Ref. Ares(2019)4235896 - 03/07/2019

Horizon 2020
European Union Funding
for Research & Innovation

Modelling and strategies for the assessment and **Op**timisation of **E**nergy **Us**age aspects of rail innovation

Deliverable D 4.2

Driving strategies and energy management for DAS

Project acronym:	OPEUS
Starting date:	01/11/2016
Duration (in months):	30
Call (part) identifier:	H2020-S2R-OC-CCA-2015-02
Grant agreement no:	730827
Due date of deliverable:	Month 27
Actual submission date:	03-07-2019
Responsible/Author:	STAV / María Marsilla and UROS/ Lukas Pröhl
Dissemination level:	PU
Status:	Final

Reviewed: (**yes**/~~no~~)

Document history		
Revision	*Date*	*Description*
1	17.01.2019	First draft
2	07.03.2019	First complete version
3	24.05.2019	Final version
Final	03.07.2019	Document finalised for submission to S2R

Report contributors		
Name	Beneficiary Short Name	Details of contribution
David Antolín	STAV	Deliverable Revision
Juan José Barriga	STAV	Co-Author
María Marsilla	STAV	Co-Author
Lukas Pröhl	UROS	Co-Author
Roberto Palacin	UNEW	Review

Table of Contents

List of Figures

List of Tables

1. Executive Summary

The work presented in this Deliverable D4.2 has been carried out in the framework of the EU Project OPEUS. The present work is also in close relation with the work carried out in WP02 and WP03, where OPEUS simulation tool has been developed and reference simulations have been done.

This deliverable reports the outcomes following the assessment of DAS strategies applied to the different scenarios considered in OPEUS project using OPEUS Tool.

For the reference scenarios, different approaches has been taken to improve the performance of vehicles, reducing energy consumption while ensuring close adherence to the timetable. This document explains the developed efficient and feasible driving strategies developed with this aim.

The first part of the report presents the development of an energy optimal driving strategy, explaining the trajectory planner of OPEUS-Tool and optimization algorithms.

The second part summarizes algorithmic improvements, strategies and energy management approaches such us:

- Algorithmic improvements and definition of reduced-order models for real-time capable prediction.
- Definition of system disturbances for the simulation of disturbed train operations.
- Slope parameter consideration in the trajectory planner.
- Increasing optimization possibilities: subsections of route depending on speed limit.
- Operational setting switching off the engine at low loads.

Operational and driving strategies have a major influence in energy consumption. Optimization algorithms have shown up to 8.2% energy savings, in the case of the reference HS300 service. These savings are increased for profiles with altitude up to 12.3%. The application of the switch-off strategy allows for high energy savings, especially in urban and regional services, with 9% and 8% savings respectively.

2. Abbreviations and acronyms

Abbreviation / Acronyms	Description
CMA-ES	Covariance Matrix Adaption – Evolution Strategy
DAS	Driving Advice/Assistance System
FFA	Firefly algorithm
FINE1	Future Improvement for Energy and Noise. EU S2R Project, Grant Agreement Number: 730818
FrMain	Freight Mainline service
GWO	Grey Wolf Optimizer
HS300	High Speed 300 service
HS250	High Speed 250 service
IC	Intercity service
IMPACT1	Indicator Monitoring for a new railway PAradigm in seamlessly integrated Cross modal Transport chains – Phase 1. EU S2R Project, Grant Agreement Number: 730816
PSO	Particle Swarm Optimization
Reg160	Regional 160 service
Reg140	Regional 140 service
Suburb	Suburban service
WP	Work Package

3. Background

The present document constitutes the Deliverable D4.2 “Driving strategies and energy management for DAS” in the framework of WP04 DAS Study of OPEUS project (S2R-OC-CCA-02-2015). The report uses WP02 and WP03 results and it contributes to WP05, task 5.2 (In-Vehicle Energy Losses Study) and to WP07 of OPEUS Project. Results of this report contributes to objectives of FINE1 project and CCA energy group of Shift2Rail too.

The reader is encouraged to read first Deliverables DO2.1 [1] and DO3.3 [2] of OPEUS Project, which describes the OPEUS simulation methodology and present simulations results respectively.

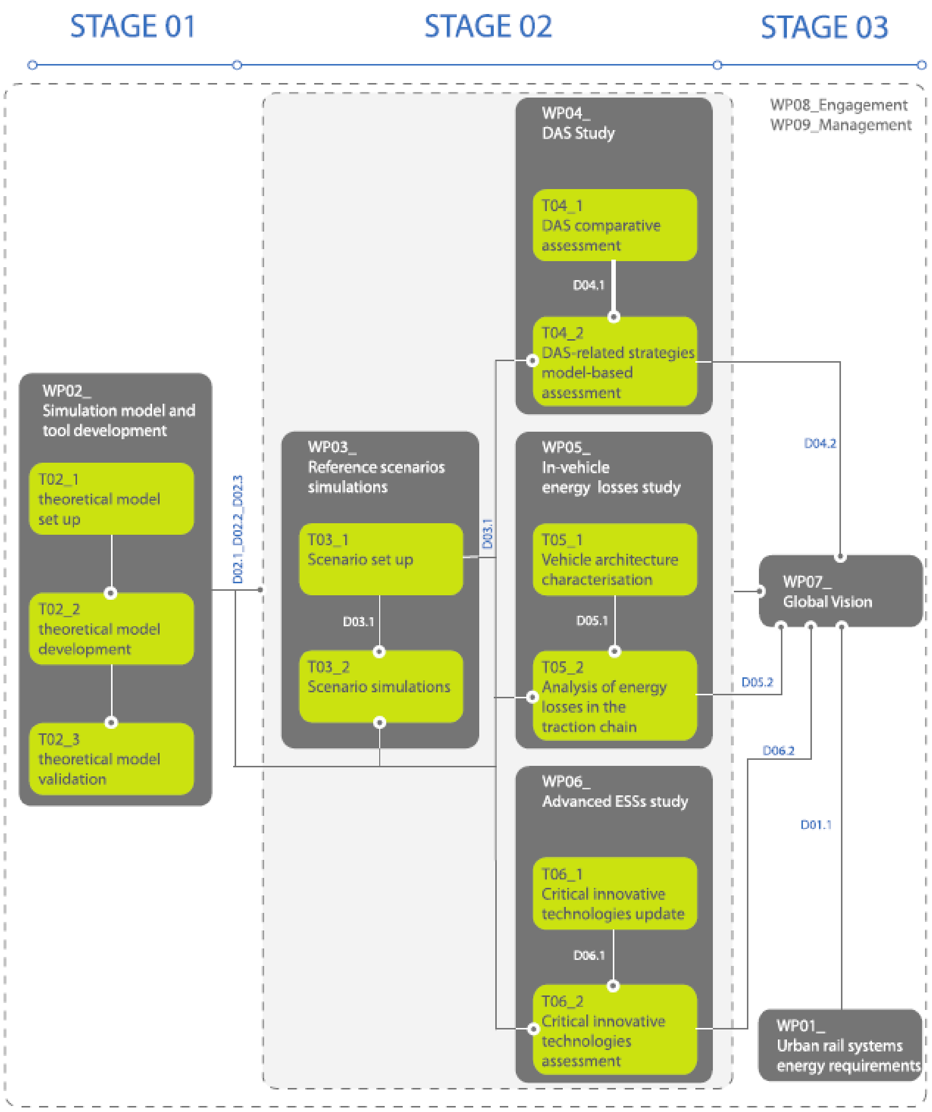


Figure 1 . Relationship between the different activities included in the OPEUS work plan

4. Objective/Aim

This document has been prepared to provide possible energy management approaches in order to implement the optimal speed profile in a form of a driver assistant system or an automatic train operation, as well as to present the corresponding simulation results. To do so, the OPEUS Tool developed in WP02 has been applied.

5. Energy optimized driving style

As introduced in Deliverable D03.3 – Part 2 [2], Chapter 8.1 "Optimization approach for the energy-optimal driving strategy", to determinate the energy optimal velocity profile, the optimization problem for the driving technique has to be solved. The objective of this section is the description for the development of an energy optimal driving strategy. For this purpose, the functionality of the trajectory planner is summarized. Furthermore, the optimization problem for the energy optimal diving strategy is denoted and several algorithms for solving the optimization problem are presented.

5.1 Functionality of the trajectory planner

The trajectory planner is an important part of the OPEUS-tool. It enables the user to determine suitable speed profiles fulfilling the timetable request. The functionality of the trajectory planner is described in the framework of the OPEUS-tool development within the deliverable report *DO2.1 – OPEUS Simulation package* [1]. Nevertheless, for the sake of better understanding, a short overview of the functionality is given here.

For calculating the total speed profile, the trajectory planner implements four different driving states, namely:

- Acceleration - limited by the maximum traction effort and the passenger comfort,
- Cruising - moving at a constant velocity level (no acceleration),
- Coasting - motion without active traction or braking at the wheels,
- Braking - limited by the maximum braking effort as well as the passenger comfort.

These driving states are combined to define the total trajectory. To determine the optimal points for changing the driving states, the trajectory parameters b_c and p_{va} are introduced. Here, the distance s_c to apply coasting is defined by the parameter b_c. With a fixed overall distance s_{end}, the coasting point is given with

$$s_c = b_c s_{end}, \text{ with } b_c \in [0; 1].$$

The parameter p_{va} characterizes the desired maximum speed v_d of the train. According to the current speed limit $v_{\lim}$ of the section, the desired speed is calculated by

$$v_d = p_{va} v_{lim}, \text{ with } p_{va} \in [0; 1].$$

The influence of the both trajectory parameters are depicted in Figure 2.

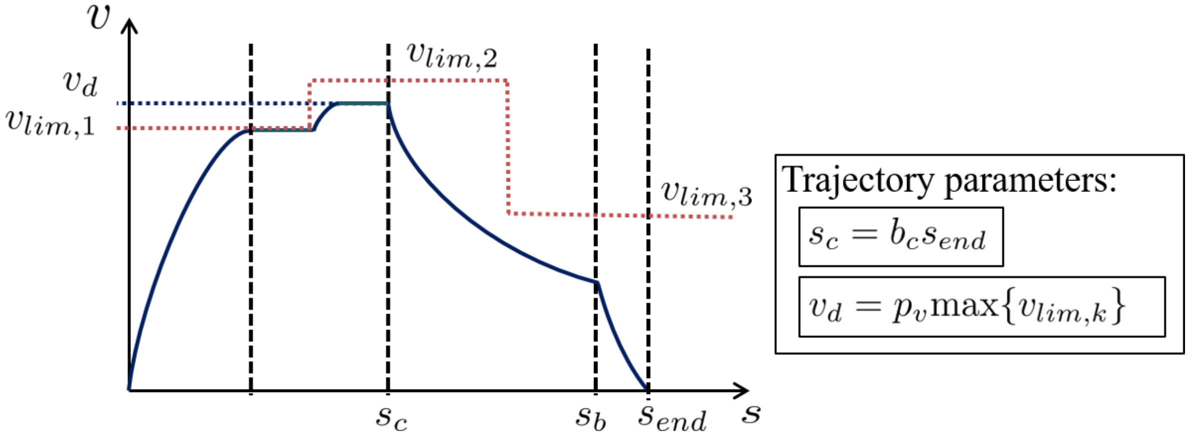
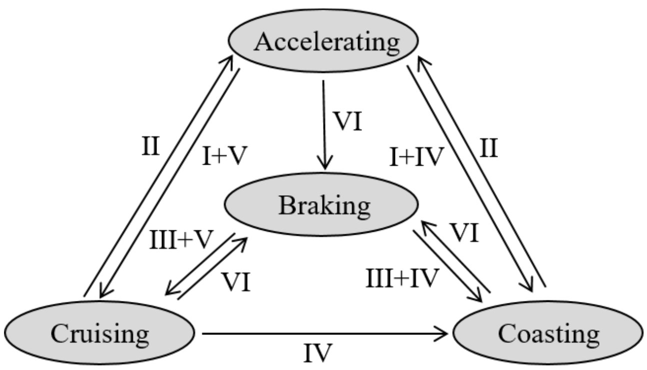


Figure 2: Impact of the trajectory parameters

Based on this parameterization, the changing between the driving states are determined by the trajectory planner module. The functionality of this module is summarized in Figure 3.



I. $(v = v_d) \vee (v = v_{lim})$
II. $(v < v_d) \wedge (v < v_{lim})$
III. $(v = v_b) \vee (v > 0)$
IV. $(s \geq s_c)$
V. $(s < s_c)$
VI. $(s \geq s_b) \wedge (v > v_b)$

Figure 3: Functionality of the trajectory planner

This functionality of the trajectory planner allows for several trajectory modes with different styles and properties. Figure 4 presents the possible trajectory modes for a simple example with only one speed restriction.

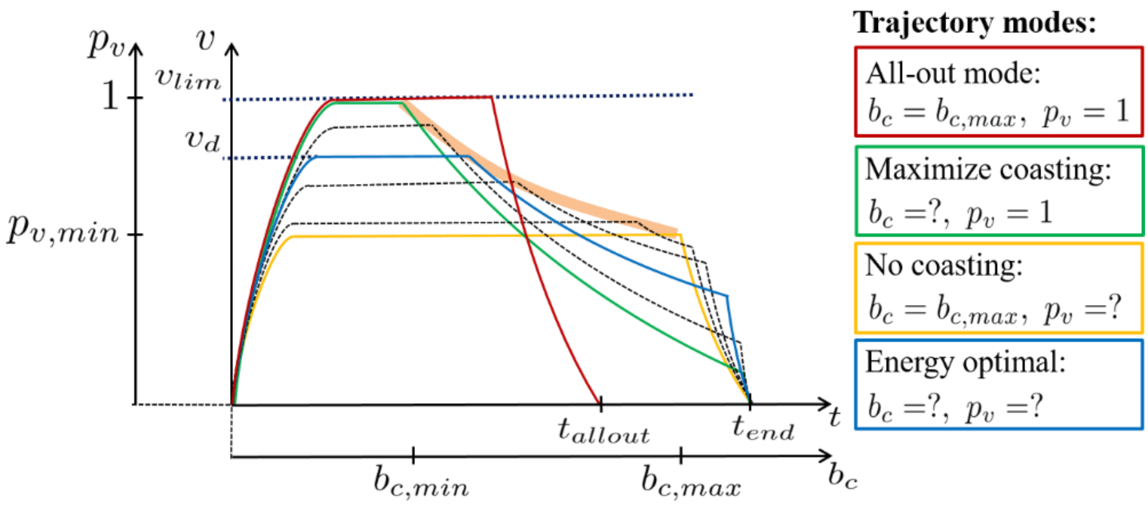


Figure 4: Possible trajectory modes

In Figure 4, the all-out mode (red curve) is characterized by $p_{va} = b_c = 1$. The trajectory profile, which is presented by the green curve, implements the maximum amount of coasting to fulfil the timetable. The maximum speed parameter p_{va} is therefore fixed to $p_{va} = 1$ as parameter b_c is determined by a bisection algorithm to accomplish the timetable. In contrast, the yellow curve is presenting a trajectory mode, where no coasting is applied. For this no-coasting mode, the coasting parameters b_c is set to the maximum, as the corresponding speed parameter p_{va} is determined via a bisection algorithm.

As indicated in Figure 4, the energy optimal solution (blue curve) for this example could be somewhere in between the no-coasting mode and the maximum coasting mode. To determine this energy optimal solution, both parameters b_c, p_{va} has to be calculated with respect to the energy consumption. The optimization problem for this task is defined below.

5.2 Optimization problem for the trajectory planning

The main objective of the trajectory planner is determining a feasible speed profile that fulfils the timetable request for a station-to-station drive. To address the desired position and time constraints for the departure (s_0, t_0) as well as for the arrival (s_f, t_f), the following penalty function is introduced

$$J_K = \begin{cases} \left(k - (k_f - k_0)\right)^2 & for \quad |k - (k_f - k_0)| > \Delta k, \\ 0 & else \end{cases} \qquad \text{with } k \in \{t, s\}.$$

The admissible time and distance differences are given by Δt respectively by Δs.

The total cost function defining the optimization problem considers the total net energy:

$$E_{total} = E_{cons} - E_{rec}.$$

Here, E_{total} is determined by evaluating the total consumed energy E_{cons} as well as the total recuperated energy E_{rec} at the catenary.

Conclusively, the total coast function can be stated with:

$$J = E_{total} + \alpha J_k,$$

where α denotes a weighting factor for the penalty function.

To determine the energy optimal parameterization (b_c^*, p_{va}^*) for the trajectory planner, the optimization problem

$$[b_c^* \quad p_{va}^*] = arg\left\{\min_{b_c, p_{va}} \{J(b_c, p_{va})\}\right\}$$

has to be solved. A selection of feasible optimization techniques is presented in the following section.

5.3 Optimization algorithms

As it is not possible to analytically derivate a gradient characteristic of the optimization problem denoted in section 5.2, some gradient-free technique are implemented. Here, the implemented optimization approaches for the optimal driving strategy are based on evolutionary algorithms. Especially, this report presents a summary of the following four algorithms:

a. PSO – default Particle Swarm Optimization,
b. GWO – Grey Wolf Optimizer,
c. CMA-ES – Covariance Matrix Adaption – Evolution Strategy,
d. FFA – Firefly algorithm.

The PSO, GWO and the FFA algorithms are inspired by the swarm/pack behaviour of animals in real nature, whereas the CMA-ES is based on stochastic observation.

The presented evolution algorithms are based on the population of randomly determined solution candidates. These possible solution candidates are stated as the particle. Every particle is characterized by a position within the parameter space $x_{i,k}$ and a corresponding cost value determined by evaluating the cost function $J_{i,k}(x_{i,k})$. Here, i states the current iteration of the algorithm as k denotes the k-th particle. The movement/evaluation of the particle specifies the characteristic of the single algorithm.

The particle movement of the **PSO** algorithm is based on the position of the best position of the total swarm – the global best position g_i^{best} – as well as on the best position of the individual particle – the personal best position $p_{i,k}^{best}$. These two reference positions are determined for every iteration of the algorithm. The current particle movement is now given with

$$v_{i,k} = w_k v_{i,k-1} + r_{1,k}\left(p_{i,k}^{best} - x_{i,k-1}\right) + r_{2,k}\left(g_k^{best} - x_{i,k-1}\right).$$

Here, w_k describes a decreasing weight function for the movement v_i of the particle itself, as $r_{1,k}$ and $r_{2,k}$ are randomly determined weighting factors to consider the global and individually best position (default PSO setting: $r_{1,k}, r_{2,k} \in [0,2]$).

The total position update $x_{i,k} = x_{i,k-1} + v_{i,k}$ is presented in Figure 5.

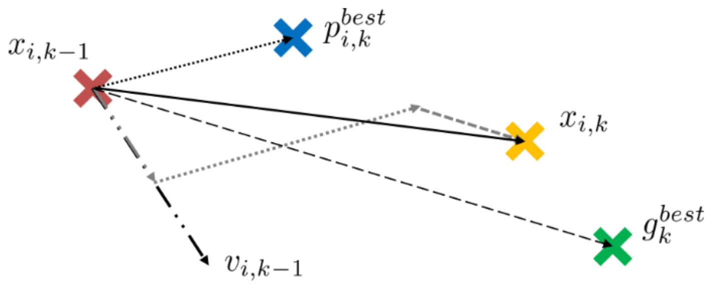


Figure 5. Particle movement for the PSO

For a more detailed description of the PSO algorithm, refer to [4]. A detailed example for the implementation of the PSO algorithm for determining the energy optimal driving style of a High-Speed train is presented in [5].

In analogy to the PSO algorithm, the **GWO** is a swarm algorithm as well. As the name denotes, the particle movement of this algorithm is inspired by the hunting behaviour of grey wolves in nature. Here, the particles are denoted as the wolves, as the total swarm is called the pack.

In contrast to the default PSO, the particle movement of the GWO is based on the position of the three leading wolves – presenting the three best positions (called alpha-, beta- and delta-wolves).

The total position update for the GWO algorithm is presented in Figure 6. Within this figure, $A_{1,2,3}$ represent the spaces for the possible positions of the three leading wolves, $d_{\alpha,\beta,\delta}$ representing the observed distances to the three leading wolves, as $C_{1,2,3}$ defines the possible space for the current position update for the k-th wolf. The total position update for the GWO is defined by:

$$\underline{x}_{i,k+1} = \frac{1}{3}\left(\underline{x}_1 + \underline{x}_2 + \underline{x}_3\right) \text{ with } \begin{cases} \underline{x}_1 = \underline{x}_\alpha - \underline{A}_1 \underline{d}_\alpha; & \underline{d}_\alpha = \left|\underline{C}_1 \underline{x}_\alpha - \underline{x}\right| \\ \underline{x}_2 = \underline{x}_\beta - \underline{A}_2 \underline{d}_\beta; & \underline{d}_\beta = \left|\underline{C}_2 \underline{x}_\beta - \underline{x}\right|. \\ \underline{x}_3 = \underline{x}_\delta - \underline{A}_3 \underline{d}_\delta; & \underline{d}_\delta = \left|\underline{C}_3 \underline{x}_\delta - \underline{x}\right| \end{cases}$$

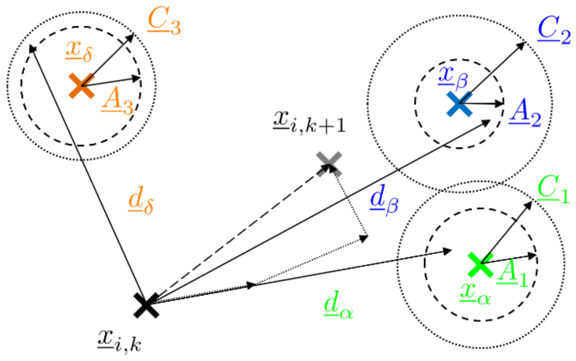


Figure 6. Particle movement for the GWO

For more a more detailed description of the GWO algorithm, refer to [6].

The third presented optimization algorithm is based on the stochastic determination of the particle. For the CMA-ES algorithm, the distribution of the particle is characterized by the covariance matrix.

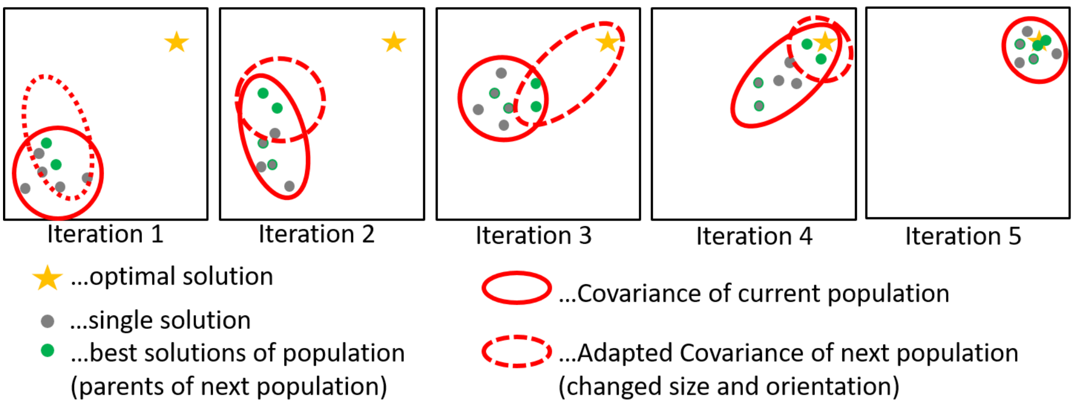


Figure 7. Particle movement for the CMA-ES

According to Figure 7, the form of the covariance matrix is adapted according to the position of the best individual particles of the current iteration. For evolutionary optimization approaches these particles are denoted as the parents of the population and determining the form of the covariance matrix of the next iteration. The position update for the next iteration than determined by the adapted covariance matrix.

More information regarding the CMA-ES algorithm can be found in [7].

All of the presented optimization approaches are implemented in the trajectory planner of the OPEUS tool and can be utilized for the determining energy optimized speed profiles. For calculating the simulation results of OPEUS deliverable D03.3, the CMA-ES algorithm is used, because the accuracy of the CMA-ES is comparatively high. Nevertheless, the other approaches are reasonable techniques as well, as they request lower calculation effort, which is advantageous for real time application.

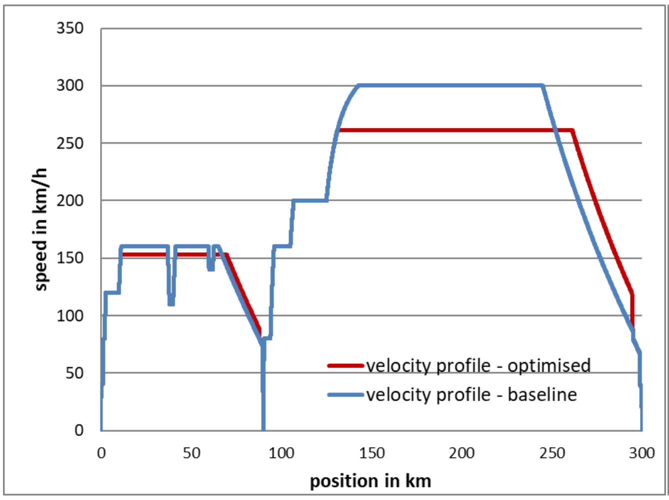
5.4 Simulation results for energy optimized trajectories

The detailed simulation results for the energy optimized operating strategy are presented and discussed in the OPEUS deliverable D03.3 –Part 2 [2]. Table 1 presents a summary:

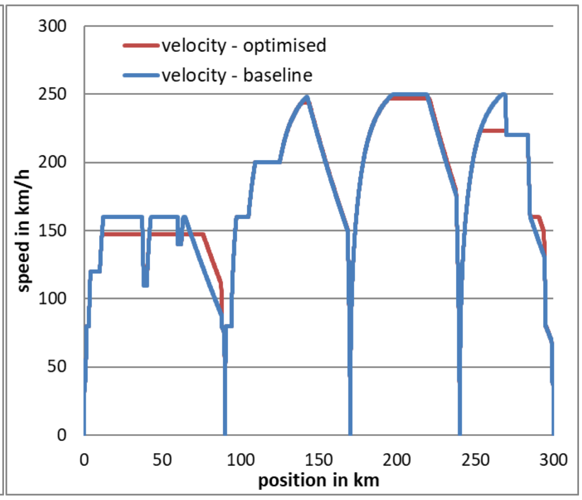
Optimized vs Baseline cases	Net energy [kWh] - baseline	Net energy [kWh] - optimized trajectory (CMA-ES)	Energy savings [kWh]	Energy savings [%]
HS300	5055	4642	413	8,2
HS250	4194	4108	86	2,1
Freight Mainline	5254	5048	206	~4

Table 1: Summary for energy optimised velocity trajectory for High Speed and Freight Services

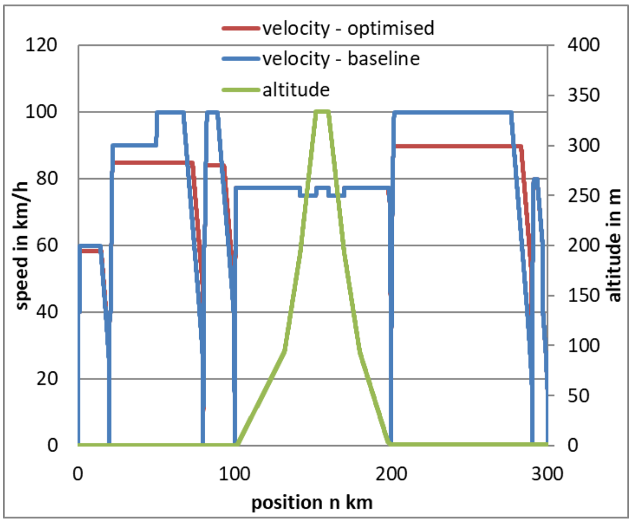
A potential energy saving up to 8% is possible with the usage of energy optimal driving strategies. Especially for the HS300 as well as for the Freight Mainline service, it shows that the avoidance of high vehicle speed has a positive effect on the total energy consumption. This is caused by a long state with constant speed and a high power request for High Speed 300 and for Freight Mainline. For the High Speed 250 service this effect is not that pronounced, as there are not such long constant high speed sections. It is reminded that reference High Speed 300 and 250 have no altitude in their trajectory, while the Freight Mainline do has a profile with altitude, as represented in Figure 8.



Speed profiles for the HS300 service



Speed profiles for the HS250 service



Speed profiles for the Freight Mainline service

Figure 8: Energy optimized velocity trajectories for HS300, HS250 and Freight Mainline service

5.4.1 Additional optimization algorithms: Genetic algorithms

In addition to the explained optimization algorithms, genetic algorithms are going to be briefly explained as well, which have not been used for the development of OPEUS-Tool, but they could be considered for a future work.

This optimization technique is based on the process of natural selection. To do so, the process begins with a set of individuals (the initial population), each of them characterized by a set of parameters (variables) that contain a possible solution for the problem.

Parting from this initial population, a selection phase is carried out to find the fittest individuals (using either a fitness function (maximization of fitness) or a cost function (minimization of the cost) as described in section 5.2), allowing them to pass their genes to the next generation. Therefore, offspring will inherit characteristics from the best individuals and will combine this (with a new characteristic – mutation – or with another characteristic from the previous generation), providing a new set of solutions. This generational process will continue until a termination condition has been reached (a found solution satisfies minimum criteria, fixed number of generations reached, etc.). This summarized process is represented in Figure 9.

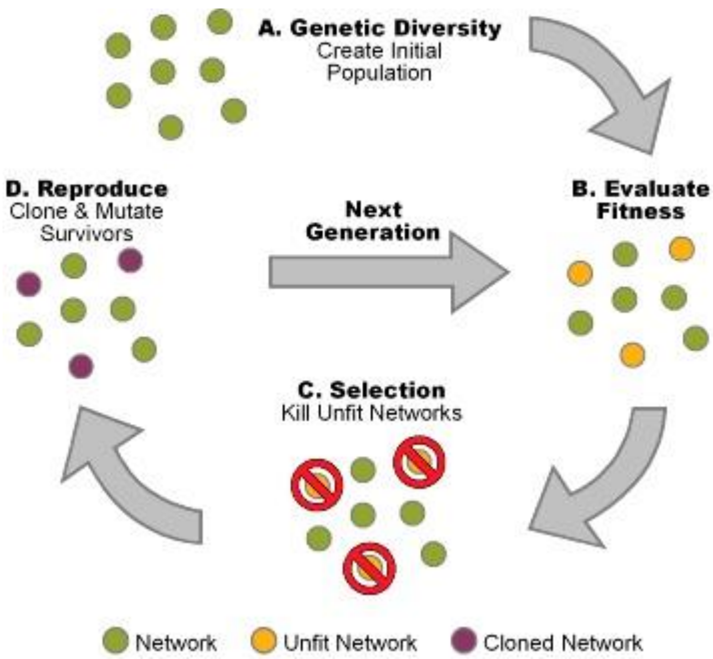


Figure 9. Genetic algorithm sequence

Further information can be found in reference document [8].

6. Algorithmic improvement and definition of reduced-order models for real-time capable prediction

For determining the speed profile for the desired tracks and trains, the trajectory planner module of the OPEUS-tool evaluates the equations of motions of the vehicle as well as the characteristic of the traction chain. For the calculation of feasible speed profiles, a high number of these simulation evaluations are necessary in order to execute the corresponding heuristic or optimization algorithm. Therefore, it is a very important request to decrease the calculation effort of the single simulations.

The presented algorithmic improvement is based on a reduction of the traction chain model. As presented in Figure 10, the power losses of the electric traction components as well as the characteristic of the auxiliary components is reduced to only one single block, which defines the total property of the traction chain.

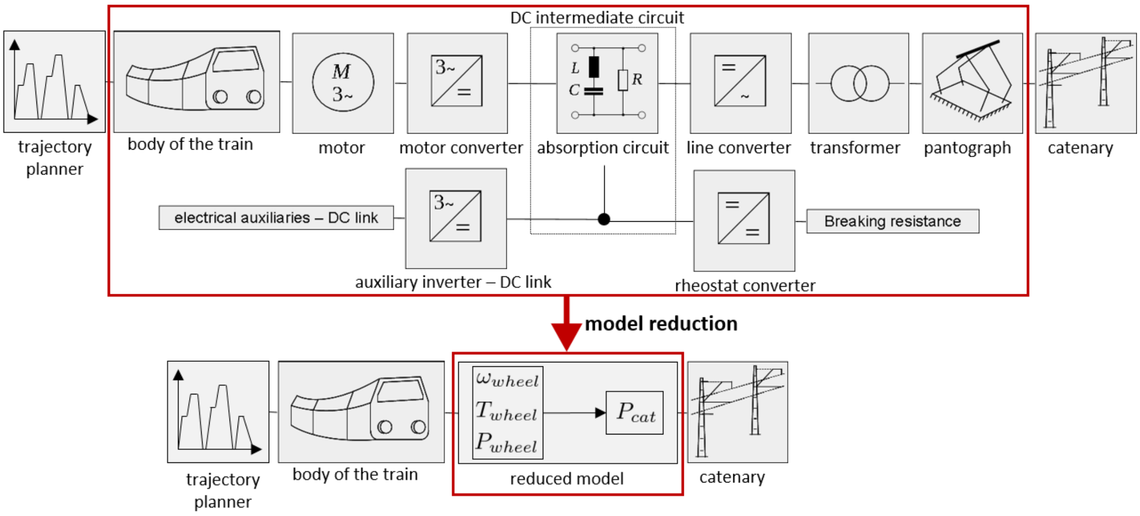


Figure 10: Reduction of traction chain behaviour

The input of this reduced traction chain model is the speed profile calculated by the trajectory planner. In combination with the mechanical properties of the vehicle, the angular velocity of the wheel ω_{wheel}, the torque at the wheel T_{wheel} as well as the power request at the wheel P_{wheel} can be determined. To map the total behavior of the traction chain, the polynomial approach for the power at the catenary:

$$P_{cat,ident} = \beta_0 + \beta_T T_{wheel} + \beta_\omega \omega_{wheel} + \beta_P P_{wheel}$$

is chosen. The coefficients $\underline{\beta_i} = [\beta_0 \quad \beta_T \quad \beta_\omega \quad \beta_P]_i$ are determined for the different driving states

$$i \in \begin{Bmatrix} acceleration \rightarrow a > 0; \\ braking \rightarrow a < 0; \\ coasting \rightarrow a < 0; \\ cruising \rightarrow a = 0 \end{Bmatrix}.$$

Taking into account that even during an acceleration phase, acceleration could be lower than 0 if the traction effort applied is not enough to overcome resistance. This is also applicable for the rest of driving states, since for example, acceleration could be greater than zero in a braking phase if the braking effort is not enough to overcome the force due to gravity inside a downhill stretch.

For future improvements of the OPEUS trajectory planner, also an assignment of the driving states regarding the power at the wheel is possible. This approach would consider an influence of the gradients regarding the driving states.

An example for the identification result is presented in Figure 11.

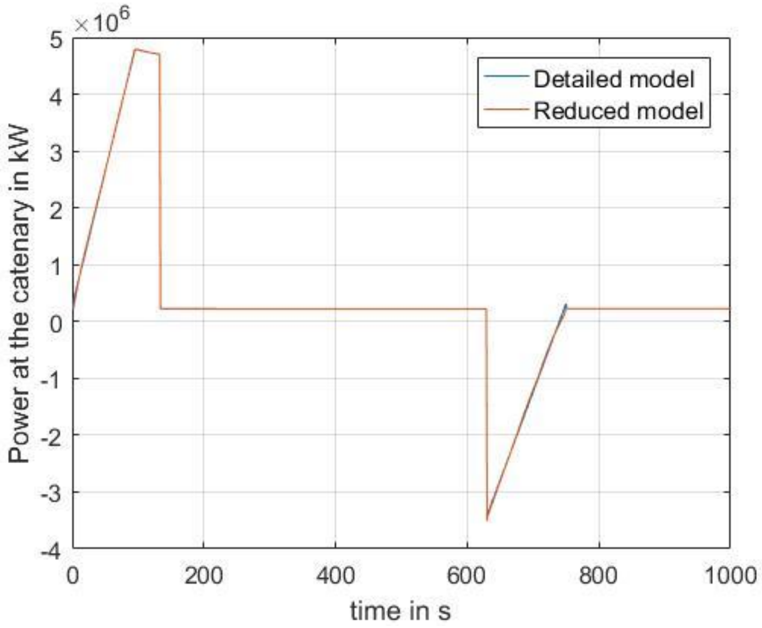


Figure 11: Mapping of the power at the catenary by a polynominal approach

In Figure 11, the power at the catenary is depicted for an easy drive cycle – acceleration, coasting, braking. The identified data fits the original data, which is evaluated with the detailed model of the traction chain.

A second technique to decrease the simulation time is the usage of the "Fast Restart" option of Matlab/Simulink, see [3]. This option utilizes, that the structure of the Simulink model does not need to change during the trajectory planning process. Therefore, there is no need for compiling the model for every simulation run. With the "Fast Restart" option, the model is only compiled once at the first evaluation. This procedure also leads to a big saving of calculation effort and time.

To assess the calculation effort of the implemented improvements, the trajectory planner was applied to determine the speed profile for the generic Regional 160 service category. For the speed profile, a maximum amount of coasting is requested (see the baseline simulation results of deliverable DO3.2). The resulting trajectory, presented in Figure 12, is covering 17 stops at station drives and several speed limits.

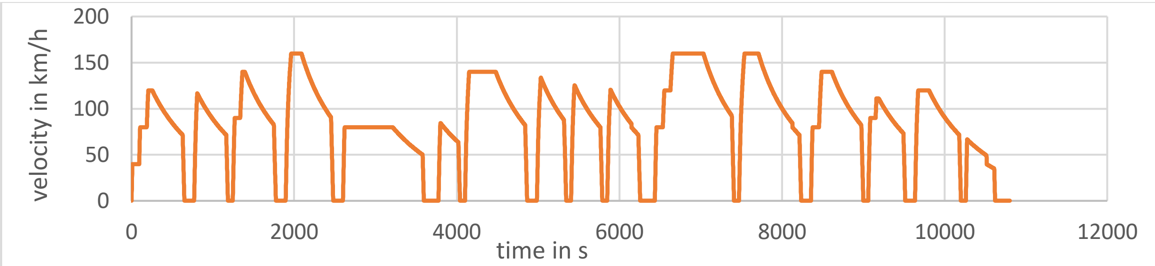


Figure 12: Baseline speed profile of the Regional 160 service profile

The reduction of calculation effort based in the algorithmic improvements, are presented in Figure 13. The calculation time is depicted for both, the calculation of the total speed profile as well as for the average calculation time for every single stop.

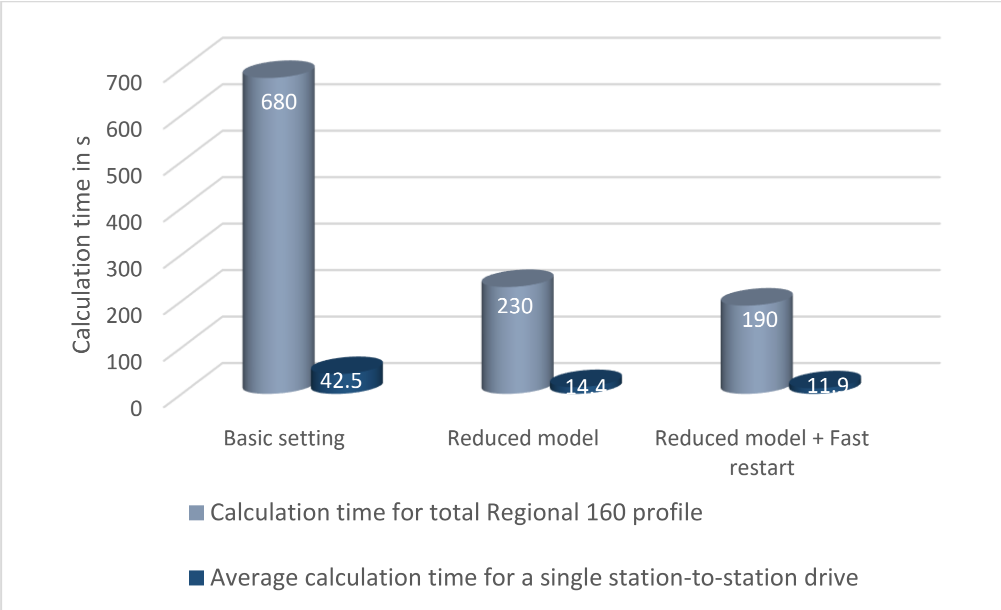


Figure 13: Calculation effort improvements for the determination of the Reg160 speed profile

With the implementation of these two improvements, the calculation time decreases about 70%. Furthermore, the average calculation time of $\approx 12s$ for a single station-to-station drive is much smaller compared to the average standstill time required by the timetable ($\approx 1 \dots 3$ min). This property could be utilized in real train application – e.g. determining the speed profile towards the next station while standing at the station.

7. Definition of system disturbances for the simulation

This chapter includes external circumstances, which may reduce the vehicle speed or even stop it. These circumstances are included to provide abnormal situations that may be encountered in a real environment, such as construction activities, semaphores or stopping in a station more time than expected.

To evaluate examples of these external circumstances, some disturbances have been introduced in the Tram service profile as well as in the Regional 160 profile as examples. The simulations results with the explained disturbances are presented in the sections bellow.

7.1 Tram disturbances

In the Tram service two external circumstances or disturbances have been considered:

a. In a first case, a stop of 30 seconds in the Tram profile has been introduced at position 5 km, to simulate a red signal (e.g.). Figure 14 shows the introduction of the mentioned disturbance and the new speed profile over position and over time.

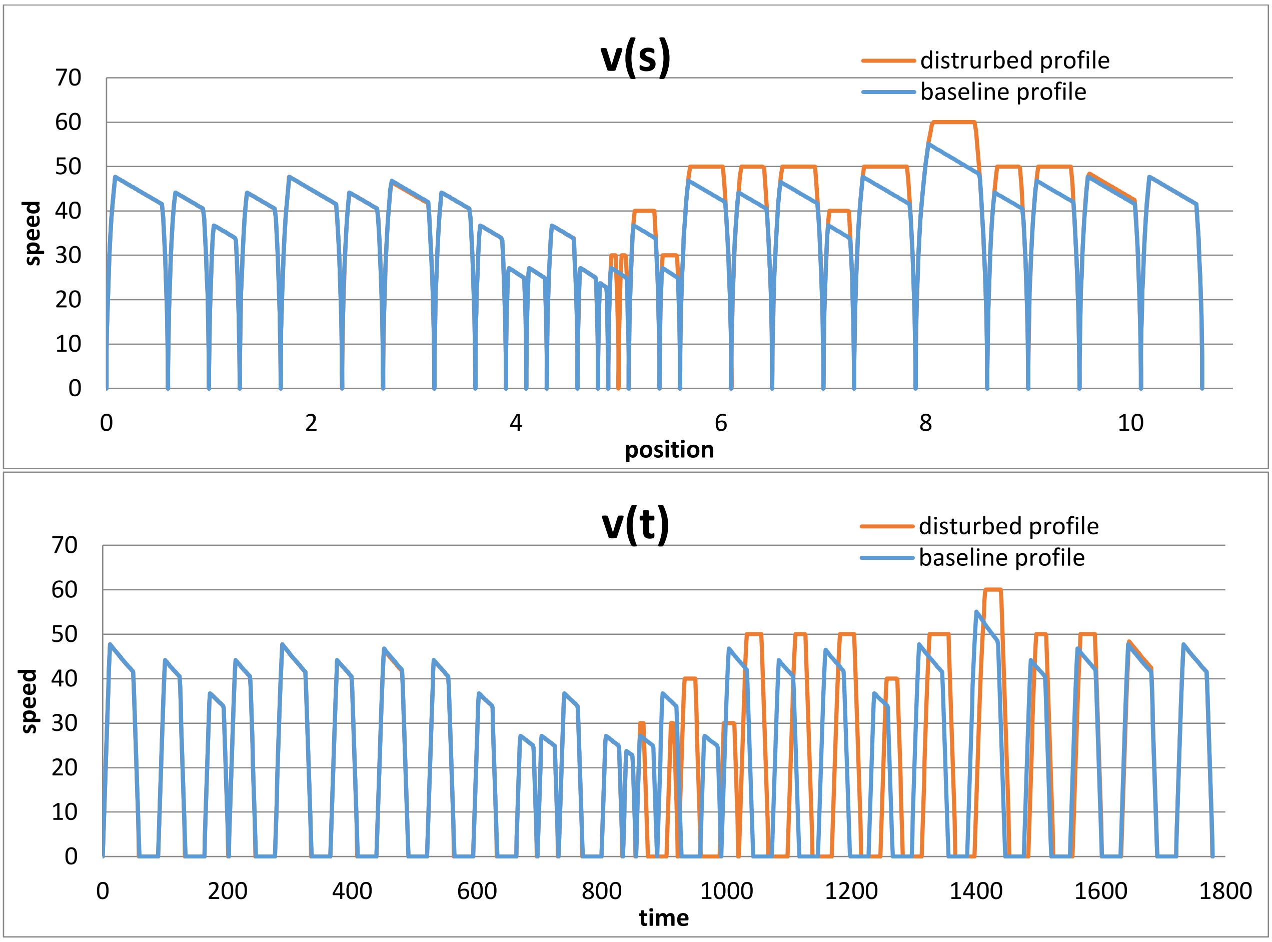


Figure 14: Speed profile adapt for disturbances in Tram service – case a) stop of 30s.

b. In a second case, a stop of only 6 seconds in the Tram profile has been introduced at position 5 km, to simulate a pedestrian crossing or a short unexpected stop. Figure 15 shows the introduction of the mentioned disturbance b) and the new speed profile over position and over time. As it can be observed, the speed profile is less altered than in case a), where a longer additional stop was introduced.

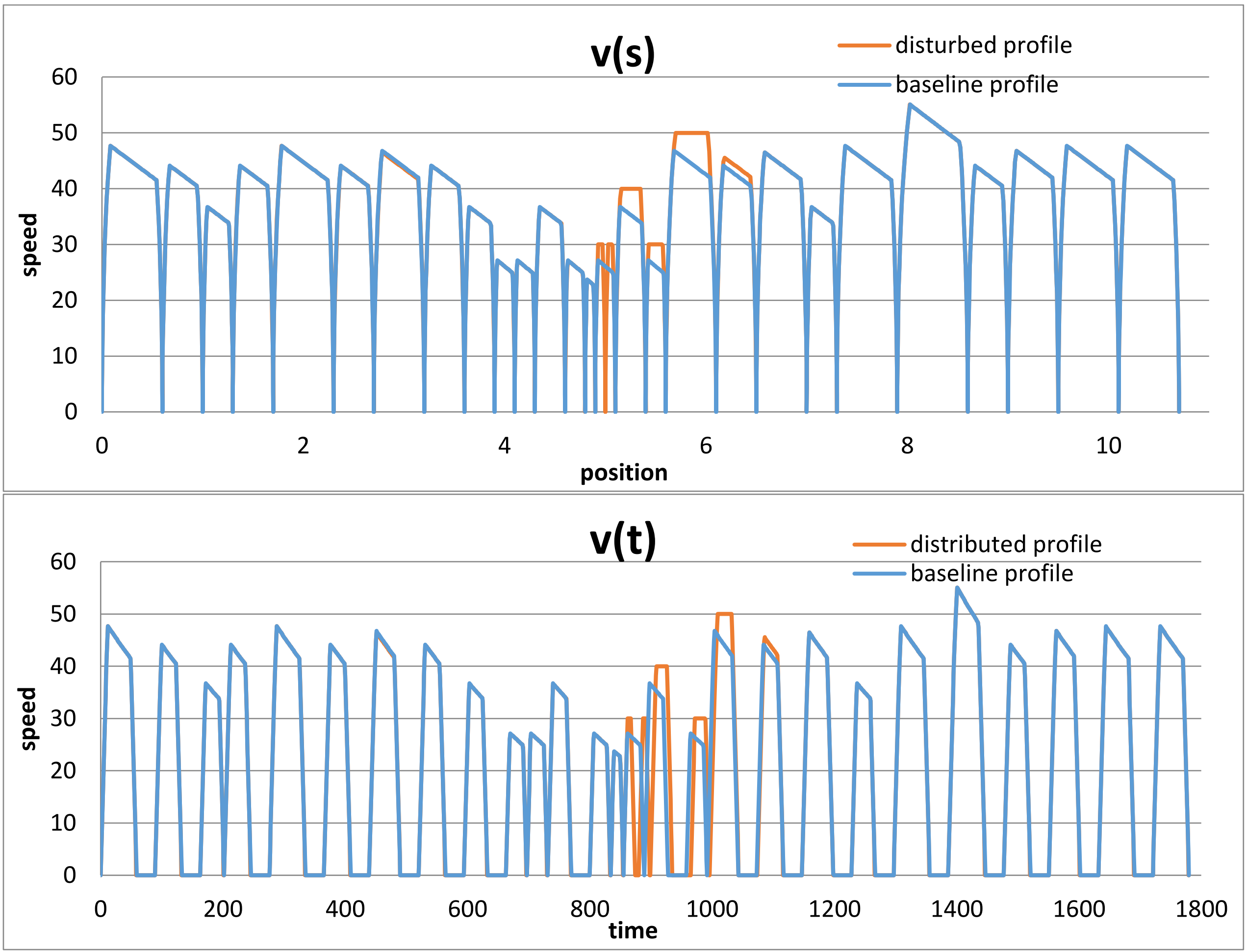


Figure 15: Speed profile adapt for disturbances in Tram service – case b) stop of 6s.

Finally, Table 2 gives a summary of the total energy consumption at the catenary level and the net energy consumption for both cases and the reference profile with no disturbances.

Tram	Consumed energy at the catenary (kWh)	Net energy (kWh)
Reference	68,6	53,8
Disturbance case a)	73,7	54,7
Disturbance case b)	69,97	53,9

Table 2: Consumption comparison in Tram service with disturbances

As expected, and in line with the new speed profiles, case a) which is having a longer additional stop, has a major energy consumption increase.

7.2 Regional 160 disturbances

For this service the following disturbances have been considered:

a. In a first case, two disturbances for an additional stop and an additional speed restriction have been introduced: at position 65 km an additional operational stop of 1 minute, a second disturbance with an additional speed restriction of 100km/h at interval position 155-165 km. This is presented in Figure 16.

b. In a second case, two disturbances have been introduced at positions 65 km and 155 km, of additional stops of 1 minute each. These disturbances are presented in Figure 17.

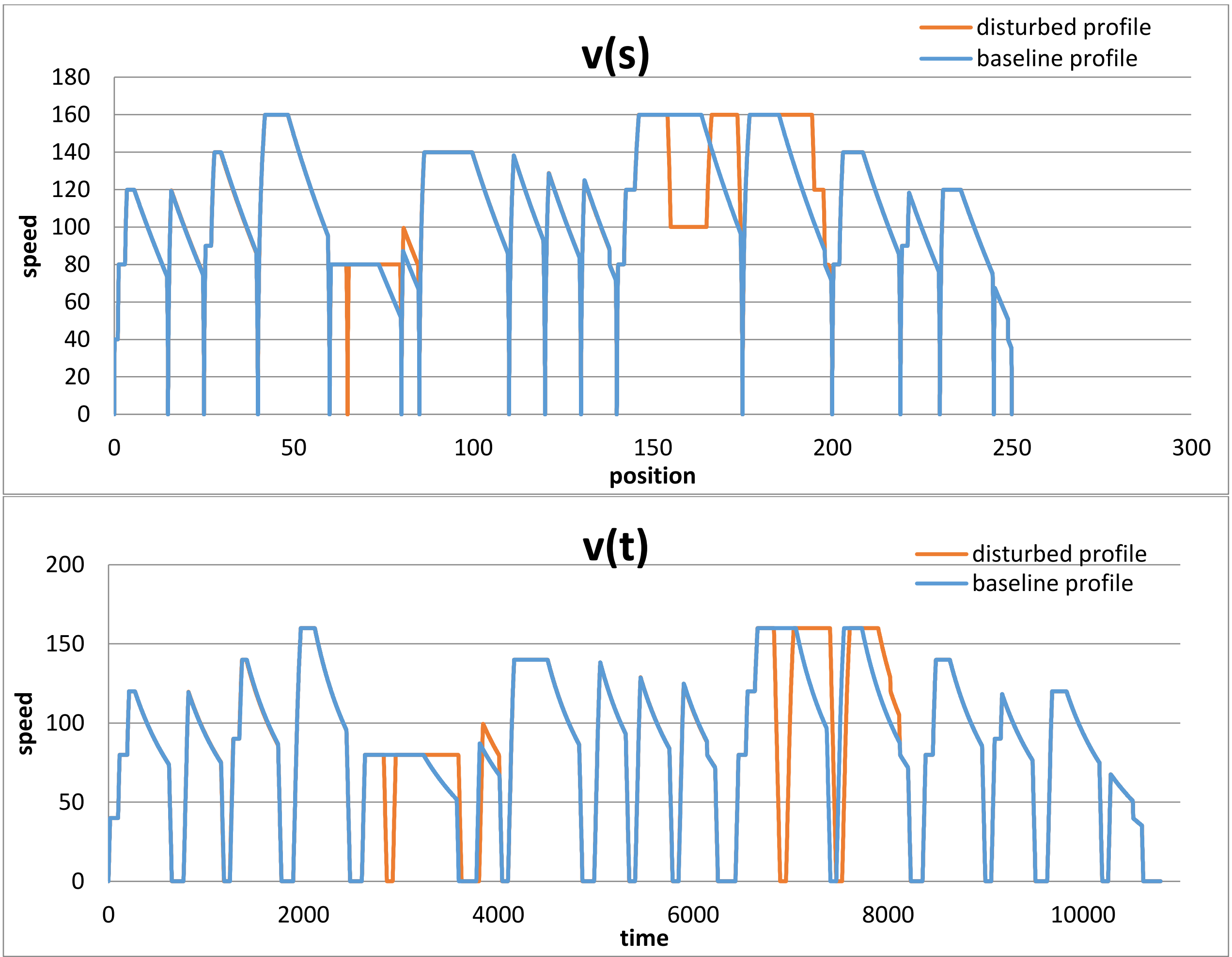


Figure 16: Speed profile adapt for disturbances in Reg160 –case a), stop and speed restriction

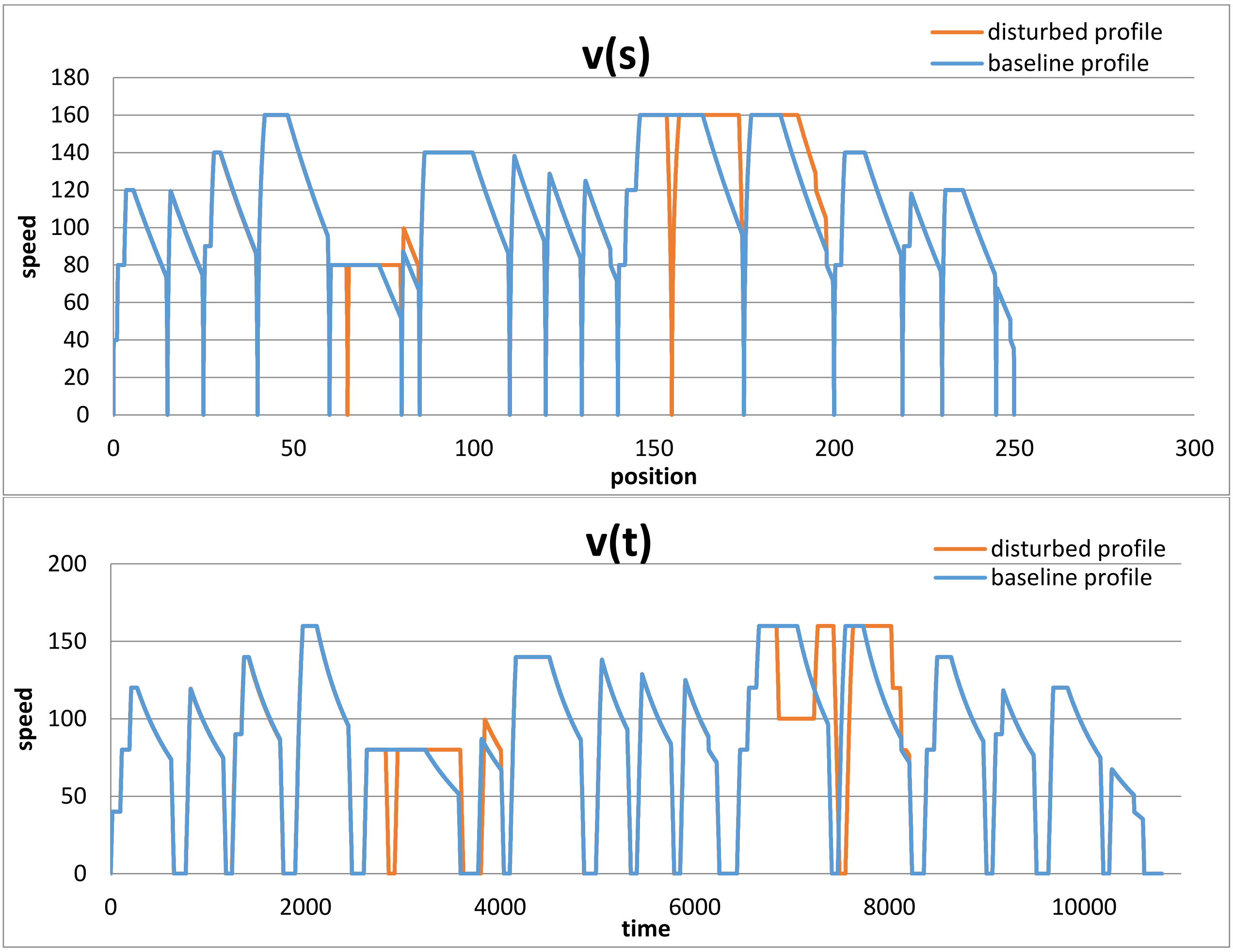


Figure 17: Speed profile adapt for disturbances in Reg160 – case b), 2 stops

Table 3 gives a summary of the total energy consumption at the catenary level and the net energy consumption for both cases and the reference profile with no disturbances.

Regional 360	Consumed energy at the catenary (kWh)	Net energy (kWh)
Reference	1560	1453
Disturbance case a)	1691	1531
Disturbance case b)	1707	1545

Table 3: Consumption comparison in Reg360 service with disturbances

As expected, external disturbances cause an increase of energy consumption. As shown in Table 3, case b) causes a higher consumption. This is due to the tractive effort required to recover from the additional stop, which highly increases the consumption compared from a speed limitation (the speed lost is way higher).

Of course, longer disturbances produced by working or construction activities on the track will cause delays in the timetable of the service profiles. In general, longer disturbances produced by working or construction activities on the track will cause a variation of service profiles, this will imply, as the DAS does not have data about this unexpected event before it happens, to recalculate the speed profile to compensate it. Therefore, this implies getting a new speed profile, which could vary between the previous one and the all-out speed profile from the route in the worst case scenario (when even going at maximum speed for the rest of the track, the train is going to arrive late).

OPEUS Tool is an off-line software, but the implemented energy strategy in OPEUS Tool can be followed by a DAS installed on-board the train, which will be capable of recognizing any disturbance and re-calculate the recommended speed profile in real time. OPEUS tool V7 also provides an "action" advice (accelerate / cruise / coast / brake) and also the objective speed, emulating the behaviour of a real DAS system.

8. Gradient – slope parameter to improve energy management

As described in Deliverable 3.3 [2], Chapter 8.3 “Influence of gradients”, the consideration of the gradient data for the determination of the optimal speed allows the usage of the train mass as an additional energy storage: The increased kinetic energy of the train (caused by increased velocity of the train during downhill sections) will be used to reduce the traction power for uphill sections. Therefore, different speed profiles depending on the current slope have to be defined in order to provide a realistic advice, maximizing the energy savings by taken profit of the descending slopes and reducing the maximum speed when ascending.

The three different gradient scenarios defined at the previous named deliverable are:

- No gradient – Flat section
- Baseline velocity trajectory – Unknown gradient
- Gradient considered for the trajectory planning

Representative gradients are applied for the below service categories. These service profiles are either forwarded from IMPACT1 (Grant Agreement number: 730816) via the FINE1 energy group:

- High Speed 300 service – from IMPACT (SPD1) via FINE1
- Regional 140 service – from IMPACT (SPD2) via FINE1
- Metro service – from IMPACT (SPD3) via FINE1
- Tram service – defined within WP4 by Stadler
- Freight Mainline service – defined within baseline scenario

In Deliverable 3.3 [2], the velocity profiles for all scenarios are determined by the heuristic trajectory planner, which is based on the maximisation of coasting.

In this deliverable the implementation of the optimisation algorithms explained above in Chapter 5 have been considered and new simulations have been carried out for HS300 service with gradient. The results are presented below.

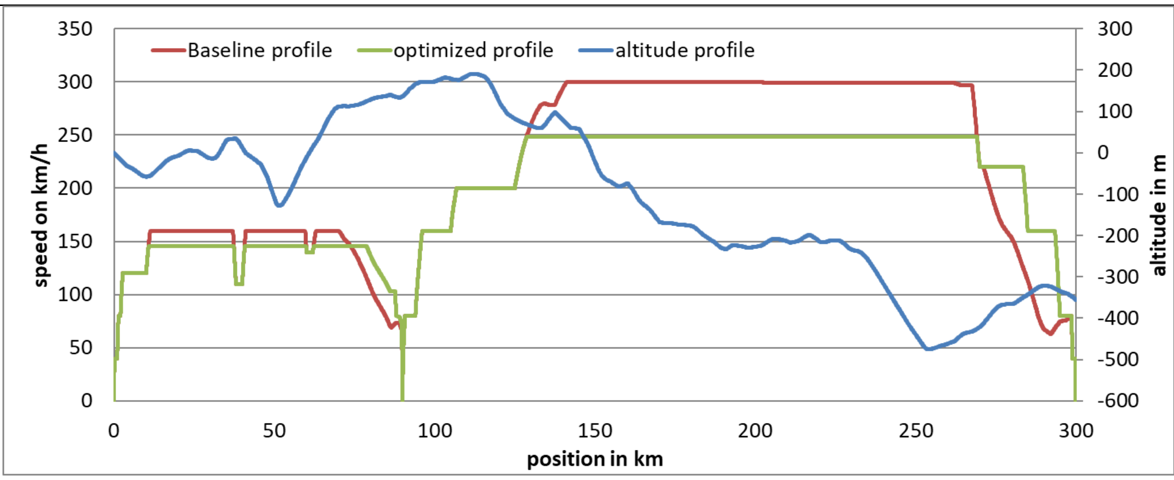


Figure 18: Velocity trajectories for HS300 energy optimized track profile with gradient

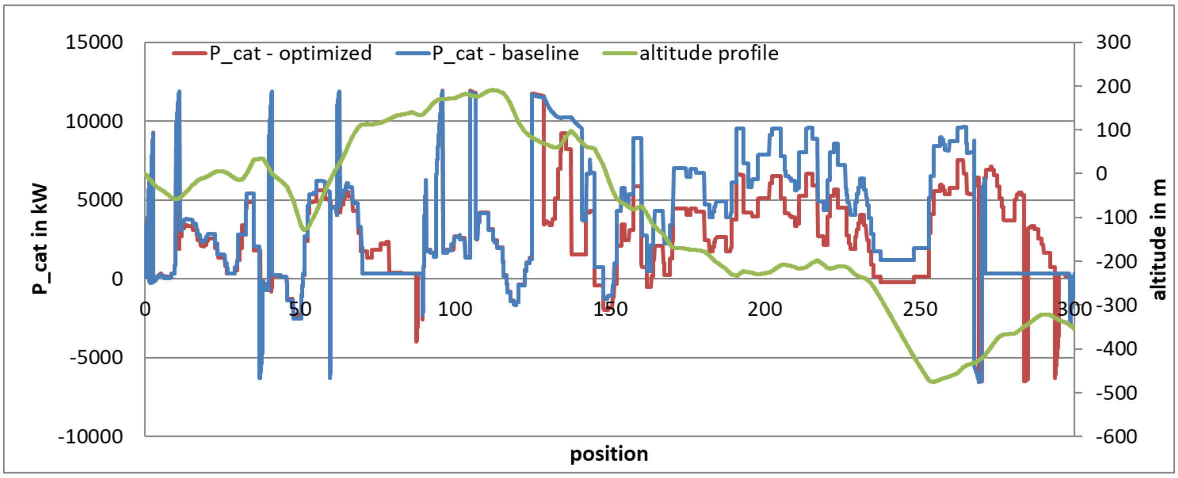


Figure 19: Power profile at the catenary for various gradient scenarios for HS300 service

	Net energy in kWh: Flat profile (baseline)	Net energy in kWh: Gradient considered trajectory planning with maximization of coasting (baseline approach)	Net energy in kWh: Gradient considered trajectory planning for energy optimized trajectory
Station A-B	1013	1311	1297
Station B-C	4042	3636	3040
Total net energy	5055	4947	4337
Total savings [kWh]	-	610	
Total energy savings [%]	-	12.3%	

In routes with gradients the optimization of the speed profile allows for high energy savings. In the example of the HS300 service with altitude 12.3% energy savings are possible by optimising the driving mode depending if the train is operating on down or up slopes. As a reminder, for the reference HS300 service (with no altitude) the savings by implementing the optimization algorithms are 8.2%, as shown in Table 1. Therefore, as real rail service profiles have gradients, higher energy savings by using optimization techniques are expected than for the flat reference profiles shown in this report.

9. Route subsections depending on speed limit

In order to obtain better optimum speed profiles, the division of route sections (first route section division has been based on station to station) into smaller ones by each speed limit change allows to increment the optimization possibilities, being able to find new and better optimum speed profiles, which translates into better results:

- A new subsection is implemented when the speed limit is reduced or changed with the goal of applying coasting more times.
- Modify speed, velocity and time of each section to find the best way to optimize the entire route.

If the driving strategy optimization is done for each route specific section[1] and not only between stations, multiple optimization points between stations are possible and the overall energy consumption shall be lower.

However, some problems were found when implementing this strategy in OPEUS Tool, which are worth to mention:

- There is need of having boundaries (timetable) on intermediate sections, as the OPEUS algorithm needs them to calculate the optimum profile. As the positions s_i of the intermediate sections are known, the intermediate times t_i are unknown as they are dependent regarding the driving style, see

[1] Specific route section is a section, where all route parameters (speed limit, curve radius and gradient) are constant. If any of those parameters are changed a new section is considered.

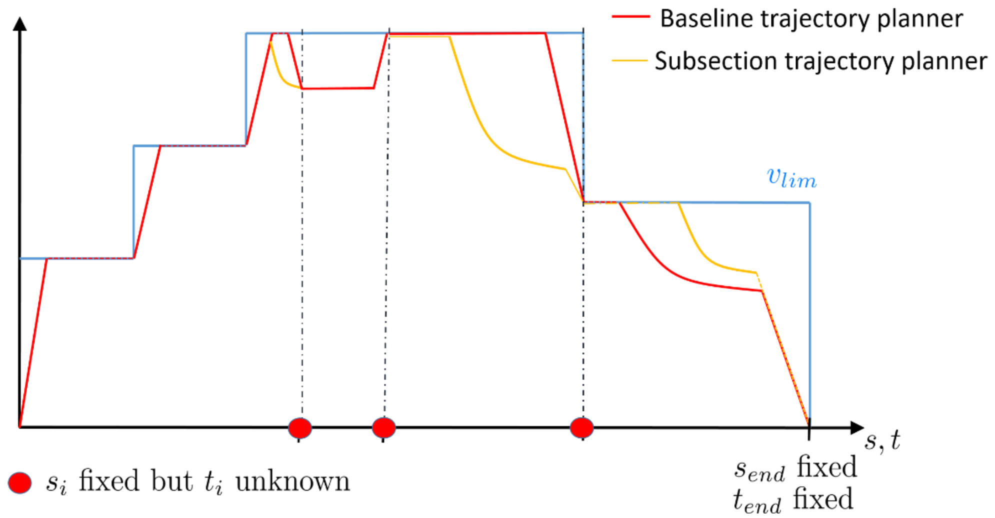


Figure 20: Unknown intermediate times for subsection coasting approach

- For the current implementation of the subsection coasting approach, the determination of the intermediate times t_i is solved with the following solution approach:
  1. A ration between the allout travel time and the total time travel time (according to the timetable) is determined:
  $$\nabla t = \frac{t_{timetable}}{t_{allout}}$$
  2. Determination of intermediate time for allout mode (time when the corresponding position is arrived in allout mode):
  $$t_{i,allout} = t_{allout}(s = s_i)$$
  3. Definition of required intermediate times based on the time ration ∇t:
  $$t_i = t_{i,allout} \cdot \nabla t$$
- Another proposal solve this problem, is to run multiple solutions with different advice configurations, combining speed reductions and coasting phases and iteratively mix them according to best relations of time-consumption cost.
- STAV has proven an alternative optimization technique based on running multiple simulations, combining different strategies (speed reduction, coasting, etc.) and evaluating their cost and time, to get the best solution of the proven samples. However, this solution has found some problems in terms of execution time (too long) and difficulty to achieve the timetable restrictions.
- The final target is to do the optimization that includes a combination of the driving strategy mode timetable with reduced speed and coasting for each route specific section.

This subsection implementation to increase optimization possibilities has been implemented in the services profiles High Speed 250 and High Speed 300 as examples. The results are presented in the next Figure 21 and Figure 22. The detailed baseline simulations with OPEUS Tool V7 are presented in OPEUS Deliverable 3.3 – part 2 [2].

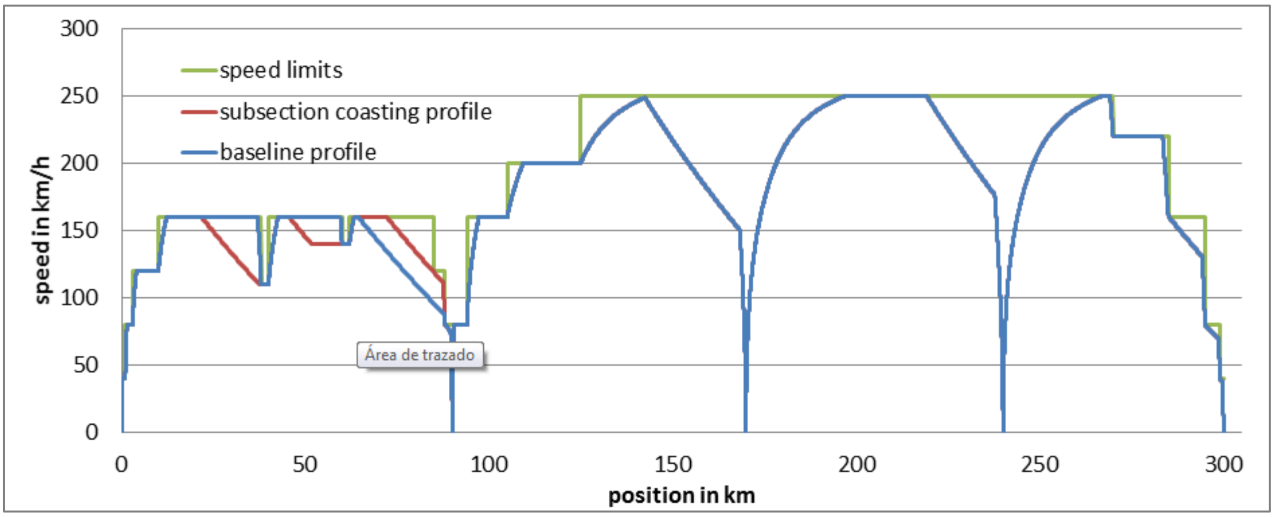


Figure 21: Speed profile for the High-Speed 250 profile with subsection coasting

As can be observed in Figure 21 by the implementation of the new subsection division more coasting sections are possible, which will allow for a reduction in the energy consumption. Because of the route service characteristics only 3 new coasting appear, so the reduction in energy consumption will be low. As presented in Table 4 the net energy savings by increasing the optimization possibilities with the mentioned subsections in comparison with the baseline simulation is 1.3%.

Net Energy in High Speed 250		
Baseline	**Subsection coasting**	**Difference - Savings**
4194 kWh	4140 kWh	54 kWh (1.3%)

Table 4: Net energy comparison between baseline and subsection coasting for High Speed 250

For the High Speed 300 service, the new speed profile is shown in Figure 22, which is very similar to the High Speed 250 service, and so are the results.

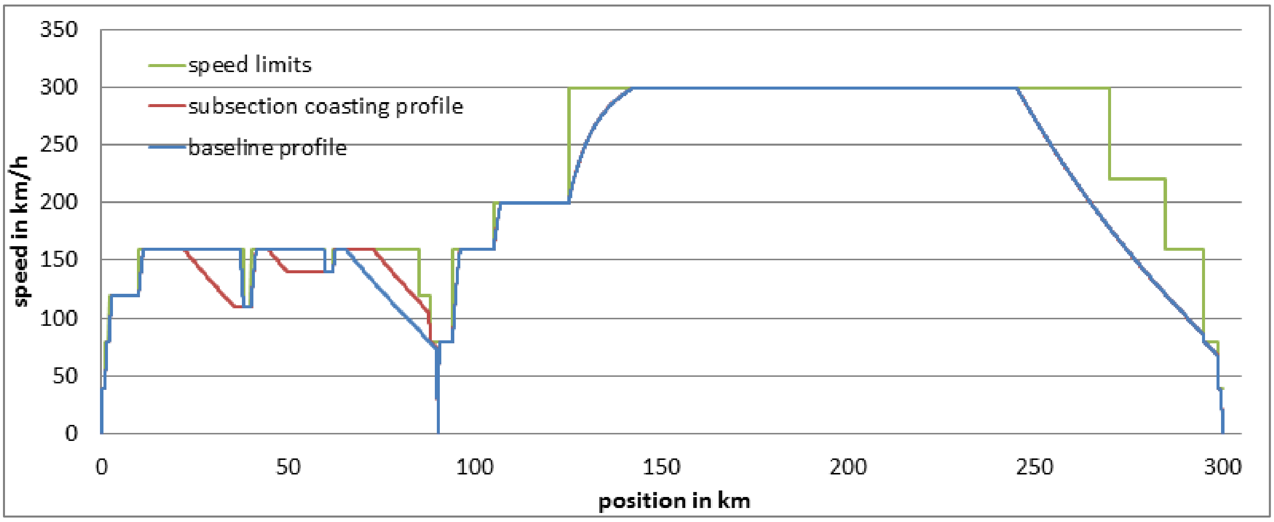


Figure 22: Speed profile for the High-Speed 300 profile with subsection coasting

As presented in Table 5**Error! Reference source not found.** the energy savings by increasing the optimization possibilities with the mentioned subsections in comparison with the baseline simulation is also 1.3%.

Net Energy in High Speed 300		
Baseline	**Subsection coasting**	**Difference - Savings**
5056 kWh	4991 kWh	65 kWh (1.3%)

Table 5: Energy comparison between baseline and subsection coasting for High Speed 300

The mentioned energy savings are not high in these examples, but yet, they are achieved just adding new coasting sections thanks to the subdivision of the route sections. This can be easily implemented in an on-board DAS.

In both cases, the energy savings are produced only in the first part of the route, as it is where speed limit changes occur and new defined “subsections” are available. More coasting is applied in this part of the routes as observed in the figures.

Note that the reference track profiles defined in OPEUS project have no gradient and no curve, but changes on these track parameters would allow for new subsections incrementing the optimization possibilities too. Therefore, application of this route section division would allow for more savings in real environment.

10. Switch off strategy

As described in Deliverable 2.1 [1], Chapter 2.5.16 “Control Unit – Load Distribution”, the simulation tool is capable of simulating the traction chain with a load distribution for the traction motors. This includes a total switch-off of some traction drives.

This operating strategy is based on the avoidance of a low load operation for the traction components[2]. For low-load operation, the efficiency of the components decreases (compared to high-load operation), which leads to a higher amount of energy losses. Furthermore, the residual traction components are forced to handle a higher power request, which increase the resulting efficiency of the remaining applied components. This approach does not account for the idle losses of the components, as long as the components are switched off.

Since traction motors are more efficient when working at high loads, balancing a low load among all of them should be avoided.[3] Therefore, in order to save energy by improving the performance of the rest of engines and avoiding energetic losses in the affected part of the circuit, the usage of the minimum amount of traction motors required for the run shall be implemented.

The equations included in OPEUS-Tool for implementing this strategy can be found in Deliverable 2.1 [1] as well as in Deliverable 3.3 [9]. Simulations using this strategy are shown in Deliverable 5.2 [10], Chapter 7.2 “Traction Motors Switch off”. Figure 23 presents the summary of the results simulations to check this energy management impact.

[2] “Traction components” includes both the traction motors as well as the corresponding motor converters.

[3] Energy losses are analysed in Deliverable 5.2 [10].

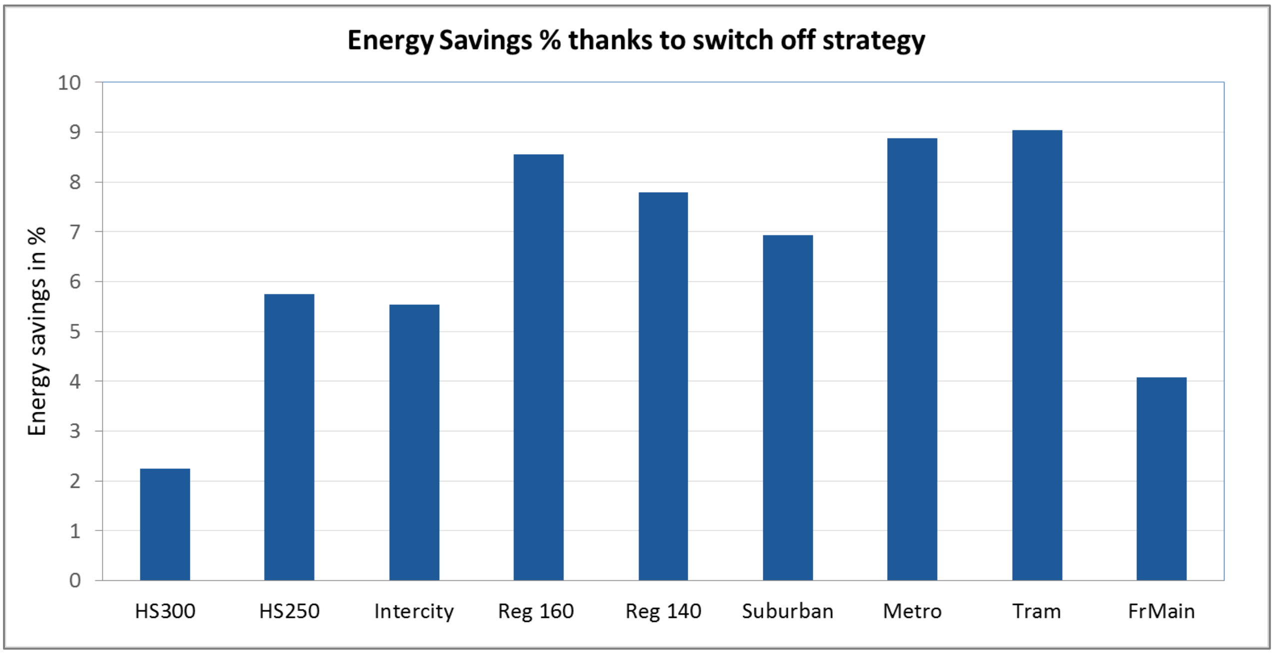
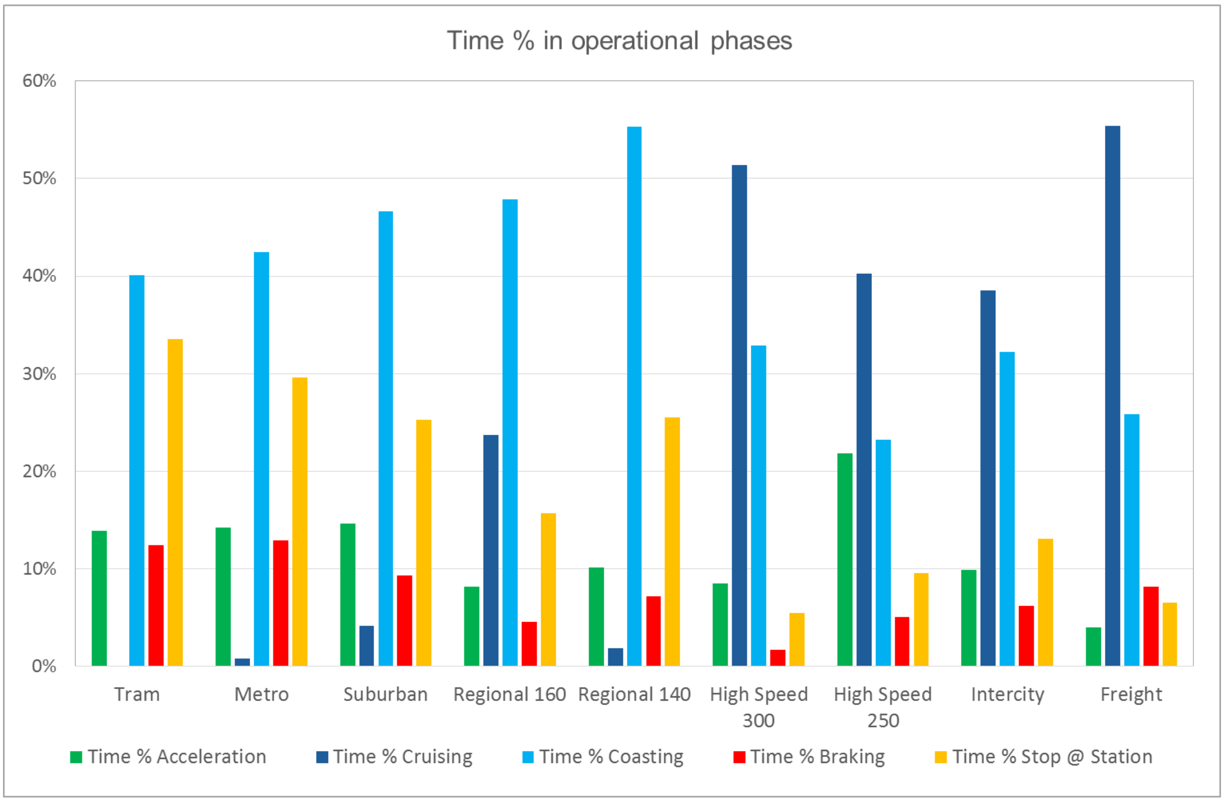


Figure 23: Energy savings using switch off strategy

The largest benefits regarding energy saving are achieved in the tram and metro services, with about 9% improvement, followed by the regional services, with about 8% improvement.

The implementation of partial switch-offs of traction components has significant effect on energy savings. It has major benefits if it is used on a service with long coasting phases (where no power is requested) or standstill at stations. Due to the high portion of standstill and coasting, Urban and Regional services offer the most significant potential for the application of this operating strategy. This can be seen in Figure 24**Error! Reference source not found.**, where the % time in the different operational phases for the different reference scenarios are shown, including the time at stations. The second part of the figure shows the total time in no load mode operation (column grey), obtained adding the coasting and stop station data, which is taken from Deliverable 5.2 [10].



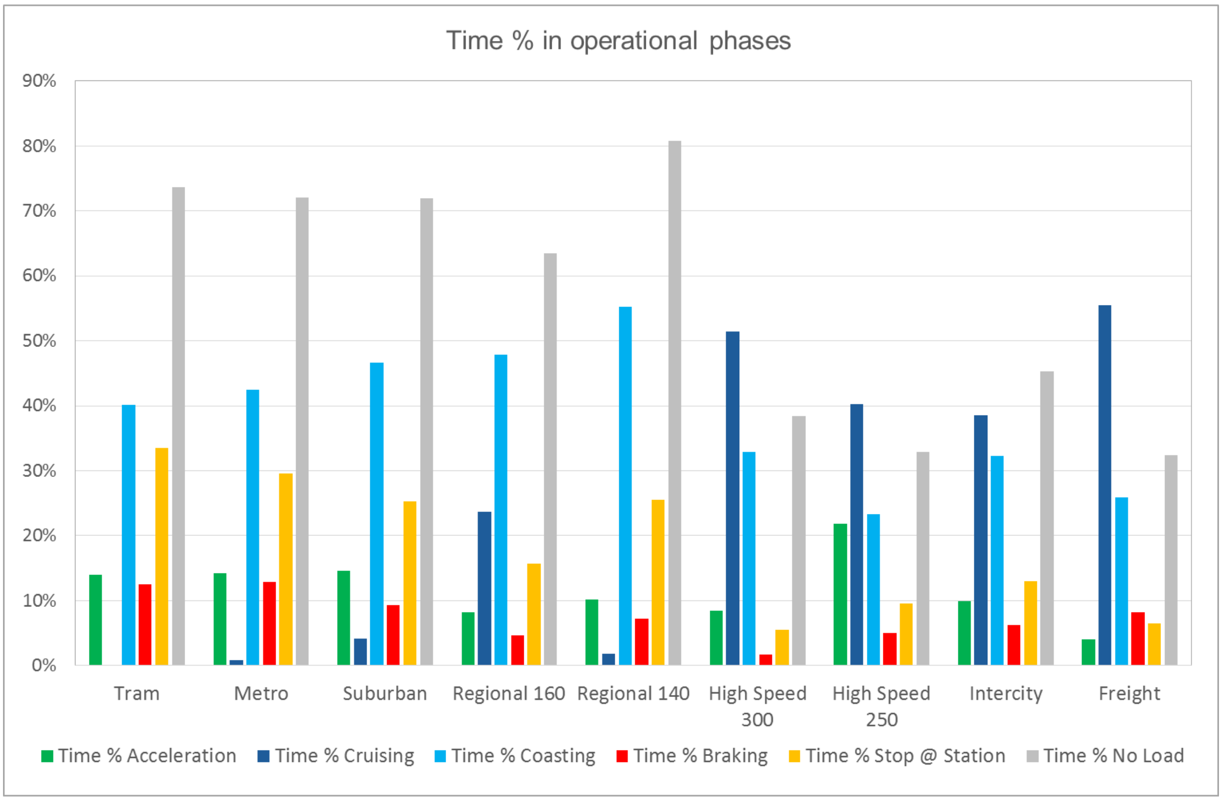


Figure 24: Analysis of % time in the different operational phases for the reference scenarios

11. Conclusions

This deliverable report includes different driving strategies in order to implement an optimal velocity profile in form of a driver assistant system or an automatic train operation.

The report also includes the implementation of algorithm improvements for computing time savings, based on a reduction of the traction chain model and on the usage of the "Fast Restart" option of Matlab/Simulink. Thanks to them the calculation time decreases about 70%.

Unexpected situations that may be encountered in a real world environment such as construction activities have been simulated to provide a solid DAS, capable of providing real time solutions for an on board system. Therefore, although OPEUS Tool is an off-line software, the implemented energy strategy in OPEUS Tool can be followed by a DAS installed on-board the train, which will be capable of recognizing any disturbance and re-calculate the recommended speed profile in real time. OPEUS tool V7 also provides an "action" advice (accelerate / cruise / coast / brake) and also the objective speed, emulating the behaviour of a real DAS system.

Different optimization algorithms have been studied when trying to find the best solution for an energy saving speed profile. Optimization algorithms have shown up to 8.2% energy savings, in the case of the reference HS300 service. In routes with gradients the optimization of the speed profile allows for high energy savings. In the example of the HS300 service with altitude 12.3% energy savings are possible by optimizing the driving mode depending if the train is operating on down or up slopes. Therefore, as real rail service profiles have gradients, higher energy savings by using optimization techniques are expected than for the flat reference profiles shown in this report.

If the driving strategy optimization is done for each route specific section[4] and not only between stations, multiple optimization points between stations are possible, increasing the coasting phases and therefore decreasing overall energy consumption. The mentioned energy savings are not high in the examples shown in the deliverable (only about 1.3%), but yet, they are achieved just adding new coasting sections thanks to the subdivision of the route sections, which can be easily implemented in an on-board DAS. As the reference track profiles defined in OPEUS project have no gradient and no curve, but changes on these track parameters would allow for new subsections incrementing the optimization possibilities too. Therefore, application of this route section division would allow for more savings in real environment.

Finally, the application of the switch-off strategy allows for high energy savings, especially in urban and regional services, with 9% and 8% savings respectively.

[4] Specific route section is a section, where all route parameters (speed limit, curve radius and gradient) are constant. If any of those parameters are changed a new section is considered.

12. References

[1] L. Pröhl, „OPEUS Deliverable DO2.1 - OPEUS simulation methodology,“ EU-project OPEUS (S2R-OC-CCA-02-2015), 2017.

[2] L. Pröhl, „OPEUS Deliverable DO3.3 - S2R innovation (state01) simulation results and periodic assessmant – Part2,“ EU-project OPEUS, 2018.

[3] Mathworks. “Get Started with Fast Restart” (accessed 5 March 2019) https://de.mathworks.com/help/simulink/ug/fast-restart-workflow.html

[4] R. Eberhart J. Kennedy. “Particle swarm optimization”. In Proceedings of ICNN’95 - International Conference on Neural Networks. IEEE, 1995

[5] L. Pröhl, H. Aschemann. Energy Optimal Trajectory Planning for Electrically Driven Railway Vehicles with Particle Swarm Optimization. ICCA2019 – International Conference on Control and Automation, Edinburgh, 2019

[6] S. Mirjalili, S. M. Mirjalili, A. Lewis. Grey wolf optimizer. Advances in Engineering Software, 69:46–61, March 2014

[7] N. Hansen, A. Ostermeier, “Completely Derandomized Self-Adaptation in Evolution Strategies”. Evolutionary Computation, Vol. 9, Number 2, Massachusetts Institute of Technology, 2001.

[8] Optimization Method of Energy Saving Train Operation for Railway Network. FU Yinping, GAO Ziyou, Li Keping. S.l.: J Transpn Sys Eng & IT, 9(4), 90-96, 2009.

[9] L. Pröhl, „OPEUS Deliverable DO3.3 - S2R innovation (state01) simulation results and periodic assessmant - Part1,“ EU-project OPEUS, 2018.

[10] “OPEUS Deliverable D05.2 Analysis of energy losses in the traction chain”, EU-project OPEUS (S2R-OC-CCA-02-2015), 2019.