Towards a Realistic Evaluation of Railway Infrastructure Capacity

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1. Introduction

1.1. Railway Infrastructure Capacity Problem and Economic Issues

In accordance with European directives ensuring free competition, national railway infrastructures are not owned by national train operating companies anymore, but are now under the responsibility of dedicated managers. As a consequence of free competition, private operating companies can request slots to infrastructure managers. One illustration of this phenomenon is Italian companies requesting slots on the French network, as part of the link between Paris and Milan. We thus observe an increasing number of actors aiming at exploiting the railway network. Moreover, rolling stock characteristics such as trains length and maximum speed often vary from one operator to another, which may implicate additional difficulties to make them circulate on the same infrastructure without implicating heavy perturbations.

In addition, the global railway traffic tends to increase, as shown by recent heavy investments consented to build new infrastructures such as the East-European high-speed line and the Polish project for a high-speed connecting Warsaw to Wroclaw and Poznan. Railway transportation also tends to be favored as a result of environment-aware policies, as it is considered as a low-polluting means of transport.

Synthetically, infrastructures tend to become more and more saturated with heterogeneous rolling stock, yielding an essential problematic for both infrastructure managers and train operators. On the one hand, infrastructure managers have to decide whether a slot should actually be sold to an operating company in order to make the infrastructure as profitable as possible. On the other hand, operating companies may want to best meet the passenger demand by designing optimized schedules before requesting slots.

From that perspective, the *capacity* of a given infrastructure may prove to be a valuable argument to arbitrate discussions between operating companies and infrastructure managers. The UIC Code 406 (1) states that capacity can be interpreted in various ways, depending on parameters that have to be taken into account, such as priorities for certain trains, environmental considerations or quality of service criteria. This paper uses the following interpretation for capacity. Given a voluntarily over-dimensioned schedule, it is defined as the maximum number of trains from this schedule that can circulate through the infrastructure within a certain time window, while preventing conflicts and respecting safety constraints enforced by the signaling system. The input over-dimensioned schedule will be named *traffic demand*. If necessary, trains can be allowed to be slightly shifted from their nominal time specified by the demand. It may also possibly be required that this maximum number of routed trains have to constitute a schedule that respects a certain *robustness*, which is its ability to absorb unforeseen delays.

1.2. Declinations of Capacity Analysis and Existing Software

Two distinct levels are usually considered when estimating an infrastructure capacity. On the one hand, the “network scale”, or macroscopic level, entails computing capacity on large sub-networks such as corridors between major cities. On the other hand, the “node scale”, or microscopic level, aims at assessing capacity in junctions and stations that often consist in bottlenecks for the network. The two approaches differ by the level of details considered. At microscopic level, only one node is considered and it is modeled as precisely as possible in order to optimize efficiently the traffic, whereas macroscopic approaches can not afford to model precisely all stations and junctions crossed by the traffic as they consider a wider view of the traffic.

Joint work between academic researchers and railway companies led to the development of capacity analysis software. One of the first efforts at macroscopic level is the work by Hachemane (2) that led to the CAPRES software, which has been used by Swiss and French companies. A more recent system is the DEMIURGE software, which is also dedicated to macroscopic level and intended as a replacement to CAPRES. In the context of the European project ARRIVAL, Abril et al. (3) also present the MOM capacity analysis system and provide a complete review of existing software.

At microscopic level, one of the first effort was put forward by Zwaneveld et al. (4) and led to the STATIONS software, included in the wider DONS project for the Dutch railways. Based on theoretical contributions brought by STATIONS, Delorme (5) suggested adaptations that were implemented in the French software RECIFE (6), which is dedicated to microscopic level capacity assessment. As put forward by Schlechte (7), the high level of details considered in microscopic studies often implicates that only small instances can be computed in reasonable time, i.e. with a moderately large initial schedule.

Many additional approaches exist, although not all of them necessarily led to user-oriented software. An exhaustive review is provided by Lusby et al. (8).

Finally, an effort to regroup microscopic and macroscopic models is made by Schlechte (7) through the NETCAST software to create aggregated large-scale networks from highly detailed descriptions provided by modeling software such as OpenTrack.

1.3. RECIFE: A Multi-Criteria Decision Support System for Assessing Capacity

RECIFE (6) is a research project originally supported by the French Nord-Pas-de-Calais region and for which research has been carried out by several partners, including IFSTTAR[1], University of Valenciennes, École des Mines de Saint-Étienne and University of Nantes. It led to the development of the RECIFE software platform which is dedicated to leading capacity studies at microscopic level. From that perspective, it contains a collection of tools useful for such studies, including, among others:

- Traffic scheduling algorithms aiming at re-ordering traffic in case of delays, as presented by Rodriguez (9);
- Optimization algorithms to saturate the infrastructure with a given traffic demand and thus obtain a capacity assessment;
- Robustness computation algorithms for saturated schedules;
- Tools for visualizing the circulation yielded by saturated schedules, Gantt diagrams of the circulation, estimation of schedules robustness according to varying primary delays, etc.

Optimization algorithms are a key point to assess capacity as they are in charge of finding a schedule that saturates the infrastructure. Their objective is to find the largest subset of trains from the traffic demand that can be routed through the infrastructure without conflicts. The number of trains in this subset is considered as the capacity assessment for this infrastructure and for the given demand.

Due to the great number of schedules that can be derived from the traffic demand, it can be an intractable problem even on modern computers. However, in the context of user-oriented software,

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obtaining good solutions in reasonable time is highly desirable.

This paper focuses on the optimization module and on its new underlying optimization algorithm which has given the best results so far for tackling this problem. Thanks to this algorithm, the module provides a capacity assessment by finding a schedule that saturates the infrastructure with trains from the traffic demand. It also provides a so-called *upper bound* which is an over-estimation of the capacity. This upper bound can in some cases allow to confirm that the capacity assessment derived from the generated schedule is optimal or close to its optimal value. More precisely, a saturating schedule is said to be *optimal* if it is not possible to derive a schedule from the same traffic demand that routes more trans in the infrastructure. The upper bound can thus be seen as a mean to evaluate the quality of the capacity assessment.

The next section presents the RECIFE optimization module by detailing its input and output data. Section 3 gives a slightly deeper technical insight to its underlying new optimization algorithm. Section 4 presents some computational results of the algorithm and section 5 gives conclusive remarks and perspectives to further improve the RECIFE platform.

2. RECIFE Optimization Module for Infrastructure Saturation

2.1. Input Data: Infrastructure and Traffic Demand

The input data of the optimization module consists in two parts: the description of the infrastructure and the traffic demand.

The infrastructure is "naturally" divided into track sections, and track sections are grouped into blocks as part of safety measures to prevent collisions. When a train enters a block, all track sections of this block are reserved at once, and none of them can host another train. Input data provide a set of available paths through the infrastructure. A path is a sequence of track sections coupled to the time elapsed since the train entry when it reserves and releases each of these track sections. These reservation and release times take into account the block system. Figure 1 illustrates an example of visualization of a route through the infrastructure in RECIFE and the relative entry and exit times for each track section of this route.

In more practical terms, the relative entry and exit times in a path are the result of the nominal circulation speed enforced by the signaling system.

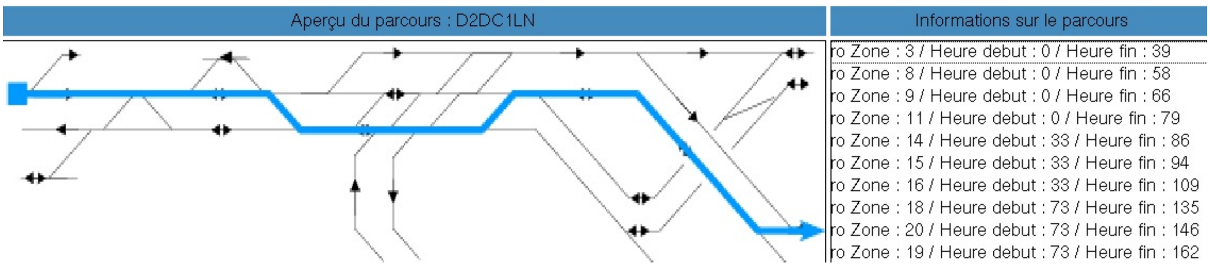

Figure 1: Visualization of a route through the infrastructure (left) and its associated description in terms of track sections occupation (right, in French)

The traffic demand consists in a set of trains that are considered as potentially incoming into the node. Each train has exactly one entry point and one exit point and one or several possible paths to go from the former to the latter. It has a nominal time at which it is ought to enter into the infrastructure and a maximum temporal shifting value that can be used to slightly delay its entry time. Finally, data specify the type of each train (e.g. high-speed train, intercity, freight, etc.).

In concrete terms, the entry and exit points represent lines of the main network from which trains can arrive and to which they can go. A small sample of traffic demand as provided by data is illustrated by the following table.

Train Type	Train #	Entry Line	Exit Line	Nominal Time	Maximum Shifting
High-Speed	7184	Paris	North High-Speed	18:00:00	30 seconds
High-Speed	9562	North High-Speed	Paris	18:05:00	30 seconds
Intercity	76732	Paris	Chantilly	18:12:00	3 minutes
Intercity	156320	Chantilly	Paris	18:16:00	3 minutes
Freight	42468	Chantilly	“Grande Ceinture”	18:02:00	5 minutes

For instance, the high-speed train 7184 arrives from Paris at 18:00 and goes towards the North High-Speed line. A maximum shifting of 30 seconds is specified, meaning that this train can be routed considering any entry time between 18:00:00 and 18:00:30.

2.2. Output: Saturated Schedule and Upper Bound

The output of the optimization module is a schedule that has the following properties:

- Trains that have been successfully routed through the node are associated to a unique path and their entry time is fixed to their nominal entry time plus a shift between zero and their maximum shifting;
- Other trains are absent from the schedule;
- There is no conflict between the trains that have been selected to be routed in the infrastructure;
- No additional train from the initial demand can be easily inserted into the generated schedule without creating a conflict (in other words, the schedule saturates the infrastructure).

It is essential to remember that the optimality of the saturating schedule is not always proven. In other words, there are cases in which it might be possible to find a schedule that routes more trains, although the optimization algorithm was not able to find such a schedule.

To overcome this drawback, the optimization module provides additional information which may be valuable to assess the quality of the saturating schedule. This information is the upper bound and consists in an over-estimation of the capacity, which means that the optimal capacity value is necessarily inferior or equal to this upper bound.

In most favorable cases, it can happen that the upper bound equals to the number of trains actually routed in the generated schedule, thus proving that the capacity assessment is actually optimal according to the initial traffic demand. Other favorable cases include those in which the gap between the actual number of routed trains and the upper bound is small (namely between one and three trains), as it indicates that the schedule is close to optimality, if not optimal. When the gap is larger, a conclusion can hardly be drawn as it can mean either that the schedule is far from optimality or the upper bound is too much over-estimated.

Although the upper bound can happen to be far from the capacity assessment, it should be noticed that it is provided at no cost in terms of computational time as it is the result of an intermediate process of the optimization algorithm.

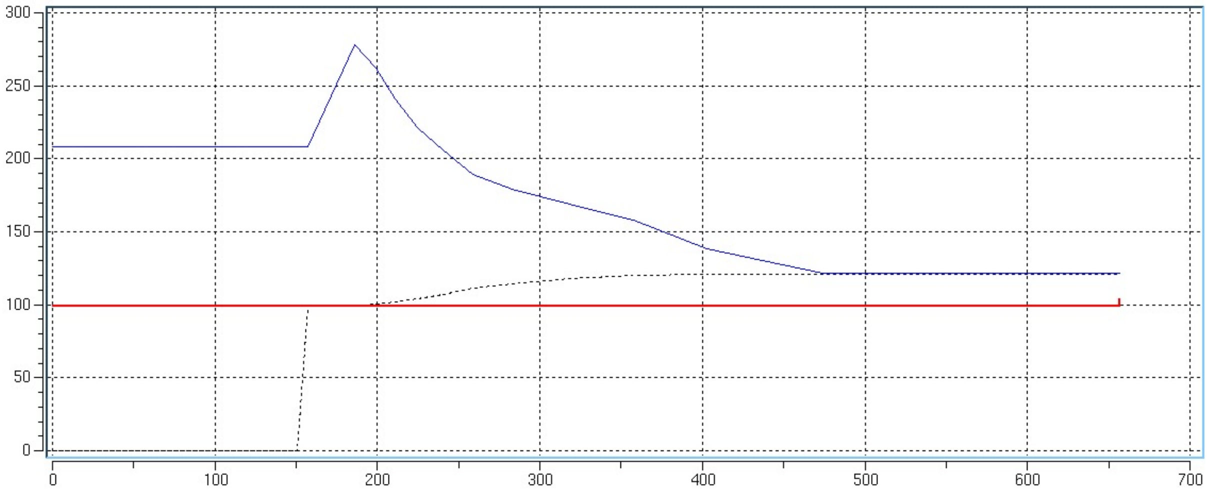

Figure 2: Visualization of the progress of the optimization algorithm : blue and black curves reach each other at the upper bound and the red curve shows the number of trains actually routed

2.3. Additional Parameters

Finally, the problem solved by the optimization module can be slightly customized by one parameter called the *granularity*. It represents a level of temporal detail for trying to route a train between its nominal time and its maximum shifting. More precisely, for a granularity value of g (expressed in seconds), the algorithm is allowed to consider routing each train every g seconds between its nominal entry time and its maximum shifted time.

As a consequence, a finer granularity increases the possibilities for routing each train, accordingly increasing chances to route more trains. However, it also implicates a more complicated saturation problem which can need a longer computational time to be solved.

3. Mathematical and Algorithmic Background

3.1. A Hybridization of Optimization Techniques

The RECIFE optimization module algorithm lies on two distinct paradigms to solve the saturation problem. Both consist in optimization techniques and are combined together in order to achieve an enhanced overall performance.

The first technique is Integer Linear Programming (ILP), which is a well-known optimization domain based on a strong mathematical theory. As suggested by its name, algorithms that rely on the ILP theory are designed to optimize linear quantities that are subject to constraints, themselves being expressed under the form of linear equalities or inequalities. The linear quantity to optimize is called the objective function and is expressed according to a set of variables. An optimal solution to the problem is an assignment of a value to each variable such that it is not possible to further improve the objective function value without violating at least one constraint.

One main characteristic (and strength) of ILP-based algorithms is that the ILP theory provides tools allowing to attain the optimal solution with certainty in finite computational time. However, real-world problems often yield large ILP formulations (i.e. containing many variables and constraints) and implicate prohibitive computational time to reach and prove optimality.

An ILP problem may specify that some of its variables can take any fractional value inside a given range whereas some others are constrained to an integer value. A formulation with many integer variables often requires successive resolutions of that same formulation in which integrality constraints are dropped (which is then called the “continuous relaxation” of the initial formulation).

Consequently, ILP problems with a large number of integer variables are much harder to solve but are unfortunately often more adapted to model real-world problems.

To compensate these difficulties, the second technique is a so-called metaheuristic algorithm. Such algorithms are designed to solve various problem which are not necessarily modeled as an ILP problem. Their main advantage is their ability to find good quality solutions (i.e. for which the objective function value should not be too far from its optimal value) in a very short time compared to exact ILP-based algorithms. However, they can not ensure that the solution is actually optimal.

The proposed approach is a simple hybridization of a ILP-based algorithm and a metaheuristic algorithm in order to obtain as quickly as possible a saturated schedule as well as assessing if it is close to an optimal schedule. The use of an ILP-based technique implicates that our problem is modeled in the form of an ILP problem.

3.2. Mathematical Model

Although this paper is not meant to provide mathematical and algorithmic details, the ILP formulation yielded by the saturation problem is presented to give an example of an ILP problem and to illustrate how real constraints for assessing capacity are transposed into a mathematical model. Presenting the ILP model requires the introduction of a few notations:

- The set of trains in the traffic demand is denoted T;
- For each train, the combination of a route across the infrastructure with an entry time between its nominal time and its maximum shifted time with respect to the granularity parameter forms a *path* for this train and is denoted c ; the set of all possible paths for a train t is written C_t;
- The set of all track sections of the infrastructure is denoted Z and the time window of the traffic demand is represented by a set of seconds, which is denoted P;
- As a track section can host at most one train at a time, each element of Z coupled with each element of P forms a unary resource (i.e. a resource that can be used by at most one train) and their set is denoted M;
- Given a unary resource m, we denote by O_m the set of all train-path couples that would occupy the resource m by circulating across the infrastructure;
- A variable denoted $x_{t,c}$ is created for each possible combination c for each train t; it is set to 1 if train t crosses the infrastructure by using combination c and to 0 otherwise.

The ILP problem that needs to be solved to obtain a capacity assessment can finally be written as follows:

$$
\begin{gathered}
max \sum_{t \in T} x_{t,c} \\
s.t. \sum_{c \in C_t} x_{t,c} \leq 1 \quad \forall\, t \in T \\
\sum_{(t,c) \in O_m} x_{t,c} \leq 1 \quad \forall\, m \in M \\
x_{t,c} \in \{0,1\} \quad \forall\, t \in T, c \in C_t
\end{gathered}
$$

The first line is the objective function and states that we aim at maximizing the number of trains present in the final schedule and taken from the initial traffic demand. The two following lines are constraints ensuring respectively that:

1. For each train, only one of its possible combinations can be selected in the final schedule;
2. Conflicts are avoided by preventing each unary resource from being used by more than one train.

Finally, the last line expresses that each variable can be set to no other value than either 0 or 1.

Obviously, the objective function and constraints are all linear on the problem variables, thus making this set of equations a valid ILP problem.

3.3. Overview of the Solution Algorithm

Once input data have been transposed into the ILP formulation as presented above, the core part of the optimization module is in charge of solving this formulation, that is finding an assignment to 0 or 1 for every variable such that the objective function is maximized and linear constraints are respected.

The algorithm starts by the ILP-based method to solve the continuous relaxation to optimality. Even though it is easier than the initial formulation containing the integrality constraints, the number of variables and constraints yielded by input data are very large and implicate the need to use an adapted solution algorithm. This algorithm is a generic technique called “Column Generation” which aims at solving very large Linear Programming formulations. It is an iterative process that can be summarized as follows:

1. Solve the continuous relaxation in which only a small subset of all possible variables is present;
2. Search for new variables in the initial traffic demand that are likely to improve the continuous objective function value if they are inserted into the formulation;
3. If such variables exist, go back to step 1 considering some of these supplementary variables; otherwise, it is considered that the optimal solution has been reached for the continuous relaxation and the procedure stops.

The implemented CG procedure contains several particularities and improvements that are detailed by Merel et al. (10). The continuous relaxation optimal objective function value provided by the CG procedure is an upper bound for the original ILP problem with integrality constraints. In other words, it is an over-estimation of the maximum value attainable for the original ILP problem.

The second part of the optimization algorithm consists in using a metaheuristic algorithm to compute quickly a saturated schedule. The metaheuristic algorithm used is a so-called Ant Colony Optimization (ACO) algorithm which has been designed to solve ILP formulations equivalent to the one presented above. The result of the CG procedure is used in a favorable way by restricting the variables considered by ACO to the set of variables considered at the last iteration of the CG procedure. In that way, CG accelerates the ACO computational time by providing a small set of most promising variables to generate a saturated schedule.

Finally, the overall result of the optimization algorithm consists of:

- The upper bound to the original ILP problem, provided by the CG procedure and corresponding to the upper bound for the infrastructure capacity;
- A solution to the ILP problem in which variables are assigned to either 0 or 1 and linear constraints are respected, corresponding to a saturating schedule containing circulation from the initial traffic demand.

4. Case Study

4.1. Infrastructure and Traffic Demand

Computational tests were made on instances yielded by real data related to the Pierrefitte-Gonesse railway junction located near Paris. As shown by figure 3, it is a crucial link between several high-traffic lines, namely:

- High-speed trains such as TGV, Eurostar and Thalys between Paris on the one side and the North High-Speed Line to Lille, Brussels and London on the other side;
- Classical passenger intercity trains linking Paris and nearby provincial towns such as Chantilly;

- Freight trains coming to and from the Chantilly line and the “Grande Ceinture” which is a track going round Paris through suburban towns such as Rungis and Versailles.

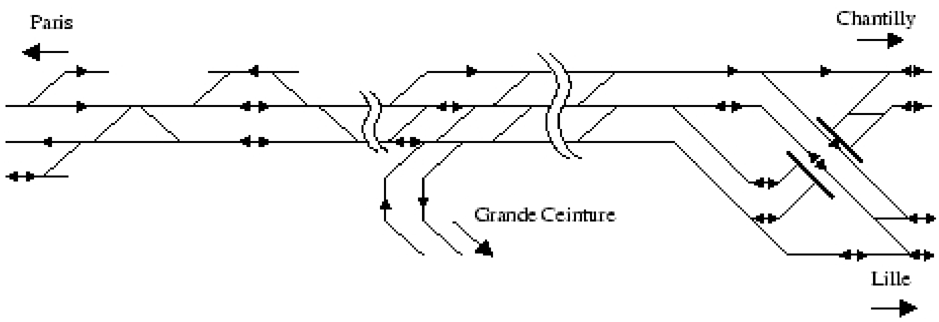

Figure 3: The Pierrefitte-Gonesse junction

The optimization module was tested against several samples of mixed traffic demand, containing a combination of high-speed, intercity and freight trains. Three traffic samples that represent a wide enough variation on the demand size were selected to be presented in this paper. An overview of these demands is given by the following table, in which high-speed trains are abbreviated by “HST” and intercity trains are abbreviated by “IC”. The table gives the number of trains in each considered traffic demand, according to their type and direction.

		Traffic Demand Number		
Train Types and Directions		1	2	3
HST	Paris → Lille	12	23	46
	Lille → Paris	9	18	36
IC	Paris → Chantilly	11	23	46
	Chantilly → Paris	8	16	31
Freight	Chantilly → Grande Ceinture	5	9	19
	Grande Ceinture → Chantilly	8	15	30
Total		**53**	**104**	**208**

The purpose of considering such a panel of traffic demands lies in three main considerations:

- The RECIFE optimization module has to be tested against various sizes of problems in order to check to what extent it produces a solution in a reasonable computational time;
- Saturated schedule patterns may differ from one traffic demand to another, implicating the need to study the optimization algorithm behavior on several cases;
- The gap between the capacity estimation and the upper bound may also vary.

Variations are also considered in terms of shifting granularity (as explained at the end of section 2) and maximum shifting allowed per train. Granularity varies between 1 and 15 seconds whereas considered maximum shifting values are between 30 and 90 seconds.

Synthetically, the difficulty for solving the problem increases when the number of train increases, when the maximum shifting increases and when the granularity is smaller. However, a finer granularity and higher shiftings may give the opportunity to route more trains through the infrastructure.

All possible combinations of granularity, maximum shifting values and traffic demand number constitute a very large range of test instances. Consequently, only some representative results have been selected in this paper.

4.2. Computational Time

Tests were made on a system equipped with an Intel Core2 Duo Microprocessor at 2.60GHz and 2GB of system memory. The following table gives the computational times, in seconds, for 27 instances yielded by varying the three parameters:

		Traffic Demand		
Max. Shifting	**Granularity**	1	2	3
30	15	32	103	397
	10	34	120	496
	5	51	186	895
60	15	49	188	808
	10	69	319	1,441
	5	156	908	4,691
90	15	94	432	2,013
	10	168	925	4,824
	5	535	4,105	24,685

Unsurprisingly, the shortest computational time is obtained for the 53-train instance with the largest granularity and smallest maximum shifting, and the longest time appears for the 208-train instance with a fine granularity and the highest maximum shifting delay. There is a factor 771 between these two computational times, which is system-independent and illustrates how the solution process can quickly become more difficult with tougher parameters.

In the four most favorable cases, the computational time is below one minute, and below five minutes in eight additional cases. The usability of the algorithm according to these measures depends on the user expectations, implicating that a conclusion can hardly be drawn by the sole knowledge of these results. However, it should be noticed that this algorithm outperforms other attempts in assessing capacity on the Pierrefitte-Gonesse junction, as shown by Merel et al. (10).

4.3. Capacity Assessment and Upper Bound

The following table presents the capacity assessment in terms of number of trains present in the saturated schedule produced by the optimization module. The table also shows the upper bound provided by the optimization module in the columns denoted “U.B.”. Results are presented for the same 27 instances as for the computational time.

		Traffic Demand					
		1		2		3	
Max. Shifting	**Granularity**	U.B.	Capacity	U.B.	Capacity	U.B.	Capacity
30	15	28	27	54	53	108	104
	10	28	27	55	53	109	104
	5	28	27	55	53	109	104
60	15	31	28	60	54	120	105
	10	32	28	61	52	122	105
	5	32	28	62	54	123	104
90	15	33	28	63	54	124	107
	10	33	28	64	53	126	105
	5	34	28	65	53	128	105

In every case, the number of trains routed in the saturated schedule is about half of the trains present in the traffic demand. This result can be explained by the structure of the traffic demand, in which trains nominal entry times are very close, thus making some of them mutually exclusive due to conflict prevention constraints.

For traffic demand 1, the capacity assessment increases (or is at least stable) when the granularity is refined or when the maximum shifting increases, which does not contradict the statement that higher shifting allowance and finer granularity gives more chances to route more trains. However, surprisingly uneven capacity assessments are observed for traffic demands 2 and 3, as more favorable parameter configurations do not necessarily implicate better capacity assessments. As an example, traffic demand 2 with maximum shifting of 60 and granularity of 10 shows a relatively poor capacity assessment. This phenomenon is explained by the use of the ACO metaheuristic algorithm which includes randomness in its search for a solution and can thus implicate a slight instability in the quality of generated schedules. Nevertheless, the global trend shows that increasing the maximum shift and refining the granularity lead to more trains routed onto the infrastructure, as nicely illustrated by the capacity assessment of 107 trains in one case for traffic demand 3.

Another interesting point is the gap between the capacity assessment and the upper bound, both of them being provided by the optimization module. It is relatively small for the smallest maximal shifting value and then progressively increases. This phenomenon is amplified with increasing number of trains. In the most favorable cases, the gap equals to one, meaning that the optimal saturated schedule does not contain more than one train than the saturated schedule actually found. In other words, it is an excellent indicator showing that the capacity assessed is very close – if not equal – to its optimal value. When the gap is higher, it can mean either that the upper bound is much too optimistic or that the capacity assessment is far from the optimal solution. These variations of the gap can be explained by considerations based on the LP theory but are out of the scope of this paper. Preliminary observations led to thinking that the gap is mainly due to the fact that the upper bound is too much optimistic.

4.4. Saturated Schedule Pattern

A deeper insight into saturated schedules provided by the RECIFE optimization module is given here in order to evaluate to what extent the capacity value provided by the module is realistic. The following table presents the distribution of train types and directions in the saturated schedule for the 208-train demand (traffic demand 3), with a maximum shifting of 90 seconds and a granularity of 5 seconds. This pattern is representative of what is obtained for other traffic demands and parameters configurations, thus illustrating the trend for all saturated schedules.

Train Types and Directions		**Number in Saturated Schedule**	**% of Initial Demand**
HST	Paris → Lille	44	96%
	Lille → Paris	17	47%
IC	Paris → Chantilly	1	2%
	Chantilly → Paris	13	42%
Freight	Chantilly → Grande Ceinture	1	5%
	Grande Ceinture → Chantilly	29	97%

It can be immediately noticed that the number of routed trains is extremely unbalanced. Firstly, for each train type, there is a significant gap between the two directions, as shown, for instance, by freight trains. Secondly, a significant though smaller gap exists between train types, with namely the relatively small number of intercity trains present in the schedule.

This phenomenon is explained by a combination of reasons which can be summarized as follows:

1. The optimization problem has an unique objective, which is the maximization of the total number of trains routed through the infrastructure;
2. As it can be noticed on figure 2, the infrastructure contains a significant number of two-way tracks that can potentially be used by same train types going in opposite directions;

3. Some routes associated to particular train types and directions use more track sections than others;
4. Routing the maximum number of trains implicitly implicates favoring paths that use as few track sections as possible and create as few conflicts as possible with other paths;

Consequently, some particular paths and directions are favored because of points 1 and 3, and two-way tracks are actually mainly used by paths going in the same direction as in creates less inter-path conflicts, as put forward by points 2 and 4. These observation logically lead to the circulation pattern presented in the table. This capacity assessment is thus essentially a theoretical which forces "ideal" conditions leading to a large total number of routed trains.

5. Conclusion and Perspectives

In the context of the RECIFE software platform, this paper has detailed an optimization module which is capable to assess infrastructure capacity on junctions and stations. This capacity assessment is provided thanks to the saturation of the considered infrastructure with as much traffic as possible from a given initial demand. Techniques used in the underlying optimization algorithm ensure a reasonable computational time in most cases, and experiments on the Pierrefitte-Gonesse case showed that this algorithm outperforms all previous attempts in terms of computational time. Combined with the other RECIFE components such as the robustness evaluation module, the optimization module proves its usefulness to lead capacity studies.

As explained, the mathematical model simply entails maximizing the number of trains routed through the infrastructure from the initial traffic demand. Although the developed algorithm is efficient to solve this hard combinatorial problem, a closer look at resulting saturated schedules shows a lack of realisticness in their structure, mainly because of a lack of balance between traffic types.

From this observation, we deduce an essential perspective for the optimization module, which is the inclusion of additional constraints and/or optimization objectives in the mathematical model in order to guide the algorithm towards more realistic solutions. Fortunately, the genericity of the ILP modeling and ILP-based solution methods such as Column Generation eases the inclusion of such additional criteria, and both the model and solution algorithm should easily evolve towards more sophisticated versions. More generally, we look for real-world criteria to study and insert in the mathematical model.

Another important concern is that it must be remember that capacity assessment also highly depends on the initial traffic demand structure. For instance, a traffic demand with a large majority of slow and long freight trains will not yield the same capacity value as if there is a majority of fast passenger trains.

This last statement enlightens the importance of being provided with data in order to test the module against additional traffic demands. Moreover, we also look forward to check to what extent the module can be adapted to other infrastructures, possibly by improving the mathematical model. The promising results in terms of computational time and the flexibility of the model give good reasons to think that the model would be successfully adapted to other cases.

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