Proceedings of the 2009 Winter Simulation Conference
M. D. Rossetti, R. R. Hill, B. Johansson, A. Dunkin and R. G. Ingalls, eds.

A DYNAMIC ARCHITECTURE FOR INCREASED PASSENGER QUEUE MODEL FIDELITY

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ABSTRACT

This study presents a dynamic queue controller to generate realistic queue formation and behaviour within a discrete event environment and a new data set to define passenger walking speeds. This new controller provides a detailed visual reference of the queue behaviour and provides information on important metrics, such as queue size. The controller, combined with the walking speed data, is validated against CCTV footage of airport passenger screening points, and the simulation outputs are compared to results obtained from queueing theory. A simulation approach provides superior results over the averaged results from queuing theory and a more useful insight into the behaviour of the system.

1 INTRODUCTION

Modelling people, pedestrians or passengers is a complex task that has as many methodologies as it has desired outcomes. Of interest in this paper is the study of queue formation as people queue for a service, such as at a supermarket checkout, ticket counter or security checkpoint. Queuing theory can provide an average result for queue metrics of interest, including queue length and in-system time, but a simulation model of the system can provide more interesting and useful results.

The behaviour of a queue influences the experience of those within and system designers. It is desirable to ensure sufficient space allocation for a queueing area during the planning stages of a project, as opposed to having a poorly designed area. Additionally, if the bottleneck process that people were queuing for was to change, knowing the effect to the queue length will determine if there is sufficient queueing area. Critical system properties affecting the human in system experience were identified as congestion and queue lengths (Gatersleben and Weij 1999) and require further theoretical investigation. People in a queue will be happier to wait if they are knowledgeable about what is causing the queue (Maister 1985).

In this paper, results for a new set of walking speeds are presented. This dataset was generated through a study at an international airport. Additionally, a new queue controller is presented to provide realistic queueing behaviour in a discrete event simulation model. The queue controller is combined with the new set of walking speeds to analyse a set of scenarios and compared with results obtained through application of queueing theory. The new controller provides a more intuitive result as to the requirements for designing the queueing area.

This paper is structured as follows. Section 2 is a review of related work in the field of modelling people in queues and open spaces, covering the different approaches to modelling and briefly refreshes the main points of queueing theory. Section 3 details the measured speed for passenger approaching a checkpoint and beaks these speeds up based on group size. Section 4 describes the dynamic proposed in this work and the results for this queue controller are presented in Section 5.

2 RELATED WORK

2.1 Pedestrian simulation

Previous research into pedestrian modelling can be broadly categorised into three approaches - microscopic, macroscopic and mesoscopic (Harney 2002), with each having their own benefits and limitations.

Microscopic models are a fine-grained approach. Each pedestrian is modelled as a distinct element within the model, allowing for a variable behaviour between pedestrians. Three distinct methodologies are evident within microscopic modelling, cellular automata, entity-based and multi agent-based. In cellular automata approaches, the world is discretised into a uniform grid, where a cell can be occupied by a single pedestrian. The state of the current and surrounding cells determine the pedestrians movement (Dijkstra, Harry and Jessurun 2000). In entity-based approaches each pedestrian is modelled as an entity within the model (Snowdon et al. 2000) and is subjected to stochastic processes including arrival and service times. In agent-based models, each pedestrian is an agent and each agent interacts with other agents and the environment (Reynolds 1999). The microscopic approach has the benefit of being able to assign different behaviours to pedestrians, removing behavioural assumptions evident in macroscopic approaches. Additionally, incorporating visualisation into a microscopic simulation will greatly assist in the verification and validation of the model, ensuring that the model behaves as desired and reflects the real world. These benefits come at a cost, the amount of computation is greatly increased, both the computation of each individual entity interacting with the environment and the visualisation of the model.

Macroscopic models are a course grained approach to pedestrian modelling. Rather than focusing on the individual, the focus is applied to the density of individuals. These methods use a mathematical approach to describe pedestrians motion and their interaction within the model, i.e. a repulsive force is applied to prevent a collision with a wall (Helbing 1992). These models have the benefit of a lower computational cost compared to microscopic models.

Mesoscopic models are aimed at bridging the gap between the macro and micro techniques. Here the environment is discretised into segments and the group of pedestrians within each segment is of interest, as opposed to the individual (Hanisch et al. 2003). This allows for more varied behaviours compared to macroscopic approaches, without the burden of computation experienced by microscopic approaches. A trade-off is immediately apparent with this approach, increasing the number of segments will increase the behavioural complexity, but will add computational cost.

When deciding which approach to take when undertaking a simulation study of a new pedestrian environment, there are many factors to consider. A framework to assist in the decision making process has been developed to provide assistance. (Ronald, Sterling and Kirley 2007). Ronald Sterling and Kirley consider the environment in which the pedestrians will exist, i.e. small or large and enclosed or open, the behaviour of the pedestrians, i.e. purposefulness and familiarity and finally highlight scale as a key factor in choosing a modelling approach. Scale refers to the detail of results required, size of the environment and the volume of pedestrians. The authors state that location dictates the modelling methodology as this is the first decision to be made.

The area of study for this work was a large-scale enclosed space. Ronald Sterling and Kirley suggest a microscopic simulation approach in order to model queues and exit processes, with an alternative model of cellular automata or mathematical if crowd densities are required.

The microscopic approach is also suited to the desired outcomes of the model, being to investigate queue formation within security checkpoints within airport terminals and provide a visualisation of the process to increase industry confidence in the model results.

2.2 Microscopic simulation

Microscopic simulation will provide the required detail for output analysis and an abstraction of the real world that is comprehendible to clients, convincing them of the models validity. To provide a visual reference of what is occurring within the model, two possibilities for methodology immediately stand out, entity-based and agent-based. The platform that is used to model the passengers will be a 3D discrete event simulation software package, as used to model other aspects of airport operations (Johnstone, Creighton and Nahavandi 2007; Le, Creighton and Nahavandi 2007).

Agent-based methods, such as the steering agents (Reynolds 1999), perceive their environment, choose and action from a set of available actions and executes that action. Simple behaviours, such as flee or seek, up to more complex behaviours like collision avoidance are easily implemented with this method, however the basic method is the same, perceive, choose and act.

Entity-based methods differ to agent-based methods in that a decision on how to act is not made by each person within the model, rather each person or entity is controlled by different processes within the model. The decision to act is not left with the person.

The approach taken in this work is to use the entity-based method. This removes the need for the person to constantly perceive their environment, fitting into the discrete event software architecture in use. When a person enters the system and must choose a queue to join, rather than them perceiving queue lengths and choosing which to join, a controller assigns them to a queue, using the same decision logic that would have been used by an agent implementation. This method is a purely discrete event implementation, firing logic when events occur, i.e. arrival to the system or arrival to the back of a queue, rather than a timed update for agents to reassess their environment. This discrete implementation does have draw backs, most obviously being a lack collision detection and avoidance. Where a steering agent, see (Reynolds 1999), allows for collision avoidance through polling the environment, the entity-based elements in our model generate events when they complete a move, signalling controllers into further action. It would be possible to add polling of the environment to the current model, allowing collision avoidance, but at the expense of a discrete environment. The value of the discrete environment allows for less computation, hence greater scale. Additionally the analysis of the system can safely ignore the impact of collisions as we are interested in travel times in highly managed processes, as opposed to travel times in open spaces.

2.3 Pedestrian Speed

The walking speed of pedestrians has been found to vary according to many aspects, including age, gender, trip purpose, walking gradient, and even city (Harney 2002). The most comparable study into walking speed found in literature was carried out in Sydney, Australia (Henderson 1971). Henderson found that the average walking speed at a pedestrian crossing was 1.44m/s with a standard deviation of 0.23m/s. This speed is taken to be the unhindered speed, i.e. the speed at which a person is walking without being constrained by others.

The walking speed of pedestrians is also influenced by social factors, such as group size. The speed at which a group moves can be viewed from different perspectives, including a leader with followers striving to keep up, or a more considerate group where all members move at the speed of the slowest member. The leader/follower is most evident in literature, an example can be seen in (Yersin et al. 2008). Here followers attempt to match the speed of the leader and maintain the group structure.

2.4 Queueing Theory

Queueing theory deals with the mathematics involved in the study of waiting lines, or queues. The basis of the problem is a customer arrives, joins a queue waiting for service, receives that service and exits. To study queueing systems, information is required on the arrival process, the service process and the queue discipline.

The arrival process deals with how arrivals are distributed over time. Most of the work in queueing theory has revolved around a Poisson distribution, this means that the interarrival time between successive arrivals is unrelated and exponentially distributed.

The service process requires information on the service time, again a Poisson distribution is commonly used, the number of servers and whether the servers are in series or parallel.

The queue discipline deals with how items are chosen from the queue for service. Common rules are FIFO (First In First Out) and LIFO (Last In First Out). Other considerations are the capacity of the queue, customers avoiding the queue due to length and customers leaving the queue due to waiting too long.

Queueing theory endeavours to answer questions about the system. Questions may include: a customer's mean waiting time in the queue, a customer's mean time in the system, the length of the queue or server utilisation. With this knowledge changes to the system can be investigated, such as implementing additional servers, prioritising customers or adjusting the size of the waiting area.

For an M/M/1 queue where λ is average arrival rate into the system and μ is the average service rate it is simple to calculate questions about the system. To illustrate the ease the average number of customers in the system is given by (1), and the total time in the system is given by (2). Similar equations have been developed for variations on the M/M/1.

$$\frac{\rho}{1-\rho} \quad \text{where } \rho = \frac{\lambda}{\mu} \tag{1}$$

$$\frac{1}{\mu-\lambda} \tag{2}$$

As queueing theory assumes an exponential arrival and service rate (Davis and Yen 1999) it is limited in direct application as not all processes meet this requirement. It is argued that even if these conditions are not met queueing theory can still be applied (Baldwin et al. 2002), however the majority of literature directs towards the use of simulation when the system does not follow a Poisson processes and is larger than a simple network of several servers (Siesennop, Callles and Campbell 1973; Ho 1987; Bitran and Morabito 1996; Davis and Yen 1999; Baldwin et al. 2002). Ho describes the effort in creating a mathematical for a complex system the equivalent, if not more, of creating a simulation model.

3 GROUP SPEED

In order to correctly model the dynamics of a queue, an accurate model of pedestrian walking speed is required. The setting for this study was in an airport, so the term pedestrian will now be replaced by passenger. The time to travel a set distance was recorded for groups of size, one, two, three and greater than four. A group was only recorded if it 1) travelled the entire distance, 2) remained moving for the entire distance and 3) was not held up by a slower group in front of it.

The data was obtained from an international airport in Australia over a period of four weeks and is shown in Table 1 and Figure 1 to Figure 4. Table 1 gives a fitted distribution to describe the data. These fitted distributions have been tested with both the Kolmogorov-Smirnov and Anderson-Darling tests. Both tests failed to reject the null hypothesis, meaning that the distribution is a good fit. The mean and standard deviation is given, however this does not provide an appropriate view of the data as the distributions are not normal. This does, however, enable comparison to other results in literature.

Table 1: Group walking speed data.

Group Size	Fitted Distribution	Mean (mm/s)	Standard Deviation (mm/s)
1	Erlang(386, 6., 128)	1155.50	327.37
2	Gamma(265, 6.29, 106)	931.62	249.43
3	Weibull(421, 1.58, 432)	812.46	246.09
4+	Erlang(253, 2., 194)	640.49	228.63

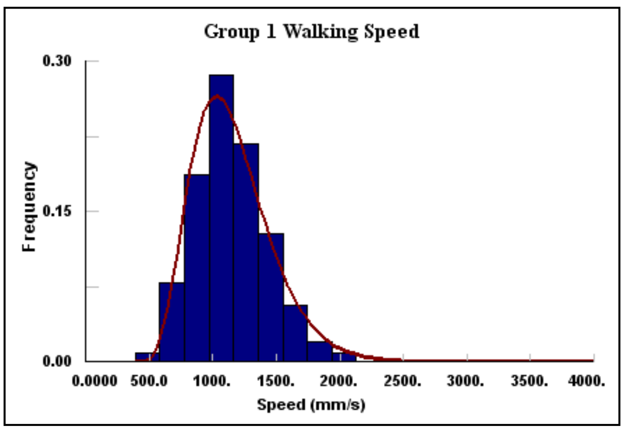

Figure 1: Walking speed for a group size of one.

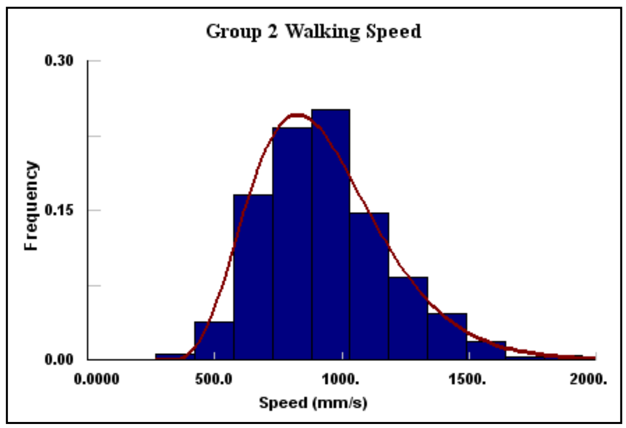

Figure 2: Walking speed for groups of two.

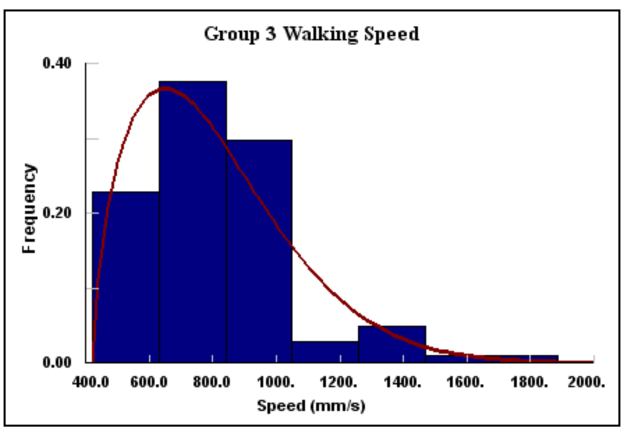

Figure 3: Walking speed for groups of three.

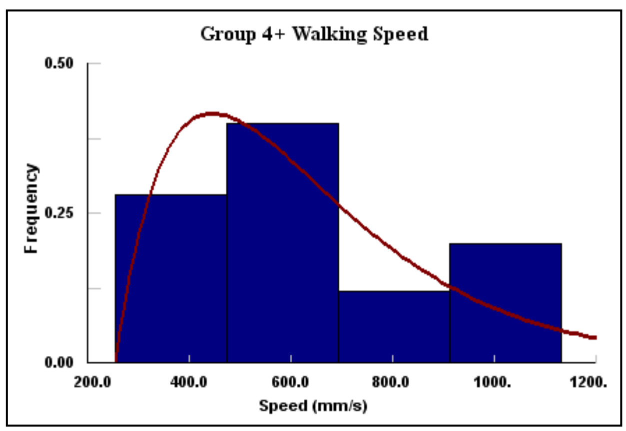

Figure 4: Walking speed for groups of four or more.

4 QUEUE CONTROL

The method for queue control presented in this paper is an entity-based microscopic approach. The aim of the queue controller is to move passengers to the end point of the queue, add them to a list of passengers in the queue, manage the queue of passengers as the queue shuffles forward and release the passenger at the head of the queue to free servers, based on a FIFO dispatch. Rather than have people queue at the one location, the queue controller will maintain their location and modify this when events to the queue occur. Figure 5 displays a typical queue that is formed.

Figure 5: Example view of queue that is typically formed.

The queue controller has a fixed end point, the head of the queue, and two dynamic points, an intermediate point and an entry point, in order to manage passengers, see Figure 6. This provides similar functionality to that described in (Fausch, Dillard and Hoffmeister 1974) where a queueing area was modelled. In Figure 6, the direction of travel is from left to right. The passenger at the far right is at the head of the queue, or the end point. The intermediate point is located behind the fifth passenger in the queue. This point reflects the point behind the last passenger in the queue. The start point is located behind the intermediate point, approximately at the sixth passenger in the queue. This point is the target for passengers. Two lists are used to maintain the location of passengers in the queue. The first list deals with passengers that are approaching the start point. As they arrive at this point they are inserted into the second list. The second list maintains the passengers location and their position in the queue, whereas the first list in unconcerned with position in the queue, rather it cares for whoever arrives at the start point first, and inserts them into the queue. This behaviour allows for overtaking as passengers approach the queue, but once they have joined it, they maintain their position. Suppose two passengers arrive five seconds apart, the second passenger is much faster and arrives at the queue before the first, with our implementation, the faster passenger is inserted into the ordered queue first.

The speed of passengers is maintained up to where they become hindered at the intermediate point. From this point, a variety of methods influence their behaviour - a desired queue speed, a reaction time to the person before them moving and a following distance amongst them.

Figure 6: Top view of a queue.

Groups of passengers are handled by proving the group a target point, then allowing the group to arrange themselves in regard to that point, i.e. a half circle with the centre at the target. Events trigger movement within the queue. When a passenger leaves the queue, the remaining passengers shuffle forward, at various times post the leaving event. As passengers reach the start and intermediate points, events are also generated. Passengers leave the queue by handshaking with a downstream controller, to ensure that the next resource is free and that the current passenger is indeed at the head of the queue.

The formation of queues with this controller, the movement of people and the location of the controller points were all compared to CCTV footage of queues to determine the performance of the controller. Parameters describing passenger movement are able to be tuned to make the queue more realistic, along with parameters associated with the controller.

This implementation allows for a realistic queue build-up and decay before processes. Passengers must travel to the head of the queue before they are able to leave the queue, and the dynamic size of the queue can give a better idea of the time in the queue when compared to a method that assumes a delay time between processes.

5 RESULTS

This section details the results for the queue when running in the simulation model and a queueing theory approach. The four scenarios that were investigated are listed in Table 2. Figure 7 shows a screenshot taken from Scenario 1.

Table 2: Scenario Definition.

Scenario Name	Arrival Rate per minute	Service Rate per minute	Server Count
1	3	4	1
2	3	4	2
3	3	4	3
4	3	8	1

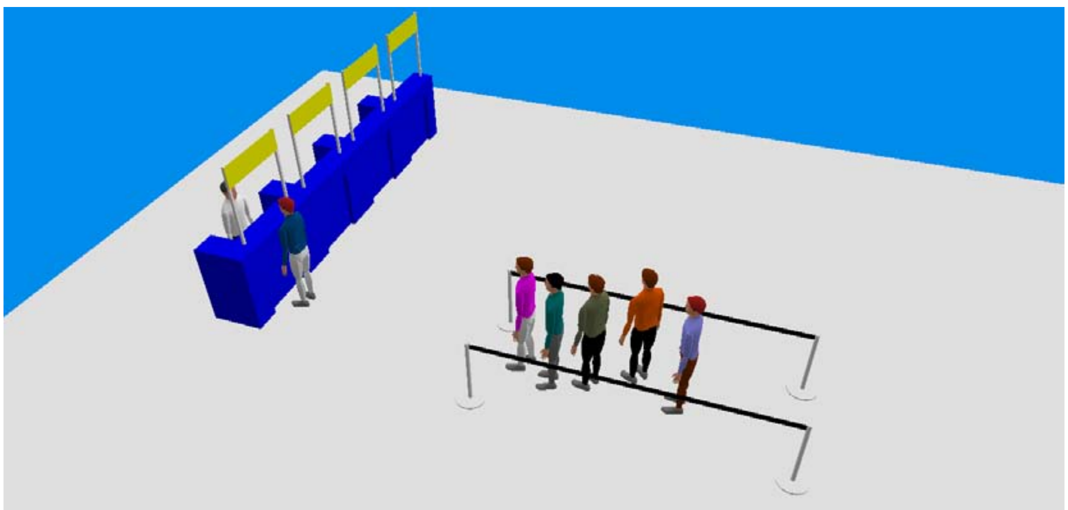

Figure 7: Graphical M/M/1 Queue.

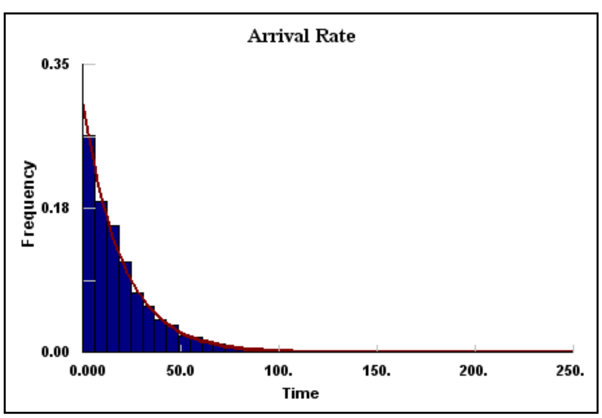

Figure 8: Validation of arrival rate distribution.

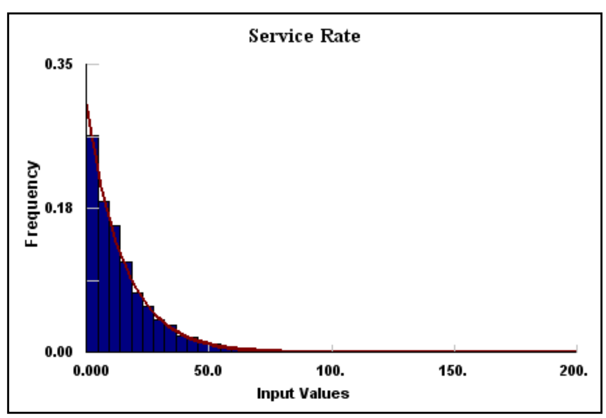

Figure 9: Validation of service rate distribution.

5.1 Validation

The model requires validation on the two main distributions in use, the arrival and service rates, shown in Figure 8 and Figure 9 respectively. These graphs show the resultant arrival and service rates generated within the model for scenario 1, together with the fitted distribution. A statistical test of these results shows no significant difference between what was generated and what was required to be generated, i.e. an exponential distribution with parameters derived from Table 2.

A simple queueing model was developed to verify implementation against theoretical results and the results are shown in Table 3. The aspects of the queue chosen for analysis are the size of the queue, the time in the queue and the time in the system. These are chosen as they reflect spatial requirements of the system, i.e. the queue length, and also reflect a passenger's experience in the system. The model was run for sufficient time to generate a steady result, i.e. further run time would not significantly alter results. An example output is shown in Figure 10. In this graph the average queue length is plotted over time for scenario 1. After 20,000 samples, the results were stable. With this figure in mind, multiple replications were run to determine if there was a difference between successive runs. An ANOVA test was applied and the results indicated that there was no significant difference between simulation runs. The results verify that the software package is a suitable tool for the analysis of queues.

Table 3: Simple queueing model results.

Scenario	Queueing Theory Results			Simulation Results		
	Average Queue Length (passengers)	Average Time in Queue (min)	Average Time in System (min)	Average Queue Length (passengers)	Average Time in Queue (min)	Average Time in System (min)
1	2.25	0.75	1.00	2.27	0.76	1.01
2	0.12	0.04	0.29	0.13	0.04	0.29
3	0.01	0.00	0.25	0.01	0.00	0.25
4	0.23	0.08	0.20	0.23	0.08	0.20

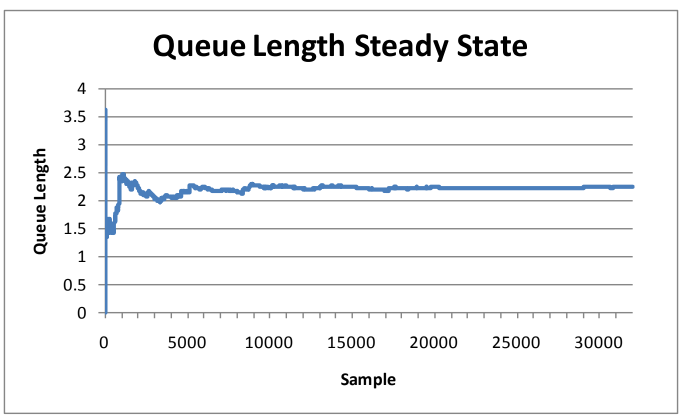

Figure 10: Average queue length over time for Scenario 1.

5.2 Queue Controller Results

Similarly to the verification replication analysis, multiple runs were performed to determine average values for the queue controller described in section 4. The queue controller was applied to the queueing system shown in Figure 7. In this system, passengers arrive according to an exponential arrival rate and travel to the back of the queue. Passengers are using a walking speed distribution based on the results from section 4. Within the queue, a passenger's speed is defined by the minimum of their speed and the speed of the passenger in front of them. The time in queue is derived from the time a passenger arrives at the back of the queue until the time they leave the queue to travel towards a server. The in-system time is derived from the arrival at the back of the queue to the time servicing is completed. Queue length is self-explanatory. The results from the simulation model are shown in Table 4

Table 4: Queueing theory and simulation results for each scenario.

Scenario	Queueing Theory Results			Simulation Results		
	Average Queue Length (passengers)	Average Time in Queue (min)	Average Time in System (min)	Average Queue Length (passengers)	Average Time in Queue (min)	Average Time in System (min)
1	2.25	0.75	1.00	9.09	2.89	3.20
2	0.12	0.04	0.29	0.23	0.08	0.36
3	0.01	0.00	0.25	0.05	0.02	0.31
4	0.23	0.08	0.20	0.52	0.17	0.35

Figure 11, Figure 12 and Figure 13 show a more detailed result for each scenario. Rather than providing an average result, the simulation results show a detailed representation of the queueing system and show extremes that queueing theory averages over. Figure 11 and Figure 13 show the cumulative percentile chart of the time in the queue and the time in the system. As expected, where the arrival rate is close to the service rate, as in scenario 1, the time in the queue and the time in the system is large. The simulation results show that the time spent in the queue can reach 9 minutes. Figure 12 shows a cumulative percentile chart of the queue length of the system over time, with a peak length of 55 for scenario 1. This chart shows that for scenarios 2,3 and 4 the queue is often empty, while for scenario 1 the queue is empty only 18% of the time.

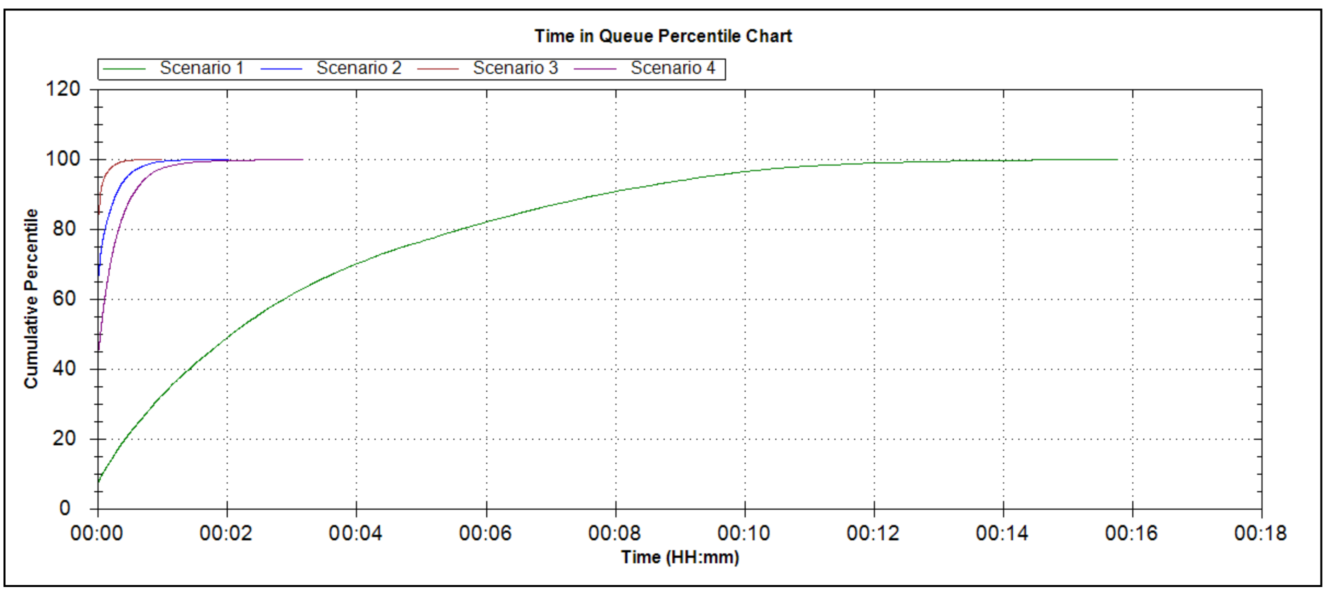

Figure 11: Time in queue for each scenario.

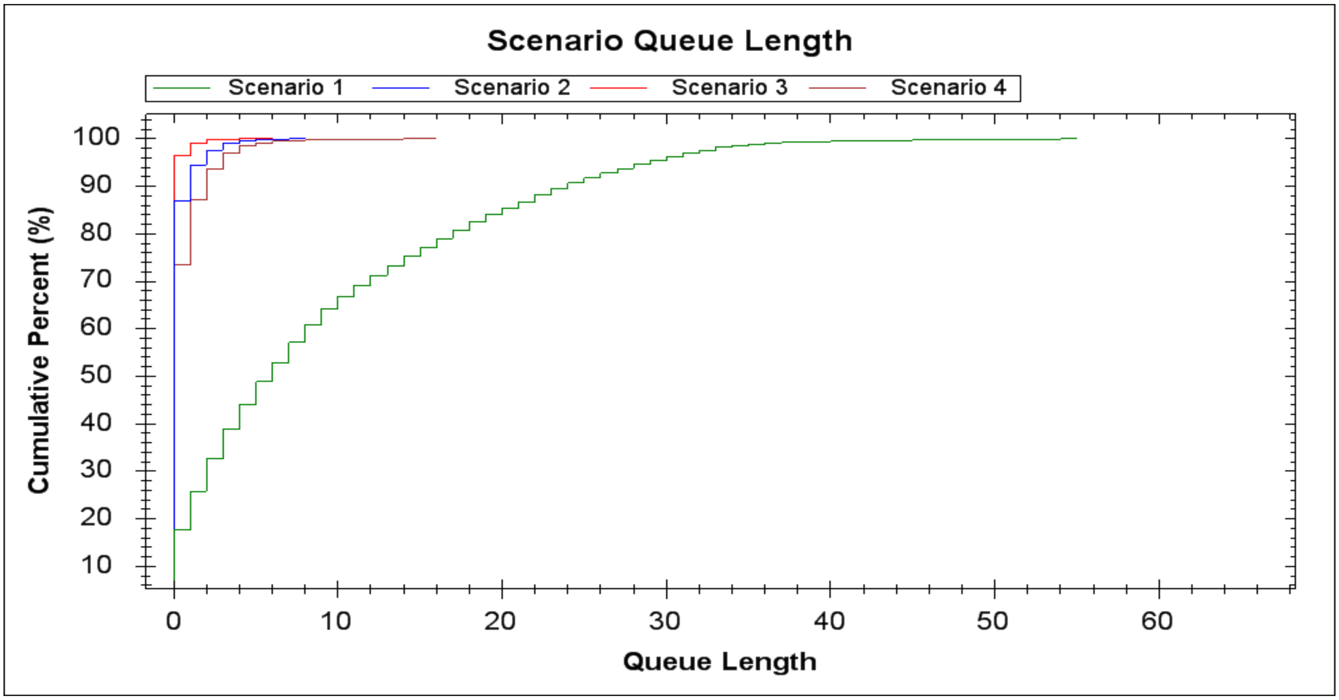

Figure 12: Queue length for each scenario.

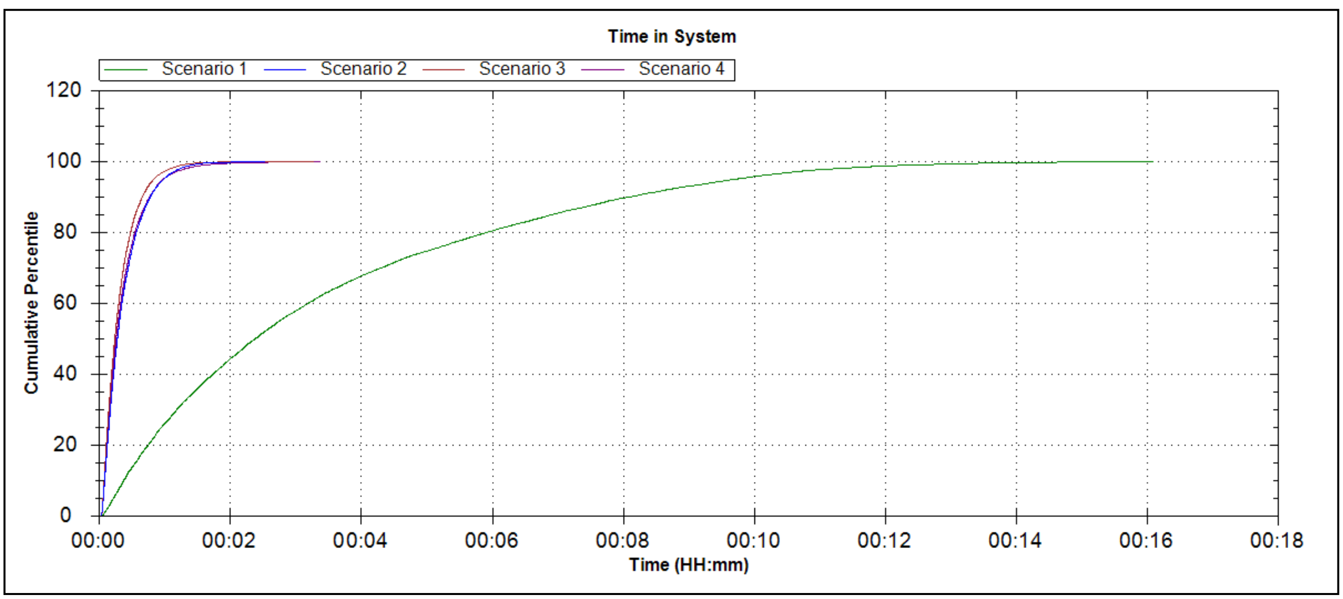

Figure 13: In-system time for each scenario.

The results from the simulation run are higher than those generated by queueing theory. This error is accounted for by the fact that passengers must travel between points in the simulation model. In the applied queuing theory, there is no allowance for journeying from the queue to the server and from the arrival point to the back of the queue. These factors could be averaged and used to modify the arrival and service rates, however the result is still an average. Simulation provides greater clarity of how the system will behave.

6 CONCLUSION

This work provided results from a study conducted at an Australian international airport into the walking speed of groups of pedestrians as they approached a security checkpoint. The data for each group was presented and a distribution fitted that was found not to be significantly different.

A queue controller that created a realistic queue and provides suitable queueing behaviour was also presented. This controller was compared to footage of similar queues to determine its fidelity. The queue controller operates in a discrete event environment operating on an entity-based microscopic simulation.

The results from a set of systems, making use of the new queue controller, were compared to the results obtained from applying queueing theory. The results from queuing theory provided an average value that was less than the results obtained from the simulation model. The reasons for these discrepancies are put down to the variability in travelling through the queue and from the queue to the server.

Simulation can provide a better understanding of the system being analysed as these results show more than just the average values provided by queueing theory. With a better understanding of the queue behaviour, better design of queueing areas can take place. Visualisation of the environment can also provide a way to validate the model more easily than a set of mathematical equations.

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