Decision support system for real-time rescheduling

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1 INTRODUCTION

Public transit systems in urban settings face numerous operational challenges, including accidents, congestion, and vehicle breakdowns, which disrupt the pre-scheduled operations. These disruptions result in delays that propagate throughout the day, increasing operational costs such as crew's overtime and deteriorating the quality of service. This paper addresses these issues by proposing a decision support system (DSS) for real-time rescheduling for a public transit system that uses historical and real-time data to dynamically optimize vehicle and crew schedules.

This paper builds on previous work in the fields of disruption management, integrated vehicle and crew scheduling, and real-time optimization. Railway and urban transit systems face numerous uncertainties (Zhan *et al.*, 2024). Recovery from disruptions typically involves multi-stage strategies. These strategies include timetable rescheduling, rolling stock rescheduling, and crew rescheduling (van Rossum *et al.*, 2024). While various methods for timetable and rolling stock recovery exist, few studies focus on the integrated rescheduling of vehicles and crews. Notably, the well-being of crew members, such as ensuring fair work distribution and respecting break periods, is increasingly recognized as a critical factor in transit system performance (van Rossum *et al.*, 2024). This study extends the work of Lai & Leung (2018) by incorporating crew well-being, vehicle availability, and passenger demand into an optimization framework. The multi-objective, multi-period model addresses the practical constraints of vehicle availability, maximum working hours, and the dynamic nature of operations.

The interested public transit system in this study operates vehicles running on shared public roads. Due to this shared nature, external factors like traffic congestion and accidents significantly disrupt transit operations. In current practice, local inspectors at various termini make real-time adjustments to motormen's duties. However, these decisions are made without access to system-wide information, leading to suboptimal decisions that do not benefit the overall network.

The proposed decision support system overcomes these challenges by utilizing auto-sensed location data of vehicles and real-time information including motormen's latest revised schedules. This decision support system allows controllers to access updated, system-wide information and revise schedules dynamically in response to disruptions and uncertainties. The core of the decision support system is an optimization model. The objective of the model is twofold: (1) to maximize route frequency, thereby improving passenger service, and (2) to minimize operational costs, specifically overtime, meal-break delays, and violations of maximum working hours for motormen. The proposed optimization model is an integer programming that equips with a rolling-horizon framework which can adapt to new information when it becomes available, making it suitable for real-time operations.

2 PROBLEM FORMULATION

The problem considered in this study is the real-time rescheduling of motormen and vehicles in a public transit system. The system's goal is to respond to disruptions in a manner that minimizes operational inefficiencies while maintaining a high level of passenger service. The core of the problem lies in the dynamic allocation of tasks to motormen, ensuring compliance with regulations such as maximum working hours and mandatory break times, while optimizing vehicle deployment across the network. The proposed integer programming model is solved using a rolling-horizon approach. The model dynamically revises the motormen's schedules and assigns vehicles to routes while considering stochastic travel times and real-time traffic data. Key decision variables in the model include motormen's assignments to specific tasks and route coverage to fulfil pre-defined passenger demands within the scheduling horizon.

Before presenting our proposed optimization model for the decision support system, we introduce the notations of sets and parameters:

T : Set of all termini.
M_t : Set of all motormen in terminal t within the next planning period.
S_t^m : Set of task sequences originating from terminal t and feasible for motorman m.
$\mathbb{Z}^+$: Set of non-negative integers.

A task could be a run in a route, a meal-break, or a duty-sign-off. We consider all possible assignments of motorman m to sequence s if and only if sequence s begins in the location where motorman m is available. Given an assignment of motorman m to task sequence s, we can determine the start-time of motorman m to execute the task sequence s. Hence, we can compute the mileage and costs of the assignment, where

α_{ms} : Estimated mileage of task sequence s.
β_{ms} : Expected overtime for motorman m executing task sequence s.
γ_{ms} : Expected meal-break delay for motorman m executing task sequence s.
δ_{ms} : Expected early meal-break for motorman m executing task sequence s.
ϵ_{ms} : Expected idle time for motorman m executing task sequence s.
ζ_{ms} : Expected time that violates the limit of maximum working hours for motorman m executing task sequence s.

On the demand side, we consider the set of routes and the coverage needed over the next several time periods. We define the following parameters:

R : Set of routes.
R' : Set of routes that are less profitable than other routes.
P : Set of time periods.
d_{rp} : Number of vehicles needed for route $r \in R$ in period $p \in P$.
$a_{rp}^{ms} = \begin{cases} 1 & \text{if assigning motorman } m \text{ to task sequence } s \text{ provides coverage of route } r \text{ in period } p; \\ 0 & \text{otherwise.} \end{cases}$

The decision variables of the mathematical model are:

$$x_{ms} = \begin{cases} 1 & \text{if motorman } m \text{ is assigned with task sequence } s; \\ 0 & \text{otherwise.} \end{cases}$$

$u_{rp} \in \mathbb{Z}^+$ is the demand under-coverage in route r in period p.
$s_{rp} \in \mathbb{Z}^+$ is the over-coverage in route r in period p.

With the introduced notations of sets, parameters, and variables, the proposed mathematical model is defined as follows:

$$\begin{aligned} \min \quad & \sum_{t \in T} \sum_{m \in M_t} \sum_{s \in S_t^m} \big(-\omega_0 \alpha_{ms} + \omega_1 \beta_{ms} + \omega_2 \gamma_{ms} + \omega_3 \delta_{ms} + \omega_4 \epsilon_{ms} + \omega_5 \zeta_{ms} \big) x_{ms} \\ & + \sum_{p \in P} \sum_{r \in R} \omega_6^{rp} u_{rp} + \sum_{p \in P} \sum_{r \in R'} \omega_7^{rp} s_{rp} \end{aligned}$$

subject to

$$\sum_{t \in T} \sum_{m \in M_t} \sum_{s \in S_t^m} a_{rp}^{ms} x_{ms} + u_{rp} - s_{rp} = d_{rp} \qquad \forall r \in R', p \in P \tag{1}$$

$$\sum_{t \in T} \sum_{m \in M_t} \sum_{s \in S_t^m} a_{rp}^{ms} x_{ms} + u_{rp} \geq d_{rp} \qquad \forall r \in R \backslash R', p \in P \tag{2}$$

$$\sum_{s \in S_t^m} x_{ms} = 1 \qquad \forall t \in T, m \in M_t \tag{3}$$

$$u_{rp} \in \mathbb{Z}^+ \qquad \forall r \in R, p \in P \tag{4}$$

$$s_{rp} \in \mathbb{Z}^+ \qquad \forall r \in R', p \in P \tag{5}$$

$$x_{ms} \in \{0, 1\} \qquad \forall m \in M, t \in T, s \in S_t^m \tag{6}$$

Denote ω_j is the weight of the j-th item in the objective function. The objective of the model is to maximize the weighted total commercial mileage hence the profit, while minimizing the weighted sum of the total overtime, total meal-break delay, total early meal-break, total idle time, and total time that violates the limit of maximum working hours for motormen, the demand under-coverage for routes and the over-coverage for the less profitable routes (i.e., the last two terms). (Note: In simulations, the values of the the weights were calculated according to the real-time traffic conditions.)

The first three sets of constraints ensure that:

(1) The demand for less profitable route r in period p (coverage) is met as much as possible (subject to the optimality of the objective).

(2) The demand for more profitable route r in period p (coverage) is met as much as possible (subject to the optimality of the objective).

(3) One and only one task sequence is assigned to each motorman arriving at terminal t within the next planning period.

The last three sets of constraints (4) - (6) specify the domains of the variables. (Note: The extended model addressing the availability of vehicles would be presented in the full paper.)

3 SIMULATIONS AND PRELIMINARY RESULTS

A simulation-based case study is conducted using real-world data from a public transit system in an Asian city. This public transit system requires about 200 motormen and operates about 250 vehicles across a network of densely populated areas, providing passenger services to thousands daily. Simulations run on a Windows 10 laptop with an Intel Core i7-8750H and 16 GB RAM. The C++ implementation of the mathematical model, solved using IBM ILOG CPLEX 12.6.2, generates hundreds to thousands of feasible task sequences per motorman within a 3-hour look-ahead period. The worst-case CPU time is 48.46 seconds, demonstrating the model's feasibility for real-time decision-making.

Simulations using two days of data with disruptions (30–90 minutes) demonstrate the effectiveness of the proposed real-time rescheduling system. Incorporating expert domain knowledge, we set $\omega_0 = 15000$, $\omega_1 = 5000$, $\omega_2 = 2000$, $\omega_3 = 800$, $\omega_4 = 1500$, $\omega_5 = 2250$, $\omega_6 = 50000$ for less profitable routes and 150000 for more profitable routes, and $\omega_7 = 40000$. The focal company traditionally relies on domain experts to manually reschedule motormen and vehicle timetables. The proposed decision support system, integrated with the optimization model, improves passenger route coverage from 86.68% to 90.76%, ensuring service reliability during disruptions. Additionally, average motormen overtime decreases from 44.65 to 10.91 minutes, with a slight but acceptable meal-break increase from 23.12 to 32.76 minutes. More critically, violations of maximum working hours drop from 31 motormen to just one, who only exceeds the limit by 16.17 minutes, compared to 94.25 minutes under the predefined schedule. These results highlight the decision support system's effectiveness in enhancing operational efficiency and crew well-being, making it a valuable tool for real-time transit management.

4 CONCLUDING REMARKS

This paper presents a novel real-time integrated rescheduling system for a public transit network in an Asian city. By leveraging historical and real-time data, the system dynamically adjusts crew and vehicle schedules to respond to disruptions. This could ensure better compliance with labor regulations, reducing potential conflicts and improving crew well-being. Simulation results demonstrate the model's effectiveness in improving operational efficiency, reducing costs, and maintaining passenger service levels. The proposed decision support system offers a practical solution for urban transit operators facing the increasing complexity and uncertainty of modern transportation systems.

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