

Impact of Symmetric Vertical Sinusoid Alignments on Infrastructure Construction Costs: Optimizing Energy Consumption in Metropolitan Railway Lines Using Artificial Neural Networks

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Received: 11 March 2019 / Revised: 20 December 2019 / Accepted: 1 June 2020 / Published online: 2 July 2020
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Abstract Minimizing energy consumption is a key issue from both an environmental and economic perspectives for railways systems; however, it is also important to reduce infrastructure construction costs. In the present work, an artificial neural network (ANN) was trained to estimate the energy consumption of a metropolitan railway line. This ANN was used to test hypothetical vertical alignments scenarios, proving that symmetric vertical sinusoid alignments (SVSA) can reduce energy consumption by up to 18.4% compared with a flat alignment. Finally, we analyzed the impact of SVSA application on infrastructure construction costs, considering different scenarios based on top-down excavation methods. When balancing reduction in energy consumption against infrastructure construction costs between SVSA and flat alignment, the extra construction costs due to SVSA have a return period of 25–300 years compared with a flat alignment, depending on the soil type and construction method used. Symmetric vertical sinusoid alignment layouts are thus suitable for scattered or soft soils, up to compacted intermediate geomaterials.

Keywords Infrastructure construction costs on railways · Symmetric vertical sinusoid alignments · Optimization of energy consumption · Artificial neural networks (ANN)

1 Introduction

The International Energy Agency reported up to 9555 million tonnes of oil equivalent (Mtoe) of energy consumption in the world in 2016. The transport sector consumes 28.8% of that energy, hence demonstrating its significant impact on global energy consumption [1].

Railways are more efficient in terms of energy consumption than road transport for both passengers and freight [2–4]. For example, despite carrying about 8% and 17% of passengers and freight across Europe, respectively (EU-28), European railways only represent about 2% of the energy consumed by the transportation sector [5]. However, it is necessary to continue reducing railways energy consumption so as to improve its competitiveness. For this reason, many strategies have been implemented to improve railways efficiency, focused on aspects as diverse as track geometry, rolling stock, driving schemes, or line operation.

The most common strategy is to focus on driving schemes because these allow higher rates of efficiency [6–8]. Previous studies have tried to reduce energy consumption focusing on manually driven trains [9, 10] and on trains equipped with automatic train operation as well [11].

This kind of strategy has been studied for metropolitan rail lines [12], freight rail lines [13–15], and high-speed rail lines [16].

Alternatively, other authors have proposed to modify rolling stock parameters to optimize energy consumption. For instance, various studies have focused on the implementation of regenerative brake [17, 18], on-board storage systems [19], and consideration of train load variations and delays as well [12]. Finally, some authors have focused on optimizing track geometry to reduce energy consumption [20–24].

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These varied research strategies show that a wide range of actions may be taken within the railway sector to continue improving energy efficiency and achieving the objective of reducing the transport sector carbon footprint. This will also improve the competitiveness of the railways sector against other transportation modes within the framework of a more sustainable world.

Regarding the modeling of energy consumption through artificial neural network (ANN) models, authors have used them to disaggregate household electricity consumption [25] and to predict energy consumption in supermarkets [26], bioclimatic buildings [27], and hotel rooms [28], obtaining interesting results.

In the railway field, Aolfazli et al. [29] built an ANN model to predict oil consumption in the Iranian rail transport, and Feng et al. [30] developed an ANN model to estimate energy consumption due to traction on a subway line.

Concerning infrastructure construction costs, authors have shown that it is hard to find common variables that influence such costs. This is mainly due to the economic and geographical differences presented by each case study [31–35].

Available construction techniques, type of soil, local prices, or costs for every work unit may also vary the overall infrastructure construction costs as well [36–38].

A key factor that explains these cost variations among railway projects is the cost of establishing the corridor, including expropriations. This cost may be as low as USD 10 million/km for a railway with no payment for building permissions or may be more than USD 200 million/km for a subway line in a difficult urban topography. In the latter, high expropriation costs, problematic geology, high costs of relocation, and compensation for existing companies and residents must be taken into account [39]. Infrastructure construction costs are also influenced by the quality of management, environmental limitations, and safety requirements [40].

The purpose of this paper is to measure the impact of symmetric vertical sinusoid alignments on infrastructure construction costs and to compare this with the reduction of energy consumption provided by such vertical alignments. The importance of this research lies in the existence of a knowledge gap in evaluating energy-efficient geometrical alignments against their extra construction costs.

This paper expands our previous research [21, 41, 42], where we developed an ANN model able to predict the energy consumption of a metropolitan railway line using measured data. In this paper, we use it to compare the energy consumption of different vertical alignments, aiming to reduce energy consumption between two stations with the same elevation.

2 Methodology

Figure 1 shows a flowchart of the methodology applied for this study, starting from data gathering and the development of a neural network to estimate energy consumption and concluding with the comparison between symmetric vertical sinusoid alignment and flat alignment in energy reduction and construction costs under different circumstances. Every step in the flowchart is described below in more detail.

2.1 Data Collection and Processing

To measure the energy consumption of the train, three MSAVDC meter devices (Mors-Smitt®) were installed in the train to measure the energy consumed by each train subsystem in real time: traction subsystem, auxiliaries subsystem, and rheostatic brake subsystem (Fig. 2). Train speed was measured too, using a Knorr sensor model BB0457681100 [41].

After validating the accurate performance of all devices, up to 13 trips with passengers on board were registered on August 4, 2014. For each trip, energy consumed in each subsystem were recorded with a sampling frequency of 1 Hz, and the train speed was recorded as well with a sampling frequency 100 HZ. (100 Hz for speed).

2.2 Artificial Neural Networks (ANN)

ANNs are one of the most popular machine learning (ML) algorithms. Their popularity lie in their ability to extract complex patterns within the data and to perceive trends that are very complex to be observed by humans or even by other computer techniques. This is possible because ANNs have an outstanding ability to derive meaning from complex or inaccurate data [21, 41, 43, 44]. McCulloch and Pitts introduced the term ANN in 1943, as they were inspired by the architecture of the nervous systems or brain connections in living beings [45].

ANNs are composed of many *neurons*. These elements are interconnected in parallel and work in unison to solve diverse problems. ANNs are used for predicting or classifying values and then optimizing them. ANNs have been applied in several topics, including transportation engineering [46–50] and railways engineering [21, 23, 24, 41, 42, 51].

The ANN chosen herein for predicting energy consumption is a two-layer *feed-forward* ANN, widely used to adjust functions [41, 52]. This kind of network is known by its classification in layers and because connections between units go strictly forward, hence avoiding loops in the network. *Feed-forward* neural networks are the most commonly used ANNs due to their simplicity and outstanding results.

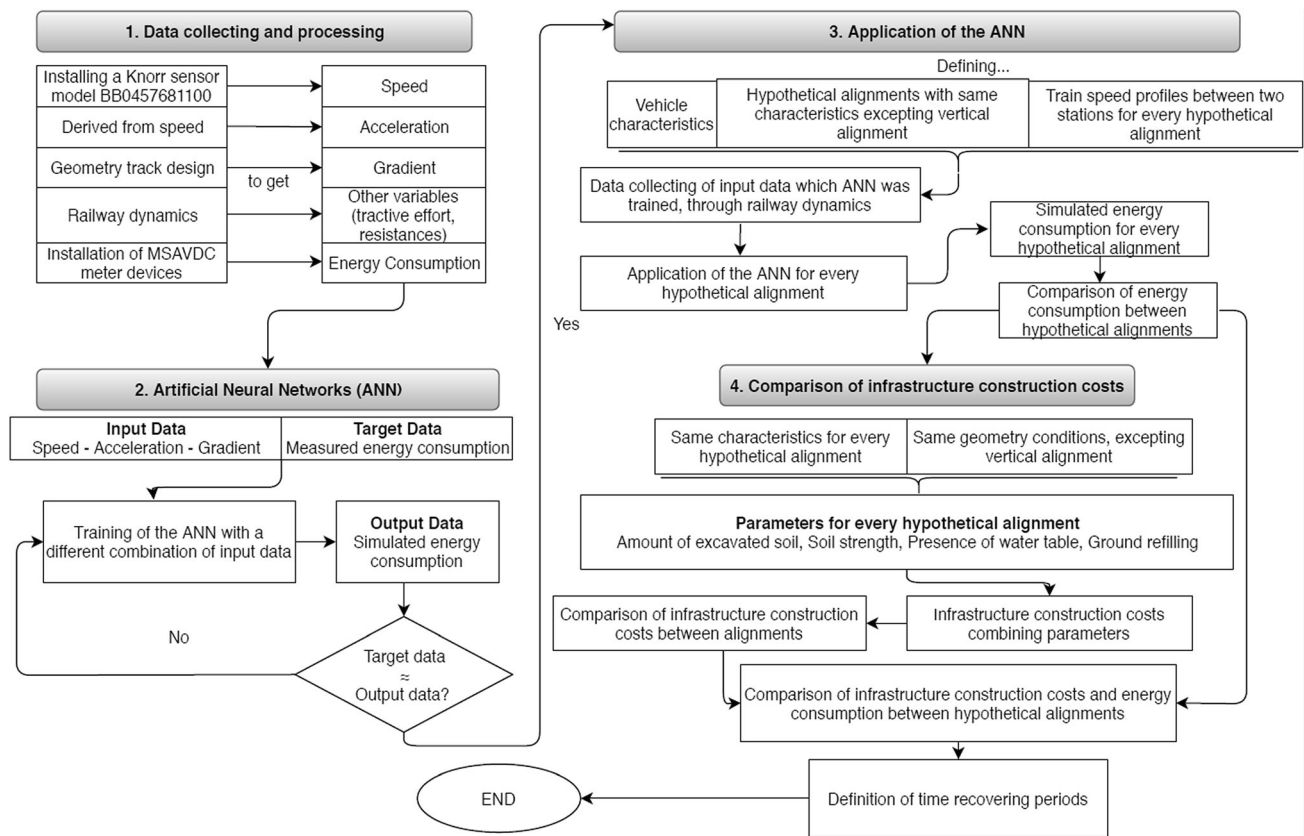


Fig. 1 Methodology flowchart Source: Authors

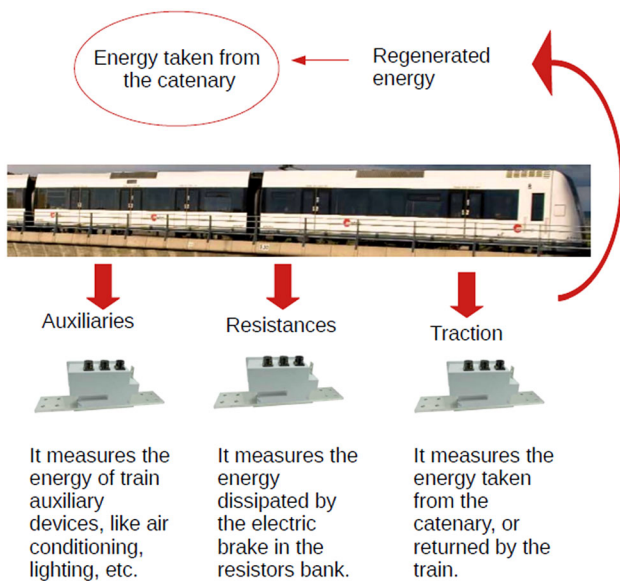


Fig. 2 Scheme of MSAVDC meter devices (Mors-Smitt®) installed on train Source: Authors

The ANN used for predicting energy consumption in this paper was trained using speed, acceleration, and gradient as input variables, while measured empirical energy consumption was the target variable. In previous works, we

showed that these input variables provide good accuracy, thus making it unnecessary to consider another input data to calibrate energy consumption [21, 41].

The training process consists of comparing available target data with the output data provided by the ANN, and adjusting the ANN parameters through an iterative process until measured energy consumption (target data) and simulated energy consumption (output data) are similar enough [41]. When the differences between target and output data are very small, the ANN is completely trained and could be used to make predictions varying the input data (to test hypothetical scenarios).

As we explained in detail in our previous research paper [41], to avoid overfitting, the data were divided randomly into three subsets: one for training (70%), one for validation (15%), and one for testing (15%). The ANN was trained with the training data, and after each iteration, a check-up with the validation data was performed.

The training method used for the proposed ANN in this paper was *back-propagation*, which aims to minimize the relative mean squared error (rMSE) by modifying the synaptic weights of the neurons after each iteration. The specific training algorithm used was the Levenberg–Marquardt algorithm, which is very efficient and widely checked.

When the validation rMSE begins to increase (while the training rMSE continues to drop), the network will start to adjust the data error (overfitting), and the training will be stopped. At this point, the test data are used to perform a final check-up for the validity of the ANN.

2.3 Application of ANN Model

After the ANN model being trained, the application of the ANN model was then carried out. In the application of the ANN model, three hypothetical scenarios were specified with their respective speed profile, considering optimal indications for efficient driving between two stations [52].

The following assumptions were considered to make an integrated analysis of vertical alignment and speed profiles for these hypothetical vertical alignments [53]:

- The vertical track layout is symmetrical with respect to the central axis.
- Parabolic curvatures are applied to vertical curves, while the gradient cannot exceed the maximum climbing capacity of the train.
- Horizontal curvatures are not considered for this analysis.
- The train accelerates to its full power unless it surpasses the comfort-limited acceleration.
- Braking system can provide the maximum allowable comfort-limited deceleration rate.

The three scenarios have the same characteristics: a 1000-m long track stretch between two stations of equal elevation. The three scenarios only differ in their vertical alignment. Figure 3 shows the three hypothetical scenarios.

- The first one is a flat alignment;
- the second one is a symmetric vertical sinusoid alignment profile with a maximum depth of $\delta = 10$ m (1.0% of the total track length) halfway between both stations of $\delta = 5$ m (0.5% of the total track length); and
- the last scenario is a symmetric vertical sinusoid alignment profile with a maximum depth of $\delta = 10$ m (1.0% of the total track length) halfway between both stations of $\delta = 10$ m [21].

Once the hypothetical scenarios were determined, the trained ANN was applied to predict the energy consumption (output) corresponding to each hypothetical alignment using speed, acceleration, and gradient as input variables.

To do so, a speed profile was defined for each hypothetical scenario based on the theoretical basis of efficient driving: the train accelerates until reaching a cruising speed and then coasts without applying traction force until it begins to apply braking to reach the final station. To calculate the speed profile for each hypothetical scenario, the characteristics of the Metro Series 4300 (Vossloh) were considered, and resistance to movement was calculated

using the Davis equation, which is a well-known resistance formula.

Finally, the energy consumption due to each scenario calculated using the three input variables defined above (speed, acceleration, and gradient) were compared among them to determine the vertical alignment with the lowest energy consumption. Note that speed optimization was not considered in this paper, as travel time was verified to be the same for each vertical alignment.

Also, it is important to mention that the three hypothetical scenarios were chosen in an empirical way. This paper does not aim to determine the optimal symmetric vertical sinusoid alignment depth to optimize energy consumption but to analyze the balance between energy savings and construction costs. A proper depth optimization could be carried out in future works.

2.4 Comparison of Infrastructure Construction Costs

Knowing the energy consumption in every hypothetical alignment [21], the differences in infrastructure construction costs were then analyzed to find the best hypothetical alignment as a balance between energy consumption and infrastructure construction costs. This analysis may help stakeholders in their decision-making process to find whether it is worth to potentially increase construction costs to reduce later operational costs.

The assumptions made for this comparison rely on the basis that all three alignments are entirely constructed below the ground level, i.e., in tunnel section, as this is the most usual situation in metropolitan railways. This is achieved by means of tunneling and excavation methods. In such methods, we will consider the amount of excavated soil, the soil strength, the presence of water table, and the ground refilling as influent parameters on infrastructure construction costs. Other parameters such as tunnel length and section are not considered since these remain invariable among the different considered alignments. This analysis is carried out in Sect. 4.3.

3 Case Study

3.1 Input Data

Line 5 of MetroValencia in Spain has 12.95 km and 18 stations. We studied a 2720-m-long track stretch within said Line 5 between the Marítim-Serrería and Alameda stations.

As we showed in previous studies [21, 41], the input variables chosen to train the ANN model were speed, acceleration, and gradient.

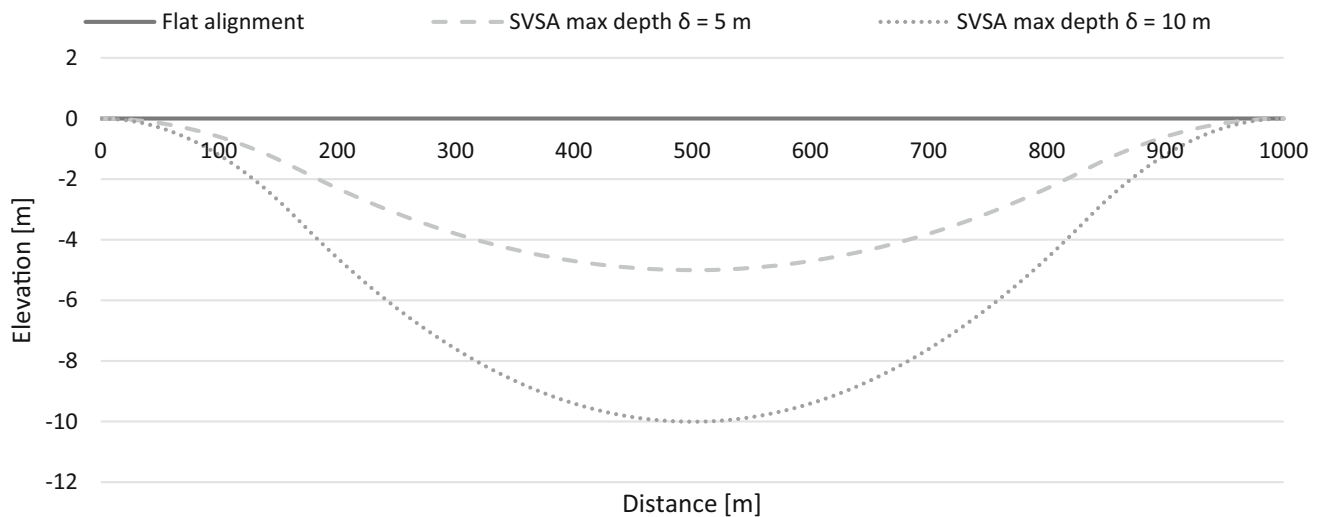


Fig. 3 Hypothetical scenarios of vertical alignments of different maximum depths between two stations *Source: Authors*

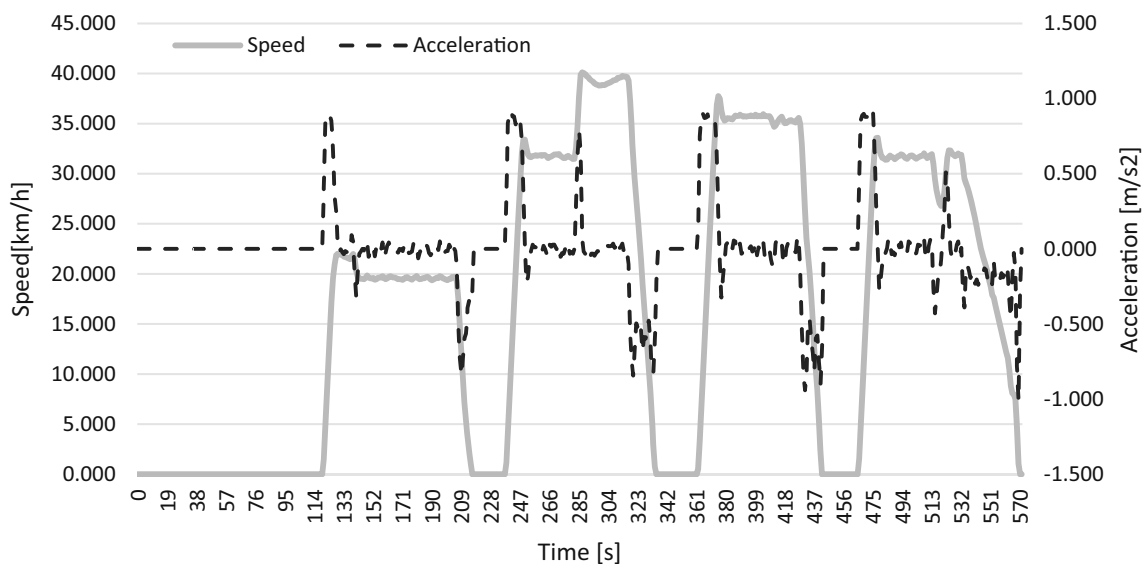


Fig. 4 Speed and acceleration of the first trip between Marítim-Serrería and Alameda *Source: Line 5 of MetroValencia in Spain, by the Authors*

As explained above, speed was directly measured using a Knorr sensor model BB0457681100. Acceleration was derived from speed. Figure 4 shows speed and acceleration signals registered during the first trip.

As for the gradient, there is a maximum gradient of 20 mm/m between the Marítim-Serrería and Alameda stations (Fig. 5).

3.2 Target Data

The monitored train was a Metro Series 4300 (Vossloh) with four cars, whose main characteristics are:

- Max. speed: 80 km/h
- Nominal tension: 1500 V DC
- Power: 1480 kW

Energy consumption measured as described above was used as target data for training ANN. Figure 6 shows an example of the registered energy consumption on the first trip from Marítim-Serrería to Alameda. The blue rectangles in Fig. 6 represent the five stations from Marítim-Serrería to Alameda, which are Maritim-Serrería, Ayora, Amistat, Aragón, and Alameda respectively from left to right.

4 Results and Discussion

4.1 Training of the ANN

Different tests were performed by combining the input variables previously defined to identify which of these input variables better fit the target data. Two criteria were used to assess the performance of the ANN model [54]:

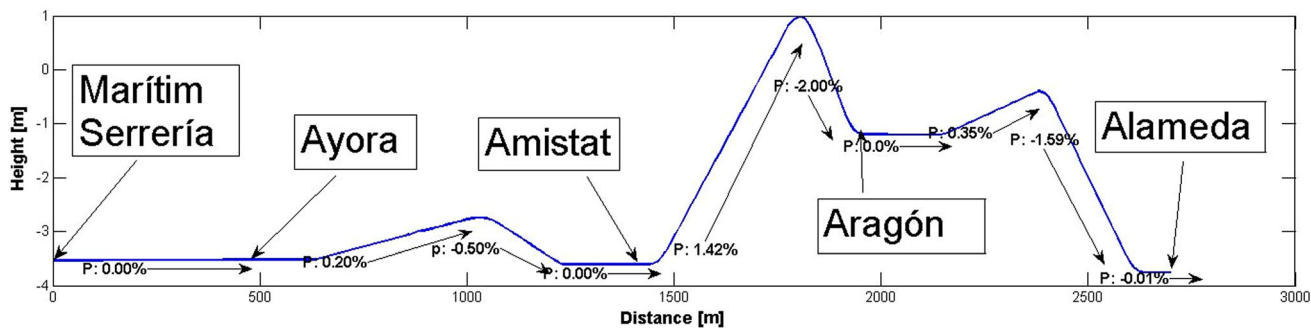


Fig. 5 Vertical layout and stations of the studied route *Source*: Line 5 of MetroValencia in Spain, by the Authors

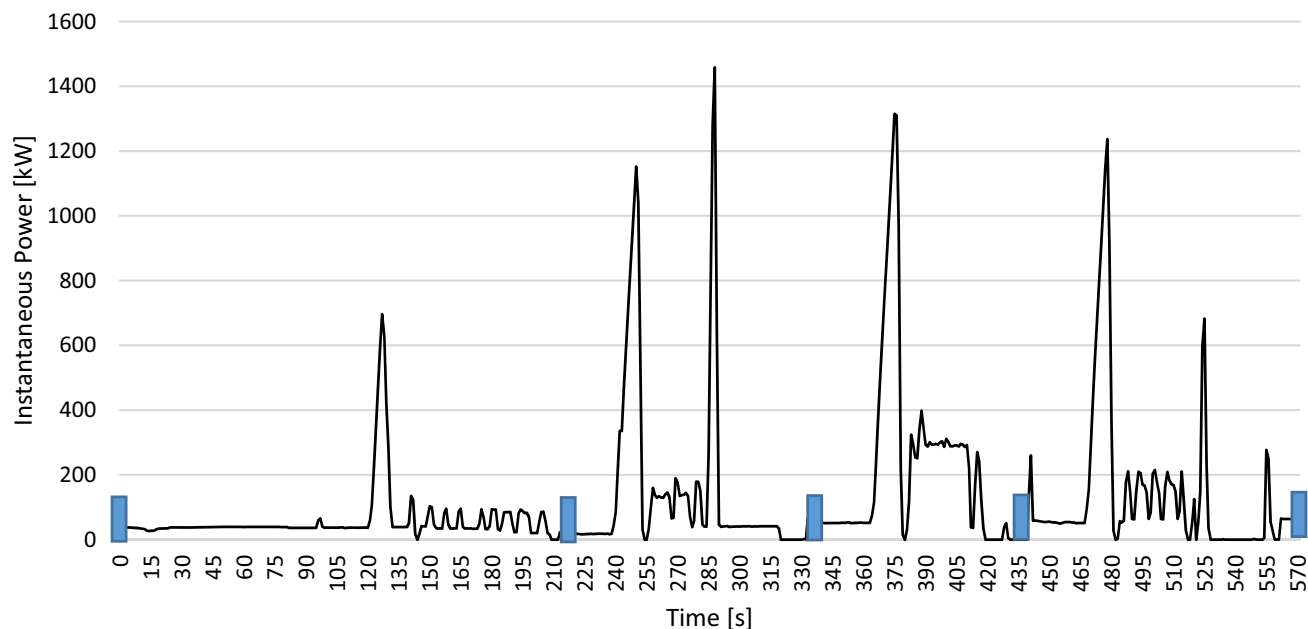


Fig. 6 An example of the registered energy consumption on the first trip from Marítim-Serrería to Alameda *Source*: Authors

- Pearson correlation coefficient (R) between target and output data must be greater than 90%.
- Mean square error between target and output data must represent only 20% or less of the target data variance [or, in other words, relative mean squared error (rMSE) must be less than 20%].

The training and validation of the ANN model were performed using the Neural Fitting Tool in MATLAB R2017a.

The neural network size was determined studying rMSE values for training and validation data, with their variation depending on the number of neurons in the hidden layer. After testing different number of neurons (Fig. 7), we found that the optimal network size was 30, because more neurons will increase validation rMSE [41].

After the training process, we analyzed the cross-validation score between target and output for training,

validation, and test data, achieving an overall correlation of 90.85% (see Fig. 8).

After several combinations, we have shown in previous research [41] that the model satisfies both criteria using speed, acceleration, and gradient as input variables. These variables have thus a significant impact on energy consumption in metropolitan railway lines.

Results show an average registered energy consumption of 7.29 kWh/km (shown in Fig. 9), while the model predicts an energy consumption of 7.11 kWh/km: the difference between both values is just 0.176 kWh/km (2.4%). Note that every trip was the same in terms of train load and number of intermediate stops between the first and last stations (shown in Fig. 6).

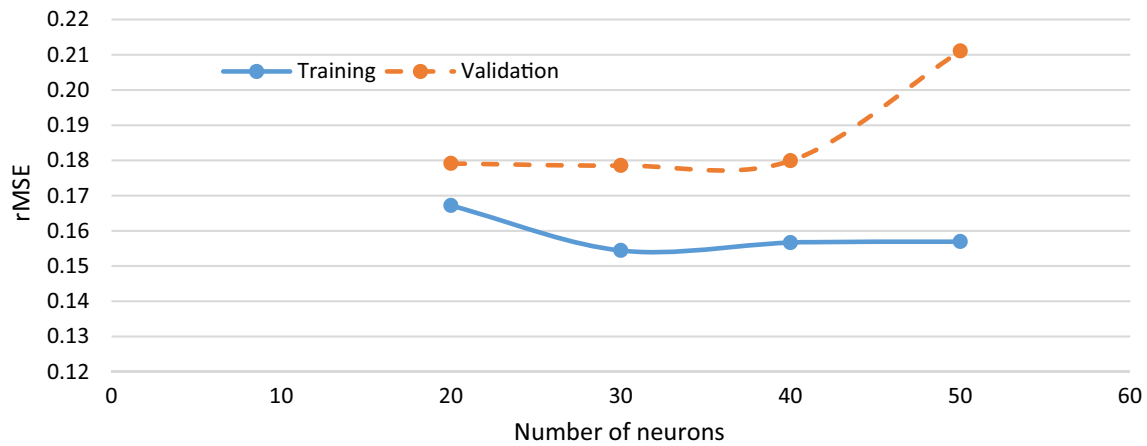
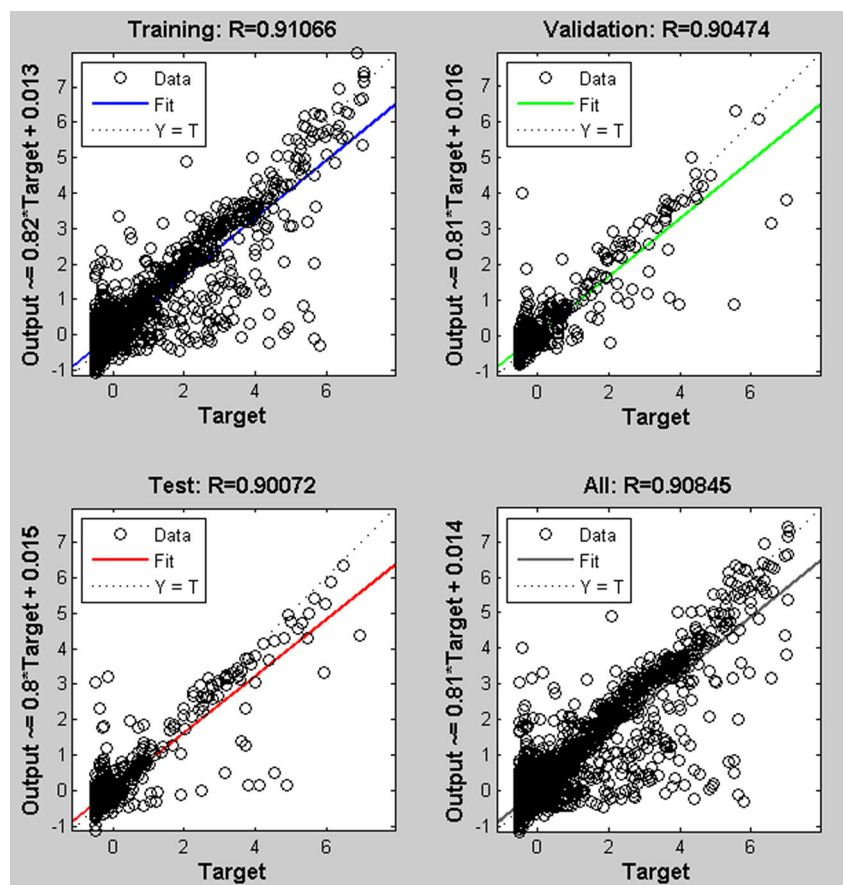


Fig. 7 rMSE value by number of neurons in hidden layer for training and validation data *Source:* Authors

Fig. 8 Cross-validation score for training, validation, test, and all data *Source:* Authors



4.2 Application of the ANN on Hypothetical Alignments

The trained ANN was used to predict the energy consumption for every hypothetical scenario using the input variables defined above.

The results show a total energy consumption of 5.81 kWh/km for the flat alignment, 4.74 kWh/km for the

symmetric vertical sinusoid alignment with a maximum depth of $\delta = 5$ m, and 4.94 kWh/km for the symmetric vertical sinusoid alignment with a maximum depth of $\delta = 10$ m.

The symmetric vertical sinusoid alignment (SVSA) with maximum depth $\delta = 5$ m obtained the lowest energy consumption, a reduction of 18.41% in comparison with the flat alignment. Remember, as we mentioned above in

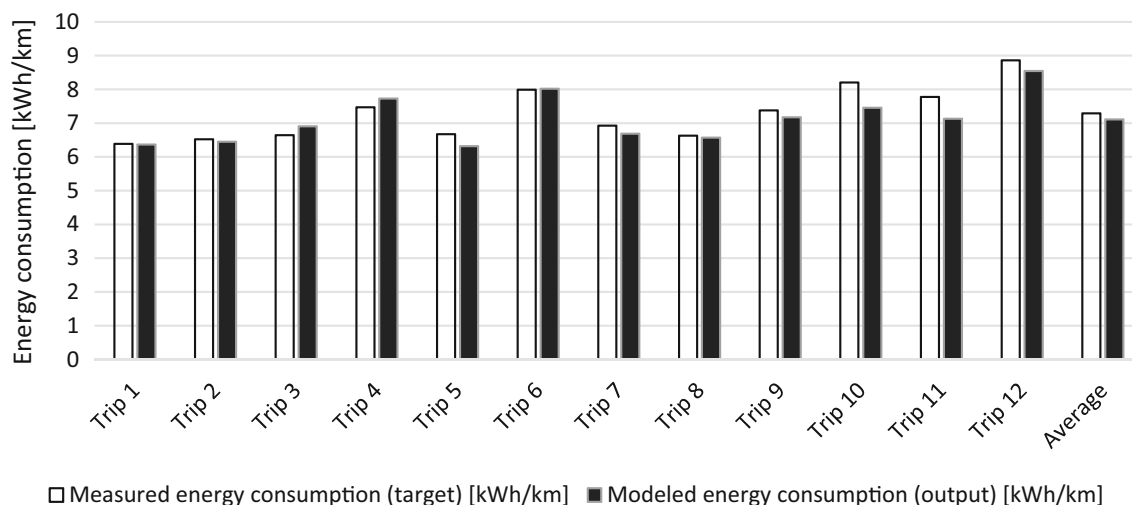


Fig. 9 Overall energy consumption in each trip *Source:* Authors

Sect. 2.3, that each trip for every hypothetical scenario had the same duration (86 s); hence, travel time did not affect the results.

To assess this saving in economic terms, we assumed an average energy cost in Spain of 0.086 €/kWh (year 2016), an average frequency of a train passing every 5 min with a commercial service of 20 h/day on workdays and an average frequency of 7 min during 18 h/day on non-workdays. With this information, the following traction costs for each scenario were obtained:

- Flat layout: 38,100 €/km/year
- SVSA with $\delta = 0.5\%$ of L: 31,100 €/km/year
- SVSA with $\delta = 1.0\%$ of L: 32,400 €/km/year

Here, L is the length between two stations, δ is the maximum depth between two stations. Therefore, it could be seen that the SVSAs have less energy cost compared with the flat layout. The SVSA with $\delta = 0.5\%$ L represents a saving of 7000 €/km/year.

4.3 Infrastructure Construction Costs

The aim of this section is to estimate the differences in construction costs between two scenarios: the flat layout and the SVSA with $\delta = 0.5\%$. SVSA with $\delta = 1.0\%$ is excluded from this analysis as this yields worse energy consumption results than the previous SVSA solution, whereas higher construction costs are expected.

The first premise to keep in mind in this analysis is the high dispersion of costs due to tunneling and excavation, which depend on so many factors as we explained in the above sections.

There are two main groups of construction techniques for undertaking an underground infrastructure: tunneling and excavation. Tunneling is usually performed using

tunnel boring machines (TMB) or the New Austrian Tunneling Method (NATM), whereas excavation is normally executed with top-down methods such as “cut and cover.”

No remarkable cost differences exist between tunneling methods as the main defining parameters, i.e., length and section, remain invariable. Hence, only differential excavation costs for top-down techniques are addressed. In this last case, the parameters considered in this study are the amount of excavated soil, the soil strength, the presence of water table, and the ground refilling.

4.3.1 Amount of Excavation

Differential costs between a flat layout and the SVSA layout in this aspect are due to the extra volume to be excavated in the latter case. Such volume is given by the following expression (Eq. 1):

$$V = B \int_0^L \left(z - \left(z - \delta L + \delta L \sin\left(\frac{2\pi}{L}x\right) \right) \right) dx = B \cdot L^2 \cdot \delta, \quad (1)$$

where B is the width of the excavation and z is the level of the tunnel crown for the flat layout, L is the length between two stations, δ is the maximum depth between two stations. In this analysis, all the dug soil has the same properties in terms of soil strength and water saturation.

4.3.2 Soil Strength

Excavation costs strongly depend on the soil strength. For this study, five categories were set up: scattered soil, soft soil, compacted intermediate geotechnical material (IGM), strong IGM, and rock. Their respective costs per cubic meter are presented in Table 1. Unitary prices have been taken from [55, 56].

Table 1 Unitary prices and performances for excavation of different types of soils

Soil type	Unitary prices in (€/m ³)	Performance in (h/m ³)
Scattered soil	2.52	0.046
Soft soil	2.83	0.057
Compacted IGM	3.16	0.068
Strong IGM	14.93	0.269
Rock	23.63	0.366

4.3.3 Water Table

In totally or partially water-saturated soils, it is necessary to drawdown the water table below the deepest excavation level. This lowering must be maintained during the whole excavation period until the excavation is waterproofed. Common drawdown water table methods can be grouped in exclusion and dewatering methods. The former group includes low-permeability walls, grouting methods, ground freezing, or fluid pressure. The latter group includes methods such as wellpoints, injection wellpoints, or deep wellpoints [57].

Although the most suitable drawdown method varies depending on the depth, soil nature, and water flow, for this example, a deep wellpoint method was considered, with an estimated unitary cost of 4.83 €/h.

4.3.4 Ground Refilling

Whereas, in some cases, the gap left by the SVSA layout above the tunnel compared with the flat layout may be used for other purposes (e.g., parking, storing, commercial uses, etc.), in other cases, this volume must be refilled, which is normally done with the same soil extracted from the excavation. For these cases, a refilling cost of 2.02 €/m³ was considered.

4.4 Discussion

Figure 9 shows that the trained ANN model can predict the energy consumption well enough as we presented in Ref. 41.

This trained ANN model with three input variables makes an accurate prediction of the energy consumption by a train if each input variable is always within the range considered during training. With that precaution in mind, the ANN could be used to test scenarios such as other hypothetical alignments, looking for reducing energy consumption.

In this study, the trained ANN was used to obtain the energy consumed by a train passing along a 1000-m-long track stretch between two stations with the same elevation and a different hypothetical alignment. It was found that the SVSA with a maximum depth of $\delta = 5$ m yielded the lowest energy consumption, reducing it by 18.4% compared with the flat alignment. This reduction is due to gravity, which contributes both to acceleration and braking

Table 2 Time (years) to recover extra construction costs with energy savings

	<i>E</i>	<i>E</i> + WTD	<i>E</i> + <i>R</i>	<i>E</i> + WTD + <i>R</i>
Scattered soil	25	30	50	50
Soft soil	30	35	50	55
Compacted IGM	35	35	55	60
Strong IGM	160	175	180	200
Rock	250	270	275	300

thanks to the gradient variation. For a metro network with a commercial service such as the one shown in Sect. 4.2, this means a saving of 7000 €/km/year.

Whereas this saving can be directly computed if the infrastructure is constructed using the TBM or NATM methods (since there are no remarkable cost differences between both layouts), it must be compared with the extra costs of excavation when a top-down procedure is utilized.

For this last case, together with the five soil classes described above, four different scenarios were considered: only excavation (*E*), excavation plus water table drawdown (*E* + WTD), excavation and refilling (*E* + *R*), and excavation with water table drawdown and refilling (*E* + WTD + *R*). Table 2 presents the equivalent time, in years, after which the energy consumption savings cancel the former extra excavation costs.

Results from Table 2 are estimative, since these strongly depend on the real technical and economic conditions of the worksite and the later train operations. That said, there is a significant step between compacted IGM and strong IGM (125–140 years) due to the excavation technique being more cost intensive. In the same line but at a lower scale, there are important differences when refilling is carried out after the excavation. This means increasing the return period about 20–25 years. The presence of water table seems to be less significant.

Bearing in mind that metro infrastructures may last more than 100 years, Symmetric vertical sinusoid alignment layouts may be a suitable solution for scattered or soft soils, or even compacted intermediate geomaterials (IGMs). Particularly suitable are the cases in which there is no need of refilling the gap above the infrastructure.

5 Conclusions

The aim of this paper is to measure the impact of symmetric vertical sinusoid alignment on infrastructure construction costs and compare this with the reduction of energy consumption provided by this type of vertical alignments.

The main reason to investigate this subject is that many strategies to optimize railways energy consumption have

been proposed in the past, but only a few rely on track geometry. However, it is important to analyze these strategies to maintain low infrastructure construction costs as well.

In that context, this paper summarizes our previous research [21, 41, 42], where we trained and validated an ANN model that predicts the energy consumption of a train in a metropolitan railway line using three input variables: speed, acceleration, and gradient. We used this ANN to compare different vertical alignments and obtain the energy consumption due to each one between two stations with the same elevation.

The trained ANN predicts an energy consumption of 7.11 kWh per km, a small difference of 2.4% compared with the average measured energy consumption of 7.29 kWh per km.

The trained ANN is a useful tool that allows the study of energy consumption of a metropolitan railway line. This method may function as a virtual laboratory where it is possible to test other hypothetical scenarios, modifying variables such as track layout and train driving style to reduce energy consumption.

A symmetric vertical sinusoid alignment profile with a maximum depth of $\delta = 5$ m halfway yielded a reduction of 18.4% in energy consumption compared with a completely flat alignment.

This, for example, in a network with an average frequency service of a train every 5 min and a commercial service of 20 h/day in labor days, represents a saving in the costs of traction of 7000 €/km/year.

Comparing the differential construction costs between flat and 5% SVSA layouts, whereas in tunneling methods such as TBM or NATM, there are no practical differences, in a top-down excavation method, the extra excavation volume for the SVSA layout may lead to substantial cost increments. These over costs are particularly important in strong IMGs or rocky grounds. Less relevant is the need of refilling and the presence of water table. In general, time recovering periods may range from 25 to 300 years between the most favorable and the most disadvantageous cases.

These results demonstrate the importance of designing energetically efficient geometric alignments. Although this strategy already allows a significant energy consumption reduction to be obtained, this can be accompanied by other strategies such as economic driving to come up with a better and more efficient transport system in terms of energy consumption. However, it is important to perform a detailed assessment of the impact of these geometric alignments because this could lead to overruns in infrastructure construction costs, which could never be recovered.

The main contribution of this research lies in its proposal of a simple ANN model for predicting the energy consumption with few input variables and, then, in using said ANN to compare different hypothetical vertical alignments in terms of energy consumption reduction. Additionally, we have compared the energy savings of energy-efficient vertical alignments against the extra costs of their infrastructure construction, thus obtaining different time recovering periods for different cases.

Next steps of research will involve an analysis on how the ANN model can be improved if energy recuperation is involved. This will allow the testing of other hypothetical operative scenarios, hence further contributing to minimize the energy consumption of the system.

Acknowledgements This paper was realized thanks to the collaboration agreement signed between Ferrocarrils de la Generalitat Valenciana and Universitat Politècnica de València, and funding obtained by the Spanish Ministry of Economy and Competitiveness through the project “Strategies for the design and energy-efficient operation of railway and tramway infrastructure” (Ref. TRA2011-26602).

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Compliance with Ethical Standards

Conflict of Interest None of the authors has any competing interests in the manuscript.

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