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A Railway Rescheduling Model with Priority Setting

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ABSTRACT

This paper presents a mathematical approach to solve railway rescheduling problems. The approach assumes that the trains are able to resume their journey after a given time frame of disruption whereby The train that experiences disruption and trains affected by the incident are rescheduled. The approach employed mathematical model to prioritise certain types of train according the railway operator's requirement. A pre-emptive goal programming model was adapted to find an optimal solution that satisfies the operational constraints and the company's stated goals. Initially, the model minimises the total service delay of all trains while adhering to the minimum headway requirement and track capacity. Subsequently, it maximises the train service reliability by only considering the trains with delay time window of five minutes or less. The model uses MATLAB R2014a software which automatically generates the optimal solution of the problem based on the input matrix of constraints. An experiment with three incident scenarios on a double-track railway of local network was conducted to evaluate the performance of the proposed model. The new provisional timetable was produced in short computing time and the model was able to prioritise desired train schedule.

Keywords: Mathematical optimisation model, mixed integer programming, service delays, railway rescheduling

INTRODUCTION

A variety of factors can lead to operational problems in railway transportation network, such as equipment failures, track damage, extraordinary passenger volumes, train accidents or weather conditions. When these unexpected incidents occur, the control managers need to reshuffle train orders, make unplanned stops and break connections, re-route trains and even delay or cancel scheduled services. Changes in the original train departure and arrival schedules can create conflicts in the use of resources, such as tracks, platforms, rolling

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stock and crew. Thus, rescheduling affected train services and managing delays with an objective to minimise traffic disruptions is the duty of the operational section of the railway company.

The main objective of this research is to present an optimal solution for solving post-disruption railway rescheduling problem. An output in the form of new provisional timetable is aimed at minimising the total delays of trains in the whole railway network. In order to achieve this objective, a mixed integer programming (MIP) model for rescheduling railway is proposed.

An earlier paper on this topic have illustrated the important elements for the proposed model construction, including the sets, parameters and variables. We have developed a mathematical model that incorporated all the technical and practical constraints that are subject to resource limitations. In this paper, we present the evaluation of the models by setting priority to a certain type of trains. Our aim is to produce a schedule which satisfies the safety rules and other operating requirements of all railway services, including the prioritised ones. This work is expected to highlight the future direction of the modelling works by bringing new ideas for multiple perspective improvements in delay management, as well as business and quality engineering process.

This paper is outlined as follows: The next section discusses some relevant literatures on the railway rescheduling model and followed by the presentation of the mathematical model. The succeeding section highlights the computational experiment, while the conclusion and further research of the study are drawn at the end of the paper.

RELATED WORKS

Over the last few decades, the topic of real-time rescheduling of railway traffic during disturbances has attracted tremendous attention from many researchers. A wide range of mathematical programming models have been utilized for solving the train rescheduling problem in managing train service delays. Mathematical programming is commonly selected to be the tool for the rail traffic analysis and solution because of its capability of incorporating observed reality of the system into the model's constraints and objective function(s). Furthermore, it is also able to address the highly combinatorial problem and interlinked nature of the rail traffic system.

Some early delay management problems were formulated as an MIP model, for example, the model based on event-activity network (Schobel, 2001). It deals with the delay involved in transportation network. The objective of the model is to minimize the sum over all delays of all customers in the network. The work was later extended by Schachtebeck & Schobel (2008) to a railway service whereby this time a priority decision was added to an integer programming (IP) model. As the rail track system is subject to a limited capacity, the priority decisions would decide the sequence of trains in passing a track. A reduction technique derived for the network is used as the basis to solve the capacitated delay management problem using exact and heuristics approaches. The work contributes a significant finding as the four heuristics suggested are able to yield a faster result than the optimal solution obtained from IP formulation.

Acuna-Agost et al. (2009) proposed two models namely an MIP model and a Constraint Programming (CP) model of which both shares common objective function in minimizing delays, changes of tracks and platform and unplanned stops. Both models differ in terms of decision variables and constraints. Although utilizing more memory as compared to the CP, the proposed MIP is found to have developed more efficient solution methods when compared to CP. This is because, in CP, a large number of binary variables is needed to model the order of trains. The authors described the complexity of these two models in relation to its allocation of tracks and platforms, connection between trains, bidirectional/multi-track lines and extra time for accelerating and braking.

A recent MIP model which is established by Narayanaswami & Rangaraj (2013) includes disruption and conflicts-resolving constraints in the model itself. The novelty of the method ensures that only disrupted trains will be rescheduled, leaving alone the unaffected trains. This is done by partitioning train sets into conflicting and non-conflicting trains by means of linear constraints. To solve the model, the traveling salesman problem (TSP) approach was applied. The model is NP-Complete as it is reduced to a TSP in a polynomial time. Since the model used a small size fictive data, it should be extended to a larger scale of real data so that the validity of the model can be proven.

A model predictive control approach attempts to reschedule trains by a discrete-time control (Caimi et al*.,* 2012). A set of alternative blocking-stairways is used as the basis for each rescheduling step. This is followed by several planning steps which are linked to each other by different temporal scopes. The concept of bi-level multi-objective formulation means three criteria are considered separately in the first level. They are then aggregated into one objective function as a weighted sum. This method is appropriate when it comes to optimising a multi-criteria objective because the choice of weights depends absolutely on the dispatcher or the experts, based on the importance of the criteria valued.

The possibilities of rerouting trains were considered by Veelenturf et al*.* (2014) in the attempt to minimise the number of cancelled and delayed trains. The IP model tested on a busy part of Dutch railway network was able to solve most of their cases in two minutes. The method was claimed to be much more flexible and efficient than the current practice which uses contingency plans.

A fuzzy rescheduling model in a double-track railway network was proposed by Yang et al. (2014). They formulate the problem by introducing a space-time network-based representation to capture the uncertainty of incident duration. Taking the duration as a fuzzy variable, a two-stage fuzzy programming model was then formulated to generate the optimised train schedule. In relation to mathematical programming aspects, the proposed model can be viewed as an initial step towards incorporating fuzzy factors into a train rescheduling process. Apart from this, last train timetable rescheduling using genetic algorithm in order to minimise the train running and dwelling times was proposed by Kang et al*.* (2015). The model modifies the original timetable as little as possible to ensure that the train delay will be minimised while satisfying both hard and soft constraints.

Tornquist & Persson (2005) formulated their combinatorial problem of real-time disturbances in railway traffic rescheduling with the objective of minimising total service delay. An iterative two-level process is used to solve the problem. The order of meeting and overtaking of trains on the track section is done at the upper level using simulated annealing and tabu search while the lower level process determines the start and end time for each train. Local reordering trains are used to obtain good quality solutions.

The study was later extended by using a heterogeneous data set with more interacting traffic, to analyse the practicality of the model and solution approach (Tornquist & Persson, 2007). In this work, the authors presented a model and solution approach for the railway traffic rescheduling problem with a highly complex setting, taking into account the large number of railway tracks and segments and each rail network direction. A mixed integer linear programming model (MILP) representing the disturbed *n*-tracked network was evaluated and demonstrated on a complex Swedish railway network. The approaches used have shown good computational capabilities and they extended their work in the attempt to improve the computing time taken towards arriving at the rescheduling solutions (Krasemann, 2012). Besides complementing the earlier approach, the new greedy algorithm is able to provide good solutions within the permitted time.

THE MILP MODEL

The MILP model presented in this paper is an extension of the model established in Tornquist & Persson (2007) and uses basically the same variables and parameters. There are two main differences between the current proposed model and theirs. First, our model prioritises electric trains (ETS) over commuter trains whenever a conflict occurs. During disruption, the commuter is set to wait and give way to the ETS while holding to the limited capacity of tracks available at different segments of the railway line. The second difference is in regard to the switches along the tracks, which are modelled explicitly in this formulation.

The rail track between any two switches is defined as a segment. B denotes the set of segments considered in the rescheduling problem where each segment is labelled with index j, where $j \in B$. While i is defined as the index of the set of trains T, the set of events E is denoted by index k. In this model, the final event of the ordered set of train event is referred to as $n_i (i \in T)$ and the disrupted event is represented by q, where $q \in E$.

An ordinary train route has a signal switch control located right before the block entrance. Once accepted, no other trains will be allowed on the block or segment without permission from the signal switch. The distance between the signals which varies along the track is based on the geographical safety aspects such as the elevation of ground and the blind spots at curves and turns.

There are two types of segment location l, which are the non-station segment and station segment. For each segment, there is a set of parallel tracks $P_j = \{1,....,p_j\}$. A standard railway safety regulation normally imposes a minimum distance between two consecutive trains to avoid accident, which is termed as time headway. It indicates the minimum duration between the time when a train exits from a segment and the subsequent train enters the same segment. The parameter H_j denotes the time headway in cases where one train is following or meeting the other on a track of segment j.

Table 1 presents the elements in mathematical programming model, consisting of variables, sets and parameters of the formulation. There are seven decision variables anticipated from the method. The first two are d_k^R and a_k^R, which represent the departure time and the arrival time of the rescheduled event k, where $k \in E$, $K_i \subseteq E$ and $L_j \subseteq E$. Another four are the common scheduling disjunctive binary decision variables, namely r_k^t, τ_i, $\gamma_{k\hat{k}}$ and $\lambda_{k\hat{k}}$. As a result of the new schedule, the amount of delay that will be recorded from the rescheduling event *k* will be denoted by the decision variable z_k.

Table 1
Variables, sets and parameters of model

Component	Type	Description
d_k^R	Decision variables	The departure time of the rescheduled event *k*
a_k^R	Decision variables	The arrival time of the rescheduled event *k*
z_k	Decision variables	The amount of delay resulting from the rescheduling event *k*
r_k^t	Binary variables	The decision if event *k* is assigned to track *t*
τ_i	Binary variables	The decision if train *i* arrives within the delay time window
$\gamma_{k\hat{k}}$	Binary variables	The decision of the order of the occurrence of event *k* and $\hat{k}$
$\lambda_{k\hat{k}}$	Binary variables	The decision of the order of the occurrence of event $\hat{k}$ and *k*
T	Set	The set of trains considered in the rescheduling problem
B	Set	The set of segment considered in the rescheduling problem
K_i	Set	The ordered set of events of train *i*
L_j	Set	The ordered set of events of segment *j*
E_k	Set	The set of event *k*
l_j	Set	The types of segment *j*
P_j	Set	The set of parallel tracks on segment *j*
w_i	Parameters	The delay time window for train *i*
H_j	Parameter	The time headway between two consecutive train on a track of segment *j*
o_k	Parameter	The direction of event *k*
Δ_k	Parameter	The minimum time for an event *k* running at a segment
d_k^S	Parameter	The scheduled departure time of event *k* as in timetable
a_k^S	Parameter	The scheduled arrival time of event *k* as in timetable
d_k^A	Parameter	The actual departure time of event *k*
a_k^A	Parameter	The actual arrival time of event *k*
M	Constant	Arbitrarily large positive constant

Unlike linear programming model which normally consists of a set of functional constraints and a single objective function to be maximised or minimised, a goal programming model seeks to satisfy several objectives or goals, subject to a set of constraints that are prioritised in some sense. The objective of a goal programming is to find a solution that satisfies the constraints and the stated goals. In some cases, the feasible solutions of the goal programming may not satisfy all the conflicting goals simultaneously. This implies that the set of feasible solutions does meet the restrictions posed by the constraints, but it does not optimise all the objective functions in one go.

The technique of pre-emptive goal programming will be applied to solve the MILP model. In this method, minimising train delays will be the first priority while maximising service reliability will be the subsequent one. This is considered as the optimal solution to the goal programming problem. In this case, we consider the delay time window w_i to be less than or equals to 5 minutes. The MILP model is given in Figure 1.

$$\text{Minimize } \sum_{i=1}^{n_i} Z_{n_i} \tag{1a}$$

$$\text{Maximize } \frac{\sum_{i=1}^{n_i} \tau_i}{\sum_{i=1}^{n_i} T_i} \tag{1b}$$

Subject to

$$a_k^R \leq d_{k+1}^R, \quad k \in K_i \quad, i \in T : k \neq n_i \quad , \tag{2a}$$

$$a_k^R \geq d_k^R + \Delta_k, \quad k \in E \quad , \tag{2b}$$

$$a_q^R \geq d_q^R, \quad q \in E \quad , \tag{2c}$$

$$a_k^R = d_{k+1}^R, \quad k \in K_i \quad, i \in T : k \neq n_i \quad , \tag{3a}$$

$$a_k^R = d_k^R + \Delta_k, \quad k \in E \quad , \tag{3b}$$

$$d_k^R \geq d_k^S, \quad k \in E \quad , \tag{4}$$

$$d_k^R = d_k^A, \quad k \in E \quad : \quad d_k^S > 0 \quad , \tag{5}$$

$$a_k^R = a_k^A, \quad k \in E \quad : \quad a_k^A > 0 \quad , \tag{6}$$

$$a_k^R - a_k^S \leq z_k \quad k \in E \quad . \tag{7}$$

$$\sum_{t=1}^{p_j} r_k^t = 1, k \in L_j, j \in B, \tag{8}$$

$$r_k^t + r_{\hat{k}}^t - 1 \leq \lambda_{k\hat{k}} + \gamma_{k\hat{k}}, \quad k, \hat{k} \in L_j, j \in B : k < \hat{k}, \tag{9}$$

$$\lambda_{k\hat{k}} + \gamma_{k\hat{k}} \leq 1, \; k, \hat{k} \in L_j, j \in B : k < \hat{k}, \tag{10}$$

$$d_{\hat{k}}^R - a_k^R \geq H_j \gamma_{k\hat{k}} - M(1 - \gamma_{k\hat{k}}), k, \hat{k} \in L_j, j \in B : k < \hat{k}, o_{\hat{k}} = o_k, l_j = 0 \tag{11a}$$

$$d_{\hat{k}}^R - a_k^R \geq H_j \gamma_{k\hat{k}} - M(1 - \gamma_{k\hat{k}}), k, \hat{k} \in L_j, j \in B : k < \hat{k}, o_{\hat{k}} = o_k, l_j = 1 \tag{11b}$$

$$d_k^R - a_{\hat{k}}^R \geq H_j \lambda_{k\hat{k}} - M(1 - \lambda_{k\hat{k}}), k, \hat{k} \in L_j, j \in B : k < \hat{k}, o_{\hat{k}} = o_k, l_j = 0 \tag{12a}$$

$$d_k^R - a_{\hat{k}}^R \geq H_j \lambda_{k\hat{k}} - M(1 - \lambda_{k\hat{k}}), k, \hat{k} \in L_j, j \in B : k < \hat{k}, o_{\hat{k}} = o_k, l_j = 1 \tag{12b}$$

$$d_k^R, a_k^R, z_k \geq 0, k \in E, \tag{13}$$

$$r_k^t \in \{0,1\}, k \in L_j, t \in P_j, j \in B, \tag{14}$$

$$\gamma_{k\hat{k}}, \lambda_{k\hat{k}} \in \{0,1\}, k, \hat{k} \in L_j, j \in B : k < \hat{k}, \tag{15}$$

$$\tau_i \in \{0,1\}, \quad i \in T \tag{16}$$

Figure 1. The mathematical model

The goals of the MIP model are represented by (1a) and (1b). The objective function (1a) is to minimise the sum of delays experienced by all trains when they reach their final destination. The objective function (1b) is aimed to maximise train service reliability. Constraint (2) governs the restrictions posed to commuter trains. Constraint (2a) indicates that a successor of a train event must wait until its predecessor has completed its journey before it can start. The minimum running time for each train event is guaranteed by Constraint (2b) while Constraint (2c) forces the disrupted event to resume journey once it recovers.

Constraints (3a) and (3b) control the strict schedule for the prioritised ETS train. Constraint (3a) ensures that each ETS train event must be directly succeeded by the next one, as far as the original schedule is concerned while Constraint (3b) guarantees that the ETS trains should strictly depart and arrive, according to the planned scheduled. Constraint (4) indicates that the reschedule departure time should never be earlier than the original time scheduled. Constraint

(5) and Constraint (6) ensure that events that have already started before disruption occurs must follow the original timetable. Constraint (7) defines the total delay of all trains as the deviation between the rescheduled and the original arrival times.

Constraint (8) restricts the utilisation of track line as one train per track. Constraint (9) is introduced to ensure that the total concurrent events at a segment must not exceed the track capacity. Constraint (10) checks the sequence between an event and its proceeding event, so as to ensure that it is either $\gamma_{k\hat{k}}$ or $\lambda_{k\hat{k}}$ will take value of '1'. Constraints (11) and Constraints (12) impose a restriction for the minimum headway between two consecutive trains using the same track. It is either the set of Constraint (11) or Constraint (12) that will become active, depending on the value of $\gamma_{k\hat{k}}$ and $\lambda_{k\hat{k}}$. In addition to this, the minimum headway H_j equals 5 minutes for both station and non-station segment j. The lateness of train i is denoted by a binary variable τ_i, over the delay time window of 5 minutes while M is an arbitrarily large positive integer. Finally, the Constraint (13) up to Constraint (16) define the domain of the decision variables.

THE COMPUTATIONAL EXPERIMENT

Computational experiments in this study are based on realistic cases drawn from a part of a local railway line in Malaysia. Sample data is composed of 23 segments, including 10 stations along the railway network connecting some major towns in Kuala Lumpur.

The experimental analysis is carried out by considering 3 incident scenarios involving a disruption on a track segment. For all cases, we consider a partial blockage, in which only one track of a segment is blocked. Segment 22 and Segment 23 have four rail tracks while the rest are equipped with a double track system. We specify beforehand that all trains going south and north will be using Track 1 and Track 2 respectively. Any additional tracks available can be used when needed. For partial blockade, which is left with only one single track, any two consecutive trains using the single piece of track need to adhere to the minimum headway of 5 minutes.

In rescheduling cases, the rail operator has established its priority settings in two aspects. First, in any conflict circumstances between types of train, a commuter must always give priority to ETS. The fast train is set to run according to the timetable as long as there is at least one track available. In this research, it is assumed that an ETS train will not experience any service delay or break down. Second, if two commuter trains of the same direction are anticipated to meet each other in less than the minimum headway requirement of 5 minutes, then the recovered disrupted train has to be given priority over the normal-scheduled train.

There are nine commuter trains running in both directions, including one ETS train heading south. Each train is assumed to be able to fit on any track and a maximum of six-car train is assumed. The location of all trains in the network is known at all times. For simplicity, the speed of trains is assumed constant and the dwell time of the trains at stations is embedded in the event duration.

There were 124 events and 1145 decision variables altogether, which technically produce a list of 2018 constraints. The time horizon was limited to 42 minutes and three incident cases were manually created to capture the rescheduling scenario. The cases were randomly selected with the aim to get solutions which satisfy the track capacity and adhere to the minimum headway requirement. We use preemptive goal programming approach in which the total service delay is computed first and the result obtained will then be used to determine the maximum train service reliability. The service reliability is computed by only considering the trains with delay time window of five minutes or less. The mathematical model is solved by using MATLAB R2014a. The computational tests were run on a 3.00GHz AMD Phenom Processor with 4Gb RAM.

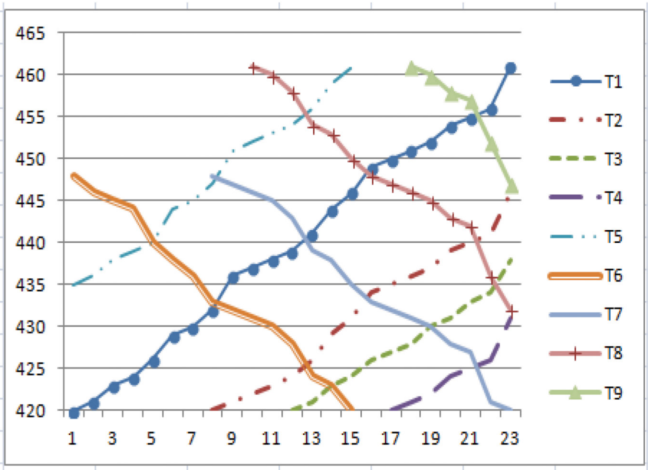

Figure 2. Original schedule

Figure 2 displays the original schedule of nine trains that run along the rail tracks. The vertical axis depicts the time and the horizontal axis indicates the segment. Each curve in the diagram represents a train, which is indicated by the number next to the line. Curves with positive gradient indicate trains heading south, while those with negative gradient indicate the opposite direction. The prioritised ETS train is denoted by Train 3.

Incident Case 1

The first scenario is a 10-minute disruption at a track segment 9 starting at $t=423$, experienced by Train 2. During the blockage period, Train 6 of the opposite direction passes the segment by using the other remaining track. When Train 2 resumes its journey at $t=433$, Train 1 is ahead running at the same direction. To maintain a safe minimum headway distance between them, the priority settings forced the normal-scheduled Train 1 to be delayed and give way to the recovered Train 2. The tiny dots along the TT_T1 and TT_T2 curves in Figure 3 represent the optimal reschedule plan generated by the optimisation model in contrast to the patterned curves which are the original timetable of the respective trains. The optimum solution obtained from the model shows that the minimum delays experienced by Train 1 and Train 2 are 2 minutes and 11 minutes respectively. As a consequence, this has brought the objective function of total delay z to be 13 minutes and its service reliability at 89% percent.

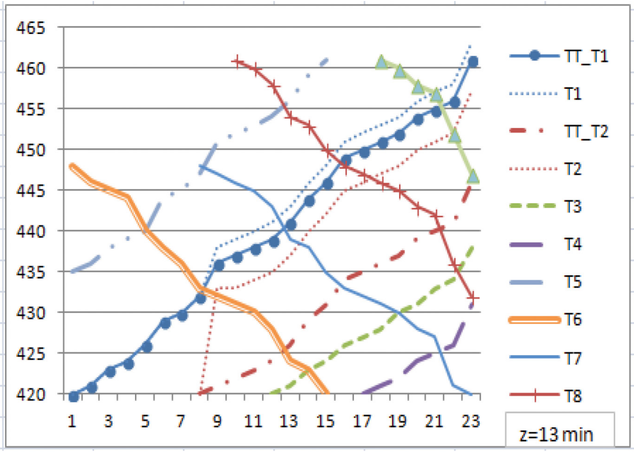

Figure 3. Rescheduling timetable for Case 1

Incident Case 2

In Case 2, a south-bound Train 4 experiences a 7-minute delay at Segment 17. Once recovered, it could not resume its journey because there is an ETS which has just passed by. Therefore, Train 4 is forced to wait for ETS to be 5 minute ahead, in compliance with the minimum headway constraint. When Train 4 is about to resume its journey at *t=435*, again it faces a conflict, now with a normal-scheduled Train 2 which is heading to the same direction. This time Train 4 is granted priority as a recovered disrupted train while Train 2 will be delayed as required by the minimum headway restriction.

On the opposite direction, Train 7 is also affected when there is a track capacity restriction at Segment 17 during which Train 4 was stranded. The tiny dotted lines along the TT_T2, TT_T4 and TT_T7 curves in Figure 4 illustrates the new reschedule plan for the affected trains. The result generated shows that the minimum delays incurred by Train 2, Train 4 and Train 7 are 5 minutes, 14 minutes and 1 minute respectively. To this end, the objective function yields the total delay *z* to be 20 minutes with a service reliability of 77%.

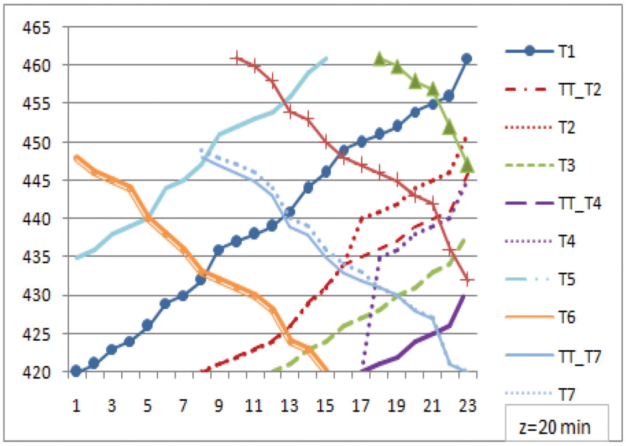

Figure 4. Rescheduling timetable for Case 2

Incident Case 3

In Case 3, Train 4 only experienced a 4-minute disruption at Segment 19. However, the total delay generated was 26 minutes, due to priority settings and capacity constraints that it has to satisfy. Having recovered from disruption, Train 4 has to wait for another 10 minutes before it can travel at a safe distance behind ETS. In the meantime, the opposite direction Train 7 is delayed to meet the capacity constraint at the affected segment. The tiny dotted lines emerging from the TT_T4 and TT_T7 curves in Figure 5 illustrates the new reschedule timetable. Due to the long total delay, service reliability has dropped to only 67%.

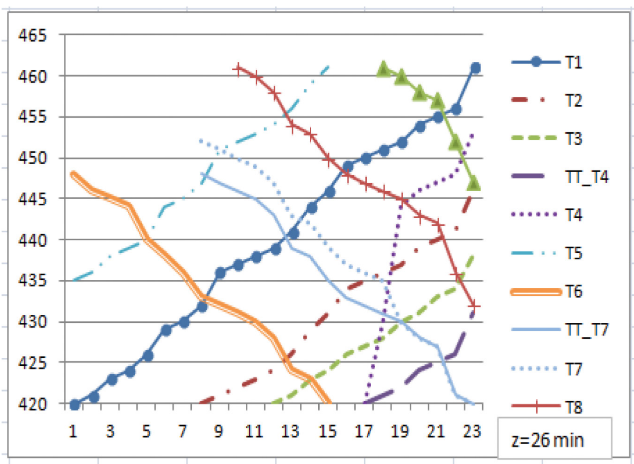

Figure 5. Rescheduling timetable for Case 3

CONCLUSION AND FURTHER RESEARCH

From the three cases that have been analysed, it has been shown that the MILP model successfully generated the rescheduling timetable. The total service delay of each affected train is attainable, together with the service reliabilities and the list of all departure and arrival times for each event. The new rescheduling timetable considers the aspects of track capacity and the minimum headway requirement practically, besides other model constraints. Ultimately, the fast train ETS runs according to the original schedule and does not experience any delay in all cases.

In spite of these results, some aspects have been disregarded in this experiment. The scope of research was limited. A more complex result might have been obtained if more segments were covered, more trains included and the time horizon lengthened. The possibility of one train overtaking the other is also neglected; while in practice, a train is allowed to overtake the damaged train at a segment loop. The model formulation also disregards the importance of connecting trains. In some railway system, a train is forced to wait for other trains to connect their passengers to their final destination.

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