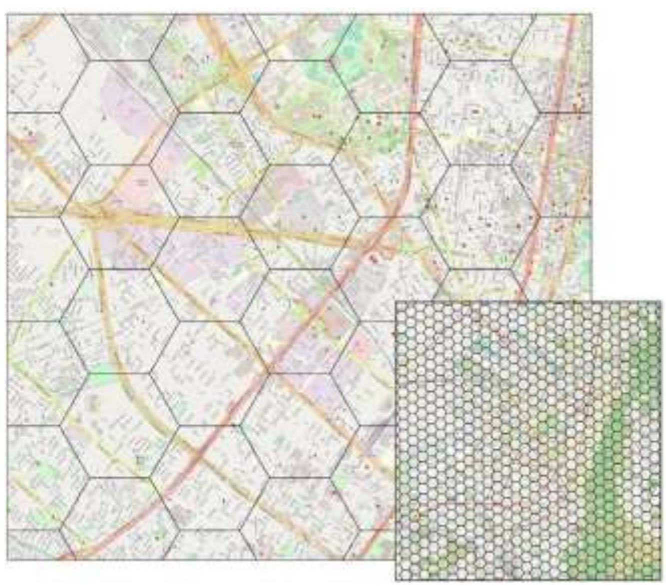
According to Figure 42 a significant of traffic accidents are evident in the central part of Melbourne. The centroid of each group or cluster is in turn the average of the positions of all points within the cluster.

Considering the grouping densities presented in Figure 5-1, it is observed that these are concentrated in the main avenues. Starting from the centroids of the central area which exists more accidentality, these are largely located near or at the intersections of the busy intersections.

6.6.2 Hexagonal polygons

In order to display point densities, a hexagon mesh is created for counting the number of PSEs and traffic accidents within each hexagon. Information used as an aggregation value for further analysis. Hexagonal mesh provides a more natural tile structure than the grid network, with greater coverage and spatial continuity.

Figure 23 shows the polygon of a regular hexagonal mesh.



Moran's Index studied (Vehicle Accidents and PSEs), with an area of 855000 square meters, with reference to the buffers created in section 6.3.2

6.6.3 Global spatial autocorrelation index

Spatial autocorrelation analysis requires some measure of contiguity. Contiguity has a broad definition according to the research question, however, most analyses in spatial autocorrelation adhere to a common definition of neighborhood relationships. For this purpose, Moran's Index [179] applies. This index tries to contrast the absence of spatial autocorrelation (spatial randomness) against the existence of spatial autocorrelation (positive or negative). The overall index is limited to establishing spatial autocorrelation in the entire geographic space under study. Moran’s index I is given by the following expression.

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \text{ para } i \neq j$$

Where $S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}$ para $i \neq j$, being *n* the sample size, that is, the total number of spatial units analysed.

To verify the existence or absence of spatial autocorrelation, the raster type layer is created based on the densities of the hexagonal polygons. Figure 44 displays in raster form the matrix of cells with values representing the degree of accidentality, to determine the spatial autocorrelation of traffic accidents.

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Figure 24 Raster map of traffic accidents

The study uses the cases of Rook's case, and Queen's case, for validation of the existence of spatial randomness of traffic accidents.

Table 26 Global autocorrelation rate in road accidents

Grid	Contiguity	Moran Index	Neighbors	Average cells
Rasterizado	Queen's case	0.38424	1376	628.561151
Rasterizado	Rook's case	0.37631	1376	628.561151

The result of the application of spatial autocorrelation with the use of queen's and Rook's cases can be seen in Table 26. Where an index of 0.384 and 0.376 is presented respectively, which indicates that there is a low positive correlation, since it is closer to zero than to value one, reaching a spatial randomness in the occurrence of traffic accidents.

6.6.4 Nearest Neighbor Index

By means of the average nearest neighbor method, you can evaluate the distribution of spatial points, validating the pattern that the spatial point has dispersion or grouping. The observed mean distance, nearest neighbor index, z-score, and expected mean distance are calculated for the analysis. The nearest Neighbor index is expressed as the relationship between the observed mean distance and the expected mean distance [180].

$$ANN = \frac{DO}{DE}$$

Where DO is the average observed distance between each point and its nearest neighbor:

$$DO = \frac{\sum_{i=1}^{n} d_i}{n}$$

And DE is the average distance expected for points given a random pattern.

$$DE = \frac{0.5}{\sqrt{n/a}}$$

In the above equations di is equal to the distance between the spatial points i and its nearest neighbors. n Corresponds to the total points and a is the area that encloses all centroids. The z-score of the nearest neighbor average is calculated as:

$$z = \frac{DO - DE}{SE}$$

Where:

$$SE = \frac{0.26136}{\sqrt{n^2/A}}$$

As a result, it should be noted that, if the index is less than 1, the pattern exhibits a grouping of spatial points; if the index is greater than 1, the trend is dispersion.

Table 27 Nearest neighbor rate in traffic accidents and PSEs

Distribution	Average Distance observed	Average Distance expected	Nearest neighboring index	Number of points	Z-Score
Accidents	5,0944	18,4031	0,2768	304030	0,0174
Events	981	836.388	1,1738	44	65.9099

Comparing the results obtained from applying the nearest neighbor index in spatial distributions (PSEs and Traffic Accidents) to verify the pattern they form in the city of Melbourne see (Table 5-2). It was found that the distribution of accidents with a value of 0.2768 shows a grouping, having as a precedent that accidents occur mostly in the main avenues and intersections of the same. Unlike PSEs which presents a dispersion trend with a value of 1.17. Since these are mostly found in the central area of the city and the others, but with less presence, scattered in the different areas of the city of Melbourne. The dispersion of PSEs is mild with a z-score of 65.9 which is not a relatively large value. For traffic accidents with a z-score of 0.017 as it is not negative, the grouping of points is not significant.

6.7 Summary of Findings

This work proposed data analysis to determine the relationship between traffic accidents (Victoria gov data) and PSEs (data from web scraping) using geostatistical methods. It was based on the realization to establish each stage and methods for processing spatial data. The different methods and algorithms used are currently used for such analysis. This allows determining the relationship presented by traffic accidents with PSEs in the city of Melbourne.

From the method proposed in the extraction of information from PSEs, the extraction of the data necessary to perform the space analysis was achieved with respect to the occurrence of traffic accidents. As a first limitation, it was obtained by not having the addresses directly from the places of occurrence of the event extracted on the web pages. An additional subsequent process was performed or to obtain the direction and geographical position through georeferencing APIs. Finally, as a result of the extraction process, a database of PSEs and traffic accidents is created with the date and location of occurrence.

Geographic information systems, visualization methods and geostatistics are used in the time-space analysis process, focusing at the buffer level and by days at different time slots. Initially, 46 event occurrence sites were obtained, which for the case study selected five places that contemplate other characteristics.

With respect to the data used, there is an imbalance of information since the number of reports of times when there is no event is considerably higher than the number of reports in the last moments; this has a thematic justification that in future work should be reviewed for the generation of more pertinent data sets to answer research questions.

CHAPTER 7

CONCLUSION AND FUTURE WORK

This chapter concludes the doctoral thesis investigated the impact of planned special events on urban non-recurrent congestion. The city of Melbourne was selected to analyse and monitor traffic congestion and its congestion impact on the presence of planned special events. This last chapter aims to summarise the main work carried out to meet this objective. The methodological, analytical and operational contributions of this research project are then listed. A section also outlines the many limitations associated with the analyses and methodologies presented. Finally, several avenues of research are suggested to continue and expand the study of traffic congestion.

7.1 Summary of Contributions

The traffic management of major events is always a major challenge for all actors involved. The differences compared to everyday traffic situations lie above all in the exclusive framework conditions of significant events, in the short-term nature of peak traffic events and their spatially concentrated effects. Based on two completed research projects, the application potential of applied geoinformatics in the context of PSEs, in particular event traffic management, is investigated in the present work.

First, a literature review made it possible to study the various parameters (definitions, acceptability thresholds, causes, impacts, solutions, "benefits" and measures) related to road congestion and to propose a report that takes into account all the relevant parameters: Road congestion is a physical and relative phenomenon that occurs when traffic parameters (volume, speed and derivatives) become less desirable than the reference values set and which varies according to time, space, cause (recurrent and non-recurrent) and the threshold of acceptability. The literature review also identified a list of indicators suitable for assessing congestion according to six categories: speed, flow and capacity, time and delay, spatial indicators, reliability and costs. Of these indicators, the simplest have been chosen in the interests of methodological development.

Secondly, PSEs for estimating congestion indicators from SCATS data has been developed. This methodology includes the processing of measurement, network and descriptive data, and merging these data to form a database that allows calculating indicators according to several visualisation objects and spatiotemporal selections.

In this thesis, we address the problem of short-term traffic congestion prediction on urban freeway networks. A multi-modal data fusion framework is proposed. Three categories of models are developed. The first category comprises of data mining or machine learning models for traffic congestion prediction for urban freeways in presence of planned special events. The second category comprises of data mining or machine learning models for traffic congestion prediction for urban arterials. The third and the last category comprises of data data mining or machine learning models for planned special impact on traffic accidents which contribute for the overall urban congestion impact of planned special events

The strength of our data mining model is the use of a deep belief network for traffic congestion prediction. This is chosen based on the state-of-the-art algorithm. In terms of accuracy and runtime, the performance is compared with multiple machine learning models.. Lastly, the major strength of this work is the development of the comprehensive analysis data fusion framework for urban traffic congestion prediction in presence of planned special events..

The usefulness of our research to academia and industry includes better intelligent route planning, monitoring and mitigation of traffic congestion on urban freeways and urban arterials by traffic management systems, reduction of traffic delays, waiting times, air pollution and noise in cities. In addition, it would help the road vehicle drivers to avoid congested traffic routes and assist the traffic managers in designing better road traffic infrastructure.

7.2 Study Limitations

The results produced in this doctoral thesis, however, have several limitations that should be highlighted. The road network also has many limitations. Only the centre line of the roads was available, and information on the width of the tracks was not available on the entire network.

Urban road networks have complex structures and many other factors can influence the traffic congestion not considered in this study. Such as local weather conditions that can have significant impacts on traffic. One of the most important limitations to traffic analyses is the lack of other explanatory data, such as work, accidents and other special events such as holidays. It is indeed challenging to analyse the variations of congestion without taking account of the many explanatory factors.

Finally, the majority of congestion indicators require a reference value and a congestion acceptability threshold. The speed limit and 60% of this speed are respectively the methodological choices made in the context of this work. These values also have their limitations since some analyses depend on these subjective assumptions.

7.3 Future Research Directions

Road congestion is a complex, variable, unpredictable phenomenon that evolves. This is an area of research where new developments will always arise to understand the impacts of recent mobility trends on the road network.

Future research could investigate in exploring hybrid AI models in comparison to the comparison approach of methods and algorithms implemented by the contribution chapter five – “short-term traffic forecasting in the presence of PSE on an urban arterial intersection” to further improve forecast results.

Future research also could be interested in the problem of updating the road network in congestion analyses. There is a need to develop indicators of heavy trends that are comparable between different networks. The study of traffic conditions on a network must consider the history of these modifications, which is not currently done.

The future research of urban congestion, which is influenced by planned special events, will be quite promising due to the availability of new data scourers. Newer data sources such as Floating Car Data (FCD) and Floating Phone Data (FPD) , different social networks data contribute to this in particular. In the coming years, it can already be seen that more up-to-date and real-time traffic information will be available to be used in developing more accurate prediction models.

With the recent developments, the provision of an open data model for mapping events, including the surrounding traffic infrastructure through geo spatial systems and spatial analysis, is promising. The spatial analysis will influence the future research direction of predicting urban congestion influenced by planned special events.

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APPENDIX

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16 March 2021

To Whom It May Concern:

This reference letter is provided at the request of Mrs. Ruwangi Fernando. Ms. Fernando participated in the Australian Postgraduate Research Internship (APR.Intern) program under my supervision. She worked with the Department of Transport (DoT) in Victoria as a member of the Demand Forecasting team from 5th August 2019 to 17th February 2020 (5 months). The Demand Forecasting team is responsible for undertaking demand analysis for to enable planning and evaluation of potential transport projects, as well as aiding many areas of the portfolio on forecast travel demand both short term and long term.

Having Ms. Fernando undertake research work with us provided the opportunity to explore an area of interest that we otherwise would not have been resourced to undertake. The ability for our branch to be able to ingest various datasets and transform them into useful insights and metrics is an important and ongoing area of development. Nowhere is this truer than in the planned disruptions space. As DoT has advanced knowledge and control of these interruptions to people's usual travel, there is an expectation that we can mitigate their impacts. But the task is made more difficult due to the large number of different organising bodies, rapidly changing timetables, and large scale of works, which can overlap in areas of influence. Hence there is an ongoing need to find ways to understand the nature and scale of travel impacts when roads or Public Transport services are interrupted, and this applies both to historic disruptions and one planned.

The first phase of Ms. Fernando's research provided us with an audit of available and useful datasets and their owners and attributes, across a wide area of the department. This itself was a worthwhile exercise as it provided us with a resource to improve visibility within our own organisation. The later stages of Ms. Fernando's internship gave us insight into specific disruptions, but also demonstrated the feasibility of the approach, and provides us with functional templates to reapply the analysis to different disruptions in future with a shorter response time.

I would like to thank Ms Fernando for her dedication to precision in her work and enthusiasm in communicating her developments. I wish her all the very best for her future endeavours. If there are any outstanding questions on this matter, feel free to contact me.

Kind Regards,

Rick Williams

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VICTORIA State Government