Performance Evaluation of SCATS-Controlled Intersections in New Zealand with Machine-Learning Delay Prediction and Signal-Timing Optimisation

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ABSTRACT

Adaptive signal systems such as the Sydney Coordinated Adaptive Traffic System (SCATS) controls traffic signal system by adjusting phase splits and cycle length in real time. The adjustments rely only on the last few seconds of detector data, the system lacks real-time predictive and optimization functionalities, allowing queues and emissions to build. Fine-tuning of signal timing by even a small increment can derive large economic and environmental benefits for the wider network. This short-coming is becoming increasingly significant in New Zealand, where transport already contributes 39 % of national CO_2 emissions and intersection delay costs Auckland more than NZ $1 billion each year.

This thesis evaluates present and future performance of two representative SCATS-controlled intersections—Albany, Auckland and Ruakura, Hamilton—and tests whether supervised machine-learning (ML) models can predict delay and recommend cycle lengths that improvises the native SCATS logic.

Field data was used to build, calibrate, and validate base SIDRA intersection models; saturation-flow rates were matched within ±5 % of observations and all lane-movements satisfied degree-of-saturation criteria. A Monte-Carlo routine expanded 14 SCATS peak-period volume logs into 98 synthetic volume scenarios, which were re-run in SIDRA to obtain delay, queue, fuel, and emission outputs. Four machine learning models—XGBoost, Random Forest, Support Vector Regression, and k-Nearest Neighbours—were trained on the synthetic dataset; the best two, XGBoost and Random Forest were combined in an ensemble to give a delay-prediction model.

Furthermore, baseline analysis (2024) found both sites operating at Level-of-Service D, with several right-turn lanes already oversaturated and 95th-percentile queues exceeding storage. Ten-year growth projections degraded both intersections to LoS F well before the planning horizon. The ML ensemble predicted average control delay with MAE ≈ 4 s veh^{-1} and, under moderate demand, shortened cycles by 15–46 s, cutting delay by 13 % and CO_2 by 5 % relative to SCATS timings; though the benefits diminished under heavy oversaturation.

Data-driven machine learning models can provide cycle-by-cycle delay forecasts and substantial performance gains, but require additional high-degree of saturations and longer cycle lengths training data for robust operation and more generalization during severe congestion. Integration of such predictors and optimizers with SCATS would provide practical step toward meeting New Zealand's 2035 emission-reduction targets.

Keywords: Adaptive traffic signal control, SCATS, Signalised intersections, Traffic modelling, SIDRA, Intersection modelling, Machine-learning delay prediction, Cycle-length, Queue management, Sustainability

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DECLARATION of AUTHORSHIP

I, Shivu Khatri, hereby declare that the content of this Master's thesis document represents solely my own work. Any materials or contributions from other authors, when utilized, have been appropriately cited and duly acknowledged. I further declare that I have not submitted this thesis at any other institution in order to obtain any other qualifications.

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ABBREVIATIONS

AI	Artificial Intelligence
ANN	Artificial Neural Network
ATSCS	Adaptive Traffic Signal Control Systems
BSF	Basic Saturation Flow
BSFR	Basic Saturation Flow Rate
CAS	Crash Analysis System
CCG	Canadian Capacity Guide
CCTV	Closed Circuit Television
CL	Cycle Length
CO	Carbon Monoxide
CO2	Carbon Dioxide
DE	Differential Evolution
DEM	Digital Elevation Model
DoS	Degree of Saturation
DT	Decision Trees
HC	Hydro Carbons
HCM	Highway Capacity Manual
IQR	Inter Quartile Range
ITS	Intelligent Transport Systems
LINZ	Land Information New Zealand
LoS	Level of Service
LR	Linear Regression
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MOVA	Microprocessor Optimised Vehicle Actuation
MSE	Mean Squared Error
NN	Neural Networks
NO	Nitrogen Oxides
NSLR	National Speed Limit Register
NSW	New South Wales
NZ	New Zealand
NZD	New Zealand Dollar
NZTA	New Zealand Transport Agency
OOB	Out of Bag
PDO	Property Damage Only
PFF	Peak Flow Factor
QL	Queue Length
RF	Random Forest

RHODES	Real-time Hierarchical Optimized Distributed Effective System
RMSE	Root Mean Square Error
RTA	Roads and Traffic Authority
SCATS	Sydney Coordinated Adaptive Traffic System
SCOOT	Split Cycle Offset Optimization Technique
SF	Saturation Flow
SFR	Saturation Flow Rate
SIDRA	Signalized & Unsignalized Intersection Design and Research Aid
SPOT	Signal Priority Optimization Technique
SVR	Support Vector Regression
tcu	through car units
TMD	Transport Model Development
TRID	Transportation Research International Documentation
TRL	Transport Research Laboratory
UK	United Kingdom
USA	United States of America
UTOPIA	Urban Traffic Optimization by Integrated Automation
VA	Vehicle Actuation
VISSIM	Verkehr In Städten-SIMulationsmodell (German for Traffic in cities-simulation model)
XGB	XGBoost

Chapter 1 INTRODUCTION

1.1 Background and Context

Signalized intersections are the hotspots for congestion and pollution due to the frequent stopping, acceleration-deceleration cycles resulting in elevated delays and emissions (Zhu et al., 2013). According to a study conducted by a traffic data analysis company, INRIX covering two-third of the USA's traffic signals, an average traffic signal causes nearly 82 hours of delay per day (Fisher, 2021). Similarly, in New Zealand, Auckland is expected to face NZ $1.9 billion of congestion costs per year in time delays by 2026 and about 17 hours of delay per year per person (ARUP and EY, 2025). One of the causes of Auckland's congestion is intersection delay which placed Auckland as the 77th worst congested city out of 500 global cities (TomTom, 2024). Furthermore, transport accounts for nearly 39% of New Zealand's CO_2 emissions and 17% of its total greenhouse gases (Ministry of Transport, 2022).

One of the targets of signalized intersections in highway networks is to optimize traffic flow and reduce delays. When their timing is sub-optimal, they induce network-wide delay and degrade overall level-of-service, thus highlighting the signalized intersection's influence in the overall network performance and the need for signal timing optimization (Hasan & Hussein, 2022). Rapid surges in traffic demands and the availability of high-quality, real-time traffic detector data now provide us with ample opportunity to analyze intersection dynamics in real time and apply data-driven signal strategies that were impossible just a decade ago.

Optimization of traffic signal control results in wide range of economic and environmental benefits. Nation-wide studies report that updated signal timing can cut delay by up to 40 %, fuel use by 10 %, and emissions by 22 %, with benefit–cost ratios exceeding 40:1 (U.S. DoT, 2008). Optimizing signalized intersections might be a critical strategy for reducing traffic delay, lowering fuel consumption and emissions as well, and directly supporting New Zealand's targets of cutting transport emissions by 41% by 2035 and achieving net zero by 2050. These improvements also align with the Government Policy Statement 2024–2034 and the National Land Transport Program 2024–2027, which prioritize congestion reduction, better travel reliability, and emission mitigation through targeted urban traffic management.

Systematic performance evaluations are required to gauge intersection efficiency and to execute signal optimization on time. Various performance measures are used to quantify the operational performance of intersections. One such performance indicator is delay, which has become the primary performance indicator at signalized intersections because it is straightforward to measure, carries clear economic significance, and is easily understood by both technical and non-technical people (Hurdle, 1984).

Delay estimation represents a fundamental performance metric for signalized intersections; however, traditional models such as Webster's delay model (Webster, 1958), (National Academies of Sciences, Engineering, and Medicine and others, 2022) are reliable only under undersaturated conditions and fail to accurately predict delays when intersections become oversaturated (Bagdatli & Dokuz, (2021), (Murat & Baskan, 2006).

Adaptive traffic signal control systems (ATSCS) are currently in practice to manage signalized intersections globally which change phase splits and cycle lengths as per the current real-time traffic demand. Such systems have huge benefits over traditional fixed-time traffic signal system in improving travel times and thus reducing delays. One of the ATSCS is Sydney Coordinated Adaptive Traffic System (SCATS) is a widely implemented adaptive traffic signal control system in New Zealand (Waka Kotahi NZ Transport Agency). SCATS operates by detecting vehicles at stop lines and uses pre-programmed logic to adjust phase splits and cycle lengths in real time (Lowrie, 1992).

However, ATSCSs cannot fully eliminate oversaturation; during severe congestion, their adaptive algorithms may fail to reallocate green time effectively and, if offsets are overly adjusted, can actually exacerbate delays. Additionally, they rely only on the past 5–10 seconds of detector data to predict demand, systems like SCATS often miss rapid traffic surges—especially during peak periods or special events—resulting in delayed responses (Stevanovic, 2010). Furthermore, one of the drawbacks of ATSCSs-controlled signalized intersections is that they can experience long queues and higher average vehicle waiting times (Agrahari, et al., 2024).

While the SCATS dynamically adjusts phase splits in real time, it lacks predictive capabilities to anticipate traffic patterns or self-learning ability to forecast key performance metrics like delays, limiting its ability to optimise signals (Essa & Sayed, (2020)).

Current research in optimizing adaptive traffic signal control system focusses on minimizing delays using reinforcement learning (Swapno et al., 2023), distributed adaptive control (Xie & Wang, 2025) and Machine Learning (ML). Research regarding optimization of adaptive traffic signal controls with ML techniques has been promising.

Machine Learning (ML) techniques have been shown to improve traffic performance parameters like average delay, queue length, number of stops, fuel consumption and overall travel time (Eriksen, et al., 2020). Machine learning can accurately predict future signal cycle lengths and phase times by capturing nonlinear relationships in real-time detectors and signal data, enabling reliable timing refinement in actuated control systems (Genser , et al., 2024). Furthermore, ML has demonstrated significant potential in urban traffic signal control by enabling real-time adaptation to complex spatial-temporal traffic patterns and reducing both queue lengths and vehicle wait times (Guo, et al., 2019).

However, no such studies have been undertaken in the New Zealand context; this thesis therefore investigates the feasibility of integrating real-time predictive and optimization functionality into existing signal control systems at two representative New Zealand intersections.

1.2 Research Questions

To address the gaps, this research undertaking seek to answer the following research questions:

1. How accurately can ML models trained on simulation data predict performance measures like delay for SCATS-controlled intersections in New Zealand?
2. To what extent can ML optimise cycle length to reduce delay and associated CO_2 emissions at SCATS intersections in New Zealand?

1.3 Research Objectives

1. Build, calibrate and validate Signalized & Unsignalized Intersection Design and Research Aid (SIDRA) models for representative intersections
2. Perform baseline performance evaluation of the intersections in terms of key performance indices, sustainability, and crash analysis
3. Test the future resilience of the intersections
4. Develop and statistically validate machine-learning models for the prediction of intersection delay
5. Develop ML models that optimizes cycle length to minimize a delay

1.4 Research Exclusions

This study is subject to some exclusions due to time, resource and logistic constraints:

- Spatial scope: Analysis is confined to at-grade, signalized intersections, grade-separated interchanges, arterial links, corridors, and network-wide performance are excluded
- Geographic scope: A limited number of intersections will be studied
- Traffic scope: the evaluation addresses vehicular movements only; pedestrian, cyclist, and public-transport interactions, modelling dedicated transit lanes are out of scope owing to limited data availability.

1.5 Thesis Structure

The thesis is structured as below:

Chapter 1: INTRODUCTION

An overview of the background and context is provided. Overall research aims, research objectives and research exclusions are stated.

Chapter 2: LITERATURE REVIEW

Comprehensive readings of relevant literatures including journals, national and international guidelines, research reports, books, international practices are covered along with summary of the literature reviews.

Chapter 3: METHODOLOGY

Describes site selection (Albany, and Ruakura) and rationale for the selection, SIDRA base models developments, and the ML framework used for delay and cycle-length prediction.

Chapter 4: PERFORMANCE ANALYSIS USING SIDRA

Presents calibration and validation SIDRA results, rigorous performance evaluation of the intersections, and explores future growth scenarios to highlight operational issues.

Chapter 5: MACHINE LEARNING ANALYSIS

Develops and statistically validates the ML delay-prediction models, compares ML-optimised cycle lengths with existing SCATS timings, discussing impacts on operational and sustainability performance.

Chapter 6: KEY FINDINGS, LIMITATIONS, AND RECOMMENDATIONS

Summarises key findings, highlights the study's methodological and data limits, and proposes future research.

Chapter 7: CONCLUSIONS

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Chapter 2 LITERATURE REVIEW

To design, calibrate, and optimize the SCATS-controlled intersections engineers rely on traffic flow theory, queuing models, and modern simulation tools (e.g., SIDRA), augmented by machine-learning approaches. This chapter reviews the state of the art in these key areas: (1) macroscopic and microscopic traffic flow fundamentals; (2) the specific behaviour of traffic at signalized intersections (capacity, saturation flow, delay, shock waves); (3) traditional and time-dependent delay models; (4) quality-of-service metrics and adaptive signal systems—focusing on SCATS; (5) transport-modelling practices in New Zealand; and (6) recent ML methods for delay prediction and signal timing optimization. By synthesizing these literatures, we identify the research gaps—particularly SCATS' lack of predictive delay capability and the need for ML-enhanced cycle optimization.

2.1 Literature Review Methodology

The literature review (Stage One of this study) was conducted using a systematic search of peer-reviewed journals, industry reports, technical guides, and conference proceedings. The following online databases were searched:

- Google Scholar
- Austroads Digital Library
- Scopus
- University of Waikato Library Electronic Resources
- Transportation Research International Documentation (TRID)
- IEEE Xplore Digital Library
- ScienceDirect

Documents published from 2000 onward were prioritized to emphasize recent advances in adaptive signal control and machine-learning applications, while early foundational studies (e.g., traffic flow theory, SCATS evolution) were included to provide historical context. Search queries combined the following keywords and phrases among others:

- "SCATS adaptive signal control"
- "SIDRA intersection calibration"
- "SIDRA intersection validation"
- "traffic flow theory"
- "performance evaluation of signalized intersections"
- "crash analysis New Zealand"
- "signalized intersection delay models"
- "saturation flow rate calibration"
- "degree of saturation SCATS SIDRA"
- "machine learning traffic delay prediction"
- "cycle length optimization"
- "machine learning in traffic control"

- "oversaturated intersection modeling"
- "New Zealand traffic signal guidelines"
- "transport modelling calibration NZTA"
- "Synthetic data generation"

Each keyword combination was evaluated for relevance by reviewing abstracts and, when necessary, full texts.

2.2 Literature Review Findings

2.2.1 Fundamentals of Traffic Flow

Traffic flow theory is used in planning, design and operational level analysis of transportation facilities, for simulations, traffic impact analysis, and sustainability analysis (Garber & Hoel, 2020). Traffic flow theory delves into the fundamental relationships among three traffic flow parameters viz. flow, density (concentration) and speed. Two primary approaches are used to study the relationship: **microscopic** and **macroscopic**. This section explains both methods and their key ideas.

Macroscopic approach treats traffic flow as continuous fluid-like stream and relates flow to the density and speed in aggregate terms. The approach basically focusses on aggregate parameters:

- Density: Number of vehicles per unit length of road
- Speed: Speed of a traffic stream as a whole
- Flow: Number of vehicles passing a particular point of road during a certain period of time

These parameters can be represented graphically as in Figure 2.1 and the relationship is termed as a traffic stream model. From the Figure, we observe that:

- At low density i.e. light traffic, speed approaches the mean free-flow speed (u_f)
- As the density approaches its maximum (k_j, jam density), speed approaches zero and flow again approaches zero
- At some density (k_m) and corresponding speed (u_m), flow passes through a maximum value $q_{m.}$ (Gerlough & Huber, 1975)

Notable macroscopic models as cited in May (Traffic Flow Fundamentals, 1990) include:

- Greenshield's linear model, the earliest one which proposed linear relationship between flow and density
- Greenberg's logarithmic model
- Underwood's exponential model
- Pipes' single regime generalized model
- multi-regime models

For further details, see May's Traffic Flow Fundamentals.

Microscopic approach is concerned with interactions between individual vehicles, driver and describes traffic flow considering gap between two consecutive vehicles, headways and their individual speeds.

Key microscopic parameters are:

- Headway: Time headway is the time difference taken by the consecutive vehicles to cross a point whereas, space headway is the physical spacing between the front bumpers of consecutive vehicles
- Driver behaviours including driver reaction times, acceleration/deceleration, lane changing decisions

Notable microscopic models as cited in May (Traffic Flow Fundamentals, 1990) include:

- car-following model
- lane-changing models
- vehicle arrival models
- microscopic traffic simulations

In summary, traffic flow analysis uses two approaches. The macroscopic method considers the traffic stream as a whole and is interested in aggregate traffic parameters while the microscopic method is focussed on individual vehicles and basically on granular level.

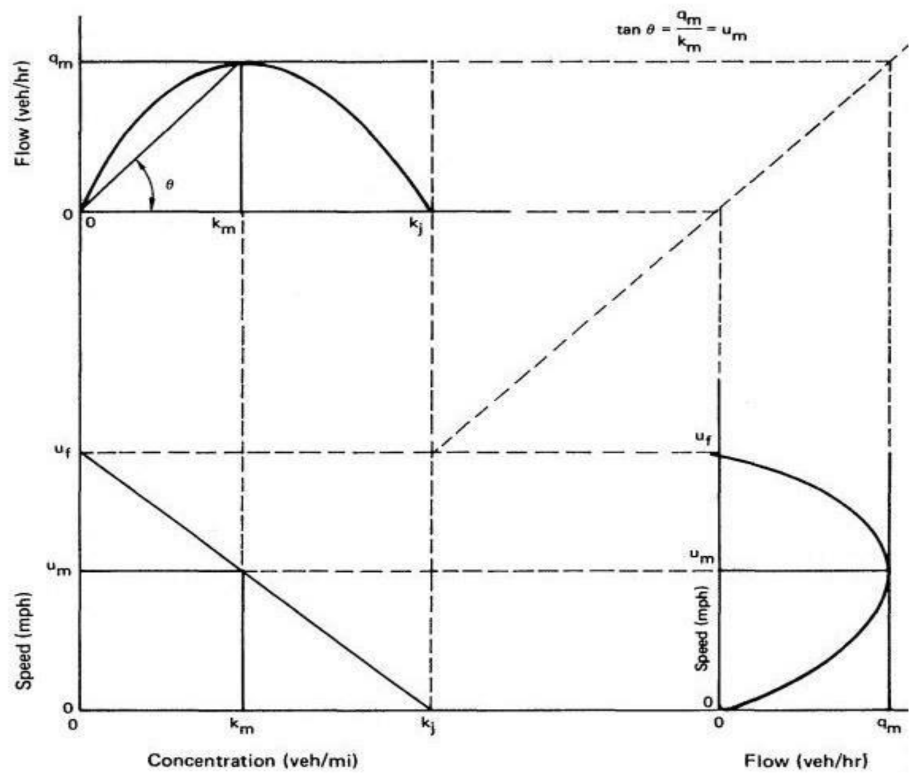


Figure 2.1. Basic Stream Flow diagram (assuming linear speed-density relationship) (Gerlough & Huber, 1975)

2.2.2 Capacity concepts

Capacity can be defined as the maximum sustainable traffic flow a lane group can handle under specific conditions. At signalized intersections, capacity is best defined for individual approaches rather than for intersection as a whole, though capacity can be derived for the whole intersection as whole. Capacity is significantly correlated to the degree of saturation of an approach. Critical lanes—those with the highest traffic demand—determine signal timing, while the critical volume to capacity (v/c) evaluates intersection efficiency. (Garber & Hoel, 2020; CCG, 2008).

National Academies of Sciences, Engineering, and Medicine and others (2022), defines capacity as the sustained maximum flow rate that can be reasonably expected to traverse a given point during a given period under prevailing roadway, traffic, environmental, and control conditions. HCM further mentions capacity as a flow rate that can be achieved repeatedly under the same sets of prevailing conditions rather than being the maximum capacity that can ever be achieved.

Capacity of a whole intersection is not considered; however capacity is meaningfully applied to major movements or approaches. Furthermore, capacity of a signalized intersection is not as strongly correlated to level of service (LoS, defined in the later section) as in other traffic facilities therefore for a holistic operational performance assessment of a signalized intersection capacity and LoS both are assessed separately (Garber & Hoel, 2020). The concept of saturation flow rate is central to the determination of capacity.

Capacity for a lane group (i) or an approach can be found from the equation 2.1 (Garber & Hoel, 2020)

$$c_i = s_i * (g_i/C) \tag{2.1}$$

Where, c_i is capacity, s_i is saturation flow rate, g_i is effective green time, C is cycle length.

The degree of saturation XXX, which measures the sufficiency of capacity to meet demand, can be expressed by the equation 2.2 (Garber & Hoel, 2020):

$$\mathrm{Xi} = (\mathrm{v/c})\mathrm{i} = \mathrm{vi}/(\mathrm{si} * (\mathrm{gi}/\mathrm{C})) \tag{2.2}$$

Critical lane is the lane with the most intense traffic demand not the one with highest volume (Roess et al., 2020).

For capacity calculations purposes, consideration of all of the lanes (basically movements) for green time calculations are not important. In every phase of a signal cycle, there is usually one lane for which the relationship between the arrivals (actual flow) and saturation flow (flow ratio), dictates the green time requirement for the phase. Such lanes are known as the critical lanes and the number of critical lanes for a signal cycle is equal to the number of phases to the cycle. The summation of green time of all the critical lanes of all the signal phases dictates the cycle length. The sum of the critical flow ratios of an intersection is termed as the intersection flow ratio which gives an idea of the quality of the intersection (Teply et al., 2008).

Critical v/c ratio is another key concept in capacity analysis of a signalized intersection, which is calculated for the whole intersection and depends upon the lane groups with maximum flow ratio (v/s). Critical v/c ratio is expressed as equation 2.3:

$$Xc = \Sigma i(v/s)ci * (C/(C - L)) \qquad 2.3$$

Where, $\Sigma_i(v/s)_{ci}$ is the summation of flow ratios for all critical lanes, groups or approaches

C is the cycle length and L the lost time

Critical v/c ratio helps assess overall sufficiency of a signalized intersection with respect to the current traffic demand and geometric designs. A v/c ratio of less than 0.85 suggests adequate capacity and no significant queues. As the v/c ratio approaches 1.0, traffic flow may become unstable and when the v/c ratio is greater than 1.0, traffic flow becomes unstable and is unable to cater for current traffic volume and the queued vehicle might require more than one signal cycle, referred as the cycle failures. Judicial balance of geometric design (road width) and v/c ratio is essential to restrict v/c ratio to less than 1.0, as overdesign might result in issues for pedestrians due to wide crossings, and speeding (Chandler , et al., 2013).

To conclude, capacity at signalized intersections depends upon high demand lanes known as the critical lanes. Capacity of a critical lane is further dependent upon the saturation flow rate. Unlike other facilities, at signalized intersections capacity and LoS are evaluated independently for holistic analysis. Critical v/c ratio helps analyse the sufficiency of a signalized intersection with respect to current traffic demand and geometric designs. Capacity analyses help engineers optimize signal timing and reduce delays, ensuring smoother traffic operations.

2.2.3 Concept of Saturation Flow

Saturation Flow Rate (SFR) can be defined as the maximum rate of flow of vehicles assuming continuous green under the prevailing conditions. Early studies defined SFR as the density at which vehicles move as closely as possible, while later studies showed queues gradually accelerating to a steady discharge rate before slowing during yellow phases. Disagreements exist among transportation agencies about when SFR declines. This section examines the concepts of saturation flow rate, its role in capacity calculations, and its variability across urban and traffic conditions.

Clayton (1941) mentioned SFR as the “Saturation density” (S) and defined it as the traffic flow rate at which vehicles are travelling “as close together as possible” at an intersection during “go” period.

Webster’s research publication in (1958, as cited in Stokes, 1988), showed the departure process of vehicles waiting in a queue which does not clear by the end of green cycle. As illustrated in Figure 2.2, when the light indication changes to green, queue discharge rate steadily increases until time b and attains a steady state queue discharge rate, termed as saturation flow rate for the given approach until light changes to yellow which steadily falls to zero at the end of the yellow interval.

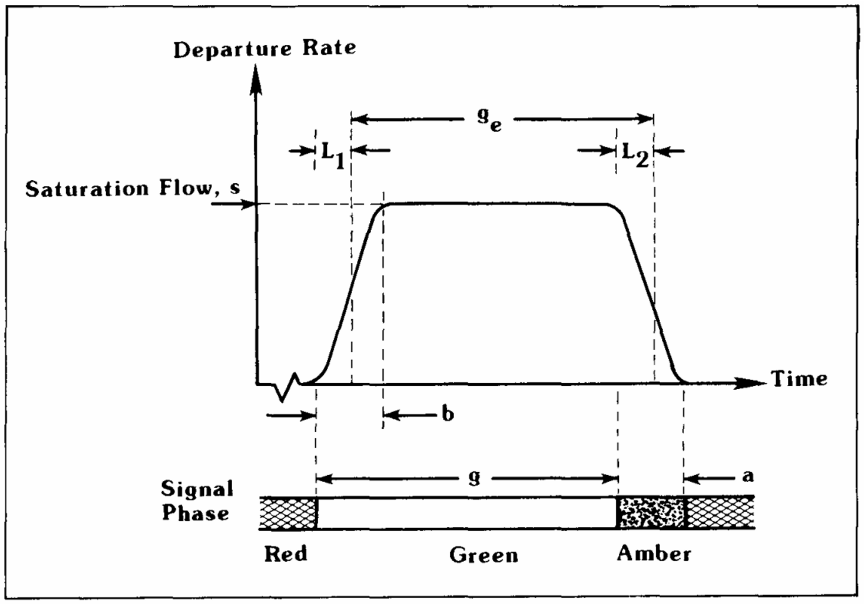


Figure 2.2. Webster's model of traffic signal departure process (Stokes, 1988)

Teply & Jones (1991) reflected the importance of SFR in analysis and design of signalized intersection. The authors compared the definition of SFR by HCM, Canadian Capacity Guide (CCG) and Australian Road Research Board and mentioned SFR as the "uniform service rate" used in queuing theory for capacity calculations. Furthermore, stated that the traditional concept indicates drop of SFR begins after the start of yellow interval as opposed to the CCG concept where the SFR drops after 30 to 50 seconds of green time, as indicated by dashed line in the figure 1.4. The author further mentioned that all the agencies agreed on the variability of the SFR due to different urban, geometric and traffic settings.

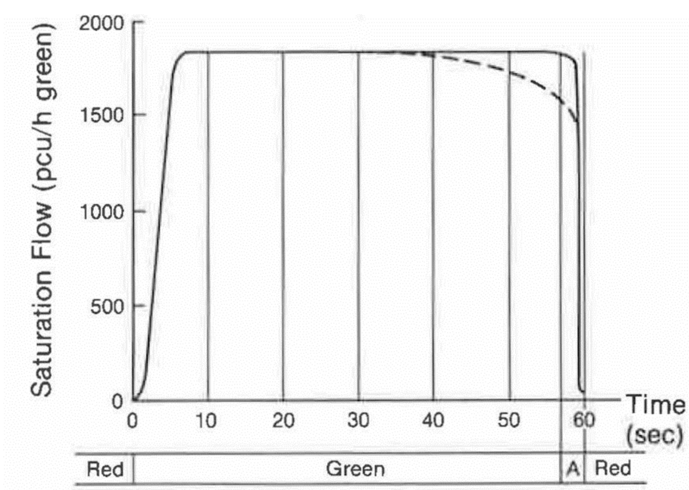


Figure 2.3. Saturation Flow Concept (Teply & Jones, 1991)

To sum up, SFR is critical for evaluating intersection capacity but varies based on definitions and context. While agencies disagree on when SFR declines (during yellow vs. mid-green), they acknowledge its dependence on local factors like road design and traffic mix. Understanding these ensures accurate capacity calculations and effective signal timing, enabling better traffic flow management in diverse settings.

2.2.4 Traffic Flow at Signalized intersections

Traffic flow theory at a signalized intersection deals with the estimation of delay and/or queue length due to the introduction of traffic signal control (Rouphail et al., 2001). These delays stem from signal phase changes, and driver reaction times. This section explains how signal cycles influence traffic movement and how engineers optimize signal timing to reduce congestion.

Traffic flow at a signalised intersection is best described by the Figure 2.4, which depicts a full signal cycle divided into three parts.

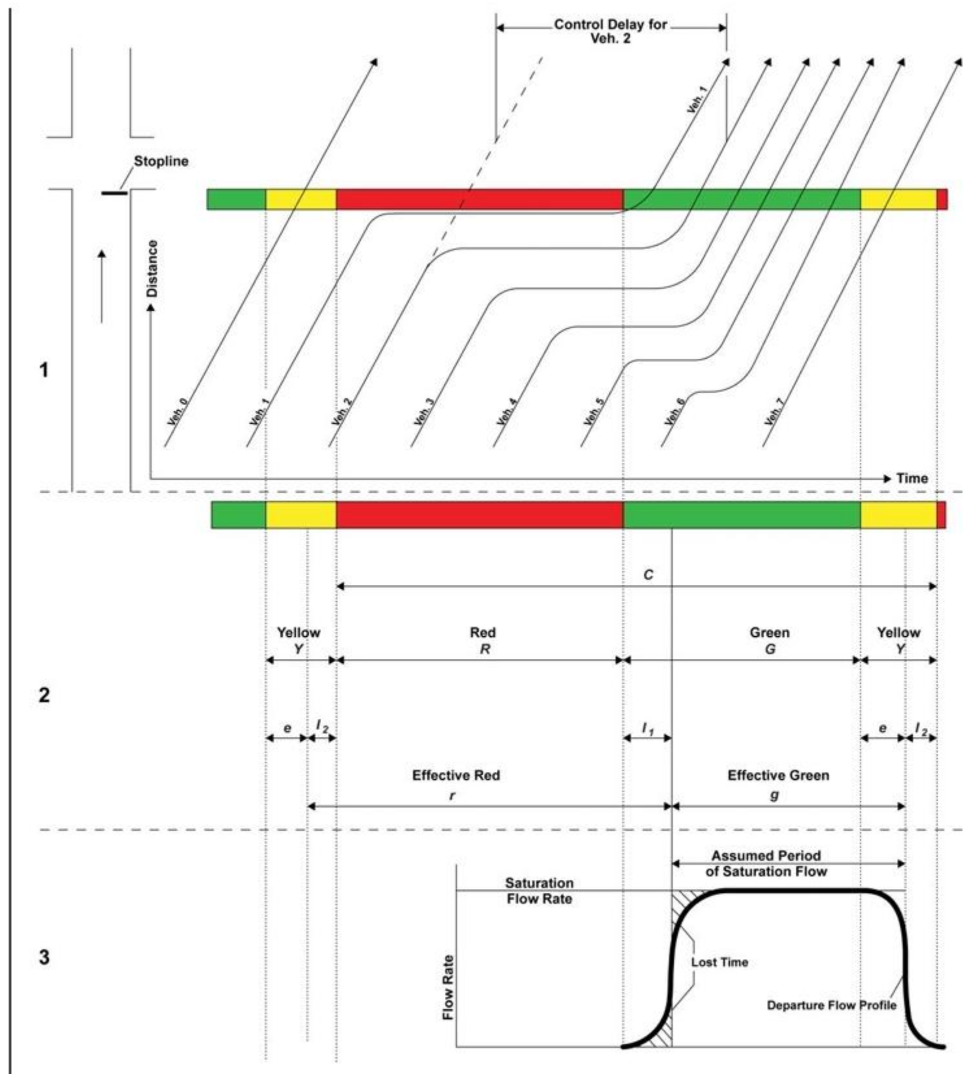


Figure 2.4.Fundamental Attributes of Traffic Flow at Signalized Intersections (HCM, 2022)

The figure depicts the flow of vehicles to an approach for one complete cycle of a signal control intersection.

- First part: the spatio-temporal variation of vehicles approaching to the intersection
- Second part: the yellow, red, and green intervals, which are further broken down into Effective Green and Effective Red times.
- Third part: depicts the flow profile diagram of the flow rate against time.

As illustrated from the figure, when the signal changes from red to green, first few vehicles depart at the headways greater than the saturation headway due to the time to react to the signal change indication and to accelerate to the normal speed. This initial lost time is referred to as the start-up lost time. When the signal changes to yellow from green, initial part of the yellow is used by the vehicles which is referred to as the extension of the effective green and the later part is referred to as the clearance lost time. Total lost time for a phase is sum of start-up lost time and clearance lost time. Effective green time is the time at which vehicles flow effectively at saturation flow rate. While the effective red time is the time at which vehicles do not proceed effectively at saturation flow rate and is calculated as the difference of cycle length and effective green (National Academies of Sciences, Engineering, and Medicine and others, 2022).

To conclude, delays at signalized intersections arise from signal phase changes and driver reaction times. Lost times reduce the effective green time available for traffic movement. By analysing these phases, engineers can optimize signal timing to minimize queues and improve traffic flow, ensuring smoother operation of intersections.

2.2.5 Traffic distributions at signalized intersection

The statistical distribution of traffic counts, headways, and departures holds a paramount importance in traffic flow theory as applied to a signalized intersection. Free-flowing traffic typically follows predictable distributions, while disruptions like signals or congestion alter these patterns. This section examines how traffic conditions—such as undersaturated conditions, oversaturated conditions and transitional states shape statistical models like normal, Poisson, and constant headway distributions. These models help explain how vehicles interact and respond to changing demands, providing a foundation for designing effective traffic control systems.

Adams (1936) made the pioneering practical observations on the probability distribution of road traffic and stated that free flowing traffic can be considered as a random series. Furthermore, the distribution conforms to the “normal distribution” and departures from normal distribution occurs when there is disturbance to free flow as in signalized intersections, sudden change in flow, roadway restrictions, or saturation flow. Also stated the effects of saturation flow on the nature of the distribution might be different.

May (1990) mentioned the Poisson distribution can be used to represent low-flow conditions and single-valued count distribution to represent congested or near capacity conditions for traffic count distributions. May classified the time-headway distributions according to traffic conditions. Under low-flow scenarios—when vehicle interactions are minimal—the distribution follows a negative-exponential form. Near capacity, heavy car-following produces nearly constant headways, modeled by a normal distribution. Between these extremes, an intermediate distribution accounts for mixed conditions in which some vehicles interact while others travel independently.

Overall, statistical models capture how traffic behaves under different boundary and transitional conditions. Free flow aligns with normal distributions, low flows with Poisson, and oversaturated (congestion) with constant headways. May's framework highlights how vehicle interactions shape headway patterns. Understanding these distributions aids in designing accurate traffic models, improving signal timing, and managing disruptions like queues or sudden flow changes effectively.

2.2.6 Queuing analysis

Queuing analysis examines how vehicles accumulate and disperse at signalized intersections due to difference in arrival and departure rates. This section explores deterministic and stochastic methods to model queues, considering factors like arrival patterns (e.g., Poisson), service times, and signal phases. Key concepts include Kendall's (A/B/C) notation for describing queuing systems, the platooning effect (vehicles passing in groups), and upstream filtering (impact of upstream signals on downstream arrivals). These models help quantify delays, queue lengths, and intersection efficiency, forming the basis for optimizing traffic signal operations.

In queuing theory, Kendall's notation (A/B/C) (e.g., M/M/1 for Poisson arrivals, exponential service, single server) is often used to classify intersection approaches. However, real intersection service is non-exponential (deterministic green/discharge), so M/D/1 approximations are common for under-saturated flows.

Little (1961) defined queuing process as a mathematically specified operations in which units arrive, wait and leave.

Miller (1961) made one of the pioneering investigations on queuing theory for road traffic using traffic data collected on a straight section of two-lane road. The study developed a random queue model by studying the distribution of traffic queues or bunches.

Heidemann (1994) analytically deduced the statistical distribution of queue length and delay assuming Poisson arrival process, fixed-time control intersection with a single lane approach.

Queuing occurs when demand flow rate exceeds the capacity or arrival headway is less than the departure headway (May, 1990).

Queuing analysis is often performed with either deterministic approach where arrival and service distributions are deterministic (fixed arrivals/service rates) or with stochastic approach where either or both distributions are probabilistic. Stochastic approach to queue analysis is only possible if the traffic intensity (the ratio of mean arrival to the mean service rate) is less than 1 to achieve steady-states where queues are finite, when the traffic intensity is greater than 1 the queue systems becomes unstable under the stochastic assumptions which leads to indefinite queue growth. Such situations are explained better by the deterministic process, which assumes linear queue growth or by resorting to microscopic simulations which can handle complex, unstable systems better at performing individual vehicles interactions (May, 1990).

May (1990) presented an example of deterministic queuing analysis at a macroscopic level for a signalized intersection with a single approach and 2 phase signal control for undersaturated condition with constant arrival rate (for the study period) and varying service rate (equal to zero for the red interval, equal to SFR (s) for green period when there is a queue and equal to arrival rate when there is no queue during the green). The queue process can be well illustrated with the aid of Figure 2.5.

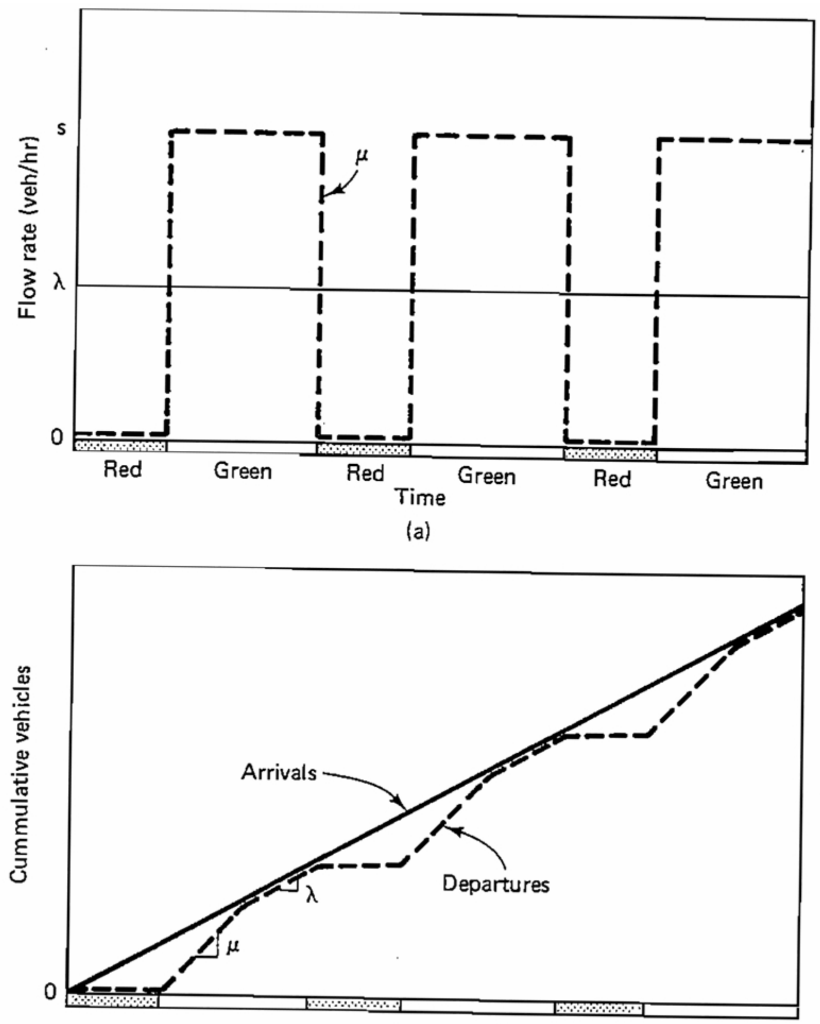


Figure 2.5. Queuing diagram for signalized intersections (May, 1990)

The queue diagram can be used to calculate different performance metrics viz. time duration of queue (t_Q), number of vehicles experiencing the queue (N_Q), queue length (Q), individual delay (d) and total delay (TD).

Two principal observations related to queuing at a signalized intersection as per (Rouphail, et al., 2001) are:

- Vehicles pass intersection in bunches separated by the time equivalent of red interval known as the platooning effect, and
- There is a limit on maximum number of vehicles that can pass the intersection during one signal cycle known as the upstream filtering effect

Rouphail et al., (2001) summarized Pacey's (1956) works on platoon dispersion, which modelled dispersion using travel-time distributions under the assumptions of normally distributed speeds and unrestricted overtaking. Hillier & Rothery, (1967) study of vehicle delays at four downstream locations from a signal showed that delay depends on signal offsets, minimum delay increases substantially as signal separation grows, and signal offset does not affect overflow delay.

National Academies of Sciences, Engineering, and Medicine and others (2022), has made the provision to account for the effect of upstream signalized intersection on the arrivals at the signalized intersection downstream known as upstream filtering adjustment factor "I" which ranges from 0.09 to 1.0 (1.0 for an isolated signalized intersection, at least 0.6 miles from the nearest upstream signalized intersection).

In brief, queuing analysis at signalized intersections relies on deterministic or stochastic models to predict delays and queue dynamics. Deterministic approaches simplify scenarios with fixed arrival rates, while stochastic methods address randomness in traffic. The platooning effect and upstream filtering adjustment factor "I" underscore how signal coordination and spacing influence traffic flow. By applying these principles, engineers refine signal timing, mitigate congestion, and enhance intersection performance, bridging theoretical models with practical traffic management needs.

2.2.7 Shock wave theory at signalized intersection

Shock wave theory explains sudden changes in traffic density and flow caused by signal cycles at signalized intersections thus help to understand traffic dynamics at signalized intersections. These waves form boundaries in time and space, marking shifts between free-flowing and congested states. When signals turn red, stationary shock waves emerge upstream (no vehicles) and backward waves form downstream (jam density). Green signals trigger forward-moving waves as queues dissipate. This section explores how this wave models queue dynamics and intersection efficiency, linking signal changes to traffic behaviour.

May (1990) defines shock wave as a boundary conditions in time-space domain that demarcates a discontinuity in flow-density conditions.

Similarly, Stephanopoulos et al., (1979) defined shock wave as the propagation of abrupt change in density.

Lighthill & Whitham (1955) as cited in Stephanopoulos et al., (1979) stated that at any point of a road, flow is the function of density.
At a signalized intersection when signal changes red from green, dual traffic states are created.

- Upstream of the stop line where there are no vehicles thus zero flow and zero density which results in a frontal stationary shock wave
- Downstream of the stop line where flow is zero and the density is jam density which results in the formation of backward forming shock wave

At the end of the red signal indication, signal changes back to green and the flow downstream of the stop line is saturation flow rate which results in the formation of forward moving shockwave. Similarly, the backward recovery shock wave is formed that dissipates the queue formed. After the complete dissipation of the queue formed, forward moving shock wave is formed May (1990) as illustrated in Figure 2.6.

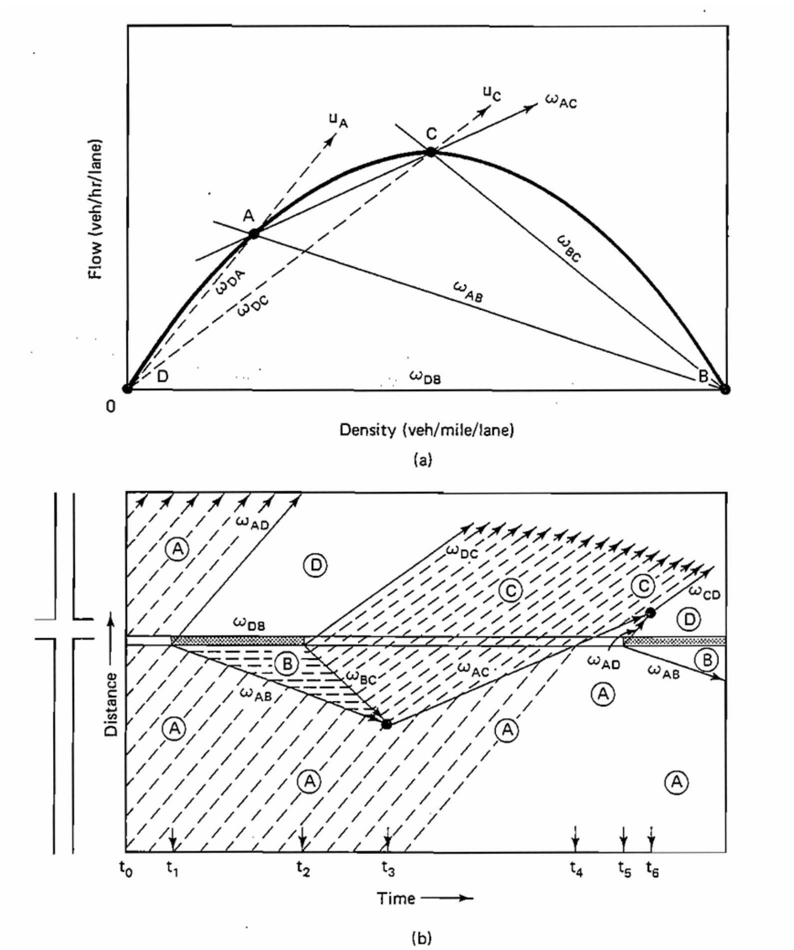


Figure 2.6.Shock wave propagation at signalized intersections (May, 1990).

Stephanopoulos et al., (1979) studied the dynamics of traffic queue at an isolated signalized intersection and employed the shock wave theory to analytically describe and mathematically model the expressions for queue length.

In summary, shock waves capture traffic disruptions caused by signal cycles. Red phases create congestion waves, while green phases generate recovery waves that clear any outstanding queues. By analyzing these patterns—stationary, backward, and forward waves—one can predict queue lengths and optimize signal timing which is useful in congestion management. This theory bridges traffic flow dynamics with practical intersection management, ensuring reduced delays

2.2.8 Concept of Delay

Delay measures the extra time drivers spend at signalized intersections due to traffic signal controls, reflecting both efficiency and user experience. It is a key metric for LoS as it quantifies wasted travel time, fuel costs, and driver frustration. The highway capacity manual defines delay as the difference between actual travel time and an ideal "target speed" scenario. While critical for intersection evaluation, delay estimation faces challenges due to unpredictable traffic patterns and complex interactions between vehicles.

Delay is used as a primary performance measure of LoS at a signalized intersection as it can be measured and easily understood by both technical and non-technical audiences. It has economic worth but involves computationally intense analytical methods for estimation (Hurdle, 1984).

Akgungor & Bullen (1999) identified delay as the most important performance measure of signalized intersection as it relates to the amount of lost travel time, fuel consumption, frustration, and discomfort of drivers. Furthermore, the author mentioned the accurate estimation of delay is difficult because of inherent randomness of traffic flows and other uncontrollable factors.

National Academies of Sciences, Engineering, and Medicine and others (2022), defines delay as the difference between actual travel time and an idealized travel time at ‘target/desired speed’. Target time is subject to a number of definitions which are:

- free-flow speed (ffs),
- vehicle’s target speed (a function of ffs),
- prevailing road conditions,
- driver’s characteristics, and
- travel time without traffic control which is used to establish the control delay.

Delay can be illustrated as in Figure 2.7, referring to the trajectory:

- T_0 is the time at which a vehicle would have arrived at the stop line had it been travelling at target speed,
- T_1 the time had it been travelling at running speed which is usually less than the target speed due to traffic interactions, and

- T_2 the vehicle is discharged at the stop line

Types of delay based on vehicle trajectory are:

- Control delay = Total delay – Traffic intersection delay, is the additional travel time due to a traffic control system, used for LoS calculations as per HCM methodology,
- Stopped delay represents the time vehicle was actually stopped, and
- Queue delay, the time the vehicle spent in queued state before reaching the stop line

Another useful delay terminology is the segment delay calculated as (T_2- T_0), which reflects the delay experienced by each vehicle since leaving the upstream signal. Segment delay is commonly used by simulation tools. Segment delay includes the control delay and delays due to traffic interactions.

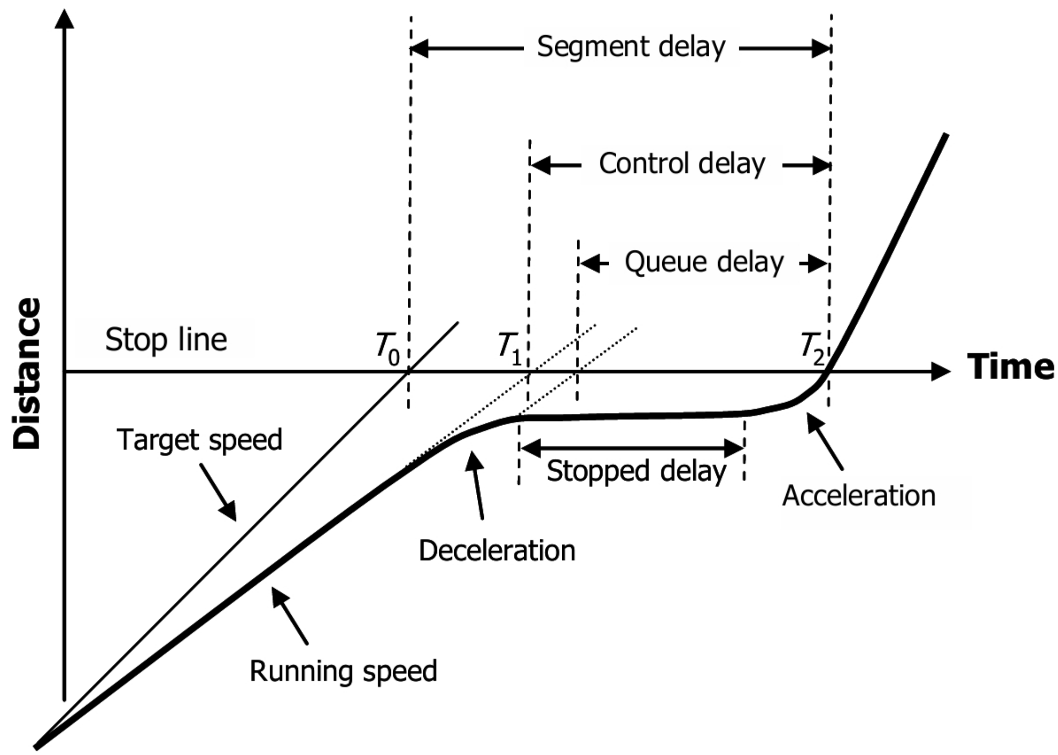


Figure 2.7. Delay terms (Highway Capacity Manual, 2022)

In short, delay captures the operational inefficiencies of signalized intersections through measurable time losses. Control delay is used for LoS assessments, while stopped delay, and queue delay each highlight different aspects of driver experience, from signal responsiveness to queue management.

2.2.9 Delay Models

Traffic flow theory applied to a signalized intersections focusses on estimation of delays which is the result of signal control at the intersection (Rouphail, et al., 2001). Delay at signalized intersections can be described by two components: deterministic and stochastic. Delay models can be classified into steady-state and time dependent delay models. Analytical models further break down delays into uniform, random, and overflow components. Actuated and adaptive control systems add complexity by linking signal timing to real-time traffic demands, requiring tailored delay estimation methods.

Rouphail et al. (2001) classified delay models into steady-state models and time-dependent models. Steady-state delay models are valid until average arrival rate does not exceed average capacity rate and the system is believed to function at stochastic equilibrium whereby queues and delays are finite and can be estimated using the steady-state queuing theory. Such models are better suited for undersaturated conditions. However, when the arrival rate exceeds the capacity rate, oversaturated conditions prevail and stochastic equilibrium ceases to exist. Another limitation of the steady-state delay model as pinpointed by the author is the assumption of arrival distributions at signals, as the assumption does not address the impact of upstream signals which may alter the arrival at the downstream intersections.

2.2.10 Delay models at an isolated intersection

Delay of an isolated intersection can be described by deterministic component and stochastic components. Deterministic component is founded in the fluid flow theory, where demand and service are treated as continuous variables (flow rates) which varies in time-space domain. Stochastic component is based on steady-state queuing theory which defines the arrival and departure distributions and captures the inherent randomness of traffic flows. Deterministic component is derived assuming:

- zero initial queue at the start of the green phase,
- uniform arrival pattern at the arrival flow rate (q) throughout the cycle,
- uniform departure at the saturation flow rate (S) while a queue is present, and departure at the arrival rate when the queue vanishes, and
- arrivals do not exceed the signal capacity

The area under the queue profile gives the total deterministic delay (cyclic delay) as illustrated in Figure 2.8. Following performance metrics can be derived from the flow profile diagram, Figure 2.8.

- average delay per vehicle (total delay divided by total cyclic arrivals),
- the number of vehicle stopped (Q_s),
- the maximum number of vehicles in the queue (Q_{max}) , and
- the average queue length (Q_{avg})

Such models works for under-saturated conditions (v/c < 0.5) due to conservative assumptions like zero initial queue and zero end queue (no overflows). As flow increases, cyclic failure occurs and resulting in additional queue and thus additional delay which can be explained using queuing theory. Further increase in flows creates highly oversaturated conditions which can be explained by fluid flow approach. This leave gaps in delay models for traffic flows at capacity (v/c ~ 1.0), which can be explained by time-dependent models Rouphail et al. (2001).

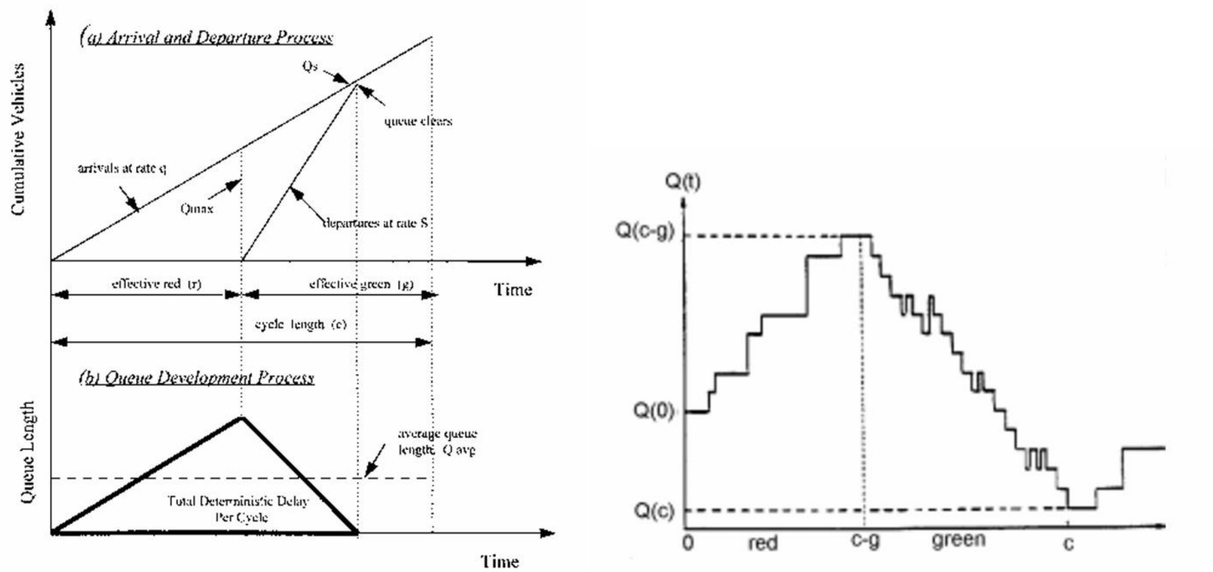


Figure 2.8.Deterministic Components and Queuing process at a single cycle (Rouphail et al., 2001)

Steady-state delay models are further sub-divided into exact expressions models and approximate models. In exact expressions models, delays are based upon the statistical distributions of arrival and departures. Notable research on this approach are made by (McNeil, 1968) who derived signal delay assuming general arrival process and constant departure but would require the average size of overflow queue therefore not a closed-form analytical estimate, (Darroch, 1964a) used a more general arrival distribution also not a closed expression of queue length. The difficulty in obtaining the exact delay expressions that is of practical use gave rise to the approximate models. Notable works by (Webster, 1958), the first classical work on estimating delay (an approximate and analytical model) consists of uniform delay term, random delay and corrective term and (Miller, 1963) estimated average overflow queue and assumed general arrival and general departure process are the examples of analytical or approximate models as cited Rouphail et al. (2001).

Time dependent delay models represent arrival and departure rates as the function of time in some deterministic way or assume arrival and departure as stationery but not necessarily under stochastic equilibrium Rouphail et al. (2001).

Australian delay model (developed by Akcelik), Canadian delay model (developed by Whiting) and HCM model are examples of time dependent delay models as cited in (Akgungor & Bullen, 1999).

Delay models for actuated controllers are based on assumptions made upon arrival process but are bound by actuated control parameters, the distribution of headways impact the green time allocated to an actuated phase and control parameters also constrain the green times. In contrast to the fixed control system, for actuated control there is an additional requirement of estimation of expected signal phase length (Rouphail et al., 2001). Further mentioned theoretical works of traffic performance estimation for adaptive control is limited with problem in estimation of initial queue in current interval.

In summary, delay models use two main approaches: deterministic (simple, fixed traffic patterns) and stochastic (accounts for random traffic changes). Steady-state delay models assume stochastic equilibrium, and stable conditions and use queuing theory to account random delays. Time-dependent models combines both approaches to explain traffic flows at varying v/c ratios. However, modern traffic signals (actuated, adaptive) make delay modelling harder due to complex traffic dynamics posed by adjacent signals, overflow queues etc.

2.2.11 Quality of service concepts

LoS evaluates how efficiently transportation facilities operate from a user's perspective, translating complex performance data into simple ratings. For signalized intersections, key performance indicators:

- control delay,
- volume-to-capacity (v/c) ratios, and
- Queue lengths

The Highway Capacity Manual focuses on vehicular LoS but also addresses pedestrian and bicycle needs through delay and circulation metrics. Other jurisdictions, like Austroads and the Canadian Capacity Guide (CCG), prioritize measures such as Degree of Saturation or v/c ratios while advocating for multimodal assessments. Despite its utility, LoS traditionally excludes safety considerations, though evolving research integrates user perceptions and broader factors like environmental impact.

Quality of service describes how well a transportation facility/service is operating as perceived by travellers. LoS is a quantitative stratification of performance/service measures that represents quality of service of a given transportation facility/service. Performance or service measures are used to determine LoS for a given facility that should be field measurable, represent traveller's perceptions, estimable for given conditions and usable. HCM defines six levels of service ranging from A to F, LoS A representing best operating conditions while LoS F the worst. LoS translates complex numerical performance values into a simple system easily understandable by practitioners, policy makers and public National Academies of Sciences, Engineering, and Medicine and others (2022).

LoS of an entire intersection, an intersection approach, or a lane group can be evaluated. Performance measures applicable to the vehicular travel mode for a signalized intersections are control delay, v/c ratio and queue storage ratio. HCM uses control delay as a primary performance measure to characterize an entire intersection or an approach while uses control delay and v/c ratio for an intersection lane group, as illustrated in table below. HCM has developed a calculation framework for performance evaluation of signalized intersection (motorized vehicle mode) based upon the critical movement analysis.

Table 2.1. LoS criteria for intersections (vehicular mode) (HCM, 2022)

Control Delay (s/veh)	LOS by Volume-to-Capacity Ratio[a]	
	≤ 1.0	>1.0
≤ 10	A	F
>10 - 20	B	F
>20 - 35	C	F
>35 - 55	D	F
>55 - 80	E	F
>80	F	F

Note: [a]For approach-based and intersection-wide assessments, LOS is defined solely by control delay.

National Academies of Sciences, Engineering, and Medicine and others (2022) allows for evaluation of quality of service as perceived by pedestrians and bicycle travel modes as well based on the delay, LoS scores, and circulation areas for pedestrians and LoS scores and delay for bicycle travel mode. In this way, HCM has defined different performance measures for different transport facilities and for different traveller modes and hence allows for multimodal mobility analysis.

Austroads (2020) has mentioned degree of saturation as the basic measure of signalized intersection performance for and has defined it as the largest of the individual movement degrees of saturation (DoS). Austroads defines the dos of a signalized approach as the ratio of demand to capacity of the approach during the same period. Furthermore, Austroads has indicated the target DoS for a signalized intersection as 0.9 also known as “practical DoS”. Austroads has further mentioned delay, number of stops (stop rate) and queue length (back-of-queue) as other performance measures.

Austroads also includes a Quality of Service framework for pedestrians, cyclists, transit users, and freight operators. This framework evaluates multiple dimensions—mobility, safety, access, information, and amenity—using both objective and subjective measures. Unlike the HCM’s purely quantitative approach, Austroads’ methodology accommodates qualitative and semi-qualitative assessments, enabling a comprehensive multi-modal LoS evaluation.

Level of service for a signalized intersection is implied as a qualitative measure of traffic flow at an intersection which depends upon the vehicle throughput Teply et al., (2008). Canadian Capacity

Guide for signalized intersection, 2008 (CCG) has listed relevant measures of effectiveness (MoE) of a signalized intersection broadly in three categories:

- Capacity related (capacity, degree of saturation, probability of discharge overload);
- Queuing related (delay, number of stops and queue length); and
- Environmental and operational related (fuel consumption, cost, and emissions).

CCG has emphasized on the use of v/c ratio as a primary performance measure of signalized intersection. As per the CCG, v/c ratio provides a discreet, definitive value and provides a clearer picture of traffic utilization and provides available intersection capacity independent of time, location, user as compared to control delay. CCG mentions the assessment of both v/c ratio and delay is necessary to evaluate the operational performance of a signalized intersection though has placed the v/c ratio as a primary measure of effectiveness.

Chakroborty & Kikuchi, (1990) mentioned LoS as a subjective and perceived measure and relating a specific LoS to a specific condition with absolute certainty is a difficult task.

Concept of LoS is ever evolving. Many researchers have long tried to incorporate user perceptions to define LoS for a given facility. Researchers have also built LoS indicator based upon safety, combination of control delay and safety index (Zhang & Prevedouros, 2003), combination of control delay and risk index Pan et al., (2008) and some researchers even have expanded the six LoS to nine or more. One of the pioneering study on user perceptions LoS on signalized intersections was made by (Sutaria & Haynes, 1977) as cited in (Othayoth, et al., 2020).

Summing up, LoS provides a standardized way to assess intersection performance using quantifiable metrics like delay and v/c ratios. While HCM emphasizes vehicular efficiency in terms of throughput, frameworks like Austroads and CCG expand evaluations to include multimodal needs and practical saturation thresholds. Current limitations -- such as the exclusion of safety, as noted by (Chandler , et al., 2013), where safety is not reflected or implied in the LoS concept, user perceptions, environmental impacts are being addressed through evolving methodologies that incorporate user feedback and composite indices.

2.2.12 Traffic Signal Systems

Traffic signal systems are broadly classified as pre-timed signal control and actuated signal control systems. A pre-timed signal system consists of pre-set traffic signal parameters for operation while an actuated signal control consists of pre-defined phase plans which are activated based on the local demand.

As the name suggests, a pre-timed signal control system consists of fixed phase sequence and phase duration each cycle and constant cycle length, which are repeated after completion of each cycle in pre-set settings. Green interval can be varied to accommodate the traffic variations by time of the day or day of a week. The operation of a pre-timed control can be coordinated or not coordinated.

Actuated signal control consists of defined phase sequences which are activated based upon the local demand for the associated phases via detectors. Duration of green is based upon the traffic demand obtained from the detector subject to the pre-set minimum and maximum green limits. Termination of the ongoing phase is based upon the maximum limit or call from the conflicting movements. An actuated phase may be skipped as well if there is no demand which is known as the variable phase. Actuated signal control can be a semi-actuated where detectors are placed only on minor movements while major movements are always given green unless a “call” from the minor movement is detected. An actuated control can also be fully-actuated where all movements are detected and the duration and sequence of each phase are based upon the actual traffic demand. Actuated form of signal control provides the maximum flexibility of operation which is adaptive to the local demand.

Signal coordination synchronizes traffic signals along a corridor to create a continuous green wave also known as the “green- wave progression” enable vehicles to pass through multiple intersections with minimal stops. It is illustrated in Figure 2.9. Signal coordination relies on three core signal parameters: cycle length, offset, and bandwidth which are fixed and pre-timed. Offset is the time difference between the start of green phase at an intersection and the next whereas bandwidth is the duration of green time allocated in the main direction to allow continuous flow. This is achieved through strategies like simultaneous progression (all signals turning green at once for short corridors) or alternate progression (staggered greens for longer routes), with flexible progression allowing dynamic adjustments for peak traffic variations. The benefits of coordinating nearby intersections (signals) include reduced stops, lower fuel consumption, and predictable travel times. While effective for stable, predictable traffic patterns, it is less suited for highly variable conditions, where adaptive or real-time systems may perform better (Roess, et al., 2020).

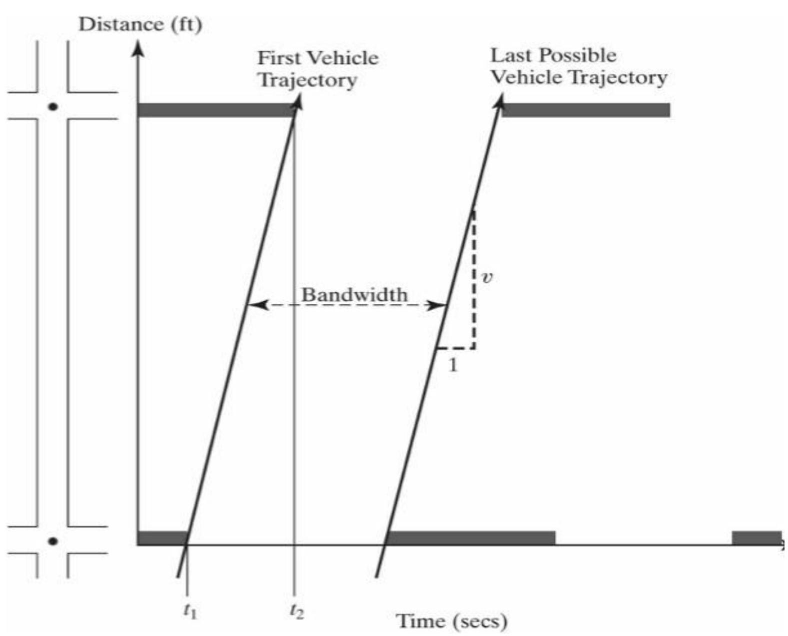


Figure 2.9. Illustrative vehicle trajectory on a Time-Space diagram (Roess, et al., 2020)

2.2.13 ATSCS

ATSCS automatically adjust signal timings in real-time based on current traffic conditions. They use traffic detectors and advanced algorithms to optimise cycle length, green splits (phase splits), and offsets. Adaptive systems are effective in managing congestion and varying traffic patterns throughout the day. ATSCS systems are designed to respond quickly to changes in traffic demand but also to avoid unstable or unnecessary changes. They aim to make small adjustments regularly, which keeps the system balanced and smooth. By working on a cycle-by-cycle basis, these systems can adapt to both short-term traffic conditions and longer-term trends throughout the day. These systems are used in many parts of the world and differ in how they work and how advanced they are. Some are simple, and others can respond to real-time traffic changes. Some well-known ATSCSs are described below.

The Split Cycle Offset Optimization Technique (SCOOT) is a fully adaptive urban traffic control system developed in the United Kingdom's Transport Research Laboratory (TRL) basically designed to manage traffic signals dynamically based on prevailing traffic conditions. Developed to overcome the rigidity of fixed-time plans and the limitations of traditional responsive systems, SCOOT continuously monitors traffic flow through vehicle detectors placed upstream of intersections i.e. mid-block detection. These detectors provide updated flow data every few seconds, allowing the system to respond on a cycle-by-cycle basis. Unlike pre-timed systems that rely on historic data or periodic updates, SCOOT operates in real time, ensuring that signal timings reflect current demand and reduce unnecessary delays and stops (TRL Limited, 2024).

SCOOT continuously seeks to reduce a performance index—usually the combined total of average queues and vehicle stops—by fine-tuning three key parameters at each cycle: overall cycle length, green-time allocation (splits) for each phase and the offsets that synchronise neighbouring intersections. Detector loops installed mid-block feed traffic counts that SCOOT converts into cyclic-flow profiles (CFPs), histograms depicting how demand varies throughout the cycle. Using these CFPs, the algorithm first estimates stop-line queues to adjust offsets, then calculates the split plan and cycle length that minimise the chosen performance index. Despite, SCOOT does not take random variations in traffic flows to improve the performance (Sadek, 2015).

Microprocessor Optimised Vehicle Actuation (MOVA) is an advanced traffic signal control method designed to improve upon traditional Vehicle Actuation (VA). It is more responsive to real-time traffic conditions and helps increase junction capacity by assessing traffic on all approaches and allocating green time to maximise flow. One key issue with VA systems is detector failure, which can cause incorrect signal timings and delays. MOVA addresses this by using a detector layout that allows backup from nearby detectors, offering more reliable performance. It is widely used at isolated intersections (TRL website, 2025).

The Real-time Hierarchical Optimized Distributed Effective System (RHODES) is an adaptive traffic signal control framework designed to enhance the operational efficiency of urban road networks through real-time prediction and optimization. Unlike conventional reactive systems, RHODES incorporates short-term traffic forecasting to anticipate future demand and proactively adjust signal timings. The architecture of RHODES is hierarchical, consisting of central-level and local-level of controls. The central control deals with network-wide optimization, while at the local level, each intersection has its own controller capable of adjusting signal phases based upon local demands in real time. This structure allows for decentralized execution of control strategies while maintaining overall system coordination. A key feature of RHODES is its use of predictive models that estimate vehicle arrival times and traffic volumes by processing data from real-time traffic detectors. These predictions inform optimization algorithms that dynamically calculate the best sequence and duration of green phases to minimize delays and improve traffic flow. The system is modular and scalable, allowing it to be applied to individual intersections or expanded to larger networks as needed. Overall, RHODES offers a balanced combination of centralized coordination and local adaptability, supported by real-time predictive capabilities that make it well-suited for complex and dynamic traffic environments (Sadek, 2015).

UTOPIA (Urban Traffic Optimization by Integrated Automation) is a third-generation adaptive traffic control system developed in Italy, designed with a hierarchical, distributed structure to improve real-time urban traffic signal coordination. It consists of a central subsystem that manages broader functions like traffic forecasting and adaptive coordination, and a local SPOT (Signal Priority Optimization Technique) controllers at each intersection, which optimize phase sequences and durations based on detector data and coordination inputs. UTOPIA also includes integrated modules for system diagnostics, data monitoring, and public transport priority, enabling it to adapt to changing traffic conditions while enhancing bus and tram operations (Pavleski, et al., 2017).

Despite their responsiveness, ATSCSs like SCOOT and SCATS do not anticipate short-term fluctuations (e.g., special event surges). Furthermore, they lack a forecasting module, often leaving them either over- or under-scaled for the next cycle. This motivates the ML approach in Chapter 5 to predict delay/cycle adjustments one cycle ahead.

2.2.14 SCATS

Sydney Coordinated Adaptive Traffic System (SCATS) is an area-wide intelligent real-time traffic control system developed by the Roads and Traffic Authority (RTA), New South Wales Government to manage signalized intersections based on prevailing traffic conditions. SCATS is an adaptive traffic control system, based upon heuristic and rule-based control algorithm which collects real-time data from inductive loops, radar, or video to measure traffic volume and occupancy, and accordingly adjusts the cycle length, phase split, and offset every signal cycle. The system consists of four main components: Central Manager, Region, Access, and TRAFF (a controller firmware in the local intersection to ensure safe signal operation regardless the status of the central manager) which work together to monitor, control, and optimise signal operations. SCATS continuously adapts to traffic demand without requiring manual intervention or periodic surveys and can be configured to operate in different modes based on time of day, holidays, or special events (Transport for NSW, brochure).

2.2.14.1 SCATS Operational Philosophy (Lowrie, 1992)

SCATS works in real-time to control traffic signals. The main aim is to reduce stops and delays and keep traffic flowing smoothly, especially when traffic demand gets high.

Traditional systems use fixed-time plans that are prepared based on past traffic surveys and patterns. These plans are not good when traffic is unpredictable and traffic itself is a random variable. SCATS works differently. It uses data from detectors on roads and changes signal timings automatically to match the current traffic situation. So, there is no need for manual updates or regular surveys.

SCATS controls the signals at two levels. One is called strategic control, which decides the overall timing for a group of intersections. The other is tactical control, which works at the local intersection level. Tactical control helps in ending a green light early or skipping it if there are no vehicles waiting. This helps in saving time in each cycle.

The system uses a parameter called "SCATS degree of saturation (DS)". The SCATS DS is the ratio of effectively used green time to the total green time on the approach which gives an idea of the efficiency of green time usage. If the green light is not used efficiently, it is counted as wasted time. SCATS tries to keep the DS value around 0.9, which means the green light is being used close to full capacity. When traffic becomes heavy, SCATS increases the cycle time to allow more vehicles to pass.

SCATS can group intersections into smaller parts called sub-systems. These can work together or separately based on how traffic is moving. If traffic between two sub-systems is low, they can run at different cycle times. If it's high, SCATS links them again to keep them coordinated.

Tactical control also helps a lot at the intersection level. For example, if there is no vehicle on a side road, that phase can be skipped. Or if there are only a few vehicles, the green can end early. But the main road phase is always kept fixed so that all intersections in the system stay in sync.

In summary, the philosophy of SCATS is based on real-time responsiveness and flexibility. It avoids relying on pre-timed traffic plans. Instead, it adjusts the traffic phase continuously using actual traffic data. This allows the system to improve traffic flow, reduce delays, and respond better to both normal and unexpected traffic conditions.

While SCATS is widely used as an adaptive traffic control system, (Pavleski, et al., 2017) clearly mentions that adaptive systems like SCATS cannot always provide an optimal solution in every traffic scenario. This limitation becomes especially apparent in corridors or more complex urban traffic networks, where real-time responsiveness may not be enough to handle unpredictable or highly variable traffic patterns.

As, Tang, et al., (2020) observed in four-leg intersections, SCATS can reduce delay but occasionally increases angle-type crashes due to more unpredictable phase sequences.

2.2.15 Transportation Modelling

Transportation modelling provides a structured framework for analysing and improving traffic systems, encompassing model types that range from **macroscopic** (aggregate flows over large areas) to **microscopic** (individual vehicle interactions), with **mesoscopic**, **hybrid**, **nanosimulation**, and **intersection-level** approaches filling the spectrum in between. Selecting the appropriate model follows a staged process of:

- defining project goals,
- confirming the need for simulation,
- scoping the network elements to include, and
- matching model granularity to analytical requirements

Microsimulation is favoured for detailed intersection analysis and macroscopic models for regional planning.

Implementation proceeds through **scoping** (establishing spatial and temporal bounds), **calibration** (tuning parameters such as saturation flow, headways and driver behaviour to match observed performance within ±5 %), and **validation** (testing against independent datasets using statistical confidence limits or hypothesis tests to ensure generalizability).

These steps yield a **base model**—a digital twin of existing conditions—that serves both as a benchmark and as the foundation for scenario analysis. While powerful, all traffic models carry uncertainties from input errors, estimation biases and specification gaps; practitioners mitigate these through sensitivity analysis, rigorous auditing and clear documentation of limitations.

The concise explanation above is adapted from Austroads (2020); for an in-depth understanding, please refer to the guideline, *Guide to Traffic Management Part 3: Transport Study and Analysis Methods* by the same author.

2.2.16 SIDRA (Signalized & Unsignalized Intersection Design and Research Aid) Intersection Software

SIDRA Intersection is a lane-based micro-analytical model to aid traffic performance analysis for complex intersections, road networks and alternative intersection designs. As a micro-analytical traffic evaluation tool, SIDRA uses lane-by-lane and vehicle path (drive-cycle) models. It uses iterative approximation methods to estimate capacity, delays, queue lengths, and stop rates. Inputs and outputs are based on Origin-Destination movements, improving accuracy for intersections with diagonal legs or U-turns (SIDRA Solutions, 2025).

The software includes calibration tools for local conditions, offering custom user setups, and sensitivity analysis to test parameter variations (e.g., signal timings). Calibration techniques, including survey methods, are detailed in the User Guide (SIDRA Intersection User Guide for Version 8, 2018).

Austroads (2020) has listed SIDRA Intersection as one of the package for single intersection modelling and has suggested the software as one of the best and commonly used tool for signal timing calculations, capacity, delay analysis and queue lengths computations of a signalized intersection.

2.2.16.1 Benefits of SIDRA INTERSECTION Software (SIDRA Intersection User Guide, Version 8, 2018)

- Unique lane-based analytical model for precise traffic flow analysis and congestion management.
- Environmental impact assessment with energy and emission models calibrated for modern vehicles.
- Automated capacity analysis for sign-controlled intersections and vehicle bunching effects at roundabouts.
- Advanced signal coordination optimizing timings, cycle times, and offsets with queue spillback consideration.
- Support for Common Control Groups (multiple intersections under a single controller).
- Platoon and network analysis to enhance signal coordination efficiency through vehicle movement tracking.
- Compatibility with global systems like SCATS for route-based signal coordination plans.
- Economic and community benefits through reduced delays, fuel consumption
- SIDRA demonstrates strong alignment between predicted control delays and field-observed data, as validated by (Al-Omari & Ta'amneh, 2007) as cited in (Al-Medath & Al-Mukaram, 2025).

2.2.16.2 Limitations of SIDRA INTERSECTION Software

- Calibration and Validation Demands: SIDRA requires extensive calibration and validation to accurately simulate intelligent transport systems (ITS) and mixed-traffic conditions, which can be resource-intensive (Al-Medath & Al-Mukaram, 2025)
- Red-Light Violation Modelling: The software does not account for driver behavior in "dilemma zones" during yellow-to-red signal transitions, limiting its ability to predict red-light violations (Al-Mukaram, 2018) as cited in (Al-Medath & Al-Mukaram, 2025).

2.2.17 Sustainability Aspects in SCATS controlled Signalized Intersections

The paper, (Chong-White, et al., 2013) evaluates the performance of SCATS. The SatE study (The Evolution of the SCATS and the Environment) aimed to quantify SCATS' transport, environmental, and economic benefits by comparing its adaptive master-link mode (full strategic and tactical control) against its fall-back mode (a simplified control method activated during system faults). Researchers employed SCATSIM (a software that allows a SCATS system to be linked to Traffic Micro simulator), to model scenarios using software like Commuter and Q-Paramics. Initial challenges in the pilot study (e.g., unrealistic delays due to phase configuration errors and incomplete trip reporting) led to refinements in the main study, which reduced the model scope to 7 intersections. The study incorporated 24-hour calibration, and used real-world data (e.g., electronic toll tags, GPS bus dwell times). Results showed master-link mode reduced total travel time by 45%, stops by 29%, and CO2 emissions by 17% compared to fall-back mode operations. The study also highlights the importance of the experimental design, including managing edge effects and SCATS dependencies (e.g., subsystem coordination), to ensure accurate simulation outcomes.

Dutta, et al., (2010) evaluates the safety performance of the Sydney Coordinated Adaptive Traffic System (SCATS) compared to Pre-timed signals using crash data (1999–2008) from two corridors in Michigan: M-59 (SCATS-controlled) and Dixie Highway (Pre-timed). The authors analysed various crash severity (Fatal, Injury types A, B, C, and Property Damage Only (PDO)) and computed crash rates per vehicle miles and intersections. Key findings include a shift from severe (A/B) to less severe (C) crashes post-SCATS installation and a 16.8% reduction in total crashes per mile. However, statistical tests (t-tests, 95% confidence) found no significant differences between SCATS and pre-timed systems except for severity B reductions. Economic analysis revealed SCATS costs nearly double the pre-timed systems, though potential savings from reduced crash severity were noted. The paper highlights insufficient statistical significance in most comparisons, reliance on historical crash data without controlling for external factors (e.g., driver behaviour), and a narrow focus on two corridors as limitations. The study highlights the SCATS' potential to mitigate crash severity but calls for further research to confirm its economic viability and broader safety impacts.

As per (Transport for NSW), TfNSW, SCATS Core enhances traffic performance by creating smoother traffic flow, which helps lower vehicle emissions and improve air quality. TfNSW claims the SCATS can reduce carbon dioxide by 6%, nitric oxide by 5%, and particulate matter (PM10) by 10%. Additionally, SCATS improves reliability and efficiency, leading to a 28% reduction in travel time, 25% fewer stops, 12% less fuel consumption, and a 15% drop in overall emissions.

In summary, SCATS contributes to the sustainability of signalized intersections by reducing fatal crashes, lowering gas emissions and fuel consumption, improving air quality, and decreasing travel times.

2.2.18 Transport Modelling in New Zealand

In New Zealand, there are currently no detailed national standards for traffic modelling except for general guidelines provided by local councils (e.g. the Requirements for Traffic Signals Design by Tauranga Transport Operations Centre) and the "Transport Model Development Guidelines" (TMD) from the New Zealand Transport Agency (NZTA). These existing guidelines offer basic advice for projects like designing roads, managing traffic, or planning public transport systems. However, these guidelines do not cover complex scenario. For example, while the Transport Model Development Guidelines include some instructions for intersection modelling (e.g., checking traffic counts and travel times), there are no specific nationwide rules for more complex scenarios. This means professionals often rely on these limited guidelines, Austroads or adapt to engineering practices.

2.2.18.1 Transport Model Development Guidelines

The TMD Guidelines provides a structured approach for developing and validating transport models in New Zealand. The document focuses on ensuring models accurately represent real-world traffic conditions and are suitable for their intended purposes, such as infrastructure planning, traffic management, or evaluating policy changes. Key sections from the guidelines outline how to compare observed data (e.g., traffic counts, travel times) with modelled outputs during calibration and validation. For example, models are categorized by purpose, such as regional assessments (Category A) or intersection/short corridor analysis (Category F), with specific criteria for each.

Intersection modelling (Category F) requires rigorous checks, such as ensuring 95% of turning movements meet the GEH statistic threshold, a statistical tool to represent goodness-of-fit of a model, and that traffic volumes fall within defined count bands. The guidelines emphasize flexibility, noting that meeting numerical targets does not guarantee a model is reliable; professional judgment is essential. The document also highlights the importance of balancing calibration accuracy with maintaining a model's ability to predict future scenarios, such as traffic growth or new infrastructure impacts.

While the guidelines provide a framework for common modelling tasks, they acknowledge limitations, such as the lack of detailed rules for highly specialized or complex traffic scenarios.

In summary, the *TMD Guidelines* emphasizes the critical importance of rigorous calibration and validation processes in intersection modelling to ensure accurate representation of real-world traffic dynamics. For intersections (Purpose Type F), the document emphasizes precision in capturing turning movements, queue lengths, and delays through targeted comparisons with observed data, such as GEH statistics, count bands, and XY scatter plots

2.2.19 Machine Learning (ML)

2.2.19.1 Introduction

Machine learning refers to computational methods that enable systems to automatically learn patterns from data and improve their performance on specific tasks without being explicitly programmed. It encompasses several learning paradigms, each designed to address different problem types and data characteristics (Samuel, 1967).

The following section provides concise overviews of some of the most widely used machine-learning adapted from (Géron, 2022):

Supervised learning involves models which are trained on data where each example is paired with its correct output, known as a label or target. The algorithm iteratively adjusts its parameters to reduce the error between its predictions and these provided labels. Such tasks typically involve either categorizing inputs into distinct groups (classification) or estimating continuous values (regression). The characteristics used to describe each example are called features (or predictors/attributes), and through exposure to numerous labelled instances, the model learns a mapping that generalizes to new, unseen data.

Unsupervised learning refers to techniques that discover structure in unlabelled data. These methods seek to identify patterns—such as clustering similar instances—and to represent high-dimensional data in more interpretable forms via dimensionality reduction or visualization algorithms. Other unsupervised tasks include anomaly and novelty detection, where models learn a profile of “normal” observations and flag deviations, and association rule learning, which uncovers frequently co-occurring attribute relationships. By operating without supervision, these approaches enable exploratory analysis and feature extraction that can reveal the latent organization of complex datasets.

Semi-supervised learning uses datasets containing both a small number of labelled examples and a larger pool of unlabelled ones. Algorithms first exploit the unlabelled data—often via clustering—to infer the underlying structure, then propagate labels from the few labelled points to similar samples. Once a more complete labelling is obtained, conventional supervised techniques refine the model, yielding improved performance with minimal manual annotation.

Reinforcement learning involves an agent that interacts with an environment by taking actions and receiving feedback in the form of rewards or penalties. The agent’s goal is to discover a policy—a mapping from observed states to actions—that maximizes cumulative reward over time. Through trial-and-error exploration and exploitation of learned strategies, the agent refines its policy based solely on the reward signals, enabling it to autonomously adapt behaviour in dynamic settings without explicit instruction.

Deep learning is another ML method which uses multi-layer neural networks to automatically learn hierarchical representations from raw data, enabling complex mappings from inputs to outputs without manual feature engineering. By stacking layers of simple computational units, these models extract progressively abstract features, which—when trained on large datasets with accelerated hardware—deliver state-of-the-art performance across tasks like vision, language and control.

For a more in-depth understanding in machine learning please refer Aurélien Géron’s Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow (2022).

2.2.19.2 Applications of Machine Learning in traffic systems

Machine learning can become a key tool for traffic signal control, using data-driven methods to manage and optimize traffic flow in real time. By analyzing historical and live traffic data, machine learning models have the potential to predict traffic conditions, estimate delays, and automatically adjust signal timings to improve how well intersections perform. Unlike traditional methods like fixed-time, machine learning can be adaptive to the changing traffic demands, handles complex interactions between multiple intersections, and boosts overall network efficiency. This results in smarter, more responsive traffic management, especially in cities where traffic patterns vary widely and unpredictably.

Murat & Baskan, (2006) developed a vehicle delay estimation model based upon the Artificial Neural Networks (ANN), artificial neural network delay estimation of traffic flows (ANNDEsT) model using the field data from ten isolated signalized intersections of Turkish cities. The study identified the results provided by the model is superior to that of the HCM delay model, Akcelik delay model and Webster delay model (analytical delay models) when compared to the field results particularly for over-saturated conditions. To generalize the model the author suggested to enrich the model with larger datasets and varying conditions.

Korkmaz & Akgüngör (2017)developed differential evolution (DE) delay estimation model for pre-timed signalised intersections using fewer input parameters, g/C ratio (ranging from 0.35-0.60) and degree of saturation (x= v/c, ranging from 0.70-1.40) and the outputs were compared to the analytical models (HCM, and Akcelik). The developed DE models outperformed the analytical models based on the statistical performance evaluation metrics.

Bagdatli & Dokuz (2021) used four different machine learning algorithms, Support Vector Regression (SVR), Random Forest (RF), Extreme Gradient Boosting (XGBoost), k nearest neighbor (kNN), to develop a delay estimation model based upon 12 isolated signalized intersections of Ankara, Turkey. The models developed using RF and XGBoost showed high performance results of delay estimation. The paper also compared the delay estimation results with the analytical models (HCM, and Akcelik) and noted the limitations of the analytical models particularly in oversaturated conditions while the developed ML based delay models excel in both under-saturated and over-saturated traffic conditions with minimal input variables.

Yuan, et al. (2023) derived average bicycle delays at signalized intersections using ML-based data-driven approach utilizing GPS cycling data. The study developed the delay models using Linear Regression (LR), RF, XGBoost, SVR, kNN, and Neural Network (NN) ML models out of which RF model performed the best with higher level of accuracy and lower validation error as indicated by relevant statistical tools. The study showcases the ability of ML models to analyse and predict complex and non-linear traffic patterns.

Ranpura, et al., (2024) developed ML models to estimate vehicular delay of a signalized intersections performing largely under heterogeneous traffic conditions using SVR, kNN, Artificial NN (ANN), RF, and Decision Trees (DT) models. The model used only the statistically relevant parameters extracted using feature selection procedure, dimensionality reduction technique which revealed the cycle time as the least significant parameter. The study highlighted the limitations of the analytical methods (Webster, Akcelik, and Indo-HCM) in predicting the vehicular delay and showed the ML models outperformed the analytical models and RF model performed the best of all the models.

Alatoom & Al-Hamdan (2024) developed different ML models using Orange software package and compared with analytical models (HCM, Akcelik, and Webster) to predict vehicular delays at signalized intersections. The study used ANN, RF, DT, SVR, kNN, XGBoost, AdaBoost, and Partial least squares (PLS) regression out of which RF model was identified to be the most robust and balanced model. The study utilized the data from eight isolated intersections in Amman, Jordan. The study used four input variables namely equivalent arrival rate, (g/C) ratio, degree of saturation, and lane group approach width (W) due to higher Pearson correlation with the output variable, control delay. The ML models showed higher accuracy than both analytical and regression models for under-saturated and over-saturated conditions. The study attributed the inaccuracy of the analytical models to usage without calibration. The paper highlighted the ML models require longer training and calculation times as compared to the conventional models.

Based on the reviewed literature, Random Forest (RF) and Extreme Gradient Boosting (XGBoost) models have shown good results for estimating vehicle delays at signalized intersections especially when traffic is under-saturated or over-saturated conditions. Also, Support Vector Regression (SVR) and k-Nearest Neighbors (kNN) models gave strong predictions if input parameters are selected carefully. These machine learning models performed better than traditional analytical methods like HCM, Akcelik, and Webster which generally don't perform well in complicated or oversaturated conditions.

Yilmaz (2025) introduced an ML-driven signal-timing framework that uses an SVR algorithm to detect high-density segments and a Random Forest algorithm to prescribe optimal cycle lengths based on real-time traffic and emergency-vehicle data, with key predictors selected via Sensitivity Analysis–Based Feature selection. The study used SUMO simulations across 97 scenarios, this approach cut average wait times by 20 %, boosted throughput by 15 % and reduced fuel use by 10 %, outperforming the default “Optimum Cycle Time” logic.

Rafique et al., (2024) explored reinforcement-learning–based cycle-length optimisation through two RL agents—turn-based (phase selection) and time-based (phase-duration adjustment)—and demonstrate that explicitly including cycle-length changes in the action space allows the time-based agent to reduce delay by up to 73 % under oversaturated conditions and achieve 38–50 % improvements across biased-demand scenarios, outperforming both the turn-based agent and fixed-cycle control.

As this, thesis will use **Random Forest**, **XGBoost**, **SVR**, and **kNN** for predicting delays (Section 5.1) and optimizing cycle length (Section 5.2), the following subsections concentrate on those four algorithms.

2.2.19.3 Random Forest Algorithm

Random Forests are a versatile ensemble method effective for regression tasks. This algorithm constructs multiple decision trees using randomized subsets of data and predictors, then aggregates their predictions through averaging. The regression variant of Random Forests offers computational efficiency, built-in error estimation, and robust handling of high-dimensional data, making it a valuable tool for predictive modelling (Cutler, et al., 2012).

"A Random Forest is an ensemble learning method that creates a multitude of decision trees during training and combines their outputs to make predictions. It reduces overfitting and increases the model's generalization ability by aggregating the results of multiple trees" (Kılıç, 2023).

The following general description on the algorithm is adapted from Cutler et al. (2012); for an in-depth understanding, please refer to the book *Random Forests* by the same authors.

Bootstrap sampling: It is a method where decision trees are trained on random subsets of the data (sampled with replacement).

Out-of-Bag (OOB) error: OOB error is the error using untrained datasets i.e. data points not included in the bootstrap sample (training subset) of a particular tree.

Random Forest uses two randomization techniques: bootstrap sampling and random predictor selection (random features at each node split). Each decision trees are trained on a bootstrap sample of the data, and at every node split, a random subset of predictors is evaluated to determine the optimal partition. This randomization reduces correlation among trees, enhancing model stability and accuracy. Predictions are derived by averaging outputs across all trees, which mitigates overfitting and improves generalization.

The algorithm uses OOB data to estimate prediction error. By calculating the mean squared error (MSE) from OOB predictions, it avoids the need for a separate validation dataset. This method is efficient and reliably tracks model performance.

Variable Importance in Random Forests is assessed through two methods:

- Permutation Importance, which quantifies a feature's impact by measuring the increase in prediction error when its values are shuffled (higher error = greater importance), and
- Gini Importance, which reflects a feature's contribution to reducing impurity (e.g., Gini index) across all splits in the trees.

Proximity scores show how often observations end up in the same terminal nodes across trees. These scores help visualize data patterns (e.g., outliers) and for regression, impute missing values using weighted averages from nearby observations.

Tuning parameters like m, number of predictors per split, (smaller values reduce tree correlation) and J (number of trees), influence performance. While defaults often suffice, increasing J stabilizes error estimates. However, excessively large trees may overfit in certain scenarios, necessitating careful node-size control.

Some of the limitations include

- Piecewise Predictions: Regression trees create step-like predictions, struggling with linear relationships,
- Instability: Small data changes can alter tree structures, though averaging across trees mitigates this,
- Longer training times for larger number of trees

To conclude, Random Forests for regression provide a flexible, robust framework for predictive modelling. Strengths include built-in error estimation, variable importance assessment, and handling of high-dimensional data. However, limitations such as piecewise predictions and sensitivity to tree size warrant consideration during implementation.

2.2.19.4 XGBoost Algorithm

XGBoost (Extreme Gradient Boosting) is a scalable, efficient machine learning algorithm optimized for regression tasks. It combines gradient-boosted decision trees with regularization, system optimizations, and advanced handling of sparse data, making it ideal for large-scale predictive modelling (Chen & Guestrin, 2016). This section explains its core mechanisms, strengths, and limitations in regression contexts.

The following general description on the algorithm is adapted from (Chen & Guestrin, 2016); for an in-depth understanding, please refer to the book *Xgboost: A scalable tree boosting system* by the same authors.

Key Features

Gradient Boosting Framework: XGBoost builds regression models sequentially. Each new decision tree corrects residual errors from previous trees. Predictions are refined iteratively, improving accuracy with minimal overfitting.

Regularization: A penalty term (λ) is added to the loss function to penalize overly complex trees. This simplifies the model and enhances generalization.

Gradient and Hessian Optimization: The algorithm uses first-order gradients (slopes of prediction errors) and second-order derivatives (curvature of errors) to optimize leaf weights. This dual approach refines predictions more efficiently than traditional gradient boosting.

XGBoost efficiently manages missing values by learning optimal split directions during training. Instead of imputing missing data like Random Forest models, it assigns default paths (left or right splits) for sparse entries. This preserves computational efficiency while utilizing all available information.

To identify optimal feature splits, XGBoost employs a weighted quantile sketch. This method approximates candidate split points in features with weighted data, reducing computational overhead. For example, in large datasets, it skips exhaustive checks, balancing speed and precision.

Limitations

- **Parameter Sensitivity**: Performance hinges on tuning parameters like learning rate (η) and tree depth. Poor choices (e.g., high η) may cause overshooting or slow convergence.
- **Memory Demands**: Column block pre-processing requires significant RAM, posing challenges for resource-constrained systems.
- **Interpretability**: Ensemble complexity limits transparency compared to simpler models (e.g., linear regression).

In summary, XGBoost excels in regression tasks through regularization, sparse data handling, and hardware-aware optimizations. Its speed and accuracy make it popular for applications like insurance risk prediction. However, users must carefully tune parameters and consider hardware limitations when scaling to large datasets.

2.2.19.5 Support Vector Regression (SVR) Algorithm

The paper by (Drucker, et al., 1996) introduces Support Vector Regression (SVR), a method for predicting numerical values, and compares it to two other techniques: bagging with regression trees and ridge regression in feature space. The focus is on understanding how SVR performs in different scenarios, especially when dealing with complex or high-dimensional data.

The following general description on the algorithm is adapted from (Drucker, et al., 1996); for an in-depth understanding, please refer to the book *Support vector regression machines* by the same authors.

Key Concepts

- Quadratic Optimization: A mathematical process to find the best model parameters by minimizing prediction errors while adhering to constraints. In SVR, this identifies support vectors—critical data points that define the regression model.
- Feature Space: A transformed representation of data where patterns are easier to capture. For example, SVR maps inputs into a high-dimensional space (e.g., using polynomial or radial basis functions) to model complex relationships.
- Regularization Parameter (U): Controls the trade-off between accuracy (minimizing prediction errors) and reducing model complexity (avoid overfitting). Higher value of U prioritizes accuracy (fits training data closely). Lower value of U prioritizes simplicity (avoids overfitting).
- Epsilon-Insensitive Loss Function: The epsilon-insensitive loss function is a core component of Support Vector Regression (SVR). It defines a "tolerance zone" (or "tube") around the predicted regression line, within which errors are ignored. Only prediction errors larger than the tube's width (ε) contribute to the loss.
- Kernel: A kernel is a mathematical function used in machine learning to implicitly map input data from its original feature space into a higher-dimensional space. This

transformation allows linear algorithms to handle non-linear relationships by working in the transformed space without explicitly computing the coordinates.

Support Vector Regression (SVR) is a kernel-based algorithm used for regression tasks. SVR predicts numerical values by identifying a hyperplane that best fits the data while minimizing prediction errors. It uses an epsilon-insensitive loss function, which ignores small errors (within a tolerance zone of width ε) and penalizes only larger deviations. For non-linear relationships, SVR employs the kernel trick (e.g., polynomial or radial basis functions) to map data into a higher-dimensional space where patterns are linear. The model balances accuracy and simplicity via regularization (controlled by parameter c), ensuring it does not overfit. Training involves solving a quadratic optimization problem to find support vectors—critical data points that define the hyperplane.

Key limitations are:

- computational complexity due to quadratic optimization, making training slow for large datasets,
- sensitivity to parameter tuning (e.g., c, ε, kernel choice), requiring expertise or grid search,
- scalability issues with very high-dimensional data unless kernels are carefully chosen, and
- Interpretability challenges, as the kernel-transformed feature space obscures direct insights into variable importance.

In summary, SVR is a powerful regression method, particularly effective for high-dimensional or noisy data. While ridge regression works better in simpler settings, SVR's ability to handle complexity and avoid overfitting makes it a valuable tool. However, success of the model is critical on proper parameter tuning, and its full potential may require more challenging real-world datasets.

2.2.19.6 K-nearest-neighbor (kNN) algorithm

The k-nearest neighbor (kNN) algorithm is a simple yet powerful non-parametric method used for both classification and regression tasks. The key idea in kNN regression is to predict the output value of a test sample by averaging the values of its k nearest neighbors in the training data, based on a distance metric such as Euclidean distance (Peterson, 2009).

The following general description on the algorithm is adapted from (Peterson, 2009); for an in-depth understanding, please refer to the book *K-nearest neighbor* by the same authors.

One of the fundamental aspects of kNN regression is the choice of distance metric, which determines how similarity between data points is measured. The Euclidean distance is commonly used, but other metrics (Manhattan) may be employed depending on the data structure. The selection of k (number of nearest neighbors used for prediction), plays a crucial role in model performance. A smaller k may lead to noisy predictions, while a larger k can smooth out predictions but may lose local patterns. The article highlights that an odd value of k is often preferred to avoid ties in decision-making, though this is more critical in classification than regression.

Feature transformation is another important consideration in kNN regression. Standardization of features ensures that variables with larger scales do not dominate the distance calculations. The article discusses z-score standardization, where features are transformed to have zero mean and unit variance, improving the model's performance. Additionally, fuzzification is introduced as a method to handle uncertainty in feature values by mapping them into fuzzy sets, though its effectiveness varies depending on the dataset.

The article emphasizes the importance of cross-validation which is basically splitting of total datasets into training and testing datasets to avoid bias in model evaluation. Cross-validation ensures that each fold maintains a representative distribution of the target variable, leading to more reliable performance estimates. The hold-out method, where a fixed portion of data is reserved for testing, is also discussed but noted to be less efficient than cross-validation since it underutilizes available data. These validation techniques help in tuning hyperparameters.

Despite its simplicity, kNN regression has limitations. The method is computationally demanding for large datasets. It also assumes that all parameters contribute equally to the distance metric, which may not hold true if some parameters are irrelevant. Furthermore, performance can degrade in high-dimensional spaces due to the "curse of dimensionality," where distances between points become less meaningful.

In conclusion, kNN regression is a versatile method that relies on local averaging of neighboring points. Its effectiveness depends on the proper selection of distance metric, value of hyperparameter set, and appropriate feature transformations. However, computational inefficiency and sensitivity to irrelevant features are notable drawbacks. Understanding these factors is essential for applying kNN regression effectively in practical scenarios.

2.3 Literature Review Summary

The chapter presented the theoretical and foundational framework moving from general traffic-flow theory to the specific tools and data-driven techniques required to improve SCATS-controlled intersections in New Zealand. It reviewed how flow, capacity, and saturation-flow concepts translate into queue formation and delay, compared classical delay/LoS models with modern fixed, actuated, and adaptive signal strategies, and highlighted SCATS's reactive DoS logic. Current NZ modelling guidance and SIDRA's lane-based framework were then examined, followed by evidence that machine-learning methods can outperform analytical formulas in predicting delay. The next chapter sets out the research design that addresses the research gaps, detailing the data sources, calibration procedures, and hybrid SCATS-ML methodology that will be applied to the Albany intersection.

Chapter 3 METHODOLOGY

The research undertaking seeks to employ a hybrid approach by integrating intersection modelling with machine learning to assess the operational performance of SCATS-controlled intersections. Intersection modelling enables analytical evaluation of traffic operations by incorporating geometric layouts, demand volumes, and signal control parameters, and providing key performance indicators such as delay, queue length, and DoS. To enhance predictive capability, machine learning models will be trained on data generated from SIDRA intersection analyses, capturing nonlinear relationships between input variables and performance outcomes. This methodology supports an adaptive and data-driven approach to intersection performance evaluation under varying traffic conditions.

This chapter presents the systematic methodology adopted to achieve the research objectives stated in the chapter 1. **Section 3.1** presents the rationale behind the selection of modelling techniques and selection of intersection modelling tool. **Section 3.2–3.6** presents the rationality of selected site, describe data collection and the build–calibrate–validate process for SIDRA base models (**objective 1**). **Section 3.7** defines the performance, sustainability, and safety metrics used in the baseline analysis (**objective 2**). **Sections 3.8–3.9** set out the design of the data, the ML delay-prediction models, and the ML cycle-length optimisation framework (**objective 4 & objective 5**). Methodological flowchart and the concise chapter summary is presented at the end of the chapter.

3.1 Model selection and software tool selection:

Selection of a modelling method largely depends upon the research objectives and the level of technical details involved. As identified in the literature reviews chapter, sub-chapter: Transportation modelling, there are five major categories of traffic modelling to undertake depending upon the granularity and scope of the traffic study. One of the objectives of this research undertaking is the performance evaluation of isolated intersections. For the performance evaluation of an isolated intersection, microsimulation modelling and intersection modelling are two modelling methods best fit for the purpose. The Transport Modelling Guidelines, (2020) mentions some instances, where both microsimulation and intersection modelling are appropriate. The guidelines has listed conditions requiring microsimulation when there is a choice between the models:

- Network size: Number of intersections to be modelled are more than 10 requiring multiple intersection modelling.
- Demand variation: When there is considerable demand variation within the peak hour with peak flow factor less than 80%.
- Complex vehicle behaviour such as shared traffic/light rail lanes, frequent kerbside stops, weaving manoeuvre that would affect performance)

As the selected intersections will be modelled as an isolated intersection (single intersection for a model), peak hour demand variability of both the intersections is not significant (peak flow factor exceeded 80% for both intersections) and complex vehicle behaviour is not reflected/observed in the intersections, microsimulation, although it would provide a more detailed simulation, is not required.

The Operational Modelling Guidelines (2021) has outlined following three techniques to simulate signal control systems at isolated intersections:

- As Fixed time signals: Peak periods SCATS average phase timings can be used to simulate the SCATS controlled intersection.

- As Vehicle actuated signal timings: Vehicle-actuated signals dynamically adjust green times and phases based on detector inputs, enabling responsiveness to real-time traffic, pedestrian demands, or public transport priority.

- SCATS operation through the SCATSIM interface: To realistically emulate SCATS signal control system, SCATSIM software can be used to replicate adaptive system behaviour.

For a list and description of the traffic-modelling software, please refer to Appendix E.

Though, use of microsimulation method is also recommended, using VISSIM would require other software tool like SCATSIM to emulate SCATS-controlled intersections. Due to budget constraints, and limited resources VISSIM microsimulation was not performed as acquiring the SCATSIM software would require budget out of the research resources, although academic version of the VISSIM software was available free of cost. (SIDRA Intersection User Guide for Version 8, 2018), (Operational Modelling Guidelines, 2021)explicitly recommends using Fixed-Time/Pre-timed (EQUISAT) option for signal analysis to emulate SCATS control algorithms for SIDRA software. Furthermore, (Austroads, 2020) recommends using SIDRA intersection for modelling isolated signalised intersections.

Since, employing SIDRA software does not require extra software and extra resources to mimic SCATS-controlled intersections, and the observed intersections conditions don't necessarily demand microsimulation, the modelling was performed using intersection modelling method employing SIDRA software.

SIDRA Intersection software (Version 8) was used to model the operational performance of the two SCATS-controlled intersections to replicate existing peak-hour conditions and to generate synthetic dataset for machine learning. The modelling focussed only on the vehicular traffic so pedestrian traffic was not considered.

3.2 Site selection

Site selection for this study was made ensuring alignment with the research goals while addressing practical limitations such as budget constraints and data accessibility. Key factors included traffic operational control type, traffic diversity, proximity to data collection hubs, and availability of SCATS logs. The criteria used for the site selections are listed below:

- Intersections under SCATS control were prioritized to focus on adaptive traffic signal systems.
- Sites with varied traffic patterns—urban intersections with peak-hour congestion and suburban intersections with mixed flows—were selected to capture operational diversity.
- Data availability, including accessible SCATS logs, traffic counts, was critical to avoid gaps caused by budget restrictions.
- Budget limitations necessitated prioritizing sites with existing infrastructure (e.g., loop detectors, CCTV) to reduce primary data collection costs.

These criteria ensured a feasible and comprehensive analysis of SCATS-controlled intersections, balancing both logistic and financial constraints. Based on these criteria, two intersections: Oteha Valley Road/Albany Expressway/Albany Highway/Dairy Flat Highway Intersection (Albany Intersection) and the Ruakura Road/Wairere drive intersection (Ruakura Intersection) were selected.

The rationale for selecting the Albany intersection is its high traffic variability from mixed urban-rural flows while the Ruakura intersection was chosen due to its proximity to the study base (University of Waikato) and inherent traffic variability due to freight-commuter mixed flows. For both intersections, the availability of the required data was pivotal in the selection.

During the initial planning phase of this research, five intersections from the cities of Hamilton, Auckland, and Wellington were proposed to capture variability in traffic conditions across different cities. However, due to time constraints, intersections from Wellington were excluded, and the scope was limited to sites in Hamilton and Auckland. Additional intersections, such as the Botany intersection (Botany Road / Ti Rakau Drive) in East Auckland, was also considered but not selected due to data and time constraints. Similarly, the Te Rapa intersection (Te Rapa Road / Wairere Drive) in Hamilton was excluded due to time constraint. Finally, the Albany and Ruakura intersections were selected as for subsequent model development and analysis.

3.3 Data sources:

Data collection process for this study focussed on obtaining relevant field data for the development of SIDRA models. Data needed for the development of the ML models were extracted from the modelled and validated SIDRA intersection models.

1. Traffic data:
   Traffic data needed for SIDRA modelling like traffic count data, signal data, vehicle classification data, etc. were sourced from the Auckland Transport for the Albany intersection and Hamilton City Council for the Ruakura intersection.
2. Geometric data:

Geometric data were sourced from Google maps, Google Earth and LINZ basemaps. Gradient data was sourced using New Zealand national 1m DEM from the most recent LIDAR survey via QGIS.

3. Speed data:
   Approach cruise speed and exit speed are required to model the SIDRA intersection. Posted speed limits for the intersections were sourced from the National Speed Limit Register (NSLR), New Zealand.
4. Crash data:
   Crash data for both intersections was sourced from the crash analysis system (CAS) database.
5. Bus stopping rate and Parking Manoeuvres rate data:
   Bus stopping rate is the number of buses stopping per hour while parking manoeuvre is the number of parking manoeuvres per hour. These data have direct impact on the SFR. HCM, 2022 the bus stopping rate and the parking manoeuvres rate are to be measured within 80 m. upstream and downstream of stop line. The data was taken from the Google Earth after verifying any bus stops or parking facilities available within the 80 m.
6. Lane utilisation:
   Lane utilisation is basically the distribution of traffic in the lanes for same direction or same movement. Unequal lane utilisation results in reduced capacity of the intersection and in turn increased delays. Lane utilisation patterns were identified from the SCATS volume logs.
7. Vehicle calibration data:
   Traffic Modelling Guidelines – SIDRA INTERSECTION (2023) suggest calibration of heavy vehicle to better reflect the mix of heavy vehicles while using default calibration parameters for light vehicles. Length of vehicle is the determining parameter for the calculation of gap acceptance factor and opposing vehicle factor. Length of bus was taken from the Public Transport - Buses, (2017) which indicates bus vehicle length ranging from 10.5 and 13.5 metres are in use in Auckland. Average length was used. Truck lengths were taken as 12.6 m. based on values from New Zealand Transport Agency (NZTA).

The (Transport Modelling Guidelines, 2020) has suggested criteria regarding collection of traffic data for day of the week and time of day criteria. Data collection for traffic studies are recommended from Tuesday to Thursday as representative weekdays due to stability in demand and minimal influence. Mondays and Fridays are avoided because they often exhibit irregular travel patterns. Data is excluded during school holidays, public holidays, and week adjacent to major events to prevent biased demand.

Similarly, the guidelines suggest targeting peak hour and collecting either side of expected peak hour to ensure the peak hour is captured for the time of day criteria.

3.4 SIDRA Setup

3.4.1 Model Periods:

The SIDRA base models were developed using the time period with the highest traffic demand from the SCATS volume logs. A peak-hour was identified from the SCATS volume logs and the interval with the highest traffic volumes within the peak-hour was chosen as the model period for the SIDRA model. The volumes corresponding to the interval was input in the SIDRA volumes dialogue.

To understand the traffic demand variability within the peak hour, the Peak Flow Factor (PFF) was calculated.

3.4.2 Movement classes:

For the purpose of simplicity only three vehicle classes- light vehicles, heavy vehicles and buses was used.

3.4.3 Lane geometry:

Lane geometries were measured as guided in the SIDRA intersection user guide, (2018) as follows:

- Approach distance is the mid-block distance between the intersections in the direction of travel. Lane length for the full length lane was set equal to the approach distance. Short lane length was measured from the stop line to the entry point at which the width is wide enough to contain a vehicle.
- Lane width was measured at the stop-line for the approach lanes perpendicular to the direction of travel while for the exit lanes it was measured at the extension of adjacent lane’s stop-line.
- Approach grade for approach lanes and exit lanes was taken as the average grade from the stop-line to the point 30 meters upstream in the direction of travel. Positive values for the uphill gradient while negative values for the downhill gradient as suggested by the guide were used.

Lane utilization is an important factor that affects traffic capacity and overall intersection performance. If lane utilization is not accurately modelled, it can lead to a mismatch between the model and the actual field conditions (Transport Modelling Guidelines-Volume 5: Intersection Modelling (2020).

Lane utilization is also stated as one of the general parameters used for calibration purpose in the SIDRA intersection user guide.

Lane utilization ratio was calculated from the SCATS volume logs.

3.4.4 Volumes:

Volume classification data for the classified movements were derived from the turn count survey.

3.4.5 Gap Acceptance:

For the gap acceptance data, SIDRA default values were taken.

3.4.6 Vehicle movement data:

Approach cruise speed and exit cruise speed were based upon the posted speed limit as mentioned earlier. When the approaches consisted of two speed limits as in the case of the Albany expressway, speed limits were derived as the weighted average based upon the speed limit length. Cruise speed is the mid-block median free-flow speeds. Free flow speeds were derived (refer Table 3.1) as suggested in the (Transport Modelling Guidelines-Volume 5: Intersection Modelling, (2020) which is based on the posted speed limit.

Table 3.1. Average free flow speeds (Transport Modelling Guidelines-Volume 5: Intersection Modelling, (2020))

Road Hierarchy	Posted Speed Limit (km/hr)							
	40	50	60	70	80	90	100	110
Highways	-	40	52	56	66	82	92	104
Primary Arterials	-	42	50	59	67	79	84	-
Secondary	-	39	48	55	62	60	75	-
Collectors	32	40	-	-	-	-	-	-
Local Roads	26	33	39	-	-	-	-	-

Negotiation speed, negotiation distance, negotiation radius and downstream distance parameters were left “Program” to be calculated by the SIDRA itself.

Same values were taken for each movement class.

3.4.7 Vehicles calibration:

Default values were taken for the calibration of the light vehicles.

Dimensions of the heavy vehicles were taken as stated earlier. Queue space was calculated by adding 2 meters to the vehicle length as suggested in the Traffic Modelling Guidelines – SIDRA INTERSECTION , (2023). The gap acceptance factors and opposing vehicle factors were taken as suggested in the SIDRA guide which can be referenced from the Appendix D.

Practical degree of saturation was taken as 0.90 as the SCATS controlled signal system targets around such range of the degree of saturation.

Vehicles occupancy and the turning vehicle effect were taken as SIDRA defaults.

For the vehicle movement timing data (signals), start loss and end gain were taken SIDRA default and minimum and maximum green times were left “Program”.

3.4.8 Phasing and Timing:

Phasing and timing data were taken to match the model period from the SCATS phase logs. Average times of each phases were used. Timing options was set to user-given phase times to represent the field conditions and as suggested in (Young Institute of Transportation Engineers-yite, 2020). Inter-green times was taken as five seconds consisting of three seconds of yellow time and two seconds of all-red time.

SIDRA default passenger car equivalents were taken for the movement classes.

3.5 Calibration of the base model

The capacity and performance of a traffic facility depend on intersection geometry and driver behaviour. Calibration parameters reflecting local road and driver characteristics, along with intersection conditions, are most critical (Operational Modelling Guidelines (2021).

The guide mentions saturation flow rate as a key parameter for the calibration of the signal controlled intersections as shown in the tabular image below. Furthermore, the use of saturation flow rate as a key calibration parameter is also supported by a number of guidelines and agencies.

Justification of the use of the saturation flow rate as the key calibration parameter:

- As identified in the literature reviews, saturation flow rate is fundamental to the capacity estimation of a signalised intersection.
- As mentioned in the guide (refer Table 3.2).
- Driver behaviour and traffic mix is directly reflected in the saturation flow which is central to the intersection performance (Austroads, Guide to Traffic Management Part 3: Transport Study and Analysis Methods, 2020).
- Guidelines including (Traffic Modelling Guidelines – SIDRA INTERSECTION , (2023)), (Operational Modelling Guidelines (2021), etc. support the use of saturation flow as the key calibration parameter for the signalised intersection.

The following calibration process was followed as suggested in those guidelines:

- Observed saturation flows are calculated using the TRL’s RR67 geometric method.
- Output saturation flows (SF) from the SIDRA were compared to the observed SF.
- Calibration factor were derived by dividing the observed SF by the output SF.
- Basic saturation flows were adjusted by multiplying the previous basic saturation flows (BSF) with the calibration factor.
- The steps were repeated until such times when the output saturation flow rates were within 5% of the observation saturation flows.

Table 3.2. Key Calibration Parameters SIDRA Intersection User Guide for Version 8, (2018)

Site Type	Key parameters used in the capacity model	Recommended key calibration parameter	Input dialog
Signals	Saturation Flow Rate	Area Type Factor	Intersection (per approach)
		Basic Saturation Flow	Lane Geometry dialog-Lane Data tab (per lane)

As mentioned in the guide, adjustments of the BSFR are due to:

- Short lane effects which result in the reduction of number of vehicles that can queue and discharge
- Under-utilisation of lanes due to preferences result in reduced effective capacity
- Down-stream blockages which can impact vehicle discharge

The SIDRA base model calibration followed the ±5% accuracy target recommended by (Austroads, Guide to Traffic Management Part 3: Transport Study and Analysis Methods, 2020), ensuring the saturation flow rate closely matched the observed data.

3.6 Validation of the base model

The base SIDRA models were validated using the output degree of saturation (utilization) parameter.

The Operational Modelling Guidelines (2021) recommends that, for validation purposes, the base model should have a degree of saturation less than or equal to 100% for all movements.

Furthermore, as stated in the Transport Modelling Guidelines-Volume 5: Intersection Modelling, (2020), where throughput rather than demand is used for model calibration, a useful validation check is that the utilization value should never exceed one.

Therefore, degree of saturation was used for validation in this study, in line with the above recommendations.

3.7 Performance Analyses

Performance analysis of the Albany and Ruakura intersections was performed focusing on operational efficiency, sustainability outcomes, and safety considerations. Operational performance was evaluated through intersection performance metrics like delay, DoS, and queue lengths.

Furthermore, manual mitigation of the current operational performance of the intersections to a target LoS and future year operational performance was also conducted.

Sustainability performance assesses fuel consumption, operational costs, and emissions to reflect environmental impacts. Additionally, crash data analysis derived from the Crash Analysis System (CAS) provided insights into safety performance.

3.7.1 Key intersection operational performance indices

The operational performance of the intersections under existing conditions was evaluated using the three standard performance indicators as derived from SIDRA outputs:

- DoS:
  Also referred to as volume-to-capacity (v/c) ratio or utilisation, indicating the proportion of lane capacity used.
- Control delay (secs/veh):
  Control Delay in SIDRA is the total delay a vehicle experiences due to intersection control and geometry, and it comprises of two delays:
  Geometric Delay is the delay for an unqueued vehicle caused by slowing down and accelerating through the intersection due to geometric features (e.g., curves, distances, control types). It reflects safe negotiation speeds, not caused by traffic. Stop-Line Delay applies to queued (stopped) vehicles and includes two parts:
    - Idling Delay – the time spent stationary at the stop line.
    - Main Stop-Start Delay – the time lost during deceleration to a stop and acceleration back to saturation speed.

  Thus, Control Delay = Stop-Line Delay + Geometric Delay, representing both traffic-induced and geometry-induced delays.
- 95 percentile queue length (m.):
  The maximum queue length likely to be observed during the peak 15-minute period.

As per the guide and (Highway Capacity Manual, 7th Edition, (2022) level of service of approach lanes of intersection or intersection as a whole is defined by the control delay. LoS stratification as per the control delay as used by those agencies can be referred from the Table 3.3 below:

Table 3.3. LoS stratification using control delay (Sourced from the guide and Highway Capacity Manual, 7th Edition, (2022))

LoS	SIDRA Method	HCM, 2022
A	≤ 10	≤ 10
B	>10 - 20	>10 - 20
C	>20 - 35	>20 - 35
D	>35 - 55	>35 - 55
E	>55 - 80	>55 - 80
F	>80	>80

Thus, LoS was used to explain the operational performance of the intersections due to its intuitiveness.

3.7.2 Sustainability Performance analysis:

Sustainability analysis of the intersections are performed in terms of the operating cost of the intersections, fuel consumptions and emissions estimates.

SIDRA reports the fuel consumption and emission estimates based on the four-mode elemental model SIDRA Intersection User Guide for Version 8 (2018).

As per the guide, intersection's cost calculation considers vehicle operating costs and the time cost of drivers and passengers. Vehicle operating cost covers the resource cost of fuel and running expenses—tires, oil, repairs and maintenance—expressed as a proportion of fuel cost. Time cost is calculated using the number of occupants in each vehicle (vehicle-occupancy factor). When pedestrian costs are omitted, the total cost for an intersection equals the sum of these two vehicle components: direct operating expenses and occupant time cost.

3.7.2.1 SIDRA setup

Default values from the guide are used for the relevant parameters as attached in the table of Appendix B.

Pump price of fuel and average income values from the table were adjusted from the April 2018 value using a cumulative inflation factor. Average consumer price inflation from 2018 to 2024 has ranged between 2% to 7% annually as per the Stats NZ. Therefore, average annual inflation rate of 3.5% was assumed.

Detailed calculation can be referenced from the same Appendix.

3.8 Delay Prediction using ML:

Four ML algorithms (XGB, RF, kNN, SVR) as identified in the literature reviews (sub-chapter: 2.2.19.2) shall be used for the development of the delay prediction ML models. The best performing ML models shall be combined to produce an ensemble model.

Evaluation of the developed models shall be made using the relevant statistical tools. For a general introduction to statistical tools for ML methods, see (Dangeti, 2017).

3.8.1 Data sets:

3.8.1.1 Raw data sets:

The machine learning dataset used in this study was developed using SCATS volume logs collected between 11 September and 25 September of the Albany intersection. To ensure typical traffic conditions, data from weekends, Mondays, and Fridays were excluded as discussed earlier. This resulted in 14 peak-period volume records corresponding to the highest 15-minute demand intervals on Tuesdays, Wednesdays, and Thursdays across the two-week period.

3.8.1.2 Monte-Carlo expansion to generate oversaturated scenarios

Most existing signal-timing studies evaluate models under undersaturated or near-capacity conditions, where queue spillback is limited and classical formulas still perform reasonably well. By explicitly testing our framework in oversaturated regimes—where arrival flows exceed capacity and delay grows non-linearly—we target the regimes that challenge SCATS logic and traditional analytical models, thereby demonstrating the added value of approach where conventional methods underperform.

As machine learning models require substantial amounts of data for effective training, the original 14 records were deemed insufficient. To address this, additional synthetic volume datasets were created using the **Monte Carlo simulation** technique. This approach involved independently multiplying the traffic volume on each approach leg by a random factor ranging from 1.00 to 1.50, allowing the generation of diverse and oversaturated traffic scenarios that are typically rare in real-world observations. This process produced 84 synthetic volume records, which, when combined with the original 14, gave a total of 98 traffic volume datasets for subsequent ML analysis.

3.8.1.3 Traffic matrix

Each of the 98 volume datasets was input into the calibrated and validated base SIDRA intersection models. The signal timing control was set using the “Optimum Cycle Time” option, which computes a cycle length that minimizes a selected performance metric. In this study, the selected performance metric was DoS, reflecting the operational principles of SCATS, which aims to balance DoS values across approaches to a target DoS of approximately 0.90. Accordingly, SIDRA models were configured with a practical DoS setting of 0.90 to emulate the SCATS logic.

Model outputs were then used to construct a structured traffic feature matrix, comprising the following input features:

- Time flag
- Traffic volumes (by approach)
- DoS
- Cycle length

The target variable for machine learning model training was:

- Average delay per vehicle (in seconds)

The matrix can be referenced from the Appendix F.

3.8.2 Machine Learning Model Development for delay prediction

3.8.2.1 Data Splitting Strategy

The final dataset (n = 98) was split into three subsets to support model training, hyperparameter tuning, and statistical evaluation of the models with (70-15-15 split strategy as suggested for the smaller database (V.C., 2023)).

- Training set (70%): Used to train the models and perform hyperparameter optimization.
- Validation set (15%): Used to monitor performance during training (e.g., for early stopping in XGBoost) and assist with model selection.
- Test set (15%): Used to assess the generalization performance of each trained model.

3.8.2.2 Objective Function:

The training process was aimed to minimize the Mean Absolute Error (MAE), which was selected due to its intuitive interpretation as the average prediction error—in this case, the predicted traffic delay in seconds.

3.8.2.3 Optimization and Validation Framework

All machine learning models were tuned using the GridSearchCV technique with five-fold cross-validation. This method ensured robust model selection and reduced the risk of overfitting by evaluating model performance across multiple data partitions.

3.8.2.4 Evaluation Metrics

Final model performance was assessed using the following statistical measures:

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- Coefficient of Determination (R^2)
- Mean Absolute %age Error (MAPE)

These metrics were used to establish a benchmark for comparing model performance in predicting intersection delay.

3.9 Signal Cycle Length Optimization using ML:

In this study, cycle length was learned from past traffic data. The model reads current volume and degree of saturation, then suggests a cycle that lengthens whenever conditions become heavier and given some boundary conditions. This data-driven approach produced realistic values without relying on pre-set formulas as with the traditional traffic signal systems.

The detailed steps are as follows:

Step 1 – Baseline Cycle Prediction ensemble model

The first model learns a starting cycle length from the volume, DoS, and time flag. The ensemble of the XGBoost and the Random Forest is used here to predict the baseline cycle length. The ensemble is set to be monotonic—to ensure cycle length cannot decrease when demand or DoS rises, eliminating unrealistic minima.

Step 2 – Delay-estimation ensemble model

Another ensemble model of XGBoost and the Random Forest was built to judge a particular cycle length chosen is good or poor. For this purpose, the ensemble model would predict average delay from the traffic matrix with the inputs: volume, DoS, and the trial cycle length.

During optimisation the algorithm generates many candidate cycle lengths, sends each one to the ensemble model, and immediately received a predicted delay. The candidate with the lowest predicted delay was selected. In this way, the ensemble model allowed testing of cycle alternatives without the computational needs of running detailed traffic simulations for each option.

Step 3 – Cycle length Bounds

Before testing, a rule was set out to exclude unrealistic short cycle lengths for lower cycle length bound. The rule was linear:

$$C_{min}=40 +60\times DoS(C) \text{ in seconds}$$

It starts at 40 s when the intersection is almost empty and climbs to roughly 100 s when the site is saturated (DoS ≈ 1).

The upper bound of 150 seconds was chosen to align with current practices of practical cycle length bounds of 40-150 seconds.

Step 4 –Trials and scoring

Within the upper and the lower bounds explained above, the algorithm tested every whole-second cycle length. For each trial value the fast machine-learning model assigned a score based on the predicted delay.

Step 5 – Selecting the Optimum cycle length

When all candidate cycles have been scored, cycle length with the least score is chosen. If two cycles differ only marginally, the shorter cycle length is taken.

Out of the 97 datasets (traffic matrix), only 20 were tested for evaluation purposes.

3.9.1 Comparison:

For each of the 97 demand scenarios, the cycle length recommended by the ML optimization model was entered into SIDRA under Timing Options → User-given cycle time. The model was then run to obtain average delay, DoS, operating cost, fuel use and CO_2 emissions. These results were compared with a second set of runs that used the same traffic volumes but let SIDRA choose its own cycle length with Timing Options → Optimum cycle time (which approximates SCATS logic).

3.10 Methodology Flowchart

Concise flowchart of the methodology is presented in below.

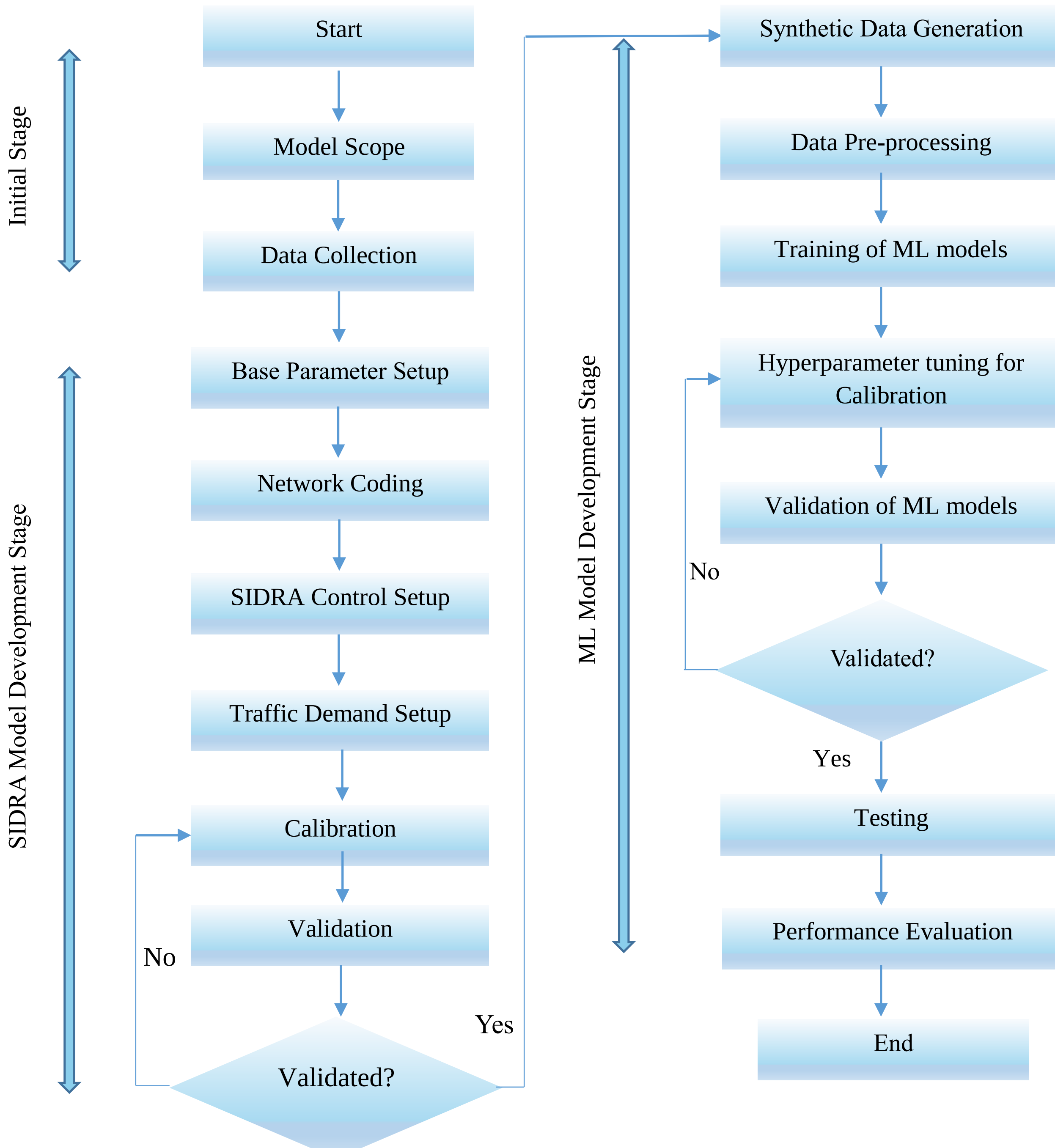


Figure 3.1. Concise flowchart of the methodology

3.11 Summary

This chapter presented the methodological framework required to achieve the research objectives. It presented the framework for building and validating base SIDRA models and introduced key performance indicators for the thorough performance evaluation of the intersections. Furthermore, the chapter developed an architecture for building delay-prediction ML models, and ML based intersection optimization framework. Together, these components provide the analytical basis with which the research questions can be answered. The next chapter builds on this framework, calibrates the models with field data, validates and evaluates how each intersection performs under present and projected traffic conditions.

Chapter 4 PERFORMANCE ANALYSIS USING SIDRA

SCATS is the dominant signal control system nationwide, understanding how well individual SCATS intersections perform—and how they will cope with future volume growth. Responding to this, this chapter (i.) **built, calibrated and validated SIDRA models** for the Albany and Ruakura intersections (**objective 1**); (ii.) **provided baseline performance evaluation** of the intersections in terms of key performance indices, sustainability, and crash analysis (**objective 2**); and (iii.) **tested the future resilience** of the intersections (**objective 3**).

Section 4.1 presents the development of SIDRA base models for the Albany and Ruakura intersections including brief description of the intersections, salient features, traffic data requirements and sources and SIDRA setups. Section 4.2 reports the findings: calibration statistics, baseline delay / queue / emissions / crash analysis, and the sensitivity tests under forecast volume growth.

4.1 Development of Base SIDRA models

4.1.1 Albany intersection:

The intersection is located in Albany, Auckland, it is a high capacity intersection located at the junction of high volume regional arterial roads. The intersection is designed to manage traffic flows to and from the Albany urban region to the northern and the southern region via the State highway (SH1). The intersection provides services to the major business hubs (like Albany Business Park, etc.), residential zones with the urban suburbs like Albany, Oteha, Rosedale, etc. and the rural communities like Dairy flat, Silverdale.

Table 4.1. Salient geometric features of the Albany intersection.

S.N.	Item	Description
1.	Intersection type	Four-way, signalized, at-grade intersection.
2.	Intersecting Roads (Posted speed limit at the approach)	• Oteha Valley Road (50 kmph) • Albany Expressway (50 kmph) • Albany Highway (50 kmph) • Dairy Flat Highway (50 kmph)
3.	No. of lanes	Four
4.	Lane types	Each intersecting road consist of divided lanes with through lanes, auxiliary turn treatments (dedicated right-turn bay and left turn slip-lane).
5.	Signal Control	SCATS-controlled signal system
6.	Pedestrian Facilities	Dedicated signalized pedestrian crossings with pedestrian refuge island.

Figure 4.1. Aerial Imagery of the Albany Intersection (LINZ Basemaps)

4.1.1.1 Traffic data specific to the intersection:

1. Traffic turn Count data:
   For the Albany intersection, traffic count data was obtained in the form of SCATS volume logs and the turn count survey both in the 15 minutes intervals. The SCATS volume logs contained count data covering 24 hour period for each day from September 11, 2024 to September 25, 2024. The turn count survey contained the data from 6:00 to 9:00 and 14:00 to 18:00 for September, 18, 2024 and September 24, 2024. The turn count consisted of vehicle classification data as classified into cars, trucks, buses, motorcyclists and cyclists.

2. Traffic signal data:
   Traffic signal data was obtained in the form SCATS phase logs for every 15 minutes intervals covering 24-hour period for September, 18, 2024 and September 24, 2024. The SCATS phase plans was also obtained.

3. Queue length:
   Queue data for each minute from 6:00 till 9:00 and 14:00 to 18:00 was obtained. The dataset did not have vehicle classification.
4. Saturation flow rates for the intersection was calculated using the TRL's RR67 geometric method, as described in the Operational Modelling Guidelines (2021). Since direct measurement of saturation flow on-site was not possible, the guidelines recommends using RR67 calculations and then adjusting the saturation flows using a local factor from a

similar intersection. Saturation flow rates thus calculated are termed as observed saturation flow rates here. For all approach lanes, BSFs were initially set to 1950 through car units per hour (tcu/h).

SFR was deducted for the intersection using the local factor calculated from the Ruakura intersection. Similarity of the intersections was considered because of the similar geometric layouts, traffic compositions and urban settings.

It was initially planned to develop the SIDRA base models using turning movement data from field surveys and signal timing data from SCATS phase logs. The model was then to be validated using queue length data.

According to the SIDRA Intersection User Guide (2018), the software provides two types of queue length outputs: back-of-queue length, which is the longest queue during the red signal in one cycle, and cycle-average queue length, which is the average queue length over the whole cycle. However, the queue length data collected for this study was not cycle-based. Instead, it was recorded minute-by-minute. Because of this difference in data format, it was difficult to use the observed queue length data to directly validate the SIDRA model. The guide also recommends using the 95th percentile back-of-queue length for validation, which could not be accurately compared due to this mismatch in data types.

Although the use of field-observed turning movement data is often recommended, SCATS volume counts were used in this study due to their alignment with the signal phase and timing data. However, the turning movement survey data was still used to determine the proportion of different vehicle types.

4.1.1.2 SIDRA Setup specific to the intersection

Model Periods:

As per the SCATS volume logs, the peak hour occurred between 08:00 and 09:00 on September 24, with a total of 3,128 vehicles recorded during that hour. The 15-minute interval from 8:15 to 8:30 had the highest volume within the peak hour, with 803 vehicles. Therefore, this 15-minute period was chosen for the SIDRA model.

PFF was 97%, which suggested the traffic demand during the peak-hour was quite steady without significant variation.

The lane utilization of through lanes of Oteha valley road, Dairy flat highway and Albany highway was significantly lower at 65% (left through lane), 65% (right through lane) and 70% (left through lane). Lane utilization of the through lanes of the Albany expressway was found to be 90% (left through lane).

Volumes:

As mentioned earlier, the 15-minute interval from 8:15 to 8:30 had the highest volume within the peak hour, with 803 vehicles and was taken for the model development.

4.1.2 Ruakura Intersection:

This intersection, an important junction in Hamilton's transportation network, connects the major arterial Wairere Road with the minor arterial Ruakura Road. Its importance stems from its proximity to Ruakura super-hub (a major industrial, and logistics area), residential areas, and University of Waikato. The intersection provides link to the broader urban Hamilton city, the Te Rapa (another major commercial hub) via Wairere drive, the state highway (SH1) and Waikato expressway. The intersection is designed to cater for commuter, and freight flows.

The latest Crash Analysis System (CAS) data shows there have been a total of 65 crashes at the intersection since 2015, out of which three are serious crash, 13 are minor crash and others are non-injury crash with no fatalities. The majority of crashes were due to turn conflicts thus reflecting need for turn treatments. 40% of the serious crashes occurred during night thus highlighting the need for safety measures. Thus, need for turn treatments, improving night driving visibility, speed management and signal optimization may lead to increased safety for the commuters.

Table 4.2. Salient geometric features of the Ruakura intersection.

S.N.	Item	Description
1.	Intersection type	Four-way, signalized, at-grade intersection.
2.	Intersecting Roads (Posted speed limit)	• Wairere drive (60 kmph) • Ruakura Road (50 kmph)
3.	No. of lanes (At the approach)	Four
4.	Lane types	Each intersecting road consist of divided lanes with through lanes, and auxiliary turn treatments (dedicated right-turn bay and left turn slip-lane).
5.	Signal Control	SCATS-controlled signal system
6.	Pedestrian Facilities	Dedicated signalized pedestrian crossings with pedestrian refuge island.

Figure 4.2. Aerial Imagery of the Ruakura Intersection (LINZ Basemaps)

4.1.2.1 Traffic data specific to the intersection:

1. Traffic turn Count data:

   For the Ruakura intersection, traffic count data was similarly obtained in the form of SCATS volume logs for every 30 minutes intervals covering 24 hour period for October 30, 2024.

   Volume classification data for the classified movements were assumed based on the Albany intersection and verified during site visit.

2. Traffic signal data:

   Traffic Signal data was obtained in the form of SCATS phase logs for every 30 minutes intervals covering 24-hour period for the same day. The SCATS phase plans was also obtained.

3. Saturation flow data:

   Saturation flow rates for some of the approach lanes were measured on-site. Saturation flow rates for all of the approach lanes except for the left-turning lane for the Ruakura road west approach, left-through lane of the Ruakura road east approach, right-through lane of the Wairere drive south approach and the right-turning lane of the Wairere drive south approach were obtained from the site using the JCT Consultancy UK's JCT traffic tools android application. It was not possible to measure the saturation flows for all of the approaches due to lack of sufficient traffics as the measurement of saturation flows requires at least nine vehicles at the start of green as mentioned in the (Operational Modelling Guidelines (2021), and due to the lack of sufficient manpower resources.

4.1.2.2 SIDRA Setup specific to the intersection

Model Periods:

As per the SCATS volume logs, the peak hour was identified as 16:30 to 17:30 on September 24, with a total of 3,558 vehicles recorded during that hour. The 30-minute interval from 17:00 to 17:30 had the highest volume within the peak hour, with 1,846 vehicles. Therefore, this 30-minute period was chosen for the SIDRA model.

PFF was 96%, suggesting the traffic demand during the peak hour was quite steady and without significant variation as with the case of the Albany intersection.

Observations showed that lane utilization of through lanes of Ruakura road east approach was lower at 71% (shared lane), 77% (right through lane) for the Ruakura road east approach. Similarly, lane utilization of the Wairere drive south approach was 86% (left through lane) and for the Wairere drive south approach it was found to be 96% (left through lane).

Volumes:

As mentioned earlier, the 30-minute interval from 17:00 to 17:30 had the highest volume within the peak hour, with 1,846 vehicles and was taken for the model development.

The Albany and Ruakura intersections' SIDRA base models are now ready for analysis, and completing the build phase of **objective 1.**

Detailed calibration reports can be accessed from Appendix A.

The detailed modelling reports can be found in Appendix G.

4.2 Results and Discussions

4.2.1 Calibration Results:

Section 4.2.1 fulfils **objective 1** by calibrating saturation flows to within ± 5 % of field values.

The calibration of both intersection models demonstrated strong alignment with field-observed saturation flows, with all SIDRA-generated outputs falling within the acceptable ±5% range (Appendix A). The Ruakura intersection required four rounds of adjustment to meet calibration criteria, whereas the Albany intersection required three rounds, reflecting slightly more consistent flow behavior in Albany. In both cases, several movements showed high basic saturation flow rates (bsfr) but lower adjusted saturation flow rates (asfr), indicating localized operational constraints.

At Ruakura, the eastbound left-turn lane exhibited very high bsfr but significantly reduced asfr, likely due to downstream blockages or gap-acceptance delays. A similar pattern was observed in the shared through/right-turn lane of the Ruakura east approach, potentially influenced by conflicting movements. Most through movements at Ruakura maintained saturation flows above 1700 tcu/hr, with the exception of the left-through lane on the west approach, which had lower utilization (71%).

At Albany, comparable conditions were noted. The right-through lane on Dairy Flat Highway displayed a high bsfr but reduced asfr, attributed to underutilization (65%) and interference from the adjacent right-turn bay. Oteha Valley Road's left-turn lane also showed a similar drop in asfr, suggesting possible downstream interference. Across both intersections, consistently high saturation flows were recorded for through movements where flow was uninterrupted.

These findings highlight that short lane effects and conflicting manoeuvers significantly influence adjusted saturation flows at both sites. Extending the length of critical lanes and adjusting signal timing to allow for longer green times are recommended to improve capacity utilization.

4.2.2 Validation Results:

Both intersection models were successfully validated using the DoS criterion (Table 4.3 and Table 4.4) as discussed in the methodology. This confirms that the calibrated models are suitable for representing existing traffic conditions.

At the Ruakura intersection, validation revealed generally low saturation across most movements. Approaches on Wairere Drive North and South exhibited DoS values below 0.5, indicating sufficient green time and appropriate geometric configuration. However, two movements approached critical levels: the left-through lane of Ruakura Road East recorded a DoS of 0.976, and the right-turn lane of Ruakura Road West reached 0.933. These values suggest that while the overall intersection is stable, localized improvements such as signal timing adjustments or dedicated phasing may be needed to prevent oversaturation.

Table 4.3. Validation (DoS) for the Albany intersection

S.N.	Leg	Approach Lane	DoS	Remarks
1	Albany Expressway	Left	0.304	Stable
2		Left-Through	0.366	Moderate delay
3		Right-Through	0.407	Moderate delay
4		Right	0.396	Moderate delay
5	Oteha Valley Road	Left	0.115	Under capacity
6		Left-Through	0.597	Approaching congestion
7		Right-Through	0.918	High congestion risk
8		Right	0.104	Underused
9	Dairy Flat Highway	Left	0.024	Free flowing
10		Left-Through	0.700	Heavy queue, moderate delay
11		Right-Through	0.455	Moderate
12		Right	0.999	Critical movement
13	Albany Highway	Left	0.130	Free flowing
14		Left-Through	0.414	Moderate
15		Right-Through	0.591	Moderate
16		Right	0.874	Near saturation

Table 4.4.Validation (DoS) for the Ruakura intersection

S.N.	Leg	Approach Lane	DoS	Remarks
1	Wairere Drive South	Left	0.180	Free-flow
2		Left-Through	0.583	Sufficient reserve
3		Right-Through	0.678	Sufficient reserve
4		Right	0.019	Very low utilization
5	Ruakura Road East	Left	0.014	Free-flow
6		Left-Through	0.976	Near capacity
7		Through/Right (Shared)	0.752	Acceptable
8		Right	0.697	Acceptable
9	Wairere Drive North	Left	0.203	Very low utilization
10		Left-Through	0.461	Sufficient reserve
11		Right-Through	0.480	Sufficient reserve
12		Right	0.505	Acceptable
13	Ruakura Road West	Left	0.400	Ample reserve
14		Left-Through	0.532	Sufficient reserve
15		Right-Through	0.750	Acceptable
16		Right	0.933	Approaching capacity

The Albany intersection showed a similar validation pattern. Movements on the Albany Expressway maintained DoS well below 0.5, pointing to effective geometry and signal timing. The right-through lane of Oteha Valley Road, however, was flagged with a high DoS of 0.918, likely due to unbalanced lane usage and higher vehicle demand. The right-turn movement of Dairy Flat Highway reached near-saturation at 0.999, posing a risk of frequent delays and potential queue spillback. The right-turn of Albany Highway also trended toward saturation, while other movements remained well within capacity limits.

In both intersections, while general operation is validated and stable, a few critical lanes are operating at or near capacity. These results indicate the need for targeted interventions, such as extending turn bays, balancing lane usage, or revising signal timings.

The built SIDRA models are now calibrated and validated thus fulfilling the **objective 1** and are ready for further analysis.

4.2.3 Key Performance Indicators

Section 4.2.3 addresses **objective 2** through a baseline assessment of delay, queues, emissions and crash analysis.

4.2.3.1 DoS and LoS:

The operational performance of both intersections, as assessed through DoS and LoS, reveals a mixture of well-performing movements and critical operational deficiencies as inferred from the tables (Table 4.5 and Table 4.6). Overall, both intersections achieve an intersection-wide LoS of D, indicating average performance, with a number of individual movements operating under congested or near-capacity conditions.

At the Albany intersection, most movements operate with sufficient spare capacity, particularly those on Albany Expressway and left-turn lanes across all approaches, which maintain DoS values below 0.5. However, several movements are approaching or at saturation. Notably, the right-turn on Dairy Flat Highway (DoS = 0.999), right-through on Oteha Valley Road (DoS = 0.918), and right-turn on Albany Highway (DoS = 0.874) are of concern. These are also reflected in poor LoS outcomes, with all three movements operating at LoS E, suggesting congestion and a high frequency of cycle failures. Multiple other movements fall under LoS D, indicating operational delays and signal inefficiencies. Suggested improvements include signal retiming, optimization of phase splits, and geometric upgrades such as bay extensions.

Similarly, the Ruakura intersection shows generally balanced DoS values across Wairere Drive North and South approaches, with most movements under control. However, Ruakura Road East left-through (DoS = 0.976) and Ruakura Road West right-turn (DoS = 0.933) are operating near capacity. The left-through movement on Ruakura East is classified under LoS F, indicating severe congestion where queues are unlikely to clear in one cycle. One movement—Ruakura Road West right-turn—operates at LoS E, and several others are under LoS D, especially on the Wairere approaches. These conditions reflect poor progression, likely due to insufficient green time or inadequate storage lengths.

In both cases, priority-controlled left-turn movements perform well under LoS A conditions and do not require intervention unless pedestrian or conflicting demand increases. However, shared lanes and turning bays on saturated approaches contribute to critical performance drops. The findings highlights the need for intersection-specific interventions, such as extending short bays, redistributing lane usage, and implementing adaptive signal timings to mitigate delay and prevent further degradation of service levels.

Table 4.5. Performance summary of the Albany intersection

S. N.	Approach	Lane	DoS	Control Delay	LoS	95 percentile	Lane Length	Probability of Short
1	Albany Expressway	Left	0.304	21.50	C	46.30	35.00	30.6
2		Left-Through	0.366	46.00	D	32.20	368.00	
3		Right-Through	0.407	46.30	D	36.10	368.00	
4		Right	0.396	54.80	D	22.20	48.50	
5	Oteha Valley Road	Left	0.115	13.20	B	22.30	49.00	
6		Left-Through	0.597	40.80	D	73.40	198.00	
7		Right-Through	0.918	58.50	E	157.40	198.00	
8		Right	0.104	48.00	D	6.70	78.00	
9	Dairy Flat Highway	Left	0.024	5.50	A	2.20	56.00	
10		Left-Through	0.700	29.30	C	135.40	289.00	
11		Right-Through	0.455	25.10	C	75.80	289.00	
12		Right	0.999	70.60	E	175.90	41.00	100
13	Albany Highway	Left	0.130	4.10	A	8.70	35.00	
14		Left-Through	0.414	37.20	D	49.40	102.00	
15		Right-Through	0.591	38.90	D	79.20	102.00	
16		Right	0.874	60.90	E	70.60	58.00	22.9

Note: Text highlighted in red indicates that the queue length has exceeded the storage length

Table 4.6. Performance summary of the Ruakura intersection

S. N.	Approach	Lane	DoS	Control Delay (s/veh)	LoS	95 percentile QL (m.)	Lane Length (m.)	Probability of Short Lane Overflow (%)
1	Wairere Drive South	Left	0.180	6.2	A	26.20	71.80	
2		Left-Through	0.583	35.3	D	99.80	1025.00	
3		Right-Through	0.678	36.4	D	126.20	1025.00	
4		Right	0.019	48.6	D	1.30	109.00	
5	Ruakura Road East	Left	0.014	6	A	2.50	27.00	
6		Left-Through	0.976	80.7	F	190.10	697.00	
7		Through/Right (Shared)	0.752	46.1	D	98.80	697.00	
8		Right	0.697	47.3	D	89.60	51.50	56
9	Wairere Drive North	Left	0.203	2.7	A	20.90	63.10	
10		Left-Through	0.461	35.8	D	79.50	585.00	
11		Right-Through	0.480	36	D	82.90	585.00	
12		Right	0.505	54.6	D	43.60	92.40	
13	Ruakura Road West	Left	0.400	9.5	A	53.30	30.00	58
14		Left-Through	0.532	42.5	D	56.90	380.00	
15		Right-Through	0.750	47.5	D	96.00	380.00	
16		Right	0.933	69.5	E	138.50	55.20	91.6

Note: Text highlighted in red indicates that the queue length has exceeded the storage length

4.2.3.2 Queue Length analysis:

Queue length analysis for both intersections reveals significant congestion risks, with multiple approach lanes either exceeding or nearing available storage capacities. This poses operational challenges such as queue spillback, short lane blockages, and potential disruptions to upstream flows.

At the Albany intersection (refer Figure 4.3), several lanes are also operating under high queuing pressure. The Dairy Flat Highway – Right lane exhibits an extreme case with 175.9 m queue vs. 41.0 m storage, registering a 100% short lane blockage probability. Other notable movements include Albany Expressway – Left (46.3 m vs. 35.0 m), Albany Highway – Right (70.6 m vs. 58.0 m), and Oteha Valley Road – Right Through (157.4 m). Although some queues like Dairy Flat

Highway – Left-Through (135.4 m) and Albany Highway – Right-Through (79.2 m) are still within storage limits, they indicate rising demand and vulnerability to congestion under peak or growing volumes.

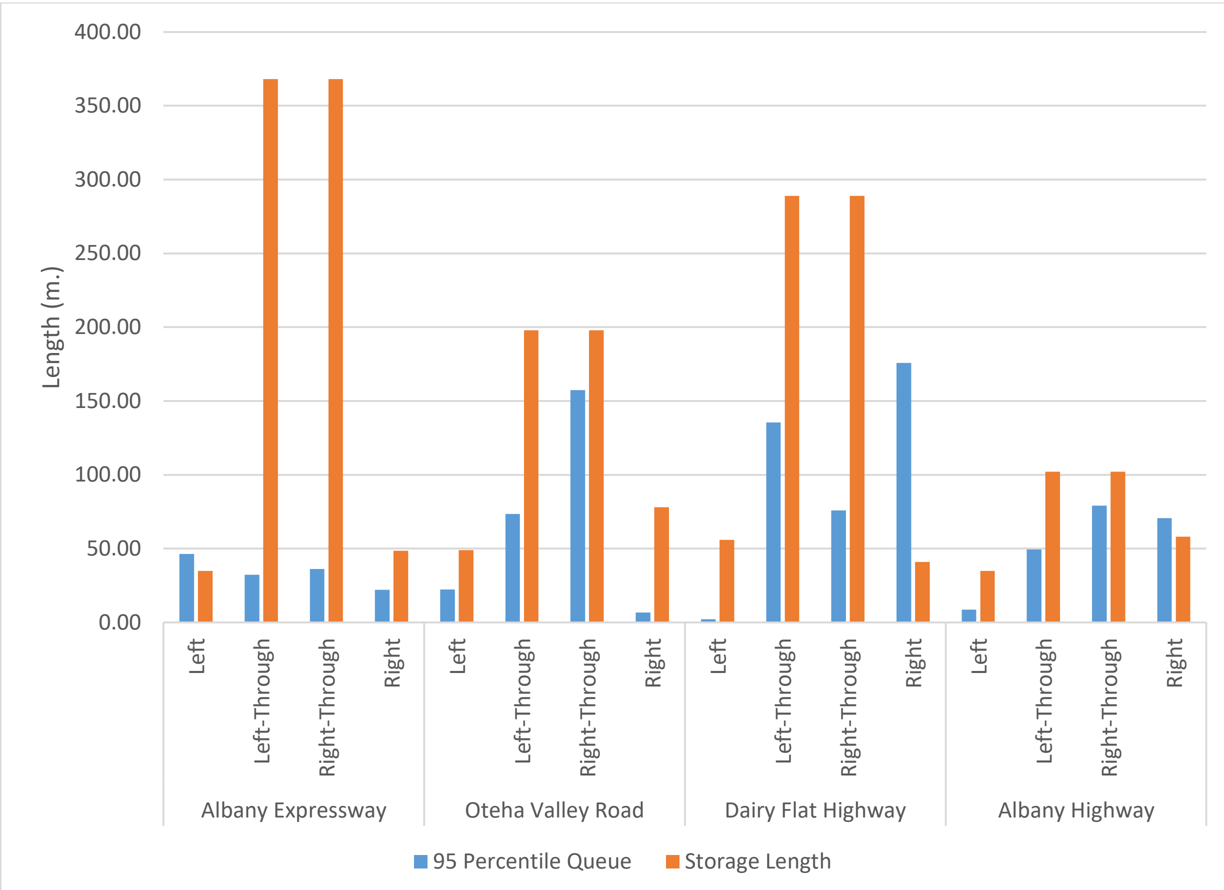


Figure 4.3. Queue Length vs Storage (Albany Intersection)

Similarly, at the Ruakura intersection (Figure 4.4), several turning lanes already exceed their available storage, with the most critical being Ruakura Road East – Right (89.6 m vs. 51.5 m), Ruakura Road West – Left (53.3 m vs. 30 m), and Ruakura Road West – Right (138.5 m vs. 55.2 m), each associated with high short lane blockage probabilities of 56%, 58%, and 91.6%, respectively. In addition, through movements such as Wairere Drive South – Left-Through (99.8 m) and Right-Through (126.2 m), and Ruakura Road East – Left-Through (190.1 m), approach critical storage thresholds. Although not yet exceeding limits, their elevated queue lengths signal growing demand, frequent cycle failures, or insufficient green time allocation.

In both intersections, turning lanes are especially constrained, primarily due to limited storage space, while through lane queuing appears linked to unbalanced lane utilization. These patterns underline the importance of intersection-wide optimization over isolated fixes. Recommended measures include signal re-timing, extension of critical turn bays, and implementation of protected phasing for saturated movements. Without intervention, these conditions are likely to worsen under increasing traffic demand, impacting not only intersection performance.

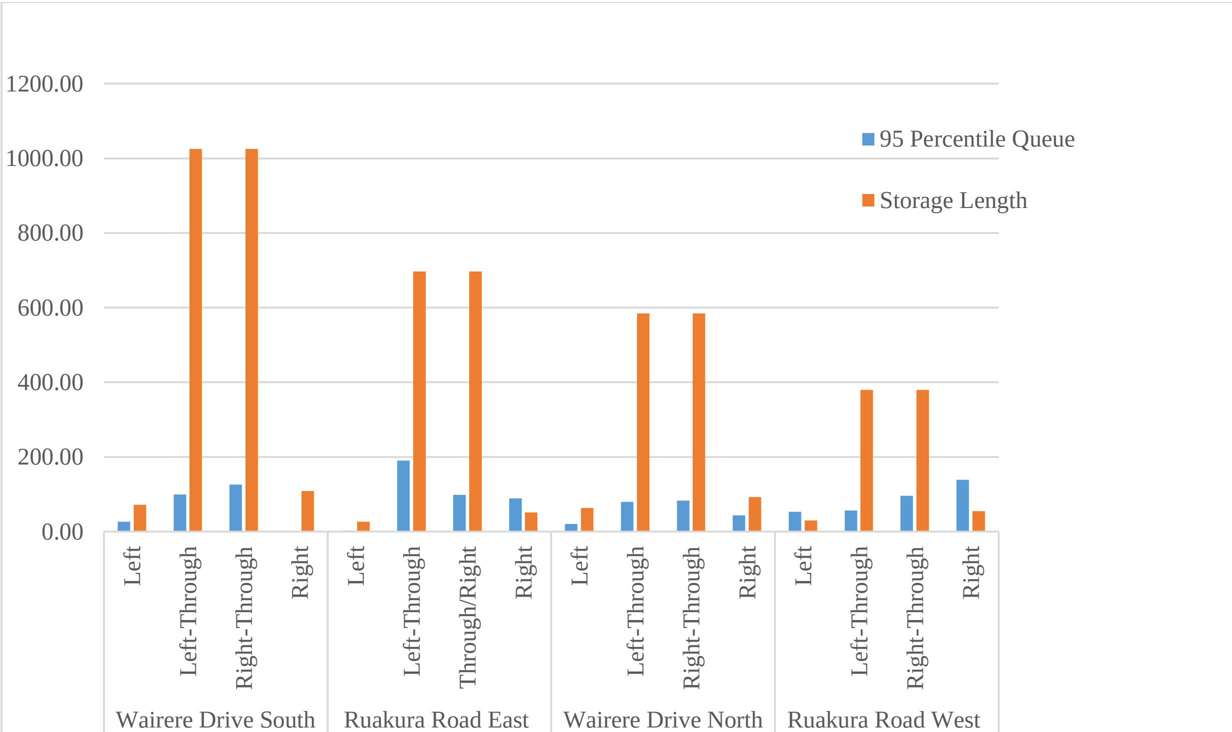


Figure 4.4. Queue Length vs Storage (Ruakura Intersection)

4.2.4 Mitigation of the current operational performance:

To enhance intersection performance and align with the standard operational target of LoS D, as recommended by guidelines (e.g., Traffic Modelling Guidelines – SIDRA INTERSECTION, 2023; Operational Modelling Guidelines, 2021), targeted manual optimization strategies were implemented at both the Albany and Ruakura intersections. These strategies aimed to address critical movements operating below the target LoS, without altering the overall cycle length of 101 seconds.

At the Albany intersection (refer Appendix G), three lanes were identified as operating below the desired LoS: Oteha Valley Road – Right-Through, Dairy Flat Highway – Right, and Albany Highway – Right. To improve their performance, two main interventions were made:

- Geometric adjustment: The right-through lane width was increased (from 3.2 m to 3.45 m) to improve saturation flow, while the adjacent left-through lane was slightly narrowed (from 3.75 m to 3.5 m) to accommodate this change.
- Signal phase redistribution: Phase times for Phases D, E, and G—serving the critical lanes—were increased, while timing of Phase A was reduced. Phase C was kept constant.

The revised phase splits improved delay conditions for the underperforming movements, with minimal impact on others. Only one movement, Dairy Flat Highway – Left-Through, experienced a minor drop in performance (from LoS C to LoS D), which remains within the acceptable threshold (refer Appendix G)

Phase changes before improvement and after the targeted improvement are tabulated below:

Table 4.7. Base case Phase summary of Albany intersection

Phase	**A**	**C**	**D**	**E**	**G**
Phase Change Time (sec)	0	19	42	60	87
Green Time (sec)	14	18	13	22	9
Phase Time (sec)	19	23	18	27	14
Phase Split	19%	23%	18%	27%	14%

Table 4.8. Revised Phase summary of Albany intersection to target LoS 'D'

Phase	A	C	D	E	G
Phase Change Time (sec)	0	14	37	57	85
Green Time (sec)	9	18	15	23	11
Phase Time (sec)	14	23	20	28	16
Phase Split	14%	23%	20%	28%	16%

At the Ruakura intersection (refer Appendix G), the focus was on improving LoS for two critical movements: Ruakura Road East – Left-Through and Ruakura Road West – Right. Unlike Albany, no geometric changes were made. Instead, signal phase times were manually adjusted:

- Phase A time was reduced, while time allocations for Phases D and E were increased to benefit the saturated movements. Phase F remained unchanged.

The revised phase splits led to effective improvement in LoS for the targeted movements, while maintaining the performance levels of the remaining approaches as can be referenced from Appendix G. Notably, no movements experienced degradation in service level.

Phase changes before and after the targeted improvement are tabulated below:

Table 4.9. Base case Phase summary of Ruakura intersection

Phase	A	D	E	F
Phase Change Time (sec)	0	36	61	88
Green Time (sec)	31	20	22	14
Phase Time (sec)	36	25	27	19
Phase Split	34%	23%	25%	18%

Table 4.10. Revised Phase summary of Albany intersection to target LoS 'D'

Phase	A	D	E	F
Phase Change Time (sec)	0	31	58	87
Green Time (sec)	26	22	24	14
Phase Time (sec)	31	27	29	19
Phase Split	29%	25%	27%	18%

By adopting a manual optimization strategy for both intersections green times was reallocated from better-performing phase movements to underperforming ones. The cycle length was preserved in both cases, avoiding disruption to overall timing structure. These adjustments illustrate a practical and cost-effective method for delay reduction and performance levelling, particularly suitable for intersections under SCATS control logic where DoS balancing is a key operational principle.

4.2.5 Future Traffic Performance Assessment

Section 4.2.5 completes **objective 3** by projecting 10-year performance under 2–3 % annual demand growth.

To evaluate long-term intersection functionality, a future traffic performance assessment was conducted for both the Albany and Ruakura intersections with a planning horizon of 10 years extending to the year 2034 as can be referenced from Modelling results indicate that both intersections, currently operating at LoS D, will deteriorate significantly over the next decade. For Albany, model projections show that LoS will drop to LoS F by 2034, with noticeable degradation beginning around 2027 (refer Table 4.11).

Table 4.11. Performance indicator during planning horizon for Albany intersection

Year	DoS	Average Delay (sec)	Intersection LoS (Sidra (Delay) method)
2024	0.999	43.2	D
2025	1.029	41.5	D
2026	1.059	45.8	D
2027	1.089	50.7	D
2028	1.119	56.2	E
2029	1.148	62.2	E
2030	1.178	68.9	E
2031	1.208	76.3	E
2032	1.239	84.8	F
2033	1.300	98.8	F
2034	1.356	111.7	F

Note: Text highlighted in red indicates that the LoS has degraded below target LoS 'D'

Similarly, the Ruakura intersection will experience worsening operational efficiency, reaching LoS F by 2034 with LoS degradation below 'D' by 2028 (refer Table 4.12). In both scenarios, the analysis reveals that turning movements will become critical, with several lanes experiencing queue lengths that exceed available storage, leading to overflow, frequent cycle failures, and blocked upstream lanes.

Table 4.12. Performance indicator during planning horizon for Ruakura intersection

Year	DoS	Average Delay (sec)	Intersection LoS (Sidra (Delay) method)
2024	0.976	39.7	D
2025	1.002	42.3	D
2026	1.026	45.4	D
2027	1.052	48.4	D
2028	1.078	51.8	D
2029	1.103	55.8	E
2030	1.128	60.4	E
2031	1.154	66	E
2032	1.181	71.3	E
2033	1.206	77.1	E
2034	1.232	83.4	F

Note: Text highlighted in red indicates that the LoS has degraded below target LoS 'D'

At Albany, these effects are particularly evident in right-turn lanes, where queue spillback is projected to intensify. At Ruakura, both through and turning lanes show vulnerability to oversaturation, especially on approaches with shared lane configurations. The growing imbalance between traffic demand and geometric/signal capacity underscores the urgency of proactive interventions.

The process included forecasting traffic volumes using annual growth rates, simulating operational conditions using SIDRA, and assessing key indicators such as LoS and 95th percentile queue lengths. While for the Albany intersection a 3% annual growth rate was adopted due to its proximity to business hubs and projected urban intensification, while 2% growth rate was used in alignment with observed development pace.

Modelling results indicate that both intersections, currently operating at LoS D, will deteriorate significantly over the next decade. For Albany, model projections show that LoS will drop to LoS F by 2034, with noticeable degradation beginning around 2027 (refer Table 4.13). Similarly, the Ruakura intersection will experience worsening operational efficiency, reaching LoS F by 2034 with LoS degradation below 'D' by 2028 (refer Table 4.14). In both scenarios, the analysis reveals that turning movements will become critical, with several lanes experiencing queue lengths that exceed available storage, leading to overflow, frequent cycle failures, and blocked upstream lanes.

Table 4.13. Comparison of Base year and Year 2034 for the Albany intersection

S.N.	Approach	Lane	LoS (Base Case)	LoS (2034)	95 percentile Queue Length (m.) (2034)	Storage Length
1	Albany Expressway	Left	C	C	66.50	35.00
2		Left-Through	D	D	42.70	368.00
3		Right-Through	D	D	47.90	368.00
4		Right	D	E	29.30	48.50
5	Oteha Valley Road	Left	B	C	43.70	49.00
6		Left-Through	D	D	99.90	198.00
7		Right-Through	E	F	359.70	198.00
8		Right	D	D	8.70	78.00
9	Dairy Flat Highway	Left	A	A	3.60	56.00
10		Left-Through	C	F	351.20	289.00
11		Right-Through	C	C	81.50	289.00
12		Right	E	F	402.80	41.00
13	Albany Highway	Left	A	A	12.90	35.00
14		Left-Through	D	D	65.10	102.00
15		Right-Through	D	D	120.50	102.00
16		Right	E	F	137.80	58.00
		Intersection	D	F		

Table 4.14.Comparison of Base year and Year 2034 for the Ruakura intersection

S.N.	Approach	Lane	LoS (Base Case)	LoS (2034)	95 percentile Queue Length (m.) (2034)	Storage Length
1	Wairere Drive South	Left	A	A	36.20	72.00
2		Left-Through	D	D	125.50	1025.00
3		Right-Through	D	D	170.80	1025.00
4		Right	D	D	1.50	109.00
5	Ruakura Road East	Left	A	A	3.70	27.00
6		Left-Through	F	F	464.40	697.00
7		Right-Through	D	E	141.50	697.00
8		Right	D	F	158.90	52.00
9	Wairere Drive North	Left	A	A	33.90	63.00
10		Left-Through	D	D	98.50	585.00
11		Right-Through	D	D	103.00	585.00
12		Right	D	E	53.30	92.00
13	Ruakura Road West	Left	A	B	82.50	30.00
14		Left-Through	D	D	68.10	380.00
15		Right-Through	D	F	224.50	380.00
16		Right	E	F	314.50	55.00
		Intersection	D	F		

Note: Text highlighted in red indicates that the queue length has exceeded the available storage length

At Albany, these effects are particularly evident in right-turn lanes, where queue spillback is projected to intensify. At Ruakura, both through and turning lanes show vulnerability to oversaturation, especially on approaches with shared lane configurations. The growing imbalance between traffic demand and geometric/signal capacity underscores the urgency of proactive interventions.

The future resilience assessment of the intersections was performed and confirmed notable performance degradation of the intersections under the projected demand, thereby meeting the forecasting requirement of **objective 3**.

4.2.6 Sustainability Performance:

The sustainability performance analysis of the Albany and Ruakura intersections highlights distinct energy and environmental profiles, due to differing traffic compositions and lane dynamics. Despite similarities, key sustainability indicators diverge significantly due to geometric and traffic demand differences.

The estimated hourly operating cost of the Albany intersection is approximately NZ $3,000, with fuel contributing 21%, running costs 53%, and delay costs 26% of the total (refer Appendix A, Figure 4.5). The northbound Dairy Flat Highway approach alone accounts for about half the total cost, despite carrying only 37% of the total volume, underscoring its inefficiency. The intersection consumes around 238 L of fuel per hour, translating to 0.074 L/veh/hr, with CO_2 emissions estimated at 565 kg/hr and NO_x emissions at 1.03 kg/hr. The bulk of emissions originate from the Dairy Flat Highway, with its right and through lanes being the largest contributors. Reducing delay in these lanes would yield the most significant operational and environmental gains.

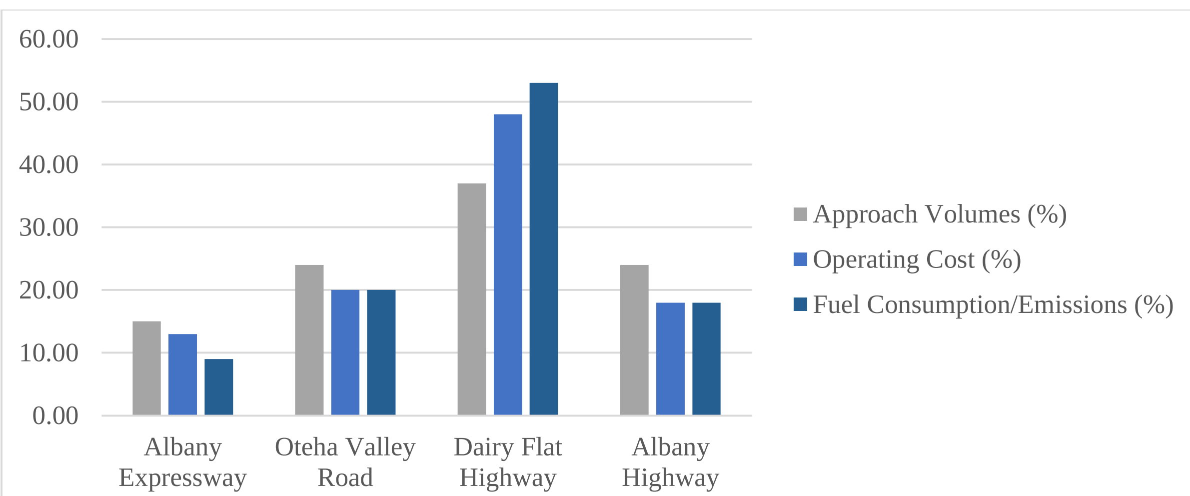


Figure 4.5. Approach Volumes vs Operating cost, Fuel Consumptions, and Emissions (Albany)

In contrast, the Ruakura intersection (refer Appendix A, Figure 4.6) incurs a higher operating cost of NZ $4,600 per hour, nearly 1.5 times greater than Albany, despite carrying only 15% more volume. This elevated cost is mainly due to higher fuel consumption (492 L/hr), with fuel accounting for 28% of the total cost and delay contributing just 2%, suggesting a more fuel-intensive intersection profile.

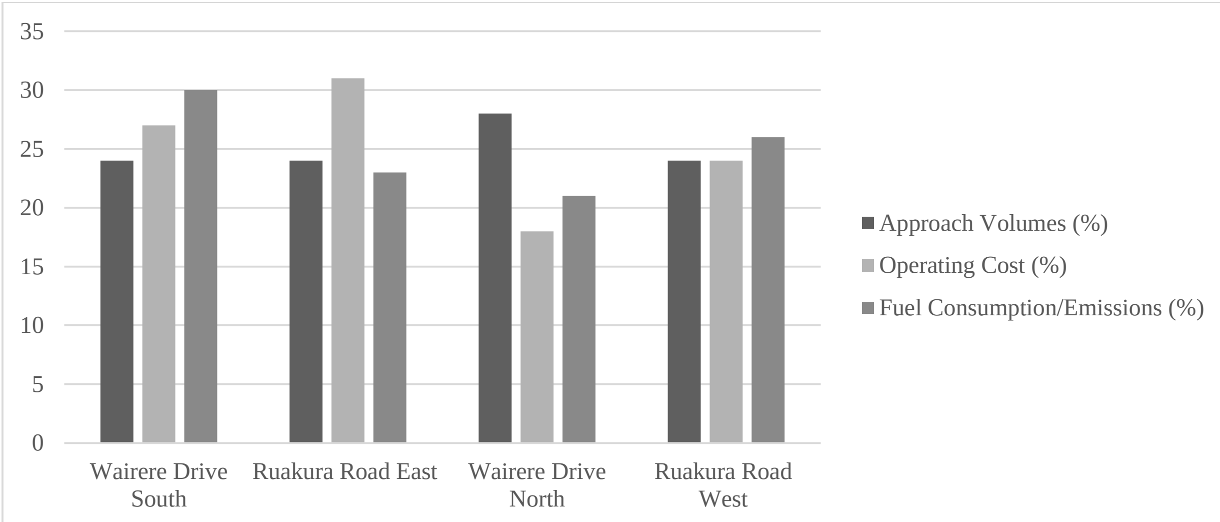
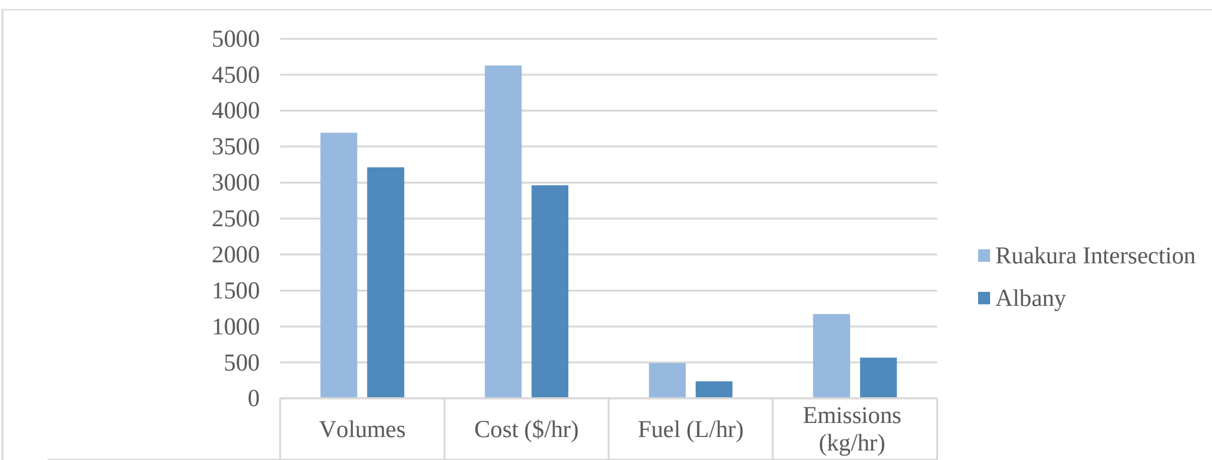


Figure 4.6. Approach Volumes vs Operating cost, Fuel Consumptions, and Emissions (Ruakura)

The Wairere Drive South approach emerges as the largest emitter, contributing 30% of fuel consumption, 25% of CO_2, and 35% of NO_x emissions, even though it only carries 16.8% of the traffic volume. Emissions at Ruakura are roughly double those at Albany, with total CO_2 emissions reaching 1.12 tons/hr and NO_x at 1.75 kg/hr. The Ruakura Road East approach is another hotspot, responsible for 31% of the cost while handling only 24% of the volume.



	Volumes	Cost ($/hr)	Fuel (L/hr)	Emissions (kg/hr)
Ruakura Intersection	3692	4628.45	492.1	1171.456
Albany	3212	2962.39	237.90	566.1

Figure 4.7. Sustainability performance comparisons of the intersections

These results indicate a fundamental contrast in sustainability profiles: Albany's cost is driven more by delay, whereas Ruakura's is driven more by fuel inefficiency. Interventions should be targeted accordingly—signal retiming and queue management at Albany can significantly reduce delay-related costs, while geometric improvements and throughput enhancements on fuel-intensive approaches like Wairere Drive South and Ruakura Road East are critical for Ruakura. Without such targeted measures, continued inefficiencies will not only increase operational costs but also worsen environmental impacts. The figurative comparisons of the intersections can be referred from Figure 4.7.

4.2.7 Crash analysis:

Crash data analysis for the Albany and Ruakura intersections, based on records from the Crash Analysis System (CAS) since 2015, provides insight into their respective safety performance. As intersections are recognized as high-risk locations within urban traffic networks, such evaluations are essential for identifying recurring patterns and supporting safety upgrades.

At the Albany intersection, a total of 55 crashes were recorded, including 8 minor-injury and 3 serious-injury crashes. A significant share—20 (≈ 36%) crashes—occurred during night-time conditions, and 12 (≈ 22%) incidents happened under wet-weather conditions. While the majority of crashes were non-injury events involving property damage, the presence of multiple serious crashes is a concern. Notably, the absence of pedestrian crossings at slip lanes presents safety risks for vulnerable users. Potential causes such as poor lane geometry, signal phasing, or visibility limitations warrant further examination. Addressing these issues through improved signage, geometric redesign, and pedestrian protection treatments would enhance safety outcomes.

In comparison, the Ruakura intersection recorded a slightly higher total of 65 crashes, with 13 minor-injury and 3 serious-injury incidents. The proportion of night-time crashes (17≈ 26%) and wet-weather crashes (8 ≈ 12%) was comparable to Albany. The majority of crashes were due to turn conflicts thus reflecting need for turn treatments.

In both intersections, while the majority of crashes were not life-threatening, the number of injury and serious injury events highlight the need for targeted safety measures. Improvements in intersection design, signal control, pedestrian facilities, and driver behavior management are critical. Although a more detailed safety performance analysis would require further data and modeling which is beyond the scope of this study, the trends observed support the prioritization of intersection upgrades under safety-driven infrastructure funding frameworks.

With baseline delay, sustainability, and crash-risk profiles now established for both intersections, objective 2 is fulfilled.

4.3 Summary:

This chapter built, calibrated and validated SIDRA models for the Albany and Ruakura SCATS-controlled intersections, providing a robust digital model of base case operations. Using these models, a holistic baseline analysis highlighted operational, sustainable and safety shortcomings that require timely intervention. A resilience test for the anticipated traffic growth for the planning horizon of 10 years (2034), then demonstrated that, without further optimisation, intersection performance will deteriorate appreciably under forecast traffic growth.

While manual reallocation of green time can achieve performance gains as demonstrated in sub-chapter 4.2.4, it is labor-intensive and cannot adapt instantaneously in real time to address fluctuating demand. Collectively, these findings motivate the data-driven delay-prediction and signal-timing optimisation work undertaken in Chapter 5, where supervised ML models will enable SCATS to anticipate delay and update cycle length in real time.

Chapter 5 MACHINE LEARNING ANALYSIS

Chapter 4 confirmed that the calibrated SIDRA models for the Albany and Ruakura intersections reproduced field saturation flows within ±5 % and was validated using DoS criteria. The developed SIDRA models are deemed to mimic the SCATS logic and therefore assumed to be the digital model of the SCATS-controlled intersections. For the purpose of ML analysis, only the Albany SIDRA model was employed due to the richer dataset of SCATS volume logs. Using the procedure detailed in **Chapter 3 – Methodology**, each scenario was run through the validated SIDRA model with the "Optimum Cycle Time" controller set to a practical DoS target of 0.90, to match the SCATS logic. The resulting traffic-performance outputs—volumes, DoS, cycle length and the synthetic average delay—were compiled into a structured traffic matrix for ML analysis.

Chapter 1 highlighted a key research gap: existing SCATS signal control provides no data-driven forecasts of delay or systematic way to refine cycle length. Bridging that gap requires (i.) a reliable delay-prediction model, and (ii.) an optimisation framework that can recommend improved cycle times.

This chapter addresses **objective 4**—develop and statistically validate machine-learning models for the prediction of intersection delay—and **objective 5**—develop ML models that optimizes cycle length to minimize a delay.

The chapter is organised as follows. **Section 5.1** describes the traffic-matrix dataset, details the training and validation of four ML algorithms (RF, XGB, SVR and kNN), and discusses their predictive accuracy relative to analytical benchmarks. **Section 5.2** explains the optimisation framework, applies it to 18 test scenarios, and evaluates the resulting improvements in delay and emissions compared with SCATS baseline timings.

5.1 Delay Prediction

Section 5.1 addresses **objective 4**. It begins with a **data description** of the 98-scenario traffic matrix derived from Monte-Carlo-expanded SCATS logs. The section then presents **model development and validation results** for RF, XGB, SVR and kNN followed by a **discussion** of statistical performance.

5.1.1 Statistical Description of the data

The delay matrix was extracted from the main traffic matrix which was intended for the development of the machine learning algorithm for delay prediction. The delay matrix can be referenced from Appendix F.

5.1.1.1 Properties of the dataset

As reference from the Table 5.1, salient properties of the delay matrix are noted as:

- The average DoS value of ≈ 1.09 suggests most synthetic datasets are over-saturated. The range of DoS is 0.82 – 1.31.
- Mean delay is ≈ 70 seconds with significant spread as suggested by standard deviation of ≈19 seconds.
- 49.5% of the dataset represents morning peak and the remainder corresponding to the afternoon peak.

Table 5.1. Statistical properties of the synthetic dataset used for delay prediction

Features	Average	Standard Deviation	Minimum	Maximum
Volumes	3799.34	359.24	2908.00	4476.00
DoS	1.09	0.11	0.82	1.31
Cycle Length	110.17	24.56	71.00	150.00
Delay	69.83	18.69	34.80	112.30

5.1.1.2 Distribution of the dataset

Statistical distribution of the features of the dataset is illustrated in the Figure 5.2 below.

Properties of the distribution are:

- Volumes: The distribution is unimodal and is slightly right-skewed, peaking near 3800 veh/h.
- DoS: The distribution is unimodal centred between 1.05–1.15 with thinning density beyond 1.25.
- Cycle length: The distribution is bimodal. A main hump around 80–95 s captures normal signal plans, while a secondary hump at 130–145 s represents extended cycles applied when volumes or DoS rise.
- Delay: The distribution is right-skewed bell shaped. Most delays are centered between 55–75 s and has a long tail past 100s. Delay distribution by time period is shown in the
- Figure 5.1 below.

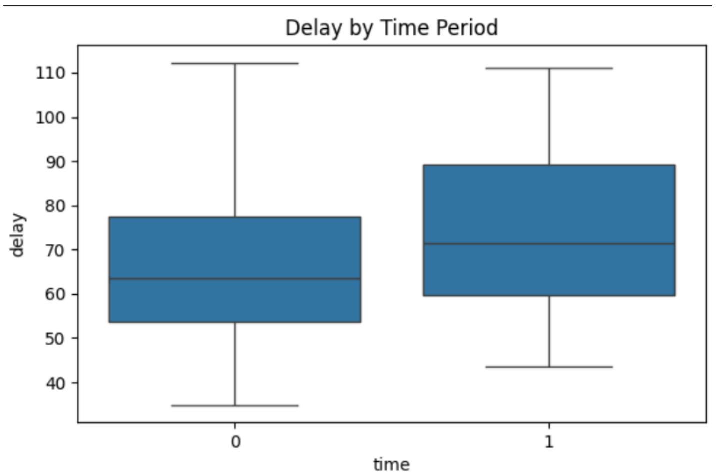


Figure 5.1. Delay data by time period (“1” represents morning peak and vice-versa)

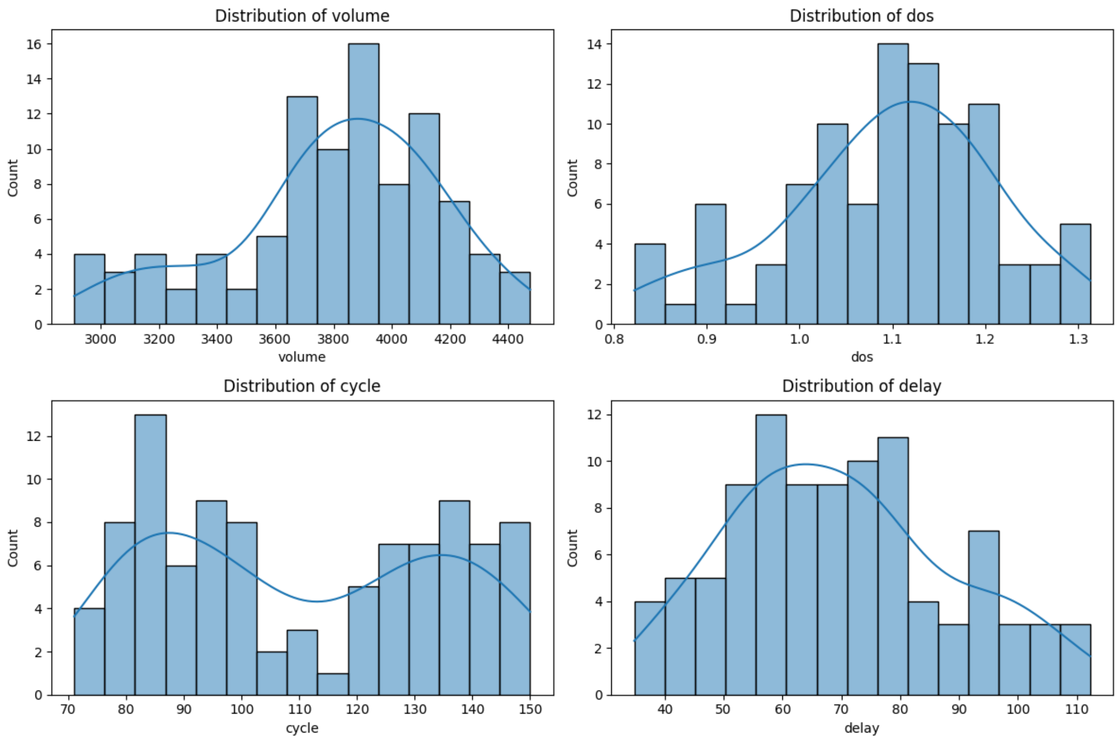


Figure 5.2. Statistical distribution of features and target of dataset

5.1.1.3 Outlier test:

To detect the outliers from the dataset, Inter Quartile Range (IQR) was used.

IQR for delay was calculated to be = 24.5 seconds

The bounds for the outlier were computed as follows:

Lower Bound: Q1 – 1.5 × IQR = 56 – (1.5 × 24.5) = 19.25 seconds

Upper Bound: Q3 + 1.5 × IQR = 80.5 + (1.5 × 24.5) = 117.25 seconds

The dataset was free from the outlier range (delay data below 19.25 seconds and above 117.25 seconds).Though, the synthetic dataset was free from statistical outliers, and output for one of the dataset was not stable from the SIDRA and was removed from the dataset. Thus, reducing to 97 datasets.

5.1.1.4 Co-relationship tests:

Before proceeding with the development of machine learning models it was deemed essential to find out the relationships between the target variable (delay) with the features. In order to find the correlation, Pearson's correlation test was performed. The correlation test result is shown in the heat-map (Figure 5.3) below.

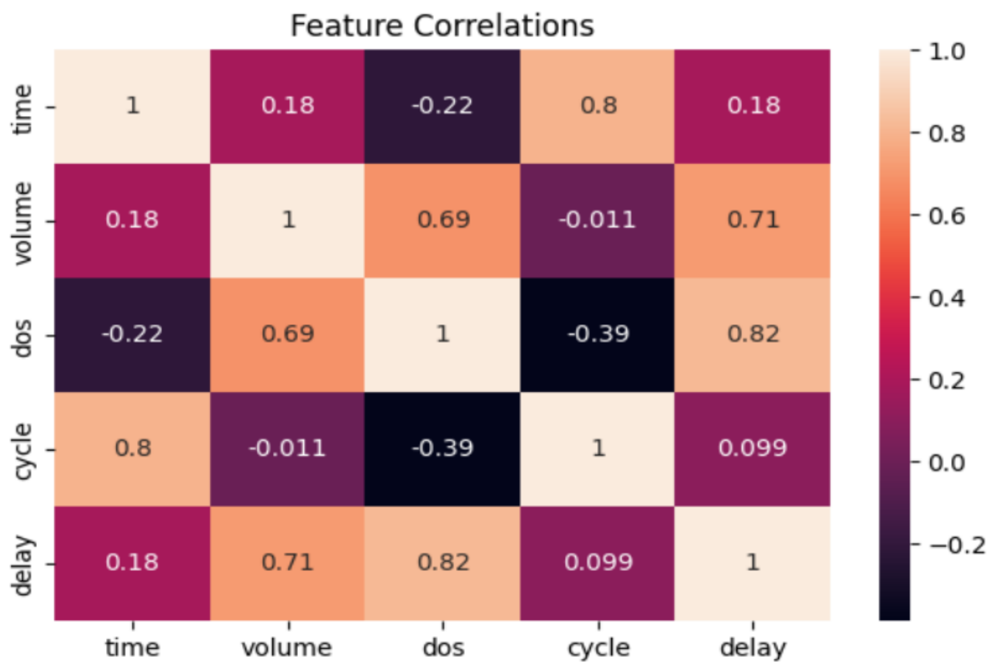


Figure 5.3. Co-relation test using the Pearson test

Following points are noteworthy from the figure above:

- Delay vs time: Pearson (p) value of only 0.18 represents weak relationship.
- Delay vs volume: p value of 0.71 represents strong relationship.
- Delay vs DoS: p value of 0.82 represents strong relationship.
- Delay vs cycle length: p value of 0.099 represents very weak relationship.

Since the p value for delay vs cycle length is very low for the Pearson correlation test. Pearson partial correlation test was used to find the relationship between delay and cycle length independent of their shared relationship with dos. The partial correlation value (r) between delay vs cycle length was found to be 0.79 which indicates a very strong relationship.

Despite the p value of 0.08, the high value of 0.79 backs using the cycle length as one of the features. Moreover,

- Cycle length is a controllable parameter in signal timing optimization.
- Traffic engineering literatures identify cycle length as a key factor in delay calculations (e.g., Webster's formula, HCM delay, etc.) which is also depicted in Figure 5.4 below.

National Academies of Sciences, (2022 pp. 4-17) mentions "*there is a strong relationship between delay and cycle length. For every intersection there is a small range of cycle lengths that will result in the lowest average delay for motorists. Delay, however, is a complex variable affected by many variables besides cycle length.*"

The direct effect of cycle length might have been masked by the effect of DoS which explains the lower p value. When the effect of DoS was removed the relationship between delay and cycle length was found to be prominent with a (r) value of 0.85.

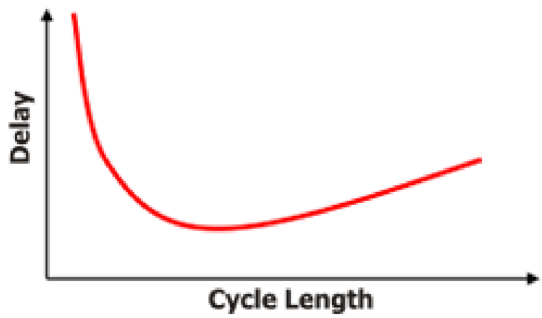


Figure 5.4. General relationship between delay and cycle length (HCM, 2022)

5.1.2 Hyperparameter Tuning:

Hyperparameter tuning grid for the ML models are listed below in Table 5.2, Table 5.3, Table 5.4, and Table 5.5.

5.1.2.1 XGBoost:

Table 5.2. Hyperparameter grid for XGBoost

Parameter	Values
n_estimators	[100, 200, 300]
max_depth	[3, 5, 7]
learning_rate	[0.01, 0.1, 0.2]
sub_sample	[0.7, 0.8, 0.9]
reg_lambda	[0.5, 1.0, 2.0]
gamma	[0, 0.1, 0.2]

Total model fits for the XGBoost model = 3^6 =729 * 5 folds = 3645, which means the model was trained 3,645 times.

5.1.2.2 Random Forest:

Table 5.3. Hyperparameter grid for Random Forest

Parameter	Values
max depth	100, 200, 300
max features	none, 10, 20
min sample splits	sqrt, 0.8
n_estimators	2, 5, 10

The Random Forest model was trained 270 times using 54 parameters combinations five times.

5.1.2.3 kNN:

Table 5.4.Hyperparameter grid for kNN

Parameter	Values
kNN metric	range (3,21, 2)
n_neighbors	'uniform', 'distance'
kNN_weights	'euclidean', 'manhattan'

Likewise, this gave a total of 180 model fits.

5.1.2.4 SVR:

Table 5.5.Hyperparameter grid for SVR

Parameter	Values
svr_C	0.1, 1, 10
svr_epsilon	0.05, 0.1
svr_gamma	'scale', 'auto'
svr_kernel	'linear', 'rbf'

This resulted in a total of 120 model fits for the SVR model.

5.1.2.5 Ensemble of XGBoost and Random Forest:

To combine the complementary strengths of the XGBoost and Random Forest, an ensemble model of the models XGBoost and Random Forest was created. The ensemble model mitigated the weaknesses of the models while combining their strengths.

5.1.3 Results and Discussions:

5.1.3.1 Overall Performance

All the models demonstrated high operational accuracy (MAE < 8 s; $R^2 \geq 0.80$), with predictions closely matching synthetic observations—especially for XGBoost and Random Forest (refer Table 5.6 and Figure 5.5 for figurative comparison). The ensemble model (XGB+RF) outperforms all individual models, achieving the lowest error (MAE: 4.09 s; RMSE: 5.98 s; MAPE: 5.44%; R^2 = 0.94), validating its suitability for real-time delay prediction (refer Figure 5.7).

Table 5.6.Statistical summary of the performance of ML models

S. N.	ML Model	MAE (secs)	RMSE (secs)	MAPE	R^2	Training Time (s)	Prediction Time (ms)
1	XGBoost	4.25	7.03	5.70	0.91	37.32	2.00
2	RF	4.79	6.19	6.63	0.93	20.27	21.00
3	kNN	4.84	6.05	7.02	0.94	0.30	1.00
4	SVR	7.43	10.55	11.57	0.80	0.18	0.00
5	XGB+RF	4.09	5.98	5.44	0.94	0.23	17

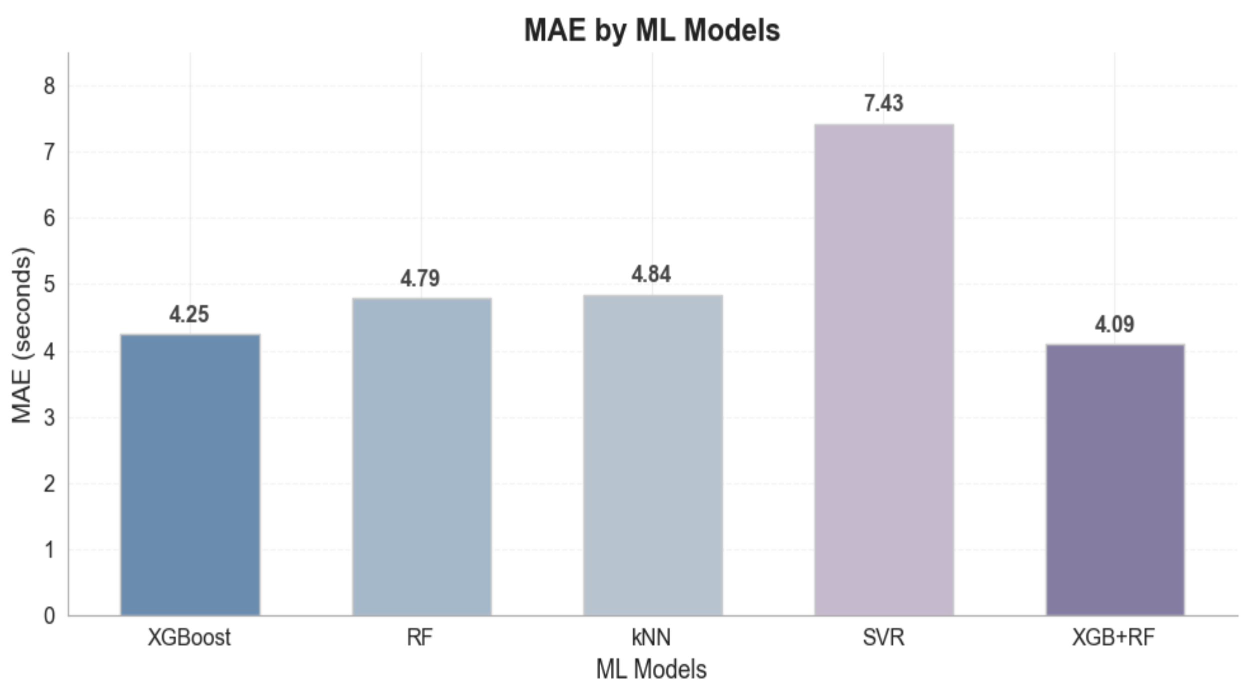


Figure 5.5. MAE distribution of the models

The results of the best hyperparameters are summarized in the Table 5.7 and the delay predictions compared with observed (synthetic data) can be referred from Figure 5.6.

Table 5.7. Hyperparameter tuning results

1	XGBoost		3	kNN	
	gamma	0		kNN metric	Euclidean
	learning Rate	0.2		n_neighbors	3
	max_depth	7		kNN_weights	distance
	n_estimators	100			
	lambda	2			
	sub-sample	0.7			
2	Random Forest		4	SVR	
	max depth	20		SVR_C	10
	max features	0.8		SVR_epsilon	0.1
	min sample splits	2		SVR_gamma	scale
	n_estimators	100		SVR_kernel	linear

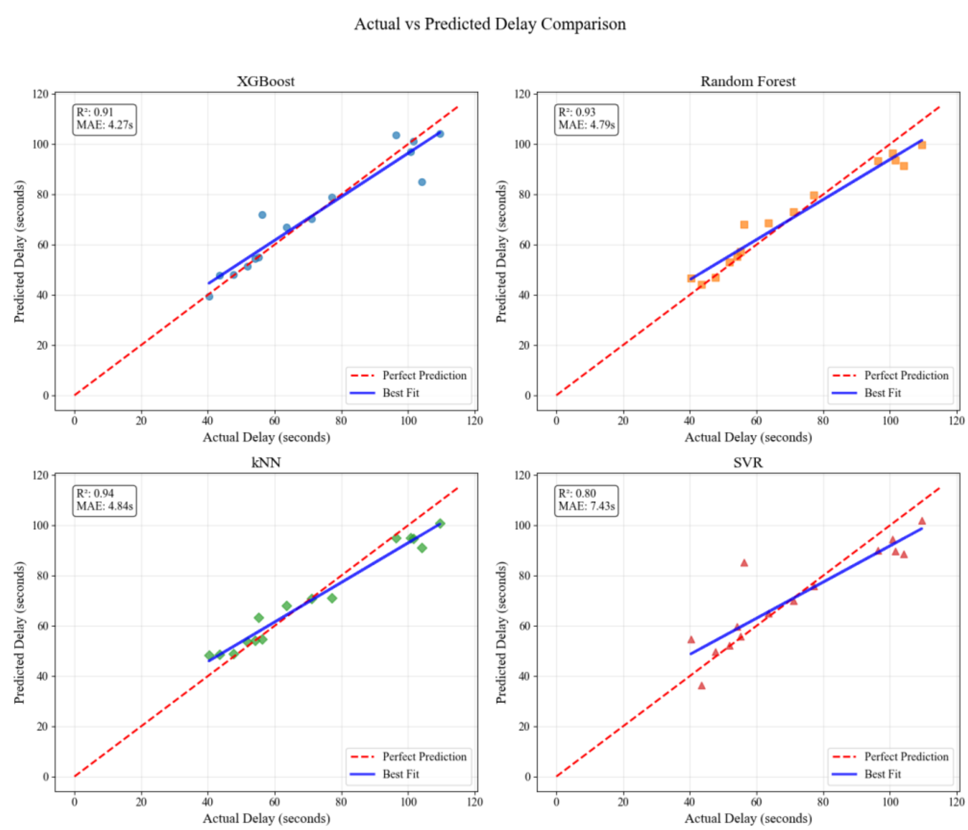


Figure 5.6. Delay predictions comparisons of each delay models with the observed (synthetic)

As referenced from the Figure 5.6, for S.N. 12 (actual delay: 56.2 seconds, refer Appendix F: Delay Matrix), all models, but especially SVR, produced significant prediction errors. SVR's large error likely results from its reliance on the overall data distribution and its sensitivity to cases that are not well represented in the training data. Unlike tree-based models (Random Forest, XGBoost), which are more robust to outliers due to their partitioning approach, SVR tends to extrapolate poorly for rare or edge-case feature combinations. This highlights the importance of either enhancing model inputs with other features or ensuring sufficient data coverage to improve prediction reliability.

Ensemble Superiority & Applicability

The results of the ensemble model can be summarized in the Figure 5.7 below:

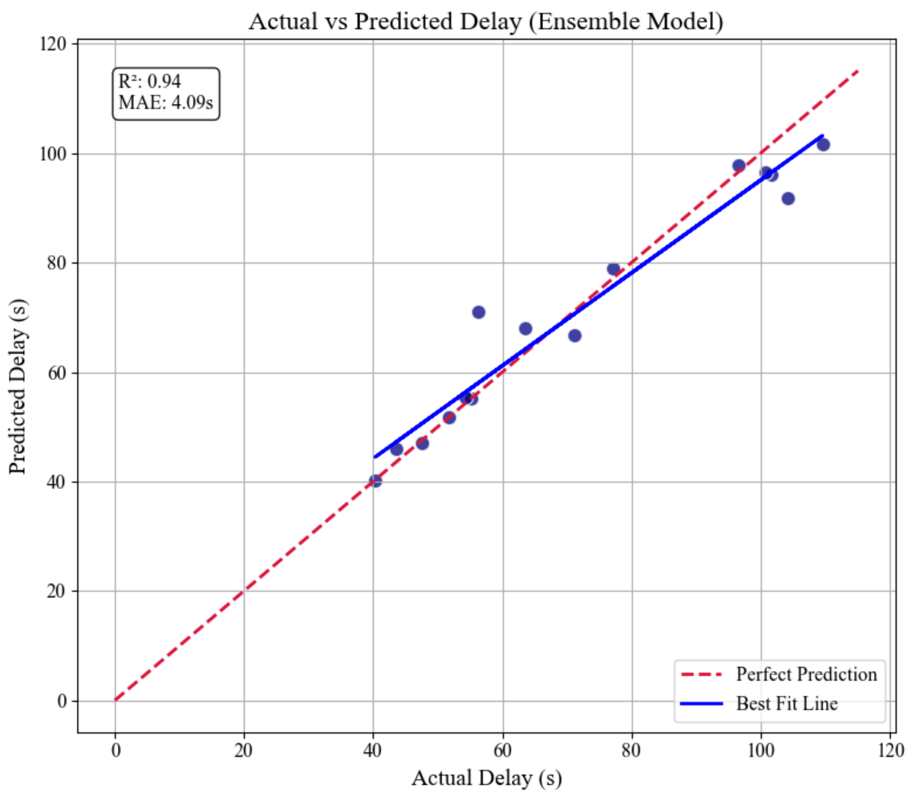


Figure 5.7. Actual vs predicted delay of the ensemble model

The XGB+RF ensemble dominates the delay prediction by:

- Accuracy: Best MAE/RMSE (4.09s/5.98s) which suggests it minimizes both average and extreme errors.
- Robustness: Explains 94% of variance (R^2)
- Efficiency: Sub-second prediction (0.0173s) and rapid training (0.23s) makes it ideal for SCATS real-time optimization.

XGBoost vs. Random Forest:

XGBoost's lower MAE (4.25s vs. RF's 4.79s) indicates superior average precision, but its higher RMSE (7.03s vs. 6.19s) reveals vulnerability to extreme errors.

RF's tightly clustered absolute errors (0.251–0.255s) explain it is resilience to outliers and can explain variance significantly.

kNN's Performance:

Best R^2 (94%) confirms strong trend capture of this model, yet worst MAPE (7.02s) and high MAE (4.84s) indicate sensitivity to delay.

SVR's Under-Performance:

Severe outliers (max error: 0.453s) in error distributions cause MAE (7.43s), making it unsuitable for real-world deployment for delay prediction.

Distribution of absolute errors of the model can be referred from the figure below:

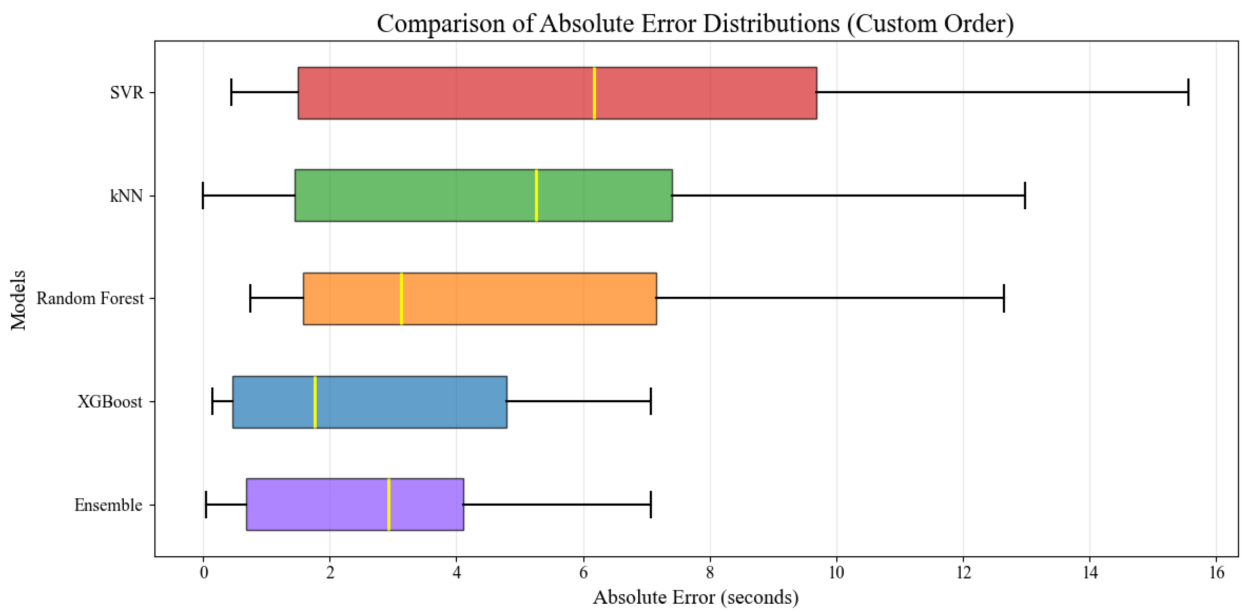


Figure 5.8. Absolute error distributions of the models

The superior result of the ensemble model can be attributed to the fact that the model is ensemble of tree-based models which are known to make better decisions based on past observations (Bagdatli & Dokuz, 2021).

5.1.3.2 Conclusion

This study demonstrates that the XGB+RF ensemble is the optimal model for delay prediction, achieving accuracy-efficiency balance. Its statistical results (MAE: 4.09s, RMSE: 5.98s), robustness to outliers, and real-time capability 17 ms prediction) makes it suited for real-time traffic control optimization system like SCATS system. While standalone models (XGBoost, RF, kNN) offer strengths, the ensemble's hybrid structure outperforms any single algorithm.

The XGB–RF ensemble achieved MAE = 4.09 s and R^2 = 0.94, thereby satisfying objective 4.

The detailed coding can be referenced from the Appendix C.

5.2 Signal Cycle Length Optimization using ML:

Section 5.2 addresses **objective 5** by embedding the best-performing predictor in a search algorithm that identifies the cycle length minimising the predicted delay

The section outlines the **optimisation algorithm and design**, reports the **results** of applying the algorithm to the 18 demand scenarios, and provides a **discussion** of delay reductions, sustainable performance analysis.

5.2.1 Data and Preparation

All of the information was extracted from the traffic matrix. Data relevant to this study were:

- volume (vehicles per hour)
- DoS (where 1 ≈ capacity)
- time (AM = 0, PM = 1)
- cycle (the cycle lengths that were actually in use when the data were gathered)
- delay (observed average delay per vehicle)

The ensemble methods were chosen due to their proven efficiency as demonstrated in the delay prediction models.

The methodology was carried out as described in the chapter: methodology; the following section presents the results and discussion.

The detailed coding can be referenced from the Appendix C.

5.2.2 Results and Discussions:

This section discusses the performance of the ML-optimized cycle length relative to the SCATS's. Two cases (S.N. 1 and S.N. 16) failed to converge and were excluded. Analyses below therefore refer to the remaining eighteen scenarios (S.N. 2–S.N. 20). Reference will be made from the Table 5.8 below:

Table 5.8. Comparison of performance of ML optimized cycle length vs SCATS (synthetic)

SN	Volume (vph)	SCATS CL (s)	SCATS delay (s)	SCATS Operating Cost (NZD)	SCATS Fuel Consumption (l/hr)	SCATS CO_2 Emissions (kg/hr.)	ML CL (s)	ML Delay (s)	ML Operating Cost (NZD)	ML Fuel Consumption (l/hr.)	ML CO_2 Emissions (kg/hr.)
1	4076	139	109.6	7401.34	408	966.4	114	111.9	7514.67	413	978.4
2	3776	124	55.4	4137.6	300.1	711.7	98	54	4083.86	300.6	713
3	3792	98	59.8	4334.12	282.5	669.4	106	63.7	4510.04	287.9	682.2
4	3892	102	85.2	6053.3	377.7	895.7	110	88.9	6246.53	383.2	908.7
5	4072	88	96.5	6313	366.7	868	120	121.1	7592	406.5	962
6	4084	83	101.7	6599.52	384.1	909.2	119	127.5	7961.75	425.6	1007.4
7	4360	140	78.6	6056.78	392.5	930.7	107	75.5	6092.36	396.1	939.3
8	3664	148	75.8	4968.89	314.7	745.8	102	60.5	4265.92	294.2	697.3
9	3212	101	40.3	2962.39	237.9	564.6	99	38.9	2904.47	237.5	563.7
10	3152	131	47.6	3228.33	251	595.8	96	41.7	3034.5	246	584
11	3632	126	86.3	5379.51	310	734.4	109	83.2	5244.43	306.5	726.2
12	4024	126	63.5	5006.15	342	810.9	102	63.5	4989.05	343.2	813.9
13	3600	80	54.2	3923.69	273.8	649.1	106	77.2	4952.08	305.7	724.5
14	4260	138	100.7	7316.23	425.8	1008.9	111	97	7072.01	420.2	995.8
15	3816	86	71.8	5021.02	300.3	711.5	109	84.1	5617.99	317.8	752.7
16	3008	130	43.5	2798.34	219.4	520.3	96	36.3	2565.33	213	505.2
17	3764	86	77.1	5076.33	319.4	756.8	111	97.9	6042.13	350.2	829.4
18	4148	150	90	6712.52	410.2	972.8	107	89.6	6659.01	410.8	974.1
19	3264	142	51.8	3431.08	254.5	603.7	97	45.6	3226.91	249.6	592.2
20	3660	142	47.6	3655.04	283.2	672	97	41.8	3441.4	278.3	660.5

5.2.2.1 Cycle-Length Optimization

Among the eighteen valid scenarios, ML recommended a shorter cycle lengths than SCATS in 11 cases and a longer cycle in the remaining 7 cases; there were no instances of equal cycles (refer Table 5.8).

Results can be summarized as below:

- ML < SCATS (11 / 18): In moderate-flow scenarios, ML has reduced the cycle length by up-to 46 s (e.g., 148 s → 102 s at S.N. 8), thereby cutting excess green time when capacity was available.

- ML > SCATS (7 / 18): In heavier-flow scenarios, ML extended SCATS cycles by up to 36 s (e.g., 83 s → 119 s at S.N. 6), ensuring no unrealistically short cycles under saturation.

Overall, ML's data-driven adjustments reduced cycles when capacity was available and only extended them when saturation made longer cycles advantageous.

5.2.2.2 Delay Performance

ML reduced delay in 10 of 18 cases (≈ 56 %) and increased delay in 8 cases (refer Table 5.8).

Results can be summarized as below:

- The largest delay reduction was –15.3 s/veh at S.N. 8 (volume = 3664 veh/h), where ML cut the cycle from 148 s to 102 s.
- At S.N. 12 (volume = 4024 veh/h), ML shortened the cycle from 126 s to 102 s yet delay remained unchanged at 63.5 s/veh—demonstrating efficiency gains without delay penalty.
- In contrast, ML's delay increased most at S.N. 6 (volume = 4084 veh/h), rising by +25.8 s/veh when cycle length was increased from 83 s to 119 s.

In summary, ML improved delay in 10 out of 18 cases—chiefly when demand was below capacity—but degraded delay in 8 scenarios under heavy saturation where SCATS's longer cycles remained more effective.

5.2.2.3 Operating Cost, Fuel Consumption and CO_2 Emissions

Across the eighteen valid scenarios, the ML optimization model reduced operating cost in 10 cases (≈ 55 %) and increased it in 8. The significant gain was achieved by cost savings of up to NZ $702.97 per hour while increase in operating cost by NZ $1362.23 per hour in one scenario. These results mirror the delay performance: when ML model successfully shortens excess green time by reducing the cycle length, operating cost falls; when ML cannot extend sufficiently under high DoS, cost rises.

Fuel consumption improved under ML in 7 (≈ 39 %) of 18 scenarios and worsened in 11. The significant fuel consumption savings of up to 20.5 litres per hour was achieved while one specific scenario fuel consumption rose by up to 41.5 litres per hour. Thus, fuel efficiency gains occur when ML trims cycles under lower DoS, but ML underperforms SCATS when demand approaches capacity.

CO_2 emissions followed fuel trends: ML reduced emissions in 7 of 18 cases and increased them in 11. In the seven moderate-DoS scenarios, CO_2 fell by up to1 %–7 % (e.g., S.N. 8: 745.8 → 697.3 kg/h, difference = –6.5 %). In contrast, under high DoS, emissions rose by 10 %–11 % (e.g., S.N. 6: 909.2 → 1007.4 kg/h, difference = +10.8 %). These results highlights that ML's cycle reductions deliver environmental benefit when traffic is moderate, but under heavy saturation it is failing to do so.

5.2.2.4 Summary

ML's optimization model reduced excessively long signal timings in the majority of moderate-demand cases and extended them under heavy demand, resulting overall delay reductions in over half of the scenarios. Operating cost, fuel consumption, and CO_2 emissions all fell when ML reduced cycle lengths but increased when it could not match SCATS's longer high-volume settings. In roughly 55% of cases, ML lowered operating costs, while fuel and emissions improved in only about 40%; the remaining cases saw penalties under near-saturated conditions. Adjusting the ML model for very high demand and training under higher cycle lengths scenario would help ML match or exceed SCATS performance across all metrics.

Delay reductions in 11 of 18 scenarios satisfy the delay-minimisation aspect of **objective 5**; however, mixed fuel and CO_2 outcomes indicate partial fulfilment.

Chapter 6 KEY FINDINGS, LIMITATIONS, AND RECOMMENDATIONS

This research undertaking was set out to evaluate and enhance the operational performance of two SCATS-controlled signalized intersections in New Zealand—Albany and Ruakura—using a hybrid methodology that combined SIDRA intersection modeling with machine learning (ML) techniques. The study proceeded in three main stages:

1. Development, calibration, and validation of base SIDRA models using field data;
2. Systematic analysis of existing performance, manual interventions to attain targeted LoS D, and projection of future conditions; and
3. Development of ML models for delay prediction and cycle-length optimization, compared against SCATS timing strategies.

6.1 Key Findings

6.1.1 Calibration and Validation of SIDRA Models

- Both intersections' SIDRA models were successfully calibrated to within ±5 % of observed saturation flow rates (SFR) using the TRL RR67 method and adjustment of basic SFR.
- Validation against DoS criteria confirmed no movement exceeded 100 % DoS in the base scenario—demonstrating that these base models accurately reflect real-world SCATS operation under peak-hour volumes.

6.1.2 Existing Operational Performance

- Under base conditions, the Albany intersection operated at an overall LoS D (average control delay ≈ 43 s/veh; intersection-wide DoS ≈ 1.00), with three critical movements (Oteha Valley Road Right-Through, Dairy Flat Highway right, and Oteha Valley Road right) at LoS E.
- Likewise, the Ruakura intersection operated at LoS D (average delay ≈ 40 s/veh; DoS ≈ 0.98), with two movements (Ruakura Road East Left-Through and Ruakura Road West Right) at LoS E–F.
- Queuing analyses revealed several lanes at both sites already exceeded available physical storage lengths (100 % short-lane blockage probability), turning lanes on Dairy Flat Highway (100 %) and Ruakura Road West right (91.6 %), indicating a high risk of overflow and upstream blockage.

6.1.3 Targeted Manual Interventions

- At Albany, widening the Dairy Flat Highway Right-Through lane and reallocating phase times (reducing Phase A, increasing Phases D/E/G) brought all critical movements to at least LoS D with no constant cycle length (101 s). After the intervention, Albany's worst movement shifted from LoS E to LoS D.

- At Ruakura, re-allocating green times (reducing Phase A, increasing Phases D/E) similarly enhanced all movements to LoS D without changing the 101 s cycle. Ruakura's critical Ruakura Road East Left-Through improved from LoS F to LoS D.

6.1.4 Projected 10-Year Performance (to 2034)

- At Albany, applying a 3 % annual traffic growth rate caused intersection LoS to fall from D (2024) after 2028. By 2034, five movement lanes operate at LoS F, with 95th-%ile queue lengths exceeding storage in six movements, indicating frequent cycle failures and likely spillback.
- At Ruakura, a 2 % annual growth rate likewise degrades LoS from D after 2029. By 2034, six movement (mostly in the Ruakura Road East approach) would reach LoS F by 2034, respectively, with 95th-%ile queue lengths exceeding storage in three movements, indicating frequent cycle failures and likely spillback.

These projections highlight that without geometric upgrades (turn-bay extensions, or additional turn lanes) or more advanced adaptive controls, both intersections will fail to meet operational targets within a decade.

6.1.5 Sustainability (Cost, Fuel, Emissions)

- Albany's hourly operating cost under base 2024 volumes was NZ $2,962 (average delay cost 26 %, fuel 21 %, running costs 53 %). Intersection-wide fuel consumption was 238 L/h, CO_2 emissions 565 kg/h, and NO_x 1.03 kg/h. The Dairy Flat Highway approach alone accounted for ≈ 50 % of total fuel and emissions despite carrying only 37 % of volume.
- Ruakura's base cost was substantially higher at NZ $4,628/h (fuel 28 %; delay 2 %), consuming 492 L/h of fuel and emitting 1.12 t CO_2/h, 1.75 kg NO_x/h—roughly double Albany's emissions despite only 15 % higher volume. The Wairere Drive South approach (16.8 % of volume) contributed ≈ 30 % of fuel use and 35 % of NO_x, highlighting highly inefficient traffic patterns.
- Under existing timing, intersection sustainability performance is heavily influenced by unbalanced lane utilization and queue-induced idling. Mitigation of critical bottlenecks (e.g., Dairy Flat right at Albany; Wairere South at Ruakura) would result substantial sustainability gain.

6.1.6 Crash Analysis (Safety)

- Albany recorded 55 crash events since 2015 (3 serious-injury, 8 minor-injury; 36 % at night; 22 % wet.
- While, Ruakura recorded 65 crashes (3 serious, 13 minor; 26 % at night; 12 % wet), with 40 % of serious crashes at night.
- Although most crashes ended in property damage only, the prevalence of injury and serious crashes—particularly under wet and dark conditions—highlights a safety needs for improved signage, protected turn phasing, and lighting upgrades.

6.1.7 ML Delay Prediction

- Four supervised ML models (Random Forest (RF), Extreme Gradient Boosting (XGBoost), Support Vector Regression (SVR), and k-Nearest Neighbors (kNN)) were trained on 98 synthetic volume/DoS datasets generated via Monte Carlo sampling of SCATS logs.
- The dataset's features—volume, DoS, cycle length, time flag—showed strong Pearson correlations with delay ($r=0.71$ for volume, $r=0.82$ for DoS; cycle length partial $r=0.79$ when controlling for DoS). No statistical outliers were detected.
- Hyperparameter tuning with five-fold cross-validation yielded best parameters.
- Performance on the test set:
- XGBoost: MAE = 4.25 s/veh, RMSE = 7.03 s, $R^2 = 0.91$, MAPE = 5.70 %
- RF: MAE = 4.79 s, RMSE = 6.19 s, $R^2 = 0.93$, MAPE = 6.63 %
- kNN: MAE = 4.84 s, RMSE = 6.05 s, $R^2 = 0.94$, MAPE = 7.02 %
- SVR: MAE = 7.43 s, RMSE = 10.55 s, $R^2 = 0.80$, MAPE = 11.57 %
- An XGBoost + RF ensemble (with optimal weight of 0.6×XGB + 0.4×RF) outperformed all: MAE = 4.09 s, RMSE = 5.98 s, $R^2 = 0.94$, MAPE = 5.44 %, with sub-second (0.017 s) prediction time.
- The XGBoost and Random Forest ensemble proved both accurate and robust to outliers, making it well suited for real-time SCATS integration.

6.1.8 ML-Based Cycle-Length Optimization

- A two-stage ML optimization was implemented. Stage 1 predicted a baseline cycle length from (volume, DoS, time) using an XGB+RF. Stage 2 estimated delay per cycle candidate via a second XGB+RF ensemble model.
- To restrict impractically short cycles, a linear lower cycle length bound was imposed based on the DoS.
- Within the minimum cycle length bound and 150 s, every integer second was tested by the ensemble delay model; the cycle with minimal predicted delay was selected.
- Among 18 valid scenarios, ML shortened cycle length vs. SCATS in 11 cases (up to –46 s) for moderate flows and extended it in seven scenarios (up to +36 s) under high DoS.
- Delay performance: ML reduced delay in 10/18 cases (largest –15.3 s) and increased it in 8 (largest +25.8 s). When ML shortened SCATS cycles under moderate loads, it maintained or reduced delay; under heavy saturation.
- Sustainability outcomes were similar to the delay changes: ML lowered operating cost in 10/18 (max –NZ \$702.97/h), but increased it in 8 (max +NZ \$1,362.23/h). Fuel and CO_2 improvements occurred in 7/18 cases (max –20.5 L/h; –7 % CO_2), but worsened in 11 cases (max +41.5 L/h; +11 % CO_2) when ML-produced cycles were inadequately short under near-saturation.

- In sum, the ML optimization model is effective in moderate-demand regimes but requires further training on high-DoS, long-cycle scenarios to match or exceed SCATS performance when demand is near or above capacity.

6.2 Contributions

- By integrating SIDRA modelling with ML, this study shows that real-time detector data can effectively drive signal timing improvements beyond SCATS heuristics approach. Importantly, a ML optimization model enables rapid, real-time cycle optimization without the computational needs of microsimulation.
- The XGB+RF ensemble achieved below-5 s average error in delay prediction using only volume, DoS, cycle, and time—metrics readily available from SCATS logs—demonstrating strong potential for real-time performance forecasting.
- The staged ML approach to cycle-length optimization constitutes a transferable framework: enforce a lower bound cycle length based on DoS, then evaluate possible cycle lengths. This approach gives a balance between responsiveness (per-second cycle increments) and accuracy (delay predictions).

6.3 Limitations:

Limitations are listed below:

- The study focused on two intersections in Auckland and Hamilton. While these are representative of New Zealand settings, results may not generalize to corridors, multi-intersection networks, or rural sites without validation.
- The ML models relied on synthetic datasets generated by Monte Carlo simulation of 14 real-world SCATS logs. Although this expanded data volume to 98 records and captured oversaturation conditions, it may not fully capture random and real traffic flows, rare extreme events, or demand fluctuations present in field operations.
- For feature extraction, SIDRA's "Optimum Cycle Time" setting was used to emulate SCATS. However, this idealized scenario does not capture all SCATS tactical decisions—e.g., day-of-week plans, incident overrides, lane blockages, or public transport priorities.
- Even with synthetic data generation, extremely oversaturated conditions (DoS $\gg$ 1.3) remain rare. Consequently, the optimization model may underperform when actual volumes or DoS exceed the training envelope.
- While XGBoost+RF ensemble delivered superior accuracy, ensemble tree models provide limited interpretability compared to simpler linear or rule-based heuristics.

6.4 Recommendations for Future Work

- Future studies should apply the SIDRA+ML framework to coordinated corridors of multiple SCATS intersections, evaluating holistic performance (e.g., network-wide travel time, corridor throughput) and testing cycle adjustments in upstream/downstream co-ordination.

- An expanded dataset drawn from continuous SCATS logs (covering months or seasons) would capture temporal variations and rare oversaturation events. Training ML models on such comprehensive data could improve generalization under varying conditions.
- Incorporating pedestrian crossing demands and public transport priority logic into both SIDRA modeling and ML features would better reflect multimodal operation, particularly in urban centers where non-vehicular users drive timing decisions.
- Implementing real-time learning—where the ML model periodically trains on the latest SCATS data—would adapt to evolving traffic patterns and maintain accuracy over time.
- Future research should optimize cycle lengths for multi-objective criteria (delay, emissions, safety).
- Explore on advanced machine-learning approaches—such as Deep Reinforcement Learning, Convolutional Neural Networks, and Graph Neural Networks.

Chapter 7 CONCLUSIONS

The research aimed to evaluate the operational performance of the two intersections in New Zealand and whether supervised machine-learning techniques could improvise the SCATS so that intersections operate more efficiently and sustainably. High-quality field observations were used to build, calibrate, and validate SIDRA models for two representative sites—Albany, Auckland and Ruakura, Hamilton—achieving saturation-flow rates within ±5 percent and keeping all lane movements within accepted degree-of-saturation limits. Baseline analysis confirmed both intersections presently operate at Level-of-Service D, with right-turn bays already oversaturated; ten-year traffic growth projections degrade operations to Level-of-Service F, showing that geometric improvements alone are insufficient. Dataset from the Albany intersection was further used for machine-learning analysis. A Monte-Carlo expansion of the Albany's 14 peak-period SCATS detector logs resulted ninety-eight synthetic demand scenarios, providing dataset for training, validating and testing four machine-learning algorithms. Among these, the best performing models; XGBoost and Random Forest was used to build an ensemble for the prediction of delay with a mean absolute error of approximately four seconds per vehicle using only data set already available to SCATS. The machine-learning optimization demonstrated that, under moderate demand, cycle lengths can be shortened by 15–46 seconds, delivering mean delay reductions of roughly 13 percent and CO_2 savings of 5 percent relative to SCATS timings. Benefits diminish under severe oversaturation, indicating the need to train models on higher degrees of saturation and longer cycles to maintain accuracy in extreme conditions. By pairing calibrated intersection modelling with predictive machine learning, this research illustrates a practical pathway to a SCATS-ML framework in which cycle lengths and phase splits are updated on a cycle-by-cycle basis, guided by continuously predicted delays. Such integration offers measurable reductions in delay, and emissions. While the study is limited to two intersections and a single growth scenario, its findings justify future work on urban networks, extreme-demand training, and multimodal performance evaluation. Ultimately, enriching SCATS with machine-learning has a potential to transfer SCATS system to a proactive system, providing a low-cost and powerful hybrid for enhancing operational, and environmental, outcomes on New Zealand's urban road network.

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APPENDIX A CALIBRATION REPORTS

Appendix A1 (Ruakura)

SFR Field Measurement

Approach	Leg	Measured Average SFR	Remarks
Wairere Drive South	Left-Through	2079.53	• Only 2/4 cycles with demand >= 9 pcus
	Right-Through	1901.14	• Only 5/9 cycles with demand >= 9 pcus • One outlier with SFR >= 2160 (not included)
Ruakura Road East	Left-Through	1758.69	• Only 6/9 cycles with demand >= 9 pcus
	Through/Right (Shared)	2005.55	• Only 2/3 cycles with demand >= 9 pcus
	Right	1846.15	• Only 1/12 cycles with demand >= 9 pcus
Wairere Drive North	Left-Through		• 0/5 cycles with demand >= 9 pcus •Unable to calculate SFR
	Right-Through		• 0/5 cycles with demand >= 9 pcus •Unable to calculate SFR
	Right	1855.01	• 4/8 cycles with demand >= 9 pcus
Ruakura Road West	Left-Through	1634.38	• Only 4/7 cycles with demand >= 9 pcus
	Right-Through	1772.86	• Only 5/10 cycles with demand >= 9 pcus
	Right	1707.58	• 8/12 cycles with demand >= 9 pcus •Two outliers with SFR < 1300

Note: Refer Operational Modelling Guidelines (2021), Appendix B for the detail calculation methods of the field SFR.

Calculation of SFR using TRL method:

		Metres		
Leg	Approach Lane	Mid-Ordinate	Chord	Radius
Wairere Drive South	Left	5.16	25.1	18
	Right	4.42	21.76	16
Ruakura Road East	Left	4.89	25.13	19
	Through/Right (Shared)	5.69	29.44	22
	Right	5.13	22.47	15
Wairere Drive North	Left	3.6	20.58	17
	Right	3.86	26.33	24
Ruakura Road West	Left	5.92	26.96	18
	Right	4.15	23.93	19

Radius calculation using chord method of respective turn lane

S.N.	Leg	Approach Lane	(δ_G)	G	Gradient Type	w_l	δ_n	f	r	SFR (TRL RR67)
1	Wairere Drive South	Left	1	0.50	Uphill	4.4	1	1	18	1876.26
2		Left-Through	1	0.50	Uphill	3.45	1	0	1	1939.00
3		Right-Through	1	0.50	Uphill	3.45	0	0	1	2079.00
4		Right	1	0.50	Uphill	3.25	1	1	16	1750.67
5	Ruakura Road East	Left	1	0.80	Uphill	4.5	1	1	19	1879.71
6		Left-Through	1	0.80	Uphill	3.25	1	0	1	1906.40
7		T/Right (Shared)	1	0.80	Uphill	3.35	1	0.55	22	1846.78
8		Right	1	0.80	Uphill	2.9	0	1	15	1827.07
9	Wairere Drive North	Left	0	1.50	Downhill	4.5	1	1	17	1892.98
10		Left-Through	0	1.50	Downhill	3.5	1	0	1	1965.00
11		Right-Through	0	1.50	Downhill	3.4	0	0	1	2095.00
12		Right	0	1.50	Downhill	3.5	1	1	24	1851.11
13	Ruakura Road West	Left	1	0.39	Uphill	4.5	1	1	18	1893.48
14		Left-Through	1	0.39	Uphill	3.4	1	0	1	1938.62
15		Right-Through	1	0.39	Uphill	3.4	0	0	1	2078.62
16		Right	1	0.39	Uphill	3	1	1	19	1761.85

Index:

Gradient Indicator (δ_G)	1 for uphill gradient, 0 for other
Gradient (G) for calculation	Gradient value, applicable only for uphill gradient
Lane width (w_l)	lane width in meters
Nearside indicator (δ_n)	1 for nearside lane, 0 for offside (nearside)
Radius (r)	radius in meters
Turning proportions (f)	turning proportions

SFR calculated with Local Factor

S.N.	Leg	Approach Lane	Measured SFR	SFR (TRL RR67)	Local factor	SFR for modelling	Method
1	Wairere Drive South	Left		1876.26		1721.23	Factored RR67
2		Left-Through		1939.00		1778.78	Factored RR67
3		Right-Through	1901.14	2079.00	91.4%	1901.14	Site-Measurement
4		Right		1750.67		1606.02	Factored RR67
5	Ruakura Road East	Left		1879.71		1724.40	Factored RR67
6		Left-Through	1758.69	1906.40	92.3%	1758.69	Site-Measurement
7		Through/Right (Shared)		1846.78		1694.19	Factored RR67
8		Right		1827.07		1676.10	Factored RR67
9	Wairere Drive North	Left		1892.98		1736.56	Factored RR67
10		Left-Through		1965.00		1802.64	Factored RR67
11		Right-Through		2095.00		1921.89	Factored RR67
12		Right	1855.01	1851.11	100.2%	1855.01	Site-Measurement
13	Ruakura Road West	Left		1893.48		1737.02	Factored RR67
14		Left-Through	1634.38	1938.62	84.3%	1634.38	Site-Measurement
15		Right-Through	1772.86	2078.62	85.3%	1772.86	Site-Measurement
16		Right	1707.58	1761.85	96.9%	1707.58	Site-Measurement

Average SFR factor = 91.7 %

Full Calibration Details

Leg	Approach Lane	Initial Basic SF	SFR for Modelling	Target Calibration Range		1st Round of Calibration			2nd Round of Calibration			3rd Round of Calibration			Final Round of Calibration		
				-5%	5%	1st OSF	1st AF	New BSF	2nd OSF	2nd AF	New BSF	3rd OSF	3rd AF	New BSF	Final OSF	Final AF	Final BSF
Wairere Drive South	Left	1950	1721	1635	1807	1922	90%	1746	1721	100%	1746	1721	100%	1746	1721	100%	1746
	Left-Through	1950	1779	1690	1868	1872	95%	1853	1779	100%	1853	1779	100%	1853	1779	100%	1853
	Right-Through	1950	1901	1806	1996	1872	102%	1950	1872	102%	1950	1872	102%	1950	1872	102%	1950
	Right	1950	1606	1526	1686	1852	87%	1691	1606	100%	1691	1606	100%	1691	1606	100%	1691
Ruakura Road East	Left	1950	1724	1638	1811	1515	114%	2220	1564	110%	2447	1606	107%	2950	1651	104%	2950
	Left-Through	1950	1759	1671	1847	1779	99%	1950	1781	99%	1950	1783	99%	1950	1789	98%	1950
	T/R (Shared)	1950	1694	1609	1779	1833	92%	1802	1696	100%	1802	1696	100%	1802	1688	100%	1802
	Right	1950	1676	1592	1760	1514	111%	2159	1618	104%	2159	1619	104%	1900	1716	98%	1900
Wairere Drive North	Left	1950	1737	1650	1823	1931	90%	1754	1737	100%	1754	1737	100%	1754	1737	100%	1754
	Left-Through	1950	1803	1713	1893	1876	96%	1950	1876	96%	1950	1876	96%	1950	1876	96%	1950
	Right-Through	1950	1922	1826	2018	1867	103%	1950	1867	103%	1950	1867	103%	1950	1867	103%	1950
	Right	1950	1855	1762	1948	1818	102%	1950	1818	102%	1950	1818	102%	1950	1818	102%	1950
Ruakura Road West	Left	1950	1737	1650	1824	1911	91%	1772	1737	100%	1772	1737	100%	1772	1737	100%	1772
	Left-Through	1950	1634	1553	1716	1647	99%	1950	1605	102%	1950	1605	102%	1950	1702	96%	1950
	Right-Through	1950	1773	1684	1862	1864	95%	1855	1764	101%	1855	1764	101%	1855	1810	98%	1855
	Right	1950	1708	1622	1793	1593	107%	2090	1648	104%	2090	1648	104%	2090	1707	100%	2090

Notes: OSF = Output Saturation Flow, AF = Adjustment Factor

SCATS Graphics

Appendix A2 (Albany)

Albany Radius calculation using chord method of respective turn lane

		Metres		
Leg	Approach Lane	Mid-Ordinate	Chord	Radius
Albany Expressway	Left	3.62	17.53	12
	Right	3.34	22.93	21
Oteha Valley Road	Left	1.96	12.85	12
	Right	2.68	16.34	14
Dairy Flat Highway	Left	5.1	28.3	22
	Right	3.58	18.47	14
Albany Highway	Left	4.43	22.56	17
	Right	3.62	17.53	12

Calculation of SFR using TRL method:

S.N.	Leg	Approach Lane	(δ_G)	G	Gradient Type	w_l	δ_n	f	r	SFR (TRL RR67)
1	Albany Expressway	Left	0	2.70	Downhill	3.4	1	1	12	1744.35
2		Left-Through	0	2.70	Downhill	3.4	1	0	1	1955.00
3		Right-Through	0	2.70	Downhill	3.4	0	0	1	2095.00
4		Right	0	2.70	Downhill	3	1	1	21	1789.28
5	Oteha Valley Road	Left	1	2.60	Uphill	4.5	1	1	12	1730.32
6		Left-Through	1	2.60	Uphill	3.75	1	0	1	1880.80
7		Right-Through	1	2.60	Uphill	3.2	0	0	1	1965.80
8		Right	1	2.60	Uphill	3	1	1	15	1637.01
9	Dairy Flat Highway	Left	1	2.00	Uphill	3.9	1	1	14	1732.58
10		Left-Through	1	2.00	Uphill	3.3	1	0	1	1861.00
11		Right-Through	1	2.00	Uphill	3.4	0	0	1	2011.00
12		Right	1	2.00	Uphill	3.3	1	1	22	1743.11
13	Albany Highway	Left	1	1.55	Uphill	4.5	1	1	14	1802.56
14		Left-Through	1	1.55	Uphill	3.4	1	0	1	1889.90
15		Right-Through	1	1.55	Uphill	3.4	0	0	1	2029.90
16		Right	1	1.55	Uphill	3.1	1	1	17	1705.56

SFR calculated with Local Factor

S.N.	Leg	Approach Lane	SFR (TRL RR67)	Local factor	SFR for modelling	Method
1	Albany Expressway	Left	1744.35	91.7%	1599.57	Factored RR67
2		Left-Through	1955.00		1792.74	
3		Right-Through	2095.00		1921.12	
4		Right	1789.28		1640.77	
5	Oteha Valley Road	Left	1730.32		1586.70	
6		Left-Through	1880.80		1724.69	
7		Right-Through	1965.80		1802.64	
8		Right	1637.01		1501.14	
9	Dairy Flat Highway	Left	1732.58		1588.78	
10		Left-Through	1861.00		1706.54	
11		Right-Through	2011.00		1844.09	
12		Right	1743.11		1598.44	
13	Albany Highway	Left	1802.56		1652.95	
14		Left-Through	1889.90		1733.04	
15		Right-Through	2029.90		1861.42	
16		Right	1705.56		1564.00	

Full Calibration Details

Leg	Approach Lane	Initial Basic SF	SFR for Modelling	Target Calibration Range		1st Round of Calibration			2nd Round of Calibration			Final Round of Calibration		
				-5%	5%	1st OSF	1st AF	New BSF	2nd OSF	2nd AF	New BSF	Final OSF	Final AF	Final BSF
Albany Expressway	Left	1950	1721	1635	1807	1831	87%	1704	1600	100%	1704	1600	100%	1704
	L/T	1950	1779	1690	1868	1867	96%	1950	1867	96%	1950	1867	96%	1950
	R/T	1950	1901	1806	1996	1867	103%	1950	1867	103%	1950	1867	103%	1950
	Right	1950	1606	1526	1686	1698	97%	1950	1698	97%	1950	1698	97%	1950
Oteha Valley Road	Left	1950	1724	1638	1811	1365	116%	2267	1428	111%	2790	1510	105%	2790
	Left-Through	1950	1759	1671	1847	1912	90%	1759	1725	100%	1759	1725	100%	1759
	T/R (Shared)	1950	1694	1609	1779	1859	97%	1950	1859	97%	1950	1859	97%	1950
	Right	1950	1676	1592	1760	1704	88%	1718	1501	100%	1718	1501	100%	1718
Dairy Flat Highway	Left	1950	1737	1650	1823	1703	93%	1819	1589	100%	1819	1589	100%	1819
	L/T	1950	1803	1713	1893	1803	95%	1846	1706	100%	1846	1706	100%	1846
	R/T	1950	1922	1826	2018	1644	112%	2187	1756	105%	2230	1757	105%	2230
	Right	1950	1855	1762	1948	1734	92%	1798	1599	100%	1887	1678	95%	1887
Albany Highway	Left	1950	1737	1650	1824	1715	96%	1950	1711	97%	1950	1711	97%	1950
	L/T	1950	1634	1553	1716	1863	93%	1814	1733	100%	1814	1733	100%	1814
	R/T	1950	1773	1684	1862	1863	100%	1950	1863	100%	1950	1863	100%	1950
	Right	1950	1708	1622	1793	1802	87%	1692	1564	100%	1692	1564	100%	1692

SCATSGraphics

Sustainability Performance Results (Albany Intersection)

S.N.	Approach	Lane	Volumes	Cost ($/hr)	Fuel (L/hr)	CO_2 (kg/hr)	CO (kg/hr)	HC (kg/hr)	No_x (kg/hr)
1	Albany Expressway	Left	224	122.33	8.00	18.90	0.01	0.00	0.01
2		Through	200	177.60	9.40	22.40	0.02	0.00	0.03
3		Right	60	90.50	3.80	8.90	0.01	0.00	0.02
4	Approach		484	390.43	21.20	50.20	0.04	0.01	0.06
5	Oteha Valley Road	Left	148	87.56	15.90	37.90	0.04	0.00	0.10
6		Through	596	497.64	31.40	74.10	0.06	0.01	0.09
7		Right	20	17.03	1.10	2.70	0.00	0.00	0.01
8	Approach		764	602.23	48.40	114.70	0.10	0.01	0.20
9	Dairy Flat Highway	Left	28	30.16	1.90	4.50	0.00	0.00	0.01
10		Through	724	725.21	88.20	210.10	0.21	0.02	0.49
11		Right	448	678.95	35.60	84.30	0.07	0.01	0.14
12	Approach		1200	1434.32	125.70	298.90	0.28	0.03	0.64
13	Albany Highway	Left	192	54.90	5.90	14.00	0.01	0.00	0.03
14		Through	396	314.15	19.20	45.50	0.04	0.01	0.07
15		Right	176	166.36	17.50	41.20	0.04	0.00	0.04
16	Approach		764	535.41	42.60	100.70	0.09	0.01	0.14
17	Intersection		3212	2962.39	237.90	564.50	0.51	0.06	1.03

Sustainability Performance Results (Ruakura Intersection)

S.N.	Approach	Lane	Volumes	Cost ($/hr)	Fuel (L/hr)	CO_2 (kg/hr)	CO (kg/hr)	HC (kg/hr)	No_x (kg/hr)
1	Wairere Drive South	Left	22	336.41	27.10	63.90	0.03	0.01	0.05
2		Through	620	925.51	119.20	283.70	0.26	0.02	0.62
3		Right	246	5.44	0.50	1.20	0.00	0.00	0.00
4	Approach		888	1267.36	146.80	348.80	0.29	0.03	0.67
5	Ruakura Road East	Left	266	27.39	3.00	7.20	0.00	0.00	0.00
6		Through/Right	510	1061.65	72.60	172.10	0.11	0.02	0.22
7		Right	120	332.31	38.40	90.90	0.08	0.01	0.14
8	Approach		896	1421.35	114.00	270.20	0.19	0.02	0.36
9	Wairere Drive North	Left	314	263.71	27.80	65.80	0.03	0.01	0.05
10		Through	420	437.68	66.70	159.50	0.16	0.01	0.26
11		Right	298	114.25	10.20	24.10	0.02	0.00	0.02
12	Approach		1032	815.64	104.70	249.40	0.21	0.02	0.34
13	Ruakura Road West	Left	204	278.70	40.00	95.00	0.08	0.01	0.16
14		Through	668	472.55	43.70	103.50	0.06	0.01	0.10
15		Right	4	372.85	42.90	101.80	0.08	0.01	0.12
16	Approach		876	1124.10	126.60	300.30	0.22	0.03	0.38
17	Intersection		3692	4628.45	492.10	1168.70	0.91	0.10	1.75

APPENDIX B INFLATION CALCULATION FOR COST MODELLING

Inflation adjustments for fuel cost and average income using CPI

1. Base Information:

Fuel price (April 2018): 2.10 NZD/L

Income (April 2018): 31 NZD/hour

Inflation period (t): April 2018 to September 2024 → 6 years and 5 months

2. Inflation Rate Data:

According to Statistics NZ:

Average CPI inflation from 2018 to 2024 has ranged between 2% to 7% annually.

Average annual inflation (r) of 3.5% is taken, which is reasonable over this period.

3. Cumulative Inflation Factor:

Using the formula for cumulative inflation:

Adjustment Factor (f) = $(1+r)^t$

Gives, f = 1.252

To adjust the base price of fuel and base average income, these are multiplied with the adjustment factor which gives,

Fuel price (September 2024): 2.63 $/L

Income (September 2024): 39 $/hour

Default Gap Acceptance Factor and Opposing Vehicle Factor, Adapted from (SIDRA Intersection User Guide for Version 8, 2018)

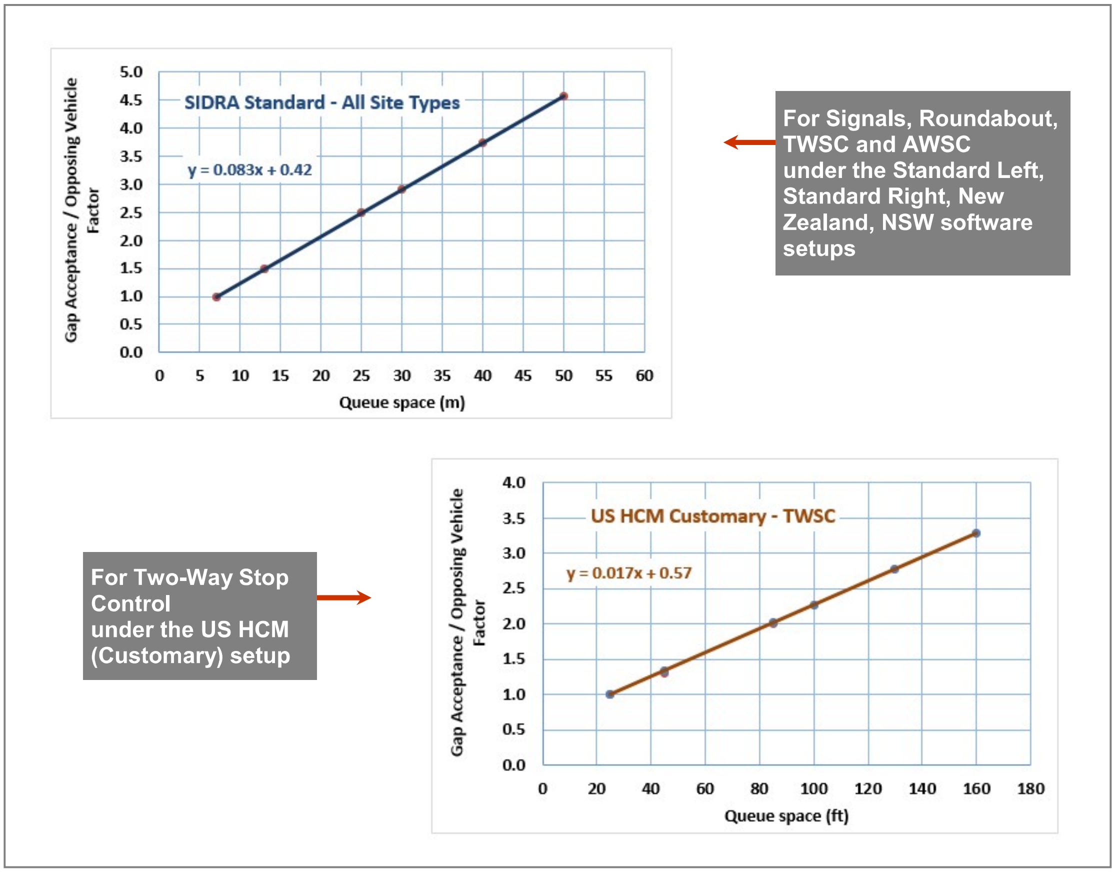

Figure 5.11.4 - Simple method to specify the Gap Acceptance Factor and Opposing Vehicle Factor parameter values for large vehicles

APPENDIX C CODINGS

1. XGBoost (Delay Prediction)

```
# XGBoost
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import time
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split, KFold, GridSearchCV
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
from scipy import stats

# Load data
df = pd.read_excel(r'D:\ValidationVolumes.xlsx', sheet_name='plan1')
X = df[['time', 'dos', 'cycle', 'volume']]
y = df['delay']

# Split data (70% train, 15% val, 15% test)
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, random_state=42
)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=42
)

# Parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [3, 5, 7],
    'learning_rate': [0.01, 0.1, 0.2],
    'subsample': [0.7, 0.8, 0.9],
    'reg_lambda': [0.5, 1.0, 2.0],
    'gamma': [0, 0.1, 0.2]
}

# Model configuration
model = XGBRegressor(
    tree_method='hist',
    eval_metric='mae',
    random_state=42,
    n_jobs=-1
)

# Grid search with timing
start_train = time.time()
search = GridSearchCV(
    model,
    param_grid,
    scoring='neg_mean_absolute_error',
```

```python
    cv=KFold(n_splits=5, shuffle=True, random_state=42),
    verbose=1,
    n_jobs=-1
)

search.fit(X_train, y_train)
training_time = time.time() - start_train

best_params = search.best_params_

# Final model training
final_model = XGBRegressor(**best_params, early_stopping_rounds=20)
final_model.fit(X_train, y_train, eval_set=[(X_val, y_val)], verbose=0)

# Prediction with timing
start_predict = time.time()
y_pred = final_model.predict(X_test)
prediction_time = time.time() - start_predict

# Calculate metrics
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

# Calculate MAPE with zero handling
non_zero_mask = (y_test != 0)
if np.sum(non_zero_mask) > 0:
    mape = np.mean(np.abs((y_test[non_zero_mask] - y_pred[non_zero_mask]) /
y_test[non_zero_mask])) * 100
else:
    mape = float('nan')

print("\n=== XGBoost Final Results ===")
print(f"Test MAE: {mae:.2f} seconds")
print(f"Test RMSE: {rmse:.2f} seconds")
print(f"Test MAPE: {mape:.2f}%")
print(f"Test R²: {r2:.2f}")
print(f"Training time: {training_time:.2f} seconds")
print(f"Prediction time: {prediction_time:.4f} seconds")
print(f"Best Parameters: {best_params}")


# =================================================================
# 2. Scatter plot of predicted vs observed
# =================================================================
plt.figure(figsize=(10, 8))

# Scatter plot
plt.scatter(y_test, y_pred, alpha=0.6, color='#1f77b4')
```

```python
# Perfect prediction line
max_val = max(y_test.max(), y_pred.max()) * 1.05
plt.plot([0, max_val], [0, max_val], 'r--')

# Add metrics to plot
plt.text(0.05, 0.95, f'MAE: {mae:.2f}s\nRMSE: {rmse:.2f}s\nR²: {r2:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Labels and title
plt.title('XGBoost: Actual vs Predicted Delay')
plt.xlabel('Actual Delay (seconds)')
plt.ylabel('Predicted Delay (seconds)')
plt.grid(True)
plt.tight_layout()
plt.show()

# ===================================================================
# 3. Box-and-whisker plot of absolute errors
# ===================================================================
absolute_errors = np.abs(y_test - y_pred)

plt.figure(figsize=(10, 6))
plt.boxplot(absolute_errors, vert=False, patch_artist=True,
            boxprops=dict(facecolor='#1f77b4', color='black'),
            medianprops=dict(color='yellow'),
            whiskerprops=dict(color='black'),
            capprops=dict(color='black'),
            flierprops=dict(marker='o', markersize=8, markerfacecolor='red'))

# Add statistics
stats_text = (f"Min: {absolute_errors.min():.2f}s\n"
              f"Q1: {np.percentile(absolute_errors, 25):.2f}s\n"
              f"Median: {np.median(absolute_errors):.2f}s\n"
              f"Q3: {np.percentile(absolute_errors, 75):.2f}s\n"
              f"Max: {absolute_errors.max():.2f}s\n"
              f"IQR: {np.percentile(absolute_errors, 75) -
np.percentile(absolute_errors, 25):.2f}s")

plt.text(0.95, 0.95, stats_text,
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Labels and title
```

```python
plt.title('XGBoost: Absolute Error Distribution')
plt.xlabel('Absolute Error (seconds)')
plt.yticks([])  # Hide y-axis as it's a single distribution
plt.grid(True)
plt.tight_layout()
plt.show()

# ================================================================
# 4. Performance table
# ================================================================
print("\n=== Performance Summary ===")
print(f"{'Metric':<15} | {'Value':<10}")
print("-" * 25)
print(f"{'MAE':<15} | {mae:.4f} sec")
print(f"{'RMSE':<15} | {rmse:.4f} sec")
print(f"{'MAPE':<15} | {mape:.2f}%")
print(f"{'R²':<15} | {r2:.4f}")
print(f"{'Training time':<15} | {training_time:.2f} sec")
print(f"{'Prediction time':<15} | {prediction_time:.4f} sec")
```

2. Random Forest (Delay Prediction)

```python
# Random Forest
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import time
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split, KFold, GridSearchCV
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error

# Load data
df = pd.read_excel(r'D:\ValidationVolumes.xlsx', sheet_name='plan1')
X = df[['time', 'dos', 'cycle', 'volume']]
y = df['delay']

# Split data (70% train, 15% val, 15% test)
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, random_state=42
)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=42
)

# Parameter grid
param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20],
```

```python
    'max_features': ['sqrt', 0.8],
    'min_samples_split': [2, 5, 10]
}

# Model configuration
model = RandomForestRegressor(
    random_state=42,
    n_jobs=-1
)

# Measure training time
start_train = time.time()

# Grid search
search = GridSearchCV(
    model,
    param_grid,
    scoring='neg_mean_absolute_error',
    cv=KFold(n_splits=5, shuffle=True, random_state=42),
    verbose=1,
    n_jobs=-1
)

search.fit(X_train, y_train)
training_time = time.time() - start_train

best_params = search.best_params_
final_model = search.best_estimator_

# Measure prediction time
start_predict = time.time()
y_pred = final_model.predict(X_test)
prediction_time = time.time() - start_predict

# Calculate metrics
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

# Calculate MAPE with zero handling
non_zero_mask = (y_test != 0)
if np.sum(non_zero_mask) > 0:
    mape = np.mean(np.abs((y_test[non_zero_mask] - y_pred[non_zero_mask]) /
                 y_test[non_zero_mask])) * 100
else:
    mape = float('nan')

print("\n=== Random Forest Final Results ===")
```

```python
print(f"Test MAE: {mae:.2f} seconds")
print(f"Test RMSE: {rmse:.2f} seconds")
print(f"Test MAPE: {mape:.2f}%")
print(f"Test R²: {r2:.2f}")
print(f"Training time: {training_time:.2f} seconds")
print(f"Prediction time: {prediction_time:.4f} seconds")
print(f"Best Parameters: {best_params}")

# =================================================================
# 1. Scatter plot of predicted vs observed
# =================================================================
plt.figure(figsize=(10, 8))

# Scatter plot
plt.scatter(y_test, y_pred, alpha=0.6, color='#ff7f0e')

# Perfect prediction line
max_val = max(y_test.max(), y_pred.max()) * 1.05
plt.plot([0, max_val], [0, max_val], 'r--')

# Add metrics to plot
plt.text(0.05, 0.95, f'MAE: {mae:.2f}s\nRMSE: {rmse:.2f}s\nR²: {r2:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Labels and title
plt.title('Random Forest: Actual vs Predicted Delay')
plt.xlabel('Actual Delay (seconds)')
plt.ylabel('Predicted Delay (seconds)')
plt.grid(True)
plt.tight_layout()
plt.show()

# =================================================================
# 2. Box-and-whisker plot of absolute errors
# =================================================================
absolute_errors = np.abs(y_test - y_pred)

plt.figure(figsize=(10, 6))
plt.boxplot(absolute_errors, vert=False, patch_artist=True,
            boxprops=dict(facecolor='#ff7f0e', color='black'),
            medianprops=dict(color='yellow'),
            whiskerprops=dict(color='black'),
            capprops=dict(color='black'),
            flierprops=dict(marker='o', markersize=8, markerfacecolor='red'))

# Add statistics
```

```
stats_text = (f"Min: {absolute_errors.min():.2f}s\n"
              f"Q1: {np.percentile(absolute_errors, 25):.2f}s\n"
              f"Median: {np.median(absolute_errors):.2f}s\n"
              f"Q3: {np.percentile(absolute_errors, 75):.2f}s\n"
              f"Max: {absolute_errors.max():.2f}s\n"
              f"IQR: {np.percentile(absolute_errors, 75) -
np.percentile(absolute_errors, 25):.2f}s")

plt.text(0.95, 0.95, stats_text,
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Labels and title
plt.title('Random Forest: Absolute Error Distribution')
plt.xlabel('Absolute Error (seconds)')
plt.yticks([])  # Hide y-axis as it's a single distribution
plt.grid(True)
plt.tight_layout()
plt.show()

# =================================================================
# 3. Performance summary
# =================================================================
print("\n=== Performance Summary ===")
print(f"{'Metric':<15} | {'Value':<10}")
print("-" * 25)
print(f"{'MAE':<15} | {mae:.4f} sec")
print(f"{'RMSE':<15} | {rmse:.4f} sec")
print(f"{'MAPE':<15} | {mape:.2f}%")
print(f"{'R²':<15} | {r2:.4f}")
print(f"{'Training time':<15} | {training_time:.2f} sec")
print(f"{'Prediction time':<15} | {prediction_time:.4f} sec")
```

3. kNN (Delay Prediction)

```
# kNN
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import time
from sklearn.neighbors import KNeighborsRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
```

```python
# ================================================================
# 1. Data Loading & Splitting
# ================================================================
df = pd.read_excel(r'D:\ValidationVolumes.xlsx', sheet_name='plan1')
X = df[['time', 'dos', 'cycle', 'volume']]
y = df['delay']

# Same 70-15-15 split
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, random_state=42
)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=42
)

# ================================================================
# 2. kNN Model Pipeline
# ================================================================
# Create preprocessing + model pipeline
knn_pipe = Pipeline([
    ('scaler', StandardScaler()),  # Critical for distance-based models
    ('knn', KNeighborsRegressor())
])

# Hyperparameter grid
param_grid = {
    'knn__n_neighbors': range(3, 21, 2),  # Odd numbers from 3 to 19
    'knn__weights': ['uniform', 'distance'],
    'knn__metric': ['euclidean', 'manhattan']
}

# Measure training time
start_train = time.time()

# Grid search with cross-validation
knn_search = GridSearchCV(
    estimator=knn_pipe,
    param_grid=param_grid,
    scoring='neg_mean_absolute_error',
    cv=5,
    verbose=1,
    n_jobs=-1
)

# ================================================================
# 3. Training & Evaluation
# ================================================================
print("\n=== kNN Training ===")
```

```python
knn_search.fit(X_train, y_train)
training_time = time.time() - start_train

# Get best model and parameters
best_knn = knn_search.best_estimator_
best_params = knn_search.best_params_

# Measure prediction time
start_predict = time.time()
y_pred = best_knn.predict(X_test)
prediction_time = time.time() - start_predict

# Calculate metrics
mae = mean_absolute_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

# Calculate MAPE with zero handling
non_zero_mask = (y_test != 0)
if np.sum(non_zero_mask) > 0:
    mape = np.mean(np.abs((y_test[non_zero_mask] - y_pred[non_zero_mask]) /
                     y_test[non_zero_mask])) * 100
else:
    mape = float('nan')

print("\n=== kNN Results ===")
print(f"Test MAE: {mae:.2f} seconds")
print(f"Test RMSE: {rmse:.2f} seconds")
print(f"Test MAPE: {mape:.2f}%")
print(f"Test R²: {r2:.2f}")
print(f"Training time: {training_time:.2f} seconds")
print(f"Prediction time: {prediction_time:.4f} seconds")
print(f"Best Parameters: {best_params}")

# ==================================================================
# 4. Scatter plot of predicted vs observed
# ==================================================================
plt.figure(figsize=(10, 8))

# Scatter plot
plt.scatter(y_test, y_pred, alpha=0.6, color='#2ca02c')

# Perfect prediction line
max_val = max(y_test.max(), y_pred.max()) * 1.05
plt.plot([0, max_val], [0, max_val], 'r--')

# Add metrics to plot
plt.text(0.05, 0.95, f'MAE: {mae:.2f}s\nRMSE: {rmse:.2f}s\nR²: {r2:.2f}',
```

```python
         transform=plt.gca().transAxes,
         verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Labels and title
plt.title('k-Nearest Neighbors: Actual vs Predicted Delay')
plt.xlabel('Actual Delay (seconds)')
plt.ylabel('Predicted Delay (seconds)')
plt.grid(True)
plt.tight_layout()
plt.show()

# ===================================================================
# 5. Box-and-whisker plot of absolute errors
# ===================================================================
absolute_errors = np.abs(y_test - y_pred)

plt.figure(figsize=(10, 6))
plt.boxplot(absolute_errors, vert=False, patch_artist=True,
            boxprops=dict(facecolor='#2ca02c', color='black'),
            medianprops=dict(color='yellow'),
            whiskerprops=dict(color='black'),
            capprops=dict(color='black'),
            flierprops=dict(marker='o', markersize=8, markerfacecolor='red'))

# Add statistics
stats_text = (f"Min: {absolute_errors.min():.2f}s\n"
              f"Q1: {np.percentile(absolute_errors, 25):.2f}s\n"
              f"Median: {np.median(absolute_errors):.2f}s\n"
              f"Q3: {np.percentile(absolute_errors, 75):.2f}s\n"
              f"Max: {absolute_errors.max():.2f}s\n"
              f"IQR: {np.percentile(absolute_errors, 75) -
np.percentile(absolute_errors, 25):.2f}s")

plt.text(0.95, 0.95, stats_text,
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Labels and title
plt.title('k-Nearest Neighbors: Absolute Error Distribution')
plt.xlabel('Absolute Error (seconds)')
plt.yticks([])  # Hide y-axis as it's a single distribution
plt.grid(True)
plt.tight_layout()
plt.show()
```

```
# ==================================================================
# 6. Performance summary
# ==================================================================
print("\n=== Performance Summary ===")
print(f"{'Metric':<15} | {'Value':<10}")
print("-" * 25)
print(f"{'MAE':<15} | {mae:.4f} sec")
print(f"{'RMSE':<15} | {rmse:.4f} sec")
print(f"{'MAPE':<15} | {mape:.2f}%")
print(f"{'R²':<15} | {r2:.4f}")
print(f"{'Training time':<15} | {training_time:.2f} sec")
print(f"{'Prediction time':<15} | {prediction_time:.4f} sec")

# ==================================================================
# 7. Optional: Validation Set Check
# ==================================================================
val_pred = best_knn.predict(X_val)
val_mae = mean_absolute_error(y_val, val_pred)
print(f"\nValidation MAE: {val_mae:.2f} (For methodology consistency)")
```

4. SVR (Delay Prediction)

```
# SVR
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import time
from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error

# ==================================================================
# 1. Data Loading & Splitting
# ==================================================================
df = pd.read_excel(r'D:\ValidationVolumes.xlsx', sheet_name='plan1')
X = df[['time', 'dos', 'cycle', 'volume']]
y = df['delay']

# Same 70-15-15 split
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, random_state=42
)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=42
)
```

```python
# ==================================================================
# 2. SVR Model Pipeline
# ==================================================================
# Create preprocessing + model pipeline
svr_pipe = Pipeline([
    ('scaler', StandardScaler()),  # Essential for SVR
    ('svr', SVR())
])

# Hyperparameter grid
param_grid = {
    'svr__kernel': ['linear', 'rbf'],
    'svr__C': [0.1, 1, 10],
    'svr__epsilon': [0.05, 0.1],
    'svr__gamma': ['scale', 'auto']
}

# Measure training time
start_train = time.time()

# Grid search with cross-validation
svr_search = GridSearchCV(
    estimator=svr_pipe,
    param_grid=param_grid,
    scoring='neg_mean_absolute_error',
    cv=5,
    verbose=1,
    n_jobs=-1
)

# ==================================================================
# 3. Training & Evaluation
# ==================================================================
print("\n=== SVR Training ===")
svr_search.fit(X_train, y_train)
training_time = time.time() - start_train

# Get best model and parameters
best_svr = svr_search.best_estimator_
best_params = svr_search.best_params_

# Measure prediction time
start_predict = time.time()
y_pred = best_svr.predict(X_test)
prediction_time = time.time() - start_predict

# Calculate metrics
mae = mean_absolute_error(y_test, y_pred)
```

```python
r2 = r2_score(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

# Calculate MAPE with zero handling
non_zero_mask = (y_test != 0)
if np.sum(non_zero_mask) > 0:
    mape = np.mean(np.abs((y_test[non_zero_mask] - y_pred[non_zero_mask]) /
                         y_test[non_zero_mask])) * 100
else:
    mape = float('nan')

print("\n=== SVR Results ===")
print(f"Test MAE: {mae:.2f} seconds")
print(f"Test RMSE: {rmse:.2f} seconds")
print(f"Test MAPE: {mape:.2f}%")
print(f"Test R²: {r2:.2f}")
print(f"Training time: {training_time:.2f} seconds")
print(f"Prediction time: {prediction_time:.4f} seconds")
print(f"Best Parameters: {best_params}")

# ===================================================================
# 4. Scatter plot of predicted vs observed
# ===================================================================
plt.figure(figsize=(10, 8))

# Scatter plot
plt.scatter(y_test, y_pred, alpha=0.6, color='#d62728')

# Perfect prediction line
max_val = max(y_test.max(), y_pred.max()) * 1.05
plt.plot([0, max_val], [0, max_val], 'r--')

# Add metrics to plot
plt.text(0.05, 0.95, f'MAE: {mae:.2f}s\nRMSE: {rmse:.2f}s\nR²: {r2:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Labels and title
plt.title('Support Vector Regression: Actual vs Predicted Delay')
plt.xlabel('Actual Delay (seconds)')
plt.ylabel('Predicted Delay (seconds)')
plt.grid(True)
plt.tight_layout()
plt.show()

# ===================================================================
# 5. Box-and-whisker plot of absolute errors
```

```python
# ==================================================================
absolute_errors = np.abs(y_test - y_pred)

plt.figure(figsize=(10, 6))
plt.boxplot(absolute_errors, vert=False, patch_artist=True,
            boxprops=dict(facecolor='#d62728', color='black'),
            medianprops=dict(color='yellow'),
            whiskerprops=dict(color='black'),
            capprops=dict(color='black'),
            flierprops=dict(marker='o', markersize=8, markerfacecolor='red'))

# Add statistics
stats_text = (f"Min: {absolute_errors.min():.2f}s\n"
              f"Q1: {np.percentile(absolute_errors, 25):.2f}s\n"
              f"Median: {np.median(absolute_errors):.2f}s\n"
              f"Q3: {np.percentile(absolute_errors, 75):.2f}s\n"
              f"Max: {absolute_errors.max():.2f}s\n"
              f"IQR: {np.percentile(absolute_errors, 75) -
np.percentile(absolute_errors, 25):.2f}s")

plt.text(0.95, 0.95, stats_text,
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# Labels and title
plt.title('Support Vector Regression: Absolute Error Distribution')
plt.xlabel('Absolute Error (seconds)')
plt.yticks([])  # Hide y-axis as it's a single distribution
plt.grid(True)
plt.tight_layout()
plt.show()

# ==================================================================
# 6. Performance summary
# ==================================================================
print("\n=== Performance Summary ===")
print(f"{'Metric':<15} | {'Value':<10}")
print("-" * 25)
print(f"{'MAE':<15} | {mae:.4f} sec")
print(f"{'RMSE':<15} | {rmse:.4f} sec")
print(f"{'MAPE':<15} | {mape:.2f}%")
print(f"{'R²':<15} | {r2:.4f}")
print(f"{'Training time':<15} | {training_time:.2f} sec")
print(f"{'Prediction time':<15} | {prediction_time:.4f} sec")

# ==================================================================
```

```
# 7. Optional: Validation Set Check
# ================================================================
val_pred = best_svr.predict(X_val)
val_mae = mean_absolute_error(y_val, val_pred)
print(f"\nValidation MAE: {val_mae:.2f} (Consistency Check)")
```

5. XGBoost + Random Forest (Delay Prediction)

```
# Ensemble XGB+RF
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import time
from xgboost import XGBRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error
from sklearn.model_selection import train_test_split

# ================================================================
# 1. Data Preparation
# ================================================================
df = pd.read_excel(r'D:\ValidationVolumes.xlsx', sheet_name='plan1')
X = df[['dos', 'volume', 'cycle']]
y = df['delay']

# Split data
X_train, X_temp, y_train, y_temp = train_test_split(
    X, y, test_size=0.3, random_state=42
)
X_val, X_test, y_val, y_test = train_test_split(
    X_temp, y_temp, test_size=0.5, random_state=42
)

# ================================================================
# 2. Model Training & Predictions with Timing
# ================================================================
# Track training times
start_xgb_train = time.time()
xgb = XGBRegressor(
    gamma=0, learning_rate=0.1, max_depth=3,
    n_estimators=300, reg_lambda=0.5, subsample=0.7,
    random_state=42
).fit(X_train, y_train)
xgb_train_time = time.time() - start_xgb_train

start_rf_train = time.time()
rf = RandomForestRegressor(
    max_depth=20, max_features=0.8,
```

```python
    min_samples_split=2, n_estimators=100,
    random_state=42, n_jobs=-1
).fit(X_train, y_train)
rf_train_time = time.time() - start_rf_train
total_train_time = xgb_train_time + rf_train_time

# Generate predictions with timing
start_pred = time.time()
xgb_test_pred = xgb.predict(X_test)
rf_test_pred = rf.predict(X_test)
ensemble_test_pred = 0.6*xgb_test_pred + 0.4*rf_test_pred
prediction_time = time.time() - start_pred

# ==================================================================
# 3. Calculate Metrics
# ==================================================================
# Ensemble metrics
mae = mean_absolute_error(y_test, ensemble_test_pred)
r2 = r2_score(y_test, ensemble_test_pred)
rmse = np.sqrt(mean_squared_error(y_test, ensemble_test_pred))

# Calculate MAPE with zero handling
non_zero_mask = (y_test != 0)
if np.sum(non_zero_mask) > 0:
    mape = np.mean(np.abs((y_test[non_zero_mask] -
ensemble_test_pred[non_zero_mask]) /
                     y_test[non_zero_mask])) * 100
else:
    mape = float('nan')

# Overfitting check
xgb_val_pred = xgb.predict(X_val)
rf_val_pred = rf.predict(X_val)
ensemble_val_pred = 0.6*xgb_val_pred + 0.4*rf_val_pred
val_mae = mean_absolute_error(y_val, ensemble_val_pred)

print("\n=== Ensemble Performance ===")
print(f"Test MAE: {mae:.2f} seconds")
print(f"Test RMSE: {rmse:.2f} seconds")
print(f"Test MAPE: {mape:.2f}%")
print(f"Test R²: {r2:.2f}")
print(f"Training time: {total_train_time:.2f} seconds")
print(f"Prediction time: {prediction_time:.4f} seconds")
print(f"Validation MAE: {val_mae:.2f} seconds")
print(f"Test-Val Difference: {abs(mae - val_mae):.2f} seconds")

# ==================================================================
# 4. Visualizations
```

```python
# ================================================================
plt.figure(figsize=(16, 12))

# 4.1 Scatter plot: True vs Predicted
plt.subplot(2, 2, 1)
plt.scatter(y_test, ensemble_test_pred, alpha=0.6, color='#9467bd')
max_val = max(y_test.max(), ensemble_test_pred.max()) * 1.05
plt.plot([0, max_val], [0, max_val], 'r--')
plt.title('Ensemble: Actual vs Predicted Delay')
plt.xlabel('Actual Delay (seconds)')
plt.ylabel('Predicted Delay (seconds)')
plt.grid(True)

# Add metrics to plot
plt.text(0.05, 0.95, f'MAE: {mae:.2f}s\nRMSE: {rmse:.2f}s\nR²: {r2:.2f}',
         transform=plt.gca().transAxes,
         verticalalignment='top',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))

# 4.2 Box plot of absolute errors
absolute_errors = np.abs(y_test - ensemble_test_pred)
plt.subplot(2, 2, 2)
plt.boxplot(absolute_errors, vert=False, patch_artist=True,
            boxprops=dict(facecolor='#8c564b', color='black'),
            medianprops=dict(color='yellow'),
            whiskerprops=dict(color='black'),
            capprops=dict(color='black'),
            flierprops=dict(marker='o', markersize=8, markerfacecolor='red'))

plt.title('Absolute Error Distribution')
plt.xlabel('Absolute Error (seconds)')
plt.yticks([])
plt.grid(True)

# Add statistics
stats_text = (f"Min: {absolute_errors.min():.2f}s\n"
              f"Q1: {np.percentile(absolute_errors, 25):.2f}s\n"
              f"Median: {np.median(absolute_errors):.2f}s\n"
              f"Q3: {np.percentile(absolute_errors, 75):.2f}s\n"
              f"Max: {absolute_errors.max():.2f}s\n"
              f"IQR: {np.percentile(absolute_errors, 75) -
np.percentile(absolute_errors, 25):.2f}s")

plt.text(0.95, 0.95, stats_text,
         transform=plt.gca().transAxes,
         verticalalignment='top',
         horizontalalignment='right',
         bbox=dict(boxstyle='round', facecolor='white', alpha=0.8))
```

```python
# 4.3 Error distribution histogram
plt.subplot(2, 2, 3)
residuals = y_test - ensemble_test_pred
plt.hist(residuals, bins=20, color='#17becf', alpha=0.7)
plt.axvline(0, color='red', linestyle='--')
plt.title('Prediction Error Distribution')
plt.xlabel('Prediction Error (Actual - Predicted)')
plt.ylabel('Frequency')
plt.grid(True)

# 4.4 Component model comparison
plt.subplot(2, 2, 4)
models = ['XGBoost', 'Random Forest', 'Ensemble']
maes = [
    mean_absolute_error(y_test, xgb_test_pred),
    mean_absolute_error(y_test, rf_test_pred),
    mae
]
plt.bar(models, maes, color=['#1f77b4', '#ff7f0e', '#9467bd'])
plt.title('Model Comparison: MAE')
plt.ylabel('MAE (seconds)')
plt.grid(True)

# Add values on bars
for i, v in enumerate(maes):
    plt.text(i, v + 0.05, f"{v:.2f}", ha='center')

plt.tight_layout()
plt.show()

# ================================================================
# 5. Weight Optimization
# ================================================================
best_mae = float('inf')
best_weights = (0.5, 0.5)

for xgb_weight in np.linspace(0.5, 0.9, 9):
    current_pred = xgb_weight*xgb_test_pred + (1-xgb_weight)*rf_test_pred
    current_mae = mean_absolute_error(y_test, current_pred)

    if current_mae < best_mae:
        best_mae = current_mae
        best_weights = (xgb_weight, 1-xgb_weight)

print(f"\nOptimal Weights: XGB={best_weights[0]:.2f},
RF={best_weights[1]:.2f}")
print(f"Best Achievable MAE: {best_mae:.2f} seconds")
```

```python
# ==================================================================
# 6. Performance Summary
# ==================================================================
print("\n=== Ensemble Performance Summary ===")
print(f"{'Metric':<20} | {'Value':<10}")
print("-" * 35)
print(f"{'MAE':<20} | {mae:.4f} sec")
print(f"{'RMSE':<20} | {rmse:.4f} sec")
print(f"{'MAPE':<20} | {mape:.2f}%")
print(f"{'R²':<20} | {r2:.4f}")
print(f"{'Validation MAE':<20} | {val_mae:.4f} sec")
print(f"{'Training time':<20} | {total_train_time:.2f} sec")
print(f"{'Prediction time':<20} | {prediction_time:.4f} sec")
print(f"{'Optimal XGB Weight':<20} | {best_weights[0]:.2f}")
print(f"{'Optimal RF Weight':<20} | {best_weights[1]:.2f}")
```

6. Cycle Length Optimization

```python
# Optimization of Cycle Length
import numpy as np, pandas as pd, xgboost as xgb
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# ── settings you may tweak ──────────────────────────────────────────────────
IN_FILE   = r'D:\ValidationVolumes.xlsx'
SHEET     = 'optimize'
OUT_FILE  = r'D:\optimised_cycles.xlsx'

C_MIN, C_MAX  = 40, 150          # absolute bounds
L_LOST        = 14               # s lost time (≈ 2 s/phase ×5 + 4 all-red)
LAMBDA        = 40               # penalty weight (raise → longer cycles)
W_XGB         = 0.6              # XGB share in each ensemble
np.random.seed(42)
# ──────────────────────────────────────────────────────────────────────────────

# 1. load spreadsheet
df = (pd.read_excel(IN_FILE, sheet_name=SHEET)
        .astype({'volume':float,'dos':float,'time':int,
                 'cycle':float,'delay':float}))

# 2. monotone baseline cycle model
X_cy, y_cy = df[['volume','dos','time']], df['cycle']
X_tr, X_te, y_tr, y_te = train_test_split(X_cy, y_cy,
                                          test_size=.2, random_state=42)

cy_xgb = xgb.XGBRegressor(
```

```
    objective='reg:squarederror',
    n_estimators=700, learning_rate=.05, max_depth=4,
    subsample=.8, colsample_bytree=.9, random_state=42,
    monotone_constraints="(1,1,0)"
)
cy_rf  = RandomForestRegressor(
    n_estimators=450, max_depth=22,
    max_features=.8, n_jobs=-1, random_state=42
)
cy_xgb.fit(X_tr, y_tr);  cy_rf.fit(X_tr, y_tr)

def base_cycle(Xdf: pd.DataFrame) -> np.ndarray:
    return W_XGB*cy_xgb.predict(Xdf) + (1-W_XGB)*cy_rf.predict(Xdf)

# 3. delay surrogate model
X_d, y_d = df[['dos','volume','cycle']], df['delay']
Xd_tr, Xd_te, yd_tr, yd_te = train_test_split(
        X_d, y_d, test_size=.3, random_state=42)

dl_xgb = xgb.XGBRegressor(
    objective='reg:squarederror',
    n_estimators=900, learning_rate=.05, max_depth=3,
    subsample=.7, colsample_bytree=.9, random_state=42
)
dl_rf  = RandomForestRegressor(
    n_estimators=550, max_depth=24,
    max_features=.8, n_jobs=-1, random_state=42
)
dl_xgb.fit(Xd_tr, yd_tr);  dl_rf.fit(Xd_tr, yd_tr)

def pred_delay(Xdf: pd.DataFrame) -> np.ndarray:
    return W_XGB*dl_xgb.predict(Xdf) + (1-W_XGB)*dl_rf.predict(Xdf)

# 4. optimiser (integer-second grid)
def optimise_cycle(vol: float, dos: float, tf: int):
    # DoS-dependent minimum (40 → 100 s)
    C_lo = int(np.clip(40 + 60*dos, 40, 120))
    grid = np.arange(C_lo, C_MAX+1)          # every 1 s

    # evaluate delay + soft penalty
    Xg     = pd.DataFrame({'dos': dos,
                           'volume': vol,
                           'cycle': grid})
    delay  = pred_delay(Xg)
    share  = L_LOST / grid
    obj    = delay + LAMBDA*np.maximum(0, share - 0.15)

    best   = np.argmin(obj)
```

```python
    tie    = np.abs(obj - obj[best]) < 0.5
    best_c = grid[tie].min()                 # shorter if tie
    best_d = delay[grid == best_c][0]
    return best_c, best_d

# 5. run on 20 random scenarios for preview
rows = []
for _, r in (df.sample(n=min(20, len(df)), random_state=42)
               .reset_index(drop=True)).iterrows():
    cyc, dly = optimise_cycle(r['volume'], r['dos'], r['time'])
    rows.append({'volume': r['volume'],
                 'dos':    r['dos'],
                 'time':   r['time'],
                 'orig_cycle': r['cycle'],
                 'opt_cycle':  cyc,
                 'opt_delay_est': round(dly, 2)})

preview = pd.DataFrame(rows)
print(preview[['volume','dos','orig_cycle','opt_cycle']])

# 6. export full optimisation for all rows
all_rows = []
for _, r in df.iterrows():
    cyc, dly = optimise_cycle(r['volume'], r['dos'], r['time'])
    all_rows.append({'volume': r['volume'],
                     'dos':    r['dos'],
                     'time':   r['time'],
                     'opt_cycle': cyc,
                     'opt_delay_est': round(dly, 2)})
pd.DataFrame(all_rows).to_excel(OUT_FILE, index=False)
print("\nSaved cycles (integer-second resolution) to:", OUT_FILE)
```

APPENDIX D GAP ACCEPTANCE AND OPPOSING VEHICLE FACTOR

Default Cost Model Parameters, Adapted from (SIDRA Intersection User Guide for Version 8, 2018)

Table 5.14.14 - Default values of cost model parameters for the Standard SIDRA ("Australia"), New Zealand and US HCM Models

Parameter	Symbol	Australia	New Zealand	USA
Cost Unit		\$ (AUD)	\$ (NZD)	\$ (USD)
Parameters for Vehicle Operating Cost	***(k_o)***			
Pump Price of Fuel in "Cost Unit" per litre (or per gallon)	($\mathbf{P_p}$)	**1.30** (\$/L)	**2.10** (\$/L)	\$ **0.60** (\$/L) (**2.30** \$/gal)
Fuel Resource Cost Factor	($\mathbf{f_r}$)	0.50	0.60	0.70
Running Cost / Fuel Cost Ratio	($\mathbf{f_c}$)	3.0	2.5	3.0
Parameters for Time Cost	***(k_t)***			
Average Income (full time adult average hourly total earnings) in "Cost Unit" per hour	(**W**)	**44.00**(\$/h)	**31.00**(\$/h)	**27.00** (\$/h)
Time Value Factor as a Proportion of Average Hourly Income	($\mathbf{f_p}$)	0.60	0.60	0.40
Average Occupancy in Persons per Vehicle	($\mathbf{f_o}$)	1.2	1.2	1.2
Calculated Values				
Vehicle Operating Cost Factor in "Cost Unit" per litre (or per gallon) of fuel	($\mathbf{k_o} = f_c\ f_r\ P_p$)	1.950 (\$/L)	3.150 (\$/L)	1.260 (\$/L) (4.830 \$/gal)
Time Cost per ***Person*** in "Cost Unit" per hour	(f_p W)	26.40 (\$/h)	18.60(\$/h)	10.80 (\$/h)
Time Cost per ***Vehicle*** in "Cost Unit" per hour	($\mathbf{k_t} = f_o\ f_p$ W)	31.68 (\$/h)	22.32 (\$/h)	12.96 (\$/h)

Pump Price of Fuel and **Average Income** values were updated in April 2018.

APPENDIX E MODELLING PACKAGES

Examples of Modelling Packages, Adapted from (Austroads, Guide to Traffic Management Part 3: Transport Study and Analysis Methods, 2020)-Appendix M

Technique	Example software	Description
Macroscopic model	EMME	Transport demand modelling software based on 4-step model (http://www.inro.ca/en/index.php, viewed November 2016)
	CUBE	For the modelling of passenger demand, including the 4-step model and activity-based models (http://www.citilabs.com/software/cube/, viewed November 2016)
	TransCAD	Combines GIS and transportation modelling capabilities in a single integrated platform. It can be used for all modes of transportation, at any geographic scale or level of detail. (http://www.caliper.com/tcovu.htm, viewed December 2016)
	CUBE Voyager	For the modelling of passenger demand, including the 4-step model and activity-based models (http://www.citilabs.com/software/cube/, viewed November 2016)
Mesoscopic model	TRANSYT	For the simulation of signalised road network, with traffic signal optimisation (http://mctrans.ce.ufl.edu/featured/transyt-7f/, viewed November 2016)
	SATURN	Macrosimulation combined with assignment and trip matrix estimation (http://www.saturnsoftware.co.uk/, viewed November 2016)
	SYNCHRO	A traffic signal optimisation tool for arterials and networks, using time-space analysis and platoon dispersion models (Sabra, Wallace and Lin 2000)
	LinSig	http://www.jctconsultancy.com/Software/LinSigV3/linsigv3.php#
Hybrid model	CUBE Avenue	Use and works with traditional four-step transportation planning models or with any model type that uses highway assignment (http://www.citilabs.com/citilabs_products/cube-avenue/, viewed December 2016)
	VISUM	Demand model based on the 4-step model with enhanced traffic assignment which incorporates a node delays and time-dynamic assignment and integrated with VISSIM (microsimulation) (http://www.ptvag.com/, viewed November 2016)
	OmniTRANS	Multimodal and multitemporal system, suitable for modelling the interactions between the various means of transport within an urban context. It supports both aggregated and disaggregated methods for modelling the mobility demand (http://www.dat.nl/en/products/omnitrans/, viewed December 2016)
	INRO Dynameq	Multiscale traffic simulation, it provides an advanced vehicle-based traffic simulation and simulation-based dynamic traffic assignment. It is scalable across wide-area urban networks and provides comprehensive vehicle-level detail throughout the model (https://www.inro.ca/en/products/dynameq/, viewed December 2016
	AIMSUN	For the simulation of a multi-modal transport network, it has the capability model hybrid assignments (http://www.aimsun.com/site/, viewed November 2016)

Technique	Example software	Description
Microsimulation	AIMSUN	For the simulation of a multi-modal transport network (http://www.aimsun.com/site/, viewed November 2016)
	PARAMICS	For the simulation of a multi-modal transport network (http://www.paramics-online.com/, viewed November 2016)
	VISSIM	For the simulation of a multi-modal transport network (http://www.ptvag.com/, viewed November 2016)
	SIDRA TRIP	A single-trip microsimulation model for assessing travel LOS, performance (delay, speed, travel time), operating cost, user cost, fuel consumption, vehicle emissions and noise in real-life road networks (http://www.sidrasolutions.com/, viewed November 2016)
Intersection model	SIDRA Intersection	For the design and analysis of single intersection (signal, roundabout, priority intersections, etc.) (http://www.sidrasolutions.com/, viewed November 2016)
	HCS	A computerised implementation of the Highway Capacity Manual (HCM), and is used to analyse signalised intersections (Sabra, Wallace and Lin 2000) updated to the HCM 2016 (http://mctrans.ce.ufl.edu/mct/index.php/hcs/https://mctrans.ce.ufl.edu/mct/index.php/hcs2010/, viewed September 2017)
	ARCADY	For roundabout analysis and it utilises empirically based models calibrated from British field data (FHWA 2000) (https://trlsoftware.co.uk/) – this UK application is more advanced

APPENDIX F TRAFFIC MATRIX AND DELAY MATRIX

DELAY MATRIX

S.N.	time	volume	dos	cycle	delay
1	AM	3152	0.905	131	47.6
2	PM	2972	0.906	93	38.8
3	AM	3384	0.891	147	53
4	PM	2908	0.832	134	46.8
5	AM	3008	0.822	130	43.5
6	PM	2988	0.822	97	36.9
7	AM	3084	0.994	106	41.2
8	PM	3208	1.147	100	48.8
9	AM	3328	0.877	149	50.1
10	PM	3312	0.906	96	39.3
11	AM	3212	0.999	101	40.3
12	PM	3080	1.186	102	56.2
13	AM	3264	0.902	142	51.8
14	PM	3116	0.832	96	34.8
15	AM	4008	1.265	115	111
16	AM	4076	1.125	100	71.1
17	AM	3888	1.107	96	65.9
18	AM	3768	1.194	109	91.2
19	AM	3892	1.183	102	85.2
20	PM	3688	1.174	95	77.4
21	PM	3528	1.171	85	73.7
22	PM	3868	1.282	82	94.8
23	PM	3764	1.19	86	77.1
24	PM	3388	1.04	93	52.6
25	PM	3700	1.178	82	70.8
26	AM	3968	1.048	131	69.8
27	AM	4260	1.199	138	100.7
28	AM	4332	1.21	141	96.2
29	AM	4456	1.175	126	91.9
30	AM	4220	1.13	113	76
31	AM	4040	1.09	122	71.5
32	PM	3632	1.158	126	86.3
33	PM	3640	1.122	102	67
34	PM	3708	1.081	102	64.9
35	PM	3488	1.033	107	57
36	PM	3216	0.934	135	53.2
37	PM	3392	1.017	133	65.3
38	AM	3900	1.056	138	72.6
39	AM	3668	1.023	123	66
40	AM	3628	1.005	109	55.2
41	AM	3776	0.975	124	55.4
42	AM	3928	1.077	150	77.9
43	AM	3664	1.049	148	75.8
44	PM	3688	1.097	82	56
45	PM	3816	1.155	86	71.8
46	PM	3688	1.104	79	53
47	PM	3632	1.089	75	53.7
48	PM	3600	1.102	80	54.2
49	PM	3680	1.136	82	63.4

50	AM	3856	1.1	137	79.9
51	AM	3836	1.2	135	103.5
52	AM	3952	1.112	141	82.6
53	AM	3700	1.032	150	71.1
54	AM	3684	1.108	140	83.7
55	AM	3984	1.214	124	102.9
56	PM	3952	1.143	83	63.8
57	PM	4072	1.177	75	69
58	PM	3728	1.126	80	63.2
59	PM	3840	1.1	88	60.1
60	PM	3924	1.085	92	61.2
61	PM	4072	1.206	83	78.2
62	AM	4100	1.125	138	89.3
63	AM	4076	1.234	139	109.6
64	AM	4476	1.167	127	94.8
65	AM	4360	1.12	140	78.6
66	AM	4132	1.174	129	100.7
67	AM	4172	1.119	123	76.2
68	PM	4072	1.135	77	57
69	PM	4208	1.193	87	74.9
70	PM	4048	1.215	79	80.5
71	PM	4328	1.246	79	79.8
72	PM	4180	1.184	95	80.6
73	PM	4288	1.267	89	95.9
74	AM	3660	0.895	142	47.6
75	AM	3836	0.981	148	60.8
76	AM	4024	1.041	126	63.5
77	AM	3852	0.988	136	57.3
78	AM	4076	1.07	131	68.6
79	AM	4168	1.035	150	68.3
80	PM	3968	1.18	86	71.1
81	PM	3880	1.301	71	104.2
82	PM	4072	1.282	88	96.5
83	PM	4176	1.276	80	94.5
84	PM	4084	1.292	83	101.7
85	PM	4392	1.313	81	112.3
86	AM	4112	1.084	142	76.2
87	AM	3880	1.066	119	68.7
88	AM	3856	0.961	138	58
89	AM	3836	1.007	119	59.6
90	AM	4148	1.133	150	90
91	AM	3860	1.043	124	64.7
92	PM	3756	1.087	88	57.1
93	PM	3900	1.076	97	55.8
94	PM	3792	1.106	98	59.8
95	PM	3912	1.028	73	42.7
96	PM	4048	1.124	82	60.1
97	PM	3604	0.986	84	42.7

TRAFFIC MATRIX

S.N	Date	Time Flag (AM/PM)	Approach Volumes				Total Volume/Demand	Critical Movement v/c				v/c	Average Delay	95% BoQ (metres)	Cycle Length	Phase Times					Green Ratios				
			V_{AE}	V_{OVH}	V_{DFH}	V_{AH}		$v/c_{(cr.AE)}$	$v/c_{(cr.OVH)}$	$v/c_{(cr.DFH)}$	$v/c_{(cr.AH)}$					G_A	G_C	G_D	G_E	G_G	G_A	G_C	G_D	G_E	G_G
1	11-Sep	AM	1248	828	592	484	3152	0.824	0.491	0.899	0.905	0.905	47.6	254.6	131	21	27	25	29	29	0.160305	0.206107	0.19084	0.221374	0.22137
2	11-Sep	PM	676	1012	924	360	2972	0.906	0.499	0.906	0.892	0.906	38.8	138.9	93	26	0	27	21	19	0.27957	0	0.290323	0.225806	0.2043
3	12-Sep	AM	1192	852	580	760	3384	0.71	0.885	0.891	0.866	0.891	53	271.8	147	21	32	28	41	25	0.142857	0.217687	0.190476	0.278912	0.17007
4	12-Sep	PM	780	716	1020	392	2908	0.826	0.804	0.832	0.83	0.832	46.8	177.8	134	45	0	29	22	38	0.335821	0	0.216418	0.164179	0.28358
5	17-Sep	AM	968	796	488	756	3008	0.513	0.822	0.818	0.816	0.822	43.5	169	130	19	21	27	36	27	0.146154	0.161538	0.207692	0.276923	0.20769
6	17-Sep	PM	648	1124	788	428	2988	0.779	0.421	0.822	0.821	0.822	36.9	126.2	97	20	0	26	31	20	0.206186	0	0.268041	0.319588	0.20619
7	18-Sep	AM	1184	688	504	708	3084	0.674	0.905	0.889	0.994	0.994	41.2	151.2	106	16	26	20	27	17	0.150943	0.245283	0.188679	0.254717	0.16038
8	18-Sep	PM	808	1024	976	400	3208	0.593	0.616	1.055	1.147	1.147	48.8	217.4	100	37	0	22	22	19	0.37	0	0.22	0.22	0.19
9	19-Sep	AM	1224	780	612	712	3328	0.684	0.866	0.875	0.877	0.877	50.1	271.3	149	23	33	25	40	28	0.154362	0.221477	0.167785	0.268456	0.18792
10	19-Sep	PM	812	980	968	552	3312	0.896	0.728	0.906	0.896	0.906	39.3	139	96	27	0	22	22	25	0.28125	0	0.229167	0.229167	0.26042
11	24-Sep	AM	1200	764	484	764	3212	0.407	0.918	0.999	0.874	0.999	40.3	175.9	101	19	23	18	27	14	0.188119	0.227723	0.178218	0.267327	0.13861
12	24-Sep	PM	716	1108	860	396	3080	0.652	0.523	1.038	1.186	1.186	56.2	257.4	102	31	0	28	22	21	0.303922	0	0.27451	0.215686	0.20588
13	25-Sep	AM	1228	748	632	656	3264	0.8	0.888	0.902	0.882	0.902	51.8	276.3	142	24	28	26	33	31	0.169014	0.197183	0.183099	0.232394	0.21831
14	25-Sep	PM	660	1000	928	528	3116	0.825	0.539	0.832	0.827	0.832	34.8	120.3	96	29	0	24	27	16	0.302083	0	0.25	0.28125	0.16667
15	11-Sep	AM	1624	1012	796	576	4008	1.163	0.871	1.265	1.243	1.265	111	528.4	115	20	20	24	19	32	0.173913	0.173913	0.208696	0.165217	0.27826
16	11-Sep	AM	1664	968	796	648	4076	1.11	0.738	1.125	1.084	1.125	71.1	441.7	100	17	26	18	23	16	0.17	0.26	0.18	0.23	0.16
17	11-Sep	AM	1472	1068	736	612	3888	1.062	0.679	1.102	1.107	1.107	65.9	357.7	96	15	21	22	20	18	0.15625	0.21875	0.229167	0.208333	0.1875
18	11-Sep	AM	1352	1060	800	556	3768	1.146	0.495	1.194	1.185	1.194	91.2	388.5	109	19	15	22	26	27	0.174312	0.137615	0.201835	0.238532	0.24771
19	11-Sep	AM	1564	1084	688	556	3892	1.132	0.563	1.175	1.183	1.183	85.2	426	102	15	22	20	23	22	0.147059	0.215686	0.196078	0.22549	0.21569
20	11-Sep	PM	744	1216	1248	480	3688	1.165	0.765	1.173	1.174	1.174	77.4	324	95	29	0	30	20	16	0.305263	0	0.315789	0.210526	0.16842
21	11-Sep	PM	772	1176	1164	416	3528	1.152	0.694	1.157	1.171	1.171	73.7	278.1	85	25	0	24	17	19	0.294118	0	0.282353	0.2	0.22353
22	11-Sep	PM	712	1436	1276	444	3868	1.274	0.537	1.281	1.282	1.282	94.8	355.4	82	24	0	23	21	14	0.292683	0	0.280488	0.256098	0.17073
23	11-Sep	PM	900	1196	1224	444	3764	1.183	1.183	1.167	1.19	1.19	77.1	311.8	86	26	0	25	18	17	0.302326	0	0.290698	0.209302	0.19767
24	11-Sep	PM	828	1144	1004	412	3388	1.027	0.615	1.029	1.04	1.04	52.6	205.3	93	25	0	31	19	18	0.268817	0	0.333333	0.204301	0.19355
25	11-Sep	PM	824	1312	1060	504	3700	1.164	0.575	1.178	1.177	1.178	70.8	245.3	82	19		23	23	17	0.231707	0	0.280488	0.280488	0.20732
26	12-Sep	AM	1360	996	804	808	3968	1.018	0.991	1.047	1.048	1.048	69.8	363.1	131	22	26	22	35	26	0.167939	0.198473	0.167939	0.267176	0.19847
27	12-Sep	AM	1588	1032	628	1012	4260	1.079	1.199	1.197	1.193	1.199	100.7	583.1	138	15	37	30	40	16	0.108696	0.268116	0.217391	0.289855	0.11594
28	12-Sep	AM	1596	1048	616	1072	4332	1.107	1.203	1.21	1.209	1.21	96.2	656.4	141	16	41	31	42	11	0.113475	0.29078	0.219858	0.297872	0.07801
29	12-Sep	AM	1636	1124	660	1036	4456	1.138	1.162	1.167	1.175	1.175	91.9	566.3	126	14	38	24	39	11	0.111111	0.301587	0.190476	0.309524	0.0873
30	12-Sep	AM	1516	1092	664	948	4220	1.02	1.122	1.119	1.13	1.13	76	467.2	113	15	31	24	32	11	0.132743	0.274336	0.212389	0.283186	0.09735
31	12-Sep	AM	1300	988	744	1008	4040	1.056	1.09	1.09	1.072	1.09	71.5	368.2	122	17	24	24	38	19	0.139344	0.196721	0.196721	0.311475	0.15574
32	12-Sep	PM	936	848	1424	424	3632	1.158	0.918	1.157	1.155	1.158	86.3	447.4	126	45	0	25	19	37	0.357143	0	0.198413	0.150794	0.29365
33	12-Sep	PM	836	968	1416	420	3640	1.108	0.694	1.122	1.12	1.122	67	346.1	102	37	0	22	20	23	0.362745	0	0.215686	0.196078	0.22549
34	12-Sep	PM	1008	948	1244	508	3708	1.078	1.053	1.078	1.081	1.081	64.9	279.5	102	33	0	25	18	26	0.323529	0	0.245098	0.176471	0.2549
35	12-Sep	PM	876	920	1228	464	3488	1.033	0.781	1.033	1.032	1.033	57	281.3	107	37	0	21	21	28	0.345794	0	0.196262	0.196262	0.26168
36	12-Sep	PM	880	744	1080	512	3216	0.934	0.915	0.934	0.913	0.934	53.2	229.2	135	44	0	27	25	39	0.325926	0	0.2	0.185185	0.28889
37	12-Sep	PM	1016	808	1160	408	3392	1.011	0.982	1.016	1.017	1.017	65.3	280.3	133	43		27	19	44	0.323308	0	0.203008	0.142857	0.33083
38	17-Sep	AM	1152	1000	700	1048	3900	1.044	1.056	1.055	1.045	1.056	72.6	367.7	138	16	22	24	44	32	0.115942	0.15942	0.173913	0.318841	0.23188
39	17-Sep	AM	1108	1060	596	904	3668	0.986	1.022	1.014	1.023	1.023	66	278	123	14	20	27	36	26	0.113821	0.162602	0.219512	0.292683	0.21138
40	17-Sep	AM	1136	972	632	888	3628	0.983	0.993	1.004	1.005	1.005	55.2	237.3	109	14	19	26	30	20	0.12844	0.174312	0.238532	0.275229	0.18349
41	17-Sep	AM	1308	996	608	864	3776	0.926	0.872	0.973	0.975	0.975	55.4	288.3	124	13	31	26	35	19	0.104839	0.25	0.209677	0.282258	0.15323
42	17-Sep	AM	1188	992	660	1088	3928	1.06	1.077	1.068	1.076	1.077	77.9	428.6	150	17	33	40	49	11	0.113333	0.22	0.266667	0.326667	0.07333
43	17-Sep	AM	1108	988	604	964	3664	1.018	1.049	1.037	1.046	1.049	75.8	343.8	148	15	25	36	43	29	0.101351	0.168919	0.243243	0.290541	0.19595
44	17-Sep	PM	700	1380	1024	584	3688	1.072	0.555	1.075	1.097	1.097	56	255.5	82	18	0	21	28	15	0.219512	0	0.256098	0.341463	0.18293
45	17-Sep	PM	732	1476	1020	588	3816	1.155	0.496	1.148	1.155	1.155	71.8	325	86	18	0	21	32	15	0.209302	0	0.244186	0.372093	0.17442
46	17-Sep	PM	920	1392	924	452	3688	0.899	0.594	1.104	1.104	1.104	53	194.6	79	19	0	23	20	17	0.240506	0	0.291139	0.253165	0.21519
47	17-Sep	PM	764	1392	968	508	3632	1.076	0.598	1.089	1.086	1.089	53.7	200.9	75	15	0	23	21	16	0.2	0	0.306667	0.28	0.21333
48	17-Sep	PM	912	1348	848	492	3600	0.754	0.659	1.102	1.091	1.102	54.2	189.8	80	19	0	24	20	17	0.2375	0	0.3	0.25	0.2125
49	17-Sep	PM	664	1412	988	616	3680	1.136	0.61	1.129	1.119	1.136	63.4	258	82	18	0	23	27	14	0.219512	0	0.280488	0.329268	0.17073
50	18-Sep	AM	1488	772	676	920	3856	1.089	1.099	1.1	1.084	1.1	79.9	509.6	137	20	36	29	39	13	0.145985	0.262774	0.211679	0.284672	0.09489
51	18-Sep	AM	1652	804	636	744	3836	1.14	1.2	1.185	1.177	1.2	103.5	546	135	18	34	27	28	28	0.133333	0.251852	0.2	0.207407	0.20741
52	18-Sep	AM	1536	836	644	936	3952	1.074	1.112	1.106	1.105	1.112	82.6	450.9	141	16	37	24	39	25	0.113475	0.262411	0.170213	0.276596	0.1773
53	18-Sep	AM	1448	748	580	924	3700	0.986	1.032	1.021	1.021	1.032	71.1	440.5	150	18	41	29	44	18	0.12	0.273333	0.193333	0.293333	0.12
54	18-Sep	AM	1396	756	588	944	3684	1.1	1.093	1.108	1.105	1.108	83.7	393.6	140	15	32	28	40	25	0.107143	0.228571	0.2	0.285714	0.17857
55	18-Sep	AM	1480	860	620	1024	3984	1.196	1.209	1.214	1.206	1.214	102.9	436.1	124	14	26	24	35	25	0.112903	0.209677	0.193548	0.282258	0.20161
56	18-Sep	PM	1056	1256	1220	420	3952	1.137	0.563	1.11	1.143	1.143	63.8	267.1	83	25	0	18	23	17	0.301205	0	0.216867	0.277108	0.20482
57	18-Sep	PM	996	1388	1168	520	4072	1.177	0.643	1.152	1.171	1.177	69	274.6	75	20	0	18	23	14	0.266667	0	0.24	0.306667	0.18667

58	18-Sep	PM	992	1284	1060	392	3728	1.126	0.564	1.114	1.125	1.126	63.2	212	80	19	0	21	21	19	0.2375	0	0.2625	0.2625	0.2375
59	18-Sep	PM	1080	1224	1092	444	3840	1.048	0.709	1.1	1.1	1.1	60.1	195.5	88	22	0	22	21	23	0.25	0	0.25	0.238636	0.26136
60	18-Sep	PM	1036	1188	1204	496	3924	1.072	0.679	1.084	1.085	1.085	61.2	232.6	92	27	0	23	25	17	0.293478	0	0.25	0.271739	0.18478
61	18-Sep	PM	1084	1196	1284	508	4072	1.203	0.824	1.206	1.203	1.206	78.2	295.6	83	24	0	20	20	19	0.289157	0	0.240964	0.240964	0.22892
62	19-Sep	AM	1648	956	700	796	4100	1.106	1.108	1.125	1.082	1.125	89.3	525.7	138	18	38	24	33	25	0.130435	0.275362	0.173913	0.23913	0.18116
63	19-Sep	AM	1444	932	668	1032	4076	1.192	1.226	1.224	1.234	1.234	109.6	495.7	139	16	25	22	40	36	0.115108	0.179856	0.158273	0.28777	0.25899
64	19-Sep	AM	1712	1108	760	896	4476	1.162	1.15	1.167	1.167	1.167	94.8	561.9	127	14	38	23	34	18	0.110236	0.299213	0.181102	0.267717	0.14173
65	19-Sep	AM	1660	1024	652	1024	4360	1.099	1.111	1.12	1.116	1.12	78.6	603.1	140	18	45	22	44	11	0.128571	0.321429	0.157143	0.314286	0.07857
66	19-Sep	AM	1572	968	848	744	4132	1.126	1.152	1.174	1.173	1.174	100.7	495.9	129	20	27	23	28	31	0.155039	0.209302	0.178295	0.217054	0.24031
67	19-Sep	AM	1668	1080	664	760	4172	1.113	0.925	1.097	1.119	1.119	76.2	484.4	123	15	37	23	31	17	0.121951	0.300813	0.186992	0.252033	0.13821
68	19-Sep	PM	884	1276	1224	688	4072	1.116	0.854	1.135	1.132	1.135	57	211.1	77	21	0	17	20	19	0.272727	0	0.220779	0.25974	0.24675
69	19-Sep	PM	1056	1156	1384	612	4208	1.193	0.851	1.19	1.18	1.193	74.9	344	87	28	0	21	19	19	0.321839	0	0.241379	0.218391	0.21839
70	19-Sep	PM	1080	1304	1092	572	4048	1.181	0.636	1.215	1.215	1.215	80.5	275.3	79	20	0	18	21	20	0.253165	0	0.227848	0.265823	0.25316
71	19-Sep	PM	960	1340	1276	752	4328	1.246	0.983	1.243	1.212	1.246	79.8	324.6	79	23	0	18	20	18	0.291139	0	0.227848	0.253165	0.22785
72	19-Sep	PM	1060	1108	1260	752	4180	1.184	1.139	1.166	1.17	1.184	80.6	334.6	95	29	0	20	20	26	0.305263	0	0.210526	0.210526	0.27368
73	19-Sep	PM	1072	1364	1152	700	4288	1.255	0.843	1.258	1.267	1.267	95.9	308.6	89	20	0	21	23	25	0.224719	0	0.235955	0.258427	0.2809
74	24-Sep	AM	1368	876	524	892	3660	0.86	0.89	0.895	0.888	0.895	47.6	318.9	142	17	45	23	45	12	0.119718	0.316901	0.161972	0.316901	0.08451
75	24-Sep	AM	1348	892	568	1028	3836	0.91	0.981	0.977	0.946	0.981	60.8	389.4	148	16	43	25	53	11	0.108108	0.290541	0.168919	0.358108	0.07432
76	24-Sep	AM	1452	1028	548	996	4024	1.03	1.041	1.033	1.03	1.041	63.5	397.7	126	13	37	25	40	11	0.103175	0.293651	0.198413	0.31746	0.0873
77	24-Sep	AM	1548	960	524	820	3852	0.961	0.988	0.982	0.981	0.988	57.3	444.8	136	18	47	22	37	12	0.132353	0.345588	0.161765	0.272059	0.08824
78	24-Sep	AM	1476	1004	584	1012	4076	1.062	1.059	1.07	1.07	1.07	68.6	462.4	131	15	38	25	42	11	0.114504	0.290076	0.19084	0.320611	0.08397
79	24-Sep	AM	1632	1040	620	876	4168	1.009	0.949	1.035	1.035	1.035	68.3	556.5	150	16	54	24	44	12	0.106667	0.36	0.16	0.293333	0.08
80	24-Sep	PM	740	1180	1164	884	3968	1.177	1.154	1.155	1.18	1.18	71.1	259.1	86	22	0	25	23	16	0.255814	0	0.290698	0.267442	0.18605
81	24-Sep	PM	832	1440	900	708	3880	1.291	1.144	1.277	1.301	1.301	104.2	374.9	71	13	0	26	16	16	0.183099	0	0.366197	0.225352	0.22535
82	24-Sep	PM	928	1260	1096	788	4072	1.28	1.276	1.282	1.265	1.282	96.5	341	88	20	0	29	20	19	0.227273	0	0.329545	0.227273	0.21591
83	24-Sep	PM	868	1392	1128	788	4176	1.248	1.247	1.276	1.268	1.276	94.5	337.1	80	18	0	27	18	17	0.225	0	0.3375	0.225	0.2125
84	24-Sep	PM	936	1344	1088	716	4084	1.273	1.263	1.292	1.29	1.292	101.7	384	83	19	0	30	17	17	0.228916	0	0.361446	0.204819	0.20482
85	24-Sep	PM	948	1508	1068	868	4392	1.309	1.254	1.313	1.312	1.313	112.3	386.1	81	17	0	29	20	15	0.209877	0	0.358025	0.246914	0.18519
86	25-Sep	AM	1760	844	640	868	4112	1.014	1.057	1.084	1.075	1.084	76.2	586.1	142	14	51	24	39	14	0.098592	0.359155	0.169014	0.274648	0.09859
87	25-Sep	AM	1488	928	684	780	3880	1.044	1.044	1.066	1.061	1.066	68.7	376.8	119	14	30	24	29	22	0.117647	0.252101	0.201681	0.243697	0.18487
88	25-Sep	AM	1556	872	716	712	3856	0.902	0.952	0.961	0.935	0.961	58	400.3	138	21	43	25	33	16	0.152174	0.311594	0.181159	0.23913	0.11594
89	25-Sep	AM	1332	1032	600	872	3836	1.007	1.002	1.002	1.001	1.007	59.6	321.7	119	13	31	27	35	13	0.109244	0.260504	0.226891	0.294118	0.10924
90	25-Sep	AM	1824	844	616	864	4148	1.099	1.112	1.133	1.095	1.133	90	677.4	150	17	52	24	38	19	0.113333	0.346667	0.16	0.253333	0.12667
91	25-Sep	AM	1356	996	608	900	3860	1.041	1.027	1.043	1.042	1.043	64.7	353.9	124	14	31	28	36	15	0.112903	0.25	0.225806	0.290323	0.12097
92	25-Sep	PM	792	1184	1092	688	3756	1.084	0.814	1.087	1.082	1.087	57.1	222.5	88	25	0	24	23	16	0.284091	0	0.272727	0.261364	0.18182
93	25-Sep	PM	804	1108	1336	652	3900	1.072	0.707	1.051	1.076	1.076	55.8	293.4	97	34	0	21	26	16	0.350515	0	0.216495	0.268041	0.16495
94	25-Sep	PM	776	1328	1108	580	3792	1.087	0.452	1.09	1.106	1.106	59.8	298.8	98	26	0	23	35	14	0.265306	0	0.234694	0.357143	0.14286
95	25-Sep	PM	876	1232	1088	716	3912	1.028	0.772	1.001	1.016	1.028	42.7	163.8	73	20	0	19	21	13	0.273973	0	0.260274	0.287671	0.17808
96	25-Sep	PM	876	1196	1260	716	4048	1.113	0.922	1.124	1.117	1.124	60.1	258.7	82	26	0	22	21	13	0.317073	0	0.268293	0.256098	0.15854
97	25-Sep	PM	764	1100	1016	724	3604	0.964	0.944	0.984	0.986	0.986	42.7	146.6	84	24	0	22	21	17	0.285714	0	0.261905	0.25	0.20238

APPENDIX G MODELLING REPORTS

INTERSECTION SUMMARY

Site: 1646 [TS1646 2024AM-Existing (18/09)]

Oteha Valley Rd/Albany Expy/Albany Hwy/Dairy Flat Hwy
20242409 08:15-08:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated Cycle Time = 101 seconds (Site User-Given Phase Times)

Intersection Performance - Hourly Values

Performance Measure	Vehicles	Persons
Travel Speed (Average)	22.3 km/h	22.1 km/h
Travel Distance (Total)	1497.7 veh-km/h	2290.7 pers-km/h
Travel Time (Total)	67.2 veh-h/h	103.5 pers-h/h
Demand Flows (Total)	3212 veh/h	4889 pers/h
Percent Heavy Vehicles (Demand)	4.4 %	
Degree of Saturation	0.999	
Practical Spare Capacity	-9.9 %	
Effective Intersection Capacity	3216 veh/h	
Control Delay (Total)	36.00 veh-h/h	55.52 pers-h/h
Control Delay (Average)	40.3 sec	40.9 sec
Control Delay (Worst Lane)	70.6 sec	
Control Delay (Worst Movement)	70.6 sec	70.6 sec
Geometric Delay (Average)	2.0 sec	
Stop-Line Delay (Average)	38.3 sec	
Idling Time (Average)	33.3 sec	
Intersection Level of Service (LOS)	LOS D	
95% Back of Queue - Vehicles (Worst Lane)	23.7 veh	
95% Back of Queue - Distance (Worst Lane)	175.9 m	
Queue Storage Ratio (Worst Lane)	0.49	
Total Effective Stops	2787 veh/h	4266 pers/h
Effective Stop Rate	0.87	0.87
Proportion Queued	0.85	0.86
Performance Index	260.0	260.0
Cost (Total)	2962.39 $/h	2962.39 $/h
Fuel Consumption (Total)	237.9 L/h	
Carbon Dioxide (Total)	564.6 kg/h	
Hydrocarbons (Total)	0.059 kg/h	
Carbon Monoxide (Total)	0.519 kg/h	
NOx (Total)	1.025 kg/h	

Site Level of Service (LOS) Method: Delay (SIDRA). Site LOS Method is specified in the Parameter Settings dialog (Site tab).
Intersection LOS value for Vehicles is based on average delay for all vehicle movements.
SIDRA Standard Delay Model is used. Control Delay includes Geometric Delay.
Site Model Variability Index (Iterations 3 to N): 0.0 %
Number of Iterations: 2 (Maximum: 10)
Largest change in Lane Degrees of Saturation for the last three Main (Timing-Capacity) Iterations: 5.7% 0.0% 0.7%

Intersection Performance - Annual Values

Performance Measure	Vehicles	Persons
Demand Flows (Total)	1,541,760 veh/y	2,346,836 pers/y
Delay	17,278 veh-h/y	26,649 pers-h/y
Effective Stops	1,337,645 veh/y	2,047,764 pers/y
Travel Distance	718,893 veh-km/y	1,099,556 pers-km/y
Travel Time	32,266 veh-h/y	49,686 pers-h/y
Cost	1,421,946 $/y	1,421,946 $/y

Fuel Consumption	114,196	L/y
Carbon Dioxide	270,987	kg/y
Hydrocarbons	29	kg/y
Carbon Monoxide	249	kg/y
NOx	492	kg/y

DETAILED OUTPUT

Site: 1646 [TS1646 2024AM-Existing (18/09)]

Oteha Valley Rd/Albany Expy/Albany Hwy/Dairy Flat Hwy
20242409 08:15-08:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 101 seconds (Site User-Given Phase Times)

OUTPUT TABLE LINKS

Signal Timing

Movement Timing Information
Site: TS1646 2024AM-Existing (18/09)

```
Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

-----------------------------------------------------------------------------------------------------
 Mov  Mov  Mov           P H A S E  M A T R I X                 Lost Tim  Req.Mov.Time     Eff. Grn
 ID   Cl.  Typ       First Green              Second Green      --------  ------------     --------
                ----------------------  ----------------------  1st  2nd  1st      2nd     1st  2nd
                 Fr    To    Op Pr Und    Fr    To    Op Pr Und  Grn  Grn  Grn      Grn     Grn  Grn
-----------------------------------------------------------------------------------------------------
South: Albany Expressway
    1   # (Slp) A      C                  C      A      Y          5   51   0.0z      0.0z     14   31
    2   #      *A      C                                           5       11.3                14
    3   #       G      A                                           5       11.0 Min             9
-----------------------------------------------------------------------------------------------------
East: Oteha Valley Road
    4   # (Slp) A      E      Y           E      A                37    5   0.0z      0.0z     23   36
    5   #      *E      G                                           5       27.4                22
    6   #       D      E                                           5       11.0 Min            13
-----------------------------------------------------------------------------------------------------
North: Dairy Flat Highway
    7   # (Slp) A      E                  E      A      Y          5   20   0.0z      0.0z     55   21
    8   #       A      D                                           5       33.5                37
    9   #      *C      D                 *G      A                 5    5  25.0      15.0      18    9
-----------------------------------------------------------------------------------------------------
West: Albany Highway
   10   # (Slp) A      E      Y           E      A                11    5   0.0z      0.0z     49   36
   11   #       E      G                                           5       19.4                22
   12   #      *D      E                                           5       17.6                13
-----------------------------------------------------------------------------------------------------
  Current Phase Sequence: Phase
  Input Phase Sequence: A C D E G
  Output Phase Sequence: A C D E G
-----------------------------------------------------------------------------------------------------
  # Combined timing results are shown for all Movement Classes except any listed separately.
  * Critical Movement/Green Period
  Y (under heading 'Op') - Movement is opposed in the indicated green period
  z This Green Period of the movement was treated as Undetected
    and not included in signal timing calculations.

  Movement Types:
  Slp  Slip/Bypass Lane Movement
  Ped  Pedestrian
  Dum  Dummy


CRITICAL MOVEMENTS AND CYCLE TIME
```

Crit Mov ID	Turn	App and Dest	Green Period	Phases Fr	To	Adjusted Lost Time	Adjusted Flow Ratio	Required Grn Time Ratio	Required Movement Time
2LV	T1	S_N	1st	A	C	5	0.056	0.063	11.3
9LV	R2	N_W	1st	C	D	5	0.178	0.198	25.0
12LV	R2	W_S		D	E	5	0.113	0.125	17.6
5LV	T1	E_W		E	G	5	0.200	0.222	27.4
9LV	R2	N_W	2nd	G	A	5	0.089	0.099	15.0
					Total:	25	0.636	0.707	96.4

Cycle Time:

Minimum	Maximum	Practical	Chosen
55	150	85	101

(Phase times user specified, cycle time = sum of phase times)

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Phase Information
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

PHASE INFORMATION

Phase	Ref. Phase	Change Time	Starting Intgrn	Green Start	Displayed Green	Green End	Terminating Intgrn	Phase Time	Phase Split
A	Yes	0	5	5	14	19	5	19	19%
C	No	19	5	24	18	42	5	23	23%
D	No	42	5	47	13	60	5	18	18%
E	No	60	5	65	22	87	5	27	27%
G	No	87	5	92	9	101	5	14	14%

(Phase times specified by the user)
Current Phase Sequence: Phase
Input Phase Sequence: A C D E G
Output Phase Sequence: A C D E G

PHASE YELLOW AND ALL-RED TIMES (INPUT)

Phase	A	C	D	E	G
Yellow Time	3	3	3	3	3
All-Red Time	2	2	2	2	2
Intergreen Time	5	5	5	5	5

Phase Yellow and All-Red parameters in this table are user-specified input values.
Intergreen Time (sum of Yellow Time and All-Red Time) is an unadjusted value.
Any adjusted values of Intergreen Time, Phase Time and Green Time determined in cases of Pedestrian Actuation, Phase Actuation and user-given or implied Phase Frequency values less than 100% are given in the PHASE INFORMATION table above.

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Movements

Intersection Negotiation and Travel Data
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

TRAVEL SPEED, TRAVEL DISTANCE AND TRAVEL TIME

From Approach	To Exit	Turn	Running Speed km/h	Travel Speed km/h	Travel Distance m	Travel Time s	Total Travel Distance Dem Flows veh-km/h	Total Travel Distance Arv Flows veh-km/h	Tot.Trav. Time veh-h/h
South: Albany Expressway									
	West	L2	43.0	32.5	493.6#	54.6#	110.6	110.6	3.4
	North	T1	42.8	22.8	530.2#	83.8#	106.0	106.0	4.7
	East	R2	43.5	22.6	588.5#	93.7#	35.3	35.3	1.6
East: Oteha Valley Road									
	South	L2	45.5	40.1	589.6#	53.0#	87.3	87.3	2.2
	West	T1	35.7	15.3	323.9#	76.3#	193.0	193.0	12.6
	North	R2	36.5	17.3	358.5#	74.4#	7.2	7.2	0.4
North: Dairy Flat Highway									
	East	L2	39.7	38.6	510.6#	47.6#	14.3	14.3	0.4
	South	T1	44.4	31.2	681.2#	78.5#	493.2	493.2	15.8
	West	R2	31.4	14.0	414.1#	106.6#	185.5	185.5	13.3
West: Albany Highway									
	North	L2	35.9	35.7	263.6#	26.6#	50.6	50.6	1.4
	East	T1	41.1	18.8	323.9#	62.0#	128.3	128.3	6.8
	South	R2	39.2	18.3	491.2#	96.4#	86.5	86.5	4.7

ALL VEHICLES:	39.5	22.3	466.3#	75.3#	1497.7	1497.7	67.2

"Running Speed" is the average speed excluding stopped periods.

Travel Time values include cruise times and intersection delays including acceleration, deceleration and idling delays.

Travel Distance and Travel Time values include travel on the External Exit section based on the Exit Distance or user-specified Downstream Distance value as applicable.

INTERSECTION NEGOTIATION DATA

From Approach	To Exit	Turn	Negn Radius m	Negn Speed km/h	Negn Dist m	App Dist m	Exit Dist m	Downstr Dist m
South: Albany Expressway								
	West	L2	15.0	23.5	23.6	368	102	NA
	North	T1	S	40.0	24.2	368	138	NA
	East	R2	14.3	23.1	22.5	368	198	NA
East: Oteha Valley Road								
	South	L2	15.0	23.5	23.6	198	368	NA
	West	T1	S	40.0	23.9	198	102	NA
	North	R2	14.3	23.1	22.5	198	138	NA
North: Dairy Flat Highway								
	East	L2	15.0	23.5	23.6	289	198	NA
	South	T1	S	40.0	24.2	289	368	NA
	West	R2	14.7	23.3	23.1	289	102	NA
West: Albany Highway								
	North	L2	15.0	23.5	23.6	102	138	NA
	East	T1	S	40.0	23.9	102	198	NA
	South	R2	13.5	22.6	21.2	102	368	NA

NA Downstream Distance does not apply if:
- Exit is an internal leg of a network
- "Program" option was specified
- Distance specified was less than the Exit Negotiation Distance
- Distance specified was greater than the exit leg length

Some Negotiation Radius, Speed or Distance values are user specified.

MOVEMENT SPEEDS AND GEOMETRIC DELAY

Mov ID	Turn	App. Speeds Cruise km/h	App. Speeds Negn km/h	Exit Speeds Negn km/h	Exit Speeds Cruise km/h	Queue Move-up Sp 1st Grn km/h	Queue Move-up Sp 2nd Grn km/h	Geom Delay sec
South: Albany Expressway								
1	L2	56.0	23.5	23.5	40.0	23.5	23.5	5.2
2	T1	56.0	40.0	40.0	40.0	28.4		2.2
3	R2	56.0	23.1	23.1	52.0	21.9		5.3
East: Oteha Valley Road								
4	L2	52.0	23.5	23.5	56.0	23.5	23.5	4.8
5	T1	52.0	40.0	40.0	40.0	34.7		1.7
6	R2	52.0	23.1	23.1	40.0	23.1		4.8
North: Dairy Flat Highway								
7	L2	40.0	23.5	23.5	52.0	23.5	23.5	3.2
8	T1	40.0	40.0	40.0	56.0	30.0		0.0
9	R2	40.0	23.3	23.3	40.0	23.3	21.6	3.2
West: Albany Highway								
10	L2	40.0	23.5	23.5	40.0	23.5	23.5	3.2
11	T1	40.0	40.0	40.0	52.0	30.0		0.0
12	R2	40.0	22.6	22.6	56.0	22.6		3.2

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Movement Capacity and Performance Parameters
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

MOVEMENT CAPACITY PARAMETERS

Mov ID	Turn	Mov Cl.	Arv Flow veh/h	Total Cap. veh/h	Prac. Deg. Satn xp	Prac. Spare Cap. %	Deg. Satn x
South: Albany Expressway							
1	L2	#	224	736	0.90	196	0.304
2	T1	#	200	492	0.90	121	0.407
3	R2	#	60	151	0.90	127	0.396
East: Oteha Valley Road							
4	L2	#	148	1291	0.90	685	0.115

5	T1	#	596	649	0.90	-2	0.918
6	R2	#	20	193	0.90	769	0.104
North: Dairy Flat Highway							
7	L2	#	28	1163	0.90	3637	0.024
8	T1	#	724	1034	0.90	29	0.700
9	R2	#	448	449	0.90	-10	0.999*
West: Albany Highway							
10	L2	#	192	1476	0.90	592	0.130
11	T1	#	396	670	0.90	52	0.591
12	R2	#	176	201	0.90	3	0.874

* Maximum degree of saturation
\# Combined Movement Capacity parameters are shown for all Movement Classes.

MOVEMENT PERFORMANCE

Mov ID	Turn	Total Delay (veh-h/h)	Total Delay (pers-h/h)	Aver. Delay (sec)	Eff. Stop Rate	Total Stops	Perf. Index	Tot.Trav. Distance (veh-km/h)	Tot.Trav. Time (veh-h/h)	Aver. Speed (km/h)
South: Albany Expressway										
1	L2	1.34	1.65	21.5	0.74	165.6	16.17	110.6	3.4	32.5
2	T1	2.57	3.75	46.2	0.76	152.6	13.84	106.0	4.7	22.8
3	R2	0.91	2.02	54.8	0.75	45.3	7.23	35.3	1.6	22.6
East: Oteha Valley Road										
4	L2	0.54	0.68	13.2	0.65	96.9	8.33	87.3	2.2	40.1
5	T1	8.58	11.77	51.8	0.99	587.2	47.55	193.0	12.6	15.3
6	R2	0.27	0.38	48.0	0.70	14.0	2.13	7.2	0.4	17.3
North: Dairy Flat Highway										
7	L2	0.04	0.13	5.5	0.49	13.7	1.00	14.3	0.4	38.6
8	T1	5.56	8.76	27.7	0.74	536.9	48.76	493.2	15.8	31.2
9	R2	8.79	15.35	70.6	1.33	593.8	60.33	185.5	13.3	14.0
West: Albany Highway										
10	L2	0.22	0.30	4.1	0.48	92.2	4.11	50.6	1.4	35.7
11	T1	4.21	6.99	38.2	0.77	306.2	26.04	128.3	6.8	18.8
12	R2	2.98	3.75	60.9	1.04	182.4	24.48	86.5	4.7	18.3

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Fuel Consumption, Emissions and Cost
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

FUEL CONSUMPTION, EMISSIONS AND COST (TOTAL)

Mov ID	Turn	Cost Total $/h	Fuel Total L/h	CO2 Total kg/h	CO Total kg/h	HC Total kg/h	NOX Total kg/h
South: Albany Expressway							
1	L2	122.33	8.0	18.9	0.01	0.002	0.014
2	T1	177.60	9.4	22.4	0.02	0.003	0.029
3	R2	90.50	3.8	8.9	0.01	0.001	0.015
		390.43	21.2	50.2	0.04	0.006	0.058
East: Oteha Valley Road							
4	L2	87.56	15.9	37.9	0.04	0.003	0.102
5	T1	497.64	31.4	74.1	0.06	0.008	0.089
6	R2	17.03	1.1	2.7	0.00	0.000	0.005
		602.23	48.4	114.7	0.10	0.012	0.195
North: Dairy Flat Highway							
7	L2	30.16	1.9	4.5	0.00	0.001	0.011
8	T1	725.21	88.2	210.1	0.21	0.019	0.485
9	R2	678.95	35.6	84.3	0.07	0.010	0.141
		1434.32	125.7	298.9	0.28	0.030	0.637
West: Albany Highway							
10	L2	54.90	5.9	14.0	0.01	0.001	0.033
11	T1	314.15	19.2	45.5	0.04	0.006	0.065
12	R2	166.36	17.5	41.2	0.04	0.004	0.037
		535.40	42.6	100.7	0.09	0.011	0.135
INTERSECTION:		2962.39	237.9	564.6	0.52	0.059	1.025

FUEL CONSUMPTION, EMISSIONS AND COST (RATE)

Mov ID	Turn	Cost Rate $/km	Fuel Rate L/100km	CO2 Rate g/km	CO Rate g/km	HC Rate g/km	NOX Rate g/km
South: Albany Expressway							
1	L2	1.11	7.3	171.3	0.14	0.018	0.125

2	T1	1.67	8.9	210.8	0.19	0.028	0.278
3	R2	2.56	10.6	252.7	0.25	0.039	0.413
		1.55	8.4	199.4	0.18	0.025	0.230
East: Oteha Valley Road							
4	L2	1.00	18.2	434.1	0.41	0.037	1.169
5	T1	2.58	16.3	383.9	0.33	0.044	0.460
6	R2	2.38	15.8	373.9	0.33	0.044	0.644
		2.09	16.8	398.9	0.35	0.041	0.680
North: Dairy Flat Highway							
7	L2	2.11	13.1	312.4	0.32	0.036	0.755
8	T1	1.47	17.9	426.1	0.42	0.039	0.983
9	R2	3.66	19.2	454.7	0.39	0.056	0.762
		2.07	18.1	431.4	0.41	0.043	0.919
West: Albany Highway							
10	L2	1.08	11.6	276.1	0.22	0.027	0.647
11	T1	2.45	15.0	354.9	0.31	0.044	0.503
12	R2	1.92	20.2	477.0	0.46	0.049	0.431
		2.02	16.1	379.6	0.34	0.042	0.507
INTERSECTION:		1.98	15.9	376.9	0.35	0.040	0.684

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Lanes

Lane Performance and Capacity Information
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

LANE PERFORMANCE

Lane No.	Effective Red and Green Times (sec) R1	G1	R2	G2	Satd Part of Green Gs1	Gs2	Arv Flow veh/h	Cap veh/h	Deg. Satn x	Aver. Delay sec	Eff. Stop Rate	Queue 95% Back veh	m	Lane Length m
South: Albany Expressway														
1	5	14	51	31	0.8	7.9	224	736	0.304	21.5	0.74	6.5	46.3	35.0T
2	87	14			4.7		95	259	0.366	46.0	0.76	4.4	32.2	368.0
3	87	14			5.2		105	259	0.407	46.3	0.77	4.9	36.1	368.0
4	92	9			3.4		60	151	0.396	54.8	0.75	3.0	22.2	48.5T
East: Oteha Valley Road														
1	37	23	5	36	4.0	0.3	148	1291	0.115	13.2	0.65	3.0	22.3	49.0T
2	79	22			11.8		224	376	0.597	40.8	0.81	10.2	73.4	198.0
3	79	22			19.7		372	405	0.918	58.5	1.09	21.8	157.4	198.0
4	88	13			1.2		20	193	0.104	48.0	0.70	0.9	6.7	78.0T
North: Dairy Flat Highway														
1	5	55	20	21	0.1	0.4	28	1163	0.024	5.5	0.49	0.3	2.2	56.0T
2	64	37			21.5		438	625<	0.700	29.3	0.80	18.4	135.4	289.0
3	64	37			10.0		286	629<	0.455	25.1	0.66	10.3	75.8	289.0
4	24	18	50	9	18.0	9.0	448	449	0.999	70.6	1.33	23.7	175.9	41.0T
West: Albany Highway														
1	11	49	5	36	1.4	0.6	192	1476	0.130	4.1	0.48	1.2	8.7	35.0T
2	79	22			7.8		156	377	0.414	37.2	0.74	6.7	49.4	102.0
3	79	22			11.7		240	406	0.591	38.9	0.79	10.8	79.2	102.0
4	88	13			11.2		176	201	0.874	60.9	1.04	10.0	70.6	58.0T

< Reduced capacity due to a short lane effect. Short lane queues may extend into the full-length lanes.
Some upstream delays at entry to short lanes are not included.
T Short lane due to specification of Turn Bay

LANE FLOW AND CAPACITY INFORMATION

Lane No.	Total Arv Flow veh/h	Lane Width m	Saturation Flow Rate: Adj. Basic tcu/h	With Lane Blockage 1st veh/h	2nd veh/h	W/O Lane Blockage 1st veh/h	2nd veh/h	End Cap veh/h	Tot Cap veh/h	Deg. Satn x	Lane Util %
South: Albany Expressway											
1	224	3.40	1713	1600	1675	-	-	88	736	0.304	100
2	95	3.40	1960	1867		-		0	259	0.366	90U
3	105	3.40	1960	1867		-		0	259	0.407	100
4	60	3.00	1920	1698		-		0	151	0.396	100
East: Oteha Valley Road											
1	148	4.50	2926	1510	2652	-	-	85	1291	0.115	100
2	224	3.75	1777	1725		-		0	376	0.597	65U
3	372	3.20	1915	1859		-		0	405	0.918	100
4	20	3.00	1669	1501		-		0	193	0.104	100

North: Dairy Flat Highway											
1	28	3.90	1857	1589	1430	-	-	81	1163	0.024	100
2	438	3.30	1828	1706<		-		0	625	0.700	100
3	286	3.40	2219	1757<		-		0	629	0.455	65U
4	448	3.30	1868	1678	1678	-	-	0	449	0.999	100
West: Albany Highway											
1	192	4.50	2056	1711	1813	-	-	83	1476	0.130	100
2	156	3.40	1809	1733		-		0	377	0.414	70U
3	240	3.40	1945	1863		-		0	406	0.591	100
4	176	3.10	1661	1564		-		0	201	0.874	100

< Reduced saturation flow due to a short lane effect
Some upstream delays at entry to short lanes are not included.
U Lane under-utilisation specified by the User

Basic Saturation Flow in this table is adjusted for area type factor, lane width, approach grade, parking manoeuvres and number of buses stopping.
Saturation flow scale (Demand & Sensitivity dialog) applies if specified.

Saturation Flow rates without (W/O) the effect of downstream lane blockage used for signal timing purposes are included in this table when the signal timing option to exclude downstream lane blockage effects is selected.

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Lane, Approach and Intersection Performance
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated Cycle Time = 101 sec (Site User-Given Phase Times)

Lane No.	Arrival Flow (veh/h)	%HV	Adj. Basic Satf.	Eff Grn (sec) 1st	2nd	Deg Sat x	Aver. Delay sec	Longest Queue m	Lane Length m
South: Albany Expressway									
1	224	2	1712	14	31	0.304	21.5	46*	35
2	95	5	1960	14		0.366	46.0	32	368U
3	105	5	1960	14		0.407	46.3	36	368
4	60	7	1919	9		0.396	54.8	22	49
	484	4				0.407	35.8	46	
East: Oteha Valley Road									
1	148	5	2925	23	36	0.115	13.2	22	49
2	224	3	1776	22		0.597	40.8	73	198U
3	372	3	1914	22		0.918	58.5	157	198
4	20	6	1669	13		0.104	48.0	7	78
	764	3				0.918	44.2	157	
North: Dairy Flat Highway									
1	28	11	1856	55	21	0.024	5.5	2	56
2	438	5	1827	37		0.700	29.3	135	289
3	286	5	2219	37		0.455	25.1	76	289U
4	448	6	1868	18	9	0.999	70.6	176*	41
	1200	5				0.999	43.2	176	
West: Albany Highway									
1	192	7	2055	49	36	0.130	4.1	9	35
2	156	4	1809	22		0.414	37.2	49	102U
3	240	4	1944	22		0.591	38.9	79	102
4	176	1	1661	13		0.874	60.9	71*	58
	764	4				0.874	34.9	79	

ALL VEHICLES

Total Flow	% HV	Cycle Time	Max X	Aver. Delay	Max Queue
3212	4	101	0.999	40.3	176

Peak flow period = 15 minutes.

Queue values in this table are 95% queue (metres)
Note: Basic Saturation Flows (in through car units) have been adjusted for grade, lane widths, parking manoeuvres and bus stops.

* Queue length exceeds short lane length due to specification of a percentile queue in the Parameter Settings dialog. For calculation of this statistic, you may specify the lane with full length.
U Lane under-utilisation specified by the User

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Driver Characteristics
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated Cycle Time = 101 sec (Site User-Given Phase Times)

Lane No.	Satn Speed km/h	Satn Flow veh/h	Satn Hdwy sec	Satn Spacing m	Average Queue Space m	Driver Response Time sec

South: Albany Expressway						
1	NA - Short Lane					
2	40.0	1867	1.93	21.43	7.37	1.26
3	40.0	1867	1.93	21.43	7.37	1.26
4	NA - Short Lane					
East: Oteha Valley Road						
1	NA - Short Lane					
2	39.0	1725	2.09	22.61	7.22	1.42
3	39.0	1859	1.94	20.98	7.22	1.27
4	NA - Short Lane					
North: Dairy Flat Highway						
1	NA - Short Lane					
2	30.0	1741	2.07	17.24	7.37	1.18
3	30.0	2114	1.70	14.19	7.37	0.82
4	NA - Short Lane					
West: Albany Highway						
1	NA - Short Lane					
2	30.0	1733	2.08	17.31	7.32	1.20
3	30.0	1863	1.93	16.10	7.32	1.05
4	NA - Short Lane					

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SCATS Parameters
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

Lane No.	Stopline Flow veh/h	Capacity veh/h	SCATS Satn Flow	SCATS MF	Hdwy at MF sec	Occ Time sec	Space Time sec	Deg. Satn x	Lane Util. %
South: Albany Expressway									
1	224	736	1631	NA				0.304	100
2	95	259	1960	1444	2.49	0.81	1.68	0.366	90U
3	105	259	1960	1444	2.49	0.81	1.68	0.407	100
4	60	151	1828	1175	3.06	1.40	1.66	0.396	100
East: Oteha Valley Road									
1	148	1291	2786	NA				0.115	100
2	224	376	1777	1448	2.49	0.83	1.66	0.597	65U
3	372	405	1915	1560	2.31	0.83	1.48	0.918	100
4	20	193	1590	1148	3.14	1.40	1.73	0.104	100
North: Dairy Flat Highway									
1	28	1163	1769	NA				0.024	100
2	438	625	1828	1610	2.24	1.08	1.16	0.700	100
3	286	629	2219	1955	1.84	1.08	0.76	0.455	65U
4	448	449	1779	1392	2.59	1.39	1.20	0.999	100
West: Albany Highway									
1	192	1476	1958	NA				0.130	100
2	156	377	1809	1474	2.44	1.08	1.36	0.414	70U
3	240	406	1945	1585	2.27	1.08	1.19	0.591	100
4	176	201	1582	1144	3.15	1.43	1.71	0.874	100

NA Not Applicable - SCATS MF was not calculated for this lane due to one of the following reasons:
- the lane is not controlled by signals (slip or continuous lane)
- movements that share this lane do not run in the same phases

U Lane under-utilisation specified by the "User"

STOPLINE FLOW: Departure flow rate in veh/h as measured at the stop line. This cannot exceed capacity.

SCATS SATURATION FLOW: This allows for area type factor, lane width, approach grade and turning vehicles. Saturation flow scale applies if specified (Demand & Sensitivity dialog). The effects of movement class, parking manoeuvres, number of buses stopping and conflicting pedestrian volume are not included.

SCATS MF: This emulates the MF (Maximum Flow) parameter used in the SCATS control system. It is calculated from the SCATS SATURATION FLOW parameter. The values estimated for conditions of low capacity per cycle where the intergreen time is high relative to the green time may not be representative of MF values reported by SCATS.

DEG. SATN: The Demand (Arrival) Flow Rate may exceed the Stopline Flow Rate, therefore x > 1 is possible.

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Lane Delays
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

LANE DELAYS

				Delay (seconds/veh)									
Lane	Deg. Satn	% Arv During	Prog. Factor	Min Del	Stop-line Delay 1st	2nd	Total	Acc. Dec.	Queuing Total	MvUp	Stopd (Idle)	Geom	Control

No.	x	Green		dm	d1	d2	dSL	dn	dq	dqm	di	dig	dic
South: Albany Expressway													
1	0.304	44.6	1.000	13.0	16.3	0.0	16.3	3.1	13.3	0.0	13.3	5.2	21.5
2	0.366	13.9	1.000	37.5	43.8	0.0	43.8	4.8	39.1	0.0	39.1	2.2	46.0
3	0.407	13.9	1.000	37.5	44.1	0.0	44.1	4.8	39.3	0.0	39.3	2.2	46.3
4	0.396	8.9	1.000	41.9	49.5	0.0	49.5	4.5	45.0	0.0	45.0	5.3	54.8
East: Oteha Valley Road													
1	0.115	58.4	1.000	6.9	8.4	0.0	8.4	2.2	6.3	0.0	6.3	4.8	13.2
2	0.597	21.8	1.000	30.9	39.1	0.0	39.1	4.8	34.3	0.0	34.3	1.7	40.8
3	0.918	21.8	1.000	30.9	42.5	14.3	56.8	5.0	51.8	2.4	49.4	1.7	58.5
4	0.104	12.9	1.000	38.3	43.2	0.0	43.2	4.1	39.0	0.0	39.0	4.8	48.0
North: Dairy Flat Highway													
1	0.024	75.2	1.000	2.1	2.3	0.0	2.3	1.2	1.2	0.0	1.2	3.2	5.5
2	0.700	36.6	1.000	20.3	29.3	0.0	29.3	4.5	24.8	0.0	24.8	0.0	29.3
3	0.455	36.6	1.000	20.3	25.1	0.0	25.1	3.9	21.2	0.0	21.2	0.0	25.1
4	0.999	26.7	1.000	15.2	33.3	34.2	67.4	4.6	62.9	3.7	59.1	3.2	70.6
West: Albany Highway													
1	0.130	84.2	1.000	0.7	0.9	0.0	0.9	0.9	0.1	0.0	0.1	3.2	4.1
2	0.414	21.8	1.000	30.9	37.2	0.0	37.2	4.5	32.7	0.0	32.7	0.0	37.2
3	0.591	21.8	1.000	30.9	38.9	0.0	38.9	4.8	34.1	0.0	34.1	0.0	38.9
4	0.874	12.9	1.000	38.3	49.0	8.7	57.7	4.5	53.2	1.9	51.3	3.2	60.9

SIDRA Standard Delay Model is used. Control Delay is the sum of Stop-line Delay and Geometric Delay.
dm: Minimum delay for gap acceptance cases
dSL: Stop-line delay (=d1+d2)
dn: Average stop-start delay for all vehicles queued and unqueued
dq: Queuing delay (the part of the stop-line delay that includes stopped delay and queue move-up delay)
dqm: Queue move-up delay
di: Stopped delay (stopped (idling) time at near-zero speed)
dig: Geometric delay
dic: Control delay

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Lane Queues
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

BACK OF QUEUE (VEHICLES)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Ovrfl. Queue No	Back of Queue (veh) Nb1	Nb2	Nb	95%	Queue Stor. Ratio Av.	95%	Prob. Block %	Prob. SL Ov. %
South: Albany Expressway												
1	0.304	44.6	1.000	0.0	4.0	0.0	4.0	6.5*	0.81	1.32	NA	30.6
2	0.366	13.9	1.000	0.0	2.7	0.0	2.7	4.4	0.05	0.09	0.0	NA
3	0.407	13.9	1.000	0.0	3.0	0.0	3.0	4.9	0.06	0.10	0.0	NA
4	0.396	8.9	1.000	0.0	1.8	0.0	1.8	3.0	0.28	0.46	NA	0.0
East: Oteha Valley Road												
1	0.115	58.4	1.000	0.0	1.9	0.0	1.9	3.0	0.28	0.46	NA	0.0
2	0.597	21.8	1.000	0.0	6.2	0.0	6.2	10.2	0.23	0.37	0.0	NA
3	0.918	21.8	1.000	1.5	11.2	2.1	13.3	21.8	0.49	0.79	0.0	NA
4	0.104	12.9	1.000	0.0	0.6	0.0	0.6	0.9	0.05	0.09	NA	0.0
North: Dairy Flat Highway												
1	0.024	75.2	1.000	0.0	0.2	0.0	0.2	0.3	0.02	0.04	NA	0.0
2	0.700	36.6	1.000	0.0	11.3	0.0	11.3	18.4	0.29	0.47	0.0	NA
3	0.455	36.6	1.000	0.0	6.3	0.0	6.3	10.3	0.16	0.26	0.0	NA
4	0.999	26.7	1.000	4.1	9.4	5.2	14.5	23.7*	2.63	4.29	NA	100.0
West: Albany Highway												
1	0.130	84.2	1.000	0.0	0.7	0.0	0.7	1.2	0.15	0.25	NA	0.0
2	0.414	21.8	1.000	0.0	4.1	0.0	4.1	6.7	0.30	0.48	0.0	NA
3	0.591	21.8	1.000	0.0	6.6	0.0	6.6	10.8	0.48	0.78	0.0	NA
4	0.874	12.9	1.000	0.4	5.5	0.6	6.1	10.0*	0.75	1.22	NA	22.9

* Short lane queue distance includes vehicles queued into the adjacent lane.

BACK OF QUEUE (DISTANCE)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Ovrfl. Queue No	Back of Queue (m) Nb1	Nb2	Nb	95%	Queue Stor. Ratio Av.	95%	Prob. Block %	Prob. SL Ov. %
South: Albany Expressway												
1	0.304	44.6	1.000	0.0	28.4	0.0	28.4	46.3*	0.81	1.32	NA	30.6
2	0.366	13.9	1.000	0.0	19.7	0.0	19.7	32.2	0.05	0.09	0.0	NA
3	0.407	13.9	1.000	0.0	22.1	0.0	22.1	36.1	0.06	0.10	0.0	NA
4	0.396	8.9	1.000	0.0	13.6	0.0	13.6	22.2	0.28	0.46	NA	0.0
East: Oteha Valley Road												
1	0.115	58.4	1.000	0.0	13.7	0.0	13.7	22.3	0.28	0.46	NA	0.0
2	0.597	21.8	1.000	0.0	45.0	0.0	45.0	73.4	0.23	0.37	0.0	NA
3	0.918	21.8	1.000	10.8	81.1	15.3	96.4	157.4	0.49	0.79	0.0	NA
4	0.104	12.9	1.000	0.0	4.1	0.0	4.1	6.7	0.05	0.09	NA	0.0
North: Dairy Flat Highway												

1	0.024	75.2	1.000	0.0	1.3	0.0	1.3	2.2	0.02	0.04	NA	0.0
2	0.700	36.6	1.000	0.0	83.0	0.0	83.0	135.4	0.29	0.47	0.0	NA
3	0.455	36.6	1.000	0.0	46.4	0.0	46.4	75.8	0.16	0.26	0.0	NA
4	0.999	26.7	1.000	30.1	69.5	38.2	107.8	175.9*	2.63	4.29	NA	100.0
West: Albany Highway												
1	0.130	84.2	1.000	0.0	5.3	0.0	5.3	8.7	0.15	0.25	NA	0.0
2	0.414	21.8	1.000	0.0	30.3	0.0	30.3	49.4	0.30	0.48	0.0	NA
3	0.591	21.8	1.000	0.0	48.5	0.0	48.5	79.2	0.48	0.78	0.0	NA
4	0.874	12.9	1.000	3.1	39.0	4.3	43.3	70.6*	0.75	1.22	NA	22.9

* Short lane queue distance includes vehicles queued into the adjacent lane.

OTHER QUEUE RESULTS (VEHICLES)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Ovrfl. Queue No	Queue Start Grn Nr	Queue Start Grn 95%	Cyc-Av. Queue Nc	Cyc-Av. Queue 95%
South: Albany Expressway								
1	0.304	44.6	1.000	0.0	3.4	5.6	1.0	2.1
2	0.366	13.9	1.000	0.0	2.5	4.1	1.2	2.4
3	0.407	13.9	1.000	0.0	2.8	4.6	1.3	2.7
4	0.396	8.9	1.000	0.0	1.7	2.9	0.8	1.7
East: Oteha Valley Road								
1	0.115	58.4	1.000	0.0	1.7	2.7	0.3	0.7
2	0.597	21.8	1.000	0.0	5.4	8.8	2.4	5.1
3	0.918	21.8	1.000	1.5	10.5	17.1	5.9	12.3
4	0.104	12.9	1.000	0.0	0.5	0.9	0.2	0.5
North: Dairy Flat Highway								
1	0.024	75.2	1.000	0.0	0.2	0.3	0.0	0.0
2	0.700	36.6	1.000	0.0	8.4	13.7	3.6	7.5
3	0.455	36.6	1.000	0.0	5.4	8.9	2.0	4.2
4	0.999	26.7	1.000	4.1	11.3	18.5	8.4	17.5
West: Albany Highway								
1	0.130	84.2	1.000	0.0	0.6	1.0	0.0	0.1
2	0.414	21.8	1.000	0.0	3.8	6.1	1.6	3.4
3	0.591	21.8	1.000	0.0	5.8	9.4	2.6	5.4
4	0.874	12.9	1.000	0.4	5.3	8.7	2.8	5.9

OTHER QUEUE RESULTS (DISTANCE)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Ovrfl. Queue No	Queue Start Grn Nr	Queue Start Grn 95%	Cyc-Av. Queue Nc	Cyc-Av. Queue 95%
South: Albany Expressway								
1	0.304	44.6	1.000	0.0	24.6	40.1	7.2	15.1
2	0.366	13.9	1.000	0.0	18.7	30.6	8.5	17.8
3	0.407	13.9	1.000	0.0	20.8	34.0	9.5	19.9
4	0.396	8.9	1.000	0.0	13.1	21.4	6.2	13.0
East: Oteha Valley Road								
1	0.115	58.4	1.000	0.0	12.3	20.1	2.5	5.3
2	0.597	21.8	1.000	0.0	39.1	63.8	17.6	36.7
3	0.918	21.8	1.000	10.8	75.6	123.5	42.4	88.5
4	0.104	12.9	1.000	0.0	4.0	6.6	1.8	3.7
North: Dairy Flat Highway								
1	0.024	75.2	1.000	0.0	1.3	2.2	0.1	0.3
2	0.700	36.6	1.000	0.0	62.1	101.4	26.3	54.9
3	0.455	36.6	1.000	0.0	40.1	65.5	14.7	30.7
4	0.999	26.7	1.000	30.1	84.1	137.3	62.2	130.0
West: Albany Highway								
1	0.130	84.2	1.000	0.0	4.7	7.7	0.4	0.7
2	0.414	21.8	1.000	0.0	27.5	44.9	11.8	24.7
3	0.591	21.8	1.000	0.0	42.3	69.0	19.0	39.6
4	0.874	12.9	1.000	3.1	37.7	61.6	20.0	41.7

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Lane Queue Percentiles
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

LANE QUEUE PERCENTILES (VEHICLES)

Lane No.	Deg. Satn x	Percentile Back of Queue (veh) 50%	70%	85%	90%	95%	98%	100%
South: Albany Expressway								
1	0.304	4.0	4.9	5.8*	6.1*	6.5*	6.7*	6.9*
2	0.366	2.7	3.3	3.9	4.1	4.4	4.5	4.6
3	0.407	3.0	3.7	4.4	4.6	4.9	5.1	5.2
4	0.396	1.8	2.2	2.6	2.8	3.0	3.1	3.1

East: Oteha Valley Road								
1	0.115	1.9	2.3	2.7	2.9	3.0	3.1	3.2
2	0.597	6.2	7.7	9.1	9.6	10.2	10.5	10.7
3	0.918	13.3	16.6	19.5	20.6	21.8	22.5	23.0
4	0.104	0.6	0.7	0.8	0.9	0.9	0.9	1.0
North: Dairy Flat Highway								
1	0.024	0.2	0.2	0.3	0.3	0.3	0.3	0.3
2	0.700	11.3	14.0	16.4	17.4	18.4	19.0	19.4
3	0.455	6.3	7.8	9.2	9.7	10.3	10.6	10.9
4	0.999	14.5*	18.0*	21.2*	22.4*	23.7*	24.5*	25.1*
West: Albany Highway								
1	0.130	0.7	0.9	1.0	1.1	1.2	1.2	1.2
2	0.414	4.1	5.1	6.0	6.4	6.7	7.0	7.1
3	0.591	6.6	8.2	9.7	10.2	10.8	11.2	11.4
4	0.874	6.1	7.6	8.9*	9.4*	10.0*	10.3*	10.5*

* Short lane queue distance includes vehicles queued into the adjacent lane.

LANE QUEUE PERCENTILES (DISTANCE)

Lane No.	Deg. Satn x	Percentile Back of Queue (metres) 50%	70%	85%	90%	95%	98%	100%
South: Albany Expressway								
1	0.304	28.4	35.2	41.5*	43.8*	46.3*	47.9*	49.0*
2	0.366	19.7	24.5	28.9	30.5	32.2	33.3	34.1
3	0.407	22.1	27.4	32.3	34.1	36.1	37.3	38.1
4	0.396	13.6	16.9	19.9	21.0	22.2	23.0	23.5
East: Oteha Valley Road								
1	0.115	13.7	17.0	20.0	21.1	22.3	23.1	23.6
2	0.597	45.0	55.8	65.7	69.4	73.4	75.9	77.6
3	0.918	96.4	119.6	140.9	148.9	157.4	162.7	166.4
4	0.104	4.1	5.1	6.0	6.3	6.7	6.9	7.0
North: Dairy Flat Highway								
1	0.024	1.3	1.7	2.0	2.1	2.2	2.3	2.3
2	0.700	83.0	102.9	121.3	128.1	135.4	140.0	143.2
3	0.455	46.4	57.6	67.8	71.7	75.8	78.3	80.1
4	0.999	107.8*	133.6*	157.5*	166.4*	175.9*	181.8*	185.9*
West: Albany Highway								
1	0.130	5.3	6.6	7.8	8.2	8.7	9.0	9.2
2	0.414	30.3	37.5	44.2	46.7	49.4	51.0	52.2
3	0.591	48.5	60.2	70.9	74.9	79.2	81.9	83.7
4	0.874	43.3	53.7	63.2*	66.8*	70.6*	73.0*	74.7*

* Short lane queue distance includes vehicles queued into the adjacent lane.

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Lane Stops
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	-- Effective Stop Rate -- he1	he2	Geom. hig	Overall h	Total Stops H	Queue Move-up Rate hqm	Total Queue Move-ups Hqm	Prop. Queued pq	Aver. Num. of Cycles to Depart
South: Albany Expressway												
1	0.304	44.6	1.000	0.57	0.00	0.17	0.74	165.6	0.00	0.0	0.68	0.68
2	0.366	13.9	1.000	0.74	0.00	0.02	0.76	71.9	0.00	0.0	0.95	0.95
3	0.407	13.9	1.000	0.75	0.00	0.01	0.77	80.7	0.00	0.0	0.96	0.96
4	0.396	8.9	1.000	0.75	0.00	0.01	0.75	45.3	0.00	0.0	0.98	0.98
East: Oteha Valley Road												
1	0.115	58.4	1.000	0.39	0.00	0.26	0.65	96.9	0.00	0.0	0.48	0.48
2	0.597	21.8	1.000	0.79	0.00	0.01	0.81	180.9	0.00	0.0	0.95	0.95
3	0.918	21.8	1.000	0.86	0.24	0.00	1.09	406.3	0.32	120.2	1.00	1.32
4	0.104	12.9	1.000	0.66	0.00	0.04	0.70	14.0	0.00	0.0	0.91	0.91
North: Dairy Flat Highway												
1	0.024	75.2	1.000	0.19	0.00	0.30	0.49	13.7	0.00	0.0	0.26	0.26
2	0.700	36.6	1.000	0.80	0.00	0.00	0.80	348.2	0.00	0.0	0.91	0.91
3	0.455	36.6	1.000	0.66	0.00	0.00	0.66	188.7	0.00	0.0	0.78	0.78
4	0.999	26.7	1.000	0.86	0.46	0.00	1.33	593.8	0.75	335.0	1.00	1.75
West: Albany Highway												
1	0.130	84.2	1.000	0.15	0.00	0.33	0.48	92.2	0.00	0.0	0.19	0.19
2	0.414	21.8	1.000	0.74	0.00	0.00	0.74	115.6	0.00	0.0	0.91	0.91
3	0.591	21.8	1.000	0.79	0.00	0.00	0.79	190.5	0.00	0.0	0.95	0.95
4	0.874	12.9	1.000	0.82	0.22	0.00	1.04	182.4	0.35	61.9	1.00	1.35

hig is the average value for all movements in a shared lane
hqm is average queue move-up rate for all vehicles queued and unqueued

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Flow Rates

Origin-Destination Flow Rates (Total)
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated Cycle Time = 101 sec (Site User-Given Phase Times)

TOTAL FLOW RATES for All Movement Classes (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Flow Rate	224.0	200.0	60.0	484.0
%HV (all designations)	1.8	5.0	7.1	3.8

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Flow Rate	148.0	596.0	20.0	764.0
%HV (all designations)	4.7	3.0	5.5	3.4

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Flow Rate	28.0	724.0	448.0	1200.0
%HV (all designations)	10.5	5.0	5.6	5.4

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Flow Rate	192.0	396.0	176.0	764.0
%HV (all designations)	7.4	4.4	1.1	4.4

Peak Flow factor value of 100% has been used for all movements since equal values of Unit Time for Volumes and Peak Flow Period were specified in the Volumes dialog.

Flow rates shown above are Arrival Flow Rates (veh/h) based on the following input specifications:
Unit Time for Volumes = 15 minutes
Peak Flow Period = 15 minutes
Effects of Volume Factors (Peak Flow Factor, Flow Scale, Growth Rate) are included.
Arrival Flow Rates may be less than Demand Flow Rates if capacity constraint applies in network analysis.

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Origin-Destination Flow Rates by Movement Class
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated Cycle Time = 101 sec (Site User-Given Phase Times)

FLOW RATES for Light Vehicles (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Flow Rate	220.0	190.0	55.7	465.7
Mov Class %	98.2	95.0	92.9	96.2
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Flow Rate	141.0	578.1	18.9	738.1
Mov Class %	95.3	97.0	94.5	96.6
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Flow Rate	25.1	687.8	422.9	1135.8
Mov Class %	89.5	95.0	94.4	94.6
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Flow Rate	177.8	378.6	174.1	730.4
Mov Class %	92.6	95.6	98.9	95.6
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

FLOW RATES for Heavy Vehicles (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Flow Rate	3.8	8.2	2.2	14.2

	L2	T1	R2	TOT
Mov Class %	1.7	4.1	3.6	2.9
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Flow Rate	6.7	14.3	0.9	21.9
Mov Class %	4.5	2.4	4.7	2.9
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Flow Rate	1.1	26.8	16.6	44.5
Mov Class %	4.0	3.7	3.7	3.7
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Flow Rate	12.9	11.1	1.6	25.5
Mov Class %	6.7	2.8	0.9	3.3
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

FLOW RATES for Buses (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Flow Rate	0.2	1.8	2.1	4.1
Mov Class %	0.1	0.9	3.5	0.9
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Flow Rate	0.3	3.6	0.2	4.0
Mov Class %	0.2	0.6	0.8	0.5
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Flow Rate	1.8	9.4	8.5	19.7
Mov Class %	6.5	1.3	1.9	1.6
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Flow Rate	1.3	6.3	0.4	8.0
Mov Class %	0.7	1.6	0.2	1.1
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

Peak Flow factor value of 100% has been used for all movements since equal values of
Unit Time for Volumes and Peak Flow Period were specified in the Volumes dialog.

Flow rates shown above are Arrival Flow Rates (veh/h) based on the following input specifications:
Unit Time for Volumes = 15 minutes
Peak Flow Period = 15 minutes
Effects of Volume Factors (Peak Flow Factor, Flow Scale, Growth Rate) are included.
Arrival Flow Rates may be less than Demand Flow Rates if capacity constraint applies in
network analysis.

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Lane Flow Rates
Site: TS1646 2024AM-Existing (18/09)

Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

LANE FLOW RATES AT STOP LINE (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Lane 1				
LV	220.0	*	*	220.0
HV	3.8	*	*	3.8
B	0.2	*	*	0.2

```
  Total           224.0       *       *   224.0
 Lane  2
  LV                  *    90.0       *    90.0
  HV                  *     3.9       *     3.9
  B                   *     0.9       *     0.9
  Total               *    94.7       *    94.7
 Lane  3
  LV                  *   100.0       *   100.0
  HV                  *     4.3       *     4.3
  B                   *     0.9       *     0.9
  Total               *   105.3       *   105.3
 Lane  4
  LV                  *       *    55.7    55.7
  HV                  *       *     2.2     2.2
  B                   *       *     2.1     2.1
  Total               *       *    60.0    60.0
-------------------------------------------------
 Approach         224.0   200.0    60.0   484.0
-------------------------------------------------
 From EAST To:        S       W       N
 Turn:               L2      T1      R2     TOT
-------------------------------------------------
 Lane  1
  LV              141.0       *       *   141.0
  HV                6.7       *       *     6.7
  B                 0.3       *       *     0.3
  Total           148.0       *       *   148.0
 Lane  2
  LV                  *   217.5       *   217.5
  HV                  *     5.4       *     5.4
  B                   *     1.3       *     1.3
  Total               *   224.2       *   224.2
 Lane  3
  LV                  *   360.6       *   360.6
  HV                  *     8.9       *     8.9
  B                   *     2.2       *     2.2
  Total               *   371.8       *   371.8
 Lane  4
  LV                  *       *    18.9    18.9
  HV                  *       *     0.9     0.9
  B                   *       *     0.2     0.2
  Total               *       *    20.0    20.0
-------------------------------------------------
 Approach         148.0   596.0    20.0   764.0
-------------------------------------------------
 From NORTH To:       E       S       W
 Turn:               L2      T1      R2     TOT
-------------------------------------------------
 Lane  1
  LV               25.1       *       *    25.1
  HV                1.1       *       *     1.1
  B                 1.8       *       *     1.8
  Total            28.0       *       *    28.0
 Lane  2
  LV                  *   415.9       *   415.9
  HV                  *    16.2       *    16.2
  B                   *     5.7       *     5.7
  Total               *   437.8       *   437.8
 Lane  3
  LV                  *   271.9       *   271.9
  HV                  *    10.6       *    10.6
  B                   *     3.7       *     3.7
  Total               *   286.2       *   286.2
 Lane  4
  LV                  *       *   422.9   422.9
  HV                  *       *    16.6    16.6
  B                   *       *     8.5     8.5
  Total               *       *   448.0   448.0
-------------------------------------------------
 Approach          28.0   724.0   448.0  1200.0
-------------------------------------------------
 From WEST To:        N       E       S
 Turn:               L2      T1      R2     TOT
-------------------------------------------------
 Lane  1
  LV              177.8       *       *   177.8
  HV               12.9       *       *    12.9
  B                 1.3       *       *     1.3
  Total           192.0       *       *   192.0
 Lane  2
  LV                  *   149.3       *   149.3
  HV                  *     4.4       *     4.4
  B                   *     2.5       *     2.5
  Total               *   156.2       *   156.2
 Lane  3
  LV                  *   229.3       *   229.3
  HV                  *     6.7       *     6.7
  B                   *     3.8       *     3.8
  Total               *   239.8       *   239.8
 Lane  4
  LV                  *       *   174.1   174.1
  HV                  *       *     1.6     1.6
  B                   *       *     0.4     0.4
  Total               *       *   176.0   176.0
-------------------------------------------------
 Approach         192.0   396.0   176.0   764.0
-------------------------------------------------
  *  Movement not allocated to the lane


EXIT LANE FLOW RATES

-------------------------------------------------
```

```
Movement Class:       LV      HV       B     TOT
-------------------------------------------------
 Exit: SOUTH
Lane:  1          557.0    22.9     6.0   585.8
Lane:  2          445.9    12.2     4.1   462.2
Total            1002.9    35.0    10.1  1048.0
-------------------------------------------------
 Exit: EAST
Lane:  1          174.4     5.5     4.3   184.2
Lane:  2          285.0     8.9     5.9   299.8
Total             459.4    14.4    10.3   484.0
-------------------------------------------------
 Exit: NORTH
Lane:  1          267.8    16.7     2.2   286.7
Lane:  2          118.9     5.3     1.1   125.3
Total             386.7    22.0     3.3   412.0
-------------------------------------------------
 Exit: WEST
Lane:  1          437.5     9.2     1.6   448.2
Lane:  2          783.5    25.5    10.7   819.8
Total            1221.0    34.7    12.3  1268.0
-------------------------------------------------
   *  Movement not allocated to the lane


DOWNSTREAM LANE FLOW RATES FOR EXIT ROADS

-------------------------------------------------
Movement Class:       LV      HV       B     TOT
-------------------------------------------------
 Exit: SOUTH
Lane:  1          557.0    22.9     6.0   585.8
Lane:  2          445.9    12.2     4.1   462.2
Total            1002.9    35.0    10.1  1048.0
-------------------------------------------------
 Exit: EAST
Lane:  1          174.4     5.5     4.3   184.2
Lane:  2          285.0     8.9     5.9   299.8
Total             459.4    14.4    10.3   484.0
-------------------------------------------------
 Exit: NORTH
Lane:  1          267.8    16.7     2.2   286.7
Lane:  2          118.9     5.3     1.1   125.3
Total             386.7    22.0     3.3   412.0
-------------------------------------------------
 Exit: WEST
Lane:  1          437.5     9.2     1.6   448.2
Lane:  2          783.5    25.5    10.7   819.8
Total            1221.0    34.7    12.3  1268.0
-------------------------------------------------
   *  Movement not allocated to the lane

Peak Flow factor value of 100% has been used for all movements since equal values of
Unit Time for Volumes and Peak Flow Period were specified in the Volumes dialog.

Flow rates shown above are Arrival Flow Rates (veh/h) based on the following input specifications:
Unit Time for Volumes =  15 minutes
Peak Flow Period =  15 minutes
Effects of Volume Factors (Peak Flow Factor, Flow Scale, Growth Rate) are included.
Arrival Flow Rates may be less than Demand Flow Rates if capacity constraint applies in
network analysis.
```

Go to Table Links (Top)

Other

Parameter Settings Summary
Site: TS1646 2024AM-Existing (18/09)

```
Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)


* Basic Parameters:
  Intersection Type: Signalised - Fixed Time Isolated
  Driving on the left-hand side of the road
  Input data specified in Metric units
  Model Defaults: Standard Left
  Peak Flow Period (for performance): 15 minutes
  Unit time (for volumes): 15 minutes.
  SIDRA Standard Delay model used
  SIDRA Standard Queue model used
  Level of Service based on: Delay (SIDRA)
  Queue percentile: 95%
```

Go to Table Links (Top)

Diagnostics
Site: TS1646 2024AM-Existing (18/09)

```
Site ID: 1646
Signals - Fixed-Time Isolated   Cycle Time = 101 sec (Site User-Given Phase Times)

Main (Timing-Capacity) Iterations for Signals

  Site Model Variability Index (Iterations 3 to N):   0.0%
  Number of Iterations:  2 (Maximum: 10)
  Largest difference in Movement Effective Green Times in the last two Main Iterations:  0 secs
```

```
    (stopping condition: 0 secs)

Lane Flow-Capacity Iterations:

  Flow-Capacity Iteration Variability Index (Iterations 3 to N):   1.6%
  Number of Iterations: 6 (Maximum: 10)
  Largest change in Lane Degrees of Saturation for the last three Flow-Capacity Iterations:
     1.7%   1.3%   0.9%
  For Signals, the results for "Lane Flow-Capacity Iterations" are reported
  for the last Main (Timing-Capacity) Iteration.

Other Diagnostic Messages (if any):
```

Go to Table Links (Top)

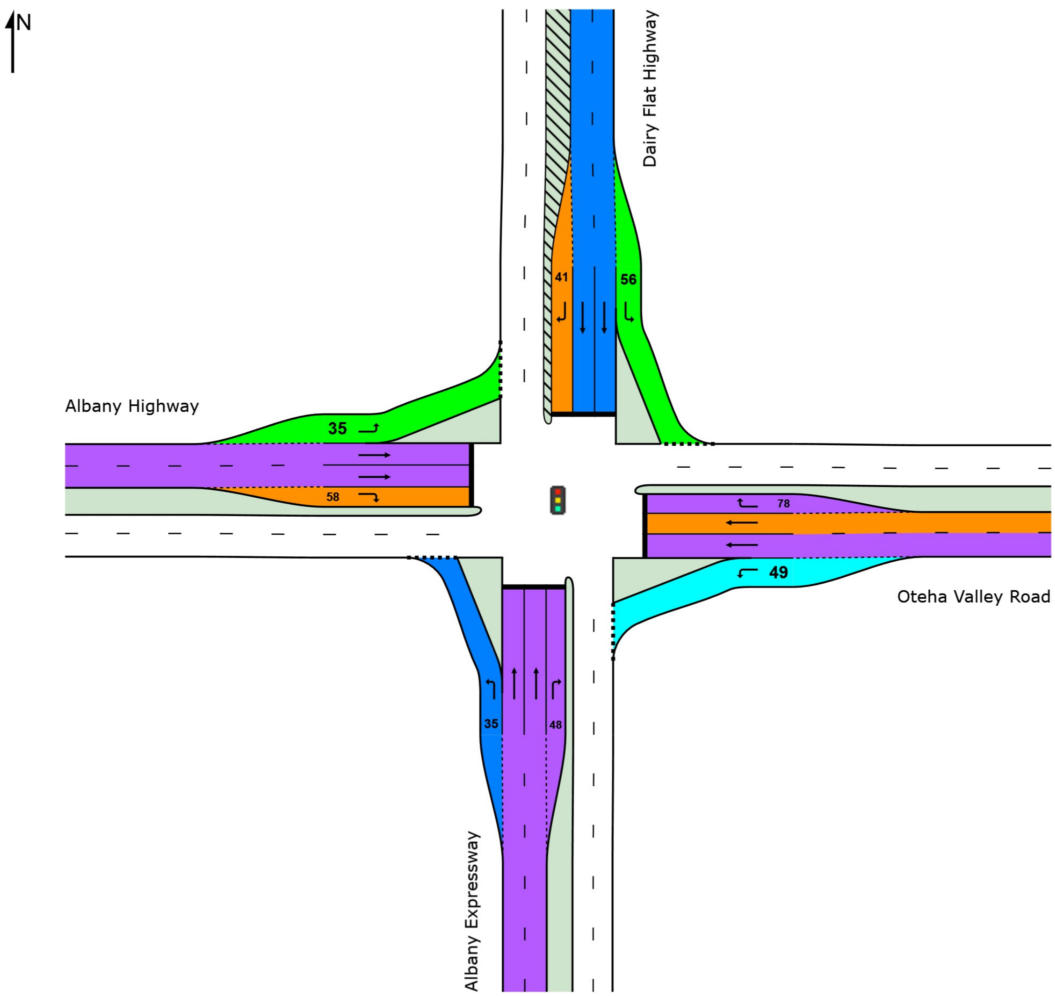
LANE LEVEL OF SERVICE

Lane Level of Service

Site: 1646 [TS1646 2024AM-Existing (18/09)]

Oteha Valley Rd/Albany Expy/Albany Hwy/Dairy Flat Hwy
20242409 08:15-08:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 101 seconds (Site User-Given Phase Times)

	Approaches				Intersection
	South	East	North	West	
LOS	D	D	D	C	D



Colour code based on Level of Service

LOS A | LOS B | LOS C | LOS D | LOS E | LOS F

Site Level of Service (LOS) Method: Delay (SIDRA). Site LOS Method is specified in the Parameter Settings dialog (Site tab).
NA (TWSC): Level of Service is not defined for major road approaches or the intersection as a whole for Two-Way Sign Control (HCM LOS rule).
SIDRA Standard Delay Model is used. Control Delay includes Geometric Delay.

PHASING SUMMARY

Site: 1646 [TS1646 2024AM-Existing (18/09)]

Oteha Valley Rd/Albany Expy/Albany Hwy/Dairy Flat Hwy
20242409 08:15-08:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 101 seconds (Site User-Given Phase Times)

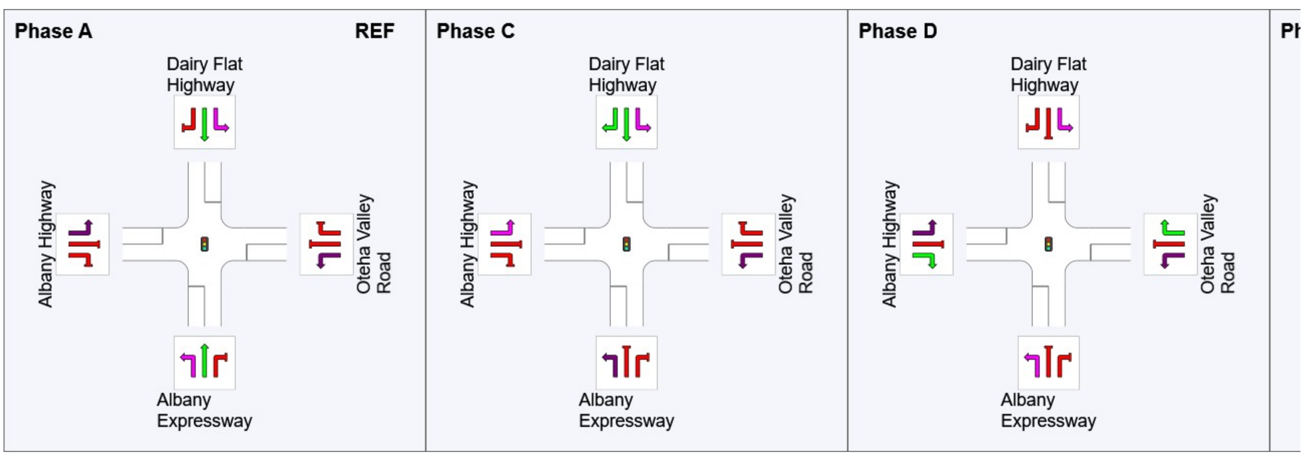
Timings based on settings in the Site Phasing & Timing dialog
Phase Times specified by the user
Phase Sequence: Phase
Reference Phase: Phase A
Input Phase Sequence: A, C, D, E, G
Output Phase Sequence: A, C, D, E, G

PHASE TIMING SUMMARY

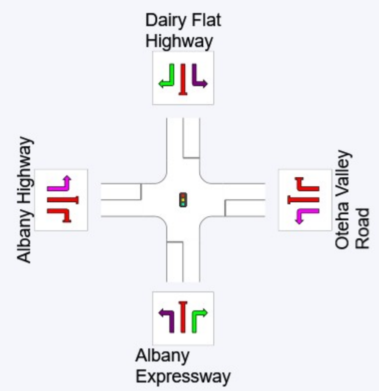
Phase	A	C	D	E	G
Phase Change Time (sec)	0	19	42	60	87
Green Time (sec)	14	18	13	22	9
Phase Time (sec)	19	23	18	27	14
Phase Split	19%	23%	18%	27%	14%

See the Phase Information section in the Detailed Output report for more detailed information including input values of Yellow Time and All-Red Time, and information on any adjustments to Intergreen Time, Phase Time and Green Time values in cases of Pedestrian Actuation, Phase Actuation and Phase Frequency values (user-specified or implied) less than 100%.

OUTPUT PHASE SEQUENCE



Phase G



REF: Reference Phase
VAR: Variable Phase

	Normal Movement		Permitted/Opposed
	Slip/Bypass-Lane Movement		Opposed Slip/Bypass-Lane
	Stopped Movement		Turn On Red
	Other Movement Class (MC) Running		Undetected Movement
	Mixed Running & Stopped MCs		Continuous Movement
	Other Movement Class (MC) Stopped		Phase Transition Applied

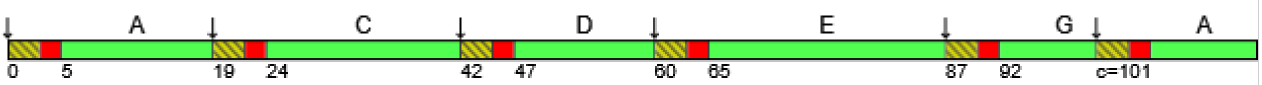
MOVEMENT TIMING

Site: 1646 [TS1646 2024AM-Existing (18/09)]

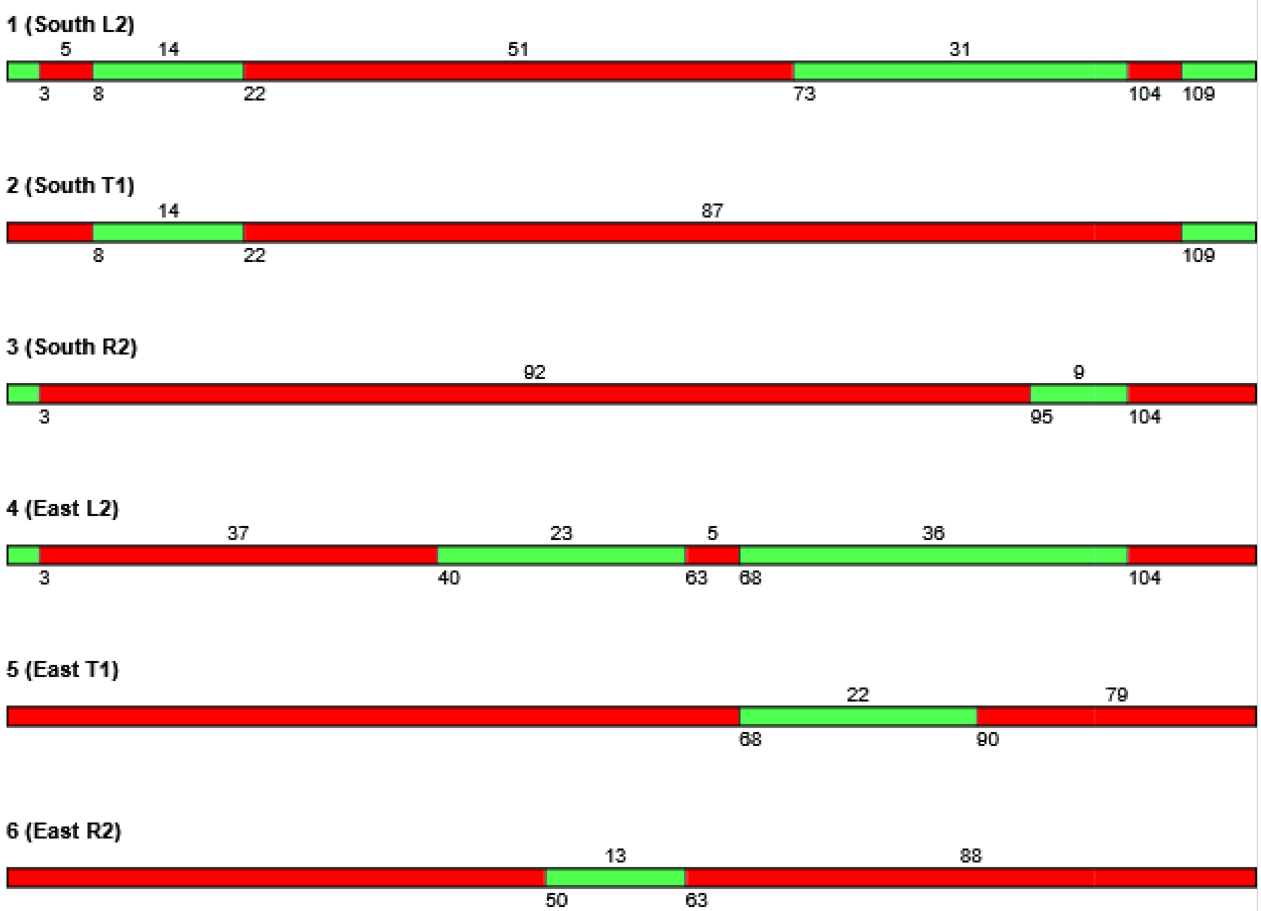
Oteha Valley Rd/Albany Expy/Albany Hwy/Dairy Flat Hwy
20242409 08:15-08:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 101 seconds (Site User-Given Phase Times)

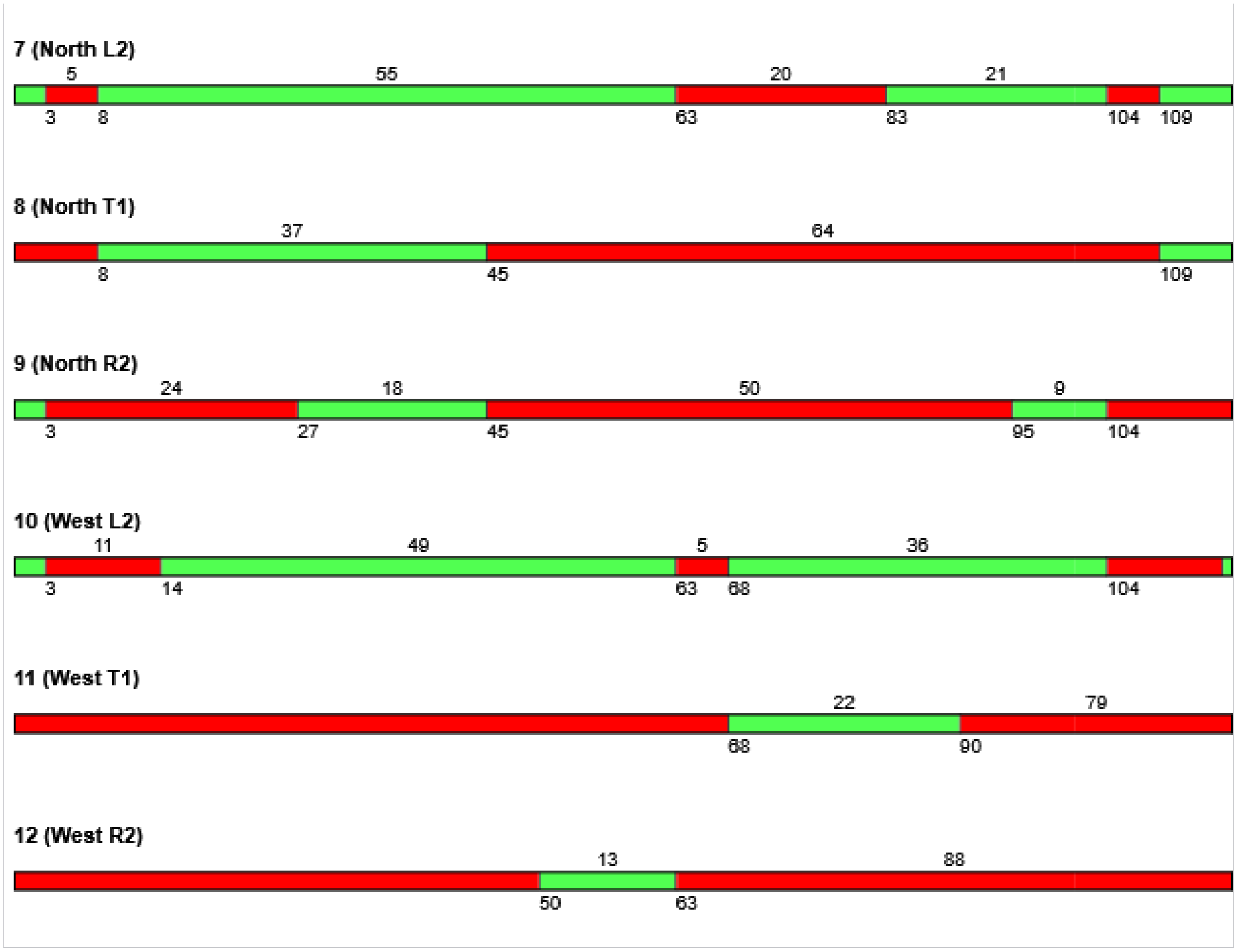
Timings based on settings in the Site Phasing & Timing dialog
Phase Times specified by the user
Phase Sequence: Phase
Reference Phase: Phase A
Input Phase Sequence: A, C, D, E, G
Output Phase Sequence: A, C, D, E, G

DISPLAYED SIGNAL TIMING - PHASES



EFFECTIVE SIGNAL TIMING - MOVEMENTS




7 (North L2)
5
55
20
21
3
8
63
83
104
109
8 (North T1)
37
64
8
45
109
9 (North R2)
24
18
50
9
3
27
45
95
104
10 (West L2)
11
49
5
36
3
14
63
68
104
11 (West T1)
22
79
68
90
12 (West R2)
13
88
50
63

INTERSECTION SUMMARY

Site: 71 [TS71 2024AM-Existing (30/10)]

Wairere Drive/Ruakura Road
20243010 17:00-17:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 107 seconds (Site User-Given Phase Times)

Intersection Performance - Hourly Values		
Performance Measure	**Vehicles**	**Persons**
Travel Speed (Average)	31.7 km/h	31.3 km/h
Travel Distance (Total)	4931.1 veh-km/h	6247.4 pers-km/h
Travel Time (Total)	155.3 veh-h/h	199.7 pers-h/h
Demand Flows (Total)	3692 veh/h	4730 pers/h
Percent Heavy Vehicles (Demand)	3.7 %	
Degree of Saturation	0.976	
Practical Spare Capacity	-7.8 %	
Effective Intersection Capacity	3781 veh/h	
Control Delay (Total)	40.71 veh-h/h	53.66 pers-h/h
Control Delay (Average)	39.7 sec	40.8 sec
Control Delay (Worst Lane)	80.7 sec	
Control Delay (Worst Movement)	69.5 sec	69.5 sec
Geometric Delay (Average)	1.0 sec	
Stop-Line Delay (Average)	38.7 sec	
Idling Time (Average)	34.2 sec	
Intersection Level of Service (LOS)	LOS D	
95% Back of Queue - Vehicles (Worst Lane)	26.0 veh	
95% Back of Queue - Distance (Worst Lane)	190.1 m	
Queue Storage Ratio (Worst Lane)	0.17	
Total Effective Stops	2961 veh/h	3863 pers/h
Effective Stop Rate	0.80	0.82
Proportion Queued	0.84	0.85
Performance Index	336.1	336.1
Cost (Total)	4628.46 $/h	4628.46 $/h
Fuel Consumption (Total)	492.2 L/h	
Carbon Dioxide (Total)	1168.8 kg/h	
Hydrocarbons (Total)	0.098 kg/h	
Carbon Monoxide (Total)	0.906 kg/h	
NOx (Total)	1.753 kg/h	

Site Level of Service (LOS) Method: Delay (SIDRA). Site LOS Method is specified in the Parameter Settings dialog (Site tab).
Intersection LOS value for Vehicles is based on average delay for all vehicle movements.
SIDRA Standard Delay Model is used. Control Delay includes Geometric Delay.
Site Model Variability Index (Iterations 3 to N): 0.0 %
Number of Iterations: 2 (Maximum: 10)
Largest change in Lane Degrees of Saturation for the last three Main (Timing-Capacity) Iterations: 8.2%   0.4%   0.0%

Intersection Performance - Annual Values		
Performance Measure	**Vehicles**	**Persons**
Demand Flows (Total)	1,772,160 veh/y	2,270,362 pers/y
Delay	19,542 veh-h/y	25,758 pers-h/y
Effective Stops	1,421,290 veh/y	1,854,080 pers/y
Travel Distance	2,366,914 veh-km/y	2,998,746 pers-km/y
Travel Time	74,554 veh-h/y	95,836 pers-h/y
Cost	2,221,661 $/y	2,221,661 $/y

Fuel Consumption	236,245	L/y
Carbon Dioxide	561,027	kg/y
Hydrocarbons	47	kg/y
Carbon Monoxide	435	kg/y
NOx	841	kg/y

DETAILED OUTPUT

Site: 71 [TS71 2024AM-Existing (30/10)]

Wairere Drive/Ruakura Road
20243010 17:00-17:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 107 seconds (Site User-Given Phase Times)

OUTPUT TABLE LINKS

Signal Timing

Movement Timing Information
Site: TS71 2024AM-Existing (30/10)

```
Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

---------------------------------------------------------------------------------------------------------
 Mov  Mov  Mov           P H A S E  M A T R I X                    Lost Tim  Req.Mov.Time      Eff. Grn
 ID   Cl.  Typ       First Green              Second Green         --------  ------------      --------
                ----------------------- -----------------------    1st  2nd  1st       2nd     1st  2nd
                 Fr     To     Op Pr Und    Fr     To     Op Pr Und  Grn  Grn  Grn       Grn     Grn  Grn
---------------------------------------------------------------------------------------------------------
South: Wairere Drive South
    1    # (Slp) A      E                 E      A      Y           5   31   0.0z      0.0z     56  15
    2    #      *A      D                                           5       28.4                31
    3    #       F      A                                           5       11.0 Min            14
---------------------------------------------------------------------------------------------------------
East: Ruakura Road East
    4    # (Slp) A      E      Y          E      A                 33    5   0.0z      0.0z     28  41
    5    #      *E      F                                           5       28.9                22
    6    #       E      F                                           5       22.0                22
---------------------------------------------------------------------------------------------------------
North: Wairere Drive North
    7    # (Slp) A      D                 D      A      Y           5   19   0.0z      0.0z     31  52
    8    #       A      D                                           5       21.5                31
    9    #      *F      A                                           5       12.8                14
---------------------------------------------------------------------------------------------------------
West: Ruakura Road West
   10    # (Slp) D      E                 E      D      Y           5   37   0.0z      0.0z     20  45
   11    #       D      E                                           5       21.5                20
   12    #      *D      E                                           5       25.8                20
---------------------------------------------------------------------------------------------------------
  Current Phase Sequence: Phase
  Input Phase Sequence: A D E F
  Output Phase Sequence: A D E F
---------------------------------------------------------------------------------------------------------
  # Combined timing results are shown for all Movement Classes except any listed separately.
  * Critical Movement/Green Period
  Y (under heading 'Op') - Movement is opposed in the indicated green period
  z This Green Period of the movement was treated as Undetected
    and not included in signal timing calculations.

  Movement Types:
  Slp  Slip/Bypass Lane Movement
  Ped  Pedestrian
  Dum  Dummy


CRITICAL MOVEMENTS AND CYCLE TIME
```

Crit Mov ID	Turn	App and Dest	Green Period	Phases Fr	Phases To	Adjusted Lost Time	Adjusted Flow Ratio	Required Grn Time Ratio	Required Movement Time
2LV	T1	S_N		A	D	5	0.196	0.218	28.4
12LV	R2	W_S		D	E	5	0.175	0.194	25.8
5LV	T1	E_W		E	F	5	0.201	0.223	28.9
9LV	R2	N_W		F	A	5	0.066	0.073	12.8
					Total:	20	0.638	0.709	95.8

Cycle Time:

Minimum	Maximum	Practical	Chosen
44	150	69	107

(Phase times user specified, cycle time = sum of phase times)

Go to Table Links (Top)

Phase Information
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

PHASE INFORMATION

Phase	Ref. Phase	Change Time	Starting Intgrn	Green Start	Displayed Green	Green End	Terminating Intgrn	Phase Time	Phase Split
A	Yes	0	5	5	31	36	5	36	34%
D	No	36	5	41	20	61	5	25	23%
E	No	61	5	66	22	88	5	27	25%
F	No	88	5	93	14	107	5	19	18%

(Phase times specified by the user)
Current Phase Sequence: Phase
Input Phase Sequence: A D E F
Output Phase Sequence: A D E F

PHASE YELLOW AND ALL-RED TIMES (INPUT)

Phase	A	D	E	F
Yellow Time	3	3	3	3
All-Red Time	2	2	2	2
Intergreen Time	5	5	5	5

Phase Yellow and All-Red parameters in this table are user-specified input values.
Intergreen Time (sum of Yellow Time and All-Red Time) is an unadjusted value.
Any adjusted values of Intergreen Time, Phase Time and Green Time determined in cases of Pedestrian Actuation, Phase Actuation and user-given or implied Phase Frequency values less than 100% are given in the PHASE INFORMATION table above.

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Movements

Intersection Negotiation and Travel Data
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

TRAVEL SPEED, TRAVEL DISTANCE AND TRAVEL TIME

From Approach	To Exit	Turn	Running Speed km/h	Travel Speed km/h	Travel Distance m	Travel Time s	Total Travel Dem Flows veh-km/h	Distance Arv Flows veh-km/h	Tot.Trav. Time veh-h/h
South: Wairere Drive South									
	West	L2	27.5	26.9	1428.6#	191.0#	291.4	291.4	10.8
	North	T1	51.1	40.2	1634.4#	146.4#	1091.7	1091.7	27.2
	East	R2	42.7	33.6	1744.3#	187.0#	7.0	7.0	0.2
East: Ruakura Road East									
	South	L2	35.0	34.3	1745.6#	183.5#	38.4	38.4	1.1
	West	T1	36.6	23.6	1102.1#	167.8#	683.3	683.3	28.9
	North	R2	42.2	31.1	1305.3#	151.0#	321.1	321.1	10.3
North: Wairere Drive North									
	East	L2	30.9	30.7	1305.6#	153.3#	347.3	347.3	11.3
	South	T1	52.1	41.3	1634.3#	142.4#	833.5	833.5	20.2
	West	R2	46.1	29.4	987.8#	120.9#	118.5	118.5	4.0
West: Ruakura Road West									
	North	L2	36.3	33.9	988.6#	104.8#	310.4	310.4	9.1
	East	T1	37.1	26.9	1102.1#	147.2#	462.9	462.9	17.2
	South	R2	42.9	28.5	1427.8#	180.4#	425.5	425.5	14.9
ALL VEHICLES:			41.7	31.7	1335.6#	151.5#	4931.1	4931.1	155.3

"Running Speed" is the average speed excluding stopped periods.

Travel Time values include cruise times and intersection delays including acceleration, deceleration and idling delays.

\# Travel Distance and Travel Time values include travel on the External Exit section based on the Exit Distance or user-specified Downstream Distance value as applicable.

INTERSECTION NEGOTIATION DATA

From Approach	To Exit	Turn	Negn Radius m	Negn Speed km/h	Negn Dist m	App Dist m	Exit Dist m	Downstr Dist m
South: Wairere Drive South								
	West	L2	15.0	23.5	23.6	1025	380	NA
	North	T1	S	50.0	24.4	1025	585	NA
	East	R2	14.2	23.0	22.3	1025	697	NA
East: Ruakura Road East								
	South	L2	15.0	23.5	23.6	697	1025	NA
	West	T1	S	39.0	25.1	697	380	NA
	North	R2	14.8	23.4	23.3	697	585	NA
North: Wairere Drive North								
	East	L2	15.0	23.5	23.6	585	697	NA
	South	T1	S	50.0	24.4	585	1025	NA
	West	R2	14.5	23.2	22.8	585	380	NA
West: Ruakura Road West								
	North	L2	15.0	23.5	23.6	380	585	NA
	East	T1	S	39.0	25.1	380	697	NA
	South	R2	14.5	23.2	22.8	380	1025	NA

NA Downstream Distance does not apply if:
- Exit is an internal leg of a network
- "Program" option was specified
- Distance specified was less than the Exit Negotiation Distance
- Distance specified was greater than the exit leg length

Some Negotiation Radius, Speed or Distance values are user specified.

MOVEMENT SPEEDS AND GEOMETRIC DELAY

Mov ID	Turn	App. Speeds Cruise km/h	App. Speeds Negn km/h	Exit Speeds Negn km/h	Exit Speeds Cruise km/h	Queue Move-up Sp 1st Grn km/h	Queue Move-up Sp 2nd Grn km/h	Geom Delay sec
South: Wairere Drive South								
1	L2	25.0	23.5	23.5	39.0	23.5	23.5	0.4
2	T1	50.0	50.0	50.0	58.0	37.5		0.0
3	R2	50.0	23.0	23.0	39.0	23.0		4.5
East: Ruakura Road East								
4	L2	25.0	23.5	23.5	50.0	23.5	23.5	0.4
5	T1	39.0	39.0	39.0	39.0	29.2		0.0
6	R2	39.0	23.4	23.4	58.0	23.4		3.0
North: Wairere Drive North								
7	L2	25.0	23.5	23.5	39.0	23.5	23.5	0.4
8	T1	67.0	50.0	50.0	50.0	42.3		2.1
9	R2	67.0	23.2	23.2	39.0	23.2		6.3
West: Ruakura Road West								
10	L2	25.0	23.5	23.5	58.0	23.5	23.5	0.4
11	T1	39.0	39.0	39.0	39.0	29.3		0.0
12	R2	39.0	23.2	23.2	50.0	23.2		3.1

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Movement Capacity and Performance Parameters
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

MOVEMENT CAPACITY PARAMETERS

Mov ID	Turn	Mov Cl.	Arv Flow veh/h	Total Cap. veh/h	Prac. Deg. Satn xp	Prac. Spare Cap. %	Deg. Satn x
South: Wairere Drive South							
1	L2	#	204	1135	0.90	401	0.180
2	T1	#	668	985	0.90	33	0.678
3	R2	#	4	210	0.90	4629	0.019
East: Ruakura Road East							
4	L2	#	22	1576	0.90	6346	0.014
5	T1	#	620	635	0.90	-8	0.976*
6	R2	#	246	353	0.90	29	0.697

North: Wairere Drive North							
7	L2	#	266	1309	0.90	343	0.203
8	T1	#	510	1063	0.90	88	0.480
9	R2	#	120	238	0.90	78	0.505
West: Ruakura Road West							
10	L2	#	314	784	0.90	125	0.400
11	T1	#	420	560	0.90	20	0.750
12	R2	#	298	319	0.90	-4	0.933

* Maximum degree of saturation
\# Combined Movement Capacity parameters are shown for all Movement Classes.

MOVEMENT PERFORMANCE

Mov ID	Turn	Total Delay (veh-h/h)	Total Delay (pers-h/h)	Aver. Delay (sec)	Eff. Stop Rate	Total Stops	Perf. Index	Tot.Trav. Distance (veh-km/h)	Tot.Trav. Time (veh-h/h)	Aver. Speed (km/h)
South: Wairere Drive South										
1	L2	0.35	0.42	6.2	0.36	74.1	16.92	291.4	10.8	26.9
2	T1	6.66	7.99	35.9	0.80	532.5	50.43	1091.7	27.2	40.2
3	R2	0.05	0.06	48.6	0.64	2.5	0.32	7.0	0.2	33.6
East: Ruakura Road East										
4	L2	0.04	0.04	6.0	0.31	6.8	1.83	38.4	1.1	34.3
5	T1	11.39	16.94	66.1	1.15	715.9	71.09	683.3	28.9	23.6
6	R2	3.23	3.88	47.3	0.86	211.5	27.83	321.1	10.3	31.1
North: Wairere Drive North										
7	L2	0.20	0.24	2.7	0.28	74.6	18.07	347.3	11.3	30.7
8	T1	5.08	6.10	35.9	0.77	394.7	33.21	833.5	20.2	41.3
9	R2	1.82	2.18	54.6	0.79	94.8	11.51	118.5	4.0	29.4
West: Ruakura Road West										
10	L2	0.83	0.99	9.5	0.48	152.1	23.12	310.4	9.1	33.9
11	T1	5.31	7.90	45.5	0.85	358.6	39.67	462.9	17.2	26.9
12	R2	5.75	6.90	69.5	1.15	342.9	42.05	425.5	14.9	28.5

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Fuel Consumption, Emissions and Cost
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated Cycle Time = 107 sec (Site User-Given Phase Times)

FUEL CONSUMPTION, EMISSIONS AND COST (TOTAL)

Mov ID	Turn	Cost Total $/h	Fuel Total L/h	CO2 Total kg/h	CO Total kg/h	HC Total kg/h	NOX Total kg/h
South: Wairere Drive South							
1	L2	336.41	27.1	63.9	0.03	0.005	0.053
2	T1	925.51	119.2	283.7	0.26	0.022	0.618
3	R2	5.44	0.5	1.2	0.00	0.000	0.000
		1267.36	146.8	348.8	0.29	0.027	0.672
East: Ruakura Road East							
4	L2	27.39	3.0	7.2	0.00	0.000	0.001
5	T1	1061.65	72.6	172.1	0.11	0.016	0.216
6	R2	332.31	38.4	90.9	0.08	0.008	0.141
		1421.35	114.0	270.2	0.19	0.025	0.359
North: Wairere Drive North							
7	L2	263.71	27.8	65.8	0.03	0.005	0.051
8	T1	437.68	66.7	159.5	0.16	0.013	0.264
9	R2	114.25	10.2	24.1	0.02	0.002	0.024
		815.64	104.8	249.4	0.21	0.020	0.339
West: Ruakura Road West							
10	L2	278.70	40.0	95.0	0.08	0.008	0.159
11	T1	472.55	43.7	103.5	0.06	0.009	0.100
12	R2	372.85	42.9	101.8	0.08	0.008	0.123
		1124.10	126.6	300.4	0.22	0.026	0.383
INTERSECTION:		4628.46	492.2	1168.8	0.91	0.098	1.753

FUEL CONSUMPTION, EMISSIONS AND COST (RATE)

Mov ID	Turn	Cost Rate $/km	Fuel Rate L/100km	CO2 Rate g/km	CO Rate g/km	HC Rate g/km	NOX Rate g/km
South: Wairere Drive South							
1	L2	1.15	9.3	219.1	0.10	0.017	0.183
2	T1	0.85	10.9	259.9	0.24	0.021	0.566
3	R2	0.78	7.5	176.4	0.11	0.013	0.033

		0.91	10.6	250.9	0.21	0.020	0.483
East: Ruakura Road East							
4	L2	0.71	7.9	186.4	0.11	0.013	0.039
5	T1	1.55	10.6	251.9	0.16	0.024	0.316
6	R2	1.03	11.9	283.1	0.23	0.024	0.440
		1.36	10.9	259.1	0.18	0.024	0.344
North: Wairere Drive North							
7	L2	0.76	8.0	189.5	0.09	0.015	0.145
8	T1	0.53	8.0	191.4	0.19	0.015	0.317
9	R2	0.96	8.6	203.6	0.19	0.019	0.202
		0.63	8.1	192.0	0.16	0.016	0.261
West: Ruakura Road West							
10	L2	0.90	12.9	306.0	0.27	0.026	0.513
11	T1	1.02	9.4	223.7	0.13	0.020	0.217
12	R2	0.88	10.1	239.4	0.18	0.020	0.289
		0.94	10.6	250.6	0.18	0.021	0.319
INTERSECTION:		0.94	10.0	237.0	0.18	0.020	0.355

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Lanes

Lane Performance and Capacity Information
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

LANE PERFORMANCE

Lane No.	Effective Red and Green Times (sec) R1	G1	R2	G2	Satd Part of Green Gs1	Gs2	Arv Flow veh/h	Cap veh/h	Deg. Satn x	Aver. Delay sec	Eff. Stop Rate	Queue 95% Back veh	m	Lane Length m
South: Wairere Drive South														
1	5	56	31	15	0.7	4.3	204	1135	0.180	6.2	0.36	3.7	26.2	71.8T
2	76	31			15.4		300	515	0.583	35.3	0.78	13.5	99.8	1025.0
3	76	31			18.6		368	542	0.678	36.4	0.81	17.1	126.2	1025.0
4	93	14			0.2		4	210	0.019	48.6	0.64	0.2	1.3	109.0T
East: Ruakura Road East														
1	33	28	5	41	0.4	0.0	22	1576	0.014	6.0	0.31	0.4	2.5	27.0T
2	85	22			20.2		359	368<	0.976	80.7	1.33	26.0	190.1	697.0
3	85	22			15.0		261	347<	0.752	46.1	0.91	13.5	98.8	697.0
4	85	22			14.2		246	353	0.697	47.3	0.86	12.4	89.6	51.5T
North: Wairere Drive North														
1	5	31	19	52	0.9	3.6	266	1309	0.203	2.7	0.28	2.9	20.9	63.1T
2	76	31			11.7		250	544	0.461	35.8	0.77	10.8	79.5	585.0
3	76	31			12.3		260	541	0.480	36.0	0.78	11.2	82.9	585.0
4	93	14			6.6		120	238	0.505	54.6	0.79	6.0	43.6	92.4T
West: Ruakura Road West														
1	5	20	37	45	1.1	10.8	314	784<	0.400	9.5	0.48	7.4	53.3	30.0T
2	87	20			8.3		166	313<	0.532	42.5	0.76	7.9	56.9	380.0
3	87	20			14.2		254	338	0.750	47.5	0.91	13.3	96.0	380.0
4	87	20			16.2		298	319<	0.933	69.5	1.15	19.2	138.5	55.2T

< Reduced capacity due to a short lane effect. Short lane queues may extend into the full-length lanes.
Some upstream delays at entry to short lanes are not included.
T Short lane due to specification of Turn Bay

LANE FLOW AND CAPACITY INFORMATION

Lane No.	Total Arv Flow veh/h	Lane Width m	Adj. Basic tcu/h	Saturation Flow Rate: With Lane Blockage 1st veh/h	2nd veh/h	W/O Lane Blockage 1st veh/h	2nd veh/h	End Cap veh/h	Tot Cap veh/h	Deg. Satn x	Lane Util %
South: Wairere Drive South											
1	204	4.40	1846	1721	1672	-	-	82	1135	0.180	100
2	300	3.45	1867	1779		-		0	515	0.583	86U
3	368	3.45	1965	1872		-		0	542	0.678	100
4	4	3.25	1687	1606		-		0	210	0.019	100
East: Ruakura Road East											
1	22	4.50	3134	1651	2985	-	-	84	1576	0.014	100
2	359	3.25	1945	1789<		-		0	368	0.976	100
3	261	3.35	1807	1688<		-		0	347	0.752	77U
4	246	2.90	1860	1716		-		0	353	0.697	71P
North: Wairere Drive North											

1	266	4.50	1863	1737	1656	-	-	82	1309	0.203	100
2	250	3.50	1970	1876		-		0	544	0.461	96U
3	260	3.40	1960	1867		-		0	541	0.480	100
4	120	3.50	1970	1818		-		0	238	0.505	100
West: Ruakura Road West											
1	314	4.50	1883	1737	1095<	-	-	82	784	0.400	100
2	166	3.40	1960	1702<		-		0	313	0.532	71U
3	254	3.40	1865	1810		-		0	338	0.750	100
4	298	3.00	2057	1707<		-		0	319	0.933	100

< Reduced saturation flow due to a short lane effect
Some upstream delays at entry to short lanes are not included.
P Lane under-utilisation found by the Program
U Lane under-utilisation specified by the User

Basic Saturation Flow in this table is adjusted for area type factor, lane width, approach grade, parking manoeuvres and number of buses stopping.
Saturation flow scale (Demand & Sensitivity dialog) applies if specified.

Saturation Flow rates without (W/O) the effect of downstream lane blockage used for signal timing purposes are included in this table when the signal timing option to exclude downstream lane blockage effects is selected.

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Lane, Approach and Intersection Performance
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated Cycle Time = 107 sec (Site User-Given Phase Times)

Lane No.	Arrival Flow (veh/h)	%HV	Adj. Basic Satf.	Eff Grn (sec) 1st	2nd	Deg Sat x	Aver. Delay sec	Longest Queue m	Lane Length m
South: Wairere Drive South									
1	204	2	1845	56	15	0.180	6.2	26	72
2	300	5	1867	31		0.583	35.3	100	1025U
3	368	5	1965	31		0.678	36.4	126	1025
4	4	0	1686	14		0.019	48.6	1	109
	876	4				0.678	29.1	126	
East: Ruakura Road East									
1	22	0	3134	28	41	0.014	6.0	3	27
2	359	4	1944	22		0.976	80.7	190	697
3	261	4	1806	22		0.752	46.1	99	697U
4	246	3	1860	22		0.697	47.3	90*	52
	888	4				0.976	59.4	190	
North: Wairere Drive North									
1	266	2	1863	31	52	0.203	2.7	21	63
2	250	5	1970	31		0.461	35.8	79	585U
3	260	5	1960	31		0.480	36.0	83	585
4	120	3	1970	14		0.505	54.6	44	92
	896	4				0.505	28.5	83	
West: Ruakura Road West									
1	314	3	1882	20	45	0.400	9.5	53*	30
2	166	3	1960	20		0.532	42.5	57	380U
3	254	3	1864	20		0.750	47.5	96	380
4	298	3	2057	20		0.933	69.5	139*	55
	1032	3				0.933	41.5	139	

ALL VEHICLES

Total Flow	% HV	Cycle Time	Max X	Aver. Delay	Max Queue
3692	4	107	0.976	39.7	190

Peak flow period = 30 minutes.

Queue values in this table are 95% queue (metres)
Note: Basic Saturation Flows (in through car units) have been adjusted for grade, lane widths, parking manoeuvres and bus stops.

* Queue length exceeds short lane length due to specification of a percentile queue in the Parameter Settings dialog. For calculation of this statistic, you may specify the lane with full length.
U Lane under-utilisation specified by the User

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Driver Characteristics
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated Cycle Time = 107 sec (Site User-Given Phase Times)

Lane No.	Satn Speed km/h	Satn Flow veh/h	Satn Hdwy sec	Satn Spacing m	Average Queue Space m	Driver Response Time sec
South: Wairere Drive South						

1	NA - Short Lane					
2	37.5	1779	2.02	21.08	7.38	1.32
3	37.5	1872	1.92	20.04	7.38	1.21
4	NA - Short Lane					
East: Ruakura Road East						
1	NA - Short Lane					
2	29.2	1870	1.93	15.64	7.30	1.03
3	29.3	1737	2.07	16.84	7.30	1.17
4	NA - Short Lane					
North: Wairere Drive North						
1	NA - Short Lane					
2	50.0	1876	1.92	26.65	7.38	1.39
3	50.0	1867	1.93	26.78	7.38	1.40
4	NA - Short Lane					
West: Ruakura Road West						
1	NA - Short Lane					
2	29.2	1903	1.89	15.37	7.22	1.00
3	29.2	1810	1.99	16.16	7.22	1.10
4	NA - Short Lane					

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SCATS Parameters
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

Lane No.	Stopline Flow veh/h	Capacity veh/h	SCATS Satn Flow	SCATS MF	Hdwy at MF sec	Occ Time sec	Space Time sec	Deg. Satn x	Lane Util. %
South: Wairere Drive South									
1	204	1135	1758	NA				0.180	100
2	300	515	1867	1608	2.24	0.86	1.37	0.583	86U
3	368	542	1965	1692	2.13	0.86	1.26	0.678	100
4	4	210	1606	1184	3.04	1.41	1.64	0.019	100
East: Ruakura Road East									
1	22	1576	2985	NA				0.014	100
2	359	368	1945	1585	2.27	1.11	1.16	0.976	100
3	261	347	1807	1472	2.45	1.11	1.34	0.752	77U
4	246	353	1772	1444	2.49	1.38	1.11	0.697	71P
North: Wairere Drive North									
1	266	1309	1775	NA				0.203	100
2	250	544	1970	1697	2.12	0.65	1.47	0.461	96U
3	260	541	1960	1688	2.13	0.65	1.48	0.480	100
4	120	238	1876	1383	2.60	1.39	1.21	0.505	100
West: Ruakura Road West									
1	314	784	1793	NA				0.400	100
2	166	313	1960	1568	2.30	1.11	1.19	0.532	71U
3	254	338	1865	1492	2.41	1.11	1.31	0.750	100
4	298	319	1959	1568	2.30	1.39	0.90	0.933	100

NA Not Applicable - SCATS MF was not calculated for this lane due to one of the following reasons:
- the lane is not controlled by signals (slip or continuous lane)
- movements that share this lane do not run in the same phases

P Lane under-utilisation found by the "Program". This includes cases where the value of lane under-utilisation due to downstream effects has been modified by the program during lane flow calculations (e.g. a de facto exclusive lane has been found).
U Lane under-utilisation specified by the "User"

STOPLINE FLOW: Departure flow rate in veh/h as measured at the stop line. This cannot exceed capacity.

SCATS SATURATION FLOW: This allows for area type factor, lane width, approach grade and turning vehicles. Saturation flow scale applies if specified (Demand & Sensitivity dialog). The effects of movement class, parking manoeuvres, number of buses stopping and conflicting pedestrian volume are not included.

SCATS MF: This emulates the MF (Maximum Flow) parameter used in the SCATS control system. It is calculated from the SCATS SATURATION FLOW parameter. The values estimated for conditions of low capacity per cycle where the intergreen time is high relative to the green time may not be representative of MF values reported by SCATS.

DEG. SATN: The Demand (Arrival) Flow Rate may exceed the Stopline Flow Rate, therefore x > 1 is possible.

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Lane Delays
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

LANE DELAYS

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Min Del dm	Stop-line Delay 1st d1	Stop-line Delay 2nd d2	Stop-line Delay Total dSL	Acc. Dec. dn	Queuing Total dq	Queuing MvUp dqm	Stopd (Idle) di	Geom dig	Control dic
South: Wairere Drive South													
1	0.180	66.4	1.000	4.6	5.9	0.0	5.9	1.9	4.1	0.0	4.1	0.4	6.2
2	0.583	29.0	1.000	27.0	35.3	0.0	35.3	4.6	30.7	0.0	30.7	0.0	35.3
3	0.678	29.0	1.000	27.0	36.4	0.0	36.4	4.7	31.7	0.0	31.7	0.0	36.4
4	0.019	13.1	1.000	40.4	44.1	0.0	44.1	4.0	40.0	0.0	40.0	4.5	48.6
East: Ruakura Road East													
1	0.014	64.5	1.000	5.2	5.7	0.0	5.7	1.7	4.0	0.0	4.0	0.4	6.0
2	0.976	20.6	1.000	33.8	46.0	34.7	80.7	5.1	75.6	2.4	73.2	0.0	80.7
3	0.752	20.6	1.000	33.8	43.8	2.3	46.1	5.1	41.0	0.4	40.6	0.0	46.1
4	0.697	20.6	1.000	33.8	43.4	0.9	44.3	4.5	39.8	0.1	39.7	3.0	47.3
North: Wairere Drive North													
1	0.203	77.6	1.000	1.8	2.3	0.0	2.3	1.3	1.1	0.0	1.1	0.4	2.7
2	0.461	29.0	1.000	27.0	33.7	0.0	33.7	4.4	29.3	0.0	29.3	2.1	35.8
3	0.480	29.0	1.000	27.0	33.9	0.0	33.9	4.4	29.5	0.0	29.5	2.1	36.0
4	0.505	13.1	1.000	40.4	48.2	0.0	48.2	4.4	43.8	0.0	43.8	6.3	54.6
West: Ruakura Road West													
1	0.400	60.7	1.000	6.5	9.1	0.0	9.1	2.5	6.8	0.0	6.8	0.4	9.5
2	0.532	18.7	1.000	35.4	42.5	0.0	42.5	4.8	37.7	0.0	37.7	0.0	42.5
3	0.750	18.7	1.000	35.4	45.4	2.1	47.5	5.1	42.4	0.4	42.0	0.0	47.5
4	0.933	18.7	1.000	35.4	46.3	20.1	66.4	4.6	61.8	1.4	60.4	3.1	69.5

Delay (seconds/veh)

SIDRA Standard Delay Model is used. Control Delay is the sum of Stop-line Delay and Geometric Delay.
dm: Minimum delay for gap acceptance cases
dSL: Stop-line delay (=d1+d2)
dn: Average stop-start delay for all vehicles queued and unqueued
dq: Queuing delay (the part of the stop-line delay that includes stopped delay and queue move-up delay)
dqm: Queue move-up delay
di: Stopped delay (stopped (idling) time at near-zero speed)
dig: Geometric delay
dic: Control delay

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Lane Queues
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

BACK OF QUEUE (VEHICLES)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Ovrfl. Queue No	Back of Queue (veh) Nb1	Nb2	Nb	95%	Queue Stor. Ratio Av.	Queue Stor. Ratio 95%	Prob. Block %	Prob. SL Ov. %
South: Wairere Drive South												
1	0.180	66.4	1.000	0.0	2.2	0.0	2.2	3.7	0.22	0.37	NA	0.0
2	0.583	29.0	1.000	0.0	8.3	0.0	8.3	13.5	0.06	0.10	0.0	NA
3	0.678	29.0	1.000	0.0	10.5	0.0	10.5	17.1	0.08	0.12	0.0	NA
4	0.019	13.1	1.000	0.0	0.1	0.0	0.1	0.2	0.01	0.01	NA	0.0
East: Ruakura Road East												
1	0.014	64.5	1.000	0.0	0.2	0.0	0.2	0.4	0.06	0.09	NA	0.0
2	0.976	20.6	1.000	3.3	11.6	4.4	16.0	26.0	0.17	0.27	0.0	NA
3	0.752	20.6	1.000	0.2	8.0	0.3	8.3	13.5	0.09	0.14	0.0	NA
4	0.697	20.6	1.000	0.1	7.5	0.1	7.6	12.4*	1.07	1.74	NA	56.0
North: Wairere Drive North												
1	0.203	77.6	1.000	0.0	1.8	0.0	1.8	2.9	0.20	0.33	NA	0.0
2	0.461	29.0	1.000	0.0	6.6	0.0	6.6	10.8	0.08	0.14	0.0	NA
3	0.480	29.0	1.000	0.0	6.9	0.0	6.9	11.2	0.09	0.14	0.0	NA
4	0.505	13.1	1.000	0.0	3.7	0.0	3.7	6.0	0.29	0.47	NA	0.0
West: Ruakura Road West												
1	0.400	60.7	1.000	0.0	4.5	0.0	4.5	7.4*	1.09	1.78	NA	58.0
2	0.532	18.7	1.000	0.0	4.8	0.0	4.8	7.9	0.09	0.15	0.0	NA
3	0.750	18.7	1.000	0.2	7.9	0.3	8.1	13.3	0.15	0.25	0.0	NA
4	0.933	18.7	1.000	1.7	9.4	2.3	11.7	19.2*	1.54	2.51	NA	91.6

* Short lane queue distance includes vehicles queued into the adjacent lane.

BACK OF QUEUE (DISTANCE)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Ovrfl. Queue No	Back of Queue (m) Nb1	Nb2	Nb	95%	Queue Stor. Ratio Av.	Queue Stor. Ratio 95%	Prob. Block %	Prob. SL Ov. %
South: Wairere Drive South												
1	0.180	66.4	1.000	0.0	16.1	0.0	16.1	26.2	0.22	0.37	NA	0.0
2	0.583	29.0	1.000	0.0	61.1	0.0	61.1	99.8	0.06	0.10	0.0	NA
3	0.678	29.0	1.000	0.0	77.3	0.0	77.3	126.2	0.08	0.12	0.0	NA
4	0.019	13.1	1.000	0.0	0.8	0.0	0.8	1.3	0.01	0.01	NA	0.0
East: Ruakura Road East												
1	0.014	64.5	1.000	0.0	1.5	0.0	1.5	2.5	0.06	0.09	NA	0.0
2	0.976	20.6	1.000	24.4	84.3	32.2	116.5	190.1	0.17	0.27	0.0	NA
3	0.752	20.6	1.000	1.5	58.2	2.3	60.5	98.8	0.09	0.14	0.0	NA

4	0.697	20.6	1.000	0.6	54.0	0.9	54.9	89.6*	1.07	1.74	NA	56.0
North: Wairere Drive North												
1	0.203	77.6	1.000	0.0	12.8	0.0	12.8	20.9	0.20	0.33	NA	0.0
2	0.461	29.0	1.000	0.0	48.7	0.0	48.7	79.5	0.08	0.14	0.0	NA
3	0.480	29.0	1.000	0.0	50.8	0.0	50.8	82.9	0.09	0.14	0.0	NA
4	0.505	13.1	1.000	0.0	26.7	0.0	26.7	43.6	0.29	0.47	NA	0.0
West: Ruakura Road West												
1	0.400	60.7	1.000	0.0	32.7	0.0	32.7	53.3*	1.09	1.78	NA	58.0
2	0.532	18.7	1.000	0.0	34.9	0.0	34.9	56.9	0.09	0.15	0.0	NA
3	0.750	18.7	1.000	1.3	56.8	2.0	58.8	96.0	0.15	0.25	0.0	NA
4	0.933	18.7	1.000	12.0	68.1	16.8	84.9	138.5*	1.54	2.51	NA	91.6

* Short lane queue distance includes vehicles queued into the adjacent lane.

OTHER QUEUE RESULTS (VEHICLES)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Ovrfl. Queue No	Queue Start Grn Nr	Queue Start Grn 95%	Cyc-Av. Queue Nc	Cyc-Av. Queue 95%
South: Wairere Drive South								
1	0.180	66.4	1.000	0.0	2.0	3.2	0.3	0.7
2	0.583	29.0	1.000	0.0	6.9	11.2	2.9	6.1
3	0.678	29.0	1.000	0.0	8.4	13.7	3.7	7.8
4	0.019	13.1	1.000	0.0	0.1	0.2	0.0	0.1
East: Ruakura Road East								
1	0.014	64.5	1.000	0.0	0.2	0.4	0.0	0.1
2	0.976	20.6	1.000	3.3	12.7	20.7	8.0	16.8
3	0.752	20.6	1.000	0.2	7.0	11.4	3.3	7.0
4	0.697	20.6	1.000	0.1	6.5	10.6	3.0	6.3
North: Wairere Drive North								
1	0.203	77.6	1.000	0.0	1.5	2.4	0.2	0.4
2	0.461	29.0	1.000	0.0	5.7	9.3	2.3	4.9
3	0.480	29.0	1.000	0.0	5.9	9.7	2.4	5.1
4	0.505	13.1	1.000	0.0	3.5	5.6	1.6	3.4
West: Ruakura Road West								
1	0.400	60.7	1.000	0.0	3.5	5.7	0.8	1.7
2	0.532	18.7	1.000	0.0	4.4	7.2	2.0	4.1
3	0.750	18.7	1.000	0.2	6.9	11.3	3.3	7.0
4	0.933	18.7	1.000	1.7	9.6	15.7	5.5	11.5

OTHER QUEUE RESULTS (DISTANCE)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	Ovrfl. Queue No	Queue Start Grn Nr	Queue Start Grn 95%	Cyc-Av. Queue Nc	Cyc-Av. Queue 95%
South: Wairere Drive South								
1	0.180	66.4	1.000	0.0	14.1	23.0	2.4	5.0
2	0.583	29.0	1.000	0.0	50.8	82.9	21.7	45.4
3	0.678	29.0	1.000	0.0	62.1	101.4	27.5	57.4
4	0.019	13.1	1.000	0.0	0.8	1.3	0.3	0.7
East: Ruakura Road East								
1	0.014	64.5	1.000	0.0	1.5	2.5	0.2	0.5
2	0.976	20.6	1.000	24.4	92.5	150.9	58.7	122.7
3	0.752	20.6	1.000	1.5	51.0	83.2	24.4	50.9
4	0.697	20.6	1.000	0.6	46.8	76.4	21.9	45.7
North: Wairere Drive North								
1	0.203	77.6	1.000	0.0	10.7	17.5	1.2	2.5
2	0.461	29.0	1.000	0.0	42.2	68.9	17.3	36.1
3	0.480	29.0	1.000	0.0	43.7	71.4	18.0	37.7
4	0.505	13.1	1.000	0.0	25.0	40.8	11.6	24.3
West: Ruakura Road West								
1	0.400	60.7	1.000	0.0	25.3	41.2	5.7	12.0
2	0.532	18.7	1.000	0.0	31.8	52.0	14.2	29.6
3	0.750	18.7	1.000	1.3	50.2	81.9	24.2	50.5
4	0.933	18.7	1.000	12.0	69.3	113.2	39.7	83.0

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Lane Queue Percentiles
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

LANE QUEUE PERCENTILES (VEHICLES)

Lane No.	Deg. Satn x	Percentile Back of Queue (veh) 50%	70%	85%	90%	95%	98%	100%
South: Wairere Drive South								
1	0.180	2.2	2.8	3.3	3.5	3.7	3.8	3.9

Lane No.	Deg. Satn x	50%	70%	85%	90%	95%	98%	100%
2	0.583	8.3	10.3	12.1	12.8	13.5	14.0	14.3
3	0.678	10.5	13.0	15.3	16.2	17.1	17.7	18.1
4	0.019	0.1	0.1	0.2	0.2	0.2	0.2	0.2
East: Ruakura Road East								
1	0.014	0.2	0.3	0.3	0.3	0.4	0.4	0.4
2	0.976	16.0	19.8	23.3	24.6	26.0	26.9	27.5
3	0.752	8.3	10.3	12.1	12.8	13.5	14.0	14.3
4	0.697	7.6*	9.4*	11.1*	11.7*	12.4*	12.8*	13.1*
North: Wairere Drive North								
1	0.203	1.8	2.2	2.6	2.8	2.9	3.0	3.1
2	0.461	6.6	8.2	9.6	10.2	10.8	11.1	11.4
3	0.480	6.9	8.5	10.1	10.6	11.2	11.6	11.9
4	0.505	3.7	4.6	5.4	5.7	6.0	6.2	6.4
West: Ruakura Road West								
1	0.400	4.5*	5.6*	6.6*	7.0*	7.4*	7.6*	7.8*
2	0.532	4.8	6.0	7.1	7.5	7.9	8.1	8.3
3	0.750	8.1	10.1	11.9	12.6	13.3	13.7	14.1
4	0.933	11.7*	14.6*	17.2*	18.1*	19.2*	19.8*	20.3*

* Short lane queue distance includes vehicles queued into the adjacent lane.

LANE QUEUE PERCENTILES (DISTANCE)

Lane No.	Deg. Satn x	Percentile Back of Queue (metres) 50%	70%	85%	90%	95%	98%	100%
South: Wairere Drive South								
1	0.180	16.1	19.9	23.5	24.8	26.2	27.1	27.7
2	0.583	61.1	75.8	89.3	94.4	99.8	103.1	105.5
3	0.678	77.3	95.9	113.0	119.4	126.2	130.4	133.4
4	0.019	0.8	1.0	1.2	1.2	1.3	1.3	1.4
East: Ruakura Road East								
1	0.014	1.5	1.9	2.2	2.4	2.5	2.6	2.6
2	0.976	116.5	144.4	170.2	179.8	190.1	196.5	200.9
3	0.752	60.5	75.1	88.5	93.5	98.8	102.1	104.4
4	0.697	54.9*	68.0*	80.2*	84.7*	89.6*	92.6*	94.7*
North: Wairere Drive North								
1	0.203	12.8	15.8	18.7	19.7	20.9	21.6	22.0
2	0.461	48.7	60.4	71.2	75.2	79.5	82.2	84.0
3	0.480	50.8	63.0	74.3	78.5	82.9	85.7	87.7
4	0.505	26.7	33.2	39.1	41.3	43.6	45.1	46.1
West: Ruakura Road West								
1	0.400	32.7*	40.5*	47.7*	50.4*	53.3*	55.1*	56.3*
2	0.532	34.9	43.3	51.0	53.9	56.9	58.9	60.2
3	0.750	58.8	73.0	86.0	90.8	96.0	99.3	101.5
4	0.933	84.9*	105.3*	124.0*	131.1*	138.5*	143.2*	146.4*

* Short lane queue distance includes vehicles queued into the adjacent lane.

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Lane Stops
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

Lane No.	Deg. Satn x	% Arv During Green	Prog. Factor	-- Effective Stop Rate -- he1	he2	Geom. hig	Overall h	Total Stops H	Queue Move-up Rate hqm	Total Queue Move-ups Hqm	Prop. Queued pq	Aver. Num. of Cycles to Depart
South: Wairere Drive South												
1	0.180	66.4	1.000	0.32	0.00	0.04	0.36	74.1	0.00	0.0	0.40	0.40
2	0.583	29.0	1.000	0.78	0.00	0.00	0.78	233.5	0.00	0.0	0.91	0.91
3	0.678	29.0	1.000	0.81	0.00	0.00	0.81	299.1	0.00	0.0	0.94	0.94
4	0.019	13.1	1.000	0.58	0.00	0.05	0.64	2.5	0.00	0.0	0.89	0.89
East: Ruakura Road East												
1	0.014	64.5	1.000	0.27	0.00	0.05	0.31	6.8	0.00	0.0	0.37	0.37
2	0.976	20.6	1.000	0.86	0.48	0.00	1.33	478.5	0.60	217.3	1.00	1.60
3	0.752	20.6	1.000	0.83	0.08	0.00	0.91	237.3	0.10	25.0	0.99	1.09
4	0.697	20.6	1.000	0.83	0.03	0.01	0.86	211.5	0.04	10.4	0.98	1.03
North: Wairere Drive North												
1	0.203	77.6	1.000	0.23	0.00	0.05	0.28	74.6	0.00	0.0	0.28	0.28
2	0.461	29.0	1.000	0.73	0.00	0.04	0.77	193.2	0.00	0.0	0.87	0.87
3	0.480	29.0	1.000	0.74	0.00	0.04	0.78	201.5	0.00	0.0	0.88	0.88
4	0.505	13.1	1.000	0.78	0.00	0.01	0.79	94.8	0.00	0.0	0.98	0.98
West: Ruakura Road West												
1	0.400	60.7	1.000	0.45	0.00	0.03	0.48	152.1	0.00	0.0	0.54	0.54
2	0.532	18.7	1.000	0.76	0.00	0.00	0.76	127.1	0.00	0.0	0.94	0.94
3	0.750	18.7	1.000	0.84	0.08	0.00	0.91	231.5	0.10	24.2	1.00	1.10
4	0.933	18.7	1.000	0.84	0.31	0.00	1.15	342.9	0.47	141.2	1.00	1.47

hig is the average value for all movements in a shared lane
hqm is average queue move-up rate for all vehicles queued and unqueued

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Flow Rates

Origin-Destination Flow Rates (Total)
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

TOTAL FLOW RATES for All Movement Classes (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Flow Rate	204.0	668.0	4.0	876.0
%HV (all designations)	2.0	5.0	0.0	4.3

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Flow Rate	22.0	620.0	246.0	888.0
%HV (all designations)	0.0	4.0	3.0	3.6

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Flow Rate	266.0	510.0	120.0	896.0
%HV (all designations)	2.0	5.0	3.0	3.8

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Flow Rate	314.0	420.0	298.0	1032.0
%HV (all designations)	3.0	3.0	3.0	3.0

Peak Flow factor value of 100% has been used for all movements since equal values of Unit Time for Volumes and Peak Flow Period were specified in the Volumes dialog.

Flow rates shown above are Arrival Flow Rates (veh/h) based on the following input specifications:
Unit Time for Volumes = 30 minutes
Peak Flow Period = 30 minutes
Effects of Volume Factors (Peak Flow Factor, Flow Scale, Growth Rate) are included.
Arrival Flow Rates may be less than Demand Flow Rates if capacity constraint applies in network analysis.

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Origin-Destination Flow Rates by Movement Class
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

FLOW RATES for Light Vehicles (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Flow Rate	199.9	634.6	4.0	838.5
Mov Class %	98.0	95.0	100.0	95.7
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Flow Rate	22.0	595.2	238.6	855.8
Mov Class %	100.0	96.0	97.0	96.4
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Flow Rate	260.7	484.5	116.4	861.6
Mov Class %	98.0	95.0	97.0	96.2
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Flow Rate	304.6	407.4	289.1	1001.0
Mov Class %	97.0	97.0	97.0	97.0
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

FLOW RATES for Heavy Vehicles (veh/h)

From SOUTH To:	W	N	E

Turn:	L2	T1	R2	TOT
Flow Rate	4.1	33.4	0.0	37.5
Mov Class %	2.0	5.0	0.0	4.3
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Flow Rate	0.0	18.6	7.4	26.0
Mov Class %	0.0	3.0	3.0	2.9
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Flow Rate	5.3	25.5	3.6	34.4
Mov Class %	2.0	5.0	3.0	3.8
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Flow Rate	9.4	8.4	8.9	26.8
Mov Class %	3.0	2.0	3.0	2.6
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

FLOW RATES for Buses (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Flow Rate	0.0	0.0	0.0	0.0
Mov Class %	0.0	0.0	0.0	0.0
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Flow Rate	0.0	6.2	0.0	6.2
Mov Class %	0.0	1.0	0.0	0.7
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Flow Rate	0.0	0.0	0.0	0.0
Mov Class %	0.0	0.0	0.0	0.0
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Flow Rate	0.0	4.2	0.0	4.2
Mov Class %	0.0	1.0	0.0	0.4
Flow Scale	1.00	1.00	1.00	-
Peak Flow Factor	1.00	1.00	1.00	-
Residual Demand	0.0	0.0	0.0	0.0

Peak Flow factor value of 100% has been used for all movements since equal values of
Unit Time for Volumes and Peak Flow Period were specified in the Volumes dialog.

Flow rates shown above are Arrival Flow Rates (veh/h) based on the following input specifications:
Unit Time for Volumes = 30 minutes
Peak Flow Period = 30 minutes
Effects of Volume Factors (Peak Flow Factor, Flow Scale, Growth Rate) are included.
Arrival Flow Rates may be less than Demand Flow Rates if capacity constraint applies in
network analysis.

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Lane Flow Rates
Site: TS71 2024AM-Existing (30/10)

Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

LANE FLOW RATES AT STOP LINE (veh/h)

From SOUTH To:	W	N	E	
Turn:	L2	T1	R2	TOT
Lane 1				

LV	199.9	*	*	199.9
HV	4.1	*	*	4.1
Total	204.0	*	*	204.0
Lane 2				
LV	*	285.4	*	285.4
HV	*	15.0	*	15.0
Total	*	300.4	*	300.4
Lane 3				
LV	*	349.2	*	349.2
HV	*	18.4	*	18.4
Total	*	367.6	*	367.6
Lane 4				
LV	*	*	4.0	4.0
Total	*	*	4.0	4.0
Approach	204.0	668.0	4.0	876.0

From EAST To:	S	W	N	
Turn:	L2	T1	R2	TOT
Lane 1				
LV	22.0	*	*	22.0
Total	22.0	*	*	22.0
Lane 2				
LV	*	344.8	*	344.8
HV	*	10.8	*	10.8
B	*	3.6	*	3.6
Total	*	359.2	*	359.2
Lane 3				
LV	*	250.4	*	250.4
HV	*	7.8	*	7.8
B	*	2.6	*	2.6
Total	*	260.8	*	260.8
Lane 4				
LV	*	*	238.6	238.6
HV	*	*	7.4	7.4
Total	*	*	246.0	246.0
Approach	22.0	620.0	246.0	888.0

From NORTH To:	E	S	W	
Turn:	L2	T1	R2	TOT
Lane 1				
LV	260.7	*	*	260.7
HV	5.3	*	*	5.3
Total	266.0	*	*	266.0
Lane 2				
LV	*	237.9	*	237.9
HV	*	12.5	*	12.5
Total	*	250.5	*	250.5
Lane 3				
LV	*	246.6	*	246.6
HV	*	13.0	*	13.0
Total	*	259.5	*	259.5
Lane 4				
LV	*	*	116.4	116.4
HV	*	*	3.6	3.6
Total	*	*	120.0	120.0
Approach	266.0	510.0	120.0	896.0

From WEST To:	N	E	S	
Turn:	L2	T1	R2	TOT
Lane 1				
LV	304.6	*	*	304.6
HV	9.4	*	*	9.4
Total	314.0	*	*	314.0
Lane 2				
LV	*	161.4	*	161.4
HV	*	3.3	*	3.3
B	*	1.7	*	1.7
Total	*	166.4	*	166.4
Lane 3				
LV	*	246.0	*	246.0
HV	*	5.1	*	5.1
B	*	2.5	*	2.5
Total	*	253.6	*	253.6
Lane 4				
LV	*	*	289.1	289.1
HV	*	*	8.9	8.9
Total	*	*	298.0	298.0
Approach	314.0	420.0	298.0	1032.0

* Movement not allocated to the lane

EXIT LANE FLOW RATES

Movement Class:	LV	HV	B	TOT
Exit: SOUTH				
Lane: 1	259.9	12.5	*	272.5
Lane: 2	535.6	21.9	*	557.5
Total	795.6	34.4	*	830.0
Exit: EAST				
Lane: 1	422.0	8.6	1.7	432.4
Lane: 2	250.0	5.1	2.5	257.6
Total	672.1	13.7	4.2	690.0

Exit: NORTH				
Lane: 1	590.0	24.4	*	614.4
Lane: 2	587.8	25.8	*	613.6
Total	1177.8	50.2	*	1228.0
Exit: WEST				
Lane: 1	544.8	14.9	3.6	563.2
Lane: 2	366.8	11.4	2.6	380.8
Total	911.5	26.3	6.2	944.0

* Movement not allocated to the lane

DOWNSTREAM LANE FLOW RATES FOR EXIT ROADS

Movement Class:	LV	HV	B	TOT
Exit: SOUTH				
Lane: 1	259.9	12.5	*	272.5
Lane: 2	535.6	21.9	*	557.5
Total	795.6	34.4	*	830.0
Exit: EAST				
Lane: 1	422.0	8.6	1.7	432.4
Lane: 2	250.0	5.1	2.5	257.6
Total	672.1	13.7	4.2	690.0
Exit: NORTH				
Lane: 1	590.0	24.4	*	614.4
Lane: 2	587.8	25.8	*	613.6
Total	1177.8	50.2	*	1228.0
Exit: WEST				
Lane: 1	544.8	14.9	3.6	563.2
Lane: 2	366.8	11.4	2.6	380.8
Total	911.5	26.3	6.2	944.0

* Movement not allocated to the lane

Peak Flow factor value of 100% has been used for all movements since equal values of Unit Time for Volumes and Peak Flow Period were specified in the Volumes dialog.

Flow rates shown above are Arrival Flow Rates (veh/h) based on the following input specifications:
Unit Time for Volumes = 30 minutes
Peak Flow Period = 30 minutes
Effects of Volume Factors (Peak Flow Factor, Flow Scale, Growth Rate) are included.
Arrival Flow Rates may be less than Demand Flow Rates if capacity constraint applies in network analysis.

Go to Table Links (Top)

Other

Parameter Settings Summary
Site: TS71 2024AM-Existing (30/10)

```
Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)


* Basic Parameters:
  Intersection Type: Signalised - Fixed Time Isolated
  Driving on the left-hand side of the road
  Input data specified in Metric units
  Model Defaults: Standard Left
  Peak Flow Period (for performance): 30 minutes
  Unit time (for volumes): 30 minutes.
  SIDRA Standard Delay model used
  SIDRA Standard Queue model used
  Level of Service based on: Delay (SIDRA)
  Queue percentile: 95%
```

Go to Table Links (Top)

Diagnostics
Site: TS71 2024AM-Existing (30/10)

```
Site ID: 71
Signals - Fixed-Time Isolated   Cycle Time = 107 sec (Site User-Given Phase Times)

Main (Timing-Capacity) Iterations for Signals

  Site Model Variability Index (Iterations 3 to N):   0.0%
  Number of Iterations:  2 (Maximum: 10)
  Largest difference in Movement Effective Green Times in the last two Main Iterations:  0 secs
    (stopping condition: 0 secs)

Lane Flow-Capacity Iterations:

  Flow-Capacity Iteration Variability Index (Iterations 3 to N):   0.7%
  Number of Iterations: 3 (Maximum: 10)
  For Signals, the results for "Lane Flow-Capacity Iterations" are reported
  for the last Main (Timing-Capacity) Iteration.

Other Diagnostic Messages (if any):
```

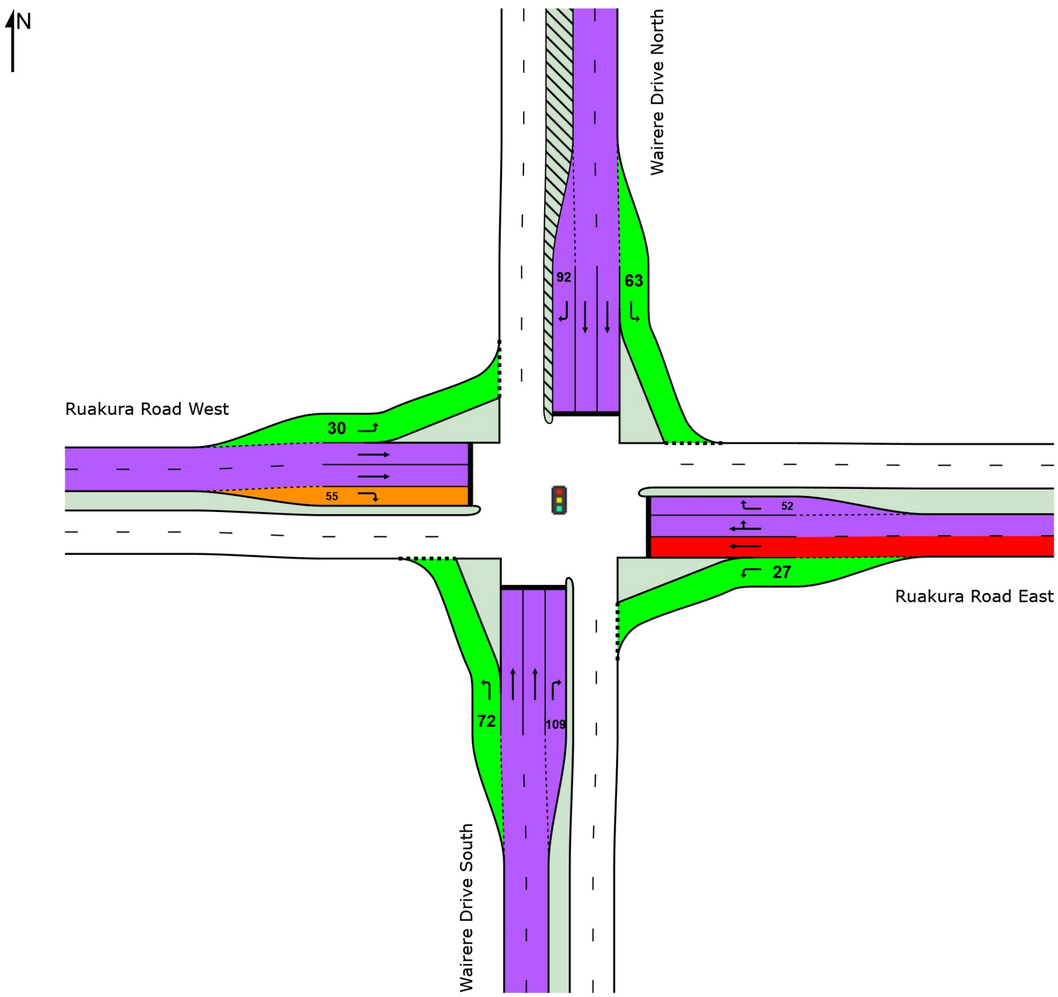
LANE LEVEL OF SERVICE

Lane Level of Service

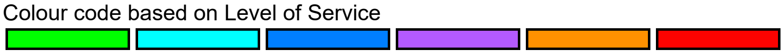
Site: 71 [TS71 2024AM-Existing (30/10)]

Wairere Drive/Ruakura Road
20243010 17:00-17:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 107 seconds (Site User-Given Phase Times)

	Approaches				Intersection
	South	East	North	West	
LOS	C	E	C	D	D



Colour code based on Level of Service



Site Level of Service (LOS) Method: Delay (SIDRA). Site LOS Method is specified in the Parameter Settings dialog (Site tab).
NA (TWSC): Level of Service is not defined for major road approaches or the intersection as a whole for Two-Way Sign Control (HCM LOS rule).
SIDRA Standard Delay Model is used. Control Delay includes Geometric Delay.

PHASING SUMMARY

Site: 71 [TS71 2024AM-Existing (30/10)]

Wairere Drive/Ruakura Road
20243010 17:00-17:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 107 seconds (Site User-Given Phase Times)

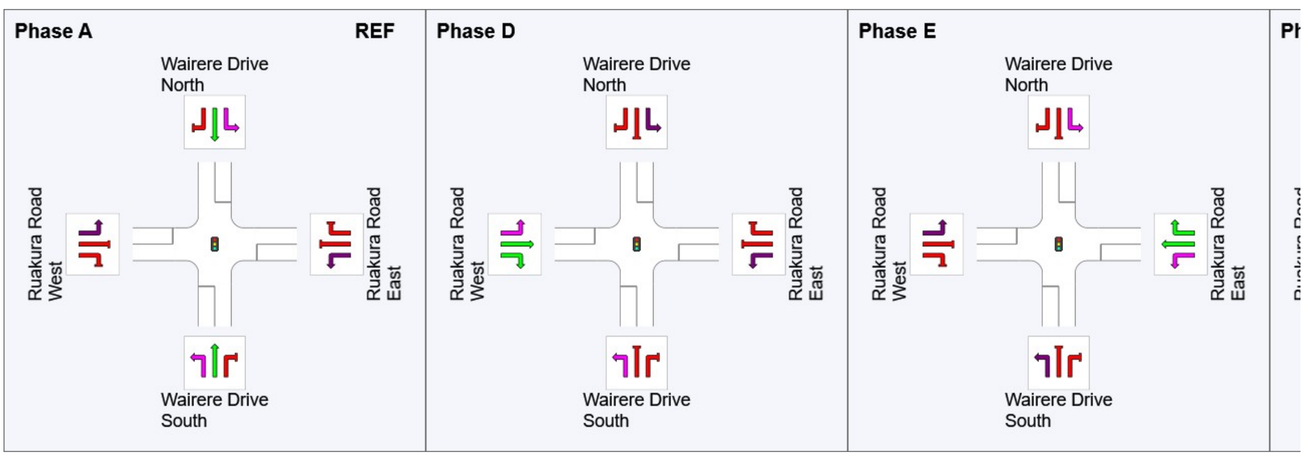
Timings based on settings in the Site Phasing & Timing dialog
Phase Times specified by the user
Phase Sequence: Phase
Reference Phase: Phase A
Input Phase Sequence: A, D, E, F
Output Phase Sequence: A, D, E, F

PHASE TIMING SUMMARY

Phase	A	D	E	F
Phase Change Time (sec)	0	36	61	88
Green Time (sec)	31	20	22	14
Phase Time (sec)	36	25	27	19
Phase Split	34%	23%	25%	18%

See the Phase Information section in the Detailed Output report for more detailed information including input values of Yellow Time and All-Red Time, and information on any adjustments to Intergreen Time, Phase Time and Green Time values in cases of Pedestrian Actuation, Phase Actuation and Phase Frequency values (user-specified or implied) less than 100%.

OUTPUT PHASE SEQUENCE



REF: Reference Phase
VAR: Variable Phase

Normal Movement
Permitted/Opposed
Slip/Bypass-Lane Movement
Opposed Slip/Bypass-Lane

Stopped Movement	Turn On Red
Other Movement Class (MC) Running	Undetected Movement
Mixed Running & Stopped MCs	Continuous Movement
Other Movement Class (MC) Stopped	Phase Transition Applied

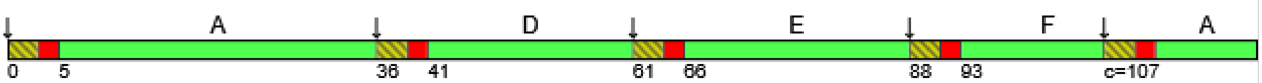
MOVEMENT TIMING

Site: 71 [TS71 2024AM-Existing (30/10)]

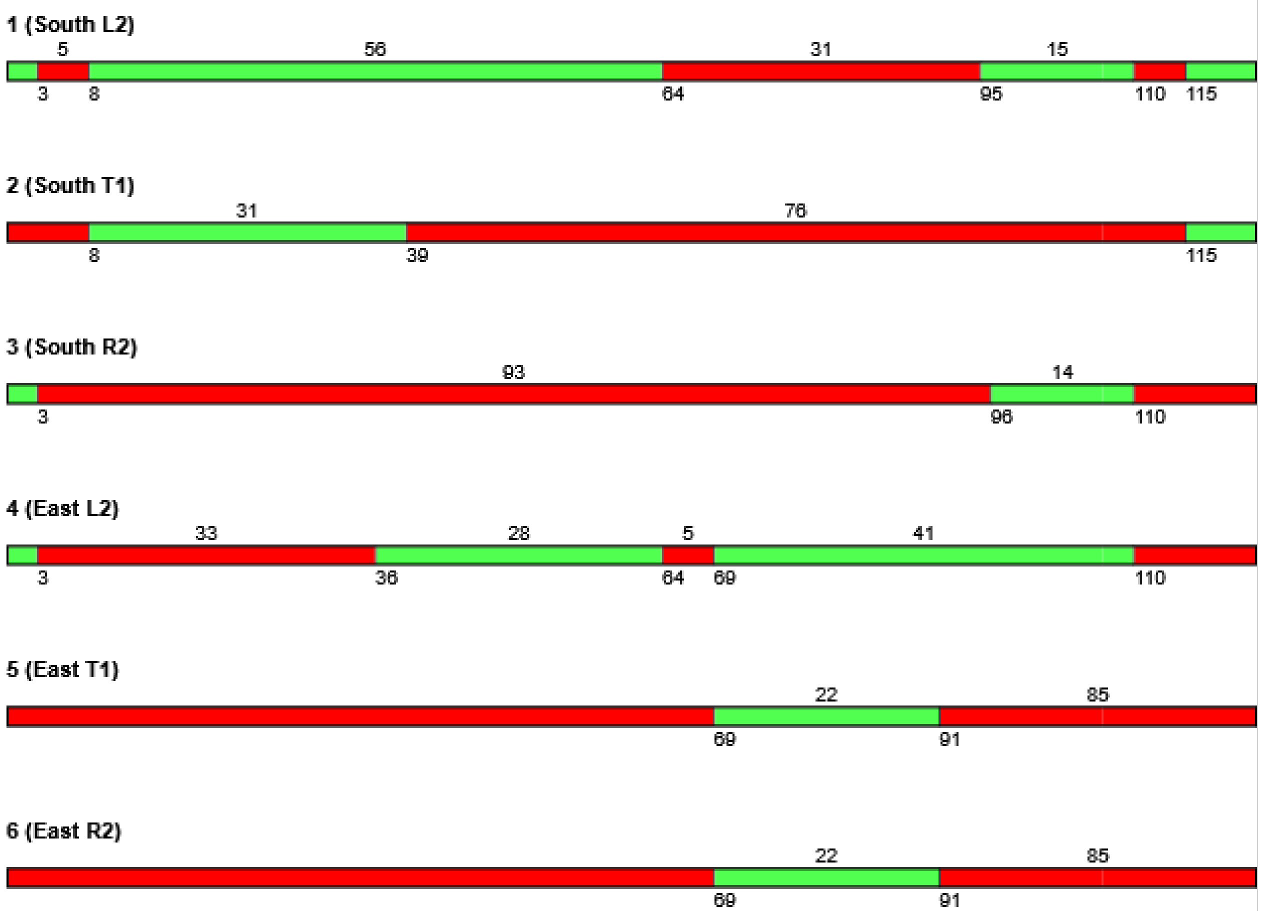
Wairere Drive/Ruakura Road
20243010 17:00-17:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 107 seconds (Site User-Given Phase Times)

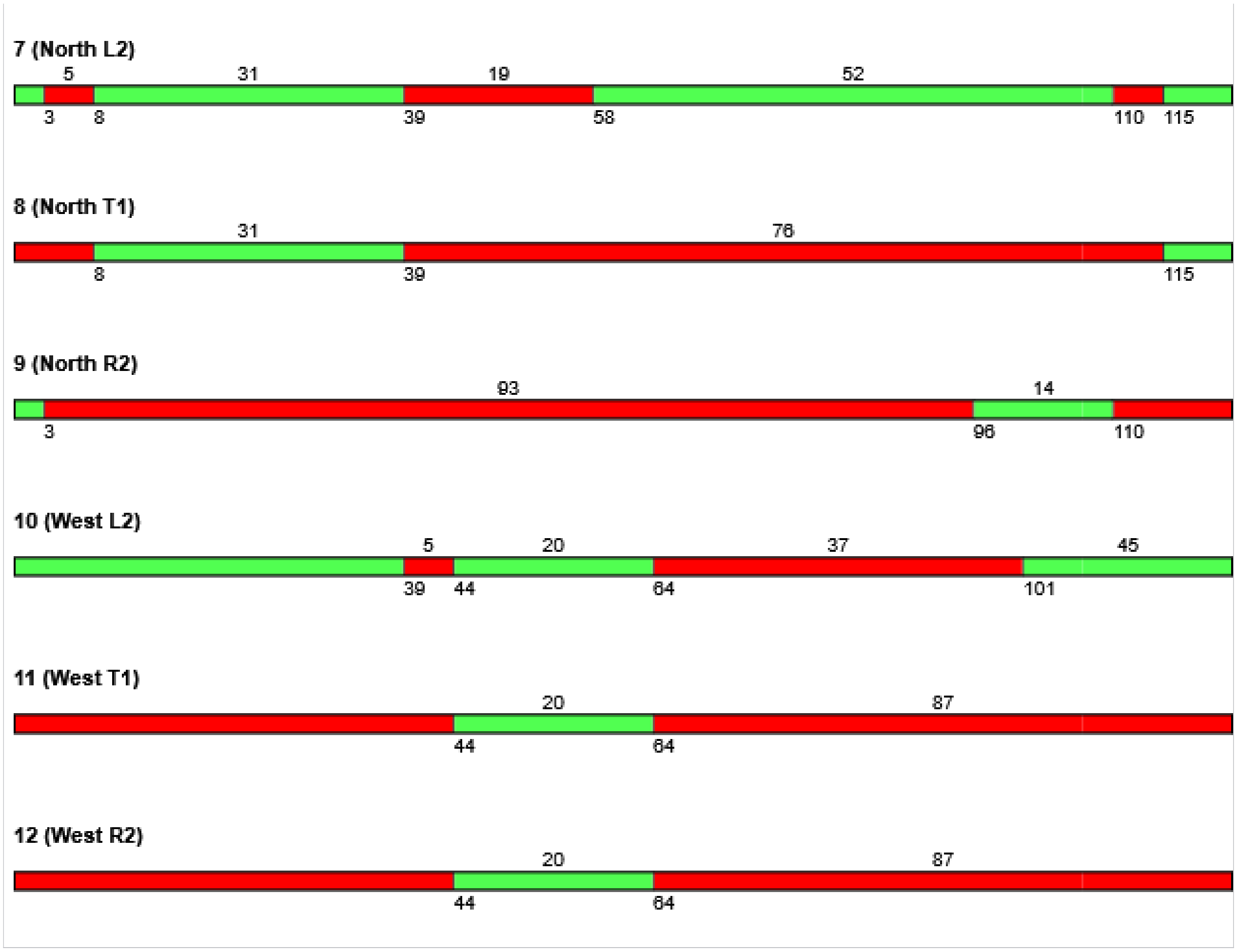
Timings based on settings in the Site Phasing & Timing dialog
Phase Times specified by the user
Phase Sequence: Phase
Reference Phase: Phase A
Input Phase Sequence: A, D, E, F
Output Phase Sequence: A, D, E, F

DISPLAYED SIGNAL TIMING - PHASES



EFFECTIVE SIGNAL TIMING - MOVEMENTS



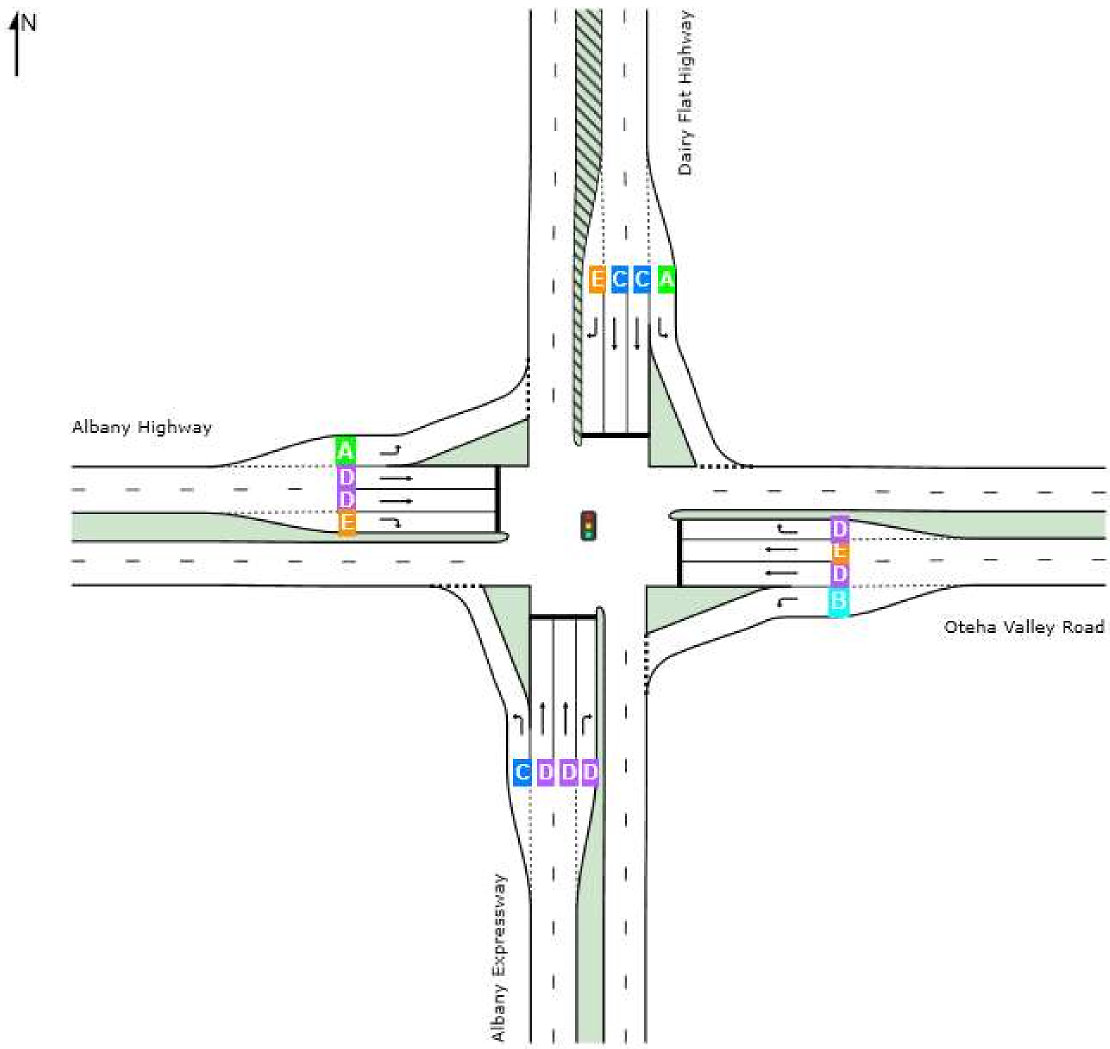


7 (North L2)
5
31
19
52
3
8
39
58
110
115
8 (North T1)
31
76
8
39
115
9 (North R2)
93
14
3
96
110
10 (West L2)
5
20
37
45
39
44
64
101
11 (West T1)
20
87
44
64
12 (West R2)
20
87
44
64

Mitigation of the base case

20242409 08:15-08:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 101 seconds (Site User-Given Phase Times)

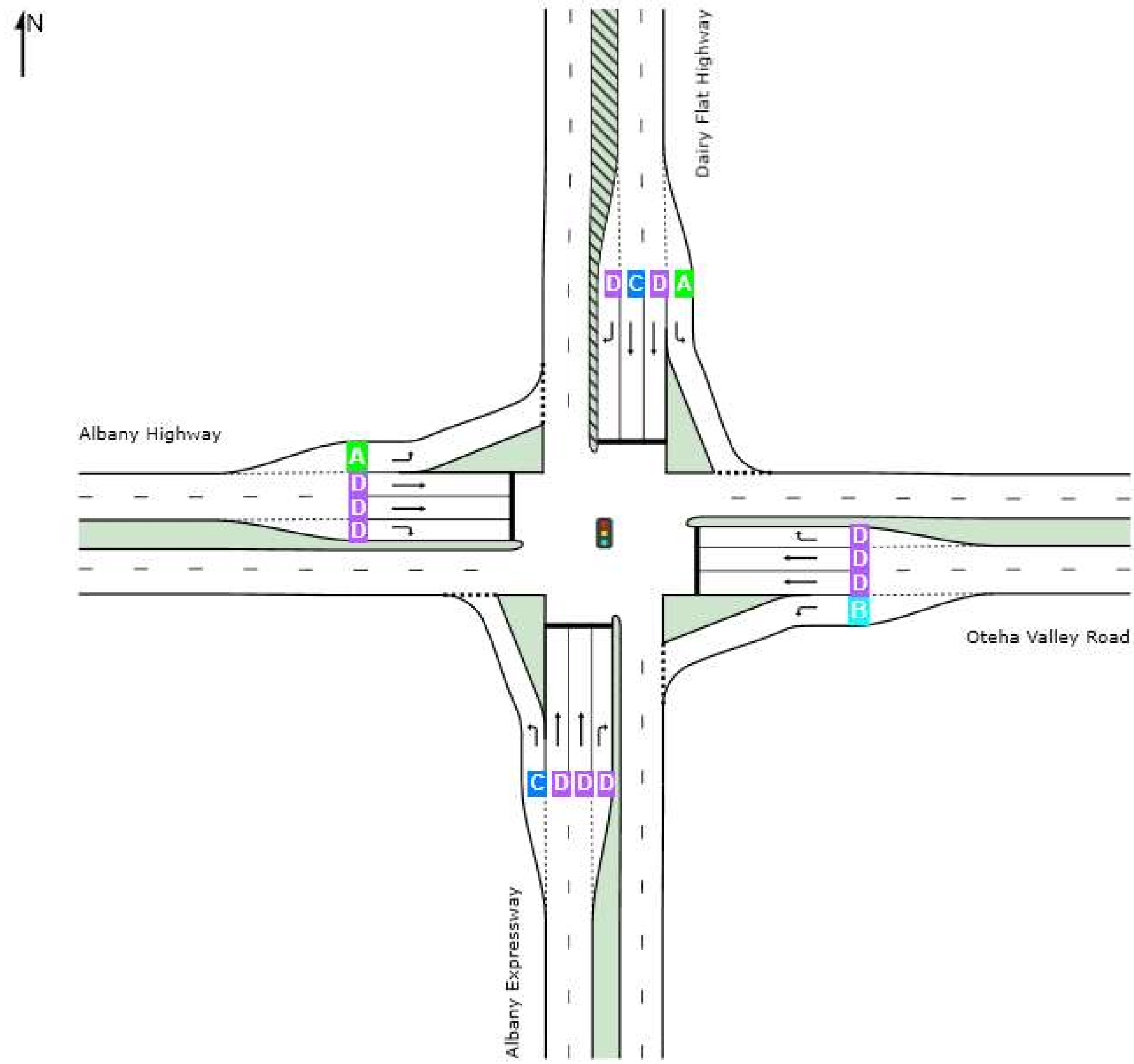
	Approaches				Intersection
	South	East	North	West	
LOS	D	D	D	C	D



Current LoS of the Albany Intersection

20242409 08:15-08:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated Cycle Time = 101 seconds (Site User-Given Phase Times)

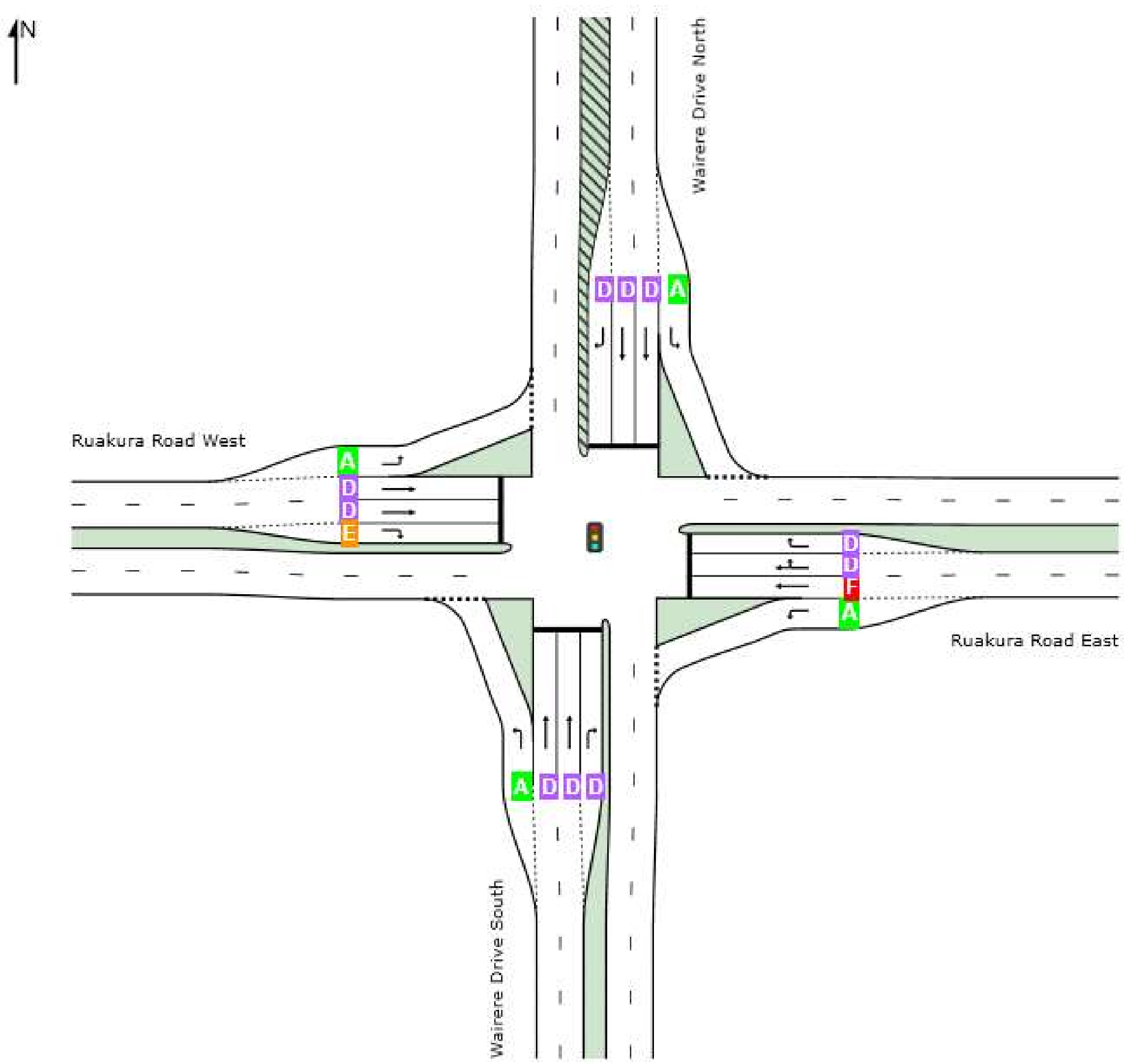
	Approaches				Intersection
	South	East	North	West	
LOS	D	D	D	C	D



Revised LoS of the Albany Intersection to target LoS 'D'

20243010 17:00-17:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 107 seconds (Site User-Given Phase Times)

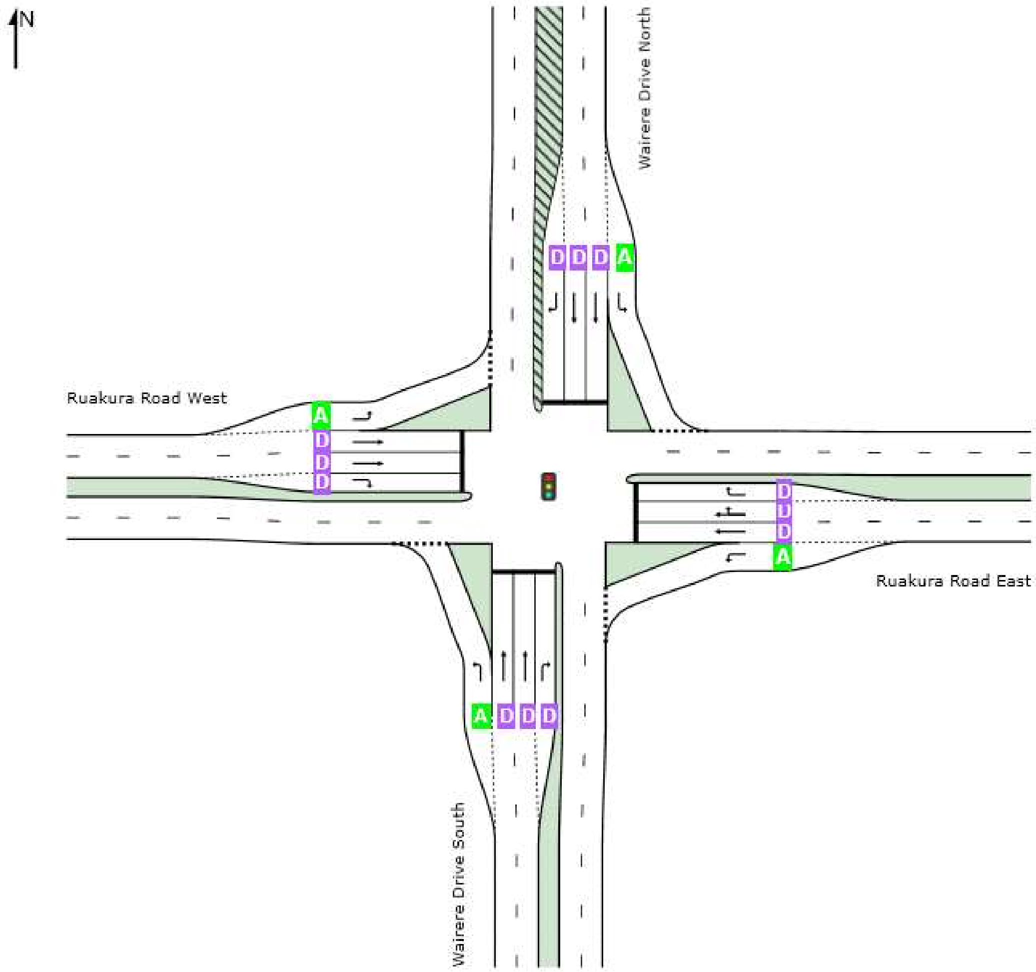
	Approaches				Intersection
	South	East	North	West	
LOS	C	E	C	D	D



Current LoS of the Ruakura Intersection

20243010 17:00-17:30
Existing Layout
Site Category: (None)
Signals - Fixed Time Isolated   Cycle Time = 106 seconds (Site User-Given Phase Times)

	Approaches				Intersection
	South	East	North	West	
LOS	C	D	C	C	D



Revised LoS of the Ruakura Intersection to target LoS 'D'