Cost functions for mainline train operations and their application to timetable optimization

Aris Pavlides Centre for Transport Studies University College London Gower Street, London WC1E 6BT United Kingdom

Andy H. F. Chow (corresponding author) Centre for Transport Studies University College London Gower Street, London WC1E 6BT United Kingdom andy.chow@ucl.ac.uk Tel: +44 207 679 2315, Fax: +44 207 679 3042

5168 words + 7 figures = 6918 words

August 1, 2015

1 ABSTRACT

This paper discusses a set of cost functions for timetabling mainline train services. Mainline train 2 services are generally heterogeneous which consist of passenger and freight trains, slow and ex-3 press services, domestic and international connections, etc. The feasibility of a timetable is subject 4 to a number of factors including availability of trains and crew, infrastructure capacity, and travel 5 demand. With the complex nature of modern railway systems and the heterogeneity of rail traffic, 6 deriving satisfactory train service schedules for passengers, train operators, and infrastructure man-7 ager is always a challenge. The cost functions presented here are used as indicators for evaluating 8 different performance associated with the corresponding timetable. The performances of interest 9 include carbon, capacity, cost, and customer satisfaction. These four performance indicators are 10 also identified as the '4C' criteria by the railway industry in Great Britain. These 4C criteria are 11 set in order to address the need to improve customer satisfaction (e.g. by providing more punctual 12 service) and operational capacity, while decreasing operational cost and carbon emission. We will 13 also demonstrate the application of these cost functions into an optimization framework which 14 derives optimal timetable for heterogeneous train services. The method is applied to Brighton 15 Main Line in south-east England as a case study. The results reveal that overall performance of 16 the railway systems can be achieved by re-scheduling and re-sequencing the train services through 17 the optimization framework, while this may have to come at the expense of slow and local train 18 services if the optimization is not properly formulated. 19 20

²¹ Keywords: train scheduling, capacity, punctuality, multi-objective optimization, genetic algorithm

22 INTRODUCTION

Railways are generally considered to be sustainable and green compared with other modes of 23 transport. The significance of railway systems can be reflected by the amount of investment made 24 around the globe, exemplified by the number of high speed railways (HSR) projects, in recent 25 years. In the UK, we have seen recently a number of large investment programmes including 26 the Crossrail project, focusing on improving reliability, journey times, and capacity of the London 27 transport network (1). In Hong Kong, over the next decade the MTR Corporation will complete five 28 new strategic rail extensions in Hong Kong and mainland China (2). Nevertheless, this sustained 29 demand has been placing tremendous pressure on the railway infrastructures. Due to the tight 30 fiscal, physical and environmental constraints, continuous construction of new tracks and purchase 31 of rolling stocks will not be a sustainable solution. Consequently, we will have to rely on effective 32 utilization of existing infrastructures in terms of timetabling the train services. 33

This study looks at the issue of timetabling mainline train services for improving the overall 34 efficiency of the rail systems. Mainline train services generally refer to connections between cities 35 as opposed to the local metro services, while timetabling is regarded as the process of deriving a 36 feasible schedule for a given set of train lines over a specific route through specifying the associated 37 arrival and departure times at each designated point. Mainline services are generally heterogeneous 38 which consist of passenger and freight trains, slow and express services, domestic and international 39 connections, etc. Moreover, the feasibility of a timetable is also subject to a number of external 40 factors including availability of trains and crew, infrastructure capacity, and travel demand. As a 41 consequent, deriving a satisfactory timetable for different stakeholders including passengers, train 42 operators, and infrastructure manager is always a challenge. 43

In this paper, we address the mainline train timetabling problem by using an optimization 44 approach. A prerequisite for formulating the optimization problem is to define a set of cost (or 45 objective) functions that can reflect different performances of interest to different stakeholders. 46 Following (3), we identify Carbon, Capacity, Cost, and Customer satisfaction as the four main 47 aspects of interest. Chen and Roberts (4) and Roberts et al. (5) further categorize and discuss them 48 according to the associated relevance to different stakeholders. These four aspects are regarded as 49 the '4C' criteria by the railway industry in UK. The 4C criteria are set in order to address the need to 50 improve customer satisfaction (e.g. by providing more punctual service) and operational capacity, 51 while decreasing operational cost and carbon emission. We believe these four are also among the 52 main objectives in railway sector in other countries apart from the UK. A set of cost functions is 53 formulated to reflect the performance of each timetable in terms of the '4C'. The cost functions 54 are then incorporated in a multi-objective optimization framework (see e.g. (6, 7, 8, 9, 10)) for 55 deriving an optimal timetable following the setting of the cost functions or objectives. 56

The optimization framework is applied to the Brighton Main Line (BML) in south-east 57 England as a case study. It is noted that different cost functions have different dimensions. This 58 study adopts the monetary values suggested by the Department for Transport (11) in the UK to 59 convert and integrate all costs into monetary units. However, the proposed approach is generic 60 and will be applicable to different systems by revising the conversion factors according to different 61 operators' or countries' needs. The results obtained from BML reveal that overall performance of 62 the railway systems can be achieved by re-scheduling and re-sequencing the train services through 63 the optimization framework, while this may have to come at the expense of slow and local train 64 services if the optimization is not properly formulated. 65

⁶⁶ The rest of the paper is organized as follows: the next section starts with introducing the

⁶⁷ specification of timetable in an optimization framework and its associated operational constraints.

⁶⁸ It is then followed by discussion of different performance indicators related to 4C and formulation

⁶⁹ of the associated cost functions. The cost functions are then used to formulated a multi-objective

⁷⁰ optimization problem for train timetabling. We also discuss the complexity of the timetabling ⁷¹ problem and present a genetic algorithm (GA) based solution approach. The optimization frame-

⁷¹ problem and present a genetic algorithm (GA) based solution approach. The optimization frame-⁷² work is applied to a case study of Brighton Main Line which is used to demonstrate the proposed

⁷³ method and the results are discussed. Finally, the paper concludes with some final remarks and

- ⁷⁴ suggestion for future work.
- 75

76 SPECIFICATION OF TIMETABLE AND ASSOCIATED CONSTRAINTS

A timetable is typically incorporated through specifying the arrival $\tau_{n,s}$ and departure times $\sigma_{n,s}$ of each train n over a set of control points s (which can be a station, junction, etc.) along its service route. An example is shown in Figure 1 in which the horizontal and vertical axes represent the time and position along the train route respectively. Each line on the diagram represents a train run which is specified by a series of departure $\sigma_{n,s}$ and arrival times $\tau_{n,s}$ at station s for each train n as specified by the timetable. Given a set of $\sigma_{n,s}$ and $\tau_{n,s}$, we can derive the running time $T_{n,s}$ of each train n between station s and s + 1 as

$$T_{n,s} = \tau_{n,s+1} - \sigma_{n,s},\tag{1}$$

and also the dwell time $D_{n,s}$ of train n at station s

$$D_{n,s} = \sigma_{n,s} - \tau_{n,s},\tag{2}$$

The setting of the variables $\sigma_{n,s}$ and $\tau_{n,s}$ will be subject to a set of operational constraints in practice. We first have the minimum section running time constraints to reflect the speed limit imposed on each track section (s, s + 1):

$$\tau_{n,s+1} \ge \sigma_{n,s} + \frac{\Delta_{s,s+1}}{v_n^*},\tag{3}$$

where $\Delta_{s,s+1}$ is the distance between stations s and s+1, v_n^* is the maximum speed limit for train n traveling from station s toward s + 1. Moreover, we also have the minimum dwell time constraints which define the minimum time have to be spent by each train n at station s:

$$\sigma_{n,s} - \tau_{n,s} \ge d_{n,s}^*,\tag{4}$$

The minimum dwell time $d_{n,s}^*$ imposed here will typically be determined by a number of factors on the demand side such as demand level of passengers or freight for that specific train at that specific station, and/or the consideration of connectivity where it is necessary to ensure a long enough dwell time for passengers or goods to transfer from one train to another at the station or interchange (12).

Finally, to implement the signaling system, each track section is further disaggregated into a series of blocks. Under the current fixed block signaling systems in practice, each block can only accommodate up to one train at a time to ensure safe operations (see Figure 2). Referring to Figure 2, denote the arrival and departure times of train n at block j between station pair (s, s + 1)

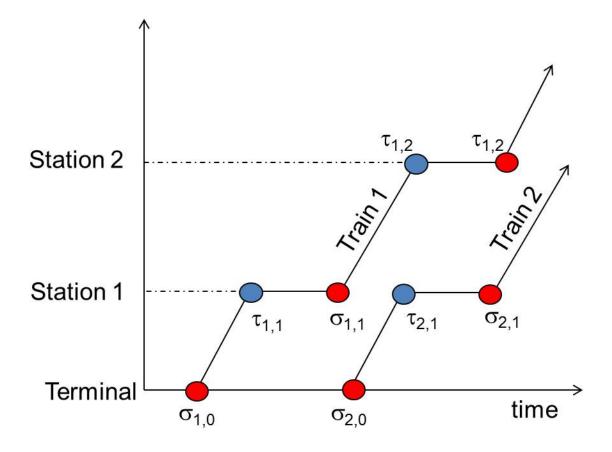


FIGURE 1 A realization of timetable with train diagram

as $\sigma_{n,s,j}$ and $\tau_{n,s,j}$ respectively. The shaded region in the figure represents the location and time period (during times t_{in} and t_{out}) that is occupied by the train of interest during which other trains are prohibited from entering. Following the specification in the current UIC (International Union of Railways) operational code (13), we have

$$t_{in} = \tau_{n,s,j} + \frac{\delta_{n,j}}{v_{n,s,j}},\tag{5}$$

where $\delta_{n,j}$ is the visual distance of train *n* to the entrance of block *j*; $v_{n,s,j}$ is the nominal speed of train *n* traveling through block *j*. The time t_{in} represents the time when the driver of train *n* observes the signal aspect at block *j* and starts to take action(s) accordingly. Moreover,

$$t_{out} = \sigma_{n,s,j} + \frac{L_n}{v_{n,s,j}},\tag{6}$$

where L_n is the length of train n. The time t_{out} represents the time when the tail of the train n clears from the block section. Because of the signaling system, it is expected congestion will occur when the train volume on a track section is high (14, 15). Following (5) and (6), the signal blocking constraint can then be written mathematically for all station pairs (s, s + 1) and signal blocks j as

$$\tau_{n+1,s,j} \ge \sigma_{n,s,j} + \frac{L_n}{v_{n,s,j}},\tag{7}$$

⁸² in which train n + 1 is the train following immediately after train n.



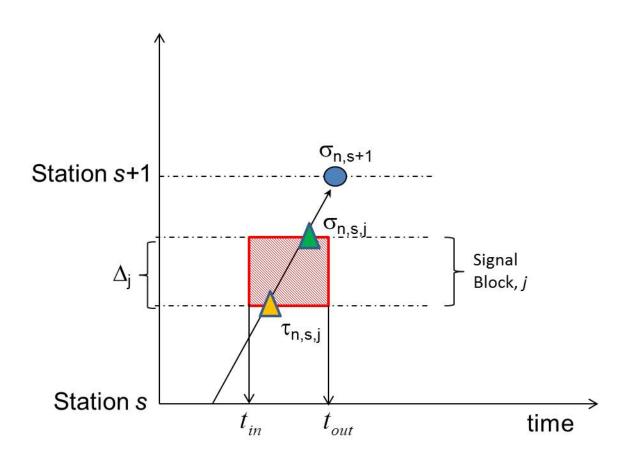


FIGURE 2 Representation of fixed block system

84 PERFORMANCE INDICATORS AND COST FUNCTIONS

With the timetable and the associated constraints specified, we can then formulate the cost func-85 tions to be used in the optimization framework which reflect various performance in railway 86 timetabling and operations. Following the comprehensive review in (4) and (5), we have selected 87 five representative performance indicators in the railway industry: train running times, customer 88 waiting times, service punctuality, utilization of trains and track resources. It is recognized that 89 the first three performances will be specifically interesting to customers (passengers and freight 90 companies), utilization of trains will be interesting to Train Operators, and utilization of track will 91 be interesting to Infrastructure Manager. 92

93

94 **Running times of trains**

Running times $T_{n,s}$ of trains n over all section (s, s + 1) can be obtained from Equation (1) in the previous section following the specification of timetable variables $\sigma_{n,s}$ and $\tau_{n,s}$ as discussed. Given

all running times $T_{n,s}$, we define the cost associated with the running time components as

$$C_T = \hat{c}_T \sum_{n=1}^{N} \sum_{s=1}^{S} T_{n,s} p_{n,s},$$
(8)

where N and S represent the total number of trains and stations in the system respectively. The 95 variable $p_{n,s}$ is a quantity associated with the demand which represents the number of passengers 96 (or amount of goods) on train n running between stations s and s + 1. Determining this $p_{n,s}$ will 97 require detailed origin-destination (OD) survey which can be difficult in practice. The quantity 98 $p_{n,s}$ may be dropped from (8) if such OD information is not available, and this will result in the 99 optimizer treating each train n equally. With this $p_{n,s}$, the corresponding timetable will then give 100 higher priority to trains carrying more passengers or goods after optimization. Finally, the notation 101 \hat{c}_T represents a monetary cost associated with running times, where some examples can be found 102 in (11, 16, 17). We will have further discussion on the choice of this c_T and other monetary cost 103 coefficients in latter section. 104

105

106 Waiting times of passengers (or goods)

Estimating the cost associated with waiting times first requires knowledge of $\lambda_s(t)$ which denotes the profile of demand for service at station s over time t. Fundamental queueing analysis (e.g. (18)) gives the total waiting time W (in the unit of [persons-time] or [goods-time]) as

$$W = \sum_{s=1}^{S} \sum_{n=1}^{N_s - 1} \iint_{\tau_{n,s}}^{\tau_{n+1,s}} \lambda_s(t) dt^2,$$
(9)

where N_s is the total number of trains serving station s over the study time period. The time interval between $\tau_{n,s}$ and $\tau_{n+1,s}$ specify the headway of train service at station s. Equation (9) can be simplified by assuming a uniform demand $\bar{\lambda}_s = \lambda_s(t)$ for all times t during the study period as:

$$W = \sum_{s=1}^{S} \sum_{n=1}^{N_s - 1} \bar{\lambda}_s [\tau_{n+1,s} - \tau_{n,s}]^2.$$
(10)

As reflected from (10), the total waiting time grows linearly with the average demand rate $\bar{\lambda}_s$ but quadratically as the service headway increases (i.e. frequency of service decreases). However, the uniform demand assumption made in deriving (10) may be valid for high frequency service (e.g. metro) while it may not be appropriate for low frequency mainline services as it is known that the arrival of passengers will cluster around the publicized scheduled service times in the timetable. Hence some detailed survey will be needed for obtaining the demand pattern if one wants to have a reasonable estimate of waiting times when deriving mainline timetable.

Finally, following the calculation of W, the eventual cost associated with waiting times is determined as

$$C_W = \hat{c}_W W,\tag{11}$$

where \hat{c}_W is the monetary cost associated with waiting times. The purpose of incorporating the waiting time into the optimization framework is to ensure that there are enough services for number of passengers or goods at the station without creating excessive waiting times. Empirical

studies conducted by the UK Department for Transport (e.g. (11, 16, 17)) suggest that this \hat{c}_W will be around two or three times larger than \hat{c}_T as the waiting time is generally regarded as a dead time.

120 **Punctuality of service**

Punctuality is measured herein as the time discrepancy between the scheduled and the actual arrival times of the train services. To quantify the punctuality in monetary unit (see (19), (20)), we adopt a schedule cost function as shown in Figure 3. In the figure, τ^* denotes the ideal arrival time of the train service while Φ is a time allowance for lateness (e.g. Φ is considered to be three minutes under the UK railway operational regulations (20)). If the corresponding train is delayed by more than Φ from the ideal arrival time τ^* , a schedule delay cost will be imposed on the Train Operator by the Infrastructure Manager for lateness. It is considered here that this schedule delay cost increases linearly with a slope of \hat{c}_P over arrival time τ , where $\tau \ge \tau^* + \Phi$. This penalty rate \hat{c}_P represents the value of lost time of customers (passengers or freight companies) per unit lateness in time (20, 21). Following this linear specification, the total schedule delay cost associated with punctuality can be determined, taking the arrival of passengers and/or goods into account, as

$$C_P = \hat{c}_P \sum_{s=1}^{S} \sum_{n=1}^{N_s - 1} \int_{\tau_{n,s}}^{\tau_{n+1,s}^*} \lambda_s(t) (\tau_{n+1,s} - \tau_{n+1,s}^* - \Phi)^+ dt,$$
(12)

where $\tau_{n+1,s}^*$ is the ideal arrival time for train n + 1 at station s, $(\tau_{n+1,s} - \tau_{n+1,s}^* - \Phi)^+ = \max[(\tau_{n+1,s} - \tau_{n+1,s}^* - \Phi), 0]$. Similar to (10), Equation (12) can be simplified by assuming uniform arrival $\bar{\lambda}_s = \lambda_s(t)$ for all times t as

$$C_P = \hat{c}_P \sum_{s=1}^{S} \sum_{n=1}^{N_s - 1} \bar{\lambda}_s (\tau_{n+1,s}^* - \tau_{n,s}) (\tau_{n+1,s} - \tau_{n+1,s}^* - \Phi)^+.$$
(13)

Finally, it is noted that this punctuality cost analysis is generally applicable to other schedule cost functions, apart from the linear assumption in Figure 3, by revising the cost function term $(\tau_{n+1,s} - \tau_{n+1,s}^* - \Phi)^+$ in (12) and (13) accordingly.

125 Utilization of trains

If the on-board loading $p_{n,s}$ of each train n between each station pair (s, s + 1) is available, we can also derive a cost associated with the utilization of trains as

$$C_L = \hat{c}_L \sum_{n=1}^{N} \sum_{s=1}^{S} \left(1 - \frac{p_{n,s}}{p_n^*} \right), \tag{14}$$

where p_n^* is the physical holding capacity of train *n* for passengers or goods, \hat{c}_L is the monetary cost associated with per unit lost due to inefficient use of train holding capacity. The cost C_L will be an useful component to be included from Train Operators' perspective for deriving effective strategies transporting passengers and goods with the least number of trains.

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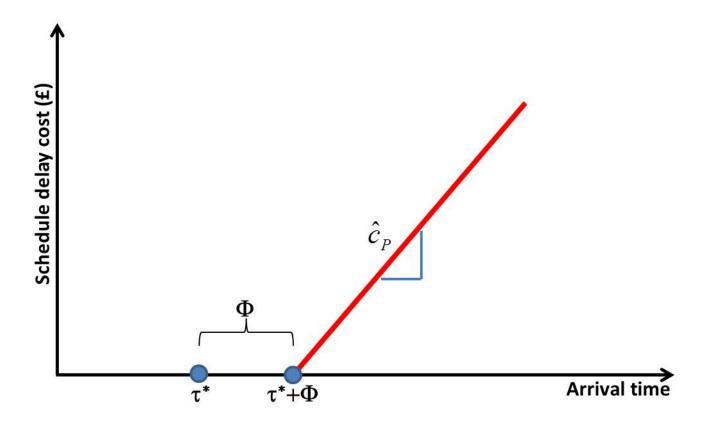


FIGURE 3 Schedule delay cost function

131 Utilization of track capacity

Utilization of track capacity is measured by using the occupation measure specified in the UIC 406 'Capacity' code (13). The occupation of a block section is defined as the total time that the block is occupied by trains within a specific study period, divided by the length of the study period. Referring to an example in Figure 4 which shows two trains passing through a block section within a specific time period T. Denote $(t_{in})_{n,j}$ and $(t_{out})_{n,j}$ respectively the entry and exit times of train n to the block (j) of interest. The occupation ratio for this block j is calculated as

$$occ_{j} = \frac{\sum_{n=1}^{N_{j}} [(t_{out})_{n,j} - (t_{in})_{n,j}]}{T},$$
(15)

where N_j is the total number of trains passing the block in T. We can then come up with a network-wide measure of track utilization as over all track sections between stations s and s + 1 in the system as:

$$OCC = \sum_{s=1}^{S} \sum_{j=1}^{J_s} occ_j,$$
 (16)

where J_s is the number of blocks along track section between stations s and s + 1. Different from previous UIC 405 standard (22) which only considers only the number of trains passing the

block sections, the UIC 406 approach captures the heterogeneity and speed differentials among trains through considering the time occupied by trains. Following the *OCC* calculated by (15), the monetary cost associated with track utilization is determined as:

$$C_U = \hat{c}_U (1 - OCC), \tag{17}$$

where \hat{c}_U is recognized as the cost per unit lost of track occupation. This C_U will be an useful indicator for Infrastructure Manager which aims to maximize the efficiency of utilizing limited infrastructure capacity.

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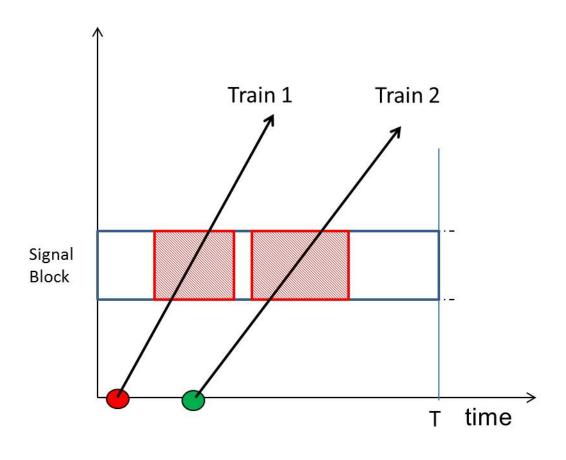


FIGURE 4 Measure of utilization of track (13)

136 Discussion

This section presents five performance indicators widely used in the railway industry and the formulations of the corresponding cost functions. It should be emphasized that the five performance indicators considered herein are mainly for illustration purposes and readers can incorporate other

¹⁴⁰ performances of interest such as energy consumption and connectivity in the proposed optimization

framework. Detailed discussions of other performance indicators and the associated cost functions can be found in (4) and (5).

It is understood that different stakeholders have different level of interest in different performances. For example, customers will obviously be concerned about the running time, waiting

time, and punctuality of their services, while they will be less interested in how the track or rolling 145 stock resources are utilized. Infrastructure manager and train operators on the other hand will be 146 very careful about planning the use of their resources (track and trains) in order to come up with the 147 most cost-effective operational strategy. Unfortunately, different performances are often in conflict 148 of each other. Utilization of track can be enhanced by running more trains within a given time pe-149 riod, while this could have an adverse effect on punctuality as it will be more likely generating 150 delays due to congestion. The conflict between different performance indicators and stakeholders' 151 interest calls for the use of multi-objective optimization technique to come up with a timetable that 152 can maximize the overall performance of the system while taking the conflicts into account. 153 154

155 APPLICATION TO TIMETABLE OPTIMIZATION

The cost functions developed in previous section are applied to formulate a multi-objective optimization problem. The optimization aims to determine the train timetable, in terms of arrival $\tau_{n,s}$ and departure times $\sigma_{n,s}$ for all trains *n* over all stations *s*, such that the following total cost is minimized:

$$C = C_T + C_W + C_P + C_L + C_U. (18)$$

The cost in (18) is in monetary unit and its cost components are integrated through the monetary cost coefficients: \hat{c}_T , \hat{c}_W , \hat{c}_P , \hat{c}_L , and \hat{c}_U as discussed. The cost minimization problem is subject to the operational constraints (3), (4), and (7).

The train timetable optimization problem is combinatoric that involves different feasible combinations of $\tau_{n,s}$ and $\sigma_{n,s}$ representing different sequencing and scheduling of trains (23, 24). Considering a scenario where there are N trains to schedule, the number of possible sequences for scheduling these trains will be N!. This has not included the infinite number of ways of setting the departure and arrival times of these trains along the service route given a sequence.

To derive a solution within a reasonable time, an optimal sequence and times of departures 164 of trains from their terminals is searched by using a genetic algorithm (GA). The genetic algorithm 165 starts with a population (e.g. with a size of around 100) of randomly generated sequences of trains 166 which are regarded as 'chromosomes'. Each chromosome is a combination of binary (0-1) bit 167 representing different train sequences. For example, consider there are three trains (A, B, C) with 168 different service paths and characteristics to schedule. This gives a total of 3! = 6 possible se-169 quences: ABC, ACB, BAC, BCA, CAB, and CBA. This can be represented by a set of 3-bit binary 170 chromosomes (which gives a total of possible 8 $(=2^3)$ combinations). Given the train sequence, 171 the corresponding departure $\sigma_{n,s}$ and arrival times $\tau_{n,s}$ of each train is then computed by using a 172 greedy search approach in the second stage. The greedy search strategy determines the $\sigma_{n,s}$ and 173 $\tau_{n,s}$ as the earliest times that each train can proceed subject to constraints (3), (4), and (7). In case 174 of a conflict occurs when two (or more) trains meet at a junction along their service lines, priority 175 is given based upon the first-come-first-serve principle. 176

With the set of chromosomes containing information of sequence and departures of trains, the optimizer starts with the 'reproduction' step which reproduces chromosomes according to their 'fitness' values in the next iteration. The fitness value is calculated based upon the value of total cost (18) associated with the train sequence and departures specified in the chromosome. Essentially a higher fitness value will be assigned to a chromosome if the chromosome achieves lower

total cost, and the fitness function FIT_i for each chromosome *i* is defined as:

$$FIT_i = \frac{A_i}{\sum A_i},\tag{19}$$

where

$$A_i = \exp\left(\left(\frac{C_{max} - C_i}{C_{max} - C_{min}}\right)p\right),\tag{20}$$

in which C_i is the value of total cost calculated from (18) based on the sequence and departures of trains specified in chromosome i, C_{max} and C_{min} are respectively the maximum and minimum cost values identified in the current iteration of optimization, p is a parameter tuning the fitness function for maximizing the efficiency of the optimizer where it is set to be 5 here. The chromosomes are 'reproduced' in proportion to their fitness value FIT_i calculated above.

Following the reproduction step, the 'crossover' operation will then randomly select and 182 'mate' two chromosomes (regarded as 'parents'). The GA optimizer separates each 'parent' chro-183 mosome into two parts, swaps with each other, and forms a new pair of chromosomes (which are 184 regarded as 'children'). This crossover process is for generating the next set of population with 185 some entirely new characteristics with respect to the previous population and hence avoiding the 186 optimisation process from trapping into local optima. Finally, the 'mutation' process randomly se-187 lects some bits in the population with a predefined probability (typically 0.005 - 0.01) and 'mutate' 188 (i.e. a '0' bit will be changed to '1' arbitrarily, and a '1' bit will be changed to '0'). This is again 189 to prevent the optimization process from trapping into local optima. The GA optimization process 190 above (reproduction-crossover-mutation) will continue until the predefined maximum number of 191 iterations (e.g. 20 - 30) is reached. Further details of GA can be found in a number of literature 192 including (25). 193

194

195 CASE STUDY - BRIGHTON MAIN LINE (UK)

The optimization framework is applied to the Brighton Main Line in southeast England (Figure 196 5). The Brighton Main Line is approximately 80-km long electrified connection linking London 197 Victoria and London Bridge with Brighton via East Croydon and Gatwick Airport. The line itself 198 has a complex structure with a variable number of tracks (four tracks from London down to Bal-199 combe Tunnel Junction and two tracks thereafter), different speed limits along the line, multiple 200 branch lines (e.g. at Junctions Horsham, Lewes), and sidings (e.g. along Ardingly, Lovers Depot). 201 Passenger operators that operate on the BML include Southern and First Capital Connect. We 202 select the section between Gatwick Airport and Brighton which is highlighted in Figure 5. This 203 is one of the busiest sections along BML. The study period is 08:00 - 10:00, which is regarded 204 as the morning peak, on weekdays. During the study period there is currently a total of 22 trains 205 running from Brighton toward Gatwick and hence Central London (the 'Up' direction) and 18 206 trains running from Gatwick toward Brighton (the 'Down' direction). We derive this 'base case' 207 train timetable with information obtained from Network Rail. The idea is to derive an optimized 208 timetable from the proposed optimization framework with the same number of trains within the 209 same study period. We then compare the 'optimized' timetable with this 'base case' timetable to 210 see how much improvement, in terms of reduction in costs, can be achieved in different aspects 211 through re-sequencing and re-scheduling. There are two different train classes running through 212

the section during the study period: Classes 375 and 442 with Class 375 used for the express 213 connection. Both train classes are used for passenger transport, while it should be noted the pro-214 posed optimization framework presented in this paper can capture any number and type of train 215 classes including freight train. Finally, it is noted that the actual origin-destination demand matrix 216 is not made available so that an average demand rate $(\bar{\lambda}_s)$ and train loading $(p_{n,s})$ will have to be 217 estimated from field observations on a weekday. In general it is recognized that the demands at 218 the major stations including Gatwick Airport, Three Bridges and Brighton are higher than other 219 stations which is expected as these are some major hubs or interchanges along the line 220

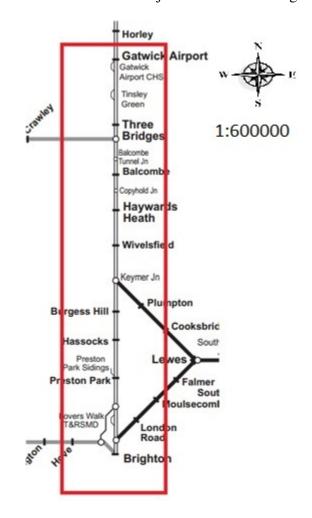


FIGURE 5 Test network - Brighton Main Line (UK)

The coefficients in the cost function (18) are set here with official documents by the British 221 government organizations. On the customer side, the monetary cost \hat{c}_T associated with running 222 times of train is set to be £5.76 (per person-hour), while the monetary costs \hat{c}_W and \hat{c}_P are both 223 £14.4 (per person-hour) for waiting times and punctuality respectively. The figures are set ac-224 cording the 'webTAG Unit 3.5.6' guidance (11) published by UK Department for Transport which 225 specifies the values of time of travelers based on an empirical study conducted by University of 226 Leeds (26). The monetary costs of waiting times and punctuality are around two times higher 227 than the one for running time. It is because waiting times and delays due to lateness are generally 228

regarded as non-productive dead loss. From the perspective of Train Operators and Infrastructure Manager, the costs \hat{c}_U and \hat{c}_L respectively for utilization costs of trains and track are set to be ± 350 (per train) following the current track usage price published by UK Network Rail (27) which specifies the cost for deploying a train on the track.

Given the network configuration and cost coefficients, the total cost (18) associated with the existing timetable is determined as £66.7k. The breakdown of this total cost into its components is shown in Figure 7. It is shown that the majority (\sim 85%) of the cost is associated with the customer related components: running times, waiting times, and punctuality. As a consequence, it can be expected that the eventual optimized timetable would favor customers over Train Operators and Infrastructure Manager. This however can be modified with revised formulation of the cost functions and coefficients.

Figure 6 shows the progress of the optimization process in which the value of total cost 240 is reduced gradually from the initial value £73.6k with randomly generated timetables to eventual 241 £62.9k with the optimized one after 15 iterations given the same number of trains to schedule, the 242 same number of passengers to serve, over the same period. The optimization process takes five 243 minutes to complete on a standard Windows 7 (64-bit) desktop computer. Similar to other im-244 plementations of genetic algorithm (e.g. (25)), the most significant improvements are observed in 245 the first few generations while the optimization process gradually converges slowly to the ultimate 246 final solution at latter iterations. 247

Figure 7 further compares the cost components before and after the optimization. As afore-248 mentioned, the optimization mainly benefit the customers' costs due to their large portion in the 249 cost components. The reduction in waiting times comes from assigning more priority to trains 250 (e.g. the express or 'fast' trains) serving major stations with higher demand over other trains serv-251 ing local area. This can be revealed from Figure 8 which compares the train diagrams under the 252 nominal and optimized timetable toward the end of the study period (after 09:00). Under the orig-253 inal timetable, the fast trains (Class 375) are hindered by the slow train (Class 442) highlighted in 254 the figure. This leads to higher costs associated with running times and hence potentially waiting 255 times and punctuality. After optimization, more slow trains are scheduled toward the end of the 256 study period with an objective to give way to the faster Class 375 trains in the front. As the number 257 of available trains is considered to be fixed, the improvements in punctuality as well as utilization 258 of trains and track, are insignificant. This however can be modified by allowing more (or less) 259 trains to be scheduled in the optimization process. One can also estimate the marginal cost of 260 adding or reducing a train with respect to the overall system performance. 261 262

263 CONCLUSIONS

This paper presents a multi-objective optimization framework which derives optimal timetables for 264 mainline train service that maximizes the system efficiency in various performance aspects. The 265 performances considered herein include running times of trains, waiting times of customers for 266 service, punctuality, utilization of trains and track. The performances considered cover different 267 stakeholders: customers, Train Operators, and Infrastructure Manager. The contributions of this 268 paper include specification of timetable and its associated operational constraints, formulations of 269 cost functions reflecting the corresponding performances, and multi-objective optimization with a 270 GA-based solution method. 271

272

The optimization framework is applied to the Brighton Main Line in southeast England.

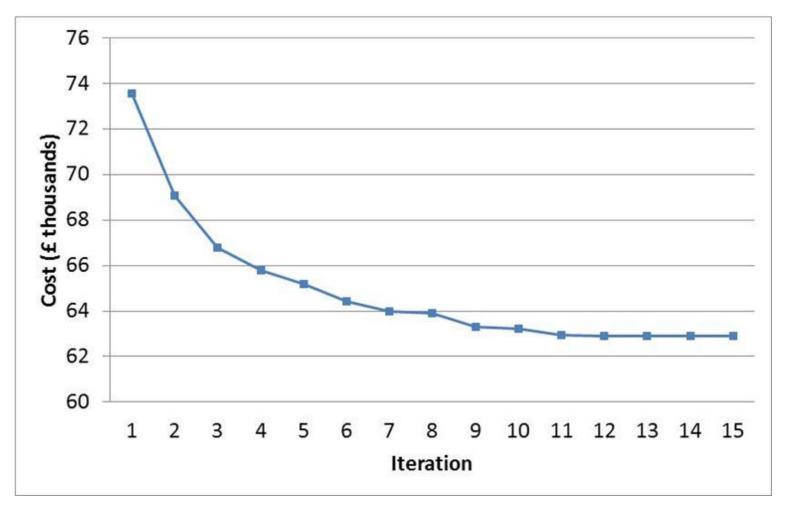


FIGURE 6 Progression of optimization process

Given the network configuration and demand, the optimal timetable is solved by a two-stage solu-273 tion procedure based upon genetic algorithm. The optimizer is shown to be able to reduce the cost 274 of operations in particular in the aspects of running times, waiting time, and punctuality. Never-275 theless, it is revealed that this is achieved by assigning higher priority to fast express trains at the 276 expense of slow local trains. This may not be a desirable result if one is interested in improving 277 the equity of different service types. In particular, it is found that current policies of many Infras-278 tructure Managers around the world tend to favour passenger train operations over freight ones 279 due to the higher demand for passenger trains, higher speeds, and less energy consumed. Such 280 timetabling and capacity allocation policy however can hurt the freight train industry in the long 281 run. Incorporating the equity of train services will be a future research direction. Finally, it is noted 282 that the focus of the present paper lies on the formulation of cost functions and their application to 283 timetabling instead of the optimization algorithm. We agree that it will be worthy of conducting 284 further research on alternative algorithms for improving the quality of the optimal solutions. 285 286

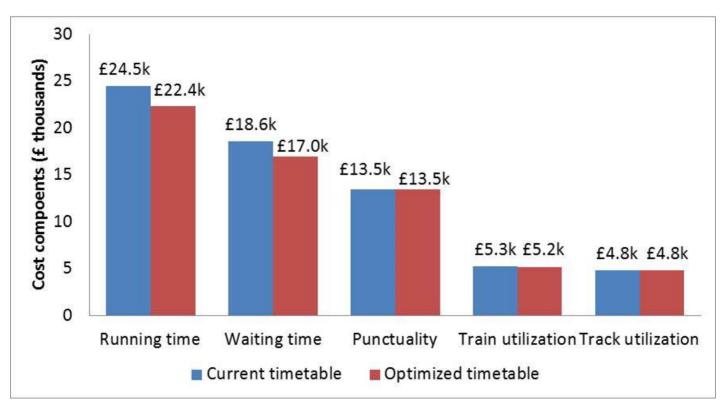


FIGURE 7 Cost components before and after optimization

287 ACKNOWLEDGMENTS

This study is funded by an Industrial CASE studentship awarded by UK Engineering and Physical Sciences Research Council (EPSRC) and Rail Safety and Standard Board (RSSB). We would like to thank Catherine Baker at RSSB for her valuable comments. The contents of this paper reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not reflect the official views or policies of RSSB, Network Rail, or any other organization. This paper also does not constitute a standard, specification, or regulation.

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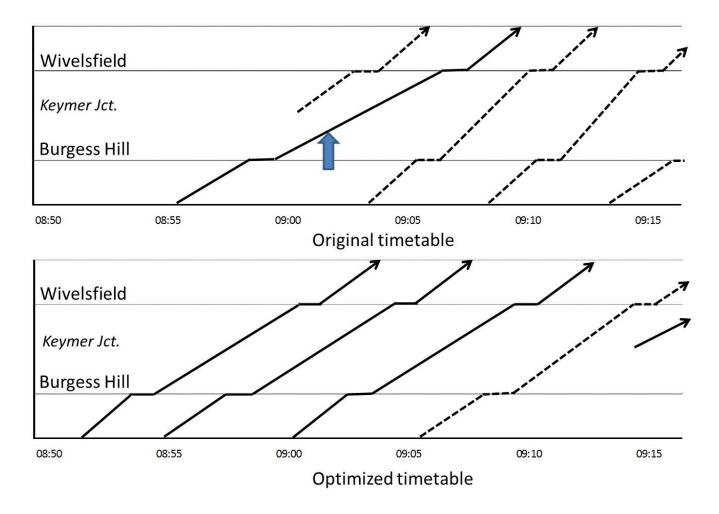


FIGURE 8 Train diagrams before and after optimization (dotted line: fast trains; solid line: slow trains)

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