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Schedule Coordination through Negotiation between Train Service Providers in an Open Railway Access Market

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Abstract—A schedule coordination problem involving two train services provided by different operators is modeled as an optimization of revenue intake. The coordination is achieved through the adjustment of commencement times of the train services by negotiation. The problem is subject to constraints regarding to passenger demands and idle costs of rolling-stocks from both operators. This paper models the operators as software agents having the flexibility to incorporate one of the two (and potentially more) proposed negotiation strategies. Empirical results show that agents employing different combination of strategies have significant impact on the quality of solution and negotiation time.

I. INTRODUCTION

An open railway access market basically consists of an infrastructure provider (IP) and a number of train service providers (TSPs). The TSPs may either compete directly by serving identical railway lines or, more commonly, compete moderately by serving overlapping lines. Through the tension generated from these competitions, the railways are not only expected to utilize their resources more efficiently, but quality of service may also be improved to attract more transportation demands towards the railways.

An example of moderate competition is shown in Fig. 1. TSP-1 is operating a line to and from stations A and F, stopping at intermediate stations B, C, D and E. On the other hand, TSP-2 is operating a line to and from stations G and J, dwelling at stations H, C, D, E and I. Despite the competition of passenger demand between stations C to E, it is possible to improve the revenue intake for both parties if passengers can travel across the two lines by coordinating the train schedules at a common transfer node (e.g. station C).

The schedule coordination problem in integrated railways, where train services are solely provided by a single authority, often concerns on the minimization of passenger waiting time by adjusting the commencement times of a set of train services. Such problem has been extensively studied in the literature. When coordinating train services at a single station, the arrival times of a service have been modeled by a set of vertices of a polygon within a unit circle [1], [2]. The problem is then to minimize the total arc lengths between the vertices on the circumference of the circle. When coordinating a set of trains at multiple transfer stations, the problem has been shown to be NP-hard [3] and it has been solved using a brand-and-bound algorithm for optimal solution [3], and using a genetic algorithm for near-optimal solutions [4].

Despite the efforts in the schedule coordination problem in the integrated railways, the effect of open market has altered the nature of the problem. Firstly, the lines are now managed by different TSPs instead of a single authority. As a result, the alignment of schedules requires a mutual agreement from more than one party, whose operating constraints and objectives may be in conflicts with the other operators. In particular, there may be constraints regarding to the earliest commencement time due to the availability of rolling-stock, and it is also desirable to consider the cost of idle time for the rolling-stock. Moreover, sensitive data such as cost rates are unlikely to reveal to the other TSP. This means decisions on the coordinated schedules are often made under incomplete information through negotiation activities. These changes prompt the remodeling of the schedule coordination problem.

Agent modeling [5] is particularly suitable for constructing distributed systems where entities are self-interested, and interact through communicative acts such as negotiation [6]. The modeling technique enables a high level of autonomy to the entities (called agents) by the encapsulation of data and reasoning logic. Applications of agent modeling are growing in railways, and they include the train coupling and sharing problem [7] and the conflict resolution of track access right between IP and TSP [8]-[10].

Fig. 1. Competition between two railway lines.
This paper proposes an agent negotiation model for a schedule coordination problem involving two train services at a single transfer station. Section II defines a formal model of the problem. Section III then describes the algorithm used in generating offers during the negotiation. Section IV presents the simulation results of a simple example. Finally, Section V delivers the conclusion.

II. NEGOTIATION MODELS

A. Cost Function

Let \( L_i \) denote the operation of a service by TSP-\( i \). The commencement time for \( L_i \) at the first station is \( \zeta_i \). Consider the problem involving two railway services, \( L_i \) and \( L_j \), both of which have a common intermediate station at \( X \). Given integer values of \( (\zeta_i, \zeta_j) \), the net revenue collected from the transfer of passengers is model by (1).

\[
Y = k_i G(\zeta_i, \zeta_j) + k_j G(\zeta_j, \zeta_i) - F(\zeta_i)
\]  

where \( Y \) is the net increase in revenue of \( L_i \); \( k_i \) is the average cost charged to a transferring passenger; \( G(\zeta_i, \zeta_j) \) is the passenger demand for transferring from \( L_i \) to \( L_j \); and \( F(\zeta_i) \) is the cost of idle time.

1) Definition of \( G(\zeta_i, \zeta_j) \): Let \( h_i \) be the total time needed for \( L_i \) to arrive at \( X \) from the first station, \( d_j \) be the dwell time, and \( k_j \) be the minimum transfer time for passenger moving from \( L_i \) to \( L_j \), then the passenger waiting time \( w_{ij} \) can be expressed by (2).

\[
w_{ij} = (\zeta_i + h_i + d_j) - (\zeta_j + h_j) - k_j
\]  

Passenger demand is assumed to be affected by the amount of waiting time at \( X \). The longer is the waiting time, the lower is the demand. In this study, the demand from \( L_i \) to \( L_j \) in relation to the waiting time is modeled by a quadratic function in (3) subject to (4).

\[
G(\zeta_i, \zeta_j) = \hat{G}_{ij} \left[ 1 - \left( \frac{\zeta_j - \zeta_i + z_j}{w_{ij}} \right)^2 \right]
\]  

\[
0 \leq \zeta_j - \zeta_i + z_j \leq w_{ij}
\]

where \( z_j = h_i + d_j - h_j - k_j \), and \( w_{ij} \) is the lowest waiting time resulting in zero demand. When the waiting time is zero, the function achieves maximum demand at \( \hat{G}_{ij} \). As the waiting time increases, progressively more passengers will opt for alternative means of travel such as automobiles.

2) Definition of \( F(\zeta_i) \): Let \( \zeta^*_i \) be the earliest time that the rolling-stock is available at the first station. This is often known as the release date in scheduling. If \( L_i \) commences at \( \zeta^*_i \), then the idle cost is zero. As the time is postponed, the idle cost increases proportionally. Let \( c_i \) be the unit cost of idle time. \( F(\zeta_i) \) is then modeled by (5) subject to (6).

\[
F(\zeta_i) = c_i (\zeta_i - \zeta^*_i)
\]  

\[
\zeta_t \geq \zeta^*_i
\]

B. Negotiation Procedures

Negotiation is conducted by exchanging offers in a series of negotiation rounds. The TSP agent submitting the first offer is called the initiator. The negotiating partner (proponent) is called the responder.

An offer at round \( k \) consists of the proposed commencement times of the initiator and the responder. Without the loss of generality, the initiator and responder are assigned to be TSP-\( i \) and TSP-\( j \) respectively. An offer is therefore modeled by (7).

\[
O^k = (\zeta_i^k, \zeta_j^k)
\]

The cost associated with the offer \( O^k \) is assumed to be stored internally by the agent, represented by \( Y^k \). Suppose TSP-\( i \) is the initiator, then the offers in the odd rounds of negotiation (i.e. \( k = 2m - 1 \), for \( m = 1, 2, ... \)) are proposed by TSP-\( i \), while offers in the even rounds of negotiation (i.e.
The general negotiation procedure is shown in Fig. 2. The action set of an agent are \{propose, accept, failure\}. At the beginning, the initiator generates the offer which maximizes (1) subject to (4) and (6). If the offer exists, it is proposed to the proponent. Otherwise, no action is taken. Upon the arrival of the counteroffer from the proponent, the agent evaluates the associated cost of the counteroffer and updates $O^i$, which is the first occurrence of counteroffer with the highest cost $Y^i$ received at round $\hat{k}$. In addition, the agent also computes the next potential offer $O'$ using one of the strategies, $S_{po}$ or $S_{max}$, which are described in the following subsection. If no potential offer can be found, the negotiation is terminated with the failure action. If the offer does exist, the agent proposes $O'$ when $Y'_i > Y^i$, and accepts $O^i$ otherwise.

C. Negotiation Strategies

1) $S_{po}$: This strategy aims to derive the Pareto-optimal solution and it requires both agents to employ this strategy to achieve the objective. According to the definition of Pareto-optimality [11], a solution $s$ is Pareto-optimal if there does not exist any alternative solution $s'$ which improves the costs of all negotiating parties.

By definition, the initiator is proposing at rounds $k = 2m - 1$ while the responder is proposing at rounds $k = 2m$. In other words, the sequence of offers generated by the initiator is $O^1, O^2, \ldots, O^{2m-1}$ and the sequence of offers of the responder is $O^1, O^2, \ldots, O^{2m}$. In this strategy, the feasible offers of an agent are arranged in descending order of their costs, that is, for the initiator, $Y^i_1 \geq Y^i_2 \geq \ldots \geq Y^i_{2m}$ and for the responder, $Y^r_1 \geq Y^r_2 \geq \ldots \geq Y^r_{2m}$.

The property of the above strategy can be proved by contradiction. Assume the condition of acceptance is detected by the initiator after round $k_o$ and $O^i$ is accepted. If $O^i$ is not Pareto-optimal, then there exists another offer $O'$ that does not decrease the cost of either agent. To determine whether such offer does exist, the offers are divided into three partitions as shown in Fig. 3.

Partition A: This partition consists of the proposals prior to round $\hat{k}$. In the odd rounds within this set (i.e. $2m - 1 < \hat{k}$), although the costs of the initiator are higher (i.e. $Y^i_{2m-1} \geq Y^i_1$), the costs of the responder are lower (i.e. $Y^r_{2m-1} < Y^r_1$). Otherwise the condition of acceptance would have been detected by the responder (Fig. 3). Since these solutions cause a decrease in $Y^r_1$, they are not Pareto-optimal. On the other hand, in the even rounds (i.e. $2m < \hat{k}$), although the costs of the responder are higher (i.e. $Y^r_{2m} \geq Y^r_1$), the costs of the initiator are smaller (i.e. $Y^i_{2m} < Y^i_1$) because by definition, $Y^i_1$ is the first highest cost among the counteroffers. Therefore, these solutions are also not Pareto-optimal.

Partition B: This partition consists of the proposals between round $\hat{k}$ and $k_o + 1$ exclusively. For the costs in the odd rounds, the same argument holds as in partition A. In the even rounds ($\hat{k} < 2m < k_o + 1$), both costs are smaller by definition. In brief, all the other offers that have been proposed cannot improve $Y^r_1$ and $Y^r_1$ simultaneously.

Partition C: To examine the remaining offers that have not been proposed, suppose the negotiation continues. In the odd rounds of negotiation, $Y^i_1$ is decreasing, so even if $Y^r_2 > Y^r_1$, the offer is not Pareto-optimal. Similarly, in the even rounds of negotiation, since $Y^r_1$ is decreasing, these proposals cannot be Pareto-optimal.

As a result, no offers can improve the costs of both parties simultaneously when the condition of acceptance is detected by the initiator. The proof for the responder can be constructed in a similar manner. This completes the proof.

2) $S_{max}$: To reach the Pareto-optimal solution, both parties must employ $S_{po}$. Despite the theoretical significance of such solution, in practice, stakeholders often aim to achieve a better cost, even if the proponent suffers from a loss. As a consequence, it is also worth examining other negotiation strategies (or combination of strategies), and compare their resultant offers from the Pareto-optimal solution obtained by $S_{po}$.

In strategy $S_{max}$, it is assumed that only one variable can be changed in $O^{i+1}$ with respect to the counteroffer $O^i$. The agent determines which variable, either $\zeta_{i+1}^j$ or $\zeta_{i}^{j+1}$, should be changed in order to maximize the difference of $Y^r_1 - Y^r_i$.

III. ALGORITHM FOR OFFER GENERATION

In the definitions of the negotiation strategies, it has been assumed that an algorithm exists in generating the necessary offers. In this section, a simple algorithm from the perspective
of TSP-1 is proposed for each strategy.

1) \( S_{\text{po}} \): Let \( n_i \) be the maximum allowable adjustment on the commencement time from the release date of TSP-1. If the earliest arrival times at the transfer station \( X \) for both train services are expected to be at close proximity, then \( S_{\text{po}} \) may employ the following algorithm for offer generation provided that \( (\zeta^* + h_i - \zeta_i) < n_i \), where \( < \) represents significantly smaller than.

Step 1: Compute the costs for all combination of solutions \((\zeta^*, \zeta_i)\) for \( \zeta_i - n_i < \zeta_i \leq \zeta_i + n_i \) and \( \zeta_i - n_i < \zeta_i \leq \zeta^* + n_i \), where \( \zeta^* = \zeta_i + h_i - h_i \).

Step 2: Sort the solutions in descending order of their costs using a sorting algorithm such as the Quicksort.

The above algorithm intuitively generates all the possible offers expected to encounter during the negotiation. Since the release date of the proponent is an unknown, it is estimated by the earliest arrival time of its service and the journey time of the proponent’s service. As the release date may either be earlier or later than this estimation, the upper and lower bounds are calculated by adding and subtracting by \( n_i \) respectively. \( n_i \) can be taken as 60min if the earliest arrival times are at close proximity (e.g. within 10min).

2) \( S_{\text{max}} \): Let the most recent counteroffer received be \((\zeta^*, \zeta_i)\). With the same definitions of \( n_i \) and \( \zeta^* \), the algorithm for \( S_{\text{max}} \) is given as follows.

Step 1: Compute the costs of all solutions \((\zeta^*, \zeta_i)\) for \( \zeta^* - n_i < \zeta_i < \zeta^* + n_i \).

Step 2: Compute the costs of all solutions \((\zeta^*, \zeta_i)\) for \( \zeta^* < \zeta_i < \zeta^* + n_i \).

Step 3: Select the best offer from steps 1 and 2. If the offer has been proposed previously, select the next best offer.

IV. SIMULATION SETUP AND RESULTS

A. Simulation Setup

The negotiation model is implemented with the aid of JADE (Java Agent DEvelopment Framework) [12]. JADE is a FIPA-compliant software framework which provides generic functions for agent development.

Table I shows the settings of two TSP agents which are used in the simulation studies. Using the data, the two agents are set up to conduct four negotiations with different combinations of strategies. If \((S_1, S_2)\) denotes the strategies employed by TSP-1 and TSP-2 respectively, the four combinations are \((S_{\text{po}}, S_{\text{po}}), (S_{\text{po}}, S_{\text{max}}), (S_{\text{max}}, S_{\text{po}}), \) and \((S_{\text{max}}, S_{\text{max}})\).

B. Results

All four negotiations have been able to settle at an agreement, and the results are summarized in Table II. The Pareto-optimal solution has been found to be \((\zeta^*, \zeta^*_i) = (13, 5)\). In this table, the costs in percentage are calculated with respect to this solution.

1) Operation of Strategies: To demonstrate how the two strategies lead to an agreement, the negotiation of \((S_{\text{max}}, S_{\text{po}})\) is examined in further detail.

TSP-1 first initiates the negotiation by proposing \((8, 0)\) – the offer that maximizes its cost function. The corresponding cost for TSP-2 is zero because the suggested commencement time is less than the released date. Since TSP-2 is employing \( S_{\text{po}} \), it generates the sequence of offers in descending order of costs. The top five offers are shown under the column of potential offer in Table III. According to this sequence, TSP-2 counter-proposes \((16, 5)\) to TSP-1.

The cost of \((16, 5)\) for TSP-1 is 87.0% (Table IV) with respect to the cost of its best offer \((8, 0)\). By \( S_{\text{max}} \), TSP-1

| Table I |
| Simulation Setup |
| \( w_{m_i}, \) (min) | 20 |
| \( c_i, \) ($/min) | 50 | 60 |
| \( \zeta_i^*, \) (min) | 7 | 5 |
| \( h_i, \) ($/person) | 15 | 22 |
| \( h_i, \) (min) | 20 | 30 |
| \( d_i, \) (min) | 5 | 7 |

| Table II |
| Summary of Simulation Results |
| \((S_{\text{po}}, S_{\text{po}})\) | \((S_{\text{max}}, S_{\text{po}})\) | \((S_{\text{max}}, S_{\text{max}})\) |
| \((\zeta^*, \zeta^*_i)\), (min) | \((13, 5)\) | \((15, 5)\) |
| \((Y_1, Y_2)\), (%) | \((100, 100)\) | \((98.5, 102.6)\) |
| \((w_{ij}, w_{ji})\), (min) | \((7, 1)\) | \((5, 3)\) |
| Rounds | 61 | 11 |

| Table III |
| Counteroffers and Potential Offers for TSP-2 |
| Round | Counteroffer | Potential Offer 1 | Potential Offer 2 |
| \((\zeta^*, \zeta^*_i)\) | \(Y_i\), (%) | \((\zeta^*, \zeta^*_i)\) | \(Y_i\), (%) |
| 1 | \((8, 0)\) | 0.0 | \((16, 5)\) | 100.0 |
| 3 | \((13, 5)\) | 97.0 | \((17, 5)\) | 100.0 |
| 5 | \((12, 5)\) | 97.0 | \((15, 5)\) | 99.5 |
| 7 | \((14, 5)\) | 98.5 | \((18, 5)\) | 99.4 |
| 9 | \((15, 5)\) | 99.5 | \((14, 5)\) | 98.5 |

| Table IV |
| Counteroffers and Potential Offers for TSP-1 |
| Round | Counteroffer | Potential Offer 1 | Potential Offer 2 |
| \((\zeta^*, \zeta^*_i)\) | \(Y_i\), (%) | \((\zeta^*, \zeta^*_i)\) | \(Y_i\), (%) |
| 2 | \((16, 5)\) | 87.0 | \((16, 4)\) | 86.9 | \((13, 5)\) | 89.9 |
| 4 | \((17, 5)\) | 84.9 | \((17, 6)\) | 84.9 | \((12, 5)\) | 89.7 |
| 6 | \((15, 5)\) | 88.5 | \((15, 4)\) | 89.0 | \((14, 5)\) | 89.4 |
| 8 | \((18, 5)\) | 82.3 | \((18, 7)\) | 82.9 | \((15, 5)\) | 88.5 |
generates two offers from this offer by holding either $\zeta_1$ or $\zeta_2$ constant. These are $(16, 4)$ and $(13, 5)$ respectively. Since the cost of the latter offer is greater, TSP-1 selects $(13, 5)$ as the potential offer. As the cost is also larger than that of the counteroffer, TSP-1 proposes $(13, 5)$ to TSP-2.

In Table III, the cost of $(13, 5)$ for TSP-2 is 97%. Upon the reception of the counteroffer, TSP-2 finds that the cost of the second best offer is $(5, 17)$ and its cost is larger than the cost of the best counteroffer received so far. Thus, it is proposed to the TSP-1.

The process iterates, where TSP-1 and TSP-2 propose alternately with offers $(12, 5), (15, 5), (14, 5), (18, 5)$ and $(15, 5)$. For TSP-2, the cost is 99.5%, which is higher than the next potential offer available, that is, 98.5%. TSP-2 therefore secures the agreement with $(15, 5)$.

2) Quality of Solutions: According to Table II, not only $(S_{po}, S_{po})$ and $(S_{po}, S_{max})$ reach the same Pareto-optimal solution, but they also require the same amount of negotiation rounds to complete the transaction. However, the adoption of $S_{max}$ by TSP-2 clearly leads to different solution paths (Fig. 4 and 5). The figures show the change in costs for TSP-1 for the entire process, and the change in costs for TSP-2 in the even rounds of the negotiation. When both agents employ $(S_{po}, S_{po})$, the odd rounds of TSP-1 and even rounds of TSP-2 decrease monotonically. Yet, the costs in the even rounds due to the counteroffers from TSP-2 are fluctuating. This is consistent with the definition of the strategy. On the other hand, when TSP-2 employs $S_{max}$, its costs do not change monotonically because $S_{max}$ generates offers by modifying the counteroffer received in the previous round. Hence, the solution can either be higher or lower than its previous offer. The fluctuations may sometime be very large because it highly depends on the quality of the counteroffers received.

The solution of $(S_{max}, S_{po})$ is not Pareto-optimal since the cost of TSP-1 is lower, even though TSP-2 has been benefited from an increase in cost. Similarly, the solution of $(S_{max}, S_{max})$ is not Pareto-optimal because the costs of both agents are smaller. The concession curves are shown in Fig. 6 and Fig. 7 respectively.

From the passenger perspective, the Pareto-optimal solution requires waiting times of 7min, and 1min for the transfers from $L_1$ to $L_2$, and $L_1$ to $L_2$ respectively. As for the suboptimal solutions, $(S_{max}, S_{po})$ reduces the waiting time of the transfer from $L_1$ to $L_2$ by two minutes but increases the waiting time by the same amount in the reverse direction. On the other hand, the waiting times obtained by $(S_{max}, S_{max})$ are identical to the Pareto-optimal solution. In other words, despite the differences resulted to the two TSPs, the change is unnoticeable to the passengers.

3) Negotiation Time: The number of rounds required for negotiation is also shown in Table II. Despite the ability to determine the Pareto-optimal solution, $(S_{po}, S_{po})$ requires a substantial amount of rounds before the negotiation is settled. On the other hand, $(S_{max}, S_{po})$ and $(S_{max}, S_{max})$ are able to
reduce the number of rounds considerably with small deviations to the TSPs costs. The use of $S_{max}$ seems to shorten the time required to complete the transaction.

By attempting to reduce the concession with reference to the counteroffer, the agent employing $S_{max}$ is likely to concede in larger steps in successive negotiation rounds.

V. CONCLUSION

We have presented a model for the schedule coordination problem involving two train services in an open access market. The problem has been modeled as two separate agents conducting individual optimizations, but interacting through negotiation. Through the agent negotiation process, the TSPs are enabled to reach a mutually acceptable agreement.

With the proposed negotiation framework, the agents are also allowed to employ their own negotiation strategies. Two negotiation strategies have been proposed. $S_{po}$ is derived so that when both agents are employing this strategy, the resulting agreement is guaranteed to reach the Pareto-optimal solution. However, as suggested by the simulation result, $S_{po}$ often requires a large number of simulation rounds before the agreement can be settled. To reduce the possibility of excessive negotiation time, TSP may opt for the use of $S_{max}$, which tends to concede at larger steps by modifying the counteroffers from the proponent. Nevertheless, the TSP is under a risk of deviating from the Pareto-optimal solution.

The paper also generates further research opportunities. For example, the algorithms used for the negotiation strategies may be replaced by more intelligent searching algorithms. Since the cost function in (1) is inherently quadratic in nature, the authors are examining the possible use of quadratic programming with the incorporation of a tree searching algorithm. In addition, it is also worth investigating the performance of other negotiation strategies other than the proposed ones in the paper.

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