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Optimal Track Access Rights Allocation for Agent Negotiation in Open Railway Markets

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***Abstract*–In open railway access markets, a train service provider (TSP) negotiates with an infrastructure provider (IP) for track access rights. This negotiation has been modeled by a multi-agent system (MAS) in which the IP and TSP are represented by separate software agents. One task of the IP agent is to generate feasible (and preferably optimal) track access rights, subject to the constraints submitted by the TSP agent. This paper formulates an IP-TSP transaction and proposes a branch-and-bound algorithm for the IP agent to identify the optimal track access rights. Empirical simulation results show that the model is able to emulate rational agent behaviors. The simulation results also show good consistency between timetables attained from the proposed methods and those derived by the scheduling principles adopted in practice.**

***Index terms*–Agent negotiation, branch-and-bound algorithm, railway open markets, track access rights.**

I. INTRODUCTION

Railway transportation is now facing stiff competition from road transportation. Since the 1950s, the rapid development of the road network in many countries has provided highly reliable and easily accessible infrastructures for automobiles. By contrast, similar growth in railways was largely hindered by the heavy regulations from governments [1], [2]. Price and service regulations were originally imposed to protect the general interest of the community from excessive monopoly, but the continuous regulatory suppression has resulted in poor adaptability to the demand in railway services, leading to severe loss of market share to road transportation. However, in recent decades, a number of restructuring activities have been conducted in many countries through deregulations [2], [3]. Some of the monopolistic railways are now restructured into open railway markets, which supposedly encourage better quality of railway services to regain the lost market share.

An open railway market, in its simplest form, consists of a group of train service providers (TSPs) and an independent infrastructure provider (IP). In the UK [4], the ancillary services of rolling stock and maintenance provisions are also separately offered by the rolling stock leasing providers (RSPs) and the maintenance service providers (MSPs) respectively. An open railway market therefore involves multiple stakeholders arranged as a supply-chain through which railway resources (e.g. track capacity and rolling stock) are supplied to the TSPs to allow ultimate train service provisions to the end-consumers.

In order to operate trains on permanent ways, TSPs have to negotiate with the IP for a track-access-rights agreement. Unfortunately, in the absence of direct managerial authority over the TSPs, the IP faces two major concerns in its operation. Firstly, it is required to schedule train services of different operational characteristics (e.g. train types and maximum speeds), and there is even a possibility of several TSPs competing for overlapping routes [5]. While the rights-of-way assignment was then an internal trade-off exercise only for the IP in an integrated railway, the stakeholder is now a mediator for the operational differences among the TSPs. The second concern is on the disputes over the track access charge [6]. As the railway market becomes more competitive and commercialized, the TSPs are likely to minimize their expenditure on track access. The same applies to the IP whose objective may be dominated by revenue maximization. Consequently, a conflict on business objectives may exist between the two types of stakeholders, which results in difficulties in setting a mutually acceptable tariff.

It is therefore beneficial to investigate various conflict resolution techniques between the stakeholders so as to determine the best mechanism for allocating the track resource efficiently. Despite the successful attempts on post-evaluation of current practices [2], [7], [8], such approaches cannot be used to examine newly proposed practices without their actual implementation. Moreover, any physical change to a system is potentially risky and expensive. Pre-evaluation studies thus provide a safer and more cost-effective means for conducting the analysis.

A modeling and simulation approach [9] has been proposed to represent open railway markets by multi-agent systems (MAS) [10]. This approach allows the assessment of various 'what-if' scenarios in open markets and examines different conflict resolution mechanisms between railway stakeholders. MAS-modeling has been employed because open markets are characterized by a set of interrelated constrained optimization problems that are distributed among the stakeholders. There are increasing MAS applications in solving this kind of distributed transportation problems [11]-[13]. MAS-modeling allows these problems to be encapsulated and solved by autonomous software programs called agents. However, these agents cannot accomplish their designated tasks without interacting (negotiating) with other agents. As a result, the open market MAS requires the local agent models in addition to some protocols for their interacting activities.

A preliminary study [14] was conducted to employ a Buyer-and-Seller Behavior Protocol [15] for an IP-TSP transaction on track access rights. A TSP agent reasoning model [14] based on fuzzy logic was also devised. The protocol provides the necessary negotiation power for both agents so that the transaction is favorable to both parties. Moreover, when an offer is rejected by the TSP agent, the IP agent is allowed to explore alternatives satisfying the same requirements before conceding to other less preferable proposals. On the other hand, the reasoning capability of the TSP is modeled by the relaxation on a set of prioritized fuzzy constraints. This allows a variety of agent objectives (e.g. expenditure-reducing and passenger-oriented) to be constructed by the appropriate assignments of a set of numerical inputs.

Nevertheless, the IP-TSP transaction is not complete without a proper IP agent handling the timetable scheduling. In order to examine whether the MAS-model can indeed simulate realistic behavior in an IP-TSP transaction, this paper devises a reasoning model for the IP agent using a Branch-and-Bound (BNB) algorithm. Section II defines an IP-TSP transaction problem for scheduling a single train on track in open railway markets. Section III proposes a BNB algorithm incorporating three procedures to reduce the computational demand. Section IV presents the simulation setup and results for analyzing the rationality of the IP agent in both single and multiple IP-TSP transactions. Section V describes the practical issues in implementing the model in practice. Finally, concluding remarks are made in Section VI.

II. IP-TSP TRANSACTION

An IP-TSP transaction is regarded as a one-to-one (bilateral) negotiation on a product between a buyer and a seller [14]. The product under negotiation is the track access rights. The buyer of the track access rights is the TSP whereas the seller is the IP. Under this context, negotiation is an iterative process in which the two stakeholders take turns to express their requirements on the product until a mutually acceptable agreement is reached, or one of them withdraws from the process. There are four components in an IP-TSP transaction, and they are described and defined below.

A. Track Access Rights

Track access rights specify the conditions for track usage by a TSP. They consist of a schedule describing the train movement in space and time. Owing to different engineering specifications such as gauge widths and energy consumption, track access rights also identify the type of rolling stocks to be operated on the rails. In addition, during the negotiation, a parameter called flex is established in some countries (e.g. the UK) to denote the time flexibility that the IP can revise the train schedule when track or station capacity becomes scarce. Flex may be defined by a set of discrete levels where the lowest and highest levels refer to the minimum (0 min) and maximum (e.g. 10 mins) flexibilities to shift a schedule profile respectively. The TSP also has to agree on a payment of track access charge (TAC) in order to obtain the permission of train operation.

Track access rights P is defined in (1), where $c \in \{1, 2, ..., \infty\}$ is the TAC (in $ or other currencies); Ψ is the train schedule defined in (2); $\omega \in \{\omega_i \mid i = 1, ..., n_\omega\}$ is the rolling stock selected for operation and $\phi \in \{\phi_i \mid i = 1, ..., n_\phi\}$ is the chosen flex level.

$$P = \langle c, \Psi, \omega, \phi \rangle \tag{1}$$

A train schedule Ψ consists of a set of IDs $S = \{s_i \mid i = 1, ..., n_s\}$ identifying the sequence of visiting stations. The movement of a train in time is described by the service commencement time (i.e. the arrival time at the first station) ζ (in hh:mm), the dwell times at each stations $T_D = \{t_{Di} \mid i = 1, ..., n_s\}$ (in min), and the inter-station runtimes $T_R = \{t_{Ri} \mid i = 1, ..., n_s - 1\}$ (in min) between adjacent stations. Hence, Ψ is formally defined as a 4-duple in (2).

$$\Psi = \langle S, \zeta, T_D, T_R \rangle \tag{2}$$

B. Negotiation Protocol

One approach to classify various types of negotiation is by the number of parties involved [15]. Negotiation is referred to as multilateral when there are more than two parties in the bargaining process. When only two agents are involved, the negotiation is bilateral. In either case, a protocol is required to specify the actions available to the parties during their communication. The following protocols have been considered in modeling the bilateral IP-TSP transactions.

1) Contract Net Protocol (CNP): CNP [16] is widely used in agent negotiation. This protocol provides a simple yet robust communication procedure to allow an agent to sell a product to an appropriate buyer agent in a distributed system. At the beginning, the seller sends a request-for-bid (RFB) message to the potential buyers in order to seek for the desired product. This message contains a user-specific description of the product and a deadline for receiving the replies. Upon the arrival of the RFB message, the buyers construct their individual bids and submit (PROPOSE) them to the company. After evaluating the received bids, the seller may award (ACCEPT) the contract to the most acceptable bidder, or refine the requirements on the product and initiate another RFB message. The buyer that has been awarded the bid is required to send a confirmation message (INFORM) to secure the contract. The process is summarized in Fig. 1.

CNP is usually applied to multilateral negotiation, where the seller agent broadcasts the RFB messages to multiple buyers. However, if the seller targets the message to a specific buyer, the negotiation is reduced to bilateral.

2) Buyer-and-Seller Behavior Protocol (BSBP): This protocol is proposed in [15] to model a bilateral negotiation on a product possessing multiple attributes. The procedure is depicted in Fig. 2. Initially, the buyer agent expresses its partial requirements using a crisp constraint (inequality), which is enveloped in a FIND message. The message is sent to a specific seller agent whose responsibility is to generate a feasible offer and submit back via a CHECK reply. The offer is accepted (DEAL) if it satisfies the buyer's reserved requirements and the buyer is willing to comply with the restrictions attached in the offer. Otherwise, the offer is rejected. In case of violations of the requirements, a FIND message enveloping a new additional constraint is supplied to the seller agent. In case of unacceptable restrictions, a REFIND message is sent to the seller to ask for a new offer while the original requirements remain.

However, if no feasible offer can be generated in response to a FIND/REFIND request, a RELAX message is issued by the seller in order to prompt the buyer to modify one of the submitted constraints. The buyer may then revise its requirements with FIND or withdraw from the negotiation (FAIL).

In CNP and BSBP, the negotiation power of the buyer resides in the possibility of refining its decisions so that it is not necessarily confined by the seller's requirements. Similarly, the seller has the rights to make the best decision not according to the buyer's responses and its internal benefits. This allows both agents to make concessions during the negotiation until their expectations coincide. Otherwise, the negotiation is terminated without any commitment made or deal reached. Despite the inability to model multilateral negotiation, BSBP has the advantage of allowing the seller to explore different alternatives under the same set of buyer's requirements before making concessions. This is particularly useful in an IP-TSP transaction where there often exist multiple track access rights that are equally favorable to the IP. For example, when the seller has two potential offers P' and P'', where P' helps the seller to collect a higher access charge than P'', P'' may still be considered as favorable as P' if P'' requires a lower capacity consumption. Despite the lower access charge collected, P'' may allow the IP to utilize the track capacity more efficiently to support more frequent train services. Owing to its flexibility in negotiation, BSBP is employed in the IP-TSP transaction.

C. Objective of TSP

According to the BSBP protocol, the tasks of the TSP agent are to derive a set of crisp constraints on track access rights, and decide how to relax the constraints when making concessions. A prioritized fuzzy constraint satisfaction approach [15] has been devised to generate and select the required crisp constraints from a set of user-specified fuzzy constraints.

The quality of the track access charge and train schedule times are modeled by a set of fuzzy membership functions $\mu_i(x_i) \in [0, 1], i = 1, ..., m$ and $x_i \in \{c, \zeta, t_{D1}, ..., t_{Dn}, t_{R1}, ..., t_{Rn-1}\}$. A crisp constraint $x_i^a \le x_i \le x_i^b$ on an attribute x_i is denoted by the bounds x_i^a and x_i^b. At the beginning of negotiation, the constraints are set at the most preferable values $\hat{x}_i = \arg_{x_i}\{\mu_i(x_i) = 1\}, \forall x_i$. A reduction of x_i^a or an increase in x_i^b corresponds to a concession on the attribute. Moreover, a priority value $\rho_i \in [0, 1], i = 1, ..., m$ is associated with each attribute to indicate their relative importance to the TSP. Given an offer P' received from the IP agent, the acceptability of the product is defined by (3).

$$\alpha(P') = \min_{1 \le i \le m}\left\{ 1 + \frac{\rho_i}{\max\limits_{1 \le j \le m}(\rho_j)}[\mu_i(x_i') - 1] \right\}, \quad x_i \in \{c', \zeta', t'_{D1}, ..., t'_{Dn}, t'_{R1}, ..., t'_{Rn-1}\} \tag{3}$$

Rolling stock and flex are modeled as restrictions imposed by the IP agent. If the TSP agent is not satisfied with the imposed restrictions attached with the offer, the IP may be requested to suggest an alternative. The TSP agent determines whether it can comply with the restrictions by two sets of fuzzy values $F_\omega = \{ f_{\omega_i} \mid i = 1, ..., n_\omega \}$, $f_{\omega_i} \in [0, 1]$ and $F_\phi = \{ f_{\phi_i} \mid i = 1, ..., n_\phi \}$, $f_{\phi_i} \in [0, 1]$, which indicate the degree of obedience to the rolling stock and flex respectively. The overall obedience level of P' is defined by (4):

$$\beta(\omega', \phi') = \min\{ f_{\omega'}, f_{\phi'} \} \tag{4}$$

The objective of the TSP agent is to maximize the satisfaction on track access rights, subject to (5), where $\tau \in [0, 1]$ is the accepting threshold to denote the minimum target satisfaction. $\tau = 0$ gives the highest possibility for successful negotiation because the TSP agent may concede over the entire range specified by the fuzzy membership functions. On the other hand, when $\tau = 1$, the TSP agent will only accept the most preferable schedule defined by the user.

$$\min\{\alpha(X'), \beta(\omega', \phi')\} \geq \tau \tag{5}$$

By employing the above TSP-model, the decision on accepting/rejecting an offer is not only subject to the quality of the schedule times and the level track access charge, but also to the restrictions on flex level and rolling stock. The use of an accepting threshold also guarantees a target level of satisfaction if an agreement is reached.

D. Objective of IP

The objective of the IP is to maximize the overall track capacity utilization and revenue collection from all TSPs. The utility function used by the IP agent in a single IP-TSP transaction is given in (6), where U is the utility value (in \$) of the transaction from the perspective of the IP agent, c is the track access charge (in \$); w_η is the unit valuation of capacity consumption (in \$) and $\Delta\eta$ is the capacity consumed by the train service (no unit). The term $-w_\eta \Delta\eta$ implies a minimization of capacity usage by the TSP's train service. The essence is that if the capacity allocated in a negotiation is minimized, the available capacity remained will be maximized, allowing the IP to negotiate more deals at later stages.

$$\max U = c - w_\eta \Delta\eta \tag{6}$$

This problem is subject to the constraint set Ξ composing of,

i) basic domains of variables: $c \in \{1, 2, ..., \infty\}$, $\omega \in \{\omega_i \mid i = 1, 2, ..., n_\omega\}$, $\phi \in \{\phi_i \mid i = 1, 2, ..., n_\phi\}$, $\zeta \in \{00:00, ..., 23:59\}$, $t_{Dj} \in \{1, 2, ..., \infty\}$, $t_{Rk} \in \{1, 2, ..., \infty\}$, $\forall j, k$.

ii) submitted TSP requirements: $c^a \le c \le c^b$, $\zeta^a \le \zeta \le \zeta^b$, $t_{Dj}^a \le t_{Dj} \le t_{Dj}^b$, $t_{Rk}^a \le t_{Rk} \le t_{Rk}^b$, $\forall j, k$; and

iii) headway requirements: $h_{\min} \le h_d$, where $h_{\min}$ and h_d are the minimum and actual headway time respectively. In conventional train operation, the actual headway time refers to the time taken for a train to arrive at a certain point along a track (e.g. a station) after the train in front (leading train) has reached the same point. On the other hand, the minimum headway time is the total sum of the minimum braking time, reaction time of driver and equipment in response to a stop signal, and the time taken by the leading train to move by its train length. When the actual headway time is larger than the minimum headway time, the train behind is prevented from colliding to the rear of the leading train. These two terms are usually measured in seconds, but in order to maintain consistency with the resolution of schedule times, they are approximated by their ceiling values measured in minutes.

TAC is derived from the sub-charges on track usage, traction energy, peak power demand and congestion. The derivations of these charges and capacity utilization are described as follows.

1) Track Usage Charge (TUC): TUC recovers the costs of using the track facilities. The charge varies with the amount of maintenance required if the service is allowed to run on the track. A number of important factors for track maintenance have been identified [17]. They include the type of rolling stock, the number of vehicles or the weight of the train, and the maximum allowable speed of the train. In many railway systems, TUC is simply calculated on the total vehicle-kilometer traveled (for passenger services) or the total gross-ton-kilometer traveled (for freight services). The charge rates vary with different types of rolling stock and they are determined by simulation software (e.g. mini-MARPAS in the UK). Having adopted the current charging practice, TUC is defined by (7) where c_1^{ω} is the charge rate (in \$/veh·km) for rolling stock ω; n_v^{ω} is the number of vehicles of ω; L_i is the length of track (in km) in inter-station run i.

$$TUC = c_1^{\omega} n_v^{\omega} \sum_{i=1}^{n_s-1} L_i \tag{7}$$

In an IP-TSP transaction, it is assumed that the available types of rolling stock are commonly known by both agents. Each type of rolling stock has a predefined number of vehicles and length. The charge rates are predetermined and are available to the IP agent only.

2) Traction Energy Charge (TEC): A power utility company charges the IP according to the units of energy consumed and the peak demand (neglecting the charges to voltage regulation and current distortion due to harmonic effects). TEC is levied to recover the units of electricity consumed by a train service. If c_2 is the charge rate (in \$/kWh) for the electricity provision and $E(\omega, t_{Ri})$ is the unit of energy consumed (in kWh) during inter-station run i when rolling stock ω completes inter-station run i at t_{Ri}, TEC is computed by (8).

$$TEC = c_2 \sum_{i=1}^{n_s-1} E(\omega, t_{Ri}) \tag{8}$$

For each type of rolling stock, the IP reserves a look-up table in which the energy consumption can be obtained according to its runtimes over a specific inter-station run. This table and the charge rate are available to the IP agent only.

3) Peak Demand Charge (PDC): PDC denotes the second component of the electricity tariff. If c_3 is the charge rate (in \$/MW) for the increase in peak power demand at the substation and $\Delta P(\omega, \Psi)$ is the increase in such demand (in MW) when rolling stock ω is running at schedule Ψ, PDC is calculated by (9).

$$PDC = c_3 \Delta P(\omega, \Psi) \tag{9}$$

A typical power-demand graph of a train is shown in Fig. 3. The maximum peak corresponds to the time when the train reaches a particular speed that consumes the highest power. Then, the train continues to accelerate to its maximum allowable speed at which the power demand becomes relatively constant. At times, the train may be switched to coasting mode, during which the traction motors are turned off and no energy is consumed. Such a demand profile is simplified and modeled as a 5-tuple by (10), where t_1 is the time (in min) required for the train to accelerate from stationary to full speed; t_2 is time (in min) between the first instance of full speed to the instance of braking before the next station; t_3 is time (in min) required to brake from the maximum speed to a complete halt; P_1 is the maximum power demand attained (in MW) during t_1; P_2 is the maximum demand (in MW) during t_2.

$$\Lambda = \langle t_1, t_2, t_3, P_1, P_2 \rangle \tag{10}$$

Unlike the derivation of energy consumption in TEC, the change in peak demand requires the information of the other train schedules. With the simplifications in (10), the peak demand is calculated by superpositioning the demand profiles from all existing scheduled services, as shown in Fig. 4.

4) Congestion Charge (CGC): CGC is used to recover the expected costs that the IP is required to pay to the other TSPs when the network becomes congested. In UK, this charge is related to the expected reaction delay caused by the train service, which is modeled as an exponential function of capacity utilization [18]. Moreover, a TSP is entitled to receive a discount on CGC if it agrees on certain flex levels. If c_4 is the charge rate (in \$/min) for the expected delay caused in the network; d_ϕ is the discount factor associated with flex ϕ; A_i is the track specific constant (in min) at section i; η_i is the resultant capacity utilization at section i, CGC is computed by (11):

$$CGC = c_4 d_\phi \sum_{i=1}^{n_s-1} A_i \exp(\eta_i) \tag{11}$$

All the charging factors in (11) are exclusive to the IP agent only. Capacity utilization for a single inter-station run is defined in (12) and computed iteratively by (14) and (15).

5) Capacity Utilization (CPU): Capacity utilization is defined as the ratio of the time taken in operating a set of trains with their minimum headways to the time taken in traveling at their actual timetables [18]. Fig. 5 illustrates the capacity utilization for a single inter-station run i within a timeframe W_i (e.g. 30 min). The timetable of a train j is denoted by its departure time t_{Pi}^{j} at station i and arrival time t_{Ai+1}^{j} at station $i+1$. Associated with each train is the minimum headway time $h_{\min}$ which includes the time for braking the train from maximum speed to a complete halt, the time taken for the rear of the front train to clear its length and a safety margin for the reaction time of drivers and equipment. $h_{\min}$ is represented by the thickness of the parallelograms. If these parallelograms are joined together by the vertices as shown in Fig. 5, the trains are operating at the minimum headway and K_i^n yields the minimum possible time (in min) spanned by the n trains on the track along inter-station run i. Capacity utilization at inter-station run i is thus defined in (12) and the cumulative capacity utilization of all inter-station runs is defined in (13).

$$\eta_i = \frac{K_i^n}{W_i} \tag{12}$$

$$\eta = \sum_{i=1}^{n_s-1} K_i^n \Big/ \sum_{i=1}^{n_s-1} W_i \tag{13}$$

K_i^n at a particular inter-station run i may be evaluated iteratively for all trains as follows. In computing K_i^2 for two consecutive trains, there are two possibilities as depicted in Fig. 6. Case (a) refers to the situation when the train behind is faster, and otherwise in case (b). Let t_{Ri}^{j*} be the inter-station runtime for the slower service. In both cases, K_i^2 can be computed by (14).

$$K_i^2 = 2h_{\min} + t_{Ri}^{j*}, \quad j* = \arg\left[\max_{j=1,2}(t_{Ri}^{j})\right] \tag{14}$$

Fig. 7 shows the instance when an additional service is operated after the second train. K_i^3 now depends on the relative runtimes of the second and third trains. In fact, for all other services in window W_i, K_i^n can be computed iteratively by (15).

$$K_i^{j+1} = \begin{cases} K_i^j + h_{\min} & \text{if } t_{Ri}^{j+1} \le t_{Ri}^j \\ K_i^j + h_{\min} + t_{Ri}^{j+1} - t_{Ri}^j & \text{if } t_{Ri}^{j+1} > t_{Ri}^j \end{cases}, \text{ for } j \ge 2 \tag{15}$$

III. OPTIMIZATION ALGORITHM

A. Combinatorial Optimization

The maximization of the utility function in (6) is combinatorial because the independent variables are all discrete as restricted by the constraint set Ξ. The common deterministic techniques [19] in solving this kind of optimization problems are integer linear programming (integer-LP), dynamic programming (DP) and branch-and-bound (BNB) algorithm. However, unlike the problems in [20] and [21], integer-LP formulation is not suitable because (6) is nonlinear. While DP may handle nonlinearity, it has the limitation that a choice (state) selected for a decision (stage) should be independent to the choices made for subsequent decisions. Otherwise, the cost at the intermediate stages cannot be evaluated. Unfortunately, the underlying variables (i.e. ϕ, ω, ζ, t_{Dj}, t_{Rk}) in (6) are strongly dependent as observed from the definitions of the sub-charges of TAC and capacity utilization in (8), (9), (11), (14) and (15). As a result, DP is also not applicable to the IP optimization problem.

A BNB algorithm is based on the idea of intelligently enumerating all the feasible points of a combinatorial optimization problem [19]. The solution space of the problem is partitioned into non-overlapping discrete subsets by branching. A subset generated by branching is represented as a node, which defines a relaxed problem to the original optimization one. Within a node, a bound (a numerical value) is calculated to indicate the best possible solution for its leaf nodes. By appropriately selecting the nodes for expansion, the optimal solution is constructed without exhaustively evaluating all instances.

There are three rules for constructing a solution for a problem. First, if there is no solution to the relaxed problem, there is no solution to the original problem. Second, if the solution to the relaxed problem is feasible, it is optimal for the original problem. Finally, if the solution to the relaxed problem is infeasible, the cost at that node provides a bound for its leaf nodes. Therefore, the requirements for resolution are to partition the solution space and to define the relaxed problem. The following subsection specifies a feasible BNB algorithm for the IP optimization problem.

B. The Basic Branch-and-Bound Algorithm

1) Partitioning the Solution Space: The sequence of branching follows the order of variables $\phi \to \omega \to \zeta \to t_{D1} \to t_{R1} \to t_{D2} \to ... \to t_{Rn_s-1} \to t_{Dn_s}$. An example of a branching tree is illustrated in Fig. 8. This sequence has the advantage of chronological arrangement of the schedule times so that the arrival and departure times at stations can be computed at a node. The restrictions on flex and rolling stock are considered at the beginning to facilitate the reduction of computational demand (refer to section III C).

2) Definition of the Relaxed Problem: This is defined as the optimization of (6) when a partial constraint set $\Xi' \subseteq \Xi$ is considered. For example, when the tree is expanded to node M in Fig. 8, the constraint set becomes $\Xi' = \{ \phi = \phi_1 , \omega \in \omega_2 , \zeta = 07:45 , 3 \le t_{D1} \le 5 , t_{R1} = 15 , 3 \le t_{D2} \le 4 , h_{\min} = 2 \}$. The bound at a node is computed by the sum of maximizing the individual sub-charges and minimizing the capacity utilization subject to the associated constraints summarized in Table I. The maximum TUC is identified by comparing the products of $c_1^{\omega} n_v^{\omega}$. For TEC, since maximum energy consumption is achieved by the operation at the minimum inter-station runtimes, it corresponds to comparing the maximum energy consumption of the available rolling stock when employing the set of shortest runtimes. The maximum PDC is evaluated by exhaustively enumerating the total power demand of all the feasible schedules. CGC is maximal when the lowest available discount rate and the rolling stock with the longest cumulative inter-station runtimes (i.e. when congestion is most severe) are employed. The minimization of CPU is achieved with the rolling stock traveling with the shortest cumulative inter-station runtimes.

Fig. 9 shows the flowchart for the BNB algorithm. k represents the current evaluating node. Initially, k is set to 0, which is the root node of the search tree. This node is inserted in $LIST$ which maintains the potential nodes generated in the algorithm. $\hat{k}$ and $\hat{U}$ record the best node and the corresponding utility value found during the algorithm, which are set to null and zero respectively initially. The algorithm then adopts a depth-first search. If a node have a utility value smaller than the current best value, the node is declared 'fathomed' and the algorithm continues with the next node in $LIST$. Otherwise, the node will be evaluated for its feasibility. If the node is feasible, it is labeled 'lived'. Since its utility value is greater than that of the current best node, $\hat{k}$ and $\hat{U}$ are updated. However, in case of identifying an infeasible solution (e.g. the root node), the node is declared 'expand'. Since its leaf nodes may contain the optimal solution, they are generated and inserted in $LIST$. When all nodes have been evaluated, the best node is returned. If the best node exists, the offer on track access rights is proposed to the TSP via a CHECK message. Otherwise, a RELAX message is issued to the TSP.

C. Computational Demand Reduction

In the worst scenario, the computational complexity of a BNB algorithm is no better than an exhaustive search when all nodes are expanded. For the proposed algorithm, the complexity can be shown to be $O(n_\phi {n_\omega}^2 {n_\zeta}^2 {n_D}^{2n_s} {n_R}^{2n_s})$, where $n_D = \max_{1 \le i \le n_s}(n_{Di})$ and $n_R = \max_{1 \le j \le n_s - 1}(n_{Rj})$. In other words, the applicability of the algorithm is limited by the size of n_s. In order to generate results within a reasonable time span, three procedures are incorporated into the basic algorithm to reduce the number of node evaluations, hence computational demand.

1) Facilitation of the Most Preferable Schedule: To minimize the information revealed to the seller agent, the original BSBP only allows the buyer agent to submit one crisp constraint within a FIND message in each negotiation. If the same restriction is imposed to the IP optimization problem, the schedule times (ζ, t_{Di} and t_{Ri}) will often be unbounded by the TSP, and the problem space is then limited solely by the headway constraints. This sometimes leads to an overwhelming size of domains (Fig. 10) which significantly increases the number of node evaluations in the algorithm.

In practice, it is natural for the TSP to express the most preferable schedule at the beginning of negotiation so that the IP may provide a feasible schedule in the proximity of its requirements. With this consideration, the efficiency of the algorithm may be improved by allowing the TSP agent to submit the most preferable schedule during the first round of negotiation (the submission of the TAC constraint is however, not compulsory). Not only does this reduce the number of node evaluations in the algorithm, but the transaction also requires fewer negotiation rounds since those used in submitting the individual constraints are now condensed to a single one.

2) Pruning by Headway Constraints: Despite the facilitation of the most preferable schedule, when the TSP agent progressively relaxes the constraints during the negotiation, the problem space for the IP inflates accordingly. This often gives rise to substantial computational demand.

Fig. 11 shows a special case, when the minimum inter-station runtime ($MIRT_k$) at an inter-station run k is greater than the maximum allowable runtime ($MART_k$) governed by the headway constraints. In such case, the leaf nodes corresponding to the situation are all infeasible. If this condition can be detected prior to the expansion at the node, all leaf nodes can be pruned.

Let EDT_k and LDT_k denotes the earliest and latest departure times at station k respectively. These are computed by (16) and (17) using the lower and upper limits of the TSP constraints.

$$EDT_k = \zeta^a + \sum_{i=1}^{k}(t_{Di}^a + t_{Ri}^a) \tag{16}$$

$$LDT_k = \zeta^b + \sum_{i=1}^{k}(t_{Di}^b + t_{Ri}^b) \tag{17}$$

Also, let EDT_k^j be the earliest departure time and LAT_k^j be the latest arrival time at station k imposed by the j-th existing schedule having arrival and departure times of AT_k^j and DT_k^j respectively, for $EDT_k \le DT_k^j \le LDT_k$. EDT_k^j and LAT_k^j are then computed by (18) and (19) according to the headway constraint. According to Fig. 11, $MART_k$ is the maximum difference of the latest arrival time due to the $(j+1)$-th service and the earliest departure time due to the j-th service. $MIRT_k$ is imposed by the requirement of the TSP agent. A node can be pruned if $\exists k, MIRT_k > MART_k$.

$$EDT_k^j = DT_k^j + h_{\min} \tag{18}$$

$$LAT_k^j = AT_k^j - h_{\min} \tag{19}$$

.
$$MART_k = \max_{\forall j}\{LAT_{k+1}^{j+1} - EDT_k^j\} \tag{20}$$

$$MIRT_k = t_{Rk}^a \tag{21}$$

3) Pruning by REFIND Message: Pruning is also possible when the IP agent receives a REFIND message in the previous round of negotiation. When this occurs, the TSP agent is requesting the IP to generate a new offer based on the previous set of constraints. As the constraint set remains unchanged, the TSP is in fact not satisfied with the restrictions imposed by the IP, that is ω and/or ϕ. In other words, all nodes that employ the same set of rolling stock and flex level can be eliminated from evaluation. Hence, if ω and ϕ are used as the first two branching parameters, the entire branch beneath this combination is not required for evaluation.

IV. SIMULATION SETUP AND RESULTS

A. Simulation Setup

For all case studies given below, the number of stations is set to 4. There are 3 types of rolling stock and 5 flex levels available for negotiation. Table II shows the vehicle numbers and track usage charge rates of 3 different types of rolling stock, in addition to their relative traction requirements (i.e. energy and power consumptions). The charge rates reflect the degree of track damage incurred by the rolling stock. In Table III, the lowest level ϕ_1 represents no flexibility and each incremental level allows an addition of 2-minute flex time. In addition, the flex discount factors reduce CGC by

5% in each successive level.

Ten case studies have been performed (Table IV). These simulations are carried out under the same track configuration consisting of 3 track sections that connect stations A, B, C and D (Table V). The track length for the middle section is comparatively long and the track specific constants for the first and third sections are higher in order to simulate long-distance service provisions between two cities. In cases 1 to 7, only one IP-TSP transaction is conducted in each case. These transactions serve the purposes of examining the ability of reaching rational agreements. The remaining 3 cases form a preliminary study on an IP agent handling multiple negotiations in a sequential manner. Each of these cases involves 10 IP-TSP transactions, in which the order of negotiations is randomly generated.

The definitions of the TSP agents are shown in Tables VI and VII. Those in Table VI are used in cases 1 to 7 and they are all expenditure-reducing agents, which are reflected by their high priorities on cost. Agents in Table VII are employed in cases 8 to 10 and they possess various objectives including expenditure-reducing and passenger-oriented. Owing to the limitation in space, the detailed settings are not shown but the vital information and objectives are described in Table VII. Table VIII summarizes the definitions of five IP agents, which share a common initial traffic condition consisting two scheduled services I1 and I2 (Fig. 12), but differ by either their settings or the initial power distributions (Fig. 13).

The agents are developed by a JAVA-based agent development toolkit called JADE (Java Agent DEvelopment) [22]. All simulations are conducted on a P4 1.6GHz PC and the simulation time is summarized in Table IX. The length of simulation depends on the computational complexity in generating the optimal solutions with each negotiation round, and the number of rounds required in each transaction. It can be seen that the majority of cases require less than 10 minutes to complete a transaction, and only three cases take more than an hour to reach an agreement. Simulation results of the track access agreements in cases 1 to 7 are depicted in Table X and the resultant timetables of cases 8 to 10 are shown in Table XI.

B. Results and Discussions

1) Pareto-optimal Solutions: In case 1, TSP-A1 is set up to negotiate with IP-1. According to Fig. 12, the preferred schedule requested by the TSP (shown in Table VI) is not occupied by any train service. Despite the availability of capacity, the request is not granted to the TSP in the final agreement (Table X).

To explain this observation, Fig. 14 is constructed to display a simplified search tree at the final round of negotiation. The accepted offer is located at node 146 whereas the preferred schedule is located at node N'. In this search problem, any solution employing ϕ_1 to ϕ_3 results in the violation of the cost constraint ($c \leq 1650$) imposed by the TSP agent. Therefore, schedules under nodes 1 to 3 are all infeasible. Similarly, the solution at node 134 (which differs from the final offer by the type of rolling stock) also exceeds the upper cost limit. The first feasible solution is in fact the optimal solution at node 146. With the adoption of ω_2, the TAC is reduced to \$1650 by the lower energy and power consumption.

The preferred schedule contained in node N' is also a feasible solution. Since the schedule has a slightly longer inter-station runtime between station B and C, the TEC is reduced whereas the CGC is increased. As the change in TEC was greater than that in CGC, the overall TAC is settled at \$1647. Despite the satisfaction of the cost constraint, its lower utility value is not justified for proposal to the TSP.

The study demonstrates the process and its feasibility in reaching a Pareto-optimal (compromised) agreement. In a negotiation of several entities, a solution is Pareto-optimal if any deviations from this solution results in worse payoffs for at least one entity [23]. From the IP's perspective, node 134 is preferred due to its higher utility value, but it is excluded by the TSP's cost constraint. On the other hand, node N' is more favorable to the TSP in terms of the cheaper TACs, but it is not in the interest of the IP. The Pareto-optimal solution at node 146 is therefore achieved through the use of BSBP (for submitting constraints) and the identification of an optimal offer by the BNB algorithm.

2) Capacity Management: In cases 2 to 4, TSP-A2 is set up to perform a transaction with three IPs separately. Case 2 is the reference study, negotiating with IP-1. The capacity weighting used by IP-2 in case 3 is doubled, whereas a higher congestion charge rate is employed by IP-3 in case 4. These simulations are constructed to examine the effects of raising these settings on capacity utilization.

According to Table X, apart from the difference in utility value, the track access agreements in cases 2 and 3 are identical. Apparently, the adoption of a higher capacity weighting carries no impact on the resulting schedule and capacity utilization. Moreover, when the negotiation processes are inspected in details, the sets of offers proposed during the negotiation in cases 2 and 3 are identical and the TSP agent's behavior (i.e. the sequence of constraint relaxation) is unaffected by the choice of capacity weighting.

In fact, to influence the TSP's response, the protocol allows the IP to propose a different offer during the negotiation process. This may be achieved by any modification in values of TAC, schedule times, rolling stock or flex. However, since both cases employ the same set of charge rates, the TAC of a given set of schedule times and restrictions remains unchanged. According to (6), increasing the capacity weighting in case 3 only reduces the corresponding utility value U of the schedules in case 2, thus the rankings of satisfaction of the solutions are preserved. In other words, the IP will generate the same set of offers to the TSP in these two cases. Consequently, the corresponding TSP behavior becomes identical.

However, raising the congestion rate in case 4 does improve the capacity utilization. The use of a higher rate causes a more severe penalty on schedules having higher capacity consumption. As the expenditure-reducing TSP is unwilling to pay for an excessive increase in TAC, it settles for shorter inter-station runtimes, resulting in better capacity utilization.

Therefore, better capacity management may be achieved by increasing the congestion rate. In most business transactions, the price of a product is often used to manipulate the level of demand.

By the same principle, when the intention of better capacity utilization is reflected on the TAC, the demand on capacity usage may be altered. On the other hand, adjusting the capacity weighting is unable to convey the same intention to the TSP agent. Although the result may suggest the elimination of the term $-w_{\eta}\Delta\eta$ in (6), capacity weighting is still required when multiple schedules of equal TAC but different capacity utilization are present. In these situations, the schedule that consumes the least capacity is selected in negotiation.

3) PDC Recovery: Cases 5 and 6 are constructed in such a way that the IP agents differ only by the initial power distributions. In case 5, when IP-4 has a constant power distribution, the TSP agent obtains the track access rights at $1653, of which $190 is the PDC. This is derived from the 49MW of peak demand (Fig. 15) when the service departs from station B at 08:09. As a consequence, a step decrease in peak demand is deliberately inserted slightly after 08:09 (at 08:11) in case 6. In this case, the first interstation runtime and dwell time at station B have been extended, leading to a cumulative delay of 2 minutes. This postpones the departure time at the station B to 08:11, where the decline in peak demand was located. The peak power is reduced to 43MW when the service departs from station A, which lowers the PDC to $130.

Since the IP is negotiating with an expenditure-reducing TSP, the schedule time constraints are usually relaxed prior to the cost constraint. When the IP encounters this type of negotiating partner, it responds by identifying the existence of any schedule with a better premium. In case 6, a lower TAC is possible by a slight adjustment of the timetable, which reduces the peak demand. By satisfying the buyer’s demand, the likelihood of securing a transaction is increased. On the other hand, in case of negotiating with a TSP who does not permit deviations on schedule times, the IP will offer the original schedule in case 5. The higher burden on the cost of peak demand will then be transferred to the TSP.

4) TUC Recovery: Cases 1 and 7 employ the same IP agent but different TSPs. In case 1, TSP-A1 is willing to accept rolling stock ω_2 and ω_3, but TSP-A3 in case 7 has a more restrictive demand on operating with ω_3 only. Despite the slight modification, there are significant variations in the resulting track access agreements.

As ω_3 is more likely to induce damage to the rails, it has the highest track usage charge rate of \$0.16/veh·km (Table II). This causes an increase in TUC from \$113 to \$338. Moreover, as ω_3 demands more energy and power, the TEC and PDC also become higher. To reduce the burden of the overall rise in TAC, TSP-A3 accepts shorter runtimes to reduce the CGC. Nonetheless, there is still an overall increase in TAC to \$1999 (compared to \$1650 in case 1).

Similar to PDC recovery, the IP is acting rationally to transfer the proper maintenance cost to the TSP. When the negotiating opponent is determined to employ a poor quality rolling stock, the IP increases the TAC so that the cost incurred on track maintenance is recovered.

5) Multiple Bilateral Negotiations: Ten TSPs with different cost and schedule time requirements are set up to compete for capacity over 3 hours in cases 8 to 10. According to Table XI, apart from two train services, B2 and B7, the track access agreements vary when different negotiation sequences are employed.

Several train services are worth inspecting. The schedule times for service B4, B5 and B6 are nearly identical in cases 8 and 9. The timing diagrams for these services in the two cases are shown in Fig. 16a. B4 departs from station A at 07:38 and it is overtaken by B5 at station B at 07:53. B6 leaves station A approximately 10 minutes after B4 and it travels behind B5 throughout the journey. However, a marked difference occurs in case 10 (Fig. 16b), B4 departs from station A at 07:34 and the inter-station runtimes are longer. There is no overtaking of B4 by B5, which now operates behind B6. Without the leading effect from B5, B6 is able to operate with faster inter-station runtimes.

The above result is a direct consequence of the negotiation order of TSP agents. The sequences in cases 8 to 10 are TSP-B $\{5 \to 6 \to 4\}$, TSP-B $\{6 \to 5 \to 4\}$ and TSP-B $\{4 \to 6 \to 5\}$ respectively. In the first two cases, the negotiation with TSP-B4 is conducted last. By the time

TSP-B4 has been served, the requested train capacity has already allocated to TSP-B5 and TSP-B6. TSP-B4 therefore needs to accept shorter inter-station runtimes and gives way to the faster service of TSP-B5 when it arrives at station B. When TSP-B4 is served first in case 10, the IP agent is able to satisfy its requirements on longer runtimes. The next services from TSP-B6 can also be scheduled with its preferred (short) runtimes because the two services are separated by sufficient distance. Nevertheless, as B6 gradually reduces the separation from B4 at the approach of station C, there remains inadequate capacity to allow B5 to operate between the two services. As a result, B5 is postponed to run behind B6.

Similarly, the negotiation order for TSP-B8, TSP-B9 and TSP-B10 in case 8 is TSP-B$\{8 \rightarrow 9 \rightarrow 10\}$, while TSP-B$\{9 \rightarrow 8 \rightarrow 10\}$ is the order used in cases 9 to 10. In case 8, TSP-B8 is able to obtain an early commencing time when capacity is available. The allocation of capacity imposes more restrictions to TSP-B9, which needs to settle for small deviations in commencing time and runtimes. Although this only leaves a limited amount of capacity for TSP-B10 to operate its service between B9 and I2 (one of the initial services), it is still possible to operate the service tightly behind B9 owing to their similar runtime characteristics. In cases 9 and 10, as the negotiation with TSP-B9 is conducted before TSP-B8, TSP-B9 can now obtain its required capacity, but the service of TSP-B8 has to be scheduled behind it. In addition, since both B8 and I2 are running with moderate runtimes, B10 cannot utilize the remaining capacity between the two services. Eventually, B10 is delayed so that it is operated after I2.

The above results are in fact consistent with the timetables achieved by the scheduling principles adopted in practice. Experience suggests that if there are conflicts in rights-of-way between train services, the train considered first usually has an advantage. Train planners often exploit this by scheduling according to the priority of services. In this application, as trains are progressively scheduled, there are more constraints to be considered. The first TSP in the sequence is therefore more likely to obtain its preferred requirements. Conversely, when several trains have already been allocated on the track, a competing TSP will probably need to compromise with less favorable schedules. In addition, when a TSP has its service postponed, there may be a chain effect to the later transactions.

Another observation from the result is on scheduling non-homogenous traffic. From Fig. 17, sequencing TSP agents according to case 8 consumes the least track capacity, whereas that to case 10 requires the highest capacity. In case 8, the better capacity utilization is achieved by first scheduling the moderate-speed train (B5), and then the faster (B6) and slower (B4) trains. By selecting the moderate case as a reference service, the compromise on homogeneity may be shared by the two extreme services. Otherwise, one particular TSP could have been overburdened, in which case the service might not be scheduled in the network. Furthermore, capacity is also improved by sequencing TSPs with similar servicing characteristics together (e.g. TSP-B9 and TSP-B10 in case 8). Conducting a transaction with considerably different train speeds (e.g. TSP-B8) between these TSPs will consume more capacity than required.

V. PRACTICAL ISSUES

According to the findings from the simulation, the software agents are able to reach a Pareto-optimal agreement. The IP agent is also capable of handling the available capacity and recovering the necessary costs. Despite the ability in exhibiting these rational behaviors, decisions made in practice are undoubtedly more complex than the model presented in this paper. For instance, in negotiating track access rights, stakeholders are likely to consider additional factors such as regulations imposed by the regulatory and safety authorities, transaction handling costs and economic forecasts [3], [24], [25]. It is therefore not our intention to replace the current human-to-human interactions with automated negotiation. However, with proper adaptation to a specific open railway market, the proposed model is expected to be a valuable tool to assist the planning of policy makers before the actual negotiation is conducted.

For example, in systems where there is fierce competition among operators of passenger and freight services at localized track sections (e.g. the West Coast Mainline in the UK), track capacity is often dominated by the regular passenger trains, and the ah hoc freight services find little room to obtain their required capacity. In these situations, the regulatory authority may request the IP to investigate a proper scheduling arrangement so that the operation of freight services is not jeopardized. The simulation tool may then be used to study the performance of any proposed policies on capacity utilization and quality of services, and their impacts on the cost recovery of the IP.

Another possible application is the determination of a proper access pricing regime [6]. As the railway markets in different countries have adopted various pricing policies (e.g. posted pricing, negotiation and auction), it is sometime beneficial to examine whether a successful policy employed in one system is applicable to another one. This is because the transferability of practices depends heavily on the organization of rail markets and the local traffic demand. In these cases, the model presented in this paper should be modified to reflect the specific situation under investigation.

VI. CONCLUSIONS

This paper has presented a MAS-model for an IP-TSP transaction in open railway access markets. With the aid of the negotiation protocol and the reasoning models for the IP and TSP agents, simulation of the negotiation activities has been made possible. In addition, results have shown that the behavior of the agents is rational, and the agents are competent to achieve their designated objectives.

In particular, when the MAS-model is incorporated with the BSBP, simulation results have demonstrated the ability of the agents to arrive at a Pareto-optimal solution that is beneficial to both parties. By employing a prioritized fuzzy reasoning algorithm, the TSP agent is able to determine the sequence of constraint relaxations that minimizes the loss in making concessions. Using the BNB algorithm, the IP is also able to reflect the costs of track maintenance, peak power and traffic congestion on track access charge, so that the resultant schedules may recover the actual cost imposed by the train services. The results on handling multiple bilateral negotiations by the IP also confirm the competitive advantage on the first-served TSP and the difficulties in scheduling non-homogenous traffic demand.

Practical railway networks often have complex layouts consisting of multiple tracks and junctions. Despite the assumption of a linear structure presented in this paper, the model may still be adapted to resolve conflicts in negotiations involving complex structures. As multiple tracks and junctions can be considered as a collection of single-track sections, the allocation of track access rights may also be regarded as a set of negotiations on consecutive track sections. In addition, since it is usually the localized track sections that experience fierce competition for track access among a number of TSPs, the simulation tool for linear structures devised here is still useful for conducting a critical analysis in these regions prior to the physical implementation of a regulatory or operational adjustment.

Nevertheless, the applicability of the presented model in large scale studies is restricted by the exponential growth of computational demand of the branch-and-bound algorithm. The performed cases studies involving four stations required a simulation time of 2 hours per transaction at maximum. The simulation tool has also examined a case involving 6 stations and 48 transactions. The average computation time was found to be one hour. Even though the simulation tool is not intended to be used for real-time scheduling and the order of simulation time (even in hours) is reasonable for small-scale studies, the computational complexity will eventually become a concern, especially for scheduling multiple track access rights in a complex network. The adoption of a heuristic algorithm (such as a genetic algorithm) and/or parallel computing is certainly a potential means to reduce the computation time.

This paper also forms a foundation for further research in modeling railway open access markets by multi-agent systems. With the implementation of this core IP-TSP transaction, further research opportunities are twofold. First, studies may continue to model the negotiations occurring in open access markets. For instance, structural research may be undertaken to investigate different strategies (e.g. first-come-first serve, highest potential TAC first, etc.) to sequence multiple negotiations so that objectives such as capacity utilization and cost recovery may be optimized. Another type of negotiation is the coordination of train schedules at interchange stations between services operated by different TSPs. By reducing the passenger transit time, TSPs expect to boost up passenger demand without jeopardizing the resource utilization cost (e.g. idle cost of rolling stock). On the other hand, the second direction of research may focus on improving the model on IP-TSP transaction. In addition, since the scheduling problem devised does not consider the details of platform layouts at stations, the platform scheduling algorithms suggested in studies [26], [27] may also be incorporated to enrich the capability of the IP agent. In addition, as the robustness of timetables in response to train delays [28] is an important attribute in railway scheduling, the IP agent model may also incorporate the objective of improving robustness during the negotiation process.

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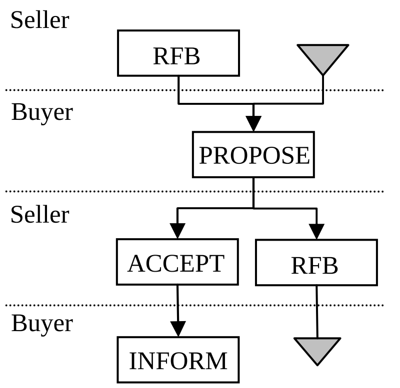


Fig. 1. Contract Net Protocol (CNP).

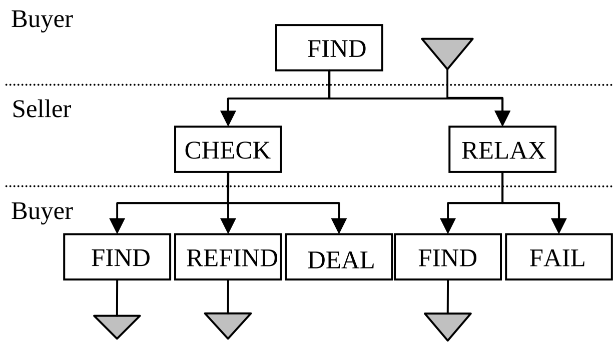


Fig. 2. Buyer-and-Seller Behavior Protocol (BSBP).

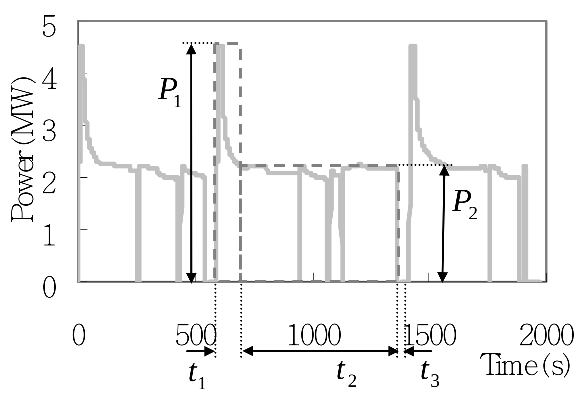


Fig. 3. Typical traction power graph for three interstation runs.

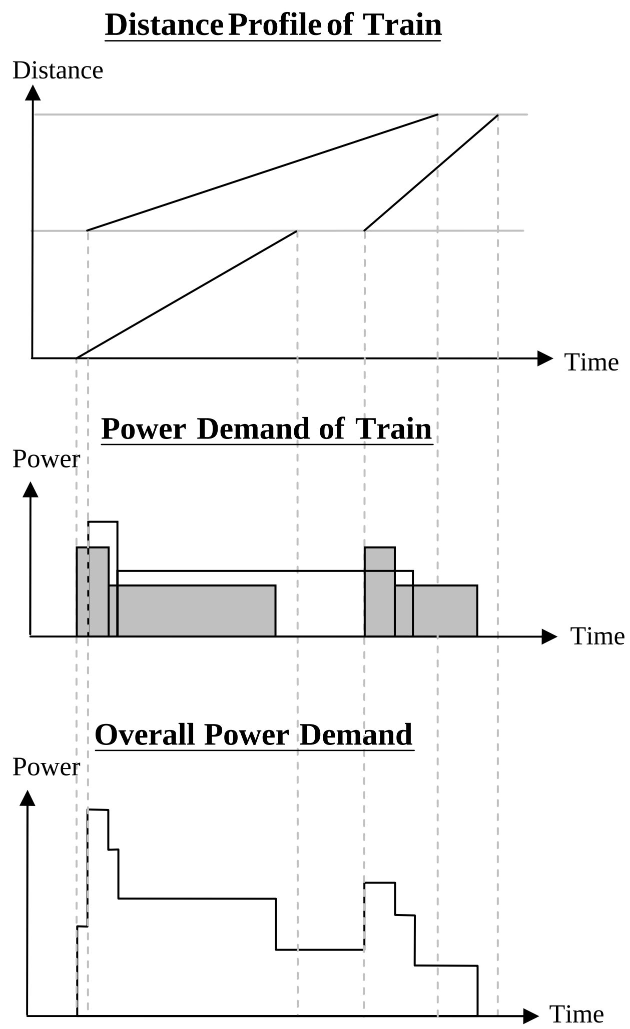


Fig. 4. Superposition of peak demand graphs.

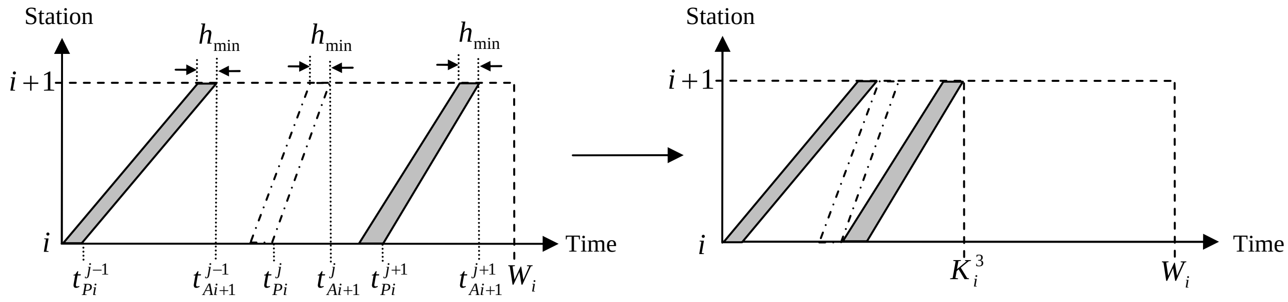


Fig. 5. Illustration of capacity utilization.

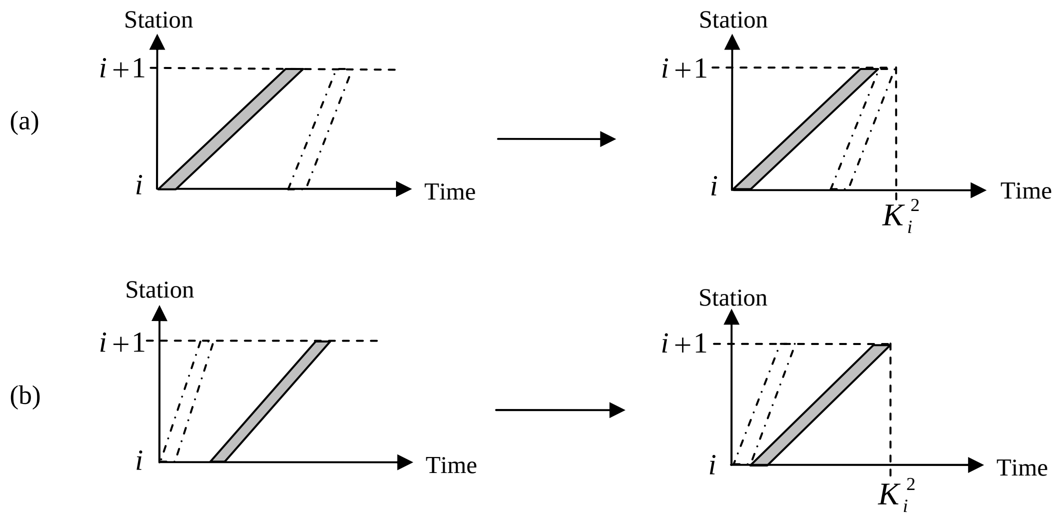


Fig. 6. Derivation of K_i^2: (a) train behind is faster; (b) train behind is slower.

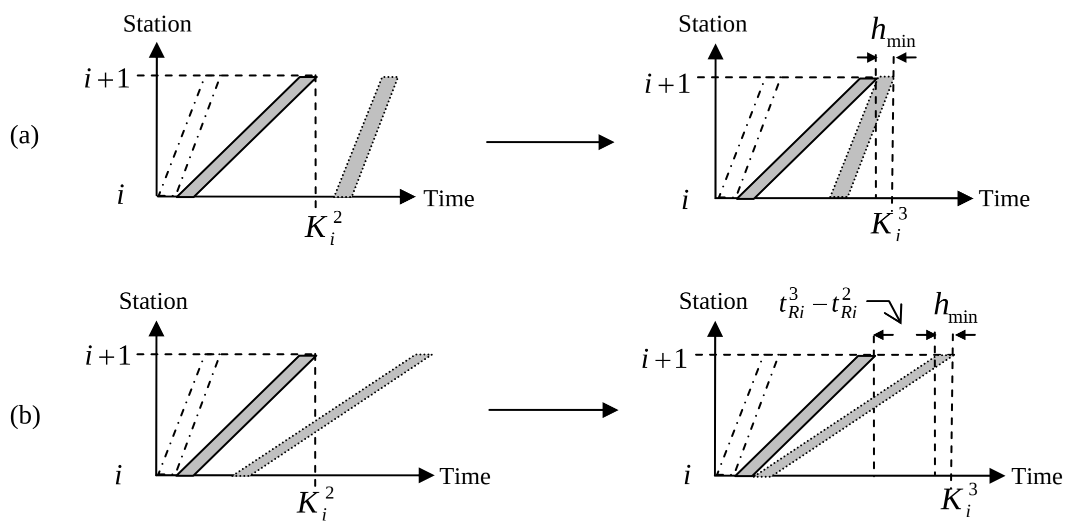


Fig. 7. Derivation of K_i^3: (a) train behind is faster; (b) train behind is slower.

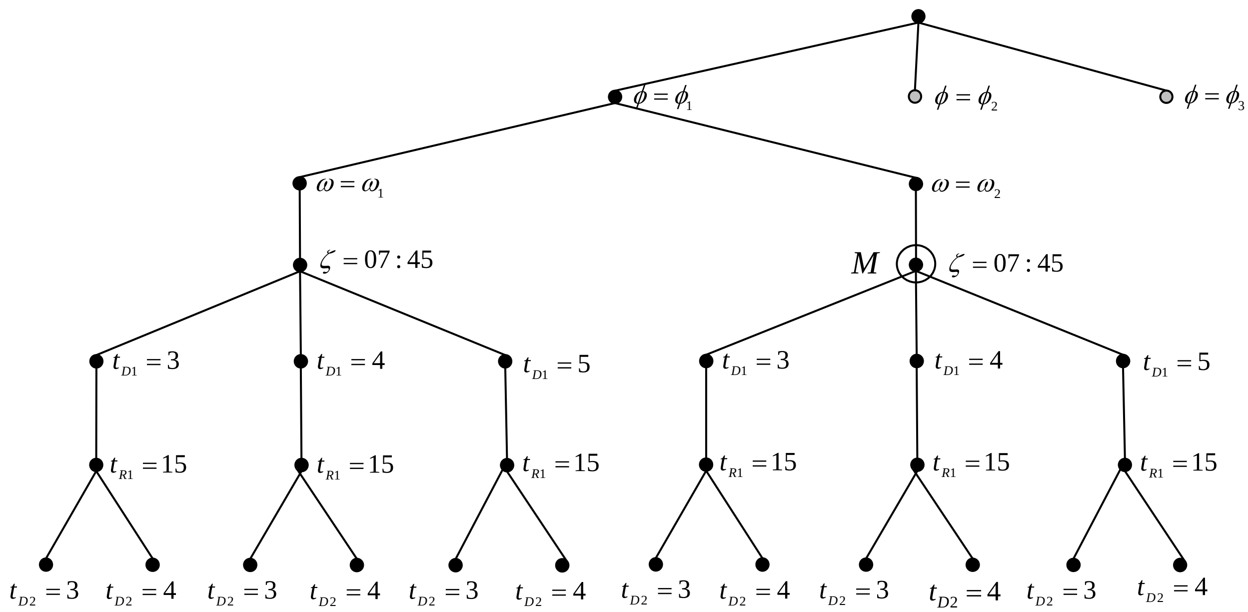


Fig. 8. Illustration of BNB search tree.

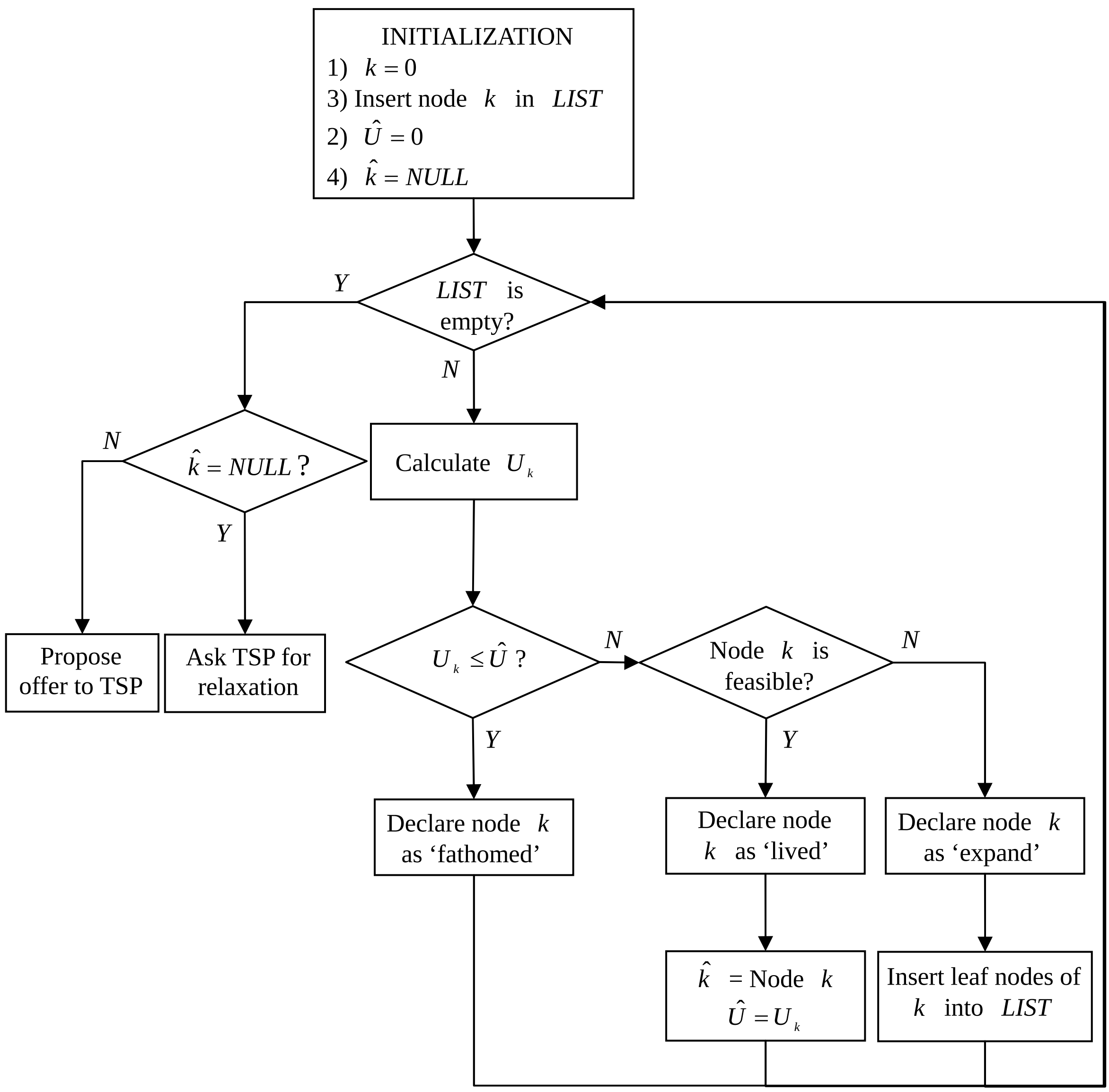


Fig. 9. A flowchart of the BNB algorithm for IP agent.

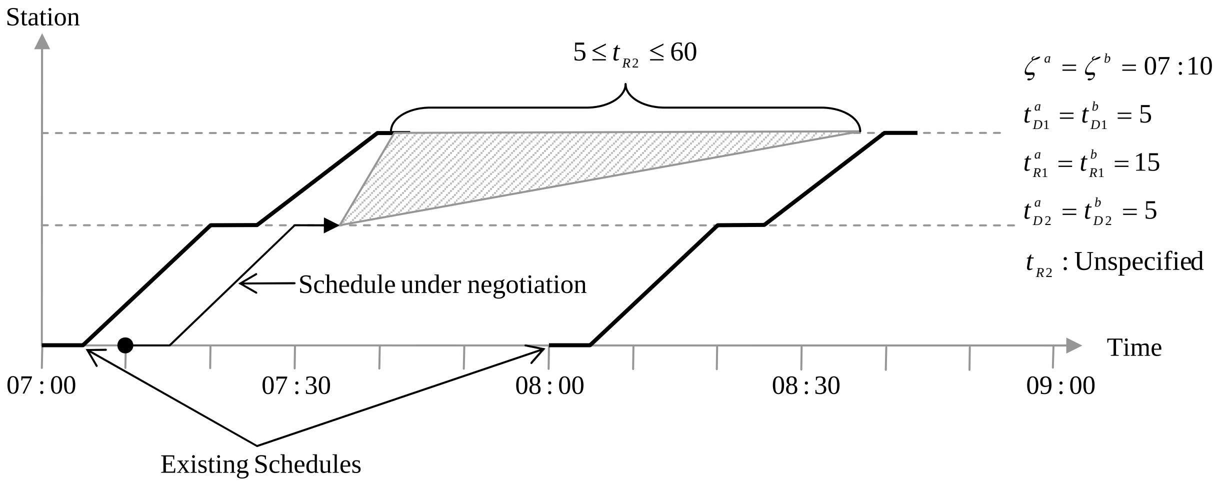


Fig. 10. Possible size of domain without specifying the most preferable schedule.

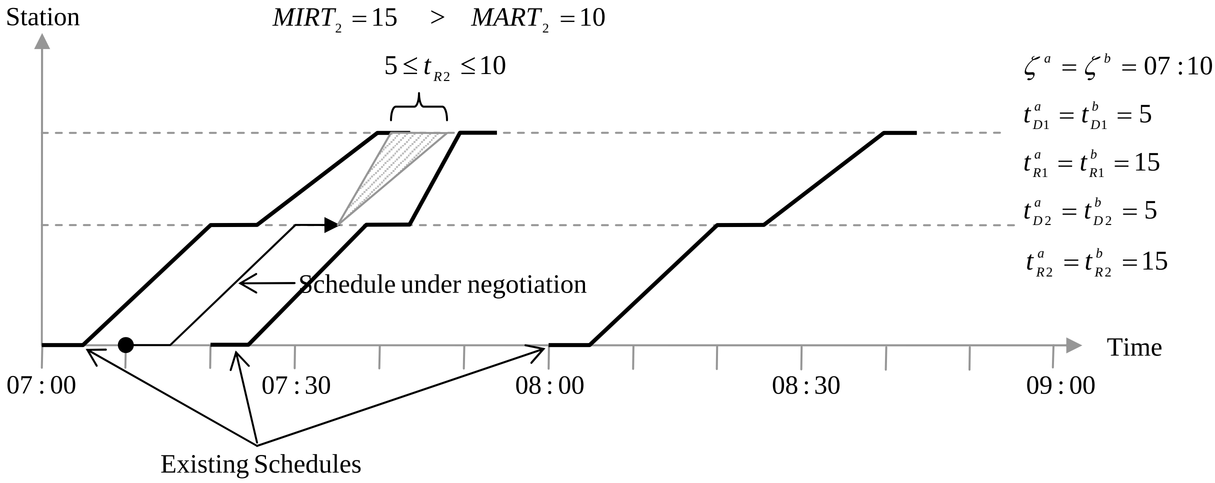
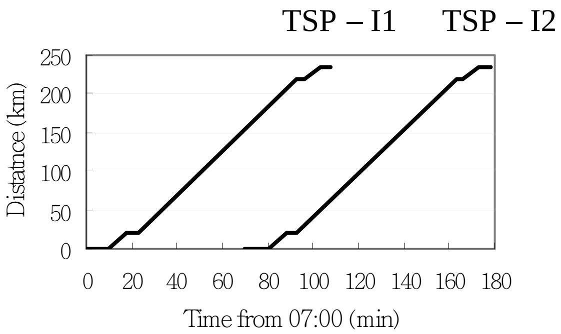


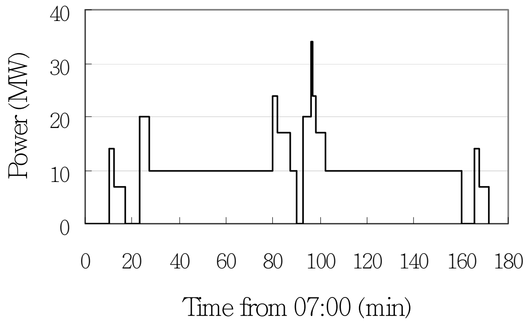
Fig. 11. Condition for pruning using capacity constraints.



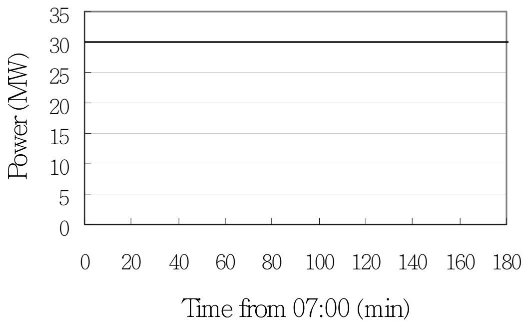
$$\Psi_{I1} = \{\, \{A, B, C, D\},\ 07:00,\ \{10,\ 5,\ 3\},\ \{8,\ 70,\ 7\}\}$$

$$\Psi_{I2} = \{\, \{A, B, C, D\},\ 08:10,\ \{10,\ 5,\ 3\},\ \{8,\ 70,\ 7\}\}$$

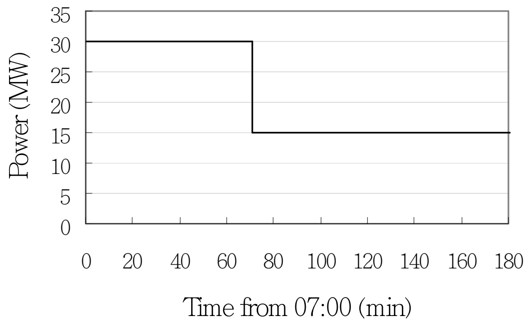
Fig. 12. Committed train schedule prior to negotiation.



(a) PD - 1



(b) PD - 2



(c) PD - 3

Fig. 13. Power distribution prior to negotiation.

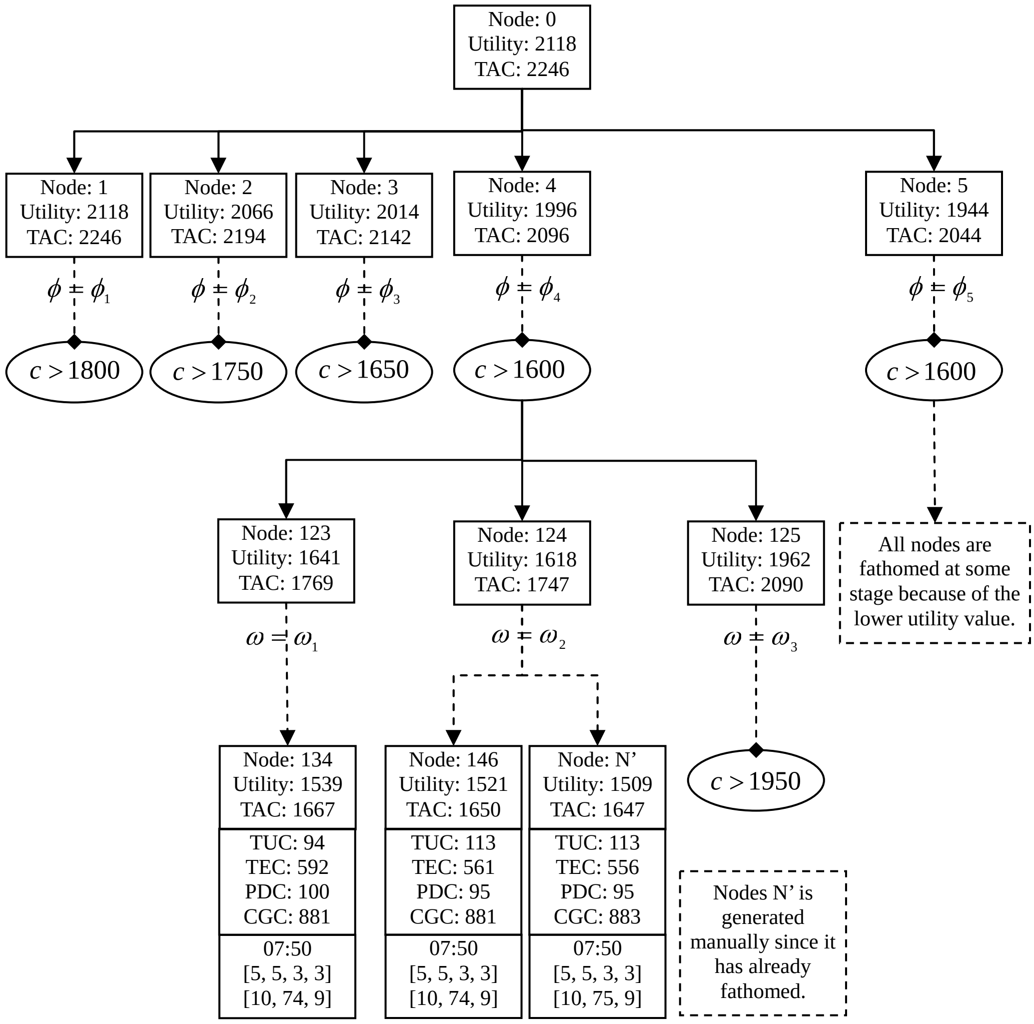


Fig. 14. Simplified tree for final round for case 1.

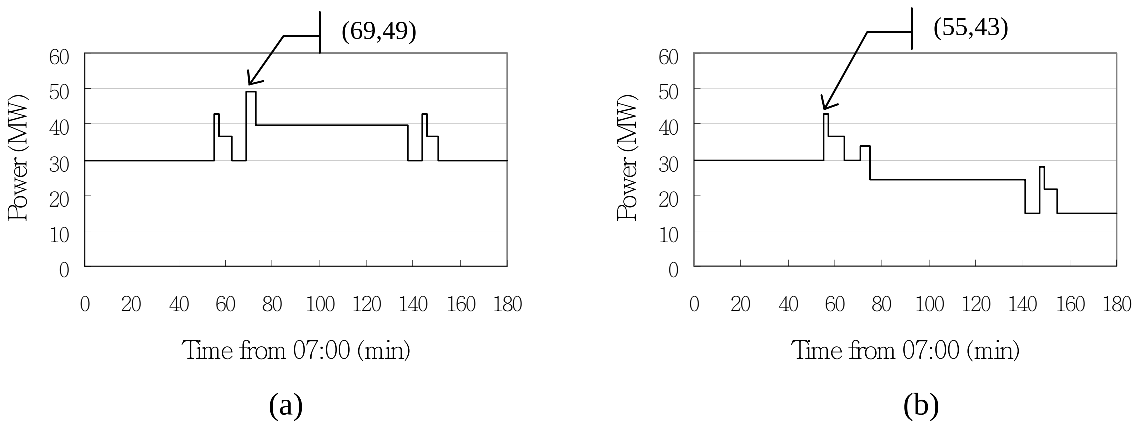
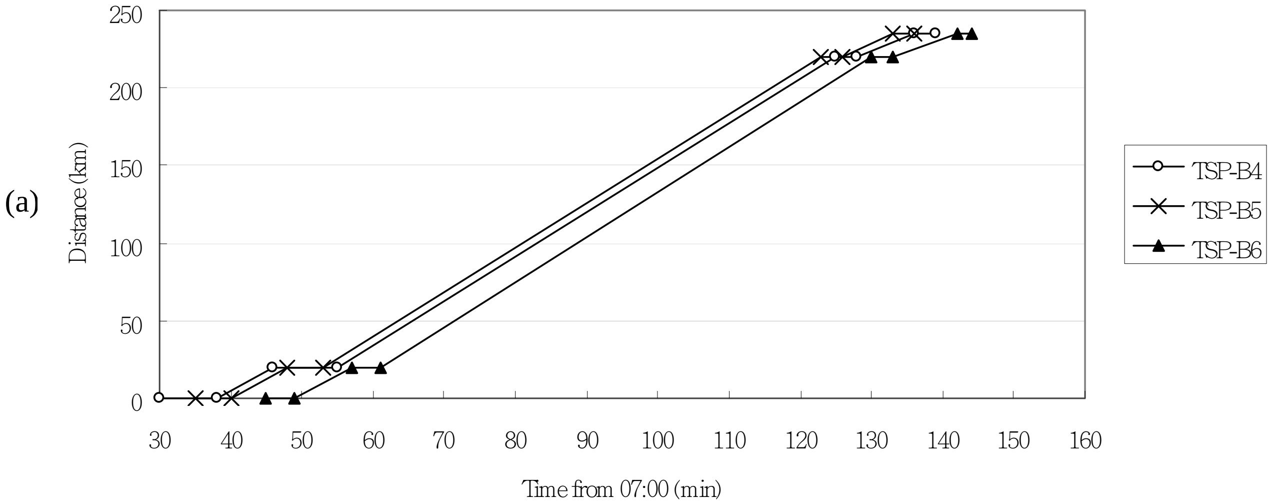


Fig. 15. Power distribution after negotiation (a) case 5; (b) case 6.



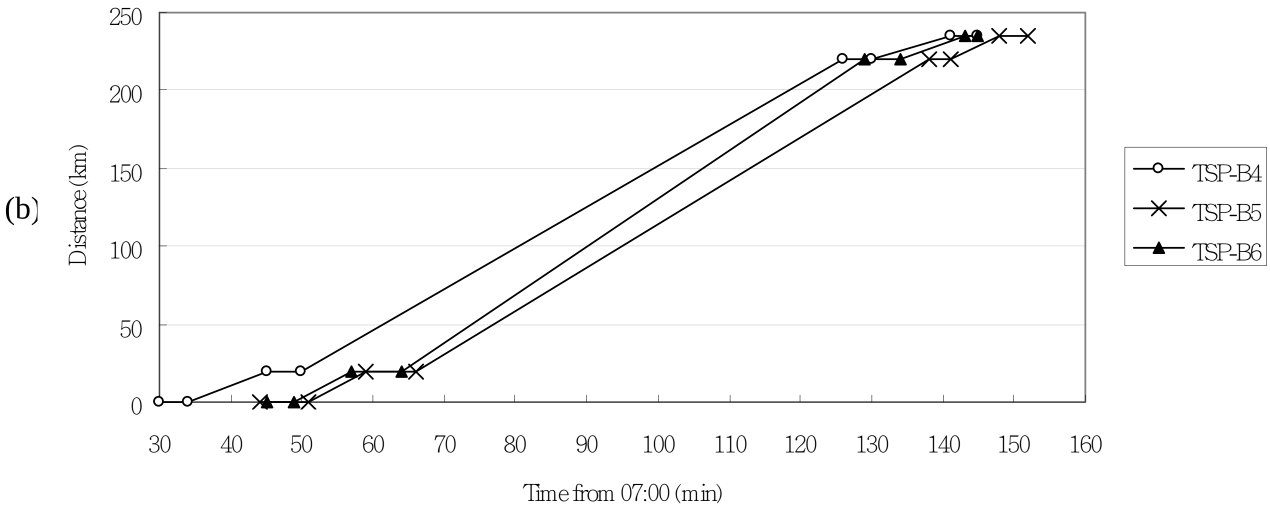


Fig. 16. Timing diagram for schedules of B4, B5 and B6 in (a) cases 8 and 9; (b) cases 10.

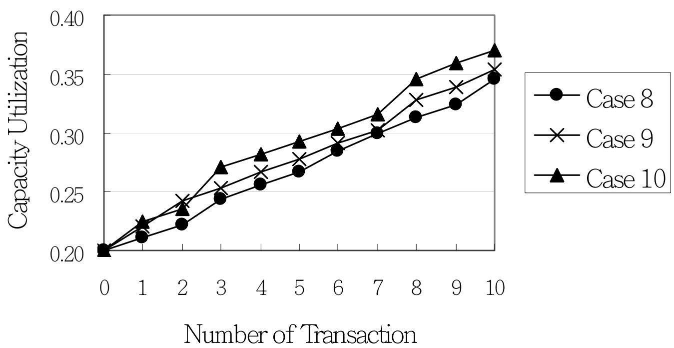


Fig. 17. Evolution of capacity utilization in cases 8 to 10.

TABLES

TABLE I
OBJECTIVES FUNCTIONS AND CONSTRAINTS FOR RELAXED PROBLEM

Terms	Objective function	Constraints in Ξ'
TUC	$\max\{c_1^{\omega} n_v^{\omega} \sum L_i\}$	Headway; rolling stock
TEC	$\max\{c_2 \sum E(\omega, t_{Ri})\}$	Headway; rolling stock; interstation runtimes
PDC	$\max\{c_3 \Delta P(\omega, \Psi)\}$	Headway; rolling stock; commencing time, dwell times, interstation runtimes
CGC	$\max\{c_4 d_{\phi} \sum A_i \exp(\eta_i)\}$	Headway; flex; rolling stock; interstation runtimes
TAC	$\max(c)$	Cost
CPU	$\min(\Delta\eta)$	Headway; rolling stock; interstation runtimes

TABLE II
DEFINITION OF ROLLING STOCK

Type	**Vehicles**	**Track usage charge rate c_1^{ω} (\$/veh·km)**	**Traction level**
ω_1	10	0.04	Medium
ω_2	8	0.06	Low
ω_3	9	0.16	High

TABLE III
DEFINITION OF FLEX LEVELS

Level	**Flex time (min)**	**Discount factor**
ϕ_1	0	1.00
ϕ_1	2	0.95
ϕ_1	4	0.90
ϕ_1	6	0.85
ϕ_1	8	0.80

TABLE IV
SIMULATION CASES

Cases	**IP**	**TSP**
1	IP-1	TSP-A1
2	IP-1	TSP-A2
3	IP-2	TSP-A2
4	IP-3	TSP-A2
5	IP-4	TSP-A1
6	IP-5	TSP-A1
7	IP-1	TSP-A3
8	IP-1	TSP-B {8, 2, 9, 1, 5, 3, 6, 10, 4, 7}
9	IP-1	TSP-B {6, 9, 1, 5, 8, 4, 2, 7, 10, 3}
10	IP-1	TSP-B {9, 8, 4, 10, 6, 2, 1, 7, 3, 5}

TABLE V
TRACK AND STATION DATA

Track	**Origin station**	**Destination station**	**Length (km)**	**Track specific constant (min)**
1	A	B	20	1.2
2	B	C	200	1.0
3	C	D	15	1.1

TABLE VI
TSP-A DEFINITIONS

Attribute	**TSP-A1**	**TSP-A2**	**TSP-A3**
$\hat{\zeta}$ (hh:mm)	07:50	07:05	07:50
$\hat{T}_D$ (min)	{5, 5, 3, 3}	{5, 5, 3, 3}	{5, 5, 3, 3}
$\hat{T}_R$ (min)	{10, 75, 9}	{10, 75, 9}	{10, 75, 9}
$\hat{c}$ (\$)	1600	1600	1600
ρ_{δ}	1.0	1.0	1.0
ρ_{T_D}	0.2	0.2	0.2
ρ_{T_R}	0.2	0.2	0.2
ρ_c	1.0	1.0	1.0
f_{ω_1}	0.0	0.0	0.0
f_{ω_2}	0.6	0.6	0.0
f_{ω_3}	1.0	1.0	1.0
f_{ϕ_1}	1.0	1.0	1.0
f_{ϕ_2}	0.9	0.9	0.9
f_{ϕ_3}	0.8	0.8	0.8
f_{ϕ_4}	0.6	0.6	0.6
f_{ϕ_5}	0.0	0.0	0.0
τ	0.1	0.1	0.1

TABLE VII
TSP-B DEFINITIONS

Name	**Start time limits (min)**	**Cost limits ($)**	**Attribute(s) of top priority**	**Runtime requirements**
TSP-B1	[07:00 | 07:10]	[1650 | 2300]	Dwell and run times between A and B	Moderate
TSP-B2	[07:05 | 07:15]	[1900 | 2750]	All schedule times	Short
TSP-B3	[07:20 | 07:30]	[1550 | 2500]	Cost	Moderate
TSP-B4	[07:30 | 07:40]	[1600 | 2850]	All schedule times	Long
TSP-B5	[07:35 | 07:50]	[1800 | 2600]	All schedule times	Moderate
TSP-B6	[07:45 | 07:50]	[1500 | 2300]	Cost	Short (between B and C)
TSP-B7	[07:50 | 08:00]	[1700 | 2500]	Dwell and run times between B and C	Moderate
TSP-B8	[08:00 | 08:20]	[2000 | 2550]	All schedule times	Moderate
TSP-B9	[08:10 | 08:20]	[1750 | 3100]	All schedule times	Long
TSP-B10	[08:15 | 08:30]	[1850 | 2950]	Dwell and run times between C and D	Long

TABLE VIII
IP DEFINITIONS

Attribute	**IP-1**	**IP-2**	**IP-3**	**IP-4**	**IP-5**
w_η ($)	5000	10,000	5,000	5,000	5,000
c_2 ($/kWh)	0.05	0.05	0.05	0.05	0.05
c_3 ($/MW)	10.0	10.0	10.0	10.0	10.0
c_4 ($/min)	250	250	350	250	250
Power model	PD-1	PD-1	PD-1	PD-2	PD-3

TABLE IX
SIMULATION TIME PER TRANSACTION

Time Range (min)	**Frequency**
1 – 10	30
11 – 20	2
21 – 30	0
31 – 60	2
60 – 120	2
120+	1

TABLE X

SIMULATION RESULTS FOR CASES 1 TO 7: FINAL AGREEMENTS BETWEEN IP AND TSP AGENTS

Category	**Attribute**	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**	**Case 7**
Track access rights	ζ (hh:mm)	07:50	07:05	07:05	07:05	07:50	07:50	07:51
	T_D (min)	{5, 5, 3, 3}	{7, 6, 3, 3}	{7, 6, 3, 3}	{7, 7, 3, 3}	{5, 5, 3, 3}	{5, 6, 3, 3}	{9, 9, 3, 3}
	T_R (min)	{10, 74, 9}	{9, 72, 8}	{9, 72, 8}	{8, 72, 7}	{9, 72, 8}	{10, 73, 9}	{8, 69, 7}
	c ($)	1650	1554	1554	1900	1744	1686	1999
	ω	ω_2	ω_2	ω_2	ω_2	ω_2	ω_2	ω_3
	ϕ	ϕ_4	ϕ_4	ϕ_4	ϕ_4	ϕ_4	ϕ_4	ϕ_4
Breakdown of utility value of IP	U ($)	1521	1463	1371	1827	1653	1567	1935
	TUC ($)	113	113	113	113	113	113	338
	TEC ($)	561	567	567	567	567	564	671
	PDC ($)	95	0	0	0	190	130	120
	CGC ($)	881	875	875	1220	875	879	870
	$\Delta\eta$	0.0256	0.0183	0.0183	0.0147	0.0183	0.0238	0.0128

TABLE XI

SIMULATION RESULTS FOR CASES 8 TO 10: COMMITTED TIMETABLES

	TSP-B1			TSP-B2			TSP-B3			TSP-B4			TSP-B5		
	Case 8	**Case 9**	**Case10**	**Case 8**	**Case 9**	**Case10**	**Case 8**	**Case 9**	**Case10**	**Case 8**	**Case 9**	**Case10**	**Case 8**	**Case 9**	**Case 10**
Arr. at A	07:05	07:05	07:05	07:05	07:05	07:05	07:20	07:20	07:20	07:30	07:30	07:30	07:35	07:35	07:44
Dep. at A	07:12	07:12	07:12	07:08	07:08	07:08	07:25	07:25	07:25	07:38	07:38	07:34	07:40	07:40	07:51
Arr. at B	07:20	07:20	07:20	07:14	07:14	07:14	07:35	07:33	07:34	07:46	07:46	07:45	07:48	07:48	07:59
Dep. at B	07:25	07:26	07:25	07:17	07:17	07:17	07:40	07:38	07:39	07:55	07:55	07:50	07:53	07:53	08:06
Arr. at C	08:35	08:35	08:36	08:22	08:22	08:22	08:51	08:49	08:50	09:05	09:06	09:06	09:03	09:03	09:18
Dep. at C	08:38	08:38	08:39	08:25	08:25	08:25	08:54	08:52	08:53	09:08	09:09	09:10	09:06	09:06	09:21
Arr. at D	08:46	08:46	08:49	08:31	08:31	08:31	09:02	09:01	09:02	09:16	09:17	09:21	09:13	09:13	09:28
Dep. at D	08:49	08:49	08:52	08:34	08:34	08:34	09:05	09:04	09:05	09:19	09:20	09:25	09:16	09:16	09:31

	TSP-B6			TSP-B7			TSP-B8			TSP-B9			TSP-B10		
	Case 8	**Case 9**	**Case10**	**Case 8**	**Case 9**	**Case10**	**Case 8**	**Case 9**	**Case10**	**Case 8**	**Case 9**	**Case10**	**Case 8**	**Case 9**	**Case 10**
Arr. at A	07:45	07:45	07:45	07:50	07:50	07:50	08:00	08:08	08:08	08:12	08:10	08:10	08:15	08:29	08:26
Dep. at A	07:49	07:49	07:49	07:55	07:55	07:55	08:05	08:15	08:15	08:15	08:13	08:13	08:18	08:32	08:29
Arr. at B	07:57	07:58	07:58	08:03	08:03	08:03	08:13	08:23	08:22	08:21	08:19	08:19	08:25	08:38	08:35
Dep. at B	08:01	08:03	08:05	08:08	08:08	08:08	08:18	08:28	08:27	08:24	08:22	08:22	08:28	08:42	08:39
Arr. at C	09:10	09:11	09:10	09:24	09:24	09:24	09:28	09:37	09:36	09:30	09:27	09:27	09:33	09:48	09:45
Dep. at C	09:13	09:14	09:15	09:27	09:27	09:27	09:31	09:40	09:39	09:33	09:30	09:30	09:36	09:52	09:49
Arr. at D	09:22	09:23	09:23	09:34	09:34	09:34	09:38	09:47	09:47	09:40	09:36	09:36	09:43	09:58	09:55
Dep. at D	09:24	09:25	09:25	09:37	09:37	09:37	09:41	09:50	09:50	09:43	09:39	09:39	09:46	09:61	09:58