A New Multi-objective Solution Approach Using ModeFRONTIER and OpenTrack for Energy-Efficient Train Timetabling Problem

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Abstract Trains move along the railway infrastructure according to specific timetables. The timetables are based on the running time calculation and they are usually calculated without considering explicitly energy consumption. Since green transportation is becoming more and more important from environmental perspectives, energy consumption minimization could be considered also in timetable calculation. In particular, the Energy-Efficient Train Timetabling Problem (EETTP) consists in the energy-efficient timetable calculation considering the trade-off between energy efficiency and running times. In this work, a solution approach to solve a multi-objective EETTP is described in which the two objectives are the minimization of both energy consumption and the total travel time. The approach finds the schedules to guarantee that the train speed profiles minimize the objectives. It is based on modeFRONTIER and OpenTrack that are integrated by using the OpenTrack Application Programming Interface in a modeFRONTIER workflow. In particular, the optimization is made by modeFRONTIER, while the calculation of the train speed profiles, energy consumption and total travel time is made by OpenTrack. The approach is used with Multi-objective Genetic Algorithm-II and the Non-dominating Sorting Genetic-II, which are two genetic algorithms available in modeFRONTIER. The solution approach is tested on a case study that represents a real situation of metro line in Turkey. For both algorithms, a Pareto Front of solution which are a good trade-off between the objectives are reported. The results show significant reduction of both energy consumption and total travel time with respect to the existing timetable.

Keywords Railway · EETTP · Multi-objective optimization

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7.1 Introduction

As known, trains move along the railway infrastructure according to a specific timetable. A timetable specifies all train movements which are to be operated in a given time window and its generation is essential. Each timetable is based on the calculation of the running times, which are the time needed to travel between two stations where a train has scheduled stops. This timetables are usually calculated without considering explicitly energy consumption, but another set of constraints and goals mainly related to capacity utilization and timetable reliability. Since green transportation is becoming more and more important from environmental perspectives, energy consumption minimization could be considered also in timetable calculation. In particular, Energy-Efficient Train Timetabling Problem (EETTP) has been defined in the scientific literature. This problem consists in the energy-efficient timetable calculation considering the trade-off between energy efficiency and running times. EETTP could reduce operating costs significantly and contribute to a further increase of the sustainability of railway transportation. The EETTP has been studied by many authors, and several solution approaches have been implemented to solve it. Most of these approaches find the best time supplement distribution on the minimum running times to calculate timetables that minimize energy consumption or which are a trade-off between this and other objectives, as the timetable robustness maximization. Other approaches, as the one introduced here, find the schedules to ensure that the trains follow the optimal energy-efficient speed profiles. In particular, the schedule is the sequence of entry times of the train itself in its each block section of its journey, where a block section is a track segment delimited by main signals for safe train separation.

In this work, a solution approach to solve a multi-objective EETTP is described, which is an extension of the single objective version introduced in (Montrone et al. [15]). The two objectives are the minimization of both energy consumption and the total travel time, that is, the sum of running times over all the sections that form the complete train itinerary. The approach finds the schedules to guarantee that the train speed profiles minimize the objectives. In particular, this approach finds the optimal driving regime combination in each block section to compose the train speed profiles. The driving regimes followed by trains usually depend on to the infrastructure and rolling stock characteristics. In each driving regime the energy consumption evolves differently. As known, the four optimal driving regimes are acceleration, cruising, coasting and braking. In particular, in the acceleration the energy consumption is maximum and the maximum power is given to the engine to reach the maximum possible speed, while in the cruising the energy consumption is smaller but the speed is constant. Both in the coasting and in the braking, the energy consumption is null. Precisely, the engine is switched off and the train moves by inertia in the coasting, while the train brakes in the braking. These optimal regimes are found by the Optimal Control Theory (Vinter [26]) according to the application of the Pontryagin's Maximum Principle (PMP) (Pontryagin [19]). The solution approach is based on modeFRONTIER and OpenTrack. In particular, modeFRONTIER is an integration platform for multi-objective and multi-disciplinary optimization developed by (Esteco S.p.A [7]) and (OpenTrack Railway Technology Ltd. [17]) is a microscopic railway simulation tool. The optimization is made by modeFRONTIER, while the calculation of the train speed profiles, energy consumption and total travel time is made by OpenTrack. The two tools are integrated, by using the OpenTrack Application Programming Interface (API), in a modeFRONTIER workflow, which describes the model to formulate the problem and enables the interaction between the optimization algorithms and OpenTrack. This approach is an extension of the one introduced in (Montrone [14]) where an internal procedure for calculation is used instead of OpenTrack. The approach is used with two optimization algorithms: the Multi-Objective Genetic Algorithm (MOGA)-II and the Non-dominating Sorting Genetic (NSGA)-II, which are two genetic algorithms available in modeFRONTIER. The solution approach considers only one train traveling on the infrastructure and it is tested on a case study that represents a real situation of metro line in Turkey. A comparison between the results obtained by MOGA-II and NSGA-II is reported. For both algorithms, the results show significant reduction of both energy consumption and total travel time with respect to the existing timetable. A Pareto Front of solution which are a good trade-off between the objectives are reported. Sometime EETTP includes also the energy recovery, that is, an efficient use of regenerative braking between trains. Indeed, when a train brakes, its mechanical energy can be fed back to the overhead wire system to be used by other trains. The approach reported here is not still able to handle EETTP with energy recovery but new modifications will be added to include it.

The paper is organized as follows. Section 7.2 reports a detailed literature review on the solution approaches to solve EETTP. Section 7.3 gives some notions about the tools andx the optimization algorithms used in this paper. Section 7.4 introduces the case study. Section 7.5 describes the solution approach presented here to solve the problem. Section 7.6 the applications, showing the obtained results on the case study considered. Finally, Sect. 7.7 concludes the paper and introduces the future works.

7.2 Literature Review

The research on the EETTP started around 1990 and it is still a great concern. A wide range of solution approaches to solve EETTP are defined until now. Some of them are described here, but for more details see (Montrone [14]) and (Scheepmaker et al. [20]).

Some solution approaches find the best time supplement distribution on the minimum running times to calculate timetables that minimizes energy consumption. In general, the results for these approaches show significant reduction of energy consumption with respect to the existing timetable. For example, (Ding et al. [6]) propose a two level iterative genetic algorithm to find time supplement distribution on the running times. In particular, the algorithm finds the train speed profile between the stations, and then, between them it distributes the time supplement to minimize energy consumption. The authors test the two level algorithm on a case study with a single train. Reference (Su et al. [23]) propose a method which is composed by three algorithms. The first algorithm finds the optimal speed profile with a given schedule, without considering the variation of the slopes, the curves and the speed limits. The second algorithm calculates the minimum running times given constant speed limits. Finally, the third algorithm distributes the time supplements to the running times for the energy-efficient timetable calculation. They test their solution approach on the metro line from Beijing to Yizhuang in China and a single train. Reference (Sicre et al. [21]) propose a solution approach based on simulation and optimization. They consider a single train with intermediate stops along a high-speed line. In particular, for each track between two stops, some possible train speed profiles that imply different running times and energy consumption are computed by a simulator. The solution approach finds the best trade-off between running time and energy consumption minimization. Then, it distributes the time supplement to the running times by an optimization model to calculate energy-efficient timetables. The authors test their approach on the Spanish high-speed line of Red Nacional de los Ferrocarriles Espanoles (RENFE) that links Madrid to Zaragoza with two stops at Guadalajara and Calatayud, and a single train. In some solution approaches, the time supplement distribution on the minimum running times is calculated taking into account also other objectives, showing anyway significant reduction of energy consumption with respect to the existing timetable. For example, (Albrecht and Oettich [1]) focus on the addition of time supplements to define timetables that are a trade-off between energy consumption minimization and the connections probability with other public transport services maximization. The authors propose an algorithm based on dynamic programming method to solve it and they test this algorithm on a metro line of Dresden in Germany with a single train.

Other solution approaches find the schedules which assure that the trains follow the energy-efficient speed profiles. For example, (Chevrier et al. [3]) present a model that builds the optimal speed profile in each section in which the line is divided. In particular, in each section the speed limit is constant and two target speeds are considered. The authors solve their model by a multi-objective evolutionary algorithm and they test the algorithm on two lines and a single train. Other solution approaches find the train speed profiles to find a timetable which minimizes the energy consumption but also is robust, that is, it will be able to handle delay, if any. For example, (Cucala et al. [4]) propose a fuzzy linear programming model to calculate both energy-efficient and robust timetables, in which the speed profile calculation is based on a genetic algorithm that makes use of the simulator introduced in (Sicre et al. [21]). The authors test the method on a real Spanish high-speed line from Madrid to Barcelona with four intermediate stops and a single train. The energy-efficient and robust timetable calculation is studied also in the European rail project ON-TIME (ONTIME Consortium [16]) where energy-efficient train speed profiles and adjusted schedules on the corridor between two main stations are computed.

The solution approaches described so far take into account only one train at a time. Instead, solution approaches to solve EETTP in which more trains at time are considered are recently studied and they show significant energy-saving compared to the existing timetable. For example, (Zhang et al. [32]) present a bi-level model in which the upper level of the model ensures the relative robustness of the timetable, while the lower level of the model optimizes the train schedules among intermediate stations to minimize energy consumption. The authors develop an iterative particle swarm optimization algorithm to solve the model and they test it on the Beijing-Shanghai high-speed railway. Reference (Wang and Goverde [27]) propose a solution approach that first modifies the train schedules to relax the given timetable by defining relaxed time windows. Then a train trajectory optimization method is developed to find optimal schedules and optimal energy-efficient speed profiles within these relaxed time windows. The train trajectory optimization includes multi-train trajectory optimization which are reformulated as a multiple-phase optimal control problem and solved by a pseudospectral method. The authors test their approach both on a single-track railway corridor and on a double-track corridor of the Dutch railway. Reference (Xu et al. [28]) present an integrated train timetabling and speed control optimization model in discrete space-time-speed network to solve EETTP. The authors solve this model by an iterative heuristic algorithm and they test it on some cases. Reference (Goverde et al. [10]) propose a solution approach that integrates energy-efficiency and robustness of the timetable, improving the dynamic programming algorithm implemented in their previous work (ONTIME Consortium [16]). This algorithm determines both the optimal distribution of the running time supplements and the dwell times along the corridor. The authors test the algorithm on a case study on the Dutch railway infrastructure with six trains. Reference (Su et al. [24]) improve the previous solution approach introduced in (Su et al. [23]). This approach is based on a model that distributes the time supplements to the running times by including also the headway times, that is, the minimum time separation between consecutive trains, to be able to deal with more that one train. They test the approach on the metro line from Beijing to Yizhuang in China. Reference (Fabris et al. [9]) present a solution approach which introduces a mesoscopic model. This model estimates the headway times and the conflicts on lines and stations as well as a calculation of running times and time-losses. The model is solve by a local search implemented heuristic and this heuristic is tested on the rail network of the north-eastern part of Italy. Reference (Li et al. [13]) propose a model to calculate the new schedules of trains taking into account energy consumption, carbon emission cost and total travel time minimization. They apply the LINGO fuzzy multi-objective optimization algorithm (svMATH [25]) and they test the algorithm with multiple trains on a line with 10 stations.

Finally, some solution approaches try to solve the EETTP in which also the energy recovery is considered. In particular, these approaches find timetables that synchronize the processes of acceleration and regenerative braking of multiple trains to minimize energy consumption. These approaches are mainly applied on the metro lines where the train acceleration and braking are usually frequent and the trains repeat the same, usually short, routes many times. Hence, the energy-saving due to the synchronization may be significant. For example, the approaches reported in the following are applied on the Beijing Yizhuang metro line in China where several trains run simultaneously. Reference (Li and Lo [12]) present a convex optimization model that extends the previous version introduced in (Li and Lo [11]) and divides both the routes and the stations into several segments in which the speed limit is constant. The segments from the up direction and down direction are assembled as a cycle, in which the time required for completing the operations is called cycle time. The model finds the optimal timetable by distributing times to different stations and inter-stations under constraint which assure the minimum time separation between consecutive trains. Reference (Yang et al. [29]) present a multi-objective integer programming model which improve the one introduced in (Yang et al. [30, 31]) where the two objectives are both regenerative braking maximization and passenger waiting time minimization. The authors propose a genetic algorithm and an allocation algorithm to solve this model. Reference (Fabris et al. [8]) present a solution based on simulated annealing optimization algorithm, which can be used both for stochastic simulation models and for timetable calculation. In particular, this approach finds the best regression between calculated and measured train speeds. The approach is tested on the north-eastern part of Italy as input for both running time calculation and microscopic simulation.

7.3 ModeFRONTIER and OpenTrack

modeFRONTIER is a multi-disciplinary software developed by ESTECO S.p.A. More details about ESTECO S.p.A. and its products are available in (Esteco S.p.A [7]). modeFRONTIER optimizes the engineering design process through the use of innovative algorithms and integration with leading simulation tools. Specifically, an engineering design process is a series of steps that the engineers must complete to find a solution of their design problem. modeFRONTIER enables the definition of the details of engineering design processes through an intuitive interface called mode-FRONTIER workflow. The modeFRONTIER workflow formulates all the logical steps composing the process and it defines the input and the output variables. In particular, it combines the Data Flow and the Process Flow. The Data Flow shows what data should be transferred from one step to the other. The Process Flow shows the sequence of actions to be taken and the conditions that have to be evaluated. The modeFRONTIER workflow allows the integration between external simulation tools as a Black Box. The Black Box contains the procedures that should be used to compute the values of the output variables according to the input variables of the engineering design process. For instance, the Black Box can be a calculator or an external tool, such as Computer-Aided Design (CAD) and Computer-Aided Engineering (CAE) tools. The Black Box is defined in the mode-FRONTIER workflow by means of particular nodes. Figure 7.1 shows this concept of modeFRONTIER integration.

modeFRONTIER contains iterative optimization algorithms for both single and multi-objective problems. Between them, there are MOGA-II and NSGA-II. Both algorithms belong to the family of genetic iterative algorithms which are inspired by the theory of Darwin on the evolution. Starting from an initial population, a genetic

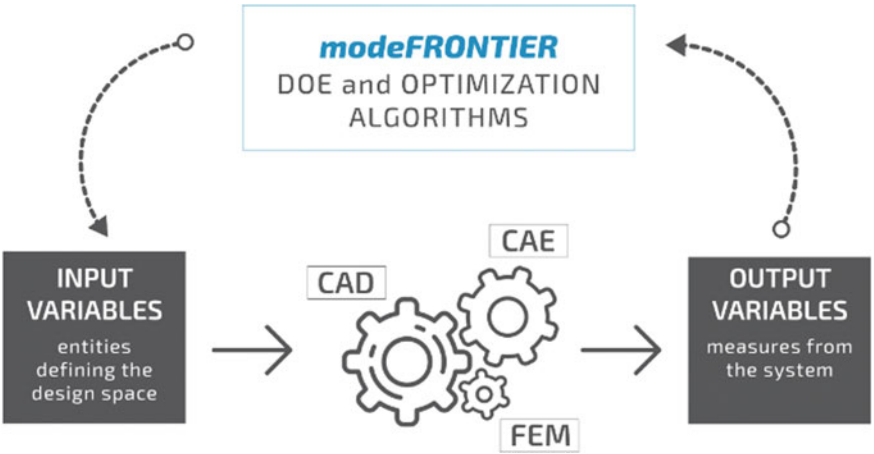

Fig. 7.1 modeFRONTIER Black Box

algorithm finds new individuals that represent the population offspring and should be better than their parents. The reproduction is repeated until the maximum number of iterations is reached. The best individuals are selected according to their fitness: the more suitable they are, the more chances they have to reproduce. More details about the genetic algorithm are described in (Sivanandam and Deepa [22]). MOGA-II is an improved version of MOGA (Poloni and Pediroda [18]) developed by Poloni that uses a smart multi-search elitism for robustness. Elitism is very important in multi-objective optimization because it helps preserving the individuals that are closest to the Pareto front and the ones that have the best dispersion. MOGA-II uses four different operators for reproduction (two-point crossover, directional crossover, mutation and selection). NSGA-II is developed by K.Deb (Deb et al. [5]) and it implements a fast and clever non-dominated sorting procedure and elitism. It works with both discrete variables and continuous: for the last case a particular crossover and mutation operation for reproduction is performed based on a Deb probability function. Moreover, modeFRONTIER contains Design Of Experiments (DOE) algorithms which are usually used to define the initial population for optimization algorithms.

Reference (OpenTrack Railway Technology Ltd. [17]) is a one of the most used microscopic railway simulator tool created in the middle of the 1990 s as a research project at the Swiss Federal Institute of Technology. Figure 7.2 shows the simulation process in OpenTrack as shown in Fig. 7.2. For the simulation, OpenTrack requires information about the rolling stock, the railway infrastructure and signaling system, and the timetable. The simulation starts based on this information and OpenTrack calculates the train movements under the constraints given by the signaling system and timetable. After the simulation, OpenTrack returns the results in the form of diagrams, train graphs and statistics. Today, OpenTrack is well-established and its accuracy is high.

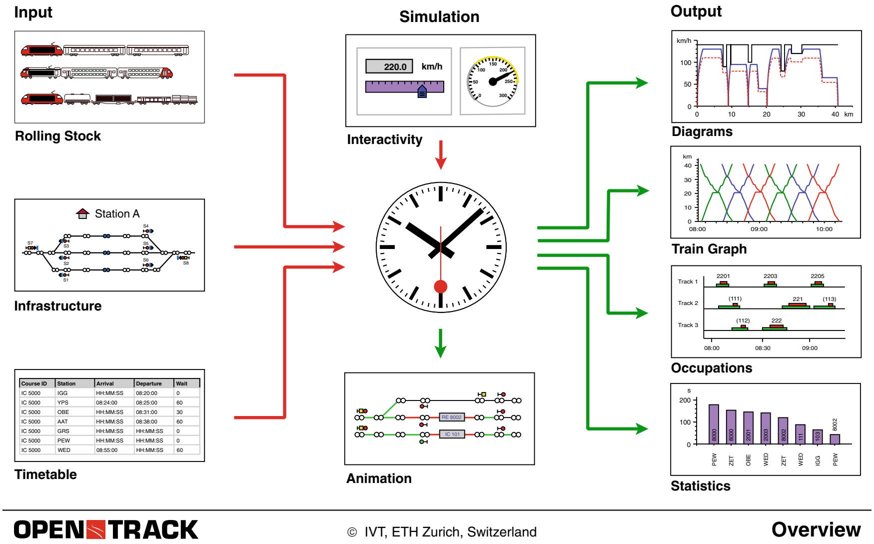

Fig. 7.2 OpenTrack

7.4 Case Study

The case study reproduces a real situation of a metro line in Turkey. Figure 7.3 shows the infrastructure considered in which physical characteristics are known. In particular, it is composed by a line with 15 block sections which can be very steep uphill and downhill. Also the curves change along the line and the values of the curve radius are known. The line contains 17 stations and each station from A to N is for specific train activities, like boarding and unloading of passengers, while the others $c1$, $c2$, $c3$, $c4$, $c5$ are only for train technical operations. A train stops in each stations and the dwell times is always 60 s. The rolling stock characteristics are known. In particular, the train mass, mass factor and length are, respectively, 270 t, 1.06 and 120 m. The maximum acceleration is $1.1\,\text{m/s}^2$ and the maximum service braking is $1.1\,\text{m/s}^2$. Both the maximum tractive force and the resistance force are given, so the driving regime combinations and the corresponding running times and energy consumption can be calculated to feed the module. Precisely, the mass-indipendent Davis's Formula is used to approximate the vehicle resistance with parameters $A = 1500\,\text{N}$, $B = 10.8\,\text{Ns/m}$, $C = 11.016\,\text{Ns}^2/\text{m}^2$ and the maximum tractive force is reported in the Table 7.1 and shown in Fig. 7.4. For more details about these forces and formula, see in (Brunger and Dahlhaus [2]).

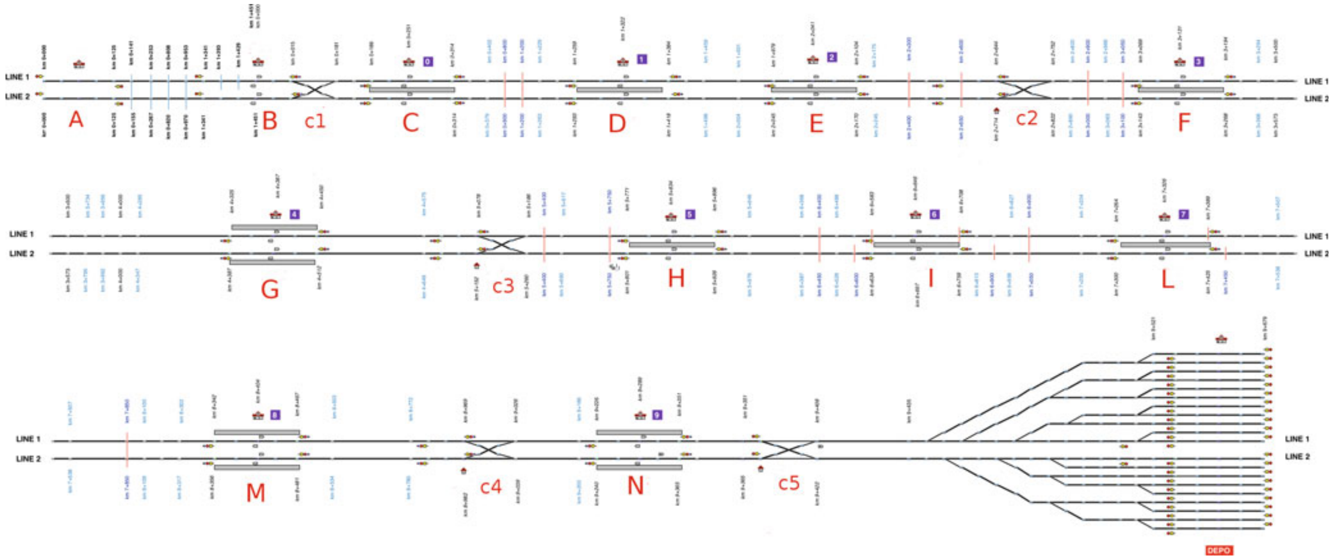

Fig. 7.3 The infrastructure

Table 7.1 The maximum tractive force

v (m/s)	Maximum tractive force (N)
$0 \leq v < 4.72$	432
$4.72 \leq v < 22.22$	$7344000/v$

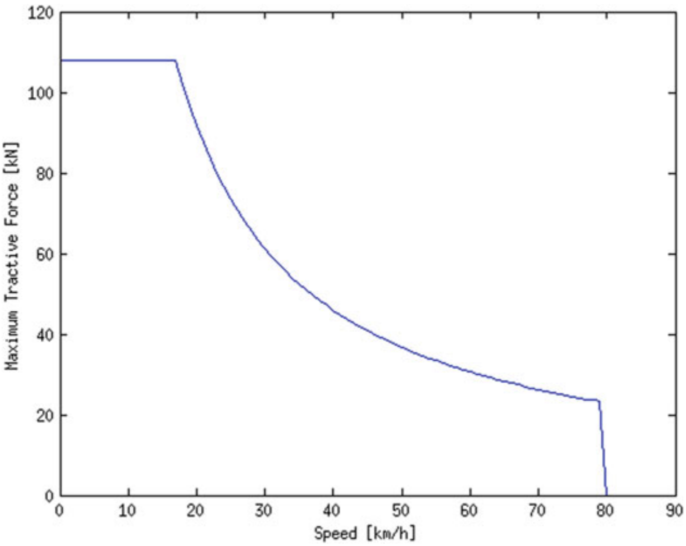

Fig. 7.4 The tractive force on case study: the horizontal axis reports the speed, while the vertical axis reports the force

7.5 Solution Approach

The solution approach solves EETTP in which the slopes, the curves and the speed limits are not constant throughout the infrastructure and energy recovery is neglected. The approach considers only single train travels along the infrastructure and must stop at all intermediate stations along its route. The solution approach integrates optimization and simulation by means of modeFRONTIER and OpenTrack (through the OpenTrack API), respectively. This approach introduces a model and the modeFRONTIER terminology is used to described it. In particular, the Black Box of the solution approach is OpenTrack called by means of a particular custom node, implemented here by means of OpenTrack API. The input variables are

- the cruising speed in each section which must be lower or at least equal to both the maximum line speed in each section and the maximum vehicle speed
- the time in which engines are switched off (this means the time instant when the cruising regime ends and starts the coasting one). The engines should not be

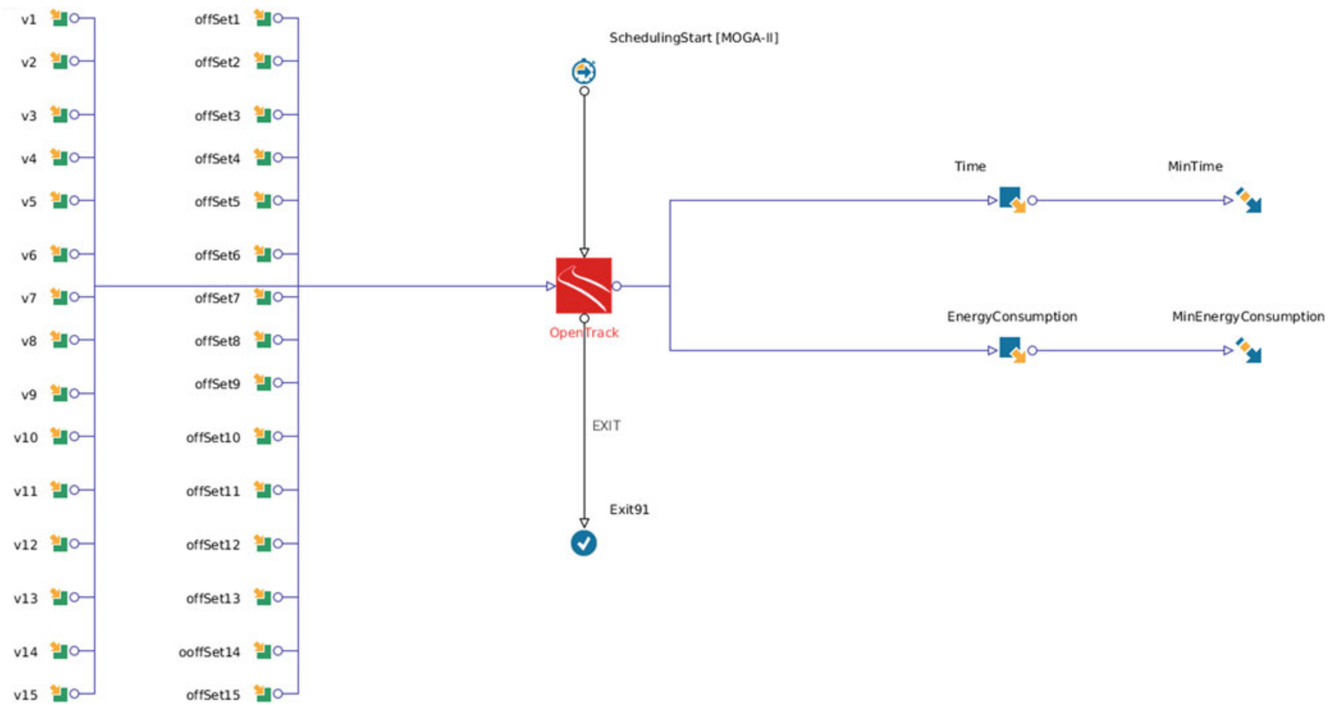

Fig. 7.5 modeFRONTIER workflow: it shows the application where MOGA algorithm is called

switched off too in advance, otherwise the train is not able to reach the end of the section nor too late otherwise the trains cannot stop in the following station.

The choice of these variables has been performed through optimization algorithms which ensure the respect of these constraints and that the train reaches the end to its journey. The output variables are the energy consumption and the travel time, that is, the sum of running times for each train. The objectives are the energy consumption and total time minimization. Of course these are two conflicting objectives because the lower is energy consumption the higher is usually the travel time, and vice versa. In this case, the aim, on the contrary, is the minimization of both of them. The model is solved by two optimization algorithms, MOGA-II and NSGA-II, respectively, which are two genetic algorithms available in modeFRONTIER. Given a random population for input variables, the genetic algorithm (MOGA-II or NSGA-II) creates new individuals and calls OpenTrack to calculate the output variables, the objectives and the energy-efficient train speed profiles. The process is iterated until the maximum number of iterations is reached. The optimal solution minimizes the energy consumption and the travel time. The modeFrontier workflow Fig. 7.5 used in this work is shown in Sect. 7.6.

7.6 Application

The solution approach is tested on case study introduced in Fig. 7.3. For both algorithms, an initial population is composed by random individuals obtained by one of DOE algoritms available in modeFRONTIER. Both algorithms are used with the default values for their internal parameters.

7.6.1 ModeFRONTIER Workflow

Figure 7.5 shows the modeFRONTIER workflow which describes the model to represent the considered case study. From right to left is possible to follow the optimization Data Flow: at the left there are the input variables, whereas at the right there are the output variables and the objective on the output variables. The green icons (square boxes with an incoming arrow) represent the input variables. The blue icons (square boxes with an outcoming arrow) represent the output variables. Objectives are represented by an arrow icon. The input variables are the cruising speed in each section (v) and the time (offSet) in which engines are switched off. The output variables are the energy consumption (EnergyConsumption) and the travel time (Time). The objectives are the energy consumption (MinEnergyConsumption) and total time minimization (MinTime). In the center, from top to bottom the icons represent the Process Flow composed by the SchedulingStart node, the OpenTrack node and the logic end of the process. Precisely, first node calls the genetic algorithm, for which

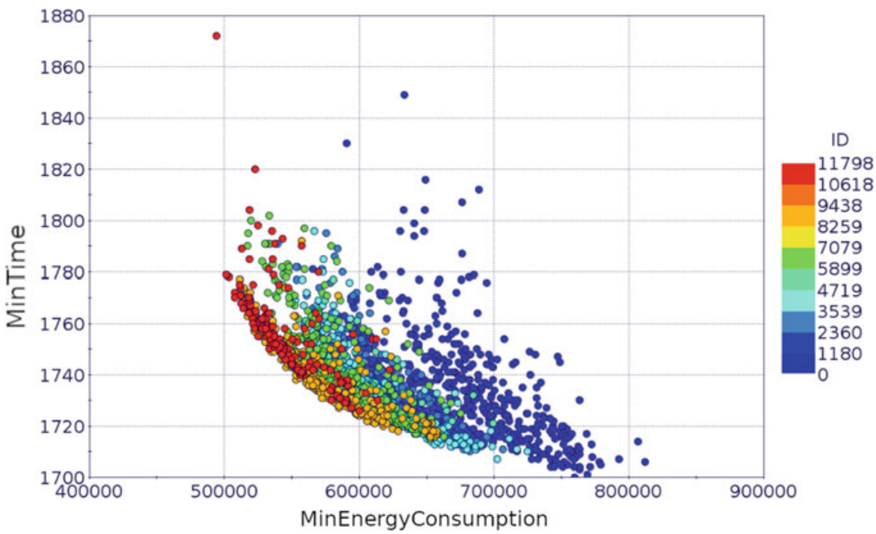

Fig. 7.6 MOGA evolution on case study

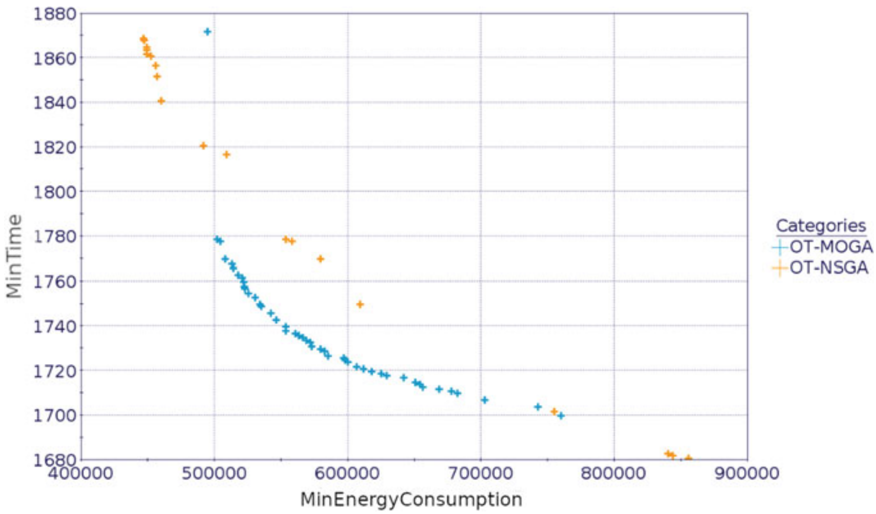

Fig. 7.7 MOGA-II and NSGA-II Pareto Fronts. In the legend, the prefix OT is added in the name to underline that the algorithms are interacting with OpenTrack

the initial population is generated internally. The OpenTrack node calls the Open-Track tool and the logic end terminates the process. The workflow is started by mean of a run command, which allows the optimization process execution.

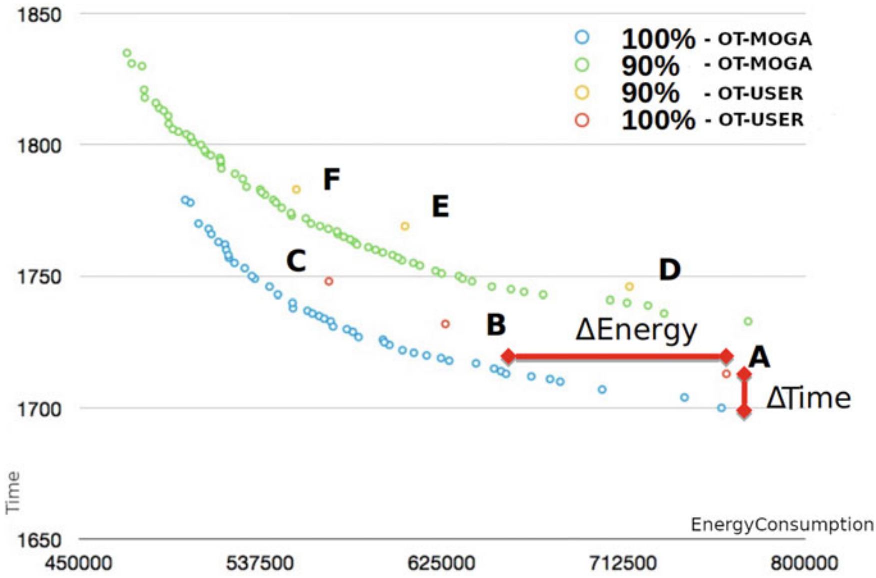

Fig. 7.8 Comparison between the solution approach and OpenTrack with 100% and 90% of trains performance. In the legend, the prefix OT is added before MOGA-II to underline that the algorithms are interacting with OpenTrack. While, the suffix USER is added after OT to underline that OpenTrack is used alone (by the user)

7.6.2 Results

Starting from the previous modeFRONTIER workflow, the optimization has been performed by using MOGA-II and NSGA-II. In both cases the result is the identification of the Pareto Front for the given problem, which is the set of solutions where it is not possible to improve one objective without worsening the other considered and conflicting objective. For example, Fig. 7.6 shows the evolution of MOGA-II algorithm in its convergence to the Front on case study considered: *the horizontal axis reports the energy consumption values (in Joule), while the vertical axis reports the travel time values (in seconds)*. Blue bubbles represent the initial population and the red bubbles the one of the last iteration. The solutions visited during intermediate iterations are the bubbles between the blue an the red ones, which have different color graduations (yellow and orange, etc). Figure 7.7 shows the Pareto Fronts found by the two algorithms. In particular, the blue cross-shaped points represent the Pareto Front found by MOGA-II, while the orange cross-shaped points the ones found by NSGA-II. The analysis of this result shows that MOGA-II finds better solutions in the energy consumption range between 500kJ and 750kJ while NSGA-II discovers better solutions when energy consumption is lower than 500kJ or the time is less then 1700s. This results will be further investigated in the future to verify if it is a systematic feature of the proposed algorithms. According to the proposed approach,

Table 7.2 Time supplement distributions

	Performance 100%		Example MOGA-II Solution			
Station	Time		Time		Margins	ΔTime %
A		01:00:00		01:00:00		
B	01:01:22	01:02:22	01:01:27	01:02:27	00:00:05	5.81
C	01:02:54	01:03:54	01:03:00	01:04:00	00:00:01	1.16
D	01:05:09	01:06:09	01:05:28	01:06:28	00:00:13	15.127
E	01:07:08	01:08:08	01:07:43	01:08:43	00:00:16	18.60
C2	01:09:00	01:10:00	01:09:40	01:10:40	00:00:05	5.81
F	01:10:44	01:11:44	01:11:26	01:12:26	00:00:02	2.33
G	01:13:03	01:14:03	01:13:55	01:14:55	00:00:10	11.63
C3	01:15:00	01:16:00	01:15:54	01:16:54	00:00:02	2.33
H	01:17:04	01:18:04	01:18:00	01:19:00	00:00:02	2.33
I	01:19:05	01:20:05	01:20:08	01:21:08	00:00:07	8.14
L	01:20:58	01:21:58	01:22:09	01:23:09	00:00:08	9.30
M	01:23:12	01:24:12	01:24:29	01:25:29	00:00:06	6.98
C4	01:25:00	01:26:00	01:26:24	01:27:24	00:00:07	8.14
N	01:26:38	01:27:38	01:28:04	01:29:04	00:00:02	2.33
C5	01:27:54		01:29:20		00:00:00	0.00
Total	00:27:54		00:29:20		00:01:26	0.00

two set of simulations have been performed respectively considering 100% or 90% of train performance in OpenTrack simulation. Figure 7.8 shows all results for these two train performances. In particular, *the horizontal axis represents the energy consumption (in Joule), while the vertical axis the total travel time (in seconds)*. The green and blue dots represent the Pareto Front found by MOGA-II (which interacts with OpenTrack) with 100% and 90%, respectively. The red and yellow dots represents the results found by OpenTrack with 100% and 90%, respectively. Points A, B and C refer to three operation situations with 100% of trains performance derived from experience and the same meaning have points D, E and F for 90% of performance. It can be noticed that the proposed approach allows both to find a possible train speed profile with the same total travel time and lower energy consumption, or with lower travel time given the same energy consumption. Time and energy- savings vary between -1% and -9% in the considered case study.

Table 7.2 shows the distribution of time supplements over the sections. Indeed, the definitions of new schedules involves a new distributions of time on each running times. It is really interesting that these supplements are not distributed among the section in a uniform way, but they depend on line configuration. This result may help in distributing these time supplements in the planned timetable.

7.7 Conclusion

The timetable calculation usually does not take into account the energy consumption. Since green transportation is becoming a central issue, the attention for energy-efficient timetable calculation is growing. This problem, called EETTP, could reduce operating costs significantly and contribute to a further increase of the sustainability of railway transportation. In this work, a solution approach to solve the EETTP is introduced. This approach requires the integration between modeFRONTIER and OpenTrack. In particular, the model is formulated into a modeFRONTIER workflow in which the output variables are calculated by means of OpenTrack. The optimization is based on MOGA-II and NSGA-II, which are two genetic algorithms available in modeFRONTIER. Both the algorithms perform well on the case study considered. In particular, MOGA-II finds better solutions in the energy consumption range between 500kJ and 750kJ while NSGA-II discovers better solutions when energy consumption is lower than 500kJ or the time is less then 1700s. However, more tests will be done to investigate the behavior of the two algorithms by increasing the number of repetitions for each run of each experiment. Moreover, more tests will be done to improve the optimization results by using other algorithms available in modeFRONTIER.

In this work, a single train running on the infrastructure is considered. Future works will be devoted to test the behavior of this approach when more trains are considered.

A particular procedure to take into account also the energy recovery is considered and the first results seem to be promised. However, this procedure is not completed and future works will be devoted to test it.

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