A Review of Online Dynamic Models and Algorithms for Railway Traffic Management

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***Abstract*—Railway timetables are developed to make operations robust and resilient to small delays. However, disturbances perturb the daily plan, and dispatchers adjust the plan to keep operations feasible and to limit delay propagation. Rescheduling approaches aim at updating the offline timetable at best, in the presence of delays. We present a survey of the recent approaches on online railway traffic rescheduling problems, which exhibit dynamic and stochastic (or, at least, not completely deterministic) aspects. In fact, while online static rescheduling has reached a wide degree of dissemination, much is still to be done with regard to the probabilistic nature of the railway traffic rescheduling problems, and also how to best take uncertainty into account for future states. Open challenges for the future research are finally outlined.**

***Index Terms*—Delay propagation, dynamic systems, railway traffic management, train rescheduling.**

I. Introduction

PROVIDING punctual and reliable services is a main goal of rail industries in order to maintain and further improve their competitive advantages in the rapidly changing multimodal transportation market. Train timetables as tactical plans are programmed and updated every year or every season (offline) to define routes and schedules of trains. In daily train operations, various sources of perturbations may influence train running times, as well as dwell and departing events, thus causing primary delays to the planned train schedule. Due to the high interdependency between trains, primary delays could propagate as secondary delays to other trains on a network.

It has been widely recognized that a timetable should be able to handle minor disturbances that occur in real time: this is called robustness, which is also viewed as the sensitivity to disturbances with stochastic variables (e.g., some segment running times follow some distribution) in a macroscopic level (see [24]). A great number of studies have been devoted to building robust timetables, by, e.g., Carey [10], Carey and Kwiecinski [11], Goverde [34], Khan and Zhou [49], and Vromans *et al.* [75]. However, no offline plans can be made robust enough against all kind of perturbations (e.g., major disruptions due to track blockage) without compromising strongly its efficiency (Kauppi *et al.* [47], Zaroliagis *et al.* [82]). To this end, online railway traffic rescheduling approaches have been defined that adjust plans to the actual ever-changing situation of delayed traffic.

Railway traffic control is the problem of adjusting train timetables according to real-time conditions, to minimize the negative effects of unexpected events. This problem has also been called the Train or Railway Dispatching Problem, Railway Dynamic Traffic Management, Railway Traffic Control. The process of adjusting the plan to the actual situation is complex and offers rich opportunities of improvement (see Informs-RAS [42] ONTIME [65], and Schaafsma and Bartholomeus [70]).

We classify the online (also called real time) and offline railway traffic rescheduling approaches into two categories: static (or open loop) and dynamic (or closed loop). Table I reports a structured view on this classification.

TABLE I
Scope of the Review

	Static Optimize only once, with perfect deterministic information	**Dynamic** optimize solutions when new/updated information is available	
Online (done during operations, short computational time of few seconds/minutes)	Online static traffic rescheduling *Open Loop Control*	Reactive dynamic *Closed Loop Control*	Proactive-dynamic *Closed Loop Control*
Offline (done months in advance, long computational time of hours)	Train timetabling	-	

Train timetabling is done only offline and statically, i.e., no accurate prediction or updated information is available, when the timetable is prepared months before operation.

Online approaches are characterized by short computational time (few seconds up to few minutes), need for real-time data, and addressing specific objective functions aiming at recovering the original plan. The online approaches can be static if they are performed only once, with full information, or dynamic if the information they are able to use changes over time. The interaction between operations, control, and operations again is clearly happening along a time dimension, i.e., only future actions can be controlled. This distinction coincides with the

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difference between open-loop control and closed-loop control. More details follow.

Moreover, we can distinguish between reactive approaches, which neglect a view of the future when taking decisions and proactive approaches. The latter considers the perturbations and the prognosis of future statuses of the network, which is known in a probabilistic and time-dependent manner. Thus, probabilities of the expected time of future events (such as an arrival at the station) would change over time and will be known with full precision only when the event actually occurs. The time resolution of the control process considered here relates to an extent in the order of magnitude of hours and involving a set of multiple trains.

The train path rescheduling is the process of updating the timetable (the published plan of train departures, passing times and train arrivals, and routes over rail network), by taking into account the current position and speed of trains, and their delays. The circulation of trains is represented, so that feasible train movements are computed, complying with the measured position and speed, train dynamics, and safety system. In particular, the crucial problem is that no two trains can be at the same time on the same block section, due to the limited capacity of the infrastructure. The blocking time theory (see, e.g., [37]) is to be used to check the safety of train movements, at the microscopic level of switches, tracks, and individual infrastructure elements. Due to the microscopic level required, optimization approaches are generally able to manage only relatively small time horizon (usually no more than 1 h) and areas (usually no more than a single dispatching area of 50 km).

This paper reviews online dynamic approaches for a railway traffic rescheduling problem. In fact, despite control of a railway network is a phenomenon that is triggered by external random processes, the uncertainty is mostly neglected in current schemes. This motivates this review and its specific focus. We refer to the recent reviews [15], [31], and [63], and the recent research works [14], [15], [57], [63], [71] for more details and a larger scope.

The rest of this paper proceeds as follows. We first analyze and cluster literature based on control setup, time dynamics, mathematical model, and details, and then, we draw connections with other railway problems and finally conclude the review.

II. Control Setup

Online control approaches are based on the general scheme reported in Fig. 1. In particular, data are measured from the real world, describing relevant factors, discussed in the following. These data are inherently online and make the problem different from offline approaches, where there is no such input. These data are used in modules that can be considered by controllers, who use certain model and rules to come up with control actions. The control actions are the input to steer the system to a certain desired state, as also described in the following.

In general, such systems are included in iterative frameworks that adjust the forecast and the solution along time, in a closed-loop control setup inspired by rolling horizon optimization, or model predictive control.

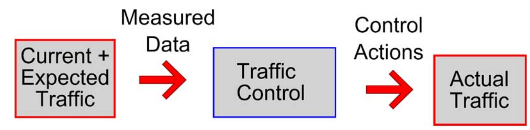

Fig. 1. Setup of traffic control.

A. Measured Data

Data that can be measured and made available to control normally include positions, and timings [60], [69], [71]. Approaches that include a speed profile of trains also need current speed of trains [16] and or speed target [56]. Moreover, the rescheduling normally aims at returning to a planned state following the timetable, thus information on the plan should be made available as well. Very few approaches consider extra information such as amount of passengers (used otherwise in line planning); mass, performance, and dynamic characteristics of trains (for speed advice [2], [72]), unless for very large deviations known as disruptions [16], [46], [60], [66].

To characterize possible future states, dynamic approaches thus need also data about random processes described in the system, such as running time prediction; expectations of entrance times and dwell times, their variability, and so forth. More will be elaborated on this, in Section III.

B. Control Actions

Control actions include all measures that a controller might take to change the traffic to a certain desired state [56]. In practice (see, e.g., [79]), this relates to the choice of

1) **time**: changing planned times at reference points (retiming) involves normally adjusting the speed profile of trains, making them go slower or faster than planned. While a stream of research considers retiming as a possibility to predict future operations [34], [48], to reduce delays [9], [23] [38], [59];
2) **speed**: the updated speed advice are provided to drivers to avoid possible conflicts or save energy [2], [34], [35], [39], [51], [66], [73], [80] due to braking and reacceleration of trains. The two objectives of saving delays and at the same time reducing energy are investigated together by a third stream of research [22], [56], [59], [67], and to a different extent by speed management policies [20];
3) **order**: changing the order of trains at shared infrastructure elements is seen as a critical action in the restricted infrastructure capacity of trains [3], [15], [16], [23], [25], [29], [44], [58], [59], [66], [71], [73]; Historically, most research has been dedicated to the meet and pass problem, i.e., finding the place where trains can be held before switches and block sections or single-track areas; a single train at a time can move between two meet locations [10], [51], [60], [66], [69], [74], [76], [78], [81];
4) **local route** in a complex interlocking area: changing the path of a train with an adjacent, very similar path, in a local area, such as changing platforms at a station or the route connection a track to a same platform [6], [16], [57], [66], [71];

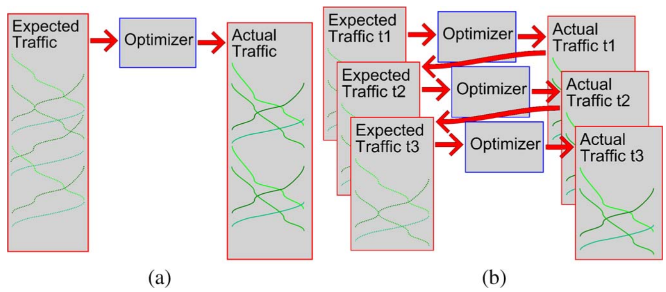

Fig. 2. (a) Open-loop control. (b) Closed-loop control.

5) **global route** in a network: a completely different rerouting possibly skipping stations and passing through different stations is computed in order to fulfill the service intended [45], [64];
6) **service**: the service is modified, by canceling part of trains, short turning trains, canceling, or adding stops [77].

Increasingly, the degree of freedom allows better solutions, but at the cost of extra computational complexity [79]. Due to the large complexity, only very few online dynamic works consider the latter two; and very few address control actions different than times, orders, and routes. The majority of approaches reviewed consider those control actions in a sequential manner, generally starting from global routing. An example, global routing decision, can be taken to avoid a blocked area, local rerouting can be then chosen to spread capacity usage at bottleneck stations; orders can be decided, and all those orders result in times associated to train operations [19]. In addition, the opposite process can be followed, i.e., first computing a set of passing times and then finding a feasible route assignment; this was done, for instance, in [6] proposed for the competition [42]. One possible drawback associated with sequential methods is that the limited options investigated in one step could dramatically downgrade the performance of the second step. To address the issue, recent studies proposed approaches that simultaneously consider the aforementioned rescheduling actions with the goal of finding the globally optimal solution [61], [66]. With regard to providing train speed advice in real-time operations, most studies focus on one train only (see, e.g., [2] and [51]), as the interrelations between trains are quite complicated and not easy to model and solve within short computational time.

C. Open-Loop Approaches

Open-loop approaches (including the online static approaches of Table I) generate rescheduling solutions based on perfect information about the current status of infrastructure, train positions and speeds, and precise prediction of delay characteristics and expected time of future events. They are run only once. Most optimization works assume this setup as it translates in solving a problem once and for all [3], [6], [10], [25], [38], [44], [57], [62], [66], [69], [79], and then suggest possible schemes for implementation in reality [16]. Prediction models (i.e., delay propagation approaches) do not control traffic so they somehow fall off those classification [5], [28], [34].

Fig. 2 clarifies further on open-loop and closed-loop approaches; in an open-loop control [see Fig. 2(a)], the optimizer is run only once, with a full knowledge of events happening far in the future.

D. Closed-Loop Approaches

Differently, in a closed-loop control, the optimizer is iteratively called at subsequent times $t_1, t_2, t_3, \ldots, t_n$, every time defining a stage with an expected traffic situation and an actual traffic; the expected traffic at time t_{i+1} depends on the actual traffic at time t_i, which in turn depends on the control actions computed at all preceding times $t_1, \ldots, t_i$. See Fig. 2(b) for a reference scheme. Closed-loop control inherently leads to issues on the consistency of solution across different stages; in fact, open-loop control avoids this problem by having a single stage. Variability of solutions across different stages is called stability (investigated in [68] and assessed by a set of metrics) and solution quality, studied, for instance, in [18] and [71]. Moreover, more operational choices are to be made, namely, when to perform an extra stage, whether it is based on deviation [56], [67], [77] or based on time steps [9], [59], [68], [71]. For the latter group, computing frequently updated solutions leads to quicker adjustments and better solutions, but at the cost of multiple changes [68]. To reduce the negative impact of multiple changes on local dispatchers (e.g., station manager), drivers and passengers [60], [68], [79] focus on generating robust train dispatching solutions that are capable of handling stochastic disturbances/disruptions with ensuring unique orders for a line or routes for a network under a stochastic and dynamic environment.

III. Dynamics of Forecasts

We discuss here a main feature of online dynamic approaches, namely, the dynamics of forecast over time. This is the answer to "what is known when?" and defines what is known among past, present, and future, and whether delays derived from real-life operations. Modeling uncertainty and predictions is essential to compute optimal and acceptable control action. The purpose of the control system is indeed to deal with deviations from the plan computed offline, i.e., delays. According to Yuan and Hansen [80] that reviews delay process and models, delays can be following Uniform, Gaussian, Negative Exponential, Inverse Gamma, or Weibull distribution; and the delay can affect a single train, a set, or all traffic. Dwell times at stations can also be perturbed.

Moreover, the delays can be expected and included in optimization schemes, and delays are influenced by the current status of traffic and network. Updates from operations in closed-loop operations enable higher reliability estimate of the future.

We refer to this with the help of Fig. 3. For an event (for example, the arrival of a train at a station), we plot different probability densities of the time at which it will happen, depending on the time at which this measurement is made. Both axes refer to time: x-axis is the time at which the event is supposed to happen (a guess) or has happened (a measurement); y-axis is the time at which this guess or measurement is done. The event has a planned time, which is expressed by the vertical green dotted line.

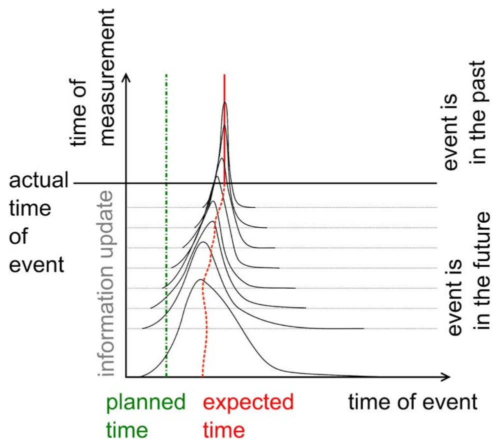

Fig. 3. Dynamic of forecasts of future events.

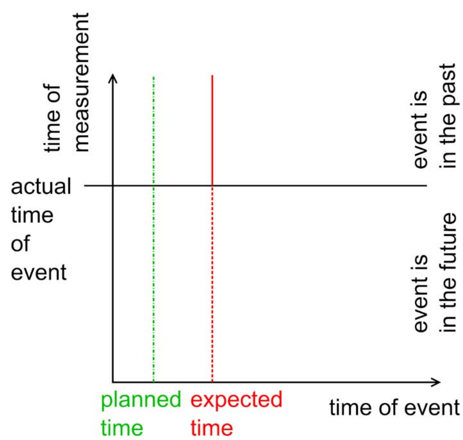

Fig. 4. Complete knowledge of future.

At time of measurement 0, we consider that the event time is far enough in the future not to be influenced; thus, we can compute an offline probability distribution and an expected value. When information updates are present, we can compute a new probability distribution of the event time until the event is actually happening. In this process, we expect the variance of the event time distribution to decrease along time, and when the event is actually happening, its realization will be deterministically known, and with no variance. We plot the evolution of the expected realization time as a red dotted line, assuming different values at different time measurement, and being vertical (i.e., constant) and solid after the actual event time.

Buker and Wendler [8] make a thorough study on delay dynamics, i.e., how delay distribution and value change over time. In principle, only the past is exactly known, whereas the future can be considered only as an expectation; nonetheless, the academic approaches reviewed often assume simpler setups with regard to information that are investigated in the following.

A. Complete Knowledge of the Future

If everything is known before taking decisions, we call it full information; static approaches assume this setting. We report this in Fig. 4. This is the simpler setting and can be, for instance, assumed for planned operations, such as maintenance, or if the reliability of predictions is very high (for instance, in closed systems) [63].

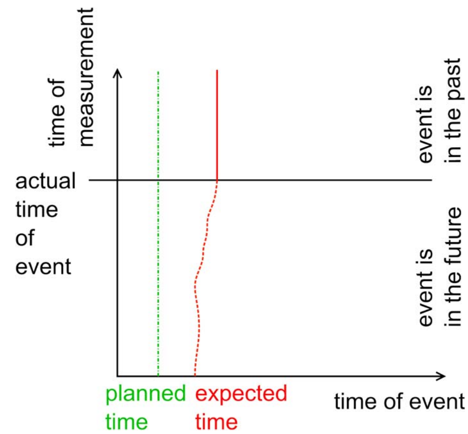

Fig. 5. Continuous information updates.

We consider in this category also all approaches that did not implement any update due to time; in this case, the expected time is fixed once for all, and the setup is corresponding to a complete knowledge of the future, or at least, the optimizer believes he knows completely the future [3], [10], [15], [16], [22], [69].

Approaches that result in a similar setup are also time decomposed. The overall problem of controlling trains is split into subproblems along the time dimension (i.e., controlling only a slice in time of the problem), but only for combinatorial purposes [30], [66]; in some limited case [9], this also addresses limited information available. At every stage, the solver knows completely the future within the stage [6], [23], [66], [71].

In addition, approaches that assume a certain knowledge of delays, for instance, as expected value that does not change along time will be described in the same terms. In this case, we point out that the optimizer does not have complete knowledge of the exact future, but only of some expectation of it. Moreover, the information available is constant along time: there is no influence of time toward a larger or better degree of uncertainty. The solution taken under full knowledge of the expected values only are then evaluated against “real” stochastic conditions, in general, represented by an external system [17], [54], [73] or real life.

B. Continuous Information Updates

The information updates can further be continuous (reported in Fig. 5), or discontinuous. Considering the behavior of current signaling system, which sends information only when a train passes a section boundary or a reference point, might lead to a semicontinuous information update (i.e., train position and speed in [59]). An incomplete knowledge of the future can still allow a description in probabilistic terms [48]; for instance, based on offline distributions (e.g., time series of recorded running times).

For an event happening in a future close enough, one might assume that the probability of its realization time is influenced by the current status of the network. For instance, a train running late in a neighboring control region has a higher

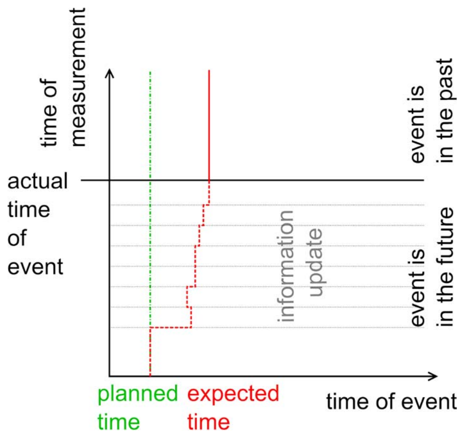

Fig. 6. Discrete information stages.

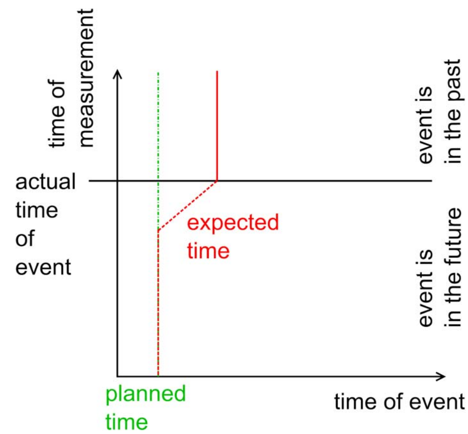

Fig. 7. No knowledge of the future.

probability of being delayed, but the exact delay can only be known when it enters the control area. Information is thus achieving a higher reliability the closer is in the future. No approach in the literature is known to be working this way; anyway, this can be considered a limit case of the following case C when the frequency of information update is very high.

C. Discrete Information Updates

When a closed-loop setup is considered, online dynamic rescheduling is organized in a succession of stages of optimization and control. For those approaches that prescribe updates in the operational plan at fixed time intervals, the update of information coincides with the stages of the closed-loop setup [9], [18]. This is reported in Fig. 6. The time intervals at which data are updated might range from 10 min ([66]; train orders in [59]), to just 1 s [9]. Prediction horizon for a single stage might range from 30 min [66] to 1 h (most approaches) or up to 3 h [23]. A different approach relies on event-based trigger to recompute the solution and update the plans, as discussed in many works (e.g., [44]). Information can also be shared to the optimizer routines at fixed intervals far away in time, such as in [64].

D. No Knowledge of the Future

The most radical approach is to neglect completely what future might be, i.e., expecting it at its planned time, until it did not happen. Thus, the actual time, when the event happened is considered, rather than forecast information. This is reported graphically in Fig. 7. In this sense, prediction has limited to no importance, and most decisions are taken based on the current situation [44] and a limited look ahead [29].

Most dispatching rules, including the first-come-first-served (FCFS) evaluated in [16] and distributed approaches [43], [52], [53], [55], [74], are considering prediction only to a limited extent. Those approaches are dynamic in nature (i.e., they take decision only at present time regardless of future evolution) but they provide in suboptimal decisions. All approaches that are implemented in real life can be considered in this category, as they exploit knowledge if the future in a minor extent, whereas they are based heavily on the precise knowledge of the present state [5], [28], [57], [59].

IV. Mathematical Models

We now review the mathematical models considered. The structure of a problem can be easily casted into a sequence of actions to be coordinated, either one after each other (i.e., stopping after having reached a station) or together (i.e., departing after the published departure time and a minimum dwell time at a platform) [37]. All models considered specify linear constraints based on discrete events, i.e., relevant times of operations are identified and considered as events whether the status of a variable or the system will change. Most optimization approaches result in linear mathematical programming structures. Those are able to address constraints and objective function in linear forms (including [9], [16], [57], [60], [66], [73]). Such structures can be expressed in a timed event graph, and further summarized into a compact set of expressions and constraints involving the $(\max, +)$ operations [34], [73]. Recently, the alternative graph [58] has been increasingly used for this purpose due to its flexibility in representing most constraints and variables in a generalized job shop scheduling model.

A. Modeling Time and Capacity

Concerning the approach with regard to time, most of the approaches consider the variables as time continuous, allowing any value in $\mathbb{R}$ for event times to be decided by processing time constraints. The other possibility is to use time-indexed variables: the problem is modeled as an assignment, i.e., a limited set of possibilities is considered defining times (often discretized to full minutes), orders, routes, and connection to choose from. Works on this second cluster include [9], [38], [61]. This latter approach allows limited complexity by greatly reducing the domain of variables at the expense of more integer variables for selecting the appropriate timing. Most offline timetabling solvers used this approach.

When modeling infrastructure capacity, exclusivity in infrastructure occupation must be granted [37] differently from most offline optimization approaches. This naturally leads to two families of formulations for modeling train orders and safety headways. If a variable is associated to every possible order, disjunctive constraints will be employed, i.e., the variable takes the logical meaning of an "OR" between the two possible orders between trains. This requires, on the one hand, identifying all train conflicts (thus, people refer to this approach also as conflict oriented). When writing a model in common mathematic formalism, such constraints normally results in big-M formulations that are known to be computationally weak. To avoid enumeration of all possible conflicting orders, the other approach is instead resorting to cumulative constraints, and models implicitly the capacity constraint on resources: the number of trains occupying one resource cannot exceed the capacity at a time; such an approach can also be called resource oriented [6], [61], [66] as it limits the cumulative use of resources by set-covering constraints, which might result in better linear relaxation, and enable also efficient and relatively easy problem decomposition.

B. *Objective*

The objective of railway traffic management is to improve performances of running traffic. Simulation models that try to replicate the flow of real life, taking decisions "here and now" [12], [14], [34], [44], [70], and have no reference to an objective function. Differently, heuristics that are not explicitly minimizing an objective function [4], [25], [29], [41], [59], [69], [71], although they take decisions that are supposed to decrease some performance indicator (such as delay). Generally, little to no quantitative information about solution quality is provided.

Mathematical optimization models have instead a well-defined objective function. Typical objectives refer to delays, being average or maximum [16], [66] and further divided into total (i.e., considering the sum of disturbance and the conflicts) or only consecutive (i.e., those caused by train conflicts only). Some approaches use the (weighted) travel time of passengers [71] or the weighted deviation with regard to the planned schedule. Other interesting objective functions might include (a combination of) passenger travel time [3], [30], deviation from timetable, minimize time to recover operations, and fall back to the original plan [6], [60], maximize punctuality; minimize running cost, or energy spent [1], [2], [22], [39], [51]. Approaches that simulate operations, or use dispatching rules, or simple heuristics have no explicit objective function. Closed-loop or time-decomposed approach might specify the objective for each subsequent stage [23], [66], or as a whole.

Finally, the formulation might be synchronous with time (i.e., decisions are taken as time goes by; among the works reviewed only FCFS, discussed in [16] can be considered here) or asynchronous (able to understand the consequences of choices taken now in the future; the majority of the works) [37].

C. *Degree of Stochasticity*

Most approaches work with deterministic variables, and if confronted with stochastic distributions, they follow a Monte Carlo approach, i.e., they provide a large set of realizations and experimentally reproduce the behavior for all those realizations. Deterministic models associate a single value to parameters and variables, as the expected times in Figs. 2–5.

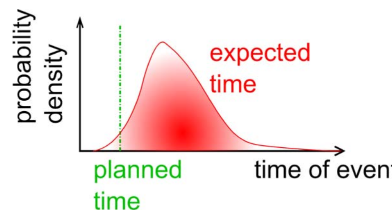

Fig. 8. Continuous probability distribution.

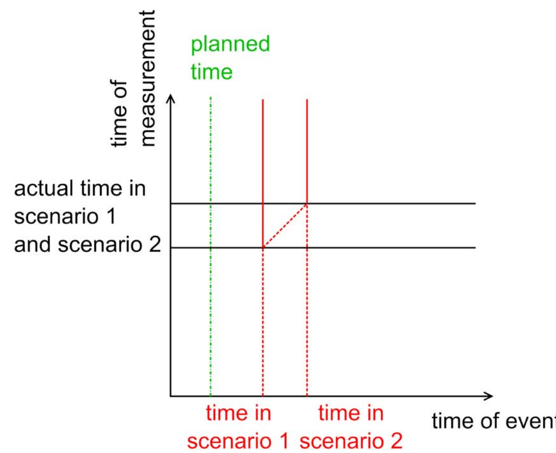

Fig. 9. Probability for event times based on two scenarios (1 and 2).

On the other hand, stochastic approaches inherently model the variables inside the model as probability distributions (the case of continuous probability distribution is reported in Fig. 8).

For example, delay propagation algorithms [34] consider the travel time of trains having a distribution. Then, they need convolution of variables to determine the resulting distribution of event times. Fully stochastic models, in which characteristic variables have a probabilistic extent, have had a very limited application into practice due to the huge complexity of convoluting stochastic variables during the decision process. In fact, optimization approaches need evaluations of solutions and that is particularly challenging in such a stochastic setting. Retiming does no need to optimize any disjunctive or cumulative variable modeling of infrastructure capacity. For this reason, only retiming is considered in [5] to avoid the need to compute expected objective values in stochastic setting. Otherwise, a single stochastic variable (thus simplifying greatly the evaluation of a candidate solution) was considered by Meng and Zhou [60]. The introduction of fully fledged stochastic programming can be the next challenge to tackle in railway operations research. For online approaches such as the one considered in this review, the evaluation in a probabilistic setting is made more complicated by the rolling horizon approach, in which delay dynamics within a stage (i.e., uncertainty of variables at a time point) need to be combined with uncertainties across the stages (i.e., the varying expectation of a variable over time).

Instead, approaches based on stochastic scenarios associate a small set of values to parameters and variables, to which they might associate a probability. This is typical of worst case analysis and has been considered in [13], [60], and [64]. A graphical description is in Fig. 9.

The solution process relates to the way, in which a solution is generated. Most approaches exploit the combinatorial structure of the problem to define mixed integer linear programming problems and use commercial solvers [6], [7], [9], [38], [57], [61], [64], [66], [71], [73], [78] or custom implementation of heuristics or exhaustive search procedures [4], [15], [16], [20], [22], [23], [43], [44], [56], [59], [62], [69], [74], [79]. The mathematical models might require much time (unacceptable for real-time problems) for even a small approximated problem, to obtain optimal solution(s) [37].

D. Level of Detail and Layout of Infrastructure

The detail considered can individually model track sections, switches and the influence of safety system (called microscopic in what follows) [16], [18], [44], [66]. Or, only the merge and passing points can be modeled explicitly as conflicting resources with finite capacity, whereas the rest is modeled roughly [25], [26], [29], [38], [41], [49], [57], [60], [62], [71]. The simplest models consider stations and track each as a single resource with unlimited capacity (macroscopic), analogous to timetabling problems. Consequently, with the modeling detail, the test case can be one or a small set of lines (e.g., [18], [22], [23], [38], [41], [44], [59], [60], [69], [71], [73], [74], [81]), a complex station (e.g., [9], [16], [66]), a terminal area of a metro line (e.g., [57]), up to a full network (e.g., [6], [30], [61]).

The layout and the details of the model might be as follows.

1) Single track, if trains need to meet or pass, and this bottleneck is a substantial part of the network.
2) Double track, the relatively common case in which trains use two relatively separate and parallel tracks.
3) Single direction, if trains head toward the same destination.
4) Double direction, if trains are going in both directions along a substantial part of a network.
5) Crossing can be found when trains in different directions are crossing each other, for example, in stations.

Most of approaches use a single track-type rail line as the context. Some other studies focus on a general (N-track) network with both bidirectional single track and unidirectional double track [6], [61], [62], [71], [78]. The modeling complexity comes from two aspects: 1) from line to network, in which one needs to model continuity in routing of vehicles, e.g., [61] and [62]; 2) from one single track-type network to mixed track-type network, in which one needs to model different usage rules in single track and double track. In aspect 2), in double-track, double-direction segments, every direction can be considered as a single-track segment (see, e.g., [61] and [71]), to avoid additional complexity and large computation time.

The literature shows that although each study used experimental beds or cases to test the proposed approaches, the input rail line, or network, signaling rules and input disturbances are different, which becomes a barrier for researchers to fairly compare the performance of their approaches with others. This is also a conclusion of [31] and [63]; approaches that make available instances to the community still rare [30] mostly due to intellectual property and confidentiality issues.

V. Interrelation With Other Railway Problems

A few other railway problems are deeply interrelated with the rescheduling problem, namely, the crew scheduling, rolling stock scheduling, and connection management (or delay management). We briefly discuss how those problems can benefit from online dynamic approach as well.

Updating an offline railway timetable to online operations requires more than only rescheduling traffic. In fact, the rescheduling plan provides a skeleton that is required to find solutions to other subproblems, such as rolling stock rescheduling, crew rescheduling, station operation plan rescheduling, determining which passenger transfers to keep.

A. Crew Scheduling

No train movement can be operated without a driver taking care of it. The crew rescheduling problem is to assign personnel to train services, so that all planned services can be run while minimizing the cost of stand-by personnel. Since the scope spans several hundreds of kilometers and multiple hours, most common models neglect capacity of the infrastructure for the sake of ease of computation. The problem is complicated by the fact that personnel might need to use train services to reach the place where they should take over a work shift, and a larger delay might arise if those services are delayed themselves. Moreover, during disruptions, circulation of vehicles need to be updated and adjusted, with particular emphasis on unavailable routes (blockades) and off-balanced vehicles (requiring deadhead trips, and spare vehicles). We refer to [36] for more details. Most approaches deal with the rolling stock circulation problem offline, i.e., based on a full knowledge of the disruption duration, and the position of available vehicles. Nielsen *et al.* [64] propose a rolling horizon approach and study in depth the interrelation between the prediction horizon, the cycle time, and the knowledge of the expected duration. In particular, the impact of (deterministic) updates of the disruption duration is taken into account. Jespersen-Groth and Clausen [46] deal with the problem of reservicing lines that have been canceled after the disruption has ended. [3] presents instead a study that explicitly considers passenger flows by means of a network loading model and greedy heuristics to solve the vehicle rescheduling problem by computing solutions for a sequence of time periods. They suggest that optimization approaches should be traded off in favor of heuristics to be able to optimize vehicle trips during operations.

B. Rolling Stock Scheduling

Similarly, no train service is possible without an available vehicle. Rolling stock scheduling is the problem to assign a vehicle for every train service that is intended to run. Spare vehicles are rare due to their high cost, thus in case of delays, services can be largely delayed by if rolling stock is not available at a given time and locations, as prescribed by the plan. Current models commonly describe the infrastructure in an approximate manner, and mostly neglect dynamic setting. We refer to [7] and [37] for more details.

C. Delay Management

Finally, the delay management problem is to decide which transfer connections should be kept or dropped while running delayed traffic [32], [33]. We refer to [26] for more details on this problem, with particular regard on the integration of constraints from stations and track. This problem is inherently online, i.e., the expected delay of both feeder and connected train are core ingredients determining the outcome of the optimization model. Anyway, most optimization approaches focused on the delay management problem with full information. A critical review of the performances of different heuristics and methods when subject to incomplete information is reported in a single study [50]. Here, the models neglect infrastructure capacity, and dynamicity is only limited to knowing only primary delays that have been recorded (no prognosis). A limitation of the work is the degree with which delay distributions and their knowledge represent a realistic situation. Gatto *et al.* [32] presents instead a theoretical analysis of the competitive ratio between approaches with limited information (only the realized delay of feeder train is known) and with perfect information. Bauer and Schöbel [4] present simple rules that can be computed offline and the result in dynamic dispatching rules to be applied online.

D. Discussion

Most approaches consider those interrelated problems in cascade, i.e., solving one of them based on the solution of the others, and incorporating this solution as the basis for an updated solution of the three problems. This is the approach mostly used in practice and academia due to the different level of details required: rescheduling has a precision of seconds and a horizon of few hours, whereas rolling stock and crew are usually optimized with a resolution of full minutes and have a horizon of one day or a week. The obvious drawback of a sequential approach is that a unified picture is missing and that the constraints that relate different subproblems (i.e., a rolling stock connection in the rescheduling model; or the capacity constraint in a rolling stock circulation model) are dealt with in a simplified and suboptimal manner.

Few approaches have been effectively able to couple more than one problem, for instance, delay management and train path rescheduling [27]; rolling stock and crew rescheduling [36], [40]; and train path rescheduling plus crew rescheduling [7]. Such a simultaneous approach strives for global optimality. The challenge is then a suitable choice of detail, horizon, and mathematical formulation to ease finding a solution in a timely manner. Such a comprehensive model will be of great interest for practice and interchange of coherent information within a company.

VI. Conclusion

This paper reviewed the most recent approaches that consider online (i.e., directly interrelated with variability of operations), dynamic (i.e., considering explicitly evolution in time and with limited information about future such as distributions or expectations only) rescheduling problems in the railway world. We analyzed approaches for the problem of railway traffic rescheduling that is solved with incomplete information in a closed-loop (inspired by a rolling horizon or model predictive control) setting. The analysis points out a few open directions of future research: integrating the different related problems, taking decisions under uncertainty, determining at best delay distributions and their prognosis, having publicly available test cases for the different problems.

Railway operations research benefits from a lot of advanced approaches related to offline mathematical models and algorithms [52]. Many challenges are left open for research.

1) Most of existing research models tend to be dedicated to one issue and look for global optimality, rather than global feasibility taking into account extra constraints typical in the railway world. In fact, considering only limited knowledge of the future might well decrease the appeal for global optimum approaches (that would be reachable in case of full and perfect information). This is also related to the variety of problems that are deeply interconnected in the railway operations: practically applicable dispatching plans need to reschedule at once train paths, crew, and rolling stock, generating solutions that are feasible for the three aspects, while being suboptimal or optimal for a selected objective. As crew and rolling stock schedules are generally very large in scale, train path is generally limited to lines or dispatching areas due to complex microscopic detail required. There is thus a need to come up with train paths solutions spanning large areas, by means of coordination between adjacent dispatching areas (see, e.g., [15]). Moreover, the feasibility of train paths needs to be ensured at microscopic level for any solution, at local and global scale.

2) In order to propose a dispatching solution for a large dispatching area, a recent research trend is to develop a hybrid approach which tries to integrate the advantages of simulation, heuristics and mathematical approaches (see, e.g., [27] or more in general, [52]). With such an approach, one can first generate a dispatching solution using macroscopic mathematical models and heuristic models on a large-scale network disregarding microscopic details of infrastructure and trains. Then one needs to check carefully capacity usage at the expected bottlenecks of the network (mostly big stations, interlocking areas, stretches with reduced amount of tracks). To do so, microscopic simulations including all operational details can ensure the feasibility of train movements.

3) Recent studies aim to solve the rescheduling problem to optimality. An optimal solution can provide a theoretical benchmark for the railway traffic rescheduling problem, with simplified description of infrastructure, signaling systems, and rolling stock characteristics. Rigorous mathematical formulations and solution algorithms (e.g., [23] and [81] were proposed for formalizing the problem and obtaining solutions). Branch and Bound algorithms seem to be promising for finding optimal solutions on single-track or double-track rail lines. However, for a network context, branching rules becomes rather complicated due to the requirement of "mutually exclusive" property for what concerns infrastructure capacity. This defines open problems for the definition of effective Branch & Bound approaches in academic setting. From a practical point of view, close-to-optimal solutions within practically acceptable computational time meet the requirement of assisting dispatchers for real-time

rail traffic management. (Meta) heuristic algorithms can be fruitful to construct solutions. It's still an open topic to provide real-time solutions with optimality or information of optimality gap.

4) Common test cases are needed in order to evaluate and compare different models and solution approaches (see, e.g., the positive example of the RAS competition [42]). This can also be resulting in investigating the limitations of iterative approaches with regard to plans and uncertainty, of available data stream from the industrial field. In fact, the deployment of advanced signaling system such as (European Train Control System) or (Chinese Train Control System) will provide high-quality real-time data available for rescheduling.

5) If the goal is to elaborate strategies for the practical use, more realistic delay distributions should be defined and investigated (see, e.g., [80]). Furthermore, it is also important to increase the effort in collecting and maintaining realistic data (based e.g., on smart card data, but also on traditional passengers counting techniques) about passenger flows within a large network subject to various types of disruptions.

6) State-of-the-art of railway traffic control research tackles uncertainty in future, for instance, by automatically categorizing train trajectories in deterministic terms. A lot of effort is to be dedicated to the relatively simple task of prognosis and precise prediction of future train/infrastructure status (see, e.g., [28]).

7) So far, so called automated train dispatching systems are implemented in many railway control systems. However, these systems are essentially visualization tools or management information systems relieving traffic dispatchers from pencil and paper [21]), and station dispatchers from setting arrival/departure routes. The main functions of such systems typically do not include automatically generating dispatching plans, which is left for future developments of decision support systems for dynamic railway traffic management. There is an emerging trend to simultaneously reschedule trains and generate train control actions (e.g., train speed profile advice).

Some of the open challenges from academia and practitioners here reviewed are or have been at the focus of ongoing or recent research project (ARRIVAL [82], ONTIME [65]). Nevertheless, further research is envisaged.

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