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RateSetter: Roadmap for Faster, Safer, and Better Platform Train Interface Design and Operation using Evolutionary optimisation

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ABSTRACT

There is a challenge ahead in the rail industry to accommodate increased demand. Time spent at the platform train interface (PTI) as passengers board and alight, rather than on the move, represents a limitation on system capacity. To overcome this, we propose RateSetter: an evolutionary optimiser that for the first time provides more effective PTI design choices based on passenger flow time and safety. An agent based passenger simulation model validated with CCTV footage is employed for fitness evaluation. The initial results provide guidelines not only for future PTI designs but also for retro-fit designs to existing infrastructure, evaluating the effectiveness and diminishing returns of PTI features for the considered scenarios. Furthermore, it is observed that the proposed optimal PTI designs could significantly reduce the flow time for the cases examined. Results show that retro-fit designs could reduce the flow time in the range of 10%-35%.

KEYWORDS

real-world applications, optimisation, platform train interface

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1 INTRODUCTION

The British mainline railway network includes approximately 6,000 platforms at over 2,500 stations. With an estimated 1.6 billion passenger journeys each year this equates to more than three billion crossings of the platform train interface (PTI) as passengers board and alight [19]. There is a challenge ahead in the rail industry to accommodate increased demand, and time spent by trains in the station as passengers board, rather than on the move, represents a limitation on system capacity [20]. In the shorter term the solution is likely to be better utilisation of existing infrastructure, including enabling faster passenger boarding behaviour. However, it is unlikely that these remedies alone will be able to support longer-term growth projections. As such, it is necessary to consider the design of future platforms and train interiors to reduce boarding and alighting times.

Interactions between platform and train features are key to identifying the best design and operational choices: improved flow rate of people from a train can only be realised if the platform is able to absorb the people (and vice versa for people boarding the train). With many thousands of design combinations possible it is not feasible to test all of them through building physical mock-ups for trial with extensive and representative passenger cohorts. To explore the feasibility of applying modern computing techniques to PTI design, this work was undertaken through a funding call by the Rail Safety and Standards Board (RSSB) in Great Britain (GB). Here, an alternative to physical mock-ups is proposed that employs parallel computing to rapidly evaluate the options, making use of existing models [17, 24] of people movement. Passenger cohorts for testing the designs are replaced by real-world human behaviours captured from CCTV on existing railway systems and represented within a people movement model.

The class of popular heuristic optimisation algorithms namely genetic algorithms (GA) is used in the current project to find the strongest combinations of train and platform design. Owing to their general purpose appeal and ease of use evolutionary algorithms have gained a wide popularity in past decades [3, 12, 18]. To our knowledge this project is the first to employ evolutionary optimisation for PTI design. Real-world CCTV footage from trains and platforms is used to validate simulated passenger flows for existing fleets, giving confidence in predictive application for novel train and platform designs. The emergent outputs of a passenger simulation model serve as the fitness criterion of the optimisation process. optimised outputs of the project focus on quick-win retro-fit options for improving existing trains and platforms, but could extend to more radical options for future stations and fleets.

The organisation of the rest of the paper is as follows. Section 2 discusses existing work and identifies key PTI features. Section 3 presents the passenger simulation model that serves as the fitness criterion of the evolutionary optimiser. Section 4 focuses on the evolutionary optimisation process, followed by Section 5 presenting the results. Section 6 presents concluding remarks and future extensions.

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2 BACKGROUND

2.1 Crowd Modelling

To build a realistic model of a operating PTI, realistic modelling of the boarders and alighters plays an important role. We consider the methods of general pedestrian modelling for train alighters and boarders. There have been numerous studies conducted to simulate pedestrian behaviour. Previous research into pedestrian modelling can be broadly categorised into two main approaches, microscopic and macroscopic.

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 [23]. These models have the benefit of a lower computational cost compared to microscopic models. However, they do not consider more complex psychological factors such as reaction to alarm and group interaction.

Microscopic modelling is a fine-grained approach. Pedestrians are modelled as heterogeneous elements, allowing for a variable behaviour between pedestrians. Three different methodologies are evident within microscopic modelling: cellular automata [11], entity-based [22] and multi-agent-based [4, 14, 21]. The microscopic approach has the benefit of being able to assign different behaviours to pedestrians, removing behavioural assumptions evident in macroscopic approaches hence being able to predict emergent crowd behaviour [4]. Within microscopic models, it is possible to study the effects on the physical domain such as movement, force and crowd safety when human behaviour such as information processing and communication is introduced [15]. Further aspects, such as collision avoidance can also be also integrated [24]. Moreover, incorporating visualisation into a microscopic simulation can greatly assist in the verification and validation of the model, ensuring that the model behaves as desired and reflects the real-world, for example, with queue formation on railway station platforms. However, these benefits come at the cost of increased computation. Both the computation of each individual entity interacting with the environment and the visualisation of the model are increased greatly.

Within our work, an agent based passenger simulation model for the PTI is developed using an agent based simulation framework called FlameGPU [17] that runs on a GPU (graphics processing unit), which offers massively parallel computation on desktop graphics card hardware. Using this approach the benefits of the microscopic modelling are captured while overcoming the challenges of high computational demand. Our simulation model is equipped with a graphical user interface as well.

2.2 Platform and Train-specific Models

In the current project we consider several existing train and platform architectures to determine the key design features that can be optimised to improve the passenger flow time and safety aspects of a PTI. Figure 1 shows an example of train layout for trains operating in GB. Figure 2 shows examples of door-step designs indicating a significant difference in passenger experience in boarding or alighting, especially for passengers with luggage. From the example designs we can identify basic features such as the heights of the platform and train, the horizontal gap between the two, the number of steps, and step height. The following section briefly reviews some models specific to rail and station design, informing the selection of train and platform features we consider in this project.

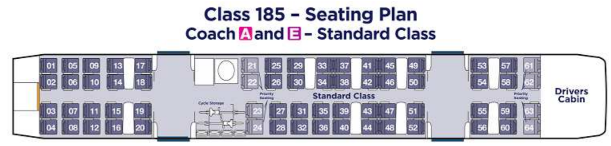

Figure 1: Train layout map example for class 185 of TransPennine Express (TPE)

Figure 2: Examples of door-step and step-free design

The work by Adamko et al. [2] proposes the optimisation of railway terminal design using a simulation model. However, this work does not incorporate a crowd model that represents pedestrians individually at the platform.

Passenger boarding and train alighting is studied in the work by Zhang et al. [25] where personal characteristics (gender, age, etc.) that influence behaviour are represented by a coefficient with a distribution dependent on the population. However, this model does not include the collective behaviour of passengers such as their distribution on the platform, choosing and changing target doors and other detailed behaviour that may influence alighting and boarding performance.

The impact of platform edge door (PED) design is studied in the work by Gonzalo et al. [13] who claim that while the presence of PEDs does not have a negative impact on the boarding and alighting time, it does affect passenger behaviour at the platform, inducing a more organised boarding and alighting process where boarders wait beside the door rather than in front of them, and give way to alighters more often than without PEDs.

Watts et al. [10] have investigated the factors influencing factors dwell time for high speed trains. Factors governing passenger boarding and alighting were identified as the exterior door width, the entry step height, platform gap, the layout of the vestibule, how and where luggage is stored, how passengers find their seat and the quality of information provided to passengers on the platform and on board. Their experimental study observing (actual) people movement showed poor boarding experience for people with lots of large luggage or small children when steps are present. A wider door width was observed to support easier/faster flow of people.

Adam et al. [1] have studied the factors affecting dwell time using agent based simulation. The experimental results suggest that designated boarding/alighting doors, and an active passenger information system give reductions in loading times of around 7.0%.

The analysis of the real-world data from PTI interfaces by Daamen et al. [9] suggests that there are clear concentrations of waiting and boarding passengers around platform access points. Stairs at the end of the platform lead to higher concentrations than locations in the middle or at one third/two thirds along the platform.

RSSB project T1054 investigated the impact of the gap fillers to increase safety at the PTI. The outcomes suggest that gap fillers should be considered as a part of the whole system to reach an optimal solution [5].

The work by Coxon et al. [8] focuses on building an agent based simulation model with 3D characters to simulate the PTI design. The authors propose to have a "peak door", i.e. a train door only for peak hours, and the adjacent space inside is transformed into a folding seating area during off peak. Furthermore, the door closure arrangements are found to play a crucial role in minimising potential passenger injuries. The ongoing RSSB project T1102 investigates the impact of various door closure arrangements and passenger familiarity with them [7].

The RSSB project T1057 is a study on the effect of luggage and suggests certain features to minimise the effects of luggage [6]. These include improved on-board signage for alighting passengers to reduce the chances of them obstructing or causing crowding on the platform or near the train doors while they work out where to go, and to display "Mind the gap" signs on train doors to increase awareness of PTI risks when encumbered with luggage.

It is interesting that existing work has evaluated the effectiveness of several PTI features. However, none of the existing work has studied PTI geometry and operation as a whole in a simulated environment rather than one or few individual features. Such a complete model of PTI is essential to predict the flow time accurately. Within RateSetter we study the effectiveness of not only individual PTI features but also the PTI system as a whole and how to improve it. We identify effective PTI features from the above existing work, and additionally, consider new features by analysis of CCTV footage. The set of considered PTI features is presented in Section 4.1.

3 PASSENGER SIMULATION MODEL

The passenger simulation in the project follows agent based modelling principles. The simulation model is built on FlameGPU, an agent based simulation framework that makes use of highly parallel computing on Graphics Processing Units (GPUs) [17]. Each passenger is an agent with an individual goal that falls in to the category of either alighting or boarding the train. Passengers with the goal of alighting from the train are seeded inside the train at the start of the simulation and choose the shortest route towards the platform. Conversely, passengers with the goal of boarding the train are seeded on the platform at the start of the simulation. These passengers are in fact a distribution based on different mobility levels resembling the real world. After all passengers have alighted, a certain percentage of boarding passengers, as defined in the initial configuration file, will navigate towards a pre-chosen seat on the train or stand in the vestibule area. The simulation ends after all passengers have boarded the train.

The Optimal Reciprocal Collision Avoidance (ORCA) algorithm [24] is used by the passenger agents to perform local collision

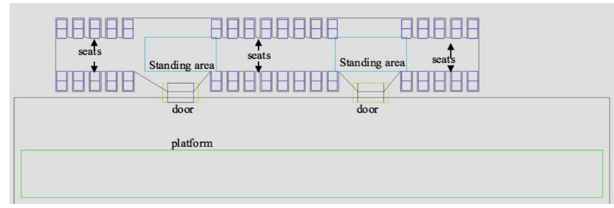

Figure 3: Sample geometrical layout defined by the PTI features

avoidance from walls and each other. It is an approach where by each passenger agent observes the velocity of others in order to find a velocity that will lead to a collision free path. The reciprocal nature of the algorithm means that the pair of potentially colliding agents takes half the responsibility for avoiding each other making the manoeuvre oscillation-free. Control of each passenger agent is done by providing each one with a two-dimensional velocity vector to their current target destination.

3.1 Use of CCTV Data

An agent based simulation depends for its validity on the quality of data defining the behaviour of the agents and their interactions. For the current study, the data on passenger behaviour at the PTI and in its vicinity were derived from CCTV footage captured on trains and platforms using existing cameras installed for security/safety monitoring. The locations at which this data was captured, and the division of the data into separate batches for model definition and later model validation, is expanded in Section 3.3. The use of CCTV data in this way is a major distinguishing feature of the RateSetter approach.

3.2 Inputs and Outputs

The PTI cases to be explored are variations around those for the trains from which the CCTV footage was captured, and therefore, our aim is to operate within the validity of this underlying data which focused on busy commuter and inter-city services. It would be inappropriate to over extend a simulation beyond the input characteristics captured, for example, PTI behaviour on an extremely busy commuter service could not be adequately predicted based on data collected on an under-utilised late-night train. The passenger model aims to capture the flow rate and interactions of passengers alighting and boarding carriages of various different designs. For each scenario, the simulation accepts the input parameters for initialisation. Then the layout generator tool translates these parameters and certain other meta parameters (i.e. walkable areas, offsets etc) required by the simulator to a geometrical layout used in the simulation. A sample layout is shown in Figure 3. Then as described in the beginning of the section the simulation runs for the generated PTI design (see Figure 4). The outputs are the passenger flow time i.e. the time from the start of the first passenger alighting to the end of last passenger boarding and the number of collisions.

3.3 Predictions for Validation Cases

The passenger behaviour and flow data previously extracted from CCTV analysis has been used for validation of the model. The

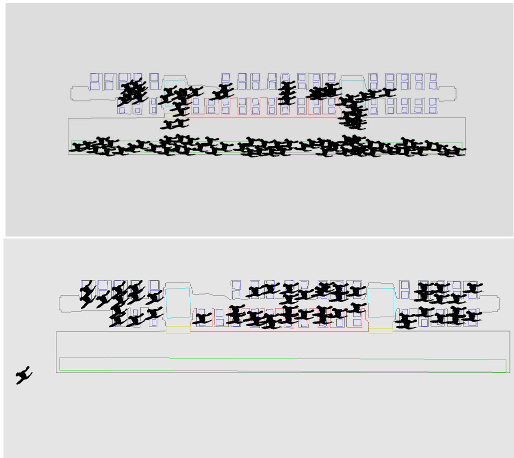

Figure 4: Sample behaviour at the PTI at alighting (top) and after boarding

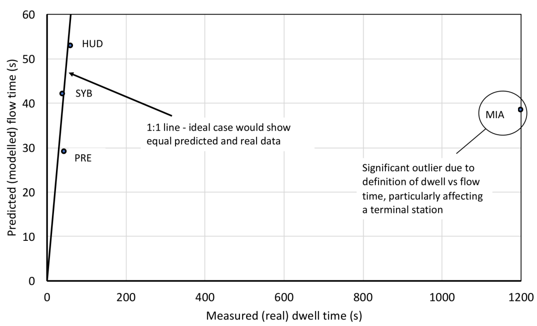

Table 5: Flow time predictions plotted against real measured data. The line marked is a 1:1 line, not a line of best fit to the data.

simulation model was run for these cases (10 repetitions and average is taken) and the outputs were compared with the actual passenger flow time and collision data extracted from CCTV analysis for each case. Note that two similar but distinct extracts of CCTV were taken for each case (the same station at similar times but on two different days) where one sample is used to train the model and the other to validate.

For validation, a diverse range of datasets was used covering busy, regional, terminal and through stations in GB. Locations include Manchester Airport (MIA), Huddersfield (HUD), Preston (PRE), Stalybridge (SYB), Manchester Piccadilly (MAN), Birmingham New Street (BHM) and London Euston (EUS). Figure 5 presents the validation results.

4 EVOLUTIONARY OPTIMISATION FOR PTI

The previous section discussed the passenger simulation model which serves as the fitness function. This section focuses on the evolutionary optimisation process together with other required components.

4.1 Platform Train Interface Features

The geometry of the PTI is captured in parameters as input to build an instance of PTI within the simulation. In this initial version of RateSetter we consider a subset of PTI features identified at the literature survey [1, 2, 5, 6, 8–10, 25]. These are the door width, the carriage length, the carriage width, the horizontal distance of the door for train car origin (horizontal origin is the left side exterior of the body), the space between left and right seats, i.e. aisle width, the seat width, the platform width, the standing area length, the seat leg room, and the step gap/influence region (see Section 5.9). Distances were measured in metres throughout.

4.2 Evolutionary optimisation Framework

The PTI optimiser framework is built using the genetic algorithm library ParadiseEO [16] which is available under an open source licence. For the GA the PTI design is captured as a real valued vector where each PTI feature is represented by a real valued variable (we call it a PTI individual). "Fitness" or quality is evaluated through a fitness function (see Section 4.6) which captures the objectives and the constraints discussed in the above sections. Algorithm 1 outlines the evolutionary optimisation process in general. The following sections will elaborate the problem specific design of each step in the algorithm.

Algorithm 1 $(\mu + \lambda)$-*EA*: Evolutionary Algorithm

1: Initialise the population P with μ PTI individuals, i.e. a spread of potential PTI designs.
2: Select $C \subseteq P$ where $|C| = \lambda$.
3: For each $I_1, I_2 \in C$, produce offspring I_1' I_2' by crossover and mutation. Add offspring's to P.
4: Fitness evaluation of all $I \in P$
5: Select $D \subseteq P$ where $|D| = \mu$.
6: $P := D$
7: Repeat step 2 to 5 until termination criterion is reached.

4.3 Initialisation

A GA individual in the population represents a potential platform train interface (PTI) instance. Such an individual is represented by a real valued vector, where each GA gene [12] represents a real valued PTI parameter described in Section 4.1, i.e. this numerically captures the full description of a particular instance of the PTI. Initiation of the optimisation can start with a population of randomly generated combinations of PTI parameters (generated within realistic bounds), or can use heuristics. In our case we use a hybrid approach, initialising the search using (i) existing PTI, and (ii) a proportion of randomly generated cases (i.e. combinations of door width and train interior layout which are feasible but do not exist at present). This hybrid approach aims to give a good starting point to the simulation without limiting the diversity in the population. In this way we can preserve diversity and still bias the process towards likely good solutions.

4.4 Parent Selection

Each step of the genetic simulation process requires the existing PTI designs to be taken in pairs as "parents" from which the next generation of PTI is created. We employ random selection without repetitions to choose which PTI to combine as parents at each step.

4.5 Variation Operators

Genetic operators are applied to the selected parents to create new offspring. These operators are inspired by the biological evolutionary operators of "crossover" and "mutation". Crossover is the process by which the next generation inherits genes from multiple (typically two) parents to create new offspring. Once two parents are selected, we choose the value for a given PTI parameter (a "gene") uniformly at random from either parent, a process of "uniform crossover "[12]. The mutation process chooses one gene uniformly at random out of the all genes in PTI individual and adds a small random perturbation to its value (e.g. a small change in door or aisle width). The exact value of the perturbation is calculated as a percentage of the current value of the gene. A percentage between -10% and +10% is drawn from a uniform distribution. The value 10% is considered based on trail runs with different values.

4.6 Fitness Evaluation

The fitness of an individual (i.e. a PTI design) is evaluated using the passenger simulator model to predict the flow time of passengers. As described in Section 3.2 the passenger simulation model is run on the PTI individual, with $Flowtime$ defined as

$$Flowtime := Time_{B_n} - Time_{A_0}$$

where A_0 denotes the time of the first passenger alighting, and B_n the time of the last passenger boarding. The respective flow time output from the passenger model is assigned to the PTI individual as the fitness score and the feasibility of the individual is decided based on the collision score.

$$Fitness := (Flowtime|collisions == 0)$$

where *collisions* defines the number of collisions.

4.7 Survivor Selection

Based on the fitness value and constraint violations feasible individuals are sorted and the best, λ individuals are selected for next generation as survivors.

5 OPTIMISATION RESULTS FOR NEW DESIGNS AND RETRO-FIT CASES

5.1 Experimental Set-up

First, PTI features were considered in subsets to explore the impact of these features on the optimisation of passenger flow rate keeping the rest of the features untouched. This was conducted by keeping specific gene(s) representing an individual/PTI constant by restricting the application of variation operators to them. The approach allowed, for example, features relevant to a retro-fit to be considered separately from those which could only be changed for a new-build case. Second, PTI design was optimised allowing all the features to vary simultaneously aiming for future PTI design.

For the passenger simulator, an input configuration file was employed to configure the simulation for a busy station with people of varying mobility levels aiming to get into a loaded train where a subset of the people intend to alight at the station. The people are generated probabilistically from a normal distribution and therefore exact behaviour varies slightly in each run.

For these initial experiments, we consider parent and offspring population sizes μ, and λ as one and the penalties for soft constraint violations as zero for the sake of simplicity. Owing to the variability of the agent behaviour (which in fact is the case for human passengers in real-world) the passenger simulation model is invoked on each PTI design for 10 repetitions and the average flowtime is recorded as the fitness of the particular PTI design/individual. The algorithm is run for 2000 generations.

The experiments were run on a Linux Ubuntu 17.04 64 bit PC with Intel Core i7-7700HQ CPU @ 2.80GHz x 8 processor, 15.5 GB memory and a GeForce GTX 1050 Ti/PCIe/SSE2. Throughout the experiments time was recorded in seconds and lengths in metres.

5.2 Aisle Width and Seat Width

Aisle width on the train is found to be a rate determining PTI parameter. Slow movement into the aisle can cause a backlog of people at the door as identified in the literature survey. Therefore, it is expected to have a significant effect on passenger flow rate even though it may at first seem remote from the PTI itself. It was assumed throughout that the train included rows of two seats either side of an aisle and, since train width was also parameterised in the model, the seat width was implicitly controlled by setting the aisle width. The simulation began with a narrow aisle (at 0.384m, the very low end of those that exist on real-world trains) to understand the evolution of flow time improvement as the aisle was widened.

The results show that the benefit to reduced flow time through increasing aisle width plateaued at an aisle width of 1.0m. Some additional marginal benefit could be produced by going to a 1.4m aisle width, with the downside that seat width would become very narrow for little flow time improvement. No constraint was placed on seat width in the simulation but, in future work a minimum acceptable seat width could be considered depending on the type of journey to be undertaken, e.g. a narrow seat and more rapid boarding would be acceptable for a short journey, but not for long, inter-city journeys.

Figure 6 shows the progression of the optimisation of the aisle width parameter. In summary, for the train layout and the busy station scenario considered, the flow time is reduced from 50 seconds to 39 seconds by varying only aisle width from 0.4m (somewhat narrow) to 1.4m (very wide) while keeping rest of the PTI features constant.

5.3 Door width

A two door carriage design is considered to investigate the effect of door width on flow time. We considered door widths in the range that exists in practice, starting from very narrow doors that were used in older vehicles (e.g. BR Mark 1 coach) that have narrow door as shown in Figure 7, through to later trains that have double doors towards the centre of the vehicle length. It was found that after some increase in width the flow time sees no further improvement with increase of door width within the range considered. This was found to be due to the inter-dependency of the door width and the vestibule capacity, and also the rate at which passengers could move into the aisle. Even when the door is widened the overall

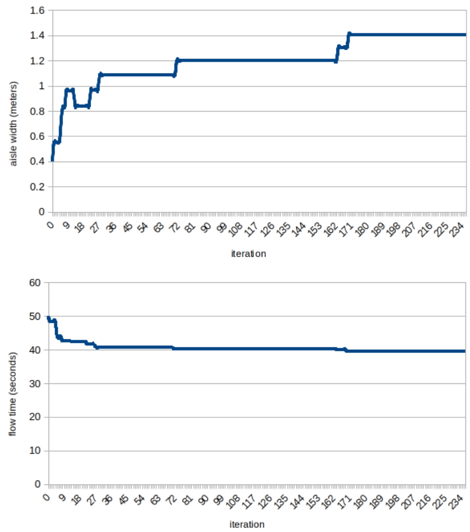

Figure 6: optimisation of PTI : variation of aisle width (on top) and flow time (bottom) respectively over iterations

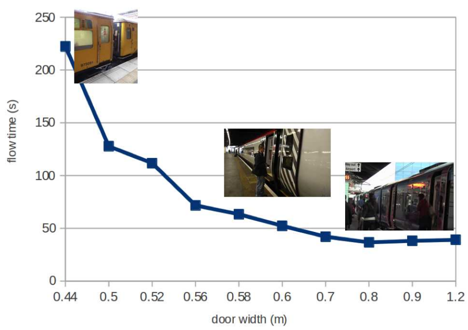

Figure 7: Door width variation over the optimisation algorithm run

performance is limited by these other factors. Based on the studied case diminishing return for increasing door width was achieved at a width of 0.8m. The inter-dependency of this value on the train interior design mean this is not a general conclusion, it is specific to the vehicle considered.

5.4 Platform Width

A wider platform can increase personal space for passengers. However, when it is too wide the passengers might be distributed further away from the door. This is reflected in improved flow time of 14s (from 52s to 38s) with reduced platform width (from 4m to 2.9m).

5.5 Standing Area

Standing area within the train shows some correlation with the flow time where increase in the standing area length from 1.7m to 2.6m resulting in reduction of flow time from 42.7s to 36.9s . When there is more space available, more passengers can gather closer to the door ready for alighting, reducing flow time. This supports the observation from the experiment on door-width, that vestibule standing area and the door width are inter-dependant. Changing one alone cannot make a significant improvement.

5.6 Carriage Length

By increasing carriage length (from 18m to 25m) flow time is also increased (36s to 52s) because passengers have to walk further to and from their seats. However, by increasing the length, the capacity of the carriage is also increased. This highlights a case in which reduction of boarding and alighting time needs to be considered alongside wider factors affecting the system. Constraints on vehicle capacity (potentially affecting the business case for the service) were not within the scope defined for the PTI investigation, but its consideration would give a better representation of the whole system.

5.7 Carriage Width

In contrast to carriage length carriage width does not significantly increase transit distance for a passenger. For the current scenario where the number of seats in a row is predetermined, this only increases the space making it easier for passenger to walk. Hence its increase (from 2.7m to 3m) improves (i.e. reduces) the flow time (from 44s to 39s). However, for an existing system the loading gauge (cross-sectional envelope through which the train must pass) will be restricted and such enlargement may not be possible.

5.8 Seat Leg Room

Seat leg room is another interesting feature that could affect the PTI performance in two different contrasting ways. It can influence the total distance for a passenger to walk in the aisle to the designated row of seats from the door and from the row to the door. It can also affect the overall performance by avoiding any collisions due to narrow leg room when seating (following boarding) and leaving the seat (when alighting). The experiments suggest that the latter aspect has stronger effect compared to the former. This is reflected in improved flow time (from 41s to 38s) with the increasing leg room (from 0.42m to 0.44m).

5.9 Region of Influence for the Platform-train Step

Most conventional PTI work has focused on the hard measurements of platform to train step height and gap. In RateSetter we considered instead the step as a region in which people slowed their movement (based on the captured CCTV data). The distance from the train and into the train over which they slowed when approaching or passing this obstacle defined a region of influence for the step.

The step gap is identified as a directly affecting PTI features in literature. As would be expected the RateSetter prediction is that by reducing the size of step gap region (1.92m to 0.78m) the flow time is reduced (from 41s to 37s). While that is not a surprising finding, the concept of a region of influence for the step/gap rather than a strict measure of its height and width does offer new insight. There may be ways to reduce the area influenced by the gap (thereby speeding boarding/alighting) even if the gap itself cannot be changed. This may be with lighting, signage, gap fillers, or other means, the effect of which on overall flow rate can be assessed.

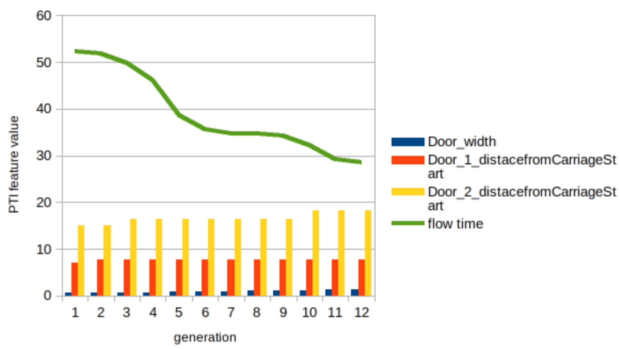

Figure 8: optimisation of multiple features simultaneously

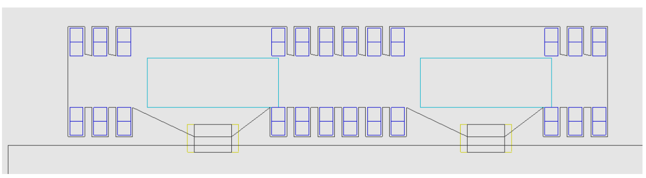

Figure 9: Train layout for optimised PTI flowrate. Seating (blue squares) is reduced, standing areas are enlarged (turquoise rectangles), doors evenly and centrally spaced.

5.10 Position of the doors

Door position along the carriage was defined relative to an origin at the left exterior wall of the vehicle. In the example case considered the location of door 1 was optimised with door 2 located 15 metres from the origin, for a carriage length of 20m. Flow time was found to improve (from 45s to 40.6s) when door 1 was positioned further away from door 2 (moving from 12m to 8m from the origin). This might be owing to the assumed even distribution of passengers on the platform. In addition, alighting passengers at the carriage ends can reach the doors in less time compared to the case when door 1 is at 12m from the origin. Considering the position of door 2 to be variable the finding was again that flow time is reduced when giving reasonable space between the two doors.

5.11 Optimisation of Multiple PTI Features for New Designs

In new train designs multiple PTI modifications can be implemented relative to existing rolling stock. Figure 8 shows an example of a significant improvement in flow time of 25 seconds from 53 to 28 seconds predicted for the case of optimising door width and door locations simultaneously. An optimised design after 2000 GA iterations for our busy station scenario is in Figure 9 with the initial and optimised parameters are presented in Table 1. Here we considered passengers as commuters without big luggage, finding the flow time is reduced by 36 seconds, from 71s to 35s between the two PTI/train geometries.

The RateSetter optimisation framework provides guidance for platform and train design, as in the above case for busy stations/trains for which lower passenger flow time is predicted for shorter carriages with fewer seats and more standing space, a smaller region over which people perceive and slow for the gap, and wide platforms with no obstacles. These outcomes have been reached by direct optimisation rather than application of prior knowledge, and it is useful to have a framework capable of highlighting diminishing returns in the factors identified. For example, the outcome that wide platforms are more efficient also shows that for the case examined most benefit has been achieved by a width of just under 2 metres. This needs to be placed in context as only the PTI has been considered, and not wider circulation issues such as passengers for other destinations passing through the same area. Similarly, for the case considered in Section 5.3, widening the door beyond 0.8m is predicted to give little improvement in the passenger flow time because it will be limited by congestion at the standing area and in the aisle. For retro-fit cases the range of variables to be considered can be restricted to those which are viable to change.

PTI feature	initial value (m)	optimised value (m)
seat length	0.4	0.3
standing area length	2.31	3.84
platform width	2.56	1.96
aisle width	0.4	1.3
door width	0.6	1.1
step gap/influence region	1.0	0.8
seat leg room	0.29	0.31
door 1 distance from carriage start	7	6
door 2 distance from carriage start	15	14
carriage width	2.7	3.11
carriage length	20	17.1
flow time	71.8s	37.6s

Table 1: Initial and optimised PTI feature values for a busy commuter station scenario. Initial values are inspired by the real world but don't represent a specific vehicle.

An important outcome of the RateSetter feasibility study has been identifying that factors beyond the PTI itself need to be considered in the optimisation process. As currently defined an optimisation will, for example, predict that reduced passenger flow time will be produced by shorter and wider vehicles since this brings more people closer to the doors. However, this neglects that capacity may be reduced, or that financially a larger number of shorter vehicles may be unacceptable. Similarly, the loading gauge may be violated by a wider train. Loading gauge was thought to be out of scope for the project at its inception, but in future work should be included to ensure the PTI optimisation operates within realistic constraints of the system overall. Such constraints may be relaxed if planning a completely new system without legacy compatibility issues.

6 CONCLUSIONS AND FUTURE WORK

RateSetter, an evolutionary optimiser framework, has been developed as a feasibility study to test the applicability of optimisation and modern parallel computer processing to PTI design for reduced passenger flow times. A key factor was capturing real world passenger behaviour through analysis of CCTV of movements on current platforms and stations. Through alternative CCTV datasets, a passenger simulator model was validated and serves as the fitness function within a genetic algorithm optimisation process. The feasibility study test cases provide insight to the relative importance of PTI features and how a future PTI could be developed.

Instead of the conventional focus on train to platform step height and gap, this PTI feature was evaluated as a region in which people slowed their movement (based on the captured CCTV data). The distance from the train and into the train over which they slowed when approaching or passing this obstacle defined a region of influence for the step. This approach may be used to evaluate ways to reduce the area influenced by the gap (thereby speeding boarding/alighting) even if the gap itself cannot be changed. This may be with lighting, signage, gap fillers, or other means, the effect of which on overall flow rate can be assessed.

An important finding is the wide range of factors which need to be considered to achieve meaningful PTI optimisation, for example, avoiding an investment in a new door design, if this simply moves a flow bottleneck to the aisle. The RateSetter feasibility project has demonstrated investigation of such interactions is possible through modelling. For meaningful predictions, the optimisation needs to consider wider issues such as train capacity and loading gauge, which were initially thought to be beyond the scope of the PTI.

In future work it is expected to conduct further validation of the RateSetter approach, for example through blind prediction of 'before' and 'after' cases of changes already being made on the network. These can help increase confidence in the approach, and highlight areas of further development needed, whether that is through improvements to the computing approach, the pedestrian model, or inclusion of additional aspects of the platform and train interior environment within the simulation. Application to operational rather than system re-design issues is also an area of great potential, for example predicting dwell time increases if a short formed train runs on a service, or if a train runs with a door out of use. This can support business decisions about how to manage such cases, and increase understanding of the value of avoiding them. Furthermore, experimentation on regional trains transporting long distance passengers with big luggage is also another potential future extension. For this, the current PTI individual is to be extended with further features namely luggage rack position and size. As observed in the current optimisation predictions, the service capacity and therefore its business case is also an important aspect that can be considered in the optimisation criterion. Through developing an updated fitness evaluation the current evolutionary optimisation can be extended to multi-objective optimisation where we consider both flow-time and system capacity as objectives.

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