Predictive and Reactive Approaches to the Train-Scheduling Problem: A Knowledge Management Perspective

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***Abstract*—Predictive and reactive train scheduling are tactical and operational decision making, respectively, under constraints (e.g., resource capacity, managerial objectives) and under uncertainty (e.g., imprecise data and information, unforeseen events). Predictive scheduling produces timetables taking into account the market demand and resources utilization levels. Reactive scheduling challenges disruptions to timetables and schedules trains and operations with imprecise plans. Expert knowledge is indispensable for finding practical solutions for both predictive and reactive scheduling. Consequently, knowledge management (KM) strategies, processes and technologies can improve the decision-making process and outcomes. This paper focuses on the following issues. Five dimensions are introduced to distinguish predictive and reactive train-scheduling activities. The combined use of data and knowledge and the differences in uncertainty levels are used to position comparatively the two scheduling approaches. The intensity of reliance on explicit and tacit knowledge is highlighted via the elaboration and classification of knowledge used in either one or both scheduling environments. The significance of train-scheduling tacit knowledge elicitation is described by, first, presenting a real case analysis which resulted in the elicitation of rich and valuable tacit knowledge (timetabling heuristics) from explicit knowledge (timetable) and, second, generalizing lessons learned from this process. The contributions of the tacit knowledge elicitation process to the enhancement of the train-scheduling system which leads to better resource utilization and customer satisfaction are itemized.**

***Index Terms*—Iran Railways, knowledge elicitation, knowledge management (KM), predictive and reactive scheduling, tacit and explicit knowledge, timetabling, train operations management, train-scheduling problem.**

I. Introduction

The train-scheduling problem concerns the appropriate allocation of resources, i.e., main and station rail lines, to a fleet of trains over a period of time. Expert knowledge is an indispensable requirement for tackling the problem [2]. In the real world, two types of train schedules are generated. Predictive schedules or timetables represent services provided by a train operating company; they are also used for train operations supervision and seat allocation purposes. Reactive schedules are generated to restore traffic flow after disruptions occur, and to include unplanned trains. Predictive and reactive scheduling are tactical and operational decision making problems, respectively, which affect the resource utilization and customer satisfaction levels significantly. An important issue when dealing with the problem in real environments is that scheduling-related knowledge exists and evolves in the minds of experts working in separate environments; and knowledge gained in either of the domains can be useful for improving decision making in both domains. Knowledge management (KM) can be used to enhance this type of decision-making.

Scheduling problem solving becomes more challenging when it involves trains which travel along a primarily single-line railway. To highlight one of the difficulties caused by human mind limitations, let us assume that for a single-track railroad the solution methodology is to resolve a set of conflicts on the occupation of track sections, where each conflict involves two trains competing for the only main track between two adjacent stations during overlapped time intervals. When resolving a conflict, the train-scheduling expert decides which train should get precedence and occupy the track first. In other words, two solutions are associated with the conflict; and the timetable production process includes resolving all train conflicts. Thus, for a problem including n conflicts, the number of solutions is estimated to be 2^n, which is only a rough estimate because resolving a conflict may create additional conflicts or eliminate some of them. As mentioned in [4] and [6], the size of the solution space grows exponentially with the number of conflicts. Consequently, the memory of experts cannot keep track of all relationships between decisions [9]. This makes it impractical to find the optimum solution manually. The complexity of the problem have also been addressed in various publications [4], [6], [7], [10], [12], [14], [15], [17] that consider train scheduling as an optimization problem.

The aim of this paper is to study the train-scheduling problem from the KM's point of view. KM's main purpose is to improve the use of company's knowledge-related assets and to renew them continuously [16]. The key asset being considered in this study is tacit knowledge i.e., knowledge that exists in the head of experts involved in the train-scheduling operations. It is difficult to describe, examine, and use this type of knowledge [11]. The study and management of expert tacit knowledge has received few attentions [5], [13], particularly in the field of train scheduling. As shown by [7], existing literature on the knowledge-based approaches to the train-scheduling problem mostly focus on the quantitative aspect, which relates to the discovery

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and application of scheduling rules. This paper's perspective is KM applied to the rail industry with the objective to improve both physical assets performance and customer satisfaction.

The rest of this paper is organized as follows. Following a discussion on the basics of the train-scheduling problems, Section II differentiates the predictive and reactive domains using characteristics such as the magnitude of the tasks and the impact of uncertainty on the mix use of data and knowledge for train-scheduling-related decisions in each domain. Section III elaborates and classifies tacit and explicit knowledge used in the predictive and reactive domains. Section IV discusses the benefits of KM through an example. Finally, the paper ends with a number of concluding remarks in Section V.

II. Train-Scheduling Problem

A. Background

This section provides insights into the two states of a train traveling along a single-track railway and their representations for scheduling purposes. In the real world, traveling trains are either halted ("standstill" state) on a station line or in motion along the main line. The characteristics rules applied to the standstill state are that trains can meet or overtake only inside station's boundaries. To avoid collisions, only one train is allowed to occupy the main line between immediate adjacent stations at a given time and consequently, station lines are used to accommodate trains waiting for the track to be released. Fig. 1 shows a station with only one line for accommodating trains. Warning and entry signals, represented by WS and ES, respectively, on the graph, help the driver of a train approaching the station either to continue the journey at a speed recommended for passing the line's intersection points or stop on the station line. The departure signal (DS) helps the driver to depart from the station safely.

The second state is moving along the main line. Running time between adjacent stations has been modeled differently in the train-scheduling literature. According to the literature survey published in [7], we classify the three methods used and highlight their differences as follows.

- The first approach assumes that running time between adjacent stations in any direction is fixed. For any train being considered, decision variables are departure times from the origin and other stations en route.
- The second approach simulates the details of train motion by modeling the acceleration and deceleration stages required for departures, arrivals, and safe passing of the line's intersection points, curves, and gradients. Train priority rules are used to resolve train conflicts.
- The third approach considers that both departure and arrival times are decision variables and thus running time is determined such that if the train is to wait at the next stop it will be run slower to save fuel. This is against the traditional method of "hurry when running and wait at the station for the required resource (e.g., a line) until it becomes available."

Limitations in the capacity of human mind affect the expert choice of running time model. Manual timetabling is more or less based on the first approach, as it is impractical for the human

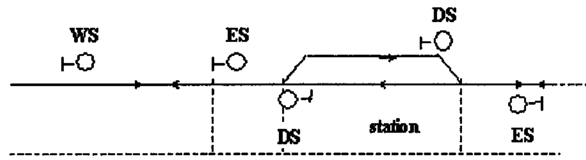

Fig. 1. Graphical representation of a simple station on a single-track railway [19].

mind to simulate acceleration and deceleration for all trains. as mentioned in the second approach. Furthermore, it is beyond the capacity of train schedulers and drivers' minds to implement the third approach manually; sophisticated technologies and decision support systems are required to compute the optimum running time and adjust train speed with planned running time. This paper focuses on the manual method (first approach) to understand the generation of explicit knowledge from expert's tacit knowledge.

Train-scheduling experts use available information (e.g., managerial objectives and performance indicators), their knowledge and expertise (e.g., on traffic management regulations, conflict resolution rules of thumb), and available data (e.g., existing resources) to generate new timetables. Traditionally, they go through the timetabling process using a distance-time graph for each corridor (see Fig. 2) [12], [21]. Each train on the graph is represented by a broken line between its origin and destination; the line consists of slanted and horizontal parts. The gradient of a slanted line represents the average speed between the two adjacent stations and the length of a horizontal line shows duration the train remains standstill in a station. A complete graph shows a feasible timetable in which all conflicts are resolved and thus the timetable can be put into practice.

The purpose of information presentation is beyond expressing information [31]; e.g., the graphical representation of a timetable facilitates the communication of information between experts during and after scheduling process and helps to overcome the limitations of expert's mind in keeping track of their conflict resolution decisions and in illustrating the spatial and temporal positions of trains and conflicts. In other words, this method tends to minimize expert's memory work load.

The manual method constitutes an overwhelming task, particularly for rail corridors with an extensive number of train services, as it needs a significant amount of efforts and time. The most recent literature survey [7] shows that advances in computer and decision technologies have resulted in major theoretical and practical progresses in the train- scheduling field. Nevertheless, the understanding of expert's heuristics is an important requirement for the design and development of effective decision making tools.

B. Predictive and Reactive Approaches

A predictive (master) schedule is a periodic timetable constructed for governing arrival and departure times based on a periodic review of demand levels and resource availability [22]. In reality, rail transport companies try to make the best use of infrastructure, fixed installations, personnel, and rolling stock in order to survive in a competitive market, which

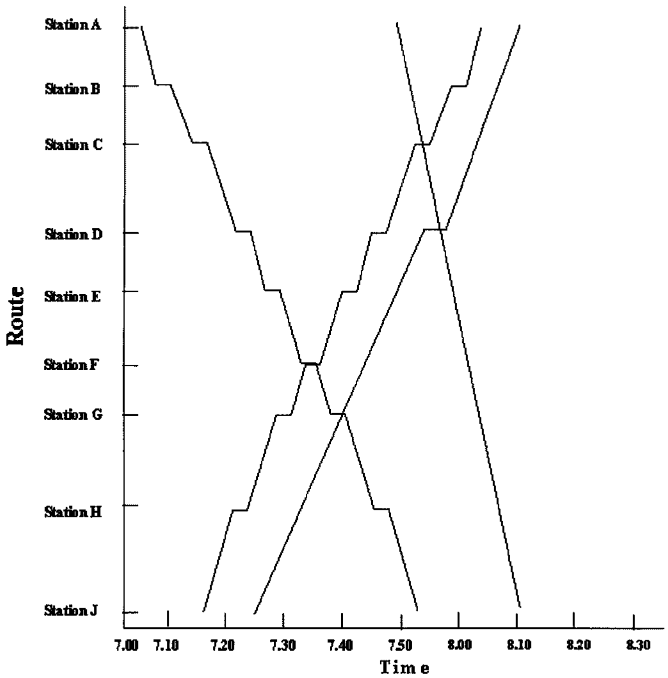

Fig. 2. Representation of a timetable as a distance–time graph.

could originate from the government's deregulation policies or merely the presence of road transport competitors. Train operations should be justifiable in terms of costs, revenues, and subsidies. A solution is to plan services for a predefined period that could vary with service type and demand patterns, ranging from a few days to a few months. Market characteristics are used to specify train route, service type, departure time, and interconnections. Planning the efficient use of crews, engines, and rolling stock through exploring the scheduling problem in an integrated environment, with iterative interaction between trains schedules and predictive allocation of other resources, is another important aspect of constructing predictive schedules. Once the schedule has been finalized formally, it is published to provide customers with the information and opportunity to plan their transportation needs in advance.

The primary function of the reactive scheduling is twofold. First, a reactive schedule is created in the wake of unpredicted events to keep the transport system as stable as possible. When problems such as accidents, equipment failures, natural disasters disrupt the traffic flow, the scheduling experts immediately start to normalize the traffic by taking effective operational decisions and resolving train conflicts. The aim is to react to events by quickly creating a new train schedule for the short term that satisfies additional constraints; for instance, no train is allowed to depart a station earlier than that given in the timetable published for customers; certain resources may be temporarily unavailable; and, the new schedule should be as close as possible to the original schedule. To keep the new schedule as close as possible to the original schedule, slack time and resources introduced in the master schedule are used by the schedulers. In addition, the cooperation of train drivers and other relevant personnel is indispensable to catch up with the master schedule. The rescheduling process is difficult since a quick decision is required while a number of factors should be taken into consideration, for instance, priorities of trains affected by the event, severity of incident, time required for repairing or removing damaged or broken rolling stock, provision of machineries for rescue operations, additional rolling stock to replace broken ones, traffic volume, and available capacity at nearby stations.

The second function of the reactive scheduling is to allocate free timeslots in the predictive schedule to other operations such as track maintenance and freight trains without precise schedules such that the scheduled trains are not delayed.

C. Comparison of the Train-Scheduling Approaches

1) Magnitude: In this section, we compare the scale of operations and decisions in the predictive and reactive scheduling stages as the two complementary parts which link transport managerial objectives at the strategic decision making level to operational arrangements amongst stations, trains, and other resources used for train operations. This link is established through the generation and circulation of traffic data (e.g., train's origin, destination, departure, and arrival times) across the company, and the bidirectional flow of information between decision-making units, i.e., button-up (e.g., reliability and punctuality achievements) and top-down (e.g., reliability and punctuality targets). This type of link can be strengthened through adopting KM policies, technologies, and processes that facilitate the flow of knowledge between human experts who are scattered across the company and deal with various aspects of the problem [32].

The magnitude of train-scheduling tasks in predictive and reactive environments depends on the availability of sufficient data, information, and knowledge, as well as organizational authority and technological means for putting decisions into practice. In railway companies like Iran Railways, the management of rail network and train operations is distributed amongst geographical regions whose activities are coordinated at the headquarters (HQ). The train-scheduling experts at the HQ deal with the production of national timetables and harmonize the activities of geographical regions for trains that pass through a multiple of regions. The experts working at the regional level produce the schedules for local trains, monitor trains in motion within their territory, and resolve train conflicts caused by unpredicted events. The computer and telecommunication technologies are used to gather, transfer and classify train operations data and draw distance-time graphs.

Fig. 3 compares five major dimensions of the predictive and reactive scheduling approaches as observed by the authors in Iran Railways.

Spatial Vision: The predictive scheduling approach considers the network wide impacts of the scheduling decisions while the reactive approach focuses on local impacts due to the lack of network wide data and knowledge required for fast decision making.

Temporal Vision: A predictive schedule is developed for a few days or weeks and it can be used repeatedly; however, a reactive schedule is created for the next few hours; and it is not reusable.

Completeness: The predictive schedule covers the whole journeys of all trains; whereas, the reactive schedule is a partial

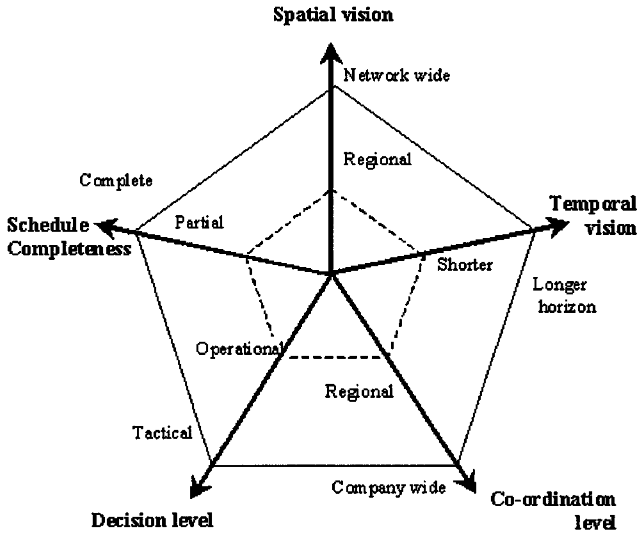

Fig. 3. Magnitude of predictive (outer pentagon) and reactive (inner pentagon) scheduling operations.

schedule which covers trains that travel within a region, i.e., the territory under the control of the regional train dispatchers.

Decision Level: The main outlook of predictive schedule generation is planning the appropriate and balanced use of railway assets, primarily, according to the economic and social objectives of the company; whereas, the reactive schedules are generated to tackle the consequences of day-to-day operational problems.

Coordination Level: A predictive schedule is used to coordinate train operations across different geographical regions in advance, while the reactive schedule coordinates stations within the region to comply with the master schedule as far as possible.

The difference in the magnitude of the scheduling tasks does not imply that the reactive scheduling process is easier. As mentioned in [3], reactive scheduling is complex as it deals with train delays and resource unavailability, unscheduled trains and operations, heavy communication demand, and physical constraints (e.g., to ensure that the characteristics of freight trains and infrastructure like bridges and tunnels match).

2) Positioning Predictive and Reactive Scheduling Approaches With Respect to Uncertainty Level and Mix Use of Data and Knowledge: The predictive and reactive scheduling decisions are made in two different environments. They are both decisions taken under constraints (e.g., rail network capacity, safety constraints, train prioritizing rules) and under uncertainty (e.g., imprecise data and information in the predictive stage, unforeseen events in the reactive stage).

Uncertainty is dealt with in different ways in the two environments.

The timetable planners, who develop predictive schedules manually, assume that the resources required for implementing the schedule in the real world are all available. Furthermore, they usually overlook the uncertain accuracy of data (e.g., running time between adjacent stations) and use data confidently. They also rely to a notable extent on the data and knowledge used in previous timetable production to produce reasonable

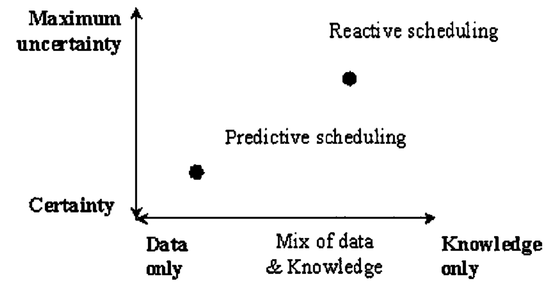

Fig. 4. Positioning the train-scheduling approaches.

and acceptable schedules. It has been shown that decision technologies can improve scheduling decisions under uncertainty by, for instance, enabling the schedulers to study the reliability of created schedules via allowing certain parameters (e.g., running time) to vary randomly. For an example, see [23].

In contrast with predictive scheduling decisions, reactive scheduling decisions are made when the current schedule is disrupted or additional trains and operations are scheduled. It is often very difficult to predict all consequences of the new scheduling decisions; and thus, expert judgments are made on the basis of imperfect data and previous experiences with a relatively short-term view of the future impacts of decisions. As the decisions are to be executed shortly after they are made, the communication with on board and station crews and adjoining regions' schedulers is an essential part of the work.

Fig. 4 maps the predictive and reactive scheduling approaches into two dimensions, i.e., mix of data and knowledge on horizontal axis and uncertainty level on the vertical axis. Both scheduling approaches use basic data about main lines (the length and number of tracks of any block, i.e., a stretch of track that links two immediate adjacent stations), stations (signaling system, the number, length, and type of lines), and the position and specifications of critical infrastructures (tight curves, tunnels, bridges, sharp gradient). Furthermore, the two scheduling tasks in the two environments are based on common basic knowledge of train operations and scheduling. However, the reactive scheduling decisions are more constrained than predictive ones, and reactive scheduling experts must draw from their previous experiences and environmental knowledge to understand and find solutions to the problems as soon as they arise. As a result, the reactive scheduling decisions depend more on expert knowledge compared to predictive scheduling.

In conclusion, although both predictive and reactive scheduling experts mainly rely on the same type of data and knowledge on train operations and rail network, the presence of uncertainty in the real world and the different outlooks of the two approaches result in additional knowledge of different amount and type to be used in each domain. For instance, the predictive scheduling experts should have adequate knowledge to establish links between the scheduling decisions and the transport targets set by the top managers, while reactive scheduling experts should have enough expertise and knowledge to handle unpredicted events efficiently and effectively. The differences and similarities of the two approaches in the use of knowledge will be expanded upon in the next section.

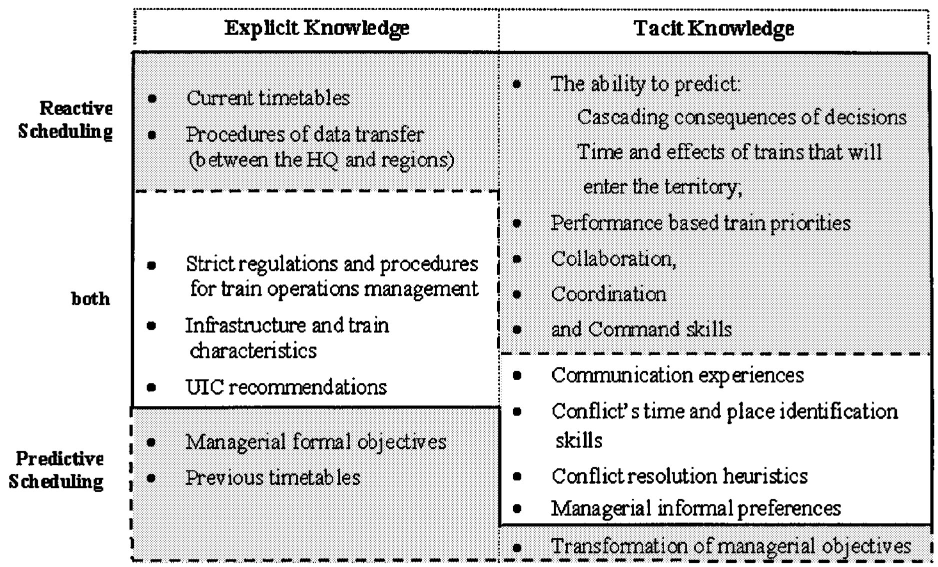

Fig. 5. Classification of predictive and reactive train-scheduling knowledge.

III. Train-Scheduling Tacit and Explicit Knowledge

Generally speaking, the notion of knowledge refers to the "scope of one's awareness," memories and experiences of a system [24]. Tacit knowledge gives an individual the capacity to interpret information and comprehend things that cannot be codified, e.g., how to ride a bicycle [18]. Tacit knowledge is usually unstructured and enhances with learning. From a management viewpoint, it is the accumulation of elements like experiences, expertise and know-how that are usually localized either in the brain of an expert or embedded in the group interactions in a workplace [1], [32]. It is difficult to formalize and reuse tacit knowledge [5]. There is often resistance to its revelation [27]. On the other hand, explicit knowledge is codified and documented in a variety of forms such as policies, procedures, reports, missions, and products, etc. Explicit knowledge is usually captured, stored, shared, reported, and disseminated (without requiring interpersonal interactions) by information systems [8]. Explicit and tacit knowledge are key assets of a company [20] that affect its success significantly.

Fig. 5 classifies the explicit and tacit knowledge used in the predictive and reactive train-scheduling contexts. Explicit knowledge used in the two contexts includes train operations regulations [25], [26], the recommendations of the International Union of Railways (i.e., UIC-code 451-1 [28] and UIC-code 919R [29]), documents used for training purposes, and the characteristics of trains and infrastructures.

Current and previous timetables are explicit knowledge used for predictive and reactive scheduling, respectively. Creating a predictive schedule from scratch would be very difficult, thus a majority of new schedules simply copy or slightly improve previous timetables. The current timetable is an important reference in the reactive context as reactive schedules are based on existing predictive schedules. The aim of reactive scheduling operations is to create a schedule with minimum deviation from the predictive one. Timetables are explicitly represented using well-recognized professional standards such as distance-time graphs, individual train journey charts, and train characteristics (e.g., length, weight, code, and service type).

The tacit knowledge of the train-scheduling domain resides mainly in the brains of timetabling and dispatching personnel involved in train operations management who usually work at the regional centers and the HQ. Experts must be able to effectively and efficiently identify conflicts (time and location) and conflict resolution heuristics. In addition, reactive scheduling experts need appropriate skills and experiences in communication, coordination, collaboration, and instruction to obtain required data and information, make appropriate scheduling decisions, and put their decisions into practice. To do so, they are in contact, at least, with the staff within their territory (at stations and on trains), and with their scheduling colleagues in the HQ and neighboring regions. In emergency situations, the scheduling and dispatching experts are responsible for coordinating many aspects of the recovery operations particularly when rolling stock have to be moved along the network. They develop the knowledge of emergency handling and recovery requirements, and they learn about the characteristics of the critical infrastructures (e.g., tunnels, bridges, etc.) and their impacts on the safe operations of trains. Moreover, through experience, schedulers become aware of formalized and nonformalized policies that greatly affect their decisions. Formalized objectives are usually well documented and the predictive scheduling experts are familiar with the communications and processes required to transform transport targets (e.g., millions of passengers per year for a corridor) into train services. Nonformalized preferences (e.g., preferred treatment for special customers) are dealt with in reactive scheduling environments.

Thanks to their tacit knowledge, the reactive scheduling experts are able to predict and take into account possible cascading consequences of their scheduling decisions on the other operating trains and resource availability within their territory. In addition, they are able to estimate the entrance time and impacts of those trains that are going to enter their territory in the next few hours; they inform, confirm, or not confirm their opinion by ob-

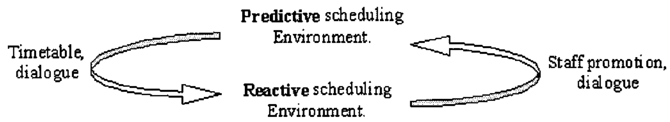

Fig. 6. Knowledge communication cycle in the train-scheduling context.

taining schedule-related information from neighboring regions via a telephone or computerized system.

To conclude, while the two train-scheduling approaches need explicit and tacit knowledge, the reactive approach is mainly based on expert's tacit knowledge while predictive scheduling is mainly based on explicit knowledge.

IV. Train-Scheduling Tacit Knowledge Elicitation

A. Real Case Scenario

The significance of obtaining tacit knowledge from train-scheduling professionals is twofold. First, it strengthens the existing links between reactive and predictive scheduling environments (see Fig. 6). Second, parts of elicited knowledge can be analyzed and used by decision technology experts to develop realistic heuristics, which are more likely to be understood and embraced in real environments compared with "black box" decision-making techniques. Fig. 6 shows that, traditionally, the tacit knowledge of reactive scheduling experts flows to the predictive scheduling environment through 1) the promotion of staff from reactive to predictive work environment and 2) day-to-day dialogue required for traffic management purposes. All these means of knowledge sharing and communication are imperfect. Staff promotion is slow; and fewer experts deal with predictive scheduling compared with reactive scheduling; thus this slow process covers only the tacit knowledge of promoted staff. Dialogue is also imperfect as it is partial and local; it is used to communicate knowledge on specific issues between the few personnel involved. Timetables are rich sources of explicit knowledge that portray the tacit knowledge used to produce them; but a timetable is the end product that does not explicitly represent and explain (give away) the underlying expert tacit knowledge. These facts urge for the application of systematic knowledge elicitation methods.

This section highlights the value of tacit knowledge elicitation method using a real case study that provides insights into the tacit knowledge of train-scheduling experts. The authors elicit tacit knowledge from explicit knowledge, i.e., trains timetable generated manually by the predictive scheduling experts, to learn from it and to increase/generate more explicit knowledge of different type, i.e., scheduling rules. This process leads to the discovery of scheduling heuristics whose excellence can be shown mathematically.

The knowledge elicitation process incorporates two main steps: 1) identifying the attributes of train conflicts and 2) discovering conflict resolution rules.

1) Identification of Attributes: Using the data from train operations along a primarily passenger transport route of Iran's rail network, the conflicts resolved in the predictive schedules of long-distance passenger trains were identified and their attributes were entered into a database designed using MS Access software. Table I shows a few indicators of the magnitude for the timetable studied, e.g., the number of single and double track blocks along the route, the average number of blocks traveled by a train, and the average number of trains traveled along a block. A key factor in this study is the number of "meets" of opposite trains in the timetable; each meet within single-track stretches of the railroad is a potential collision that must be prevented by timetabling decisions.

Table II shows train conflict attributes identified in the timetable studied. We classify the attributes into *absolute* and *relative* classes. For a given conflict, absolute attributes represent the specifications of the two trains involved and the conflict that took place. Relative attributes point to the trains that satisfy certain criteria (i.e., earliest entry, earliest leave, and shortest running time), as explained in Table II; a comparison of the absolute attributes is required to find out a relative attribute.

It has been discovered that a train-scheduling expert may take the opportunity to resolve a conflict at a station where either of the involved trains has to stop for reasons other than conflict resolution purposes. Examples of such reasons are passenger boarding, alighting, technical works associated with engine, and passenger prayers. To some extent, this method could be considered an opportunistic approach that is aimed at minimizing delays imposed on trains and passengers. In addition, the official rules and guidelines considered for directing trains may limit expert choices when resolving a conflict. For example, local trains are delayed when they are involved with nonlocal trains. Practical limitations can also influence experts' decisions; e.g., approaching train moving uphill toward a station may get precedence to the opposite train which runs downhill where the geographical conditions of the crossing point (station) justify the decision formally. Therefore, the downhill train is delayed at the station. Exploring all meets between opposite trains taken place in single-line areas showed that 38 meets take place along the main track, and in 24 cases arrangements have been made for the trains to meet within station boundaries. Therefore, in what follows, we focus on situations where trains meet outside station areas and the scheduling experts are expected to use the rules of thumb to decide which train should get precedence without being forced to decide as such by limitations of the above types.

2) Knowledge Discovery: A careful exploration of 38 conflicts occurred along the single track stretches of the railroad revealed that the train that gets precedence in a conflict satisfies the "earliest leave" criterion unless train operations management rules and guidelines recommend otherwise (e.g., the above example of nonlocal versus local trains).

A detailed analysis of the conflict scenarios reveals the value of the above rule of thumb. In this analysis, an activity refers to a stage of the train journey that needs a block. Therefore, the total number of activities associated with a train is equivalent to the number of blocks traveled by the train. Table III shows 13 different possible temporal relationships between activities $A1$ and $A2$ involved in a conflict, where $R1$ and $R2$ represent running times, RE(1) and RE(2) show ready-to-enter points in time, and RL(1) and RL(2) represent ready-to-leave times for the two activities, respectively. It is worth noting that the 13 scenarios can reduce to five scenarios, as illustrated in Fig. 7(a)–(e). To show the goodness of the heuristic, Isaai and Singh [30] compared the

TABLE I
MAGNITUDE INDICATORS FOR THE REAL CASE TIMETABLE PRODUCED BY EXPERTS

No. of Trains			Railroad			Trains per block	Blocks per Train	No. of Train Meets on	
Up	Down	Total	Single blocks	Double blocks	Length			Single line	Double line
11	11	22	40	10	926 km	18.64	42.36	62	21

TABLE II
CLASSIFICATION AND DEFINITION OF THE TRAIN CONFLICT ATTRIBUTES

Category		Attribute
Absolute	Conflict	*Conflict- id*: the sequential identification number of the conflict. *Resource-id*: the identification number of the requested main line or station line.
	Train	*Train-id*: train's identification number (it shows travel direction from / to the Capital. *Ready-to-Enter*: earliest time the train is available to occupy the requested block. *Running time*: time required to traverse the block occupied. *Ready-to-Leave*: earliest time the train leaves the block if entered at earliest start time. *Ready-to-Leave = Ready-to-Enter + Running time*
Relative		*Train-id (Earliest Entry)*: the train that is available first to occupy the requested block. *Train-id (Earliest Leave)*: the train that leaves the block first if entered at its Ready-to-Enter time. *Train-id (Shortest Running time)*: the train that traverse the block occupied in a shorter time.

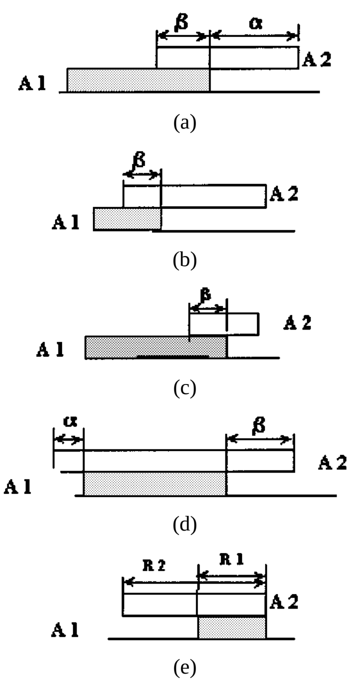

Fig. 7. Distinct train conflict scenarios.

TABLE III
COMPARISON OF THE ELICITED HEURISTIC WITH LOCALLY BEST SOLUTIONS

Conflict scenario	Ready-to-Enter	Running time	Ready-to-Leave	Activity selected by		Fig. (7.)
				Heuristic	Best locally	
1		R1 < R2	RL(1) < RL(2)	A1	A1	b
2		R1 = R2	RL(1) < RL(2)	A1	A1	a
3	RE(1) < RE(2)		RL(1) < RL(2)	A1	A1	c
4		R1 >R2	RL(1) = RL(2)	A1	A1	e
5			RL(1) > RL(2)	A2	A2 if α <β	d
6			RL(1) < RL(2)	A1	A1 if α <β	d
7		R1 < R2	RL(1) = RL(2)	A2	A2	e
8	RE(1) > RE(2)		RL(1) > RL(2)	A2	A2	c
9		R1 = R2	RL(1) > RL(2)	A2	A2	a
10		R1 > R2	RL(1) > RL(2)	A2	A2	b
11		R1 < R2	RL(1) < RL(2)	A1	A1	d
12	RE(1) = RE(2)	R1 = R2	RL(1) = RL(2)	A1 and A2	A1 and A2	d
13		R1 > R2	RL(1) > RL(2)	A2	A2	d

activity which is given priority by the heuristic and the best decision which minimizes waiting times of the two trains at the conflict point (local waiting time). They concluded that in four out of five scenarios (i.e., *a*, *b*, *c*, *e*) resolved by the heuristic local waiting time is minimized; and the goodness of the heuristic decision in scenario *d* depends on the values of α and β as represented in the diagram (see Table III). In fact, the heuristic tends to minimize total local waiting time summed over all the trains.

B. Lessons Learned

In Section III, we discussed the fact that reactive scheduling relies more on tacit knowledge than explicit knowledge. This is shown in Fig. 8. Section IV-A highlighted that, although predictive scheduling depends more on explicit knowledge, expert tacit knowledge is still an invaluable asset. Therefore, the elicitation of expert tacit knowledge of train scheduling, which mainly comes from "reactive" scheduling, can yield value added to the rail transport industry. The comparison of the diagrams represented in Fig. 8 shows that the gap between reactive and predic-

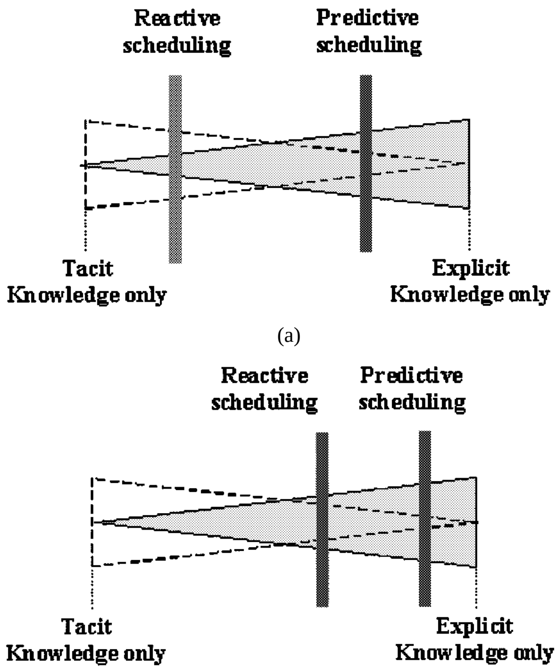

Fig. 8. Positioning train-scheduling approaches (a) before and (b) after knowledge elicitation.

tive scheduling will reduce if tacit knowledge elicitation takes place; and consequently, the amount of explicit knowledge will increase. Furthermore, the explicit knowledge obtained in this process can be used by the scheduling experts in both reactive and predictive fields to improve the decisions and the decision making system; tacit knowledge transformed into explicit knowledge and information can then be categorized, shared, and used for many other technical and managerial purposes within the rail industry such as:

- sharing with personnel who have not yet gained the knowledge via experience (e.g., accidents happen rarely and not all experts get directly involved in accident management to learn from first hand experience);
- renewing vocational education syllabuses;
- revising the regulations of train operations management;
- revising the assumptions used in the predictive scheduling stage;
- reducing the possibility of knowledge loss due to human expert retirement or loss.

As a result, the following improvements in the train-scheduling system would be achieved.

- the generation of better predictive schedule which, for example, reduces the cascading impacts of disruptions on the performance, punctuality, and reliability of services;
- the reduction of work burden and pressure on the experts due to the use of a better-defined code of practice resulting from the elicitation of tacit knowledge;
- making better reactive scheduling decisions and more successful and faster emergency handling operations.

From a business management perspective, the advantages of the elicitation of implicit knowledge are:

- better utilization of rolling stock and fixed installations through better predictive scheduling decisions and better scheduling reactions to unpredicted events;
- less customer dissatisfaction as a result of reducing delays imposed on passenger trains and freight wagons in transit.

V. Concluding Remarks

In this paper, we demonstrated that KM methods could be used to meet the two objectives of a business corporation, i.e., economic utilization of assets and customer satisfaction. Knowledge elicitation was introduced as a means which could transform the tacit knowledge of experts responsible for operational decision making into the explicit knowledge directly usable for enhancing tactical and operational decision making.

The context of our research was two knowledge-based decision-making problems under constraints and uncertainty, i.e., the predictive and reactive scheduling of train operations across a rail network. It was shown that predictive scheduling relies more on data and explicit knowledge and, in contrast, reactive scheduling decisions are more tacit knowledge-based. Furthermore, the elicitation of tacit knowledge contributes to the above-mentioned objectives of the company through revisions of operational regulations, vocational training subjects, and scheduling assumptions using the elicited knowledge. In other words, it was shown that the knowledge elicitation process acts as a part of feedback chain which links the decision-making system to the outside world, without which tacit knowledge obtained by experts in their interactions with the environment may not be used in the best possible way.

Further work is required to highlight other potential applications and advantages of KM concepts for the rail industry.

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