The simulation of lift systems and the modelling of passenger movements

Muna Hamdi and David Mulvaney
Department of Electronic and Electrical Engineering
Loughborough University
Loughborough LE11 3TU
UK

Abstract

In modern high-rise buildings, a suitable control algorithm has to be chosen so that lifts can respond to passenger requests in such a way as to transport them quickly and efficiently to their destinations. The aim of the current work is to assess new scheduling approaches and intelligent monitoring techniques, to aid the design of new lift systems and to improve the performance of existing installations. To achieve this, a lift simulator has been implemented to allow the modular comparison of alternative scheduling and monitoring approaches and to provide an accurate model of lift dynamics. In addition, a model of passenger movements has been developed from an analysis of data gathered from installed lift systems, thereby allowing the realistic simulation of landing calls, car calls and door opening times.

1 Introduction

Lift simulators are developed for two principal purposes, namely to aid the design of new lift installations and to assess the relative performances of alternative scheduling strategies. The current work falls into the second category [1]. The first lift simulators were built in hardware; modern software systems bring flexibility to lift simulation. As well as aiding the understanding of the effects on the lift system of different traffic patterns, a lift simulator allows potential customers to view the performance of proposed lift installations. At the design stage, a simulator may aid in the selection of the number of lift cars which will provide sufficient handling capacity under the control of a suitable scheduling system, while maintaining efficient building space utilisation. In buildings whose function may alter during their lifetime, a lift simulator enables the development of an adaptable control algorithm to provide flexible efficient transportation under a variety of operating conditions.

The conventional way of calculating the performance of lift systems is based on probability theory in conjunction with simplifying assumptions. For example, during the up-peak period, most calculations assume evenly populated floors, transportation of the same average load in each car from the ground floor and equal interfloor heights. However, the calculated interval (the average time between successive lift car arrivals at the main floor with cars loaded to any level [2]) and handling capacity do not give adequate information for all traffic patterns and a lift simulator is required to produce a more accurate description of system performance under different scheduling algorithms, traffic patterns and building specifications. Using a lift simulator, different patterns of traffic can be tested and goals such as minimising waiting or journey time can be monitored to optimise scheduler performance and to produce an efficient building design in terms of serving of shops, restaurants, or entrances [2-8]. For example, simulation results have indicated that there is no direct connection between interval and waiting time. The interval depends on the number of lift cars and lift capabilities, while in addition to the lift performance, waiting times depend on passenger arrival patterns and, particularly at peak times, the performance of the scheduler [4,5].

One of the most difficult problems in lift system design is accounting for the unpredictability of the traffic patterns, such as when the next landing calls is going to occur, how many passengers are behind a call, how long it will take them to get into a lift and which destination each is going to choose. The missing knowledge makes the task of providing optimum real time decisions by the scheduler impossible in practice. In general, the more we know about the building and lift environment and the more accurate the data supplied to the scheduler, the better will be its performance. An intelligent lift scheduler uses the assistance of a prediction system which analyses the daily traffic data of the lift system and compares it with previous analysed data in order to identify general trends in the traffic density and distribution. These expected values can then be used to aid the production of scheduling decisions. At times of peak demands on a group of lifts, the need for an intelligent co-ordinated scheduling lift system is necessary to minimise the passenger waiting time and to prevent long queues developing. Rapid data processing by a simulator will allow its use as a part of a traffic monitoring system which observes traffic fluctuations and feeds back useful information to the scheduler.

The analysis of the distribution of passengers arriving at a given floor requiring to use a lift falls in the domain of queuing systems [9]. The literature indicates that by generating a random number from a suitable Poisson distribution the time of arrival of the next passenger arrival can be estimated [10]. This implies that the probability distribution of the time intervals between passenger arrivals will be exponential. In the current work, it has been possible to assess such theoretical assumptions as access has been obtained to real lift installations and relevant data has been gathered directly. However, passenger information is not available directly at a lift installation, as only data relating to passenger activities monitored by the lift system can be recorded. Hence, it was necessary to carry out further processing work on these data in order to produce an appropriate model to estimate the distribution of passenger arrivals. This model is now available for use in the lift simulator itself. It has also been possible to derive for each floor the distribution of car calls which result from landing calls. This is used for generating car calls in the lift simulator.

This paper describes the implementation of a lift simulator as a part of an intelligent real-time scheduling system, figure 1. In the following section a definition of the intelligent lift system is given and the significance of the use of a lift simulator as an essential part of its development. The remaining sections discuss the lift simulator itself and how data extracted from lift installations have been used to develop a model of passenger movements.

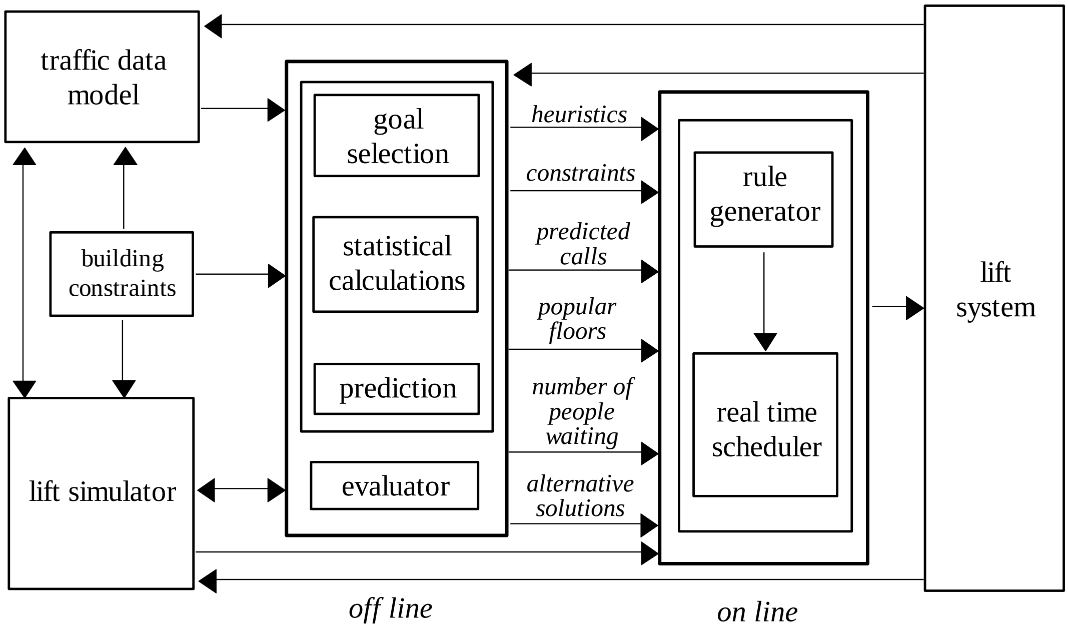


Figure 1 Intelligent lift scheduling system

2 Intelligent real time lift scheduling system

A lift scheduler operates in continuous state space and in continuous time as a discrete event dynamic system; its state is not fully observable and the problem is non-stationary due to changing passenger arrival rates [11]. In modern lift scheduling systems, there may be a number of goals, such as minimising one or some combination of the following: waiting time, average waiting time, transfer time, crowding inside the car and energy consumption. In addition, it may be possible to simplify the complexity of determining the optimum route to the goal state by identifying sub-goals, examples of which are landing priorities and parking policies.

In order to satisfy the goals, an intelligent monitoring system is required to assist the real time scheduler. The monitoring system is responsible for analysing the domain knowledge available about the building and the traffic, and for providing the scheduler with the following.

- The strategy or the objectives that the scheduler must follow.
- A prediction of the traffic type, for example the timely detection of up-peak traffic, the most probable landing call or car call for the next state, the number of passengers waiting, popular floors and priority floors.
- An evaluation of the current state which helps the scheduler correct its action and suggest alternative solutions.

Most of this information can be communicated off-line, that is, it need not be synchronised with the immediate real-time scheduling calculation.

In general, the greater the quantity of knowledge that is maintained regarding the state environment, the better will be the performance of the scheduler. It is apparent that to achieve an optimum call allocation strategy, it is essential to know the current and future passenger traffic flows. Clearly, this cannot be achieved in practice and the traffic flows can only be estimated from that data available in the lift system. The current work described in this paper has followed the stages outlined below.

- Use as much of the available traffic data as possible and ensure this is of the best possible quality, for example, even car loads and the patterns of photocell activations are important in predicting passenger movements.

- Perform statistical analysis on the traffic data in order to identify and learn traffic patterns.

- Extract rules for strategy selection, prediction, evaluation and generating alternative solutions.

- Use a simulator as part of the off-line system to assist in data analysis and decision making.

To achieve the above, an accurate simulation of the lift system is required. This simulator must be able to generate information such as the door, load, and position status of each lift car in order to provide different and varied examples of performance in response to a range of traffic levels. In the literature, many examples of the use of lift simulation for testing, evaluating and assisting in the task of providing the best scheduling algorithm[11-16].

3 Lift simulation

A lift simulator is a discrete event, fixed-time increment, dynamic, stochastic simulation of a group of lifts [7]. The simulation should give as close a resemblance to the real world as possible. Figure 2 shows the main modules of the lift simulator. The simulator is configured during an initialization stage in order to define information about the building, such as number of floors, floor heights, lift speed, acceleration and door timing. The current simulation employs examples of existing buildings with traffic models extracted from real traffic data, see section 4. The simulator normally begins at the start of the day when there is little or no activity in the building and assigns the individual lifts to pre-defined parking floors ready to receive the early morning traffic. In the simulator, the following sequence of events occurs for each passenger. Following arrival, a landing call is generated, the scheduler assigns a lift to answer the call, car doors open, as passengers enter they press their destination buttons thereby generating car calls, after the last passenger has entered the doors are closed and the lift moves to answer the car calls. At each time step, the system state is updated and the scheduler receives information of landing calls, lift car calls, lift position, lift loading and door status. The time step can be set to meet a range of accuracy requirements. As the day goes by, the traffic intensity changes through up-peak period, normal activity, lunch peak period, normal activity again and finally down-peak period. Under light traffic conditions, when there is no activity in the lift system, the time step can be modified so that the simulation jumps in time to the next person’s arrival.

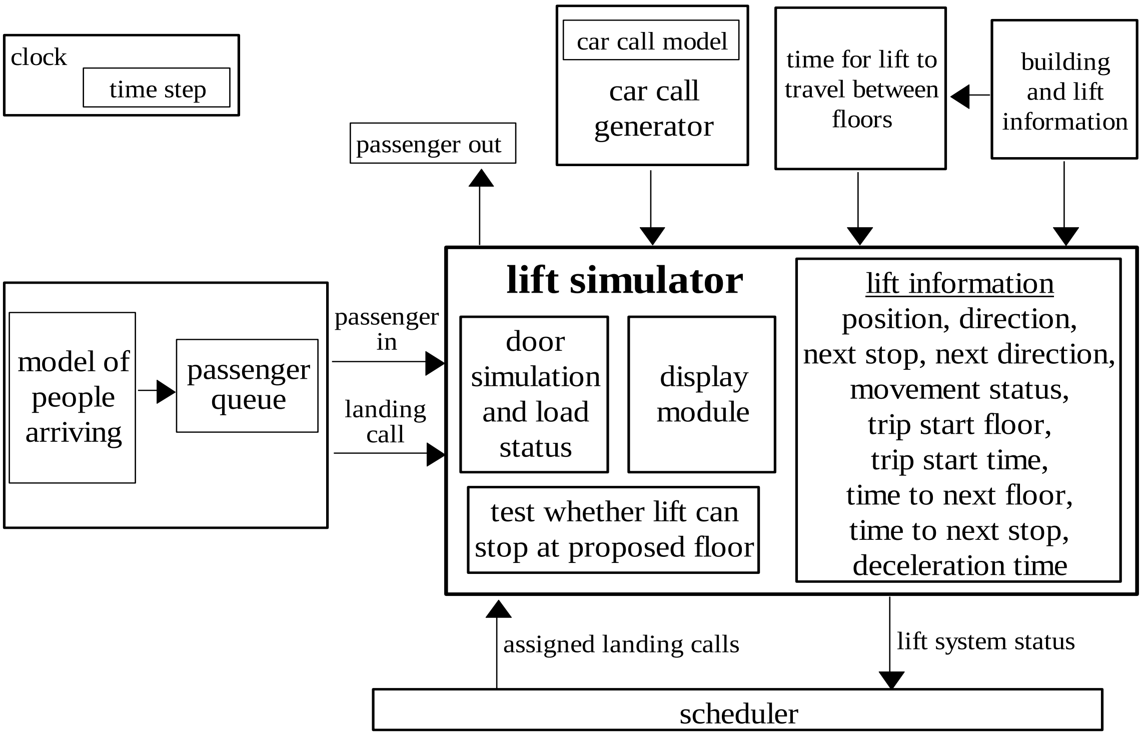


Figure 2 Lift simulator

Figure 3 shows an example of the visual part of the simulator displaying the lift group activity. The example shows an 18 floor building; the columns represent the individual lift shafts and the rows represent the floors. In addition, the first two columns to the left show the number of passengers behind up and down landing calls at each floor. The first row below each of the lift shafts labels the shaft indicating the locations of car calls *, assigned down landing calls ↓ and assigned up landing calls ↑. The numbers shown in the shafts themselves represent the number of passengers behind a call at each floor. The total number of passengers in a car and the number of passengers behind assigned landing calls are displayed

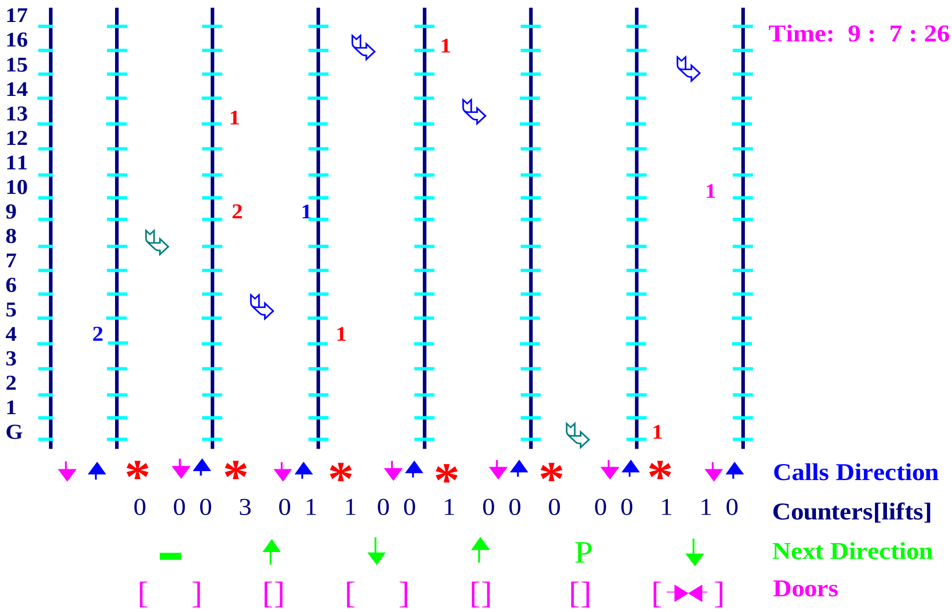


Figure 3 Example of the lift simulator visual display

in the same sequence, in the second row below the lift shafts. The remaining two rows show the lift's next direction and the door status. Lift movement between floors is indicated by scrolling the lift symbol within the shaft, which flashes to denote movement, and the lift load status is indicated by the colour of the lift symbol. A clock displaying the time of day is shown at the top right of the screen; the user can freeze the display and then single step the simulator to permit closer inspection of the scheduler's operations. The simulator display is capable of showing an installation having a maximum of 18 floors with six lift cars and for a building which has more than one group of lifts each can be displayed separately.

When the lift is assigned a landing call as its next destination it starts moving towards that floor. Jerk, acceleration, maximum speed and floors heights are used to determine the time a lift takes to make interfloor journeys and these are saved in a lookup table. While a lift is moving the scheduler might assign other landing calls to the lift provided that the lift has sufficient time to decelerate and stop. As the lift stops at a floor, its doors start opening. Figure 4 shows an example of door states and timings. Each time a passenger gets into the lift, the counter on the display is updated and a car call is generated in the direction of the landing call. As passengers leave the lift, the doors remain open in dwell state until a passenger arrives and a car call is issued (or until the lift is reassigned by the scheduler). Otherwise, at the end of the dwell period, the lift doors begin closing. While closing, if further passengers arrive, then it is assumed that they press the landing call button and the doors reopen as long as the number of passengers in the lift car is less than the maximum number allowed. The dwell period and the passenger's entrance and exit times are usually set at the beginning of the simulation, but, if required, these can be varied by the scheduler to suit a particular traffic intensity requirement.

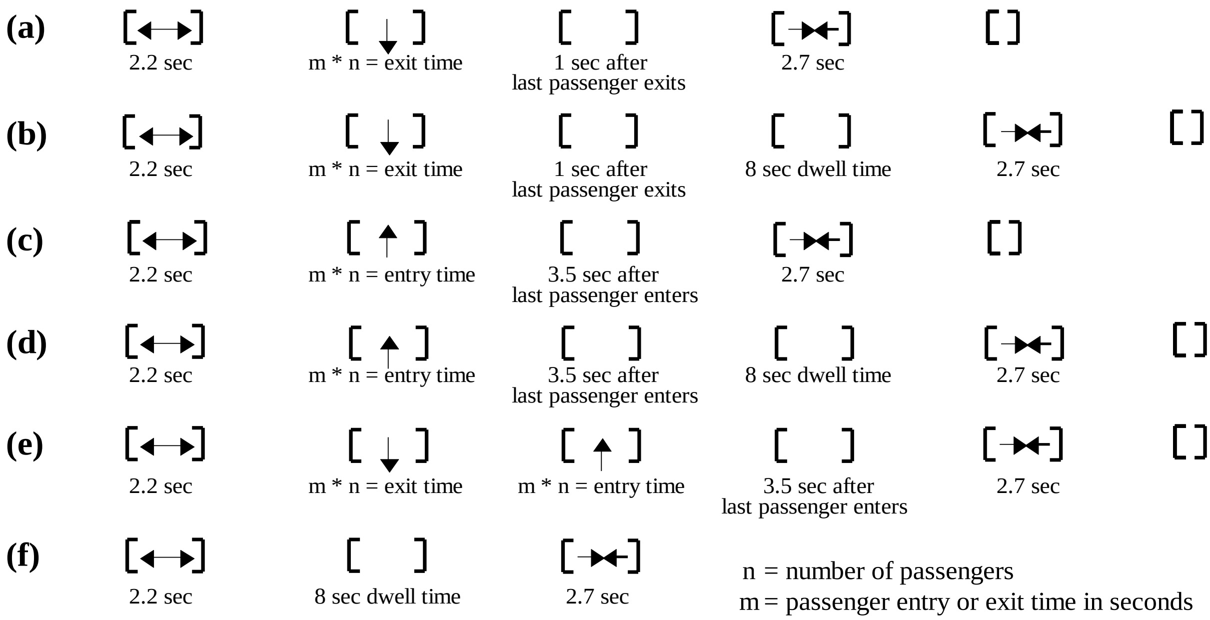


Figure 4 Door states and time intervals for **(a)** normal passenger exit, **(b)** passenger exit but the lift is not further assigned by scheduler, **(c)** normal passenger entry, **(d)** expected passenger entry but no car call is issued, **(e)** normal passenger exit and entry, and **(f)** free lift sent to parking landing.

The following can all be monitored for performance assessment purposes: passenger arrival time, landing call time, landing call cancellation time, door opening time, loading time, passenger car call, door closing time, car departure time and transfer time. The validity of a traffic pattern under the influence of a given scheduler can be assessed by comparing the outputs of the simulator with those of the real system.

4 Derivation of a passenger arrival model

The passenger and car call models are extracted from real lift systems, overcoming the need to identify theoretically the traffic patterns. Although theoretical traffic calculations would still be needed in the planning stage, in an installation the initial traffic assumptions would be gradually replaced by real traffic examples when the intelligent monitoring system starts working in the building. Average arrival rates and passenger destination frequencies from each floor can be calculated from information such as car calls, landing calls, photocell activations, door status and lift moving status. Examples of full working days for varieties of traffic patterns, have been prepared to test the performance of the scheduler. The data patterns vary depending on the number of people in the building, the number of passengers using the lifts, popular floors (such as those having a restaurant or smoking room), and time of the day (such as up peak and lunch time). The monitoring system has the responsibility of monitoring these patterns and identifying popular floors and expected peak times. For example, morning arrival in a building can start at 7am, reaching its peak at 8am and then begins to slow down again at 9am. The same traffic pattern can repeat the next day or another pattern may emerge with arrival starting at 8am reaching its peak at 8:30am and slowing again at 9:30am. It often appears that, for the same number of passengers entering the building, the intensity of traffic at any given time during the up-peak period depends on when arrival begins and with what initial intensity.

Building traffic data has been acquired from a number of installations. This consists of data sampled each second and contains landing call locations, car call destinations, photocell activations, lift positions, door status, directions of movement of the lifts, whether each lift is stationary or moving and the load status of each lift. It is important to note that the data do not contain information regarding the movements of individual passengers in the lift system, yet this is precisely the data required for the simulator. In particular, it is impossible from the above data to determine exactly the number of passenger waiting at a landing when the lift arrives in response to a landing call. Hence, using the above data, we wish to extract a suitable estimate of the passenger arrival rates and their movements through the building. If these can be estimated adequately from the data this would avoid the need to resort to counting passengers manually.

Another advantage of being able to gather the traffic data from a real lift installation is that the data can easily be acquired over a longer period of time and from a greater number of landings and lifts simultaneously than is normally possible using manual counting. This has allowed a detailed assessment of assumptions often made regarding the nature of the probability distribution of the passenger arrival rates, namely that it follows a Poisson distribution and hence the time interval between passenger arrivals follows an exponential distribution.

The investigation of the data acquired from the lift installations has been extensive, and following figures are able to provide only a brief but representative insight into the results which have been produced. All the data were obtained from the lift system represented in figure 3 and this serves a building used for business purposes with a population of approximately 900. In order to make clear the meanings of some of the terms used in the figures which follow, figure 5 shows the typical sequence of events which occurs when a lift is sent in response to a landing call.

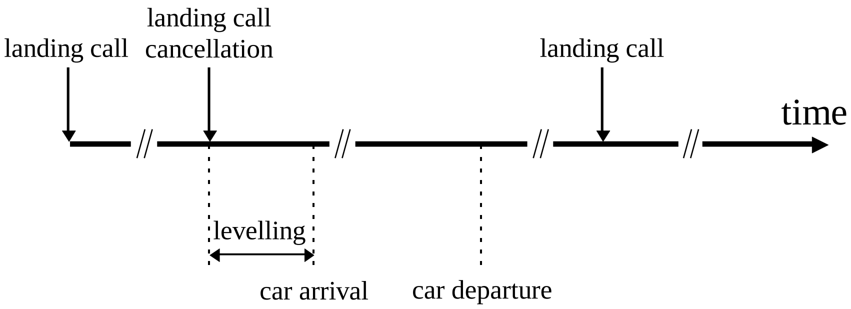


Figure 5 The sequence of events following the issue of a landing call

In order to develop the passenger model, the validity of the assumption found in the literature that the time interval between passenger arrivals follows an exponential distribution was assessed. Figure 6 shows the distribution of intervals between consecutive landing calls. It can readily be observed that this distribution is not exponential in nature and this can easily be explained by considering the sequence of events following the issue of the landing call. Most importantly, if a lift is not already waiting at a landing, it will take time for a lift to arrive in response to the call and for the doors to open. Consequently, as can be seen from figure 6, the time period between the issues of consecutive landing calls will take at least 12 seconds. Furthermore, during this period the landing call remains in force and hence additional passengers may arrive who will not be directly detected by the lift system.

The significant difference that can occur in the distribution of intervals between passenger arrivals and that of intervals between landing calls can be illustrated by considering two types of passenger traffic. In the case where there is a relatively large number of passengers arriving over a period of time at a single floor, the performance of the scheduler may worsen and it will take longer for landing calls to be answered and hence for the next landing call to be issued. In the case where there are few passengers entering the system, there will be correspondingly long time intervals between landing call buttons being pressed. Comparing the two cases, although the time intervals between passenger arrival is significantly different, the time intervals between landing calls may be similar.

In order to better understand the nature of the traffic, a variety of intervals between the events highlighted in figure 5 were considered. By plotting for a given landing the time interval between the issue of landing call and its cancellation, the performance of the scheduler can be studied, for example in figure 7. An example of the distribution of the time intervals between landing calls and car arrivals is drawn in figure 8. In comparison with figure 7, the main part of the curve is shifted to the right reflecting the levelling time of around four seconds, but the frequency values at one and two seconds largely remain, as these occur when a lift is already at the landing and no levelling period is required. Including the loading time and both the door opening and closing times provides the distribution of time intervals between landing calls and car departures, figure 9. During this period, any further landing calls cannot be observed.

In order to estimate the passenger arrival rate at a particular landing, the current work investigated employing the time interval between car departure and the issue of the next landing call. This is effectively the time interval remaining once the system delays illustrated by figures 7, 8 and 9 have been removed from the time intervals between consecutive landing calls. Only during this interval is the landing call button available for passengers to press, and hence it is the only time during which the arrival of a passenger can be observed (and their arrival which is indicated by their pressing of the landing call button also ends each interval). Clearly, this can only be an *estimate* of the passenger arrival rate, and it is recognized that errors will occur as the arrival of further passengers cannot be observed until the car departs and as more than one passenger may arrive at a time. An example of the results obtained from this approach are shown in figure 10. Figure 11 shows the results of fitting to the raw data an exponential curve *f(t)* of the form shown below.

$$f(t) = A\lambda e^{-\lambda t}$$

where λ is the average time interval between the car departure and the next landing call being issued and

$$A = \lambda T$$

where *T* is the time during which observations are made.

In general, the hypothesis of an exponential form for the distribution of the intervals between car departure and the next landing call agreed with the data. However, on investigation of the area under the curve in figure 11 (which should be equal to the number of passengers arriving during the observation time), it was found that 206 passengers arrived, similar to the number of landing calls issued. Measuring the time interval between the car departure and the next landing call did not provide sufficiently good estimates of the number of passengers. This is probably due to the fact that the data are non-stationary, that is, there is significant change in the arrival rate over the length of the observation period and hence the shape of the underlying exponential function is continually changing. Rather than requiring the fit of single exponential curve as shown in figure 11, the real data comprises, over time, a family of exponential curves. By adopting sufficiently short time windows, the variation in the arrival rate could be identified, but as it would contain fewer examples of arrivals, the variance of the data would be significantly increased resulting in estimates of poorer quality.

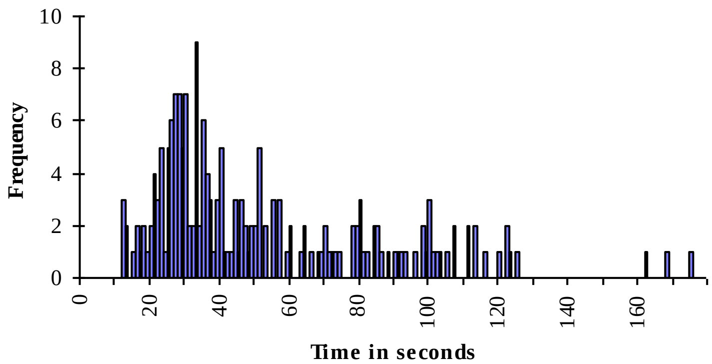


Figure 6 Distribution of the intervals between landing calls on the terminal floor between 7am and 10 am

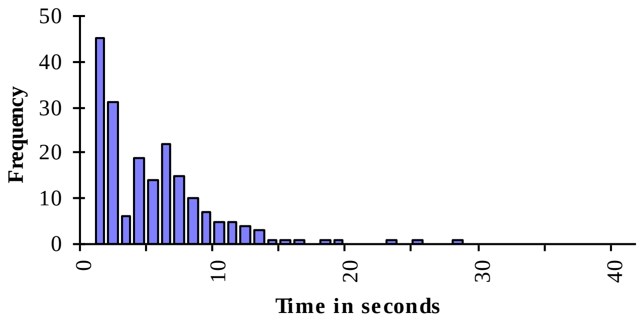


Figure 7 Distribution of the intervals between landing calls and their cancellations on the terminal floor between 7am and 10 am

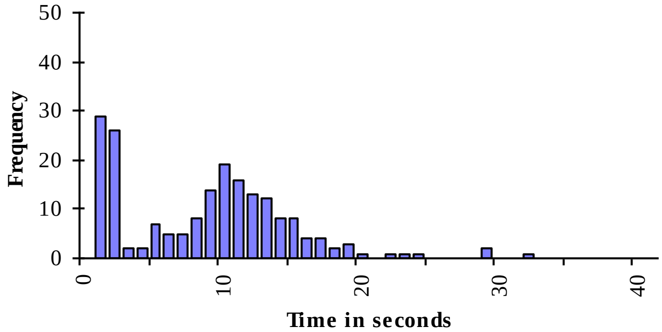


Figure 8 Distribution of the intervals between landing calls and car arrivals on the terminal floor between 7am and 10 am

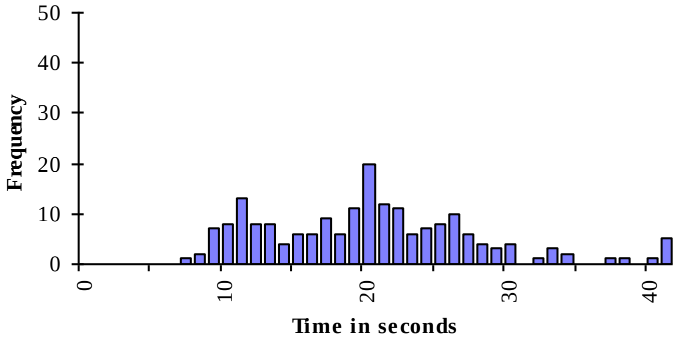


Figure 9 Distribution of the intervals between landing calls and car departures on the terminal floor between7am and 10 am

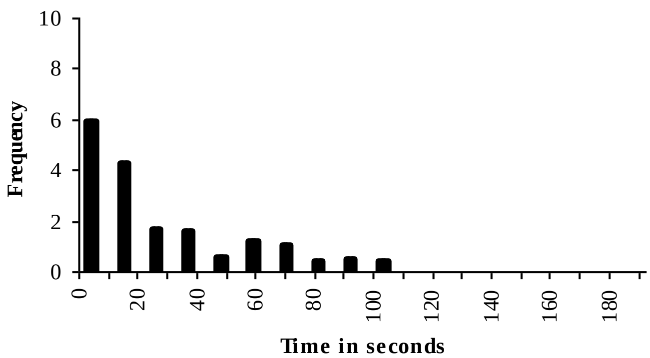


Figure 10 Distribution of the intervals between car departures and next landing calls on the terminal floor between 7am and 10 am

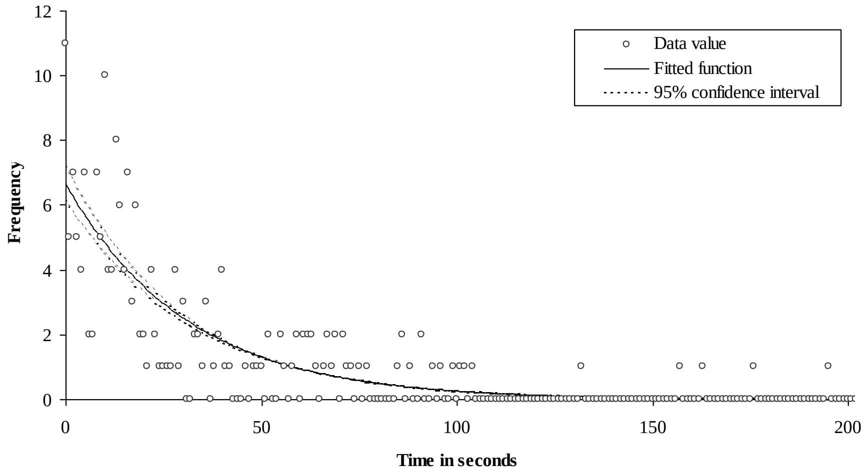


Figure 11 Test of the exponential nature of the distribution of the intervals between car departures and next landing calls on the terminal floor between 7am and 10 am

An alternative method was now required to model the passenger arrival. In its development, the following points were considered.

- To observe changes in arrival rates, the mean arrival rates during consecutive five minute windows were used. The window length was so chosen as to be consistent with that used in the calculation of lift handling capacity during the up-peak period[6].

- Cars arrive at a floor in response to a landing call at that floor, a car call to that floor being issued by passengers already in the car, or following a specific action of the scheduler.

- The number of car calls issued and the number of photocell activations both provide an indication of the number of passengers entering the car.

A set of rules was developed to estimate the number of passengers waiting at landings to enter the car, based on the number of car calls issued and the number of photocell activations. The rules are shown in Figure 12. In general, when passenger departures are detected, or when an inconsistently large number of photocell activations are detected, the method bases its estimations on the number of car calls issued following boarding. When the photocell count is valid and is greater than the number of new car calls, it is used directly to represent the number of passengers.

As a result of the investigation of car calls and photocell activations, a model of passenger arrival could be generated for use in the simulator. Figure 13 shows the passenger arrival rate extracted from a real lift installation using the rules of figure 12 and that obtained from the model by adopting the same arrival rate for a Poisson distribution in the lift simulator. To assess the validity of the rules, figure 14 shows a comparison between the landing call rates for both the real lift installation and for those obtained in the lift simulator using the model. It can be seen that there is close correspondence between the two curves, except during the morning up-peak period (between about 8am and 10am). This is probably due to a known difference in the performance between the real and the simulated scheduling systems during the up-peak period, and work is currently being undertaken to confirm this.

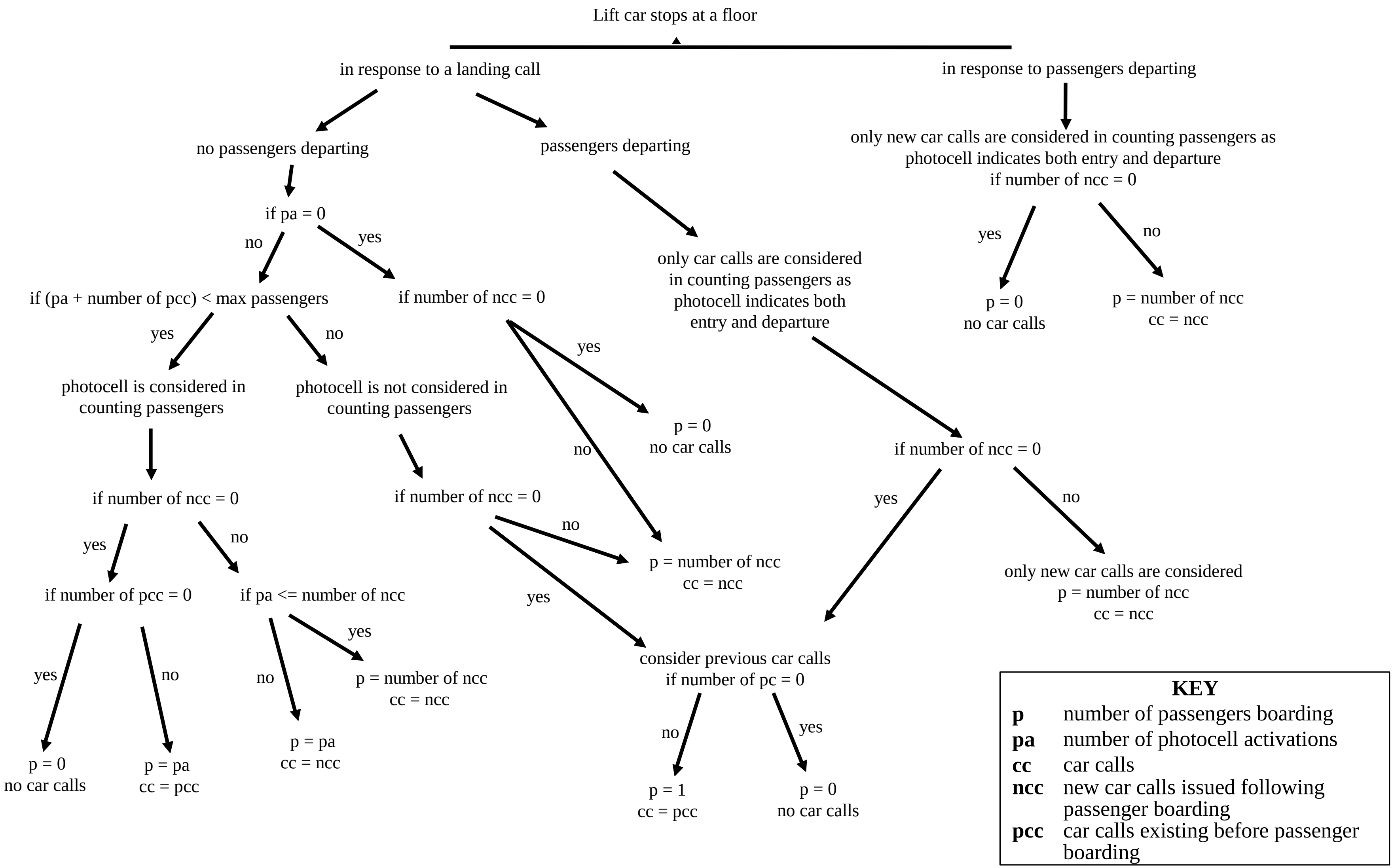
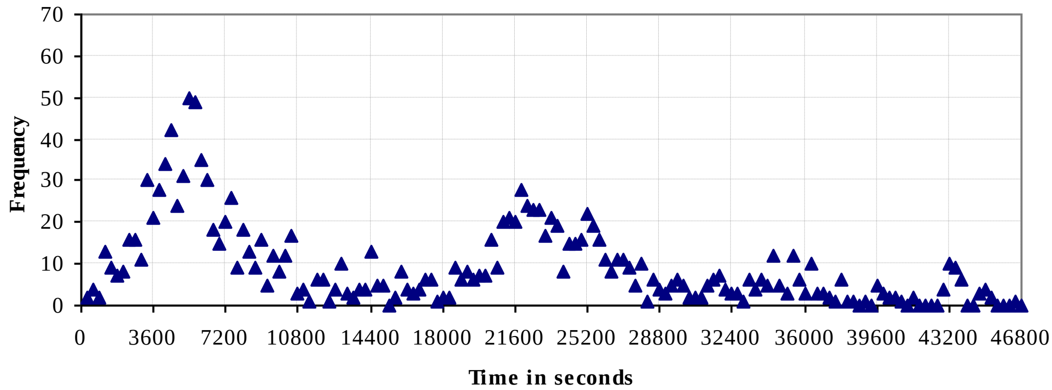
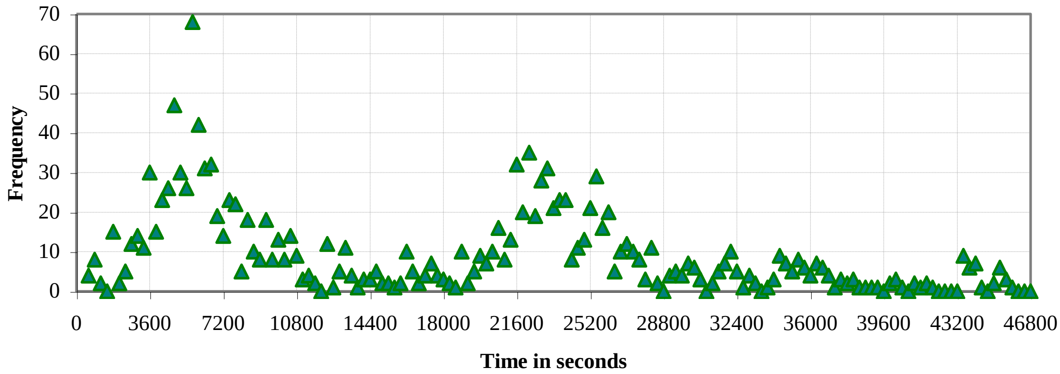


Figure 12 The rules used to extract an estimate of passenger numbers from car calls and the number of photocell activations

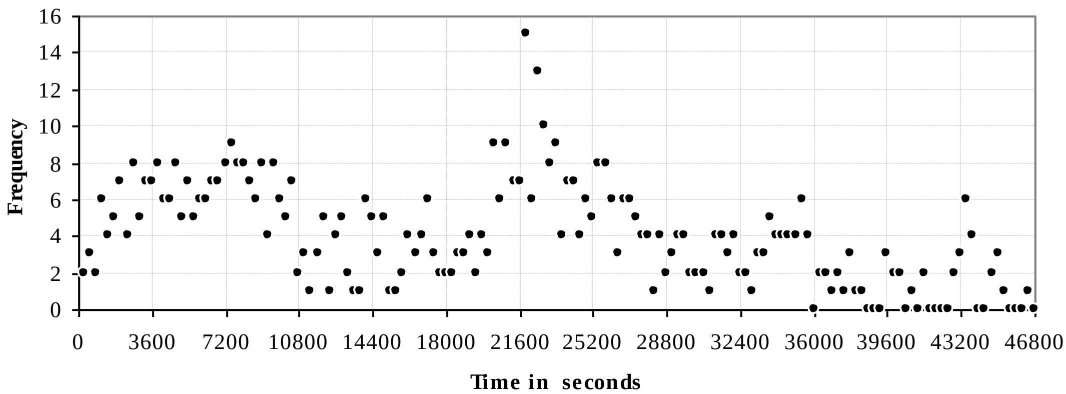


(a) passenger arrival in a real lift installation extracted using the rules in figure 12

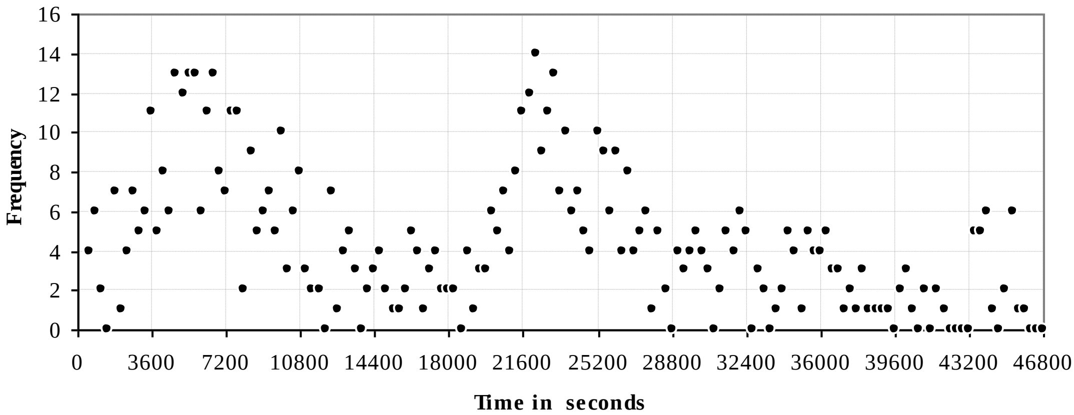


(b) simulation of the passenger arrival in (a)

Figure 13 Comparison of extracted passenger arrival using the rules of figure 12 with simulated passenger arrival on the terminal floor between 7am and 8pm



(a) landing call variation in a real lift installation



(b) simulation of the landing call variation in (a)

Figure 14 Actual and simulated landing calls on the terminal floor between 7am and 8pm

The passenger model described above permits the simulation of passengers entering the lift system, but not their movements within it. An additional model is required in order to simulate the pressing of car call buttons by passengers to communicate their desired destination once they enter a lift. Figure 12 includes the rules applied to observations of real lift installations to obtain the car call distributions for use in the lift simulator. Using the rules, then for each landing, the number of car calls to all other landings served is recorded during each five minute window [10]. This car call frequency model can be used directly in the simulator, or alternatively a mathematically smoothed version may be used in which the car call distribution for a given interval is found from the mean of current and previous windows.

5 Conclusion and future work

Lift simulation is an essential part of lift system design and testing. In our simulation, we make use of real system data in order to maintain a close imitation of actual lift motion and time delays. The availability of the traffic model can replace the need to identify separately specific traffic patterns such as up peak and down peak with the monitoring system being given the responsibility of generating relations between floors and their traffic density.

Lift simulation can also be used as a part of a real time system to assist the scheduler in searching for the best assignment solution, for example by supplying the expected next lift state configuration which the scheduler can base its present decision. Also the performance of the scheduler can be tested in special cases, such as when one of the lift cars is out of order. The condition can either be induced directly from the keyboard at any time or by registering the time of occurrence before the start of the simulation run. The performance of any scheduler is greatly dependent on the quality of data it receives. The quality of data provided by the lift system can be improved by using simulation results. For example, during simulation, the lift simulator is able to supply the scheduler with better load status information than the data usually available from the real system. This can be used to assess the importance of attaching more accurate load sensors to a real lift.

A number of extensions to the current lift simulator system could be made to improve the model of passenger behaviour. Under certain traffic conditions a passenger may choose to board a lift moving in the direction opposite to that of intended travel. Also under light traffic conditions, a passenger might press a button to close the lift car doors after getting into the lift.

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Biographical notes

Muna Hamdi received a BSc in control and system engineering in 1984 and an MSc in computer engineering in 1989. She has working experience of designing real time automatic control systems. Currently she is studying for a PhD in intelligent lift scheduling systems.

David Mulvaney has over ten years’ experience of designing and implementing knowledge-based systems. These include an expert system for scheduling military aircraft training flights, a knowledge-based system to aid the assembly of surface mount components and a real-time artificial intelligence system for radar data fusion. Current work includes the investigation of artificial intelligence techniques for lift scheduling and the classification of surface texture data. He is a co-holder of an EPSRC award for the intelligent assessment of water quality using an on-line imaging nephelometer.