A Total Cost Approach (TCA) for Optimising Energy-Saving Measures in Disruption Conditions

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Abstract: - Power supply required for operating rail convoys represents a great cost item for train companies which are paying increasing attention to energy-saving and energy-recovery measures aimed at reducing traction energy consumption and maximising the sustainability of railway system. Indeed, such a transport mode is able to move large volumes of passengers with high energy efficiency and low environmental impact. However, energy saving strategies affect both rail operations and passengers' satisfaction, and have to be properly implemented in the case of disruption conditions. Specifically, the paper analyses the implementation of energy-efficient speed profiles in a perturbed condition characterised by fleet unavailability and provides a rescheduling methodology based on an ad-hoc optimisation framework, taking into account the trade-off between service providers and service customers' needs. Indeed, on one hand, the lower the number of operating convoys, the lower the energy consumption; but, on the other hand, this implies a reduction in service frequency with an increase in passenger waiting times. Finally, the proposed approach has been applied in the case of a regional rail line in the south of Italy, in order to point out its usefulness.

Key-Words: - Railway systems; energy-saving; energy-recovery; disruption conditions; total cost approach; optimisation framework.

1 Introduction

Although the promotion of public transport systems based on a rail technology allows to provide numerous social benefits (see, for instance, [1]–[9]), these systems require high construction and operational costs, especially in terms of energy consumption. Hence, reducing energy consumption is one of the main goals pursued by train operating companies in order to decrease operational costs. For this purpose, several energy-saving and energy-recovery strategies have been proposed.

The formers consist in adopting energy-efficient driving behaviours based on the definition of proper driving speed profiles, differing from the so called *Time Optimal* (*TO*) condition which provides the shortest travel time duration but implies the maximum mechanical kinetic energy consumption. In particular, as shown by [10], eco-driving measures can be classified according to two approaches:

– the insertion of an inertial phase (indicated as coasting phase) between the cruising and the breaking phases;
– the imposition of lower speed limits.

Since the coasting is an inertial phase, during it the train proceeds along the line without energy requests and, at the same time, reduces the cruising duration which is an energy-consuming step. Moreover, the dissipation of mechanical energy (during the inertial phase) implies a reduction of the travel speed of the train which will require a lower brake effort to be stopped. This is a key element considering that the braking is an energy-wasting phase in the absence of recovery strategies or storage devices. On the other hand, the adoption of lower maximum travel speeds implies lower energy requests in the acceleration and cruising phases and a lower energy waste in the braking phase. In addition, it is worth noting that the first strategy requires reporting to the train the switching points for the initiation of the coasting phase; while, the second one is more straightforward to be implemented, since it requires simply communicating a different speed limit. Therefore, the technological level of the rail system may affect the choice between these two approaches. However, as shown by [11], such energy-efficient speed profiles intrinsically imply an increase in train running time, resulting in an increase in passenger travel time, which has to be suitably balanced by auxiliary operational time rates. For example, [12] proposed to use for this purpose the layover time, i.e. the time spent by the convoy at the terminus station in a stop condition waiting for the planned departure instant, thus preserving timetable stability. However, irrespective of the nature of operational times exploited, the trade-off phenomenon between service providers need (i.e. the reduction in energy consumption) and service customers satisfaction (i.e. the increase in passenger travel time) still remains and has to be properly modelled for an accurate evaluation of system performance ([13], [14]).

Besides, there are some policies aimed at re-utilising the energy dissipated during the braking phase. Such amount of energy can be exploited at the same time (e.g. by synchronising acceleration and deceleration phases of convoys running on the line) or accumulated and made available later. Obviously, the first option is more challenging to be implemented since the symmetry in infrastructure layout and operational times is required. Moreover, in the case of delays, such an energy exchange could become unfeasible. On the other hand, on-board and way-side storage devices can be adopted for storing the amount of energy dissipated in the braking phase and releasing it when required by the same convoy (i.e. on-board devices) or by another convoy running on the same line (i.e. way-side devices) ([15], [16]). Specifically, the so-called supercapacitors are being largely investigated in the literature, thanks to their ability to store a large amount of energy in a very small time period (i.e. the braking phase) ([17]–[19]). Finally, by means of bidirectional substations, the energy dissipated during the brake can be fed back to the main grid ([20], [21]).

However, the implementation of energy saving strategies becomes more challenging in disruption conditions. As widely shown in the literature [22], rail transport is very vulnerable to breakdowns, which can involve different system components ([23], [24]), different network typologies ([25], [26]) as well as a different failure severity ([27], [28]). In an energy consumption perspective, a very significant disruption event is represented by fleet limitations due to a breakdown involving rolling stock ([29], [30]). Indeed, on one hand, the lower the number of operating convoys, the lower the energy consumption; but, on the other hand, this implies a reduction in service frequency with an increase in passenger waiting times. Therefore, in this context, the above mentioned trade-off effect is further amplified, since also waiting times are involved. By a methodological point of view, the rescheduling process consists in two successive steps [31]. The initial phase concerns the identification of potential conflicts on the basis of the current state of the infrastructure, the characteristics of operational times, the availability of rolling stock, the position and travel speed of each convoy. This is followed by a problem-solving phase which, according to the results of the previous step and the delays actually occurred, identifies the most appropriate strategies for re-establishing normal operating conditions. More in detail, rescheduling problems are generally modelled by means of the so-called *Alternative Graph* ([32]–[34]), originally proposed by [35], or through *Mixed-Integer Linear Programming* (MILP) formulations ([36]–[38]). Furthermore, given the computational complexity characterising them, metaheuristic algorithms are largely used as resolution methods. Among the others, we can find: *Neighbourhood Search*, together with its variants namely *Variable Neighbourhood Search* and *Adaptive Large Neighbourhood Search* ([[39]–[41]); *Tabu Search* [42], *Genetic Algorithm* [43], *Simulating Annealing* [44] and *Ant Colony Optimisation* [45].

In this context, our aim is to develop an ad-hoc optimisation framework for implementing eco-driving measures in the case of a rolling stock breakdown, by preserving passenger satisfaction.

What follows is thus organised: Section 2 describes the proposed approach; Section 3 shows its feasibility by providing an application on a real regional rail line; Section 4 presents the main findings and future research opportunities.

2 The Total Cost Approach

The definition of the optimal intervention strategy in the case of rail system disruptions may be classified as one of the aspects of the *Mass-Transit Optimisation Problem* (*MTOP*) whose aim is to identify the optimal solution which minimises an objective function, that is [46]:

$$\hat{\boldsymbol{y}} = \arg\min_{\boldsymbol{y}} Z\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) \tag{1}$$

subject to:

$$\boldsymbol{y} \in S_{\boldsymbol{y}}\left(\overline{\boldsymbol{FC}}\right) \tag{2}$$

$$\boldsymbol{f} = \boldsymbol{\Lambda}\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) \tag{3}$$

$$\boldsymbol{B}\left(\boldsymbol{y}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) \le \overline{\boldsymbol{B}} \tag{4}$$

$$\boldsymbol{ORSP} = \boldsymbol{OP}\left(\boldsymbol{y}, \boldsymbol{f}, \overline{\boldsymbol{FC}}\right) \tag{5}$$

where $\boldsymbol{y}$ is the vector of parameters describing the intervention strategy; $\hat{\boldsymbol{y}}$ is the optimal value of $\boldsymbol{y}$; $Z(\cdot)$ is the objective function to be minimised; $\boldsymbol{f}$ is the vector describing passengers' features (such as user flows); $\boldsymbol{ORSP}$ is the vector describing the optimal rail system performance; $\overline{\boldsymbol{FC}}$ is the vector describing the failure context; $S_{\boldsymbol{y}}(\cdot)$ is the feasibility set of $\boldsymbol{y}$ depending on failure context; $\boldsymbol{\Lambda}(\cdot)$ is the assignment function which, being expressed as a fixed point problem (see, for instance, [47]–[49]), allows to determine passengers' features; $\boldsymbol{B}(\cdot)$ is a vector expressing the budget functions providing the budget requirements (in terms of number of rail convoys, energy resources, etc.) for implementing strategy $\boldsymbol{y}$ in the failure context $\overline{\boldsymbol{FC}}$ and in the case of system performance $\boldsymbol{ORSP}$; $\overline{\boldsymbol{B}}$ is the vector expressing the budget limits; $\boldsymbol{OP}(\cdot)$ is the function expressing the operational policy adopted for optimising rail system performance, as for instance, the implementation of Energy Saving Strategies ([14], [50]).

The general formulation of the objective function $Z(\cdot)$ in the case of *Total Cost Approach* (*TCA*) consists in considering all costs corresponding to a certain solution, that is:

$$Z_1\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) = UGC\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) + \\ + OC\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) \tag{6}$$

where $Z_1(\cdot)$ is the traditional objective function $Z(\cdot)$ in the case of Total Cost Approach; $UGC(\cdot)$ is the user generalised cost expressed as a weighted sum of travel times and monetary costs; $OC(\cdot)$ represents the operational costs of the considered rail system.

Generally, the operational cost term may be expressed as the product between the train travelled distance and the corresponding unitary cost, that is [51]:

$$OC\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) = \\ = uc \cdot TTD\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) \tag{7}$$

where $uc(\cdot)$ represents the unitary cost and $TTD(\cdot)$ the train travelled distance. However, in the case of the implementation of Energy Saving Strategies, it is necessary to reduce the operational cost value since the monetary value of the energy saving represents an economic saving. Therefore, in the problem (1) it is necessary to adopt a different objective function being calculated as follows:

$$Z_2\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) = Z_1\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) + \\ - ESV\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) \tag{8}$$

with:

$$ESV\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) = \\ = c_{kWh} \cdot \left(EC_{TO}\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) + \\ - EC_{ES}\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right)\right) \tag{9}$$

where $Z_2(\cdot)$ is the objective function which takes economic savings into account; $ESV(\cdot)$ is the monetary value of the implementation of the Energy Saving Strategy; c_{kWh} is the monetary value (i.e. unitary cost) associated to a 1 kWh of energy; $EC_{TO}(\cdot)$ is the energy consumption in *Time Optimal* (*TO*) condition; $EC_{ES}(\cdot)$ is the energy consumption in *Energy Saving* (*ES*) condition.

Finally, since the analysed disruption may vary the number of carried passengers, in order to obtain an unbiased estimation of the objective function values, we propose to adopt a unitary objective function to be minimised in problem (1), that is:

$$Z_3\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right) = \frac{Z_2\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right)}{TD\left(\boldsymbol{y}, \boldsymbol{f}, \boldsymbol{ORSP}, \overline{\boldsymbol{FC}}\right)} \tag{10}$$

where $Z_3(\cdot)$ is the unitary value of the objective function; $TD(\cdot)$ is the travel demand corresponding to intervention strategy $\boldsymbol{y}$, in the case of failure context $\overline{\boldsymbol{FC}}$, with system performance $\boldsymbol{ORSP}$ and passengers' features $\boldsymbol{f}$.

3 A Regional Rail Line Application

In order to show the utility and the feasibility of the proposed approach, we have applied it in the case of a rolling stock disruption occurred on a regional rail line: the 'Naples-Sorrento' regional rail line serving the metropolitan area of Naples, in the south of Italy. Main details of the considered railway can be found in [52].

In particular, the ordinary condition consists in a service performed with an 18-minute headway by means of 9 triple-header rail convoys (i.e. a total number of 27 railcars). Moreover, the implementation of an Energy Saving Strategy based on the imposition of a unique speed limit for any trip direction (i.e. outward and return trip), according to the approach proposed by [14], is assumed. Details of the ordinary service condition may be found in Tables 1 and 2.

In the disruption scenario, we assume the unavailability of a triple-header rail convoy (i.e. the failure concerns 3 railcars). Hence, the total number of working railcars becomes 24. In this case, it is possible to reschedule the rail service according to two different scenarios: 8 triple-header rail convoys (intervention scenario no. 1) or 12 double-header rail convoys (intervention scenario no. 2).

Following the methodology proposed by [12] and [14], it is possible to reschedule the rail service by determining new service parameters and new Energy Saving implementation schemes, as shown by Tables 3 and 4.

Moreover, by adopting the objective function described by equation (10), we may identify the intervention scenario 1 as the optimal one since, although it implies greater waiting times and lower energy savings, it allows to adopt a lower number of travelling rail convoys, thus providing a considerably lower operational cost.

Table 1 – Service parameters in ordinary service conditions

Number of available railcars	*Number of railcars per convoy*	*Total number of rail convoys*	*Service headway [min]*	*Speed limit in the outward trip*	*Speed limit in the return trip*	*Number of daily round convoy runs*
27	3	9	18	70	71	53.0

Table 2 – Objective function terms in ordinary service conditions

Average travel time [min]	*Average waiting time [min]*	*Daily convoy distance [train–km]*	*Total daily operational cost [€/day]*	*Daily energy consumption in Time Optimal condition [kWh]*	*Daily energy consumption in Energy Saving condition [kWh]*	*Objective function value [€/pax]*
32.9	9.0	4,514	191,870	62,825	50,681	9.73

Table 3 – Service parameters in disruption conditions

Intervention scenario	*Number of available railcars*	*Number of railcars per convoy*	*Total number of rail convoys*	*Service headway [min]*	*Speed limit in the outward trip*	*Speed limit in the return trip*	*Number of daily round convoy runs*
1	24	3	8	20	79	76	47.5
2	24	2	12	13.5	71	70	70.5

Table 4 – Objective function terms in disruption conditions

Intervention scenario	*Average travel time [min]*	*Average waiting time [min]*	*Daily convoy distance [train–km]*	*Total daily operational cost [€/day]*	*Daily energy consumption in Time Optimal condition [kWh]*	*Daily energy consumption in Energy Saving condition [kWh]*	*Objective function value [€/pax]*
1	32.5	10.0	4,045	171,958	56,334	50,214	9.41
2	32.9	6.8	6,004	255,223	55,732	45,022	10.99

4 Conclusions and Research Prospects

The implementation of Energy Saving Strategies for reducing energy requirements allows considerably improving the sustainability of rail transport. However, in the case of system failure, it is necessary to reschedule the service in order to achieve new optimality service conditions.

In this paper, we have proposed a methodology based on the Total Cost Approach (TCA) in order to identify new optimality conditions in the case of

breakdowns concerning the rolling stock. In particular, in order to show the applicability of the proposed approach, we have applied it in the case of a real regional rail line in the south of Italy.
Numerical applications have shown that, due to the definition of operational costs based on the number of travelling rail convoys, rather than the number of travelling railcars, the optimal condition can be properly identified by minimising an *ad-hoc* objective function, being determined by subtracting energy savings and by dividing by the number of travelling passengers.
As research prospects, we suggest to apply the proposed approach in the case of different networks, such as metro line contexts, as well as by adopting a different estimation framework for operational costs (e.g. based on the number of travelling railcars).

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