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Energy Optimisation for Subway Trains by Interactive Track Alignment Planning

M. Flurl, R. Morelos, R.-P. Mundani, E. Rank

Chair for Computation in Engineering
Technische Universität München, Munich, Germany

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Abstract

The basis for planning a subway tunnel is the so-called *alignment model* describing the specific course of the track. The alignment itself is one of the fundamental sources for a train's overall energy consumption in the operational phase, which in general lasts for many decades. Thus, even small changes to the alignment can have a major impact on the overall energy consumption. Currently, the alignment's influence on the energy consumption is not, or only rudimentarily, considered in the planning of new subway tunnels.

Our approach, presented in this paper, aims to overcome this deficiency based on an autonomous energy simulation to support the engineer while planning the alignment. This simulation calculates the changes in the energy consumption with every modification made by the planning engineer, in the background and in real time. Thus, this model allows *a priori* prediction of the energy consumption during the planning phase, in contrast to other existing approaches that only allow *a posteriori* calculations during the operational phase. Additionally, we will present ideas for energy optimisation, in particular, an automatic energy optimisation approach based on an *ant colonisation algorithm*.

Keywords: alignment modelling, energy consumption, trains, energy efficiency optimisation.

1 Introduction & motivation

The basis for planning a subway tunnel is the so-called *alignment model* describing the specific course of the track [1]. This model comprises two alignments: a horizontal and a vertical one. The former one delineates the projection of the track course into the x-y-plane, whereas the latter one specifies the z-coordinate of the resulting course (see section 3.1). Thus, an alignment model defines the changes of the height position of a train operated on the resulting track as well as the curves the train fol-

lows. Hence, the alignment model serves as a basis for the train's potential energy consumption as well as for the curve resistance, which is why it is one of the fundamental sources for a train's overall energy consumption in the operational phase. Since in general this phase lasts for many decades, even small changes to the alignment can have a major impact on the overall energy consumption and, thus, on the operational costs. Currently, the influence of the alignment on the energy consumption is not – or only rudimentarily – considered in the planning of new subway tunnels. This shortcoming is based on the more or less trivial fact that the tools used during the alignment modelling typically do not support the planning engineer with respect to the resulting energy consumption. Strategies to optimise a subway train's energy consumption are primarily concerned with the operational phase of the tunnel and not the planning phase. Typical investigations in this respect mostly address possibilities to optimise a train's speed profile, whereas our approach focusses on the early planning phase of a tunnel. As to that, at least the following strategy has been established: Directly after leaving a station, the tracks are made to slope downward in order to support the train's acceleration by its own weight, whereas the energy needed to overcome the height difference before the next station is regained from the train's kinetic energy while the train decelerates. Nonetheless, detailed quantitative information regarding this energy consumption is not available to the planning engineer.

Our approach presented in this paper aims to overcome this deficiency based on an autonomous energy simulation to support the engineer while planning the alignment. This simulation calculates the changes in the energy consumption with every modification made by the planning engineer – in the background and in real time. It takes the train's speed profile and specific friction influences into account, but focuses on the impact of changes to the alignment. Thus, this model allows a priori predictions of the energy consumption during the planning phase in contrast to other existing approaches that only allow a posteriori calculations during the operational phase.

Before we present this simulation model in chapter 3, we provide a brief overview of related work considering the energy consumption of trains in general as well as approaches to optimise energy consumption. In the following chapter 4, we will validate this model comparing calculated values with measured values from the Metro Bilbao (*https://www.metrobilbao.eus/*). In chapter 5, we will present some ideas for energy optimisation by modifying the vertical alignment of the track manually, whereas in chapter 6 we will provide an approach for an automatic energy optimisation based on an ant colonisation algorithm. Finally, we will draw conclusions and provide an outlook.

2 Related work

Arguably, the study of energy efficiency of track alignments has to be assessed as a niche in scientific research: In a first instance, it would probably have to be assigned to the field of traffic route engineering. First of all, there are various and fundamental insights that concern the rail vehicles itself. In particular, there has been plenty of research effort on the description of the appearing forces and on their effects to the

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trains' operation, naturally including the influences of friction. For detailed information concerning the railway vehicles themselves, we refer the reader to Iwnicki [2], Popp [3], and Janicki [4]; especially for the study of friction influences, we refer to Lukaszevicz [5].

Fundamental research regarding energy efficiency of track alignment was conducted by Howlett [6,7,8,9,10] focussing on the proof that optimal speed profiles exist, yet without providing a constructive algorithm to compute these profiles. Likewise, Jong & Chang studied the optimisation of speed profiles for a given alignment profile [11,12]. They presented a C++ based computer simulation in which two force based algorithms were implemented. The first algorithm minimises the travel time considering given boundary conditions, whereas the second one tries to minimise the energy consumption. Friction influences are only integrated in a very basic manner, and the possibility of recuperation of energy is not supported, whereas the automatic integration and generation of speed limits due to the given alignment course is emphasised. Kim et al. developed a so-called *train performance simulation* (TPS) comprising three base components: a force module describing the general physical conditions, an alignment module and finally a train operating component [13]. In principle, changes to the vertical alignment are possible, whereas the horizontal alignment is fixed, and the possibility to integrate the recuperation of energy is not considered. The results primarily provide train steering patterns, i.e. patterns for automatically operating a train by a so-called ATO unit (*automatic train operation*), thus mainly addressing the train operator. Bureika et al. provide an analytical solution to calculating optimal control parameters (i.e. traction and braking forces) which led to the development of an algorithm that determines the energy-efficient control or optimal phase trajectory of an entire route [14].

In contrast to this research concentrating on the operational phase our work addresses the tunnel planning engineers – since we want to predict the resulting energy consumption already in the early planning phase. In the following, we will start with a very brief introduction to alignment modelling and then present the specific energy model.

3 The simulation model

3.1. Alignment modelling

The basis for the planning of a subway tunnel is the *alignment model* defining the specific track course. Thereby, two two-dimensional curves – the horizontal and the vertical alignment – are superposed in order to represent the three-dimensional track course. Here, the horizontal alignment represents the projection of the track into the x-y-plane. The vertical alignment describes the z-coordinate of a spatial point depending on the stationing, i.e. the length of the stretch on the horizontal alignment until the corresponding x-y-coordinates of the point are reached. Figure 1 shows this super-positioning of horizontal and vertical alignments, resulting in a three-dimensional curve.

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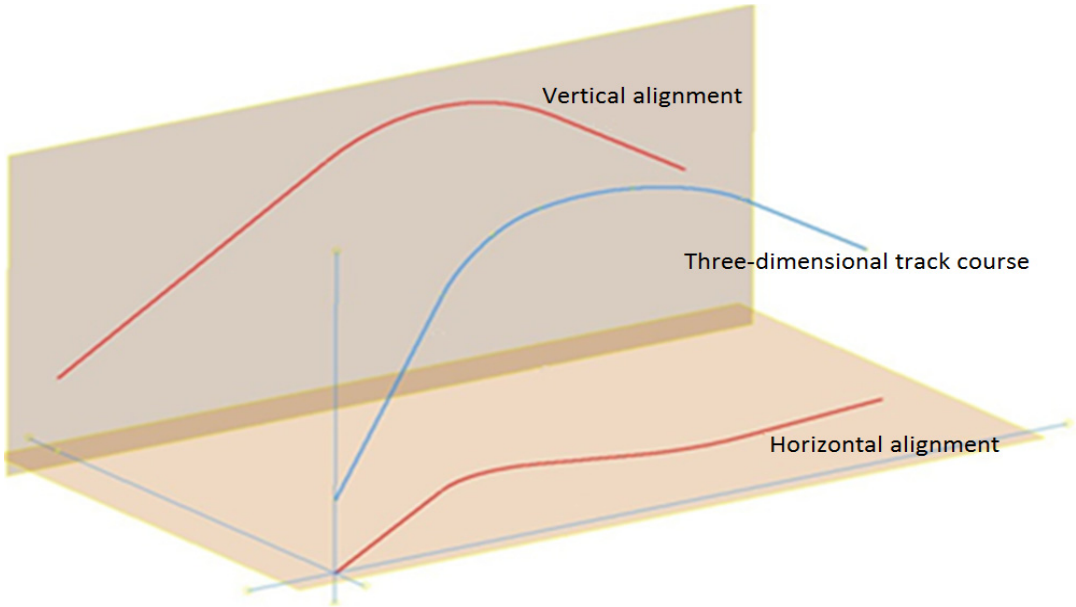

Figure 1: The superposition of horizontal and vertical alignment results in the three-dimensional track course.

The horizontal alignment comprises a set of specific curves, usually using sequences of straight lines, transition curves such as clothoids, and circular elements. The transition curves ensure a smooth junction in the curvature between straight line elements with a curvature fixed to zero and circular elements with a constant non-zero curvature.

In a first step, to create a vertical alignment, the designer typically defines a set of fixed points, the so-called points of vertical intersection (PVI), connects them with straight lines, and finally introduces transition curves such as parabolas between two intersecting line segments, see Figure 2.

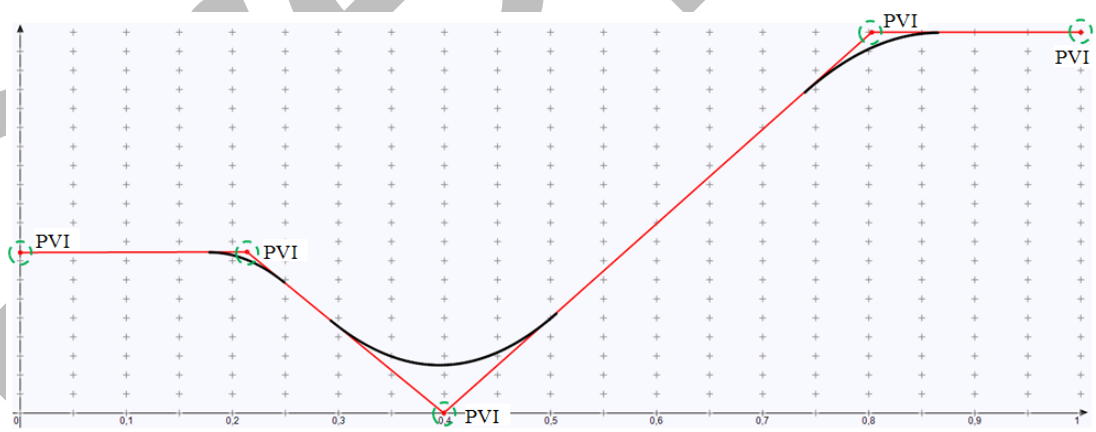

Figure 2: Example for a vertical alignment containing five points of vertical intersection (PVI), four line elements, and three parabolic transition curves

For a detailed discussion of alignment modelling, we refer the reader to the annually published AREMA Manual for Railway Engineering [15], to Ji [16], or Amann [1].

3.2. The physical model

We will use a simple and straightforward physical model that distinguishes four basic influencing factors: kinetic and potential energy, friction and curve resistance. For the sake of simplification, our calculations are based on assuming subway trains as mass points concentrated in the trains' centre of gravity.
Changes to each of these energy terms are given by an integral

$$\Delta E = W = \int_{\boldsymbol{x_1}}^{\boldsymbol{x_2}} F(\boldsymbol{x}) d\boldsymbol{x}, \tag{1}$$

where $F(\boldsymbol{x})$ is the acting force along a curve from $\boldsymbol{x_1}$ to $\boldsymbol{x_2}$. Thanks to using an *alignment model*, we can assume that all point coordinates as well as velocity values are uniquely determined by the stationing s, i.e. $\boldsymbol{x} = x(s)$ and $\mathbf{v} = \mathrm{v(s)}$; this also holds for acting forces, i.e. $F = F(\boldsymbol{x}) = F\big(x(s)\big)$.

3.2.1. Kinetic energy

Changes to the kinetic energy ΔE_{kin} result from an accelerating or decelerating force, and, in our context, describe the energy needed to accelerate a train or the energy released when the train decelerates, respectively. These two fundamental cases are considered by a positive and a negative sign of the resulting energy value and must be taken into account when summing up the basic factors, see chapter 3.2.4.

ΔE_{kin} is given by $\Delta E_{kin} = \frac{1}{2} \cdot m \cdot (v_2^2 - v_1^2)$ (see, e.g. [17]), where $v_2 = v(s_2)$ and $v_1 = v(s_1)$ are the velocity values at the beginning and the end of the considered motion determined by the stationing values s_1 and s_2. Thus, changes to the kinetic energy only depend on the start and end velocities, independent of the specific curve and velocities profile.

3.2.2. Potential energy

Changes to the potential energy ΔE_{pot} result from the weight, and, in our context, describe the energy needed to move a train upwards or the energy released when the train moves downwards, respectively. Once again, a positive or a negative sign distinguishes these two cases and must be considered when calculating the energy balance.

ΔE_{pot} is given by $\Delta E_{pot} = m \cdot g \cdot (h_2 - h_1)$, where $h_2 = h(s_2)$ and $h_1 = h(s_1)$ are the height positions (of the train) at the beginning and the end of the considered motion, whereby these positions are calculated in relation to an arbitrarily chosen zero height level h_0. Thus, changes to the potential energy only depend on the start and end height – and they are similar to the changes to the kinetic energy, independent of the specific curve and the velocities profile.

3.2.3. Influence of friction

During a train run, several influences of friction emerge. A quite simple, but effective method to describe these influences is given by the *Davis Equation* , which was introduced by W. J. Davies as early as in the 1920s and is still used today [18,19,20]. The *Davis Equation* calculates an overall friction force R by summing up velocity-independent influences such as the rolling and bearing friction, velocity dependent influences such as flange friction or effects of sway and oscillation, and, finally, influences that depend on the square of the velocity, such as air resistance:

$$R = A + B \cdot v + C \cdot v^2 \tag{2}$$

These influences are weighted by the parameters A, B and C and have to be determined experimentally.

Some sample values for these parameters are given in Table 1, according to Iwnicki [2]. The overall impact resulting from the *Davis Equation* is then calculated by an integral along the track, i.e.

$$\begin{aligned} E_R &= \int_{s_1}^{s_2} A + B \cdot v(s) + C \cdot v^2(s)\, ds \\ &= A \cdot (s_2 - s_1) + \int_{s_1}^{s_2} B \cdot v(s) + C \cdot v^2(s)\, ds. \end{aligned} \tag{3}$$

One further influence factor emerges from the friction between the wheels' flanges and the rail track while driving along curves, the so-called curve-resistance. This friction force, F_{CR}, can be assumed linearly dependent on the curvature, i.e. the inverse of the curve radius r. This leads to an equation $F_{CR} = D \cdot \frac{1}{r}$ [2] with a specific constant D and an energy effort that is calculated by the integral

$$E_{CR} = \int_{s_1}^{s_2} \frac{D}{r} ds. \tag{4}$$

Parameter / Train type	A $\left[\frac{N}{ton}\right]$	B $\left[\frac{N \cdot h}{ton \cdot km}\right]$	C $\left[\frac{N \cdot h^2}{ton \cdot km^2}\right]$
French Bogie	14.7	0	0.00218
ICE	9.81	0.024525	0.053955

Table 1: Exemplary values for the parameters A, B and C of the *Davis Equation*

3.2.4. Energy balance and total energy

As stated previously, to calculate the total energy consumption, the integral according to the definition $\Delta E = W = \int_{x_1}^{x_2} F(\boldsymbol{x}) d\boldsymbol{x}$ has to be calculated, where the force F is the total force resulting from the sum of the several acting forces, thus, leading to the several energy terms previously discussed; in our context these forces are given by the force to accelerate or decelerate the body F_K, the weight F_W, and the total friction force F_F

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$$F = F_K + F_W + F_F. \tag{5}$$

In general, an integral represents a balance of positive and negative sections, i.e.in the one-dimensional case sections with a positive integrand (above the horizontal axis) and sections with a negative integrand (below the horizontal axis). Concerning the calculation of total energy, positive and negative sections physically represent sections where energy has to be provided or energy is released, respectively.

Exemplarily, on a downward section the influence of the weight results in a negative potential energy value E_W. If in the same section the train should be accelerated this amount of energy E_W can be used to provide the needed kinetic energy E_k or to provide the energy to overcome the friction losses E_F.

Since we want to calculate the total energy to be provided, we have to determine the sections resulting in positive energy values. This can be done by discretising the total stretch in small segments and calculating an energy balance taking into account the different signs of the several influencing factors on every segment.

4 Simulation validation

To assess the model's quality, simulation results were compared with real world measurements. To this end, we used data provided by the operators of the Metro Bilbao. In detail, this data contained:

- the horizontal and vertical alignment information,
- the measured velocity, depending on the stationing, i.e. the speed profile,
- the mass of trains and wagons as well as their combinations,
- the number, and thus, the approximate mass of the passengers,
- the incoming current and the voltage overhead.

Table 2 shows the results of this comparison regarding twelve different sections. Here, the first column lists the names of the different sections, while the second one shows the measured energy consumption, and the third one the values calculated by the simulation. The measured values contain losses due to the efficiency of engine and gearbox, which were unknown to the authors and, thus, were assumed by introducing an efficiency factor (according to typical literature values [21]). Finally, the fourth and the fifth column show the percentage values by dividing calculated and measured values, assuming efficiency factors of $\epsilon = 93\%$ and $\epsilon = 85\%$, respectively. This comparison indicates that the range of the calculated values reaches an accuracy between 89% and 95% with an efficiency factor of $\epsilon = 93\%$, whereas assuming a factor of $\epsilon = 85\%$ leads to a range between 97% and 104%. In both cases, the calculated results coincide very well with the measured data.

Apart from comparing the absolute consumption values on specific stretches, we compared the measured energy consumption with the calculated values depending on the stationing, i.e. the cumulated energy consumption up to a specific stationing value.

This is shown for the section from Extebarri to Bolueta in Figure 3, where the blue dashed curve represents the energy consumption assuming an efficiency factor of $\epsilon = 93\%$, whereas the red dotted curve assumes an efficiency factor of $\epsilon = 85\%$.

Specific section		Measured value [J/kg]	Calculated value [J/kg]	Engine and gearbox efficiency $\epsilon = 93\%$	Engine and gearbox efficiency $\epsilon = 85\%$
1	Casco Viejo → San Tutxu	421.2	401.4	95.30%	104.3%
2	San Tutxu → Casco Viejo	133.7	120.0	89.75%	98.20%
3	Casco Viejo → Abando	177.2	158.1	89.22%	97.62%
4	Abando → Casco Viejo	178.4	158.8	89.01%	97.39%
5	Etxebarri → Bolueta	189.4	170.0	89.75%	97.14%
6	Bolueta → Etxebarri	242.7	223.6	92.13%	100.8%
7	Indautxu → San Mames	166.0	157.9	95.12%	104.1%
8	San Mames → Indautxu	161.0	153.4	95.28%	104.3%
9	Bolueta → Basarrate	209.1	195.7	93.36%	102.4%
10	Basarrate → Bolueta	181.2	164.9	91.00%	99.57%
11	San Inazio → Lutxana	343.5	326.0	94.90%	103.8%
12	Lutxana → San Inazio	227.4	215.6	94.81%	103.7%

Table 2: Measurements of the Metro Bilbao and values calculated by the simulation

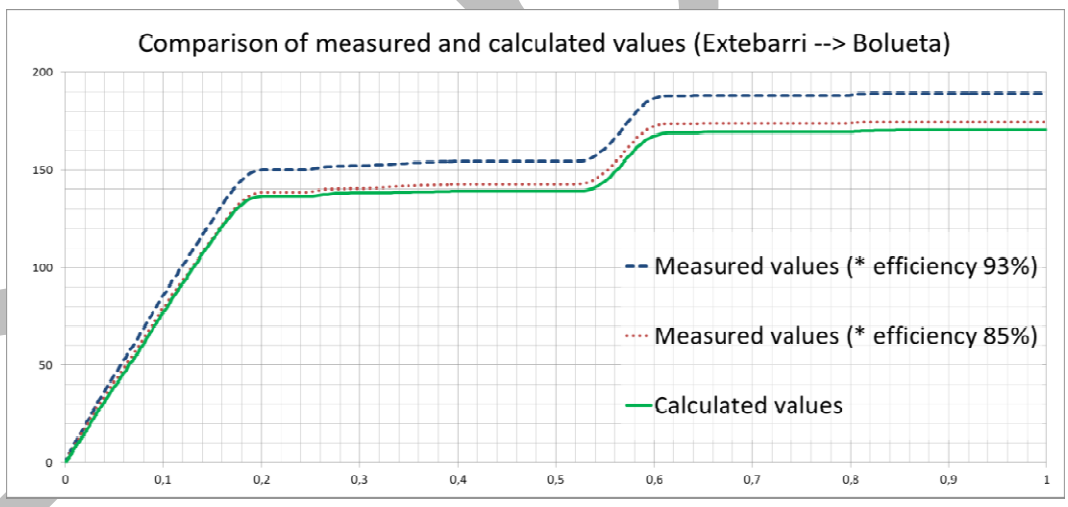

Figure 3: Total energy consumption on the section Extebarri to Bolueta, depending on the stationing. The measured and calculated values are represented by a blue dashed, a red dotted, and a solid green curve.

Finally, the solid green curve represents the values calculated by the simulation. In particular, it can be seen that the courses of all three curves are very similar; a fact that nicely confirms our calculations. The agreement even improves when reducing the unknown efficiency factor to a best correspondence slightly below $= 85\%$.

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5 Manual track modification and energy optimisation

In a first step, the presented simulation model was designed to support the engineer in estimating the changes in the energy consumption due to modifications in the underlying alignment. In this section, as an introduction to optimisation possibilities, we present an example of how this functionality can be used to reduce the energy consumption by experimenting with the vertical alignment, before we present an approach to automatically modify the vertical alignment to minimise the resulting energy consumption.

The basis for this example is the section in Bilbao from Casco Viejo to Abando, where the train starts in Casco Viejo at a level of $-3.1m$ and descends to a level of $-12.2m$. The station in Abando is on a level of $8.7m$. The first test is now to stretch the vertical profile downwards by digging deeper. This situation is shown in Figure 4, where the upper solid blue curve represents the original profile, whereas the lower dotted red curve represents the profile emerging from "digging deeper".

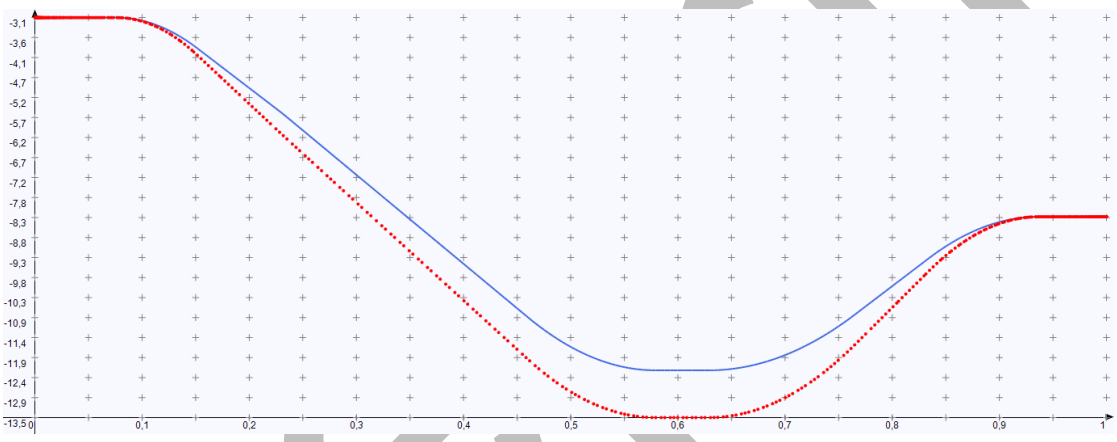

Figure 4: Optimising the energy consumption by changing the vertical alignment

In this second profile, the maximum depth is $-13.5m$, leading to a maximum difference of $1.3m$ between the original and the manually modified profile. Using a tunnel boring machine to excavate the tunnel tube, there should not be any significant difficulties or higher costs compared to the original profile. The resulting changes in the energy consumption are given in Table 3.

Maximum depth [m]	Energy consumption[J/kg]
-12.2	155.0
$-13{,}5$	147,9

Table 3: Two different height profiles and the resulting energy consumption

Thus, a very simple modification in the vertical alignment leads to a significantly lower energy consumption. In the given case, the reduction is about 4,8%. The reason for this lower energy consumption is easy to see: Since the downwards section at the beginning of the stretch is steeper, a higher percentage of the acceleration is

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caused by the weight, whereas the longer upwards ride is supported by the kinetic energy released during deceleration, without increasing the overall energy consumption.

6 Automatic track modification and energy optimisation

6.1. Automatically modifying vertical alignments – specification of the optimisation task

As discussed in chapter 3.1, a vertical alignment is composed of Points of Vertical Intersection (PVIs), connected by straight lines and transition curves – guaranteeing a smooth junction between the various line segments, see Figure 2. In this chapter, we want to present an approach to optimise the energy consumption on a given section by automatically creating "improved" height profiles. The basic idea for creating a new height profile is to change the vertical position of one or more PVIs. To this end, a specific range of values for the vertical coordinates of the several PVIs is defined. Typically, this range is restricted by specific constraints that are well known to the planning engineer, for example subsurface buildings, the electric cable net, or the sewage pipe system. By automatically shifting the y-coordinate of a PVI in-between this range, it is possible to gain new vertical alignments. Exemplarily, this is shown in Figure 5. Here, the blue vertical alignment originates from the green one by shifting the left PVI upwards and the right one downwards. Subsequently, we denote a specific PVI with PVI_k, the set (or group) of points resulting from shifting one specific PVI_k with $PVIG_k$.

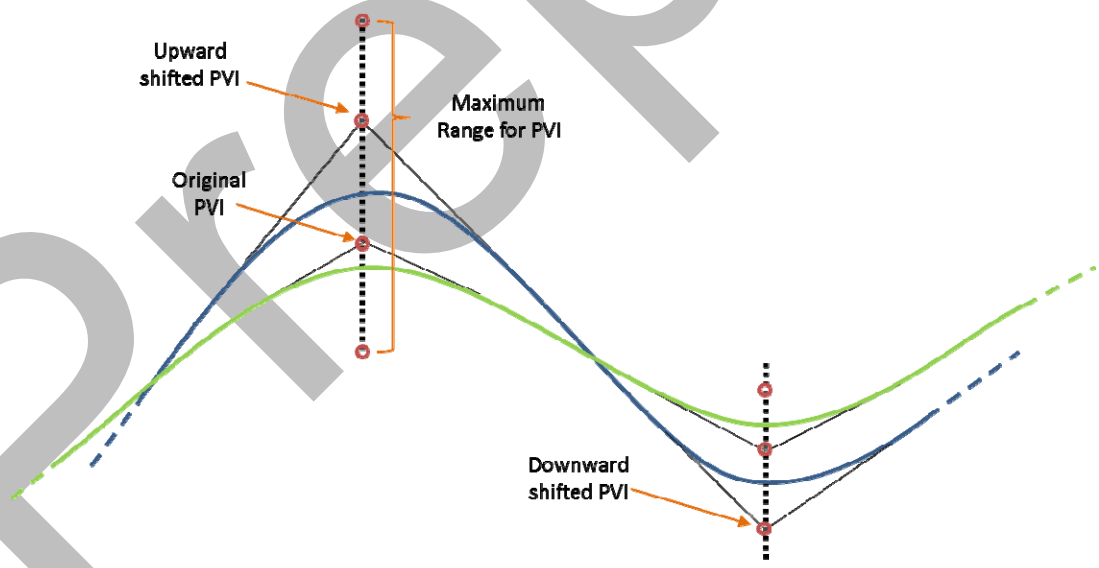

Figure 5: A new vertical alignment is achieved by shifting the left PVI upwards and the right one downwards.

Additionally, the alignment engineer specifies a discrete step size within the range, in which the several PVIs can be moved. Due to this restriction to a discrete step size, for every specific PVI_k the associated set $PVIG_k$ is finite as well as the

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number of possibilities for new height profiles is finite – each with a specific energy consumption: Within a finite number of possible height profiles, it is possible to determine the profile resulting in the lowest energy consumption. However, obtaining the optimal height profile by testing all possible realisations can be extremely time-consuming since a huge number of possibilities has to be calculated (resulting from the fact that, in principle, every element of a specific set $PVIG_k$ is connected with every element of the set $PVIG_{k+1}$ of the next group as well as with every element of the previous group $PVIG_{k-1}$ – with the natural restriction for the boundary points). Thus, a specific new height profile is gained by connecting an element of the first group $PVIG_1$ to a an element of the next group $PVIG_2$ and so forth, until the end point of the track alignment is reached as is illustrated in Figure 6.

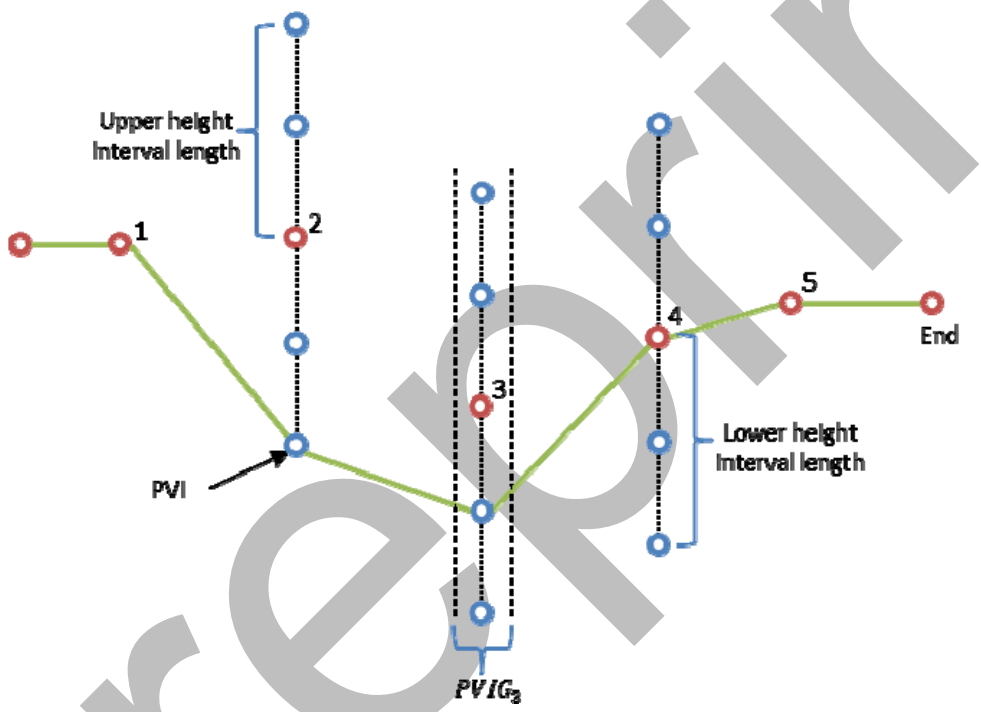

Figure 6: Example of a complete route given the task of height profile optimisation

6.2. Elitist ant system

The Ant System, introduced by Dorigo [22], was the first *ant colony optimisation* (ACO) strategy to show successful performance in solving optimisation problems such as the famous *Traveling Salesman Problem* [23]. Since its creation, many variations have been proposed to improve ACO, such as the mutation process and local searching technique for the *Generalised Travelling Salesman Problem* (GTSP) including research by Yang [24]. Our ACO strategy is based on the so-called *Elitist Ant System* algorithm (EAS) which has been proven in the TSP to quickly find better heuristic solutions than its original predecessor, the *Ant System* algorithm [25].

In nature, ants initially scout different paths from their colony to a food source and back, leaving a pheromone trail. As the pheromone evaporates over time, a

stronger scent designates a shorter path. Eventually, subsequent ants will choose a trail with stronger scent and follow it, reinforcing the scent with their own pheromone. The ants will continue to explore different paths, but, over time, more and more ants will follow a popular path until, eventually, they all choose the shortest route because of its high pheromone intensity.

As an optimisation strategy, ACO does something similar: Digital ants are expected to find the "best route", or an optimal solution, depending on the objective they are given, e.g. finding the shortest route between a set of cities: Every ant starts at a random city and chooses the path with the highest probability value to head for the next city. The probability value is calculated based on *visibility,* e.g. the distance between the present and different city, and the *pheromone intensity*, i.e. the pheromone values left by previous ants that followed the same path. The *elitist strategy* that improves the original Ant System basically reinforces the paths of the best route found. This way, the ants find better routes within a lower number of iterations. For a detailed description of the EAS we refer the reader to [25].

As previously discussed, in our context, the objective is to minimise the energy consumption of a train. Therefore, virtual ants are expected to find the route of minimum trip energy. For every iteration cycle, a specified amount of ants starts at a random element of a set $PVIG_k$. Then, every ant will calculate the path probability of traveling to any element of the next set $PVIG_{k+1}$ group, according to the path's energy requirement (visibility) and a pheromone value induced by previous ants.

The ant then takes the path with the highest path probability and moves to an element of the next set $PVIG_{k+1}$. This process is repeated for the next PVI until the ant completes a route by visiting exactly one element of every set $PVIG_i$. At the end of every iteration loop, every ant's total trip energy is determined, and its individual path is assigned a value to either increase the pheromone intensity or decrease it by evaporation with the next cycle.

Every ant stores information about its trail and the energy required. After a certain number of iterations, ants that consumed less energy are stored and their information is made available.

However due to the given context, one further restriction was added to the EAS strategy, regarding the height profile design: the maximum grade. Due to railway regulations, an official maximum track slope has to be considered (depending on the train's characteristics).Within our EAS strategy, the maximum allowable grade can be defined as a parameter and, if necessary, the range for a specific PVI to move about, can be adapted automatically. This way, regardless which element of the following set $PVIG_{k+1}$ an ant visits next, the paths will never exceed the maximum grade.

6.3. Optimisation results using the EAS approach

Our approach using the EAS algorithm has been (algorithmically) tested with existing alignment data from the Metro Bilbao. Exemplarily, we now present the optimisation of the original vertical alignment of the stretch Bolueta to Etxebarri (using an EAS with the restriction of a maximal allowable grade of 4.5%).

Initially, the PVIs were given a maximum variation of the y-coordinate of 10m in an upward direction and 10m in a downward direction (upper and lower height interval lengths), except for PVIs that were assigned a $0{,}0m$ value, meaning that they should not be moved, due to specific design requirements. While running the EAS algorithm, these intervals were automatically changed to comply with the maximum grade restriction. Table 4 presents the basic parameters for the EAS algorithm in this example: Eight PVIs in the original vertical alignment, their relative stationing (percentage of the whole stationing length) and height are given, and the lower and upper height interval lengths are automatically adapted to fulfil the maximum grade restriction. Finally, the number of divisions per segment defines the step size delineating the specific location of every element of a set $PVIG_k$ associated to a specific point PVI_k.

PVI	Stationing	Height [m]	Lower height interval [m]	Upper height interval [m]	No. of divisions (per side)
1	0.126	33.5	0	0	0
2	0.241	31.8	1.35	0.415	3
3	0.294	30.8	0.415	0.659	3
4	0.372	29.5	0.659	1.93	3
5	0.552	32.4	1.57	1.57	3
6	0.668	33.06	0.994	1.15	3
7	0.734	33.2	1.15	0.994	3
8	0.835	34.08	0	0	0

Table 4: Optimisation properties used on the section Bolueta to Etxebarri

In a first step, we calculated all possibilities like this, in order to determine the best possible profile, i.e. the profile with the lowest energy consumption, as a reference solution.

In Figure 7 we observe the original profile (blue colour) and the optimal profile (red colour) which is the best profile according to the calculation of all permutations and was also found as the best solution provided by the EAS algorithm (using 29 ants and 4 cycles). Additionally, a third not optimal profile resulting from a calculation run with 15 ants and 4 cycles is depicted in green colour.

Here, the original profile leads to a total energy consumption of 208.5 J/Kg (Figure 8 – topmost curve in brown colour). As can be seen in Table 5, evaluating all permutations leads to the optimal path reducing the energy consumption by 15.34 J/Kg to a value of 193.2 J/Kg (Figure 8 – third curve in violet colour). The in-between curve in orange colour results from the EAS approach with using 29 ants and 4 cycles.

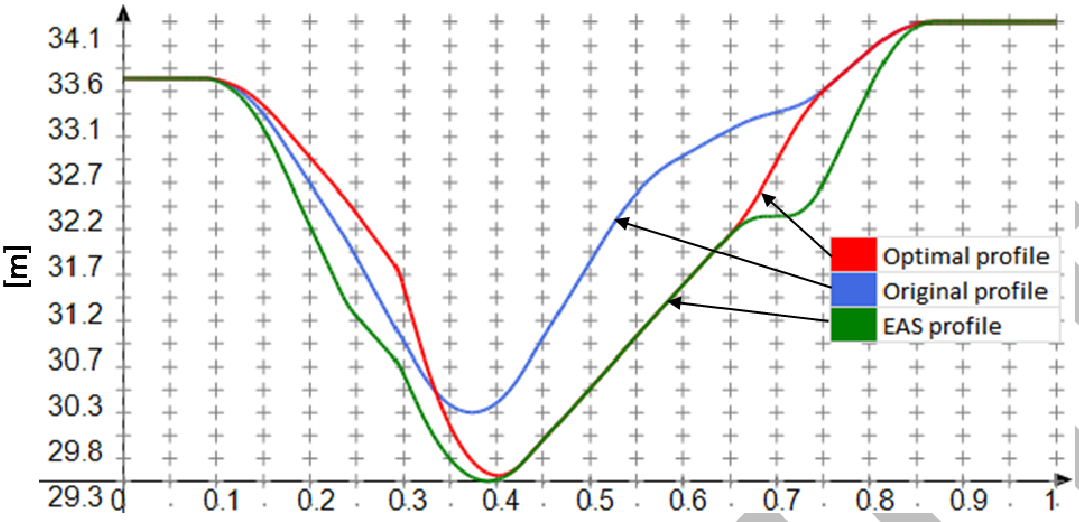

Figure 7: Original, calculated improved, but not optimal, and finally, optimal height profiles regarding the section from Bolueta to Etxebarri

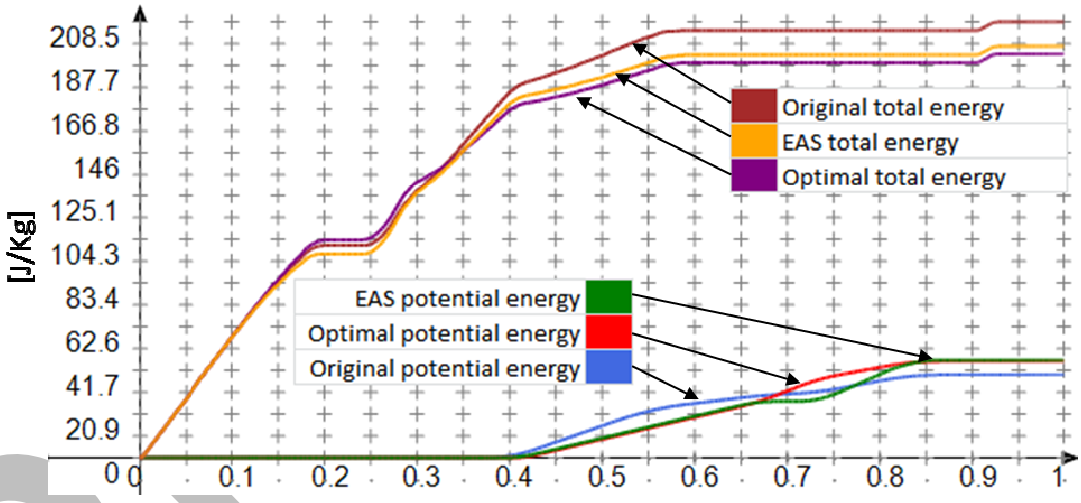

Figure 8: Energy profiles regarding to the section from Bolueta to Etxebarri

Method	Best Path [J/Kg]	Reduction [J/Kg]	Iterations	Runtime [hh:mm:ss]
EAS	196.8	11.66	5m x 4t	00:00:12
EAS	193.4	15.04	15m x 4t	00:00:21
EAS	193.2	15.34	57m x 4t	00:01:08
EAS	193.2	15.34	29m x 4t	00:00:34
Permutations	193.2	15.34	531441	08:49:43

Table 5: EAS results compared with all possible permutations

For every cycle *t, m* ants are uniformly distributed and every ant must complete a route as explained in section 6.2. Once every ant has finished its route, the pheromone value is upgraded and a new cycle releases a new batch of ants. While testing our EAS approach, we varied the number of ants and kept the number of cycles constant as described in the column "iterations" in the result Tables 5, 6 and 7. The visibility and pheromone parameters were fixed. The results of the various calculations are given in Table 5. Here, we can observe the ACO converging to the best profile when increasing the number of ants – as it was expected. As an example, using twenty-nine ants and four cycles, the EAS found the optimal solution which is an improvement of 7.35%.

Figure 8 shows energy profiles for potential and total energy consumption depending on the stationing – for the original profile, and for the optimal profile.

For calculating all possible profiles in the example, we observe a time consumption of 08:49:43 hours, whereas the EAS approaches took between 12 seconds and 1 minute, 8 seconds. This reduction to a time span of no more than approximately one minute is suitable basis to directly integrate considerations regarding energy consumption into early planning phases.

Table 6 and Table 7 show two more examples comparing the EAS approach with calculating all permutations. The first one stems from the section from Casco Viejo to Abando, a sample with only a few variation possibilities that results in a short overall calculation time, and the second one represents the section from San Inazio to Lutxana.

Method	Best path [J/Kg]	Reduction [%]	Iterations	Runtime [hh:mm:ss]
EAS	141.673	3.89	2m x 4t	00:00:06
EAS	141.657	3.90	5m x 4t	00:00:07
Permutations	141.657	3.90	2197	00:08:33

Table 6: Comparison of calculating all permutations and using the EAS approach on the section from Casco Viejo to Abando

Method	Best path [J/Kg]	Reduction [%]	Iterations	Runtime [hh:mm:ss]
EAS	282.344	5.5	2m x 4t	00:00:17
Permutations	282.344	5.5	16807	02:16:00

Table 7: Comparison of calculating all permutations and using the EAS approach on the section from San Inazio to Lutxana

7 Outlook & conclusion

In this paper, we presented an approach for an autonomous energy simulation, automatically recalculating changes to the energy consumption of a sub-way train as soon as an alignment expert changes the underlying alignment data. We assessed the

model's quality by comparing simulated results with real-world measurements and showed possibilities to reduce the energy consumption by experimenting with the vertical alignment. An ACO-based approach was introduced, pointing out possibilities to automatically create energy-improved alignment versions. In future work, we are planning to extend this approach to twin tunnels, taking both driving directions into account during a single simulation run. Additionally, we want to ascertain whether different optimisation approaches may lead to even better results, i.e. more accurate results as well as faster simulation runs.

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References

[1] Amann, J., Flurl, M., Jubierre, J. R., Borrmann, A.: An Approach to Describe Arbitrary Transition Curves in an IFC Based Alignment Product Data Model. In: Proc. of the 2014 International Conference on Computing in Civil and Building Engineering, Orlando, USA, 2014

[2] Iwnicki, S.: Handbook of Railway Vehicle Dynamics. CRC press, Taylor & Francis Group, USA, 2006

[3] Popp, L., Schiehlen, W.: Ground Vehicle Dynamics. Springer, Berlin Heidelberg, Germany, 2010

[4] Janicki, J, Reinhard, H., Rüffer, M.: Schienenfahrzeugdynamik. Bahn Fachverlag, 3. Auflage,Berlin, Germany, 2013

[5] Lukaszewicz, P.: Energy Consumption and Running Time for Trains: modelling of running resistance and driver behaviour based on full scale testing. Doctoral Thesis. KTH, Superseded Departments, Vehicle Engineering, 2001

[6] Howlett, P.G.: An Optimal Strategy for the Control of a Train. In: The ANZIAM Journal, Vol. 31, pp. 454-471, 1990

[7] Howlett, P. G., Milroy, I. P., Pudney, P. J.: Energy-efficient train control. In: Control Engineering Practice, Vol. 2, No. 2, pp. 193-200, 1994

[8] Howlett, P., Cheng, J.: Optimal driving strategies for a train on a track with continuously varying gradient. In: The ANZIAM Journal, Vol. 38, pp. 388, 1997

[9] Howlett, P.: The optimal control of a train. In: Annals of Operations Research, 98, pp. 65-87, 2000

[10] Howlett, P.G., Pudney, P.J., Vu, X.: Local Energy Minimization in Optimal Train Control. In: Automatica, Vo. 45, Issue 11, pp. 2692-2698, 2009

[11] Jong, J.-C.: Analytical Solutions for Predicting Train Coasting Dynamics. In: Proc. of the Eastern Asia Society for Transportation Studies (EAST), Japan, Fukuoka, 2003

[12] Jong, J.-C., Chang, S.: Algorithms for Generating Train Speed Profiles. In: Journal of the Eastern Asia Society For Transportation Studies, Vol. 6, pp. 356-371, 2005

[13] Kim, K., Chien, S.: Simulation-Based Analysis of Train Controls under Various Track Alignments. In: Journal of Transportation Engineering, Vol. 136, No. 11, 2011

[14] Bureika, G., Subacius, R., Kumara, M., Research on Energy Efficient of Rolling-Stock Operation, Vilnius Gediminas Technical University, Transport Engineering Faculty, 2009.

[15] The American Railway Engineering and Maintenance-of-Way Association (AREMA). Manual for Railway Engineering, AREMA, 2015

[16] Ji, Y.: Durchgängige Trassen- und Brückenplanung auf Basis eines integrierten parametrischen 3D-Infrastrukturbauwerksmodells. Doctoral Thesis, Chair for Computational Modelling and Simulation, Technische Universität München, Germany, 2014

[17] Feynman R.P., Leigthon, R.B., Sands, M.: The Feynman Lectures on Physics, Vol. 1: Mainly Mechanics, Radiation, and Heat, Addison Esley, 1th edition, USA, 1977

[18] Hay, W.W.: Railroad Engineering, 2nd edition, John Wiley & Sons, Inc., Canada, 1982

[19] James, R., Jungbauer, W.G., Abrams, B.S.: Train Accident Reconstruction and FELA and Railroad Litigation, Lawyers & Judges Publishing Company, Inc., 4th Edition, 2005

[20] Denver, T., Pan, L., Benson, D.: Analysis of railroad energy efficiency in the united states. MPC Report No. 13-250, USA, 2013

[21] Klimentev, L., Jenek, J. F.W., Meyer, H.J.: Comparison of Energy Efficiency by Using simulation Tools. In: Landtechnik 67, No. 4. pp. 256-259, 2012

[22] Dorigo M. Optimisation, learning and natural algorithms [in Italian],PhD thesis, Dipartimento di Elettronica, Politecnico di Milano, Italy, 1992.

[23] David L. Applegate, Robert E. Bixby, Vasek Chvátal, William J. Cook, The Traveling Salesman Problem: A computational study, Princeton Series in Applied Mathematics, Princeton University Press, 2006.

[24] Yang, J., Xiaohu, S., Marchese, M. , Liang, Y.: An ant colony optimisation method for generalised TSP problem, Jilin University, 2008.

[25] Dorigo M., V. Maniezzo & A. Colorni: The Ant System: Optimisation by a Colony of Cooperating Agents. Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, Volume 26, Issue 1, pp. 29-41, 1996.