

Intelligent Gatelines

WP10 Dissemination Plan



Lead Investigator:



Post-Doc Research Fellow:



07 November 2019

CUBIC



1. Introduction

In this document, the dissemination works carried out by the University of Portsmouth and the project partners are provided. The document starts with the conference papers in section 2. Section 2 also includes talks and poster presentations given by the University of Portsmouth and Cubic Transportation Systems during the Intelligent Transportation Cluster Launch at the University of Portsmouth in June 2019. Planned journal publication is provided in section 3.

2. Conferences

2.1. 2019 INFORMS Annual Meeting Seattle

- **Title:** “Real-time Crowd Prediction and Optimal Configuration of an Intelligent Gateline System Using Queuing Theory”
- **Date:** October 20 - 23, 2019
- **Location:** Washington State Convention Center & Sheraton Seattle Hotel; State: (USA) Washington
- **Authors:**
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- **Abstract:** This research seeks to develop and operationally demonstrate --using the existing knowledge in the field of Queuing Theory, a gateline that is capable of automatically self-reconfiguring to maximise peak throughput while preventing station overcrowding. The proposed technology will be equipped with means to: (1) Identify flow of people within the station environment, and learn to predict the crowds before they arrive at the gateline, (2) reconfigure the direction of individual walkways in a safe and controlled manner, freeing the staff at the gates to engage and support customers. It will inform and aid staff to make operational decisions on gate configuration or temporary station closure, which if sub-optimal, adversely affect network capacity, safety and customer experience.

The operation of this intelligent gateline is modelled as a discrete sequence of events in time. Each event is assumed to occur at a particular instant in time and marks a potential change of states --number of passengers and gateline configuration, in the system. Overhead sensors are used to record in real-time: passengers' ID, timestamps, coordinates within the desired field of view, and passengers' directions. From these captured data, a queue simulation model is developed based on the sensors' recorded distribution of the inter-arrival times, a uniformly distributed service time and the number of available service gates. The minimisation of the overall customers' waiting times will be considered as the objective function of the optimisation model. In order to reduce the mathematical complexity, the convexity of the objective function is established. The objective function being convex, the global optimum is found by computing the minima.

Experimental results are provided for system evaluation. From the output of the simulations (based on real station passenger flow data) it can be concluded that the Gateline efficiency (in terms of passenger throughput) can be increased using Intelligent Gatelines for a typical station with rush hour peaks in the morning and evening. It can also be inferred from the data that a spike in passenger numbers will make Intelligent Gatelines suggest a change in gate direction (one or more walkways) which will reduce queuing and congestion. The simulation runs show that the model developed can yield an optimal configuration of the gateline within a reasonable computational time.

2.2. Operational Research Annual Conference (OR61)

- **Title:** “Optimising passengers’ throughput in an intelligent gateline system”
- **Date:** September 3 - 5, 2019
- **Location:** University of Kent, Sibson Building, Park Wood Rd, Canterbury CT2 7FS
- **Authors:**
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 - [REDACTED], Cubic Transportation Systems Ltd, AFC House, Honeycock Lane, Salfords, Surrey, RH1 5LA, United Kingdom
- **Abstract:** In this work, a mathematical model is developed for predicting the configuration of mainline train and metro stations gateline before passengers travelling through the station reach the service gates. The optimisation model is based on Queueing Systems. A Multi-Server service node queue model implemented through discrete event simulation of passengers travelling from and towards service gates is considered. The solution is incorporated in the design of an advanced feedback controller connected to a virtual Station Controlled Unit (vSCU). The vSCU is designed such that it could remotely operate by staff to improve staff mobility. Computation results have shown significant improvement compare to current existing gateline technologies used in mainline train and underground stations.

2.3. Intelligent Transportation Clusters Launch Event

- **Title:** “Design of an Intelligent Gateline Controller”
- **Date:** June 13, 2019
- **Location:** University of Portsmouth
- **Authors:**
 - [REDACTED] School of Physics and Mathematics, University of Portsmouth, Lion Gate Building, Lion Terrace, Portsmouth, P01 3HF, UK. Tel: Tel: + [REDACTED]
 - [REDACTED], Cubic Transportation Systems Ltd, AFC House, Honeycock Lane, Salfords, Surrey, RH1 5LA, UK
- **Presentation and poster**

In addition to the poster created by the University of Portsmouth and Cubic on the behalf of all the partners involved in the project, an oral talk was delivered at the Intelligent Transportation Launch Event by Dr Eric Longomo from the University of Portsmouth and Mark Dynes from Cubic Transportation Systems. A copy of the poster is provided below.

Intelligent Gateline Poster



Title: "Real-time Crowd Prediction and Optimal Configuration of an Intelligent Gateline System Using Queueing Theory"

Dr. Eric Longomo, Prof. Djamilia Ouelhadj
School of Mathematics and Physics,
University of Portsmouth

Mark Dyne, Dr. Steffen Reymann
Cubic Transportation Systems Ltd

INTRODUCTION

This work seeks to develop and operationally demonstrate a gateline that can automatically self-reconfigure to manage passengers throughput. If successful, the work will represent an upgrade to the existing Cubic product used daily in majority of rail stations throughout the UK.

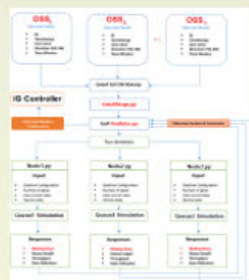
The proposed technology will be equipped with means to:

- Identify flow of people within the station environment, and learn to predict the crowds before they arrive at the gateline.
- allow the gateline to reconfigure the direction of individual walkways in a safe and controlled manner without manual supervision, freeing staffs at the gates to interact with and support customers.
- Remove requirement on staff to make operational decisions on gate configuration or temporary station closure

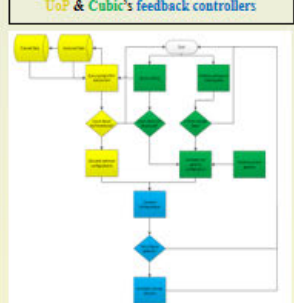


ADVANCED CONTROLLER DESIGN

UoP's Advanced Controller Design



Intelligent Gatelines Combining Controllers



IMMEDIATE BENEFITS

- Throughput optimisation & Queue reduction
- Congestion Management and Safety maintained



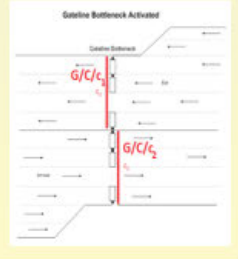
OPTIMISATION OF THE MATHEMATICAL MODEL

$$\min_{c_1, c_2 \geq 0} x_1 M_1'(c_1) + x_2 M_2'(c_2)$$

$$\begin{aligned} & \lambda_1 < 1 \\ & c_1 \mu_1 < 1 \\ & \lambda_2 < 1 \\ & c_2 \mu_2 < 1 \end{aligned}$$

$N^i, N^o > \frac{C}{2}$ Customers threshold
 $c_1, c_2 \geq 1$ Capacity threshold
 $c_1 + c_2 = C$
 $N^i + R_{pass} < K_{max}$

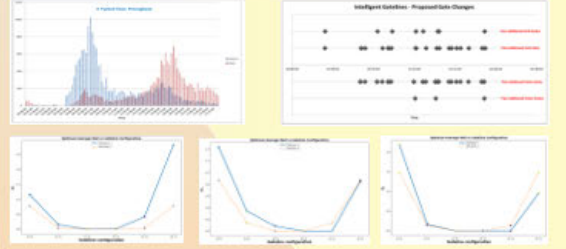
N^i : Number incoming people to the platform
 C : Total number of gates in both directions
 K_{max} : Maximum Platform capacity
 R_{pass} : Remaining passengers in the platform



2. Mobile staff enhancing customer experience



RESULTS



LONG TERM BENEFITS OF THE SYSTEM



CONCLUSION

From the output of simulations (based on real station passenger flow data) it can be concluded that gateline efficiency (in terms of passenger throughput) can be increased using Intelligent Gatelines for a typical station with rush hour peaks in the morning and evening. We can infer from the data that a spike in passenger numbers will make Intelligent Gatelines suggest a change in gate direction (one or more walkways) which will reduce queuing and congestion.

REFERENCES

- M. Jain, Finite capacity m/m/r queueing system with queue-dependent servers, Computers & Mathematics with Applications 50 (2005), no. 1, 187 - 199.
- Xiaocun Mao and Zhiguo Wu, The optimizing of the passenger throughput at an airport security checkpoint, Open Journal of Applied Sciences (2017), 485 -501.
- Hanchuan Pan and Zhigang Liu, A queueing network based optimization model for calculating capacity of subway station, Discrete Dynamics in Nature and Society (2007), 1 - 8.



3. Journal papers

3.1. Journal to be submitted to Transportation Research Part C: Emerging Technologies

- **Title:** “Real-time Crowd Prediction and the Optimal Configuration of an Intelligent Gateline Controller”
- **Authors:**
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 - [REDACTED], Transport for London, Zone Yellow 4, 5 Endeavour Square Stratford, London, E20 1JN, UK
- **Estimated submission date:** November 2019
- **Impact factor:** 5.775
- An initial draft of the journal is attached to the document

3.2. Journal to be submitted to the European Journal of the Operational Research

- **Journal to be submitted to Transportation Research Part C: Emerging Technologies**
- **Title:** “Multi-server queue system based optimisation model for optimising passengers’ throughput in real-time using overhead people counting sensors data”
- **Authors:**
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- **Estimated submission date:** Work in Progress
- **Impact factor:** 3.806
- Work in Progress

4. Impact case study for REF2021

A Research Excellence Framework impact case study describes the realised changes and benefits experienced by identified beneficiaries in society that have arisen as a result of research. The causal link between the underpinning research and the societal impact are established in the narrative and evidenced in terms of the reach and significance of the change.

The Intelligent Gateline project has been selected by the Research and Innovation Services at the University of Portsmouth for submission to the Research Excellence Framework 2021 for UoA 10: Mathematical Sciences. The project has been selected on the basis of its outstanding impacts. In the recent Mock REF, the impact case study was graded 4*.

Real-time Crowd Prediction and the Optimal Configuration of an Intelligent Gateline Controller

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³Transport for London

November 14, 2019

Abstract

This research seeks to develop and operationally demonstrate an intelligent gateline controller that is capable of automatically self-reconfiguring to maximise peak throughput while preventing station overcrowding. The proposed intelligent gateline controller will be equipped with means to: (1) Identify flow of people within the station environment, and learn to predict the crowds before they arrive at the gateline, (2) reconfigure the direction of individual walkways in a safe and controlled manner, freeing the staff at the gates to engage and support customers. It will inform and aid staff to make operational decisions on gate configuration or temporary station closure, which if sub-optimal, adversely affect network capacity, safety and customer experience.

The operation of the intelligent gateline controller is modelled using queuing systems as discrete event simulation. Each event is assumed to occur at a particular instant in time and marks a potential change of states in the system including number of passengers, status of individual service gates and gateline configuration. Overhead sensors are used to record in real-time passengers' ID, timestamps, coordinates within the desired field of view, and passengers' directions. From these captured data, a queue simulation model is developed based on the sensors' recorded distribution of the inter-arrival times, a uniformly distributed service time and the number of available service gates. The minimisation of the overall customers' waiting times is considered as the objective function of the optimisation model.

Experimental results are provided for the system evaluation. From the output of the simulations –based on real station passenger flow data, it can be concluded that the Gateline efficiency (in terms of passenger throughput) can be increased using the Intelligent Gatelines for a typical station with rush hour peaks in the morning and evening. It can also be inferred from the data that a spike in passenger numbers will make Intelligent Gatelines suggest a change in gate direction (one or more walkways) which will reduce queuing and congestion. The simulation results show that the model developed can yield an optimal configuration of the gateline within a reasonable computational time.

Keywords: Predictive Modelling, Queueing Theory, Intelligent Gateline, Passenger throughput, Optimisation

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1 Introduction

Gatelines play an important role in many public transit transport systems. In mainline train and Metro stations where revenue protection and passengers' safety are critical -especially during peak hours, gatelines are used to guard against revenue losses and to manage the influx of passengers in and out of the station while preventing platform-overcrowding and potential station closures due to safety concerns. Modern gatelines can be configured so that any individual walkway can allow entry towards the platform, away from the platform, or to allow passage in either direction. further more, latest version of gatelines can be pre-programmed and manually re-configured to meet changing needs.

The work undertaken in this paper is part of an innovation project involving a partnership between the University of Portsmouth (UoP), Cubic Transportation Systems, Arriva UK Trains (AUKT) and Transport for London (TfL). The project title is *“Intelligent gatelines; using situational awareness to improve customer experience, gate throughput and increase gateline staff effectiveness at mainline and metro stations”*.

The Intelligent gatelines (IG) project was awarded funding under the Rail Safety and Standards Board (RSSB) Train Operator Competition 2016. The fund was designed to encourage greater collaboration between train operating companies and the rail supply chain and enables the winners to move their projects into the delivery phase, subject to contract. The project started in September 2017 and has had a duration of just over 2 years, finishing in October 2019 with test trials and validation taking place throughout the last months of the project. The Connected Places Catapult (CPC) was appointed as an external party to review and validate the innovation's design methodology and evaluation method.

The overall goal of the project is to develop an Intelligent Gateline Controller (IGC) that is capable of automatically self-reconfiguring to maximise peak throughput while preventing station overcrowding. The IGC implements a queuing theory model through discrete event simulation to predict in real-time the optimal configuration of an intelligent gateline system few moments before commuters -alighting a train or entering the station, arrive at the gateline in order to reduce passenger waiting time and to decrease the probability of queues forming around the vicinity of the gateline. To achieve this goal, a gateline configuration optimisation model based on an infinite capacity multi-server queue G/C/c is developed integrating inflow and outflow passengers.

The implementation of the solution has demonstrated a radical change to the gateline that is capable of automatic self-reconfiguration maximising peak throughput and managing average total throughput in order to prevent overcrowding within the station. The IGC does this without manual supervision, freeing the staff at the gates to adopt a more customer facing roles, hence improving the quality of support provided to customers. The IGC presents many benefits among which we count the following:

1. Each individual gate can be automatically configured to be inflow or outflow to maximise throughput
2. provision of additional capacity for large crowds that temporarily appear as a train arrives or when a departure platform is announced
3. advanced prediction of gateline configuration prior to passengers arriving at the gateline.
4. management of average throughput to prevent station overcrowding and enhance platform safety by restricting access to platforms when allowable maximum capacity is on the brink of being breached
5. alleviate the requirement on those staff to make decisions on gateline configuration or temporary station closure, which if made in a sub-optimal manner, can adversely affect network capacity, safety and customer experience
6. improved customer experience
7. capability for real time access to gate data

8. The functionality can be disabled when it is not relevant, such as when the operator has chosen a gate to be one-way only (e.g. exit only) and wishes for the gate to remain so.

In section 2, we provide a brief review of the literature –presenting an analysis of existing gateline technologies including similarities and dissimilarities with the current work in subsection 2.1. The literature on Queueing Systems and Queue Simulations and their relevance to the current study are covered in subsection 2.2. In section 3, a brief description of the Intelligent gateline design framework is provided including an defined impact assessment in subsection 3.1. In section 4, Queueing models for passenger flows are developed. The section introduces both the M/M/c and discrete event simulation of the G/C/c models of passengers needing service in subsections 4.3 and 4.4 respectively. In subsection 5, the optimisation models used to support the gateline configuration decisions for both the M/M/c (subsection 5.1) and G/C/c (subsection 5.2) queue models are provided. In section 6, we detail the integration of the predictive controller into Cubic system. In section 7, we outline the Intelligent gatelines’ simulation trial tests and comparative results for M/M/c and G/C/c simulation models in subsection 7.1. In section 8, live trials design at Blackhorse road underground station are provided including the system setup at the station in subsection 8.1 and computational results for the live trials tests in subsection 8.2. We provide the conclusion in to the work section 9.

2 Literature Review

In this section, relevant works related to the current research are provided. The review of the literature is split into two main parts. The first part is dedicated to existing gateline technologies linked to the current study. The second provides a concise review of queueing systems used in transportation with a particular emphasis on those linked to the research work of this paper.

2.1 Existing gateline technologies

The Intelligent Gatelines solution sits in the context of throughput management, crowd control, fare collection and more widely, in the ecosystem of intelligent mobility and door-to-door travel experience. There are increasing demands to speed up throughput at stations, as many stations have not been designed to accommodate today’s commuter volumes. At the same time, designers of the high capacity stations of the future want a throughput equivalent of a line of people walking briskly.

This demand drives towards a future of gateless systems and its corresponding challenges of combining free flow, efficient fare collection and crowd control. Existing technologies used at some airports and security gates include biometric sensors (fingerprint scanning, face recognition, etc.). Biometric tunnels scan passenger faces as they walk through. Wi-fi, Bluetooth, radio-frequency identification (RFID) and cameras can be used to detect and track passengers. A number of airports already have cameras embedded in the ceiling that log people’s moves. To enhance security, the cameras ensure that the person who checked in is also the person who dropped off the luggage and who eventually boarded the plane. Singapore Technologies (ST) Engineering Ltd launched a gateless automatic fare collection (AFC) system at the Singapore International Transport Congress and Exhibition (SITCE) in July 2018

The system adopts long-range radio-frequency identification (RFID), facial recognition and stereoscopic people-counting camera technologies, to allow commuters to walk through barrier-less passageways without tapping fare cards. Commuters need to register an account and take a photo at the Interactive Traveller Terminal (ITT) to be issued with an RFID card, wristband or key tag for hands-free access. Travel cards and key tags in bags or pockets, wristbands and facial features will be automatically detected by the system as the passenger approaches. The passageway lights up in green or red to indicate valid and invalid access respectively.

According to ST Engineering, commuter verification takes less than one second (the current Mass Rapid Transit (MRT) fare gate system takes about 1.5 seconds to process each commuter) and the

potential to improve operational efficiency for rail operators is more than 50 per cent. A similar system is being piloted at four MRT stations - Bedok, Kembangan, Redhill and Tiong Bahru - to help people with disabilities, though physical gates have to open for commuters to pass through [?]. Going gateless requires a shift to a new revenue model for train operators, moving from revenue protection to fraud protection. There is also work to be done to win the public over to this model, due to concerns about giving biometric information and how the data is kept.

In terms of fare collection technologies, these involve the latest electronic payment systems, ranging from magnetic stripe and smart card to systems allowing payments and validation via smart phones. Besides the technological choice, there is also the aspect of gathering data in order to optimize pricing and passenger traffic. The Department for Transport is pushing the rail industry all the time for more complex and more flexible ticketing models. There is a constant drive for more integrated flexible ticketing. While gatelines can contribute to overcrowding at stations as flow through gates provides a bottleneck by design, this feature can also be used for Health and Safety purposes, to limit access to platforms, for instance. In that particular case, gateless methods would not resolve the Safety aspect. In separate projects, Cubic have been exploring this Gateless Gateline technology, but this (Intelligent Gatelines) project assumes a gated Gateline so this Singapore Innovation is related but not directly applicable.

A Competitor analysis was undertaken and direct competitors for metro and security gates were documented, a review of smart motorways projects –given technological similarities, was carried out, and academic research into automating crowd flow control was also considered [3]. Through the analysis of products developed by competitors, an observation can be made that means of coping with sudden surges in passengers’ volume to prevent bottleneck are lacking –posing safety concerns

To palliate the safety concern posed by a gateless approach for the platforms or other competitors at the gates, this research seeks to capture crowds in advance before queues develops and predicts the optimal gateline configuration in a way that minimise queue length and thus waiting time in both flow directions.

2.2 Queueing systems in transportation

Queue systems are integral to transportation. In most commercial means of transport —especially those where constantly changing masses go daily through service gates, the concept of queueing systems is of great importance. This research study relies heavily on Queueing systems through the use of multiserver service node —a next event simulation approach, to create the most accurate response to constantly changing masses heading towards train stations’ service gates. The aim is to develop an optimisation model for an infinite queue system capable of simultaneously minimising passengers’ variance in waiting time both for the inflow and outflow while, at the same time, maximising both individual gate’s traffic intensity and the average gateline throughput. This approach in turn, has the potential of increasing the overall station output rate (the number of passengers passing through the station in a period of time), reduce passengers’ mean journey time and overall experience, and finally improve safety.

Minimising variance in waiting time and maximising throughput represent the most important outcome of numerous works in the literature related to the current study, and these works have achieved this in abundance. Chen et al. [1] developed a two-phase multi-server series and parallel queue model to optimise the passengers’ throughput at an airport security checkpoint while maintaining adequate levels of safety and security. They obtained an improved queue system by altering the service stations jobs -which were considered as parameters of the queue system, whilst keeping the same amount of service stations. Using a simulation model, the flow of passengers through a security checkpoint was analysed to identify potential bottlenecks. The results showed in details that the bottlenecks were caused by an imbalance at service points throughout the system. An improved queue system to the initial process was developed to improve passenger throughput, reduce waiting time difference and simulate how the changes affected the system. Their model created two improved layouts for the service area

Similarly to the study carried out by Chen et al.[1] , Mao and Wu [5] used an $M/M/c$ queueing model to

review airport security checkpoints and staffing, and to identify potential bottlenecks affecting passengers throughput and variance in waiting time. In their work, Mao and Wu [5] developed an optimisation model where security channels c were taken as control variables in order to improve traffic volume and decrease waiting time variance by reducing bottlenecks through security checks in body and baggage screenings. Their model was cost effective in the sense that running costs increased with each higher c , though reducing the service time per customer without risking security errors. Their model focused on exploring the relationships between the average response time in the system, the average time spent in the queue and the amount of servers c available. These relationships, coupled with adjustable number of servers (security channels) formed the basis of the optimisation process in [1]. The works done in [1, 5] differ to the current in the sense that there is no counterflow to the system and the models are tailored towards identifying bottlenecks within the system and rearranging workstation combinations in a way that prevent congestion build-ups.

In studies of direct relevance, Pan and Liu [6] assessed the capacity of a subway station using a network of $M/G/C/k$ state-dependant queuing models with the aim of maximising the station’s output rate while using the probability of passengers’ selection of facilities –such as the number of corridors or stairs and escalators, as adjustable variables. Each variable was considered as a level with the model assuming the likelihood of selecting the closest facility to their previous level is high. This method also allowed the possibility of tracking single passenger through the system to carefully monitor the build-up of bottlenecks. Each level (type of facility) were assigned a unique service rate and capacity (the maximum amount of people allowed taking into account safety concern).

Zeng et al.[7] carried out a study on the optimisation of gate congestion of railway container terminals using a $M/E_k/C$ transient queuing model based on the distribution of the inter-arrival times and service time. In their model, Zeng et al.[7] sought to minimise the total cost of the gate system –which incorporates the total operation and waiting costs, by finding the optimal number of gates (or channels) through different time periods using the Equally Likely Combinations heuristic solution (ELC). The conclusion being that average waiting time can be obtained by the ELC transient solution dynamically and effectively.

Jain [2] developed a multi-server queueing system with queue dependent heterogeneous servers and investigated the relationship between the number of servers and the throughput, and the effect of varying the number of servers on costs and profits. A relation was created for cost of varying the number of servers against the cost of lower throughput for various service times and arrival rates. This work could be adapted to our case, balancing the affect of altering the number of gates in the inflow direction against the throughput of the outflow. Due to the fact that the system developed in the current work consider both flow directions, minimising the two costs will maximise the overall throughput in both directions.

3 Intelligent gateline design framework

The IGC incorporates two design solutions -working both independently or combined to provide the optimal gateline configuration. These encompass the following:

1. Simple damped feedback controller: Sensors are added to the area around the gatelines to monitor waiting times, the average throughput in each direction and crowding. Logic is added to the gateline controller so that it modifies the gateline configuration, achieving maximum throughput of each walkway. The gateline targets a maximum throughput and balances the queuing times in both directions.
2. Predictive controller: In addition to the current queue length at the gates, the IGC controller uses queueing models implemented through discrete event simulation to predict the length of the queue in advance. The gatelines can be pre-configured before crowding develops.

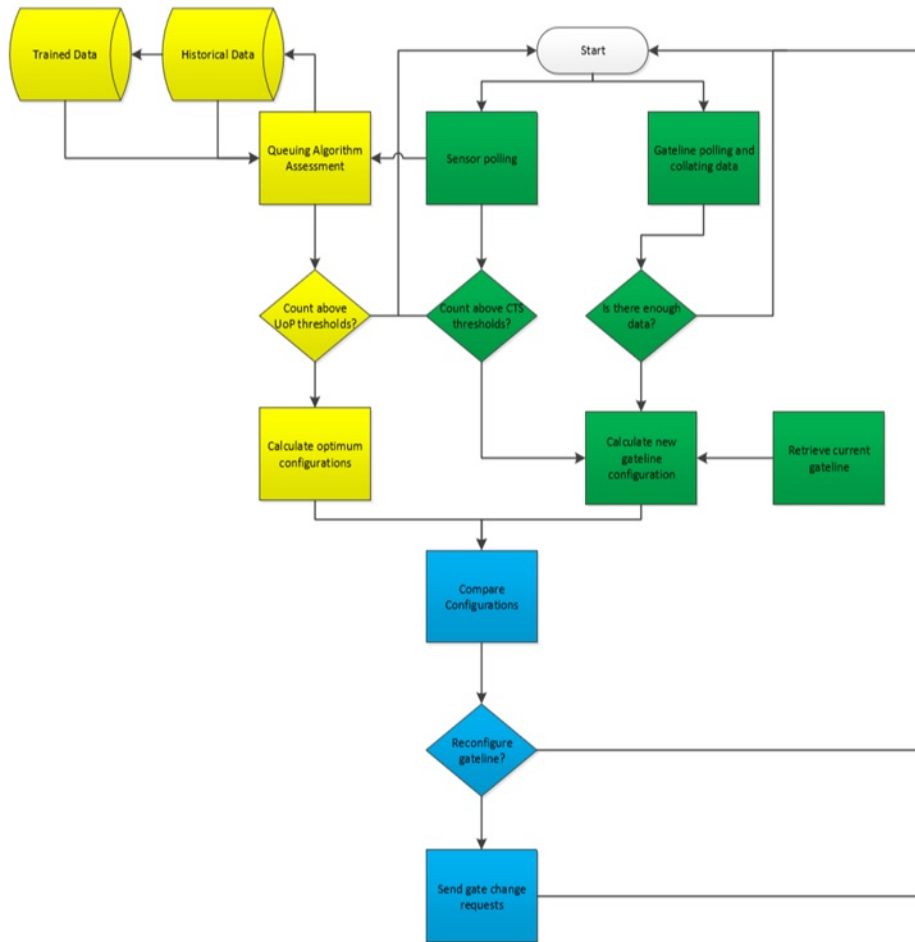


Figure 1: Intelligent gateline design framework

Figure 1 shows the the IG design framework. Both theoretical and simulation models are considered in the gateline prediction. The theoretical model is developed by assuming a M/M/c queue model. That is, both the inter-arrival and service rates follow exponential distributions. The simulation model is developed based on a generally distributed inter-arrival rate and uniformly distributed service rate –G/C/c queuing model. Both models have for inputs, a live stream of passengers’ timestamps accessed through overhead sensors, a given constant service rate and a fixed number of service gates.

3.1 Impact assessment

A successful implementation of the advanced feedback controller will require improving a number of Key Performance Indicators (KPIs) internally determined by the project team. These include:

- Maximised walkways utilisation and average gateline throughput.
- Minimised overall passenger waiting time variance.
- Safely managed passengers’ flow to prevent platform overcrowding (and potential station closure)
- Reduced inflow and outflow queues.
- Increased station capacity
- Relieving station staffs from manually operating the SCU (Station Control Unit –which controls the gateline) to occupy a more customers’ engaging role.

3.2 Predictive controller design steps

The primary focus is to build an end-to-end process of the internal operation of the predictive controller with a reduced level of complexity -considering a single server, in four distinctive steps which are briefly described below and elaborated in great details in subsections 4.4 and section 7.

- **Step 1:** Development of a predictive analytical model: In this step, a theoretical infinite-capacity multi-server queueing model based on the M/M/C Queue model is developed. The model is used for validating the behaviour of the next step model.
- **Step 2:** Development of a simulation model: This step consists of two main parts. These include:
 - **Handling Xovis line cross events with potentially infinite stream of input:** Sensors data are collected for a period of time –through POST requests, and saved to a list. The list is considered as a single event occurring in a determined time window. Throughout the time window, live-stream passengers’ data are accessed in real time through overhead sensors. These data constitute the input to the next part.
 - **Multi-servers Queue simulation from live-stream input data:** In this step, passengers’ inter-arrival time are computed using recorded timestamps from the event streams. Due to mathematical intractability, an assumption is made that the service rate is approximately two seconds per passenger (the approximation stems from a recent Cubic’s average throughput estimation of roughly 33 passengers per minute per individual gate). The total number of service gates in the station is fixed.
- **Step 3:** Optimum gateline configuration generation: In this step, the number of inflow and outflow service gates –c1 and c2 respectively, are set as design variables. The optimal configuration of the gateline is computed by selecting the values of c1 and c2 that provides the smallest waiting time variance while meeting the model constraints.
- **Step 4:** Sending a gateline configuration change request to the controller: In this step, the optimum gateline configuration for a time window is fed to the IGC through POST requests in a JSON data format.

The above mentioned steps have been implemented and represent the generic core methodology that could be applied to any station design.

3.3 Intelligent gateline controller flowchart

Figure 2 below, shows the system automation flowchart. The flowchart only focuses on how the prediction is made through multi-server queue simulations. The system predicts in advance the optimal configuration of the gateline system that balances entrance and exit flow. The gateline system is modelled as a discrete sequence of events in time. Each event is assumed to occur at a time window and marks a potential change of gateline configuration. The automation involves four main steps. These include:

1. **Passengers’ data acquisition:** In this step, an infinite livestream of passenger data are accessed through a number of servers which collect data from a web of overhead passenger count sensors. The data gathered consists of the following: (1) a unique object ID allocated to each passenger, (2) timestamps when a passenger crosses a specified line, (3) Line name to determine the line crossed by the passenger, and (4) the walking direction of the passenger. These data are collected from a specified time window and saved in the

2. **Data Filtering:** In this step, the data collected in the previous step are cleaned to select only customers that can be included in the prediction. Following the filtration, the data gathered are then sorted into Nodes. These nodes represent clusters of data considered in the same data group in the flow and counter flow directions
3. **Prediction of gateline configuration:** In this step, filtered Nodes data are then fed into the predictor algorithm which runs both the queue simulations and the optimisation for each Node. For each Node, the predictor collects filtered inputs (Model parameters, total number of gates, interarrival times, service rates), run queue simulation and performs baseline configuration optimisation. After computing the optimum configuration which minimises the passengers' waiting time, the solution is passed on to the intelligent gateline controller through POST requests.
4. Event's solution are recorded for historical purpose so that the system can learn as time rolls forward.

Among the aforementioned KPIs, the minimisation of the overall customers waiting times will be considered as the objective function of the optimisation model –and the most important outcome of this study, while some of the remaining KPIs will reap the benefits from an optimised waiting time in the queue system. Experimental results will be provided for model validation. The results should show that the model can provide accurate reflection of the operation of the intelligent gateline system and can yield the optimal gateline configuration within reasonable computational time.

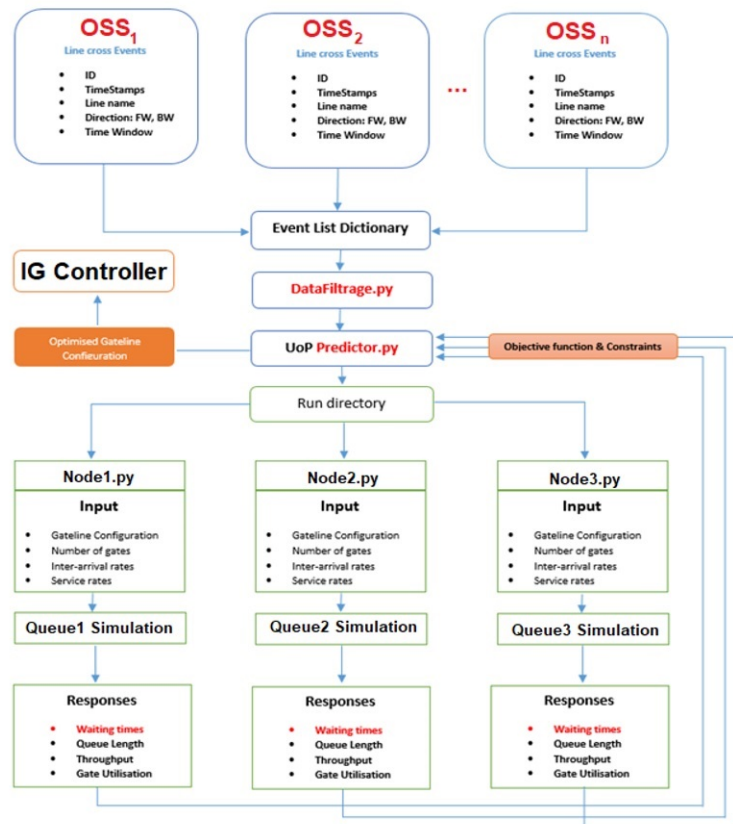


Figure 2: Showing integration to the cubic system

4 Queueing models for passenger flow prediction

In this section, a passenger flow model is developed. The model is able to predict: Queue length at the gates, optimisation of gates configuration to use in both passengers' flow directions, determination of real time maximum throughput of each gate in both flow directions, and the determination of the optimum average waiting time.

The key performance indicators of the systems such as average waiting and number of passengers in the system and in the queue are computed through both theoretical queue M/M/C mode or through discrete event simulation –using a G/C/c Multi-server service node approach, of passengers going through service gates in the entry and exit flow direction.

4.1 Notations and Assumptions

The following terminologies and assumptions are used in the proposed models:

- *Passengers* are considered as entities that arrive at random times to a service gate and wait for their ticket to be validated, then leave for the platform.
- Passengers that have arrived at the gateline but are waiting for their service to start are in the *queue*
- Each individual *gate* –server, can only service one passenger at a time.
- The *arrival time* is taken to be the time a passenger arrives at the back of the queue. In this work, the arrival time (Timestamps) are recorded through overhead sensors. More details on how timestamps are generated are provided in section 3.3
- the *departure time* is considered as the time the passenger leaves the gate.
- The *inter-arrival time* is the time between successive arrivals of passengers.
- The gateline system is following the standard **G/C/c** Queueing model. That is, we consider a multiserver queueing system with a single channel. The computation of the responses in queue system is based on a Next-Event simulation approach.
- There are c parallel gates, each potentially serving in the inflow and outflow directions in total of c_1 and c_2 respectively.
- Passengers are served according to First-In, First-Out, **FIFO** queue discipline.
- The **service time** is the amount of time a passenger is delayed at the gateline if no one else is present. The service time depends on the experience of the passenger. In this work, the service rate per passenger is assumed to follow a constant profile with mean $\mu = 2$ secs.
- The number of gates used in either side of the gateline strongly depends upon the number of passengers present in the field of view of the camera –see figure 10, according to a threshold policy governed by the following rules:
 - At least one service gate is permanently available on each side of the gateline.
 - The Queue starts when the total number of gates is greater than the number of passengers, including those being served by the gate.

4.2 Queueing models

The developed queueing models use three key information including input of the system, system's state probabilities and system outputs.

- **The input of the system** which consists of the arrival rate λ , the service rate μ and the number of servers c .
- **the probability** that there are n number of passengers (or events) in the system within a period of time. Here, we want to calculate the probability that there are in the system:

0	passengers with probability	P_0
1	passenger with probability	P_1
...
n	passengers with probability	P_n

- **The output of the system** which consist of metrics or Key Performance Indicators that allow to gauge the performance of the queue. These consist of:

L_s	Length of the system
L_q	Length of the queue
W_s	Total response time
W_q	Waiting time in the queue

The values of L_s , L_q , W_s and W_q depend on the computed probabilities.

4.3 M/M/c queueing model

Here, steady state assumption is made. The steady state probability of n people being in the system for the standard M/M/c model is given by

$$P_n = \begin{cases} \left[\frac{1}{n!} \left(\frac{\lambda}{\mu} \right)^n \right] P_0 & \text{if } n \leq c \\ \left[\frac{1}{c!} \left(\frac{\lambda}{\mu} \right)^c \left(\frac{\lambda}{c\mu} \right)^{n-c} \right] P_0 & \text{if } n > c \end{cases} \quad (4.1)$$

Or,

$$P_0 + P_1 + \dots + P_{n=+\infty} = \sum_{n=0}^{+\infty} P_n = 1 \quad (4.2)$$

$$P_0 = \left[\sum_{n=0}^{c-1} \frac{\rho^n}{n!} + \frac{\rho^c}{c!} \left(\frac{1}{1 - \frac{\rho}{c}} \right) \right]^{-1} \quad (4.3)$$

4.3.1 Additional M/M/c queue assumptions

In order to derive the performance metrics of the M/M/c queueing model, the following additional assumptions are made:

1. **Assumption on queue formation** in the system, there will be no queue formed until the number of customers are greater or equal than the number of gates in any flow direction. That is, a passenger will enter the queue only when on arrival he/she finds all the service gates busy.

Hence, if $n - c$ represents the number of passengers in the queue, we can write L_q as:

$$L_q = \sum_{n=c}^{\infty} (n - c) P_n \quad (4.4)$$

The performance metrics of the queue model are given by:

$$L_q = \left[\frac{\rho^{c+1}}{(c-1)!(c-\rho)^2} \right] P_0 \quad (4.5)$$

$$W_q = \frac{L_q}{\lambda} \quad (4.6)$$

$$W_s = \frac{L_s}{\lambda} \quad (4.7)$$

$$L_s = L_q + \frac{\lambda}{\mu} \quad (4.8)$$

$$W_s = W_q + \frac{1}{\mu} \quad (4.9)$$

Substituting equation 4.5 and into equations 4.8 and 4.9 and combining the resulting equations with equation 4.3, lead to the following:

$$L_q = \left[\frac{\rho^{c+1}}{(c-1)!(c-\rho)^2} \right] \times \left[\sum_{n=0}^{c-1} \frac{\rho^n}{n!} + \frac{\rho^c}{c!} \left(\frac{1}{1 - \frac{\rho}{c}} \right) \right]^{-1} \quad (4.10)$$

$$W_q = \frac{\left[\frac{\rho^{c+1}}{(c-1)!(c-\rho)^2} \right] P_0}{\lambda} \times \left[\sum_{n=0}^{c-1} \frac{\rho^n}{n!} + \frac{\rho^c}{c!} \left(\frac{1}{1 - \frac{\rho}{c}} \right) \right]^{-1} \quad (4.11)$$

$$L_s = \frac{\lambda}{\mu} + \left[\frac{\rho^{c+1}}{(c-1)!(c-\rho)^2} \right] \times \left[\sum_{n=0}^{c-1} \frac{\rho^n}{n!} + \frac{\rho^c}{c!} \left(\frac{1}{1 - \frac{\rho}{c}} \right) \right]^{-1} \quad (4.12)$$

$$W_s = \frac{1}{\mu} + \frac{\left[\frac{\rho^{c+1}}{(c-1)!(c-\rho)^2} \right]}{\lambda} \times \left[\sum_{n=0}^{c-1} \frac{\rho^n}{n!} + \frac{\rho^c}{c!} \left(\frac{1}{1 - \frac{\rho}{c}} \right) \right]^{-1} \quad (4.13)$$

2. Assumption on uniqueness of the service rate

Transformations are considered in order to prove the uniqueness of the service rate.

- Transforming from $M/M/c$ to a single $M/M/c'$ queue (or from one $M/M/c$ to c $M/M/1$)



Figure 3: Showing an apparatus of the gateline

Assuming that the average waiting time W_s of $M/M/c$ is w and that the arrival rate λ and service rate μ are given. Since the total number of $cM/M/1$ (i.e. for each gate) with arrival rate $\frac{\lambda}{c}$ from $W_s = W'_s$

W'_s is the average waiting time of the $M/M/1$ queue.

$$w = W'_s = \frac{1}{\mu' - \frac{\lambda}{c}} \quad (4.14)$$

Since $W'_s = \frac{1}{\mu' - \frac{\lambda}{c}}$ for $M/M/1$

Hence,

$$\mu' = \frac{1}{w} + \frac{\lambda}{c} \quad (4.15)$$

- Transforming from $cM/M/1$ queues to a single $M/M/c$. Assumption is made that the average w' of $M/M/1$ is $W'_s = w'$ with given arrival rate $\frac{\lambda}{c}$ and service rate μ' . Thus,

$$w' = \frac{1}{\mu' - \frac{\lambda}{c}} \quad (4.16)$$

$$w' = W_s = \frac{1}{\mu} + \frac{\left[\frac{\rho^{c+1}}{(c-1)!(c-\rho)^2} \right]}{\lambda} \times \left[\sum_{n=0}^{c-1} \frac{\rho^n}{n!} + \frac{\rho^c}{c!} \left(\frac{1}{1 - \frac{\rho}{c}} \right) \right]^{-1} \quad (4.17)$$

From the above equation,

$$\sum_{n=0}^{c-1} \frac{\rho^n}{n!} = 1 + \rho + \frac{1}{2}\rho^2 + \frac{1}{3!}\rho^3 + \dots + \frac{1}{n!}\rho^n + R(\rho, 0) \quad (4.18)$$

From Taylor expansion,

$$e^v = 1 + v + \frac{1}{2}v^2 + \frac{1}{3!}v^3 + \dots + \frac{1}{n!}v^n + R(v, 0) \quad (4.19)$$

Hence, n corresponds to the number of gates in a $M/M/c$ model. Thus,

$$\sum_{n=0}^{c-1} \frac{\rho^n}{n!} \approx e^\rho \quad (4.20)$$

Equation 4.17 becomes:

$$w' = W_s = \frac{1}{\mu} + \frac{\left[\frac{\rho^{c+1}}{(c-1)!(c-\rho)^2} \right]}{\lambda} \times \left[e^\rho + \frac{\rho^c}{c!} \left(\frac{1}{1 - \frac{\rho}{c}} \right) \right]^{-1} \quad (4.21)$$

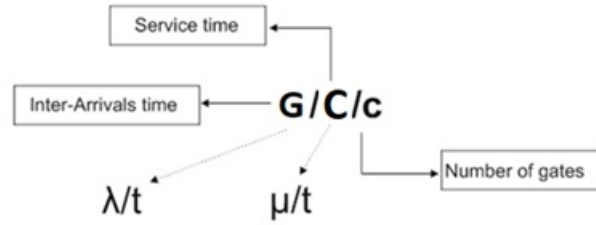
From the equation 4.21, we can obtain the uniqueness of the service rate for the $M/M/c$ queueing model.

4.4 Discrete event simulation for multiple server queue

In general, in a queueing system, we are interested in the variability in arrival rates or service times. If these are constantly varying, a steady state assumption as made in section 4.3 is fine. The alternative is to use a discrete event simulation framework and keep track of individual passengers.

The discrete event simulation developed in this work considers the following assumptions:

- The gateline system is following a G/C/c Model. This stands for general distribution arrival time, constant service rate and c number of servers (service gates)



- There are c parallel gates, each potentially serving in the inflow and outflow directions in total of c_1 and c_2 respectively.

Discrete event simulation for multiple server service node proposed in this work draws on the work of Leemis and Park [4]. The gates are considered to be the servers and are aligned in parallel. At any point within the computation window of interest, the state of each gate will be either busy or idle and the state of the queue will be either empty or not empty.

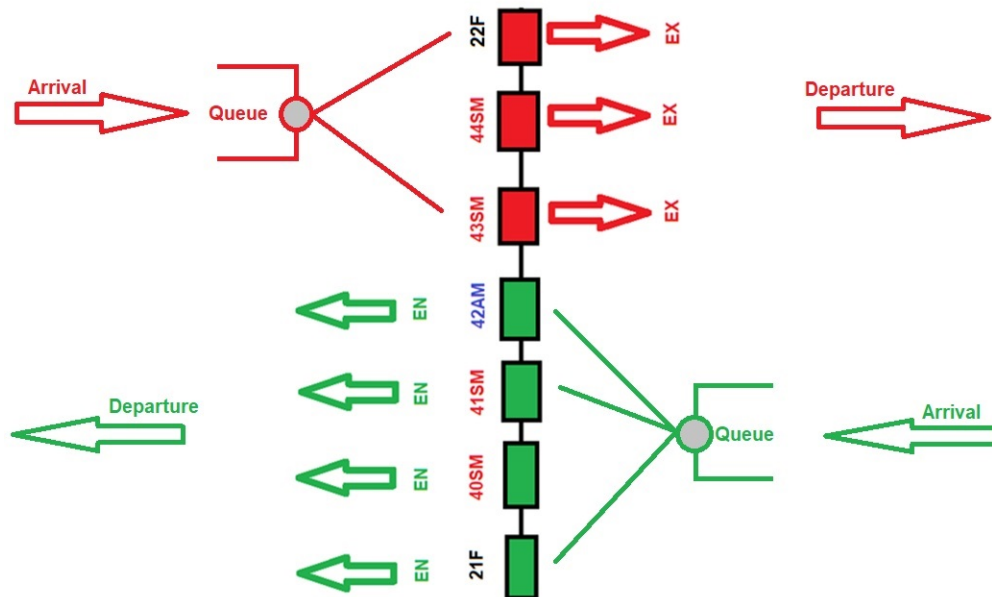


Figure 4: Multi-server service node system diagram

Figure 4 shows a dual multi-server nodes system diagram –capturing the entry and exit nodes. Passengers randomly arrive at the nodes seeking to go through the gates. In this study, the arrival time is considered to be the timestamp at which a passenger is first picked up by the overhead sensors. At the completion of the service after the passenger has validated his/her ticket, the passenger departs. In the system, there will be no queue formed in any flow direction until the number of passengers is greater or equal than the number of gates available in that particular direction. That is to say, the customer enters the queue when on arrival in the system he/she finds all the servers busy. The choice of the gate to be used is random. Each gate operates independently and an assumption is made that they are identical and equally efficient. Therefore, if $l(t)$ represents the number of passengers in the service node at time t , then 2 cases arise:

1. if $l(t) \geq c$, then all gates are busy and the number of passengers in the queue is given by $q(t) = l(t) - c$, with c being the number of available gates.
2. If $l(t) < c$, however, then the state status of available gates need to be determined to find out which gates are busy and which are idle. Hence, for $s = 1, 2, \dots, c$, define the number of passengers, $x_s(t)$ being serviced at the gate at time t . This number could be either 0 or 1. Or equivalently, $x_s(t)$ is the state of gate s at time t (with 0 meaning the gate is idle and 1 translating to busy).

Thus, if $q_{EN}(t)$ and $q_{EX}(t)$ represent the number of passengers in the queue at time t in the entry and exit respectively, we have:

$$q_{EN}(t) = l(t) - \sum_{s=1}^{c_1} x_s(t), \quad s = 1, \dots, c_1 \quad (4.22)$$

$$q_{EX}(t) = l(t) - \sum_{s=1}^{c_2} x_s(t), \quad s = 1, \dots, c_2 \quad (4.23)$$

Equations 4.22 and 4.23 represent the complete state description for entry and exit nodes. These equations are justified by the fact that the number of passengers in the queue at time t is the result of the subtraction of the number of busy gates from the number of passengers in the system at time t .

4.4.1 Events

The types of events that can alter the state variables $l_{EN}(t), x_1(t), \dots, x_{c_1}(t)$ in the entry and $l_{EX}(t), x_1(t), \dots, x_{c_2}(t)$ in the exit are:

- An arrival at time t which increases the number of people in the system by 1. That is, $l_{EN}(t) + 1$ in the case of a entry direction arrival and $l_{EX}(t) + 1$ for exit arrival. If the number of people in the node is less than the number of available servers, an idle gate is selected and the status of the gates is set to busy. Else, all the gates are busy.
- A completion of service through a gate s at time t . This decreases the number of people in the node to $l_{EN}(t) - 1$ in the case of an entry direction arrival and $l_{EX}(t) - 1$ for exit arrival. If the number of passengers is greater than the number of gates, a passenger is selected from the queue to start service. Else, the status is set to idle.
- There are $c_1 + 1$ and $c_2 + 1$ event types in the entry and exit nodes respectively.

In the implementation, assumptions are made that the initial states are empty nodes for both entry and exit. The service nodes are assumed to be initially idle. That is,

$$\begin{aligned} l(0) &= 0; \\ x_1(0) &= x_2(0) = \dots = x_{c_1}(0) = 0; \\ x_1(0) &= x_2(0) = \dots = x_{c_2}(0) = 0 \end{aligned}$$

The first event must be an arrival.

Data are gathered for a determined amount of time τ , at the end of which the node is then purged by processing any remaining passengers. The terminal state is an empty node and the last event is a completion of service. if N is the number of people in a node event list and The time-integrated statistic is the area given by equations 4.24 and 4.25,

$$A_{EN} = \int_0^t l_{EN}(\theta) d\theta, \quad \text{for entry node} \quad (4.24)$$

$$A_{EX} = \int_0^t l_{EN}(\theta) d\theta, \quad \text{for exit node} \quad (4.25)$$

Then, the average waiting time is computed by dividing the area by the number of passengers in the event list as follows:

$$W_{EN} = \frac{\int_0^t l_{EN}(\theta) d\theta}{N}, \quad \text{for entry node} \quad (4.26)$$

$$W_{EX} = \frac{\int_0^t l_{EX}(\eta) d\eta}{N}, \quad \text{for exit node} \quad (4.27)$$

5 Gateline configuration optimisation model

Both the aforementioned M/M/c and G/C/c queuing models are easy to integrate into an optimisation model in order to determine the optimal configuration of the gatelines. In this section, we propose an optimisation model for the gateline system configuration for both the theoretical M/M/c and simulated G/C/c queue models. The objective of the optimisation is to minimise the passengers' waiting time at the gateline in a determined time window while meeting the restrictions placed on the total number of gates in both flow directions, and the platform capacity.

5.1 Optimisation model based on M/M/c

The optimisation model proposed for the theoretical M/M/c Queue model is as follows:

$$\begin{aligned} \min_{c_1, c_2 \geq 0} \quad & \mathbf{x}_1 w'_T(c_1) + \mathbf{x}_2 w'_T(c_2) \\ \text{s.t.} \quad & \frac{\lambda_1}{c_1 \mu_1} < 1 \\ & \frac{\lambda_2}{c_2 \mu_2} < 1 \\ & N^i, N^0 > \frac{c}{2} \\ & c_1 + c_2 = C \\ & N^i + R_{pass} < K_{max} \end{aligned} \quad (5.1)$$

In equation 5.1,

- $w'_T(c_1)$ and $w'_T(c_2)$: denote the average waiting times of a single passenger during the time window T in the inflow and outflow directions respectively. The expression for $w'_T(c_1)$ and $w'_T(c_2)$ are derived by replacing c by c_1 and c_2 respectively in equation 4.21, yielding:

$$w'_T(c_1) = \frac{1}{\mu} + \frac{\left[\frac{\rho^{c_1+1}}{(c_1-1)!(c_1-\rho)^2} \right]}{\lambda} \times \left[e^\rho + \frac{\rho^{c_1}}{c_1!} \left(\frac{1}{1 - \frac{\rho}{c_1}} \right) \right]^{-1} \quad (5.2)$$

and,

$$w'_T(c_2) = \frac{1}{\mu} + \frac{\left[\frac{\rho^{c_2+1}}{(c_2-1)!(c_2-\rho)^2} \right]}{\lambda} \times \left[e^\rho + \frac{\rho^{c_2}}{c_2!} \left(\frac{1}{1 - \frac{\rho}{c_2}} \right) \right]^{-1} \quad (5.3)$$

- $\mathbf{x}_1, \mathbf{x}_2$: weights of the objective function
- N^i : number of incoming people to the platform
- C : total number of gates in both the inflow and outflow directions

- K_{max} : maximum platform capacity
- R_{pass} : remaining passenger in the platform

Equation 5.1 comprises two main parts: (1) the waiting time of the inflow passengers (travelling towards the gateline) and (2) the waiting time of the outflow passengers (travelling away from the gateline). Figure 5 illustrates a simultaneously activated gateline bottleneck in each side of the gateline. The goal of the optimisation is to simultaneously minimise the inflow and outflow waiting time variance. This mathematically translates to finding the optimum number of service gates c_1 and c_2 that balances the flow of passengers going through the service gates.

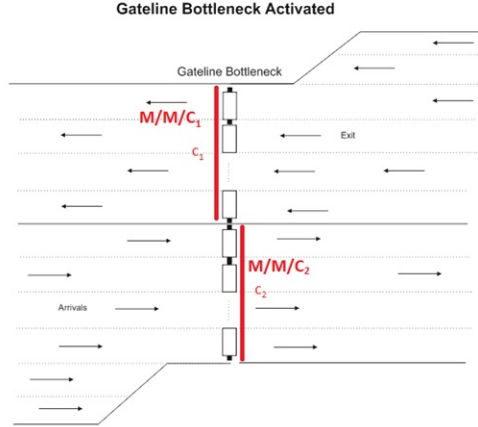


Figure 5: Simultaneously activated gateline bottleneck in the inflow and outflow directions

5.2 Optimisation model based on G/C/c

For the Discrete Event Simulation for G/C/c Multiple Server Queue model, the optimisation model is given by the following expression:

$$\begin{aligned}
 \min_{c_1, c_2 \geq 0} \quad & \omega_1 W_{EN}(c_1) + \omega_2 W_{EX}(c_2) \\
 & N^i, N^0 > \frac{c}{2} \\
 & c_1 + c_2 = C \\
 & N^i + R_{pass} < K_{max}
 \end{aligned} \tag{5.4}$$

In equation 5.4,

- $W_{EN}(c_1)$ and $W_{EX}(c_2)$: are the average waiting time of a single passenger during for the considered time window in the entry and exit directions respectively.
- ω_1, ω_2 : weights of the objective function
- N^i : number of incoming people to the platform
- C : total number of gates in both the inflow and outflow directions
- K_{max} : maximum platform capacity
- R_{pass} : remaining passenger in the platform

The optimisation model in equation 5.4 consists of two main parts: (1) the waiting time of the inflow passengers (travelling towards the gateline) and the waiting time of the outflow passengers (travelling

away from the gateline). Figure 6 illustrates a simultaneously activated gateline bottleneck in each side of the gateline.

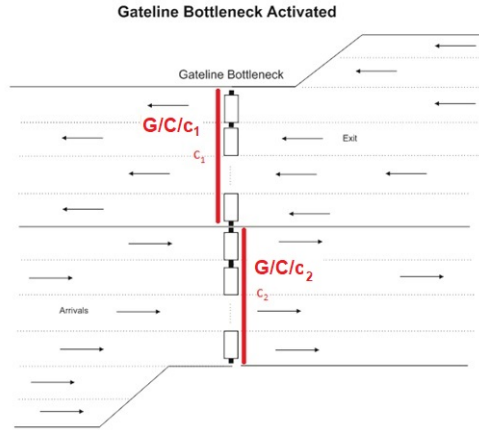


Figure 6: Simultaneously activated gateline bottleneck in the inflow and outflow directions

6 Integration of the predictive controller into Cubic system

Figure 7 depicts the integration of the predictive controller into the Cubic system. The different steps used in the integration of the University of Portsmouth predictor into the Cubic system are as follows:

1. **Accessing sensors data:** The predictor (**predictor.py**) accesses data from the Cubic sensors (or **xovis-simulator.py** could be run to simulate a Xovis server) through POST requests. In the case where **xovis-simulator.py** is run, the delay between messages is set to 1 seconds which is quite fast. The delay could be lengthened in instances where requirement is made to receive the messages faster. A single Instance of these messages -termed event stream hereafter, are received in a JSON data format.

To receive event streams, port 7777 has been configured in **predictor.py** for the purpose. In the actual live test-bed implementation, a Xovis **data push** is set-up. To run the **xovis-simulator.py**, **xovis-events.json** located in the same folder is needed since **xovis-simulator.py** uses event stream stored in this file.

Every time an event stream –which includes **lines data** of interest, is opened the python predictor script stores (append) the event in a list in real-time. The data storing process is performed for a pre-determined time window after which the optimal gateline configuration is computed. Prior to collecting line crossing live data the following is considered:

- Establishing directional convention as to what forward (FW) and backward (BW) mean. For instance, by default forward direction could mean going into the station and backward, leaving the station. Establishing this, is meaningful in order to manage passengers inflow and outflow.

In the above detailed approach –used for handling Xovis line cross events with potentially infinite stream of input, the following data are retrieved: passengers' **ID**, **timestamps**, **line name** and **Cartesian coordinates** within the Field of View (FoV)

2. **Advance Prediction:** This step consists of simulating an infinite-capacity queueing model using the data based on the event streams retrieved from the previous step and computing the optimal gate configuration. Individual's initial timestamps are taken as arrival times from which the real-time inter-arrival distribution is determined. The service rate is taken to be 33 people per minute which we round to roughly 1 passenger every 2 seconds.

3. **Transferring solution back to the IG controller:** After computing the optimum configuration, the solution is passed on to the intelligent gateline controller –through POST requests, in a JSON data format.
4. **Storing solutions:** Event’s solution are recorded for historical purpose. This is useful for future development as Machine Learning could be applied so that the system can learned as time rolls forward.

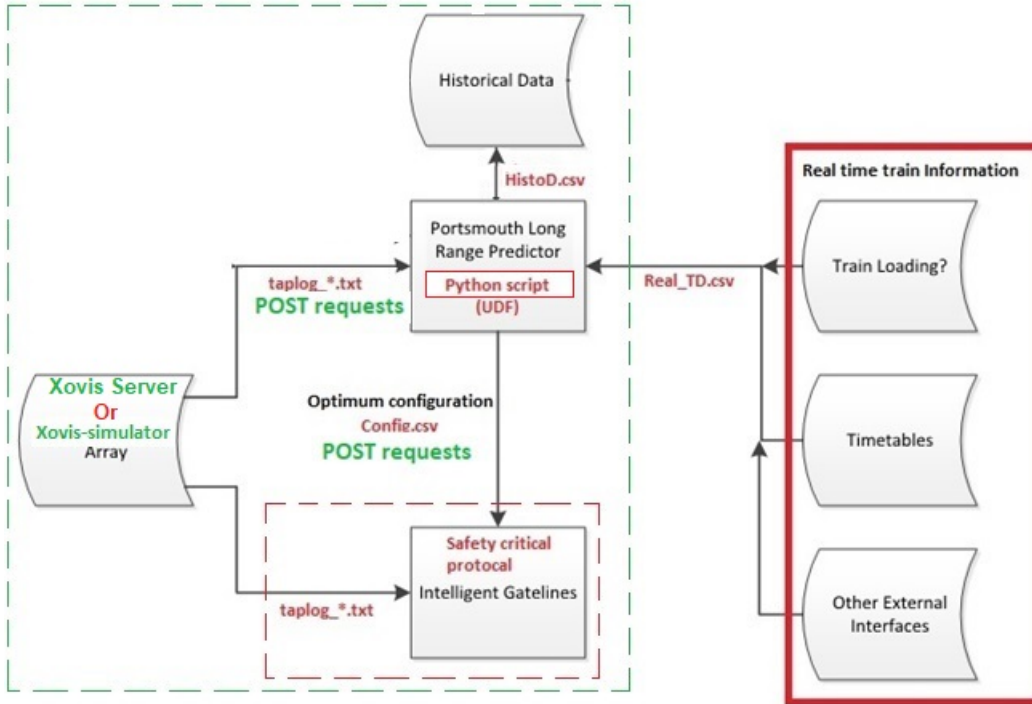


Figure 7: Integration of the predictive controller into the Cubic system

Figure 7 illustrates a schematic apparatus of the integration of the predictive controller into the Cubic infrastructure. A http server **Xovis-simulator.py** (that listens for Xovis POST messages and which is incorporated into the python script **predictor.py**), is used. The server just parses the Xovis message and dumps out the parts of the message needed –**IDs, Timestamps, line name, direction**, to a list. As previously mentioned, optimal configuration of the gateline is then iteratively computed after events are collected for some set time window. In this way, **predictor.py** is continually re-calculating the optimal gateline configuration after the time window has elapsed. Graph illustrating the optimal configuration is updated and potential gate change request is sent to the IG controller at the end of each iteration.

7 Simulation trials

In this section, an outline of the Intelligent gatelines’ simulation trials is provided. A simulator was developed to mimic Xovis –overhead sensors, server. Data sets used by the simulator were provided by the stations planned for trials. This stage was also used to initiate the integration of the advance controller as described in section 6 into Cubic system.

7.1 Lab Simulation Results

The computational experiments using a simulator was carried out to compare the efficiency of theoretical M/M/c and the Simulation G/C/c models. The tests were carried out at the Cubic Innovation Center

(ICC). The experiments were used to simulate both queue models with an adjustable number of service gates. There are a total of 7 gates to be used both in the inflow and the outflow directions. Event streams are pre-recorded using a web of Xovis sensors -people counting overhead sensors to acquire passengers' timestamps (arrival times), Cartesian location (x and y coordinates and heights of passengers) within the camera's Field of View as described in figure 10. Service gates are randomly assigned to passengers when more than one gate is available. For the queue simulation, we are interested in the Optimum waiting time per passenger (mean response time).

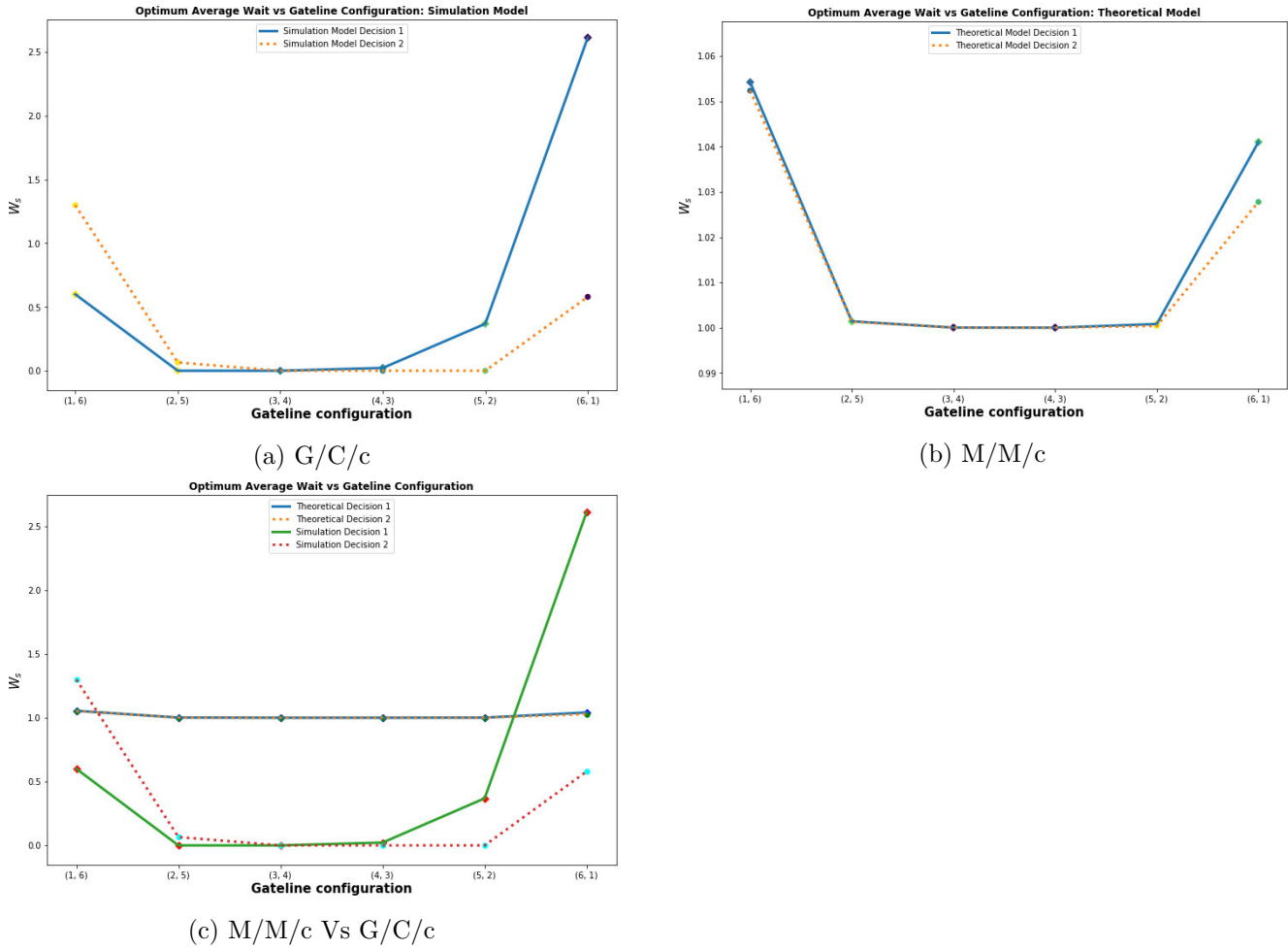


Figure 8: Comparison between Simulated G/C/c and M/M/c Queue models.

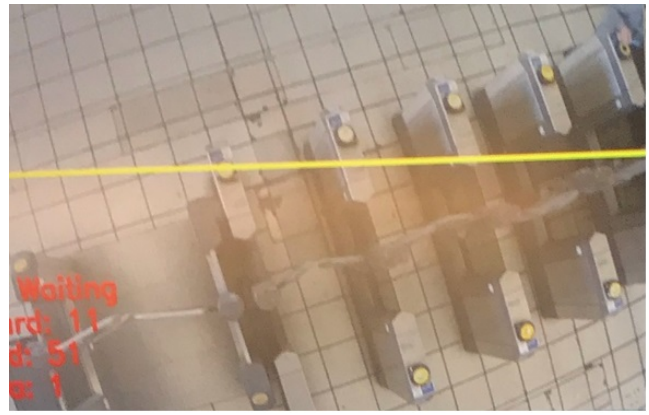
The results of the simulation on figure 8 show that Although the solution found by both the G/C/c and the M/M/c queue models were similar in terms of the optimality of the gateline configuration, the G/C/c performed better than the M/M/c model in terms of the reduction in waiting times. Therefore, the G/C/c model was selected for live pilot test at Blackhorse road underground station.

8 Live trials at Blackhorse road underground station

Blackhorse road underground station was selected for the live trials. The station is a residential type on the TfL fare controlled zone 3 of the London underground network.



(a) The gateline at Blackhorse Road station



(b) Camera view of the gateline at Blackhorse road

Figure 9: Blackhorse road station

To feed passenger livestream data to the IG system at BHR, a web of 9 Xovis sensors were installed overhead to measure throughput, velocity and build-up of crowds at station entry/exit point, at the gateline or at the top of the escalators. Figure 10 provides a level view at Blackhorse road station.



Figure 10: Overhead sensors' Overview at Blackhorse road station

8.1 System set up

The testing at the station included three components including:

1. **Virtual Station Control Unit (vSCU):** Staff mobility is a key component of the Intelligent Gateline concept, and the vSCU –shown in figure 11, was developed as a conduit for the Intelligent Gateline system and interface for staff to monitor and control the gateline remotely. The vSCU allows for a supervised mode which requires staff to accept changes requested for a gate's direction; also functionality to change open the entire gateline in case of emergencies.



Figure 11: virtual Station Control Unit

2. **The Intelligent Gateline controller:** The Intelligent Gateline Controller interprets multiple camera and sensor inputs to evaluate the need to alter the gateline to optimise passenger flow. The controller sends requests to the vSCU and logs decisions and requests sent. The controller has two goals. One is to identify and predict clusters of people before they reach the gateline and the other to equally react when crowds start building up around the vicinity of the gateline. The idea is to predict the optimal configuration of the gateline and what should be the configuration in 20, 40, etc secs for example, before customers reach the gateline. The project used different controller designs:

- A simple damped feedback controller Sensors are added to the area around the gatelines to monitor waiting times, the average throughput in each direction and crowding.
- Controller with predictive analytics In addition to the current queue length at the gates, novel predictive analytics provided by the University of Portsmouth predict the length of the queue in advance.

Logic is added to the Intelligent Gateline controller to combine the solutions from both algorithms and calculate the gateline configuration that achieves maximum throughput while balancing the queuing times in both directions.

3. Sensors to count passengers in relevant areas of the station.

8.1.1 Gateline configuration changes

The configuration of the gates changes throughout the week, with the WAG set to Manual so IG just ignores them, the middle gate (42) set to Automatic most of the time and the remaining gates set to Supervised which requires staff interaction to enable the required change.

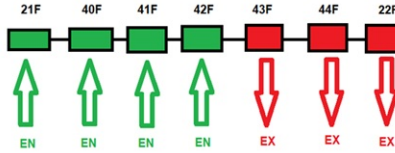


Figure 12: Baseline, morning gateline configuration default setting at Blackhorse road.

Figure 12 depicts a baseline, morning configuration default setting scenario at Blackhorse road underground train station. In this scenario, it is assumed that the gateline configuration illustrated in figure 1 above is static. With 4 gates (21e, 40e, 41e and 42e) set to entry directions and 3 gates (43x, 44x and 22x) set to the exit directions.

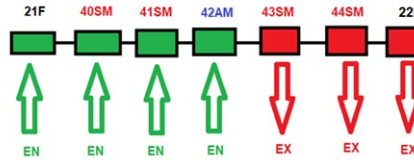


Figure 13: Showing the Intelligent gateline semi-autonomous mode.

Figure 13 depicts a semi-autonomous configuration setting scenario at Blackhorse road underground train station, whereby gates 21e and 22x are fixed to entry and exit respectively. Gates 40, 41, 43 and 44 are set to supervised mode –meaning that any request sent to these gates need staffs’ approval before being executed. Finally, gate 42 is set to automatic mode. That is, no staffs’ approval is needed for this gate to be changed.

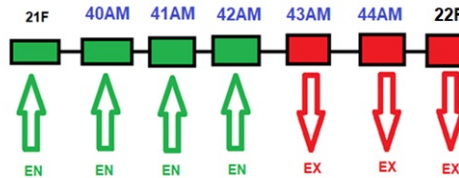


Figure 14: Showing fully Automated Gateline Configuration.

Figure 14 shows a fully automated gateline configuration setting scenario at Blackhorse road underground train station, whereby bar gates 21e and 22x fixed to entry and exit respectively, the remaining gates 40, 41, 42, 43 and 44 are set to automatic mode. The scenarios described in figure 3, 4 and 5 above will be taken into consideration in the following sections when discussing the influence of the intelligent gateline on waiting times and throughputs.

8.2 Live trials computational results

In this section, computational experiment using trial data are carried out. The results are gathered as quantitative data to mainly determine the effectiveness of improving throughput and waiting time. The trials were carried out at Blackhorse Road –a residential station based in zone 3 of the London underground network.

As shown in figure 15, the passenger flow is predominantly entry in the mornings and exit in the evenings during working week days. The weekends flow is significantly lower and more evenly spread. Figure 15 also shows that the throughput per hours seems to have high peaks in the first 4 days of the week and drop from Friday through the weekends.

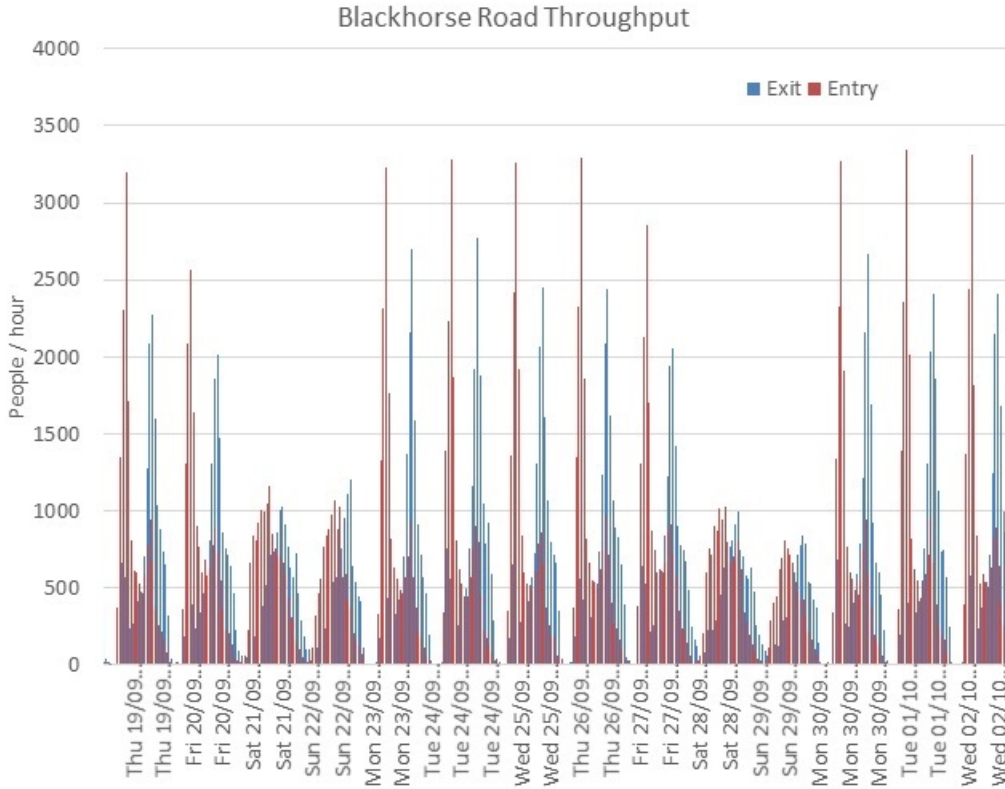


Figure 15: Passenger flow over a 2 week period –a very consistent and predictable pattern

8.2.1 Throughput optimisation

In order to evaluate the impact of the intelligent gateline on passengers’ throughput, 2 cases were taken into consideration. The first case consisted of monitoring –through a number of time windows, how the intelligent reacts to sudden spike in the number of passengers. In the second case, the project team established a direct comparison between peak-time baseline data –where the gateline management was set to manual mode as described in figure 12, and peak-time data when the intelligent gateline system is set to semi-autonomous mode as described in figure 13.

Table 1: Sample Rush Hour Gate Requests

Total number of Optimal gate configurations	Gates Changed	Gate Requests	Dbl Gate Request
366	1	106	1

Table 1 provides a sample rush hour of gate requests for the first case. Here, the morning peak-time (6h30 m to 9h30 am) from October 3rd 2019 was considered. Computations were performed every 60 seconds. A total of 366 computations were logged, of which 106 required Gate changes. Only 1 gate change was made in this time which was the automatic gate (41) and since the flow was heavily weighted to entry for most of that time a forth exit gate was rarely required. Nearly all of the unheeded requests were to add another entry gate (43). The double gate request was made when there was a spike in exits most likely when an overland train arrived.

Table 2: Sample of Intelligent Gateline log

Time	Gate _E	Gate _X	Gateline	Gate Requests	Gate Changed by
07:57.3	44	41	21e,40e,41e,42e,43x,44x,22x	—	—
07:58.3	42	22	21e,40e,41e,42e,43x,44x,22x	—	—
07:59.3	35	9	21e,40e,41e,42e,43x,44x,22x	—	—
08:00.3	49	5	21e,40e,41e,42e,43x,44x,22x	43e	G
08:01.3	41	7	21e,40e,41e,42e,43x,44x,22x	43e	G
08:02.3	36	7	21e,40e,41e,42e,43x,44x,22x	43e	S+G
08:03.3	45	10	21e,40e,41e,42e,43x,44x,22x	43e	S+G
08:04.3	52	8	21e,40e,41e,42e,43x,44x,22x	43e	G
08:05.3	38	5	21e,40e,41e,42e,43x,44x,22x	43e	G
08:06.3	54	10	21e,40e,41e,42e,43x,44x,22x	43e	G
08:07.3	38	11	21e,40e,41e,42e,43x,44x,22x	43e	S+G
08:08.3	51	1	21e,40e,41e,42e,43x,44x,22x	43e	G
08:09.3	48	11	21e,40e,41e,42e,43x,44x,22x	43e	S+G
08:10.3	68	31	21e,40e,41e,42e,43x,44x,22x	43e	G
08:11.3	51	17	21e,40e,41e,42e,43x,44x,22x	43e	G
08:12.3	69	1	21e,40e,41e,42e,43x,44x,22x	43e	G
08:13.3	48	11	21e,40e,41e,42e,43x,44x,22x	43e	G
08:14.3	63	3	21e,40e,41e,42e,43x,44x,22x	43e	G
08:15.3	59	7	21e,40e,41e,42e,43x,44x,22x	43e	G
08:16.3	76	5	21e,40e,41e,42e,43x,44x,22x	43e	S+G

Table 2 provides a small sample size of instances of logged gate configuration requests – full spreadsheet of the log can be found in Appendix B. The results show that in peak time, during considered spikes in passengers’ number, there is on average in every 60 seconds in the entry direction, 35 passengers when no gate request is made and 50 passengers when gate requests are made. On average, an increase of roughly 42.86% in entry throughputs. As for the Exit direction, there is on average 7 passengers when no gate request is made and 11 passengers when gate requests are made. On average, an increase of roughly 57.14% every 60 seconds in exit throughputs.

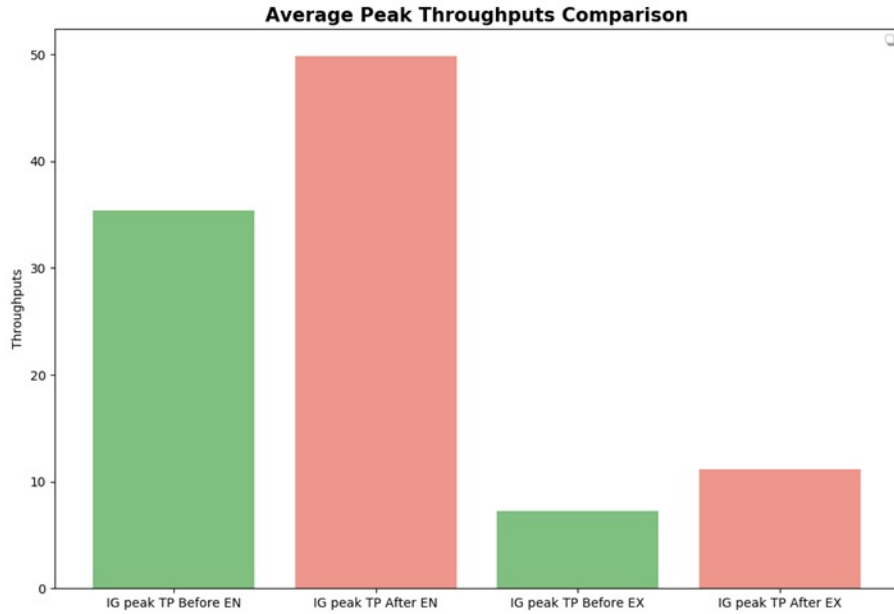


Figure 16: Throughput during spike in passenger number

Based on the data provided in table 1 and the graphs provided in figure 16 above, it can be concluded that:

1. Gateline efficiency (in terms of passenger throughput) can be increased using Intelligent Gatelines by approximately 30% for a typical station with rush hour peaks when the gateline is fully autonomous –see figure 3. For that potential to be fully materialised, the staff needs to acts on all the gate requests made.
2. We can infer from the data that a spike in passenger numbers will make Intelligent Gatelines suggest a change in gate direction (one or more walkways) which will reduce queuing and congestion. The staffs need to act on the gate change requests made by the intelligent gateline to fully capitalise on the benefits of the IG system.

The results for the second case whereby a direct comparison on average between peak-time baseline data –where the gateline management was set to manual, and peak-time data when the intelligent gateline system is set to semi-autonomous mode, are shown in Figure 7. Although not visually noticeable on the graph, there is an increase in average Entry and Exit Peak throughput of 0.016 % and 3.108 % respectively.

8.2.2 Waiting times

The waiting times at the vicinity (Node 2) and at entry/exit points (Node 1) are produced using queueing models. For the Intelligent Gateline system, each 60 seconds, an optimal configuration of the gateline is generated that specifies in which direction the gates have to be setup. Overhead Xovis sensors are used to record passengers’ data which include: IDs, timestamps, Cartesian coordinates, lines and zones data in both directions of the flow in real-time. The queue model is developed based on live stream passengers’ timestamps –accessed through overhead sensors, a given constant service rate and a fixed number of service gates. Then, the model predicts in advance, using Node 1 and Node 2, the queue lengths and the waiting times in queue. The optimal gateline configuration at Node 1 and Node 2 is generated that specifies the optimal entry and exit setups and that takes into account the safety constraints.

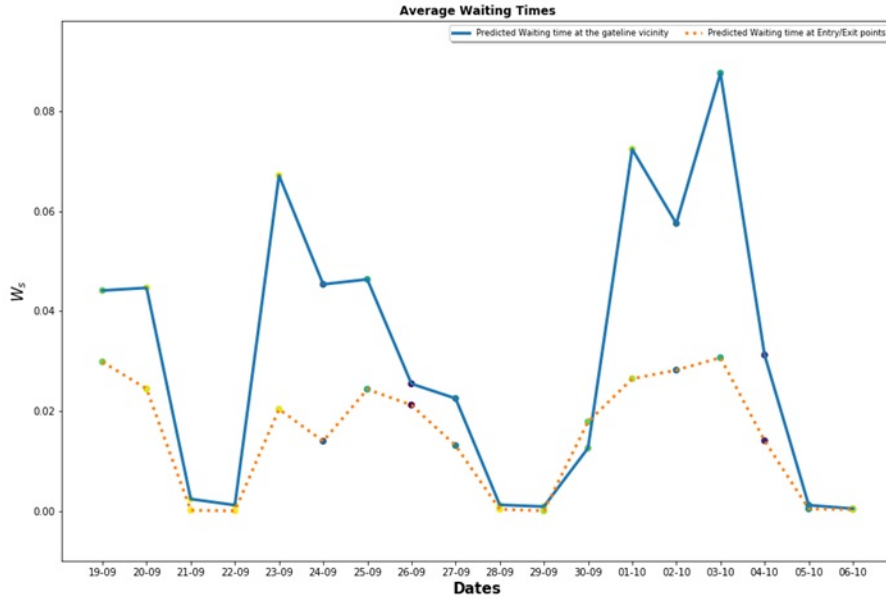


Figure 17: Average waiting times per minute over a 2 weeks span

In Figure 17, the average waiting times per minute over a fortnight are shown. The computations are based on the scenario described in figure 3, whereby, gate 20e and 21x are set to entry and exit respectively and the remaining gates (40, 41, 42, 43, 44) are set to automatic. It could be observed in Figure 17 that during the busiest time of the week –the first 4 days, the average waiting times per minute is projected to be higher and when the station is less busy the waiting time will be low.

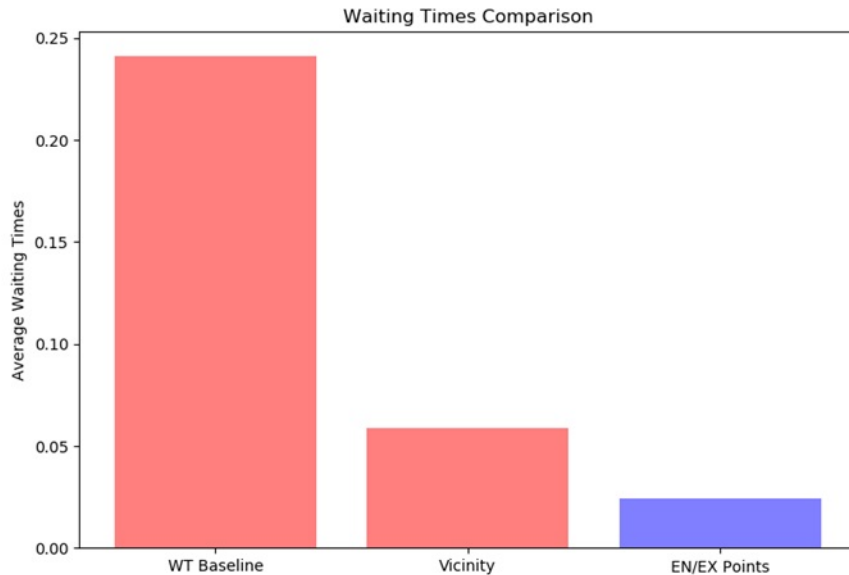


Figure 18: Showing bar charts plots of Average Waiting Times. .

In the bar charts shown in Figure 18, a comparison is made between the waiting times obtained using the scenario described in Figure 12 (baseline) and that of scenario 3 –described in Figure 14. We observed a reduction of waiting times at the gateline vicinity and entry/exit points of 75.6 % and 89.63 % respectively when the gateline is working autonomously with only gates 20e and gate 21x fixed to entry and exit respectively and the remaining gates (40, 41, 42, 43, 44) set to automatic mode.

8.2.3 Staff Feedback

Appendix A provides TfL’s Staff feedback for the live trials. The responses to questionnaires put to staff show an overall largely positive view of the IG system by staff. Supervised Gate requests seemed to be a distraction for staff. This is comprehensible as the supervised mode requires manual intervention. The results of staff questionnaire show that 66% of the staff were happy with the idea of a fully automatic gateline and viewed it as an upgrade on the existing system which is very encouraging for a product in a pilot stage. The vSCU interface was positively received and staff could see the potential benefits going forward.

8.2.4 Safety Changes

For IG to prove the concept of platform safety a zone was created shown in [Figure 1 bottom left] at the top of the downward escalator near the entrance to the overground train platforms. Staff had mentioned that this was a safety concern when it became too crowded and would have to close the gateline for safety reasons. IG uses a three-tiered approach to throttle the passenger flow through the gateline, when thresholds are breached a number of gates are set to closed to stop the use of the gate until it’s safe to resume customer entry During the two week period of close scrutiny there were ten occurrences of the Platform Safety thresholds being breached, this is broken down in Figure 8 Safety Threshold Data

Table 3: Safety Threshold Data

Threshold Capacity (%)	Entry Gates Remaining	Days Occurring	Escalation Occurrences
80	2	8	–
90	1	4	4
95	0	6	7

Table 3 shows Safety Threshold Data. Given gates were mostly in supervised mode it would need a member of staff to acknowledge the change and that is the reason for the escalations where no action was taken but there’s an occurrence in a log file of some automatic gates being changed due to the safety thresholds being breached, flow reduced, crowd disperses, and gates reopen.

9 Conclusion

In this work, we have developed and operationally demonstrated –through simulation trials and live deployment at an actual station, an innovative Intelligent Gateline system. capable of self-reconfiguration. The developed IG system uses predictive analytical models -using queueing systems, to maximise passengers’ throughput, cut down waiting times and streamline staff effectiveness at train stations. Using a virtual Station Control Unit operated through portable devices, the IG system provides greater staff flexibility and accommodate a more customers’ engaging role for staff.

From the trials results, and the discussion carried out in section 8.2, it can be observed that the efficient of the gateline (in terms of passenger throughput) can be streamlined using Intelligent Gatelines for a residential station where gateline changes would typically happen twice a day. The projection of these results also indicates that the intelligent gateline can lead to gains in gateline efficient in crowded stations where peak times are characterised by significant surge in customers volume in both flow directions.

It can be inferred from the data that a spike in passenger numbers will make Intelligent Gatelines change direction of the gates which will reduce queuing and congestion. Due to the fact that these occurrences can happen quickly, it would not always be possible for a member of staff to gain access to the SCU or individual gate keypad to change a gate walkway direction. This provides the Intelligent Gatelines with a significant advantage in aiding the efficiency of a stations gateline and provides station

staff with the information required to ensure optimum passenger flow in their station. As confidence in the system grows, supervised mode gates will be swapped over to the automatic mode and that will help increase efficiency further.

Further more, the intelligent gateline can significantly reduce passenger waiting time around the vicinity of the gateline by 75.6%. The results also further prove that in instances where passengers are picked much earlier and the prediction is ran in advance before passenger reach the gateline, passengers' waiting time can be cut down further by as much as 89.63%.

In addition, Intelligent Gatelines offers transport providers a cheaper alternative to increase throughput through a station without having to add more gates by making the gateline more efficient. Given predicted rises in public transport passengers and certain stations with no space for expansion Intelligent Gatelines will be essential for busy stations.

10 Acknowledgements

The Intelligent Gateline project was funded by Rail Safety and Standards Board (RSSB) involving a partnership between the University of Portsmouth, Cubic Transportation Systems, Arriva UK Trains, Transport for London (TfL) and RSSB. The authors acknowledge the support of all the project partners for the successful completion of the project.

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Appendix A

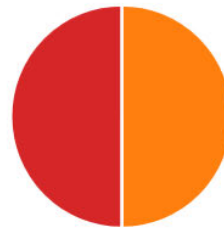
A.1 Staff Feedback Results

Intelligent Gateline Survey

6 Responses 05:59 Average time to complete Active Status

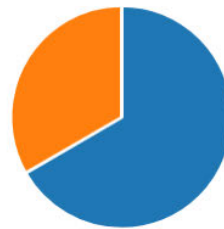
1. Number of years of service

0-3 years	0
4-6 years	3
7-10 years	0
11+ years	3



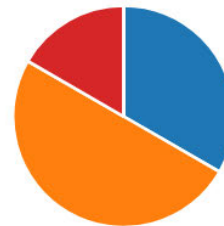
2. What is your Role

CSA	4
CSM	2
ASM	0



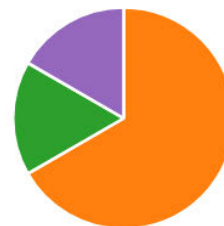
3. If the control interface (App) was available on a TfL tablet, how satisfied would you be with a Tablet Controlled Gateline?

Very satisfied	2
Somewhat satisfied	3
Neither satisfied nor dissatisfied	0
Somewhat dissatisfied	1
Very dissatisfied	0



4. Does the use of Intelligent Gatelines improve customer service by increasing interaction with Customers?

Strongly agree	0
Agree	4
Neutral	1
Disagree	0
Strongly disagree	1



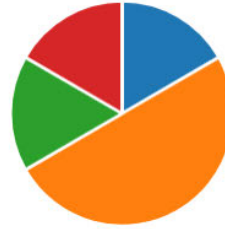
5. Thinking about decisions made by the Intelligent GateLine, were they sensible?

Strongly agree	1
Agree	3
Neutral	1
Disagree	1
Strongly disagree	0



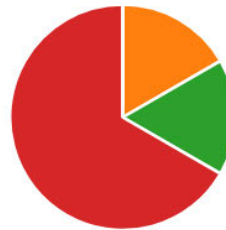
6. Would the gate direction benefit from being changed more during the course of the day?

Strongly agree	1
Agree	3
Neutral	1
Disagree	1
Strongly disagree	0



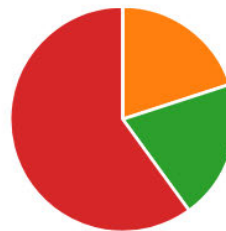
7. Did gate changes hinder you/colleagues at any point?

Strongly agree	0
Agree	1
Neutral	1
Disagree	4
Strongly disagree	0



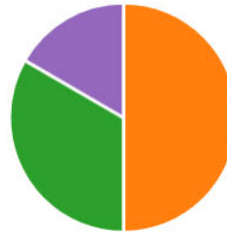
8. Did gate changes hinder customer at any point?

Strongly agree	0
Agree	1
Neutral	1
Disagree	3
Strongly disagree	0



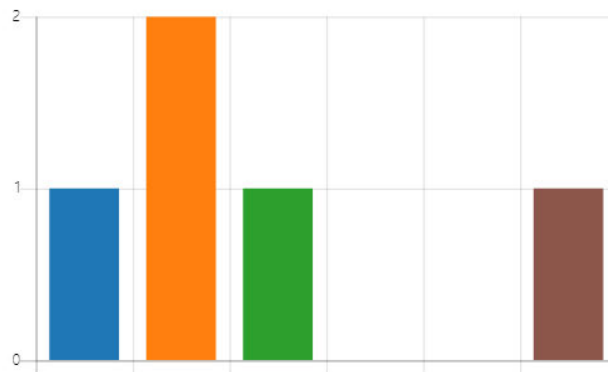
9. Based on your personal experience over the trial period, do you think the Intelligent Gateline has led to a reduction to passenger waiting times?

● Strongly agree	0
● Agree	3
● Neutral	2
● Disagree	0
● Strongly disagree	1



10. Based on your personal experience over the trial period, do you think the Intelligent Gate has led to less occasions of opened gatelines when crowding occurs?

● Strongly agree	1
● Agree	2
● Neutral	1
● Disagree	0
● Strongly disagree	0
● N/A	1



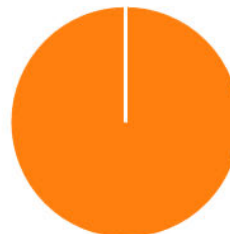
11. Does acknowledging the supervised gate changes divert your attention from customer service?

● Strongly agree	1
● Agree	2
● Neutral	2
● Disagree	1
● Strongly disagree	0



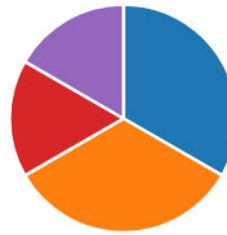
12. Were the different gate modes useful? (Manual, Supervised, Automatic)

● Strongly agree	0
● Agree	5
● Neutral	0
● Disagree	0
● Strongly disagree	0



13. Would you be confident in a fully automated system without having to acknowledge gate changes?

Strongly agree	2
Agree	2
Neutral	0
Disagree	1
Strongly disagree	1



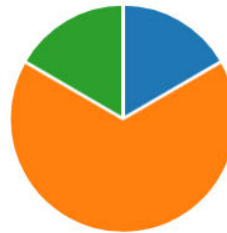
14. Was the overall look and feel of the tablet interface intuitive?

Strongly agree	2
Agree	2
Neutral	2
Disagree	0
Strongly disagree	0



15. Was the camera view of the gateline helpful?

Strongly agree	1
Agree	4
Neutral	1
Disagree	0
Strongly disagree	0



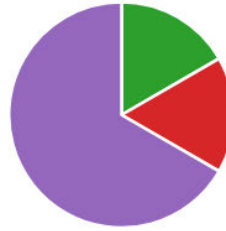
16. Do the popups on the tablet give enough information?

Strongly agree	0
Agree	4
Neutral	2
Disagree	0
Strongly disagree	0



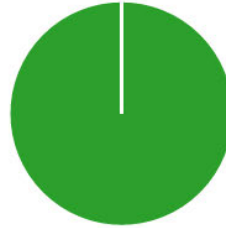
17. Intelligent Gateline system what frequency of popups would you prefer?

● Every 30seconds	0
● Every minute	0
● Every 2 minutes	1
● More than 2 minutes	1
● User Configurable	4



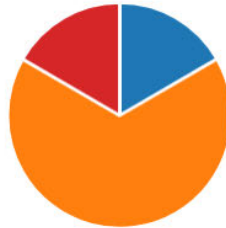
18. Did you engage with the popups?

● All the time	0
● Most of the time	0
● Sometimes	6
● Rarely	0
● Never	0



19. Could the tablet control interface be helpful to aid revenue protection?

● Strongly Agree	1
● Agree	4
● Neutral	0
● Disagree	1
● Strongly disagree	0



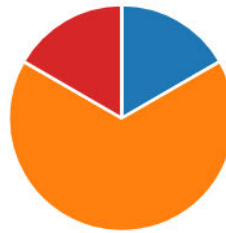
20. Do you feel the Intelligent gateline system would benefit customer experience?

● Strongly Agree	2
● Agree	3
● Neutral	0
● Disagree	1
● Strongly disagree	0



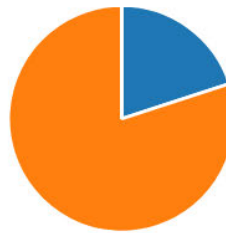
21. Do see the tablet control interface app replacing the station control interface, thus reducing station clutter?

● Strongly Agree	1
● Agree	4
● Neutral	0
● Disagree	1
● Strongly disagree	0



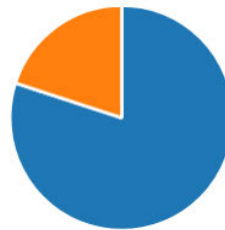
22. Is the Intelligent Gateline an upgrade to the current system?

● Strongly Agree	1
● Agree	4
● Neutral	0
● Disagree	0
● Strongly disagree	0



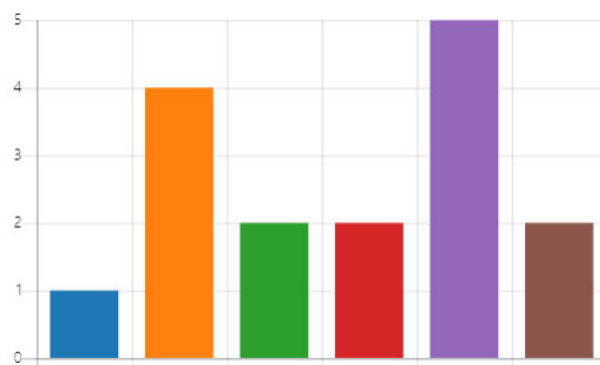
23. Which day of the week has the Intelligent system been most useful

● Weekdays (Mon to Fri)	4
● Weekends (Sat - Sun)	1



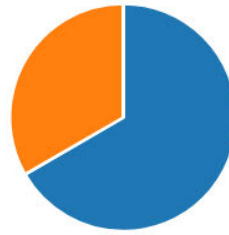
24. Which times of day was the intelligent gateline system useful?

● AM	1
● AM peak	4
● Noon	2
● PM	2
● PM peak	5
● Evenings	2



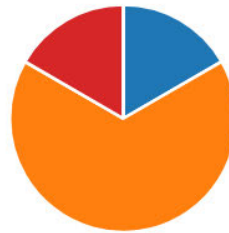
25. Would the addition of platform sensors and train loading feedback aid in crowd control at the gateline and platform?

Strongly Agree	4
Agree	2
Neutral	0
Disagree	0
Disagree	0



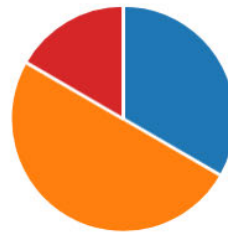
26. Overall, how satisfied are you with the Intelligent Gateline System?

Very satisfied	1
Somewhat satisfied	4
Neither satisfied nor dissatisfied	0
Somewhat dissatisfied	1
Very dissatisfied	0



27. Would more stations benefit from an Intelligent Gateline System?

Strongly agree	2
Agree	3
Maybe	0
Disagree	1
Strongly disagree	0



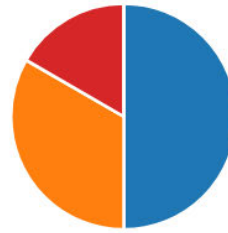
28. Would more stations benefit from a Tablet Controlled Gateline

Strongly agree	3
Agree	2
Neutral	0
Disagree	1
Strongly disagree	0



29. Would you like to see the system rolled out to more stations?

Strongly agree	3
Agree	2
Neutral	0
Disagree	1
Strongly disagree	0



30. What would you like to see added to the Intelligent Gateline System?

5
Responses

Latest Responses

"The system is not dynamic enough, it reacts too slowly with the chan...

"gate fault reporting"

"Automatic model is very useful and a more responsive system would ...