Neural Networks for modelling the energy consumption of metro trains

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Abstract

This paper presents the application of machine learning systems based on neural networks (NN) to model the energy consumption of electric metro trains, as a first step in a research project that aims to optimise the energy consumed for traction in the Metro Network of Valencia (Spain). Experimental dataset was gathered and used for training. Four input variables (train speed and acceleration, track slope and curvature) and one output variable (traction power) were considered. The fully trained NN shows good agreement with the target data, with relative Mean Square Error (rMSE) around 21%. Additional tests with independent datasets also give good results, (rMSE = 16%). The NN has been applied to five simple case studies to assess its performance, and has proven to correctly model basic consumption trends (e.g. the influence of the slope), and to properly reproduce acceleration, holding and braking, although it tends to slightly underestimate the energy regenerated during braking. Overall, the NN provides a consistent estimation of traction power and the global energy consumption of metro trains, and thus may be used as a modelling tool during further stages of research.

Keywords

Energy efficiency, machine learning, neural networks, rolling stock, traction power

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Highlights

- Neural networks (NN) are a powerful computational modelling tool
- A NN has been trained to model energy consumption of metro trains
- The NN shows a good fit with the real data measured in the Valencia metro network
- The NN has been tested with 5 case studies that simulate basic consumption trends
- This network may be now used to assess energy consumption and improve efficiency

1. Introduction

At present there is an increasing concern regarding the environmental impact of our society. Climate change and scarcity of natural resources are clear threats that must be addressed at all levels. One of the key elements that define our society and is thus greatly related to such threats is transport. Efficient transportation of people and goods is essential to our economy and has a great influence in the overall environmental impact of human activities.

Railways is one of the most promising transport means in terms of energetic and economic efficiency [1, 2], and has thus become a priority for many governments over the past years, particularly in Europe (e.g. EU 2020 Horizon R&D programme and Shift2Rail Initiative) and North America (e.g. New High-Speed Networks in the USA as part of the 2009 Federal Stimulus Package).

However, it is not always easy to accurately assess the energetic consumption of a railways service. In fact, often railway managers do not know exactly the energy (and cost) that each of their trains consume in real-time. This is particularly true for non-electrified lines, where consumption is normally controlled simply by measuring the fuel level at the tank after each service [3]. However, even in electrified lines the most common trend regarding energy supply is for electric companies to measure (and charge) the energy provided from their substations to railway companies, which includes not only the energy used for traction, but also that of auxiliary services, infrastructure, power losses, etc. Consequently, the exact energy consumed by trains in real-time is usually unknown [4].

Therefore, in order for railway services to increase their energetic efficiency, it is essential that energy consumption is accurately measured and modelled. In this way, the influence of factors such as track layout, degree of maintenance, operation schemes, etc. may be studied in depth, hence allowing a better management of existing lines and a more efficient planning of future networks.

Several studies have focused on energy efficiency in the railway sector over the past years. For example, Douglas et al. [5] carried out a comprehensive review of different measures to reduce the energy consumption of railways and their effectiveness, and found that reductions up to 30% could be achieved solely by implementing eco-driving. Su et al. [6] also assessed different energy saving through a deterministic model (Optimal Train Control Model), including not only driving schemes but also modifications in both the rolling stock (weight reduction) and the infrastructure (slope optimisation).

Most studies regarding railways' energy efficiency aim to reduce energy consumption through the optimisation of different operation elements (although the main focus is on driving schemes). In order to do so, a good number of authors first develop a modelling tool capable of predicting the energy consumption of a train and then use this tool to simulate several scenarios and to choose the most efficient ones, often by means of optimisation algorithms. A noteworthy example of this approach are the works of Domínguez et al. [7-10], who have carried out several studies focused on the Madrid Metro Network (Spain). These studies rely on a time-step, modular train simulator [11] based on the Davis equation [12] with increasing complexity (e.g. adding regenerative break, on-board storage systems, multi train modelling, etc.) which is then used to create several driving scenarios which are sorted out with regard to their energy efficiency by means of heuristic algorithms. The works of Sicre et al. [13-15] follow the same pattern, although in this case their focus is on High Speed railway lines. Tian et al. [16] also base their study on a deterministic train simulator, which is by far the preferred option by all the authors reviewed.

However, despite being a common choice, time-step deterministic train models have also certain drawbacks. They may be time-consuming and their reliability strongly depends on the careful definition of several parameters that are not always known or properly estimated (e.g. train running resistance, train rotational mass, etc.). An example of this complexity can be found in [11].

A promising alternative as a modelling tool for railways energy consumption are Neural Networks (NN), which are computational models that have been extensively used over the past years to model many different phenomena in fields as diverse as medicine, chemistry or finances. Many of these applications have become common practice in their respective areas.

In the field of engineering, one can find examples of the application of NN in areas like coastal engineering [17], and structure modelling [18]. However, its use in railways engineering is relatively rare, and focused mainly on track quality and maintenance [19, 20]. Only a few attempts have been made to model train energy consumption with NN [21-23], but these are mostly preliminary research where NN only play an auxiliary role to other models.

In contrast with traditional models, a neural network, provided that it is properly trained, does not rely on several parameters which must be known beforehand, may learn rather complex, non-linear phenomena and may provide a large number of simulations with reduced time and computing requirements [24].

Therefore, it is clear that there is a gap of knowledge regarding the application of NN to model railways energy consumption. This paper aims to fill this gap by developing and training a NN capable of modelling the consumption of electric trains. The network is trained with actual consumption data measured in the Valencia Metro Network operated by *Ferrocarrils de la Generalitat Valenciana* (FGV), as it was done in a preliminary research [25]. However, this time the NN has been trained systematically using a more comprehensive set of data that covers the entire Metro Network. Furthermore, the trained NN has been thoroughly tested with five schematic case studies designed to evaluate its performance and assess whether it properly models the energy consumption of a running train with regard to significant factors such as the track slope, speed profile or driving style. The final objective of the paper is to obtain a fully trained and reliable NN that will be used as a modelling tool in further research, aiming at optimising the energy consumption of the Valencia Metro Network.

In the long term, the development of this kind of tool may be useful not only to study the energy efficiency of existing railway networks, but also to analyse prospective lines before construction through the estimation of their energy requirements. In this way, additional technic and economic criteria related to energy costs may be included in the long term planning of railway lines.

The paper is divided as follows: First, the process of data gathering and processing is explained, the NN structure is defined and the training process is outlined. Secondly, the NN is trained and validated, and it is applied to five predefined case studies. Finally, the results obtained are thoroughly discussed, and the main conclusions reached are presented.

2. Materials and methods

2.1. Data gathering and processing

In order to gather the data required to train the NN, a thorough monitoring programme was carried out in the Valencia Metro Network (Spain) operated by FGV. A 4-carriage Metro Series 4300 vehicle was equipped with three DC voltage and current sensors (MSAV-DC model, developed by *Mors Smitt* in accordance with EN 50463). One was placed right below the pantograph to measure the global energy input/output i.e. the energy that the catenary supplies to the train and the regenerated energy that the train gives back to the catenary. Another one was placed at the electric panel that feeds all the vehicle auxiliary systems (heating, cooling, lights, etc.). The last one was placed in the rheostatic brake to account for the regenerated energy dissipated during braking. It is worth noting that, as the Valencia Metro Network operates with a DC system (1500 V) with no on-board energy storage or reversible substations, the energy regenerated during braking is only given back to the line if there is another train nearby that may use it for traction. Otherwise, the energy regenerated is dissipated in the rheostatic brake. Each sensor provides current (I), voltage (V) and electric power (P) data. The train was also equipped with an odometer to measure its speed. The energy data measured by the DC sensors was sampled at 1 Hz, while the odometer sampling frequency was 100 Hz.

The monitored train operated normally along lines 1, 2, 3, 5 and 7 of the Valencia Metro network between July and October 2014. Up to 229 train services were monitored, which accounts for more than 230 hours of data. This data was then processed in MATLAB 8.5.0 (The MathWorks, Inc.) to obtain, for each train service, the speed profile, travel time and energy consumption. Regarding the latter, at any given second, the total energy supplied to the train, the energy share consumed for traction and the energy share consumed by auxiliary systems were obtained (or, when braking, the share of regenerated energy consumed in the rheostatic brake and the share given back to the line).

2.2. Neural Network development and training

NN are computational models based on several simple elements (neurons) that operate in parallel. Inspired by the structure of biological nervous systems, they can be trained to reach a target output from a certain input by modifying the weights, which are the values of the connections between the elements that form the network.

There are many different network structures depending on the problem to be solved (Function fitting, pattern recognition, etc.). In this case, the objective is to obtain the train energy consumption (output) depending on variables (input) such as train speed, track profile, etc. In order to do so, a three-layer feed-forward structure was chosen, as this scheme is rather common and powerful for function fitting [24].

The first layer ("input layer") corresponds to the input data. The second layer ("hidden layer") is made of a certain number of neurons (the exact value being one of the parameters to be evaluated during the training process) with a Log-Sigmoid transfer function. The third layer ("output layer") consists of a single neuron with a linear transfer function. The overall network equation is:

$$O_k = \hat{g}\left(\sum_{j=0}^{M} w2_{kj} \cdot g\left(\sum_{i=0}^{N} w_{ij} \cdot I_i\right)\right) \tag{1}$$

Where O_k is the network output , M is the number of output elements, I_i is the input, N is the number of input variables, w_{ij} are the weights of the first layer, $w2_{kj}$ are the weights of the output layer (bias values correspond to w_{j0} and $w2_{k0}$), g is the Log-Sigmoid transfer function and ĝ is the linear transfer function. This structure allows the NN to identify non-linear relations between input and output data [24].

The network thus created must be then trained and validated. However, prior to that, both input and output data should be pre-processed, removing constant values and normalizing both vectors within the range [-1, 1], to avoid saturation of the Log-Sigmoid transfer function [24].

Training was carried out by means of a Back-propagation method, trying to minimise the Mean Square Error (MSE) between the network output and the target data by respect to the network weights (w) and bias (b):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - o_i)^2 \qquad (2)$$

Where *N* is the number of data, t_i is the target output and o_i is the network output. The specific algorithm used for training was the Levenberg-Marquardt Algorithm [24]. The whole process of creating, training and validating the NN was done by using the Neural Fitting Tool available in MATLAB 8.5.0 (The MathWorks, Inc.).

One of the most common issues when trying to train a NN is *overfitting* i.e. that the network performance is affected by the specific error of the data used for training and thus fails to properly generalise. This issue is strongly related to the number of neurons in the hidden layer and hence an optimum network size should be determined [24]. This may be done through ‘rules of thumb’ based on previous experience [26] or rather through a systematic analysis [17]. In any case, the most common option is to use *early stopping* training [25, 26], dividing the data randomly in three subsets, one for training (70% of the data), another for validation (15%) and the last for testing (15%). This prevents, to a certain degree, the NN from *overfitting*, and thus there is not a limit to its size *a priori* [27]: the higher number of neurons in the hidden layer, the better. However, in order to keep the NN as simple as possible, a small number of neurons (10) was chosen at first, and then more neurons were added to achieve a better fit with the target data. Each NN with increasing size was then tested using an additional dataset, and when the error obtained with this second test started to increase (or at least no further improvement was obtained), no additional neurons were added to the hidden layer.

Another key issue was the definition of the input vector. Different variables (namely train speed and acceleration, track slope and track curvature) and combinations thereof were tested to determine which ones had more influence in the energy consumption [25]. The procedure followed is based on the one found in [28], and relies on the following criterion (relative mean square error):

$$rMSE = \frac{MSE}{Var(C)} \tag{3}$$

Where MSE is the mean square error as described in (2) and Var(C) is the variance of the measured consumption data (C). This is an indication of the proportion of the data variance not explained by the model, and allows evaluating the dependence of the NN on the particular training data to be fitted.

Each variable was used as a single input for the NN, and after 100 training runs were carried out, the variable with the lowest rMSE (for all three stages: training, validation and test) was chosen and combined with each of the remaining variables in a NN with two input parameters. After another 100 runs, the best of these pairings in terms of lower rMSE was chosen and combined with each of the remaining variables, and so on until no further improvement was achieved.

Furthermore, as a final criterion for the fully trained NN (once both the input variables and the network size were defined), the rMSE was required to be lower than 0.25, or, in other words, that only 25% or less of the data variance is not explained by the NN. This is a somewhat arbitrary threshold, but it is in line with what other authors have considered as acceptable [28, 29] when training NN.

2.3. Case studies

Five case studies were devised to further test the fully trained NN and check its reliability. All of them were made up to represent relatively simple scenarios to check whether the NN provides sound, logical results and has correctly learned the expected trends of energy consumption (for instance, that a train accelerating should consume more energy than one coasting, under equal conditions). Cases 1 and 2 both represent a train running along a flat, straight track stretch, accelerating up to a given top speed, then maintaining that speed for a while and then braking until full stop. The difference between them is the top speed (60 km/h for case 1 and 40 km/h for case 2) and the acceleration and deceleration ratios (1 m/s^2 for case 1 and 0.5 m/s^2 for case 2).

Cases 3 to 5 have the same speed profile, which is similar to that of cases 1 and 2 but with an in-between acceleration rate (0.8 m/s^2) and a top speed of 60 km/h. The difference between these case studies is the track slope, which is completely flat for case study 3, constantly uphill (20 mm/m) for case 4 and constantly downhill (-20 mm/m) for case 5. The purpose of cases 1 and 2 is to assess whether the network correctly models the traction power required to achieve different top speeds at different acceleration rates. The purpose of cases 3 to 5 is to assess whether it correctly takes into account the influence of the track slope. Figure 1 shows the speed profile of each case study.

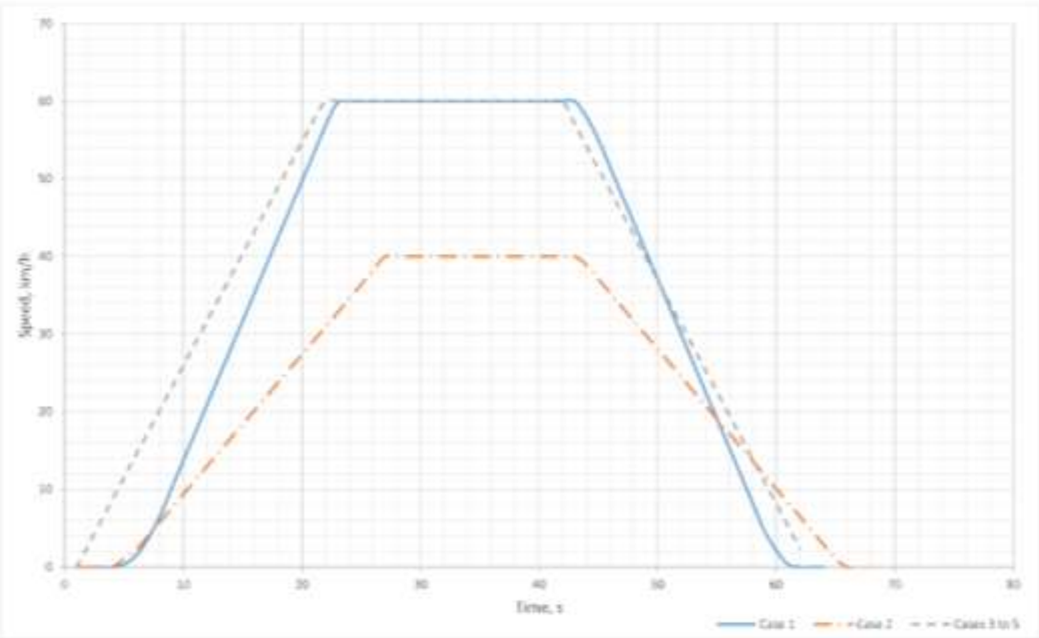


Figure 1. Speed profile for each case study.

3. Results and discussion

3.1. Data pre-processing

As explained before, a three-layer feed-forward NN was created and trained to model the energy consumption of metro trains. The target variable was traction power (kW), which was obtained from the data available by taking all non-traction consumption (i.e. auxiliary systems and energy dissipated in the rheostatic brake) from the overall input power measured in the pantograph. The dataset chosen for training combined six journeys chosen randomly among the 229 measured services with the only condition of covering the whole metro network. This yields a dataset of up to 14701 elements, of which 10291 were used for the training itself (70%), 2205 for validation (15%) and 2205 for test (15%). The secondary test dataset combined three additional journeys with up to 7573 elements. Figure 2 shows an excerpt of the training dataset.

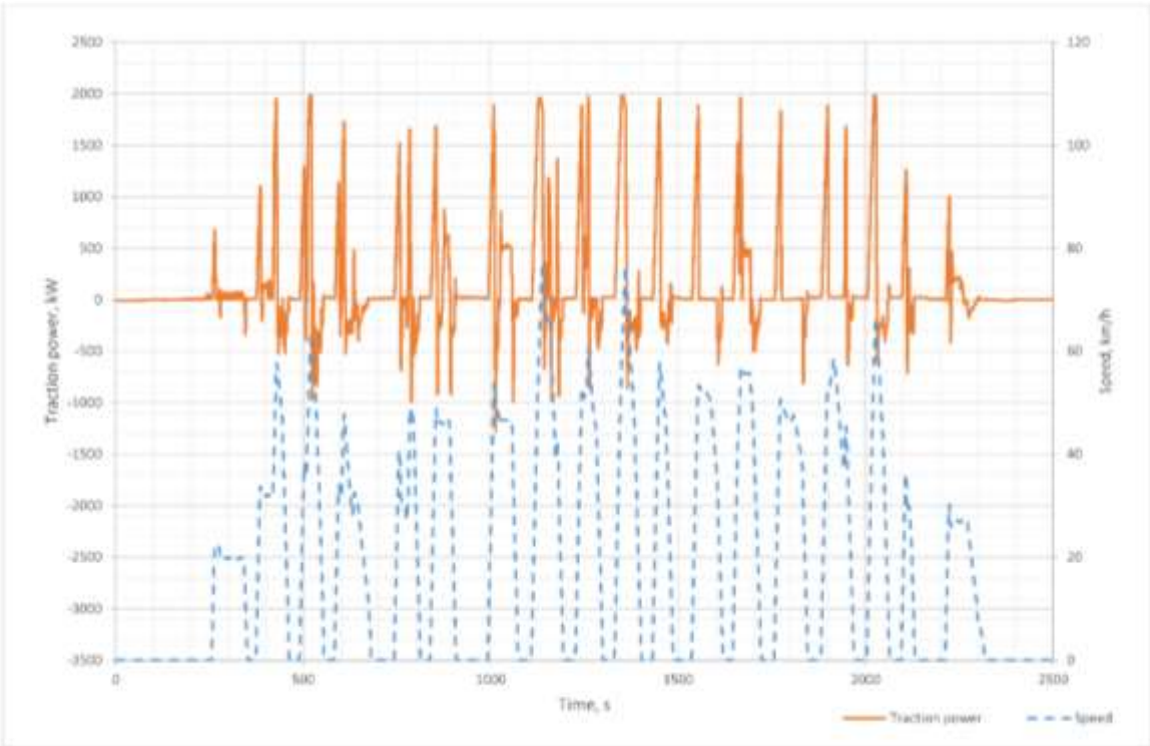
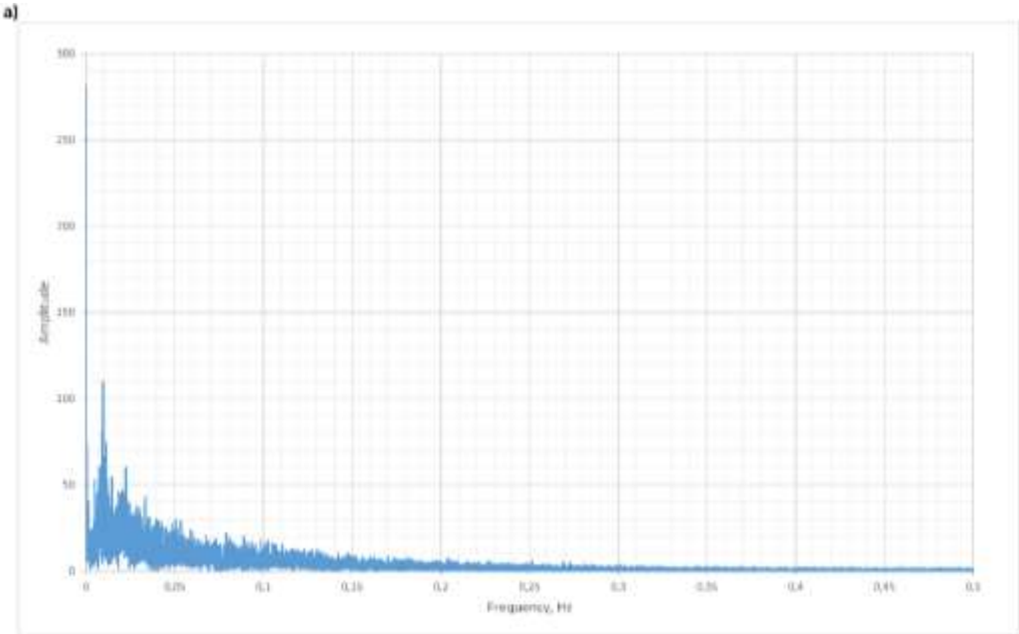


Figure 2. Detail (only one journey) of the training dataset (speed and traction power).

The traction power signal shows some level of noise, particularly during braking events when power is generated by the train engine, in contrast to acceleration events where the signal is much clearer. This may be due to driving style, as drivers sometimes tend to brake intermittently, applying short, gentle bursts to adjust their speed instead of applying a continuous effort as they do when accelerating, thus causing an irregular energy regeneration. Another reason, compatible with the previous one, is that the train’s braking system includes not only the electromechanical device (which regenerates energy) but also a pneumatic device (which does not), and both operate together to provide the full braking effort required at any given time. Therefore, only a fraction of the total kinetic energy is converted into regenerated electric energy, and this fraction may be quite irregular.

In any case, this noise may affect the NN training and thus the signal was filtered to remove it. Figure 3a shows the spectrum of the traction power signal. The core of the signal is within the 0-0.05 Hz range, while there is some noise between 0.05 and 0.2 Hz. Over 2 Hz the spectrum amplitude is negligible. A low-pass Butterworth filter was used, trying different number of poles (1 to 4) and cut-off frequencies ranging between 0.05 and 2 Hz. Finally, a 4-pole filter with a cut-off frequency of 0.15 Hz was used as this combination yielded the best results in terms of removing the noise without altering the peaks of the signal. Other filters were tried (including a three point weighted moving average filter) but gave inferior results compared to the low-pass Butterworth. Figure 3b shows a comparison between the original and the filtered signal for an excerpt of the training dataset.

a)



b)

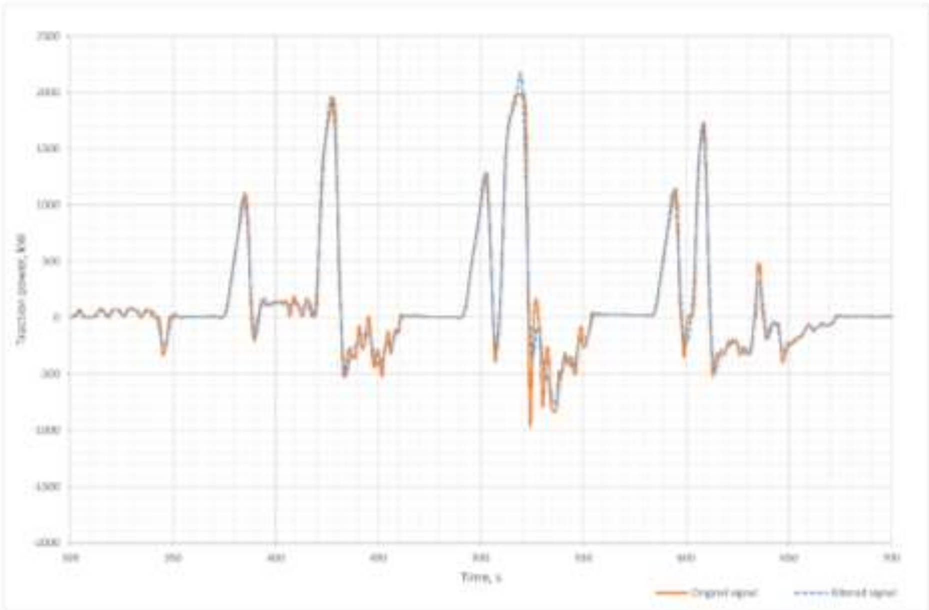


Figure 3. a) Unfiltered traction power spectrum (training dataset). **b)** Original vs filtered traction power signal (excerpt from training dataset).

3.2. Network training and validation

As explained before, four input variables were considered (train speed, train acceleration, track slope and track curvature). Table 1 shows the results obtained after each training round for each variable (were each value is the average of 100 training runs), including the secondary test with the independent dataset.

From Table 1 it is clear that train acceleration is by far the most influential variable in traction power because the obtained rMSE is clearly smaller than the rest, and thus was chosen as the first input variable to be included in the final NN. Acceleration was then combined with the remaining variables, and it was found that the best results were obtained when paired with train speed (second training round). Neither slope nor curvature added any significant improvement when combined with speed and acceleration, but they were both finally included as they provided a slight improvement during the secondary tests. The results for all these training rounds are also shown in Table 1.

Variable	Training		Validation		Test		Test 2	
	R	rMSE	R	rMSE	R	rMSE	R	rMSE
First training round								
Train speed	0.31	0.900	0.31	0.907	0.30	0.913	0.26	0.937
Train acceleration	0.73	0.462	0.73	0.466	0.73	0.465	0.74	0.762
Track slope	0.12	0.983	0.12	0.990	0.11	0.994	0.20	0.966
Track curvature	0,06	0.994	0.06	1.001	0,05	1.003	0.03	1.000
Second training round								
Acceleration + Speed	0.87	0.236	0.87	0.236	0.87	0.235	0.92	0.163
Acceleration + Slope	0.74	0.458	0.73	0.462	0.73	0.458	0.76	0.424
Acceleration + Curvature	0.73	0.462	0.73	0.464	0.73	0.461	0.75	0.447
Third training round								
Accel. + Speed + Slope	0.88	0.232	0.87	0.236	0.87	0.235	0.93	0.147
Accel. + Speed + Curv.	0.88	0.234	0.87	0.238	0.87	0.236	0.92	0.158
Last training round								
All four variables	0.88	0.230	0.88	0.230	0.88	0.232	0.93	0.147

Table 1. Mean training results for each combination of variables after 100 training runs.

Therefore, the NN was finally trained with four input variables (train speed, train acceleration, track slope and track curvature) as this was considered enough to reach the minimum threshold defined for the rMSE.

3.3. Network size

In order to identify the optimum number of neurons in the hidden layer (and once the number and type of input variables had been determined), a NN was trained several times with increasing size. Figure 4 shows the average rMSE obtained after 100 training runs for each network size, compared with the rMSE obtained for the second, independent testing dataset.

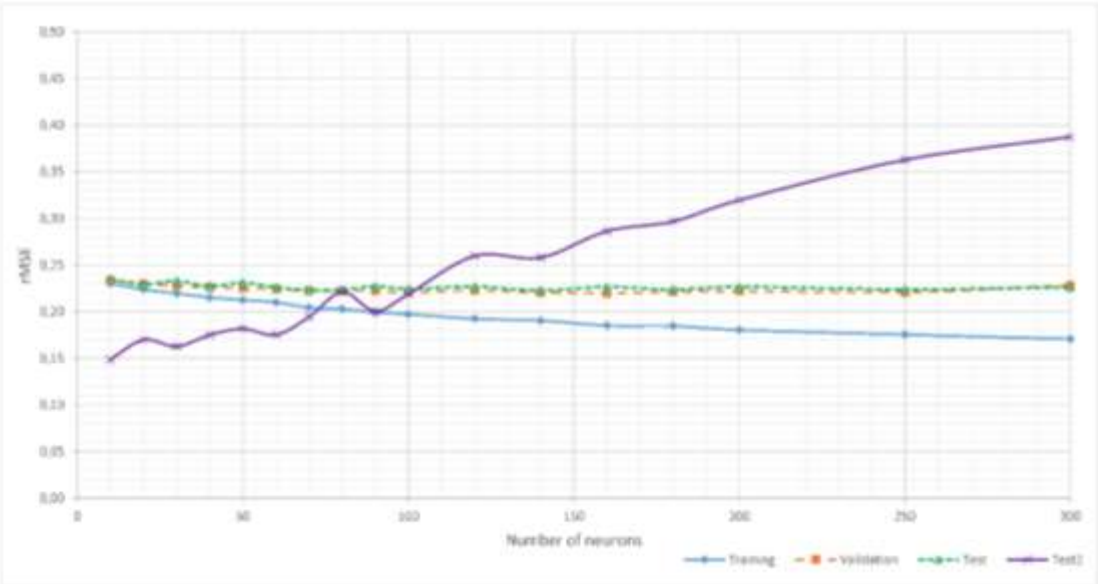


Figure 4. Mean rMSE for different network sizes.

As the figure shows, the training, validation and test rMSE tend to decrease as the number of neurons increase. This is because a more complex NN (i.e. with more neurons) is more capable of fitting the training data. On the other hand, the 2nd test rMSE stays somewhat stable (albeit with some oscillations) between 10 and 60 neurons, then rises steadily until it surpasses the training rMSE and keeps rising as the network size increases. Taking into account these results, and trying to keep the NN as simple as possible, its size was finally set to 60 neurons. This yields both a good training rMSE (21%) and 2nd test rMSE (18%).

3.4. *Definitive training results*

Once the NN size and input variables have been properly determined, the NN is fully trained. Figure 5 shows the comparison between measured and modelled traction power for the complete training dataset (including validation and test subsets).

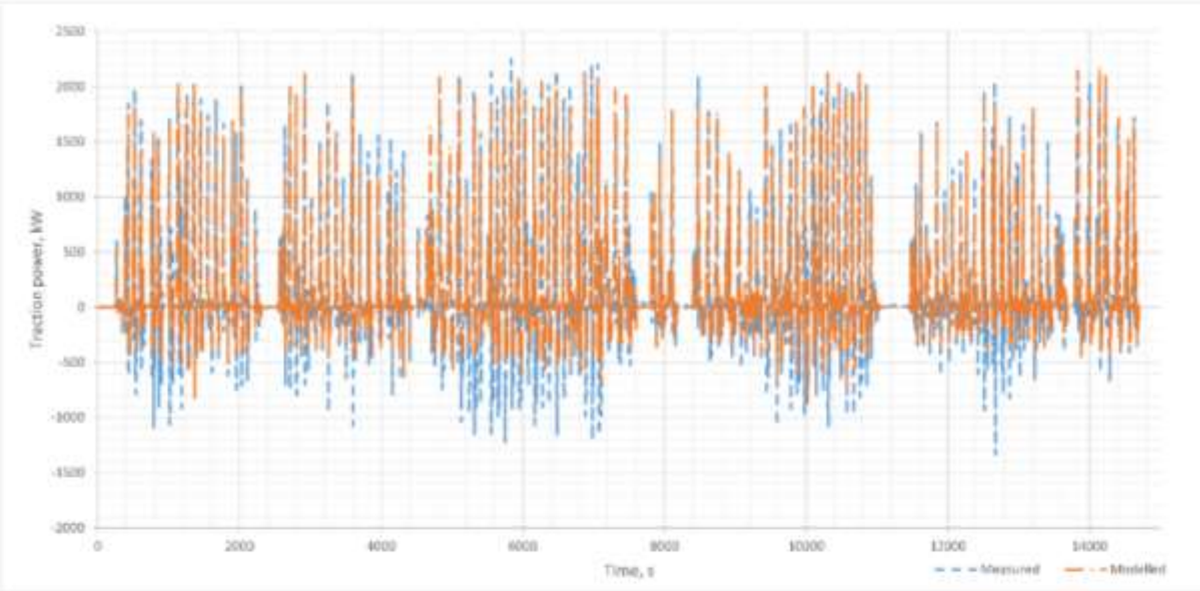


Figure 5. Modelled vs measured traction power. Training dataset.

The total energy consumed by all the journeys included in the dataset was measured as 573.51 kWh, while the NN yielded a value of 562.04 kWh. The difference represents a 2%. With regard to the NN performance, the rMSE obtained was 0.21 for training, 0.2 for validation, 0.21 for the first test and 0.16 for the secondary test. All these values are within the required thresholds.

While the overall result is good enough, it is clear that the NN tends to underestimate the negative peaks, which correspond to regenerated energy during braking events. This may be due to the facts explained in section 3.1 regarding the signal noise, which was only partially removed by the applied filter. Nevertheless, the overall result is rather good as shown by the aforementioned rMSE values.

Figure 6 shows the comparison between the NN output and the second, independent testing dataset. In this case, the total energy measured was 267.40 kWh while the NN yielded a value of 291.72 kWh (a 9.1% difference). The same trend of good agreement during traction and slightly worse during braking can be seen in this case.

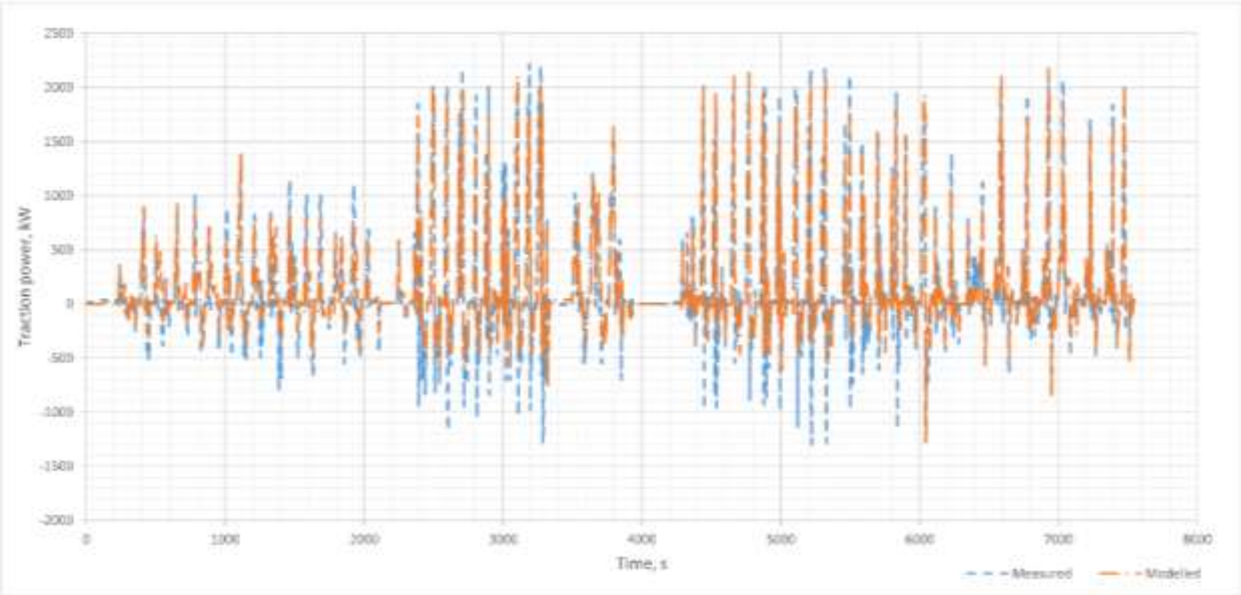


Figure 6. Modelled vs measured traction power. Second test dataset.

In any case, the results obtained show that the NN has been fully trained according to the pre-established criteria and yields a good estimation of the traction power.

3.5. Application to case studies

The fully trained NN was then applied to the predefined five case studies, whose purpose is to serve as an additional test of the NN performance as well as to make sure that it has properly learned logical energy consumption trends. Figure 7 shows the comparison between modelled and measured traction power for case studies 1 and 2.

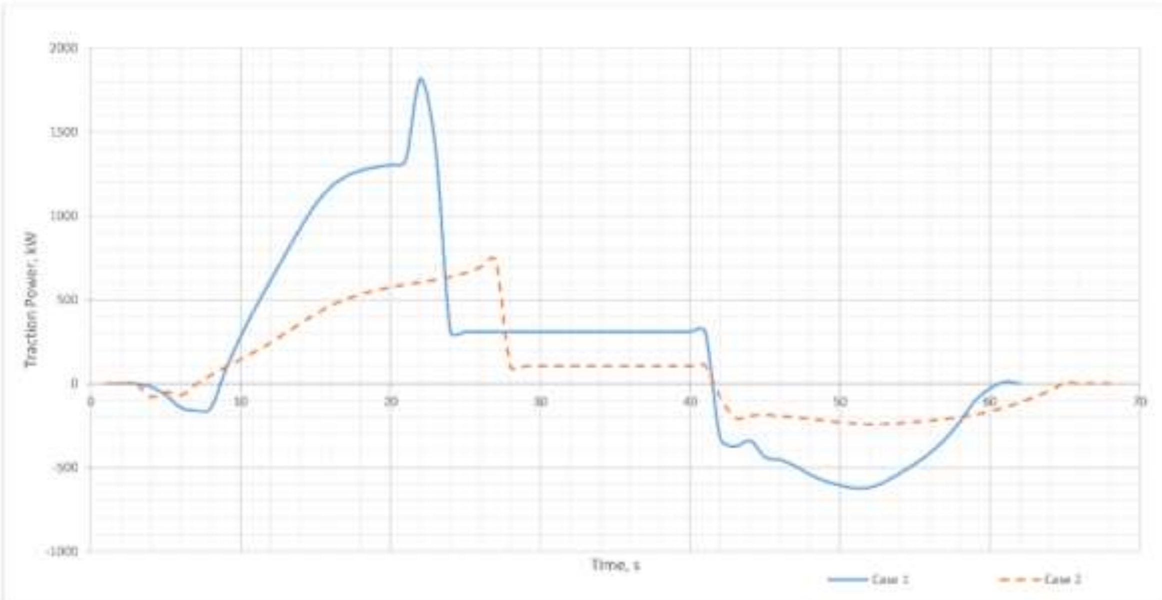


Figure 7. Traction power modelled by the trained network for tests 1 and 2.

The results are consistent with the expected behaviour of a train. In case 1 the train accelerates faster and reaches a higher top speed, hence the higher power consumed for traction during the acceleration stage with regard to case 2. The power required to keep the speed constant is also higher in case 1. Finally, during the braking stage, in both cases the NN yields a negative traction power (i.e. regenerated power) which is higher in case 1 than in case 2 as the deceleration rate is bigger. Overall, the NN provides a result that is in agreement with the logical, expected outcome. Table 2 shows the total energy consumed at each of the three stages (acceleration, constant speed, deceleration) in both cases, further pointing out that the NN delivers a sound estimation.

Case study	**Acceleration**	**Constant speed**	**Braking**	**Global**
Case 1	4.03	1.55	-2.25	3.32
Case 2	2.43	0.41	-1.18	1.66
Case 3	4.68	1.59	-2.26	4.01
Case 4	4.29	5.13	-1.87	7.56
Case 5	4.63	0.52	-1.75	3.40

Table 2. Energy consumption (in kWh) at each stage for case 1 to 5.

Figure 8 shows the modelled traction power given by the NN for case studies 3 to 5. The NN correctly models the first traction peak in the three cases, which corresponds to the acceleration stage until the train reaches a speed of 60 km/h. There is no clear difference between the three traction peaks, perhaps because the difference in slope is not big enough to affect the traction power required to reach 60 km/h, given the relatively small acceleration rate.

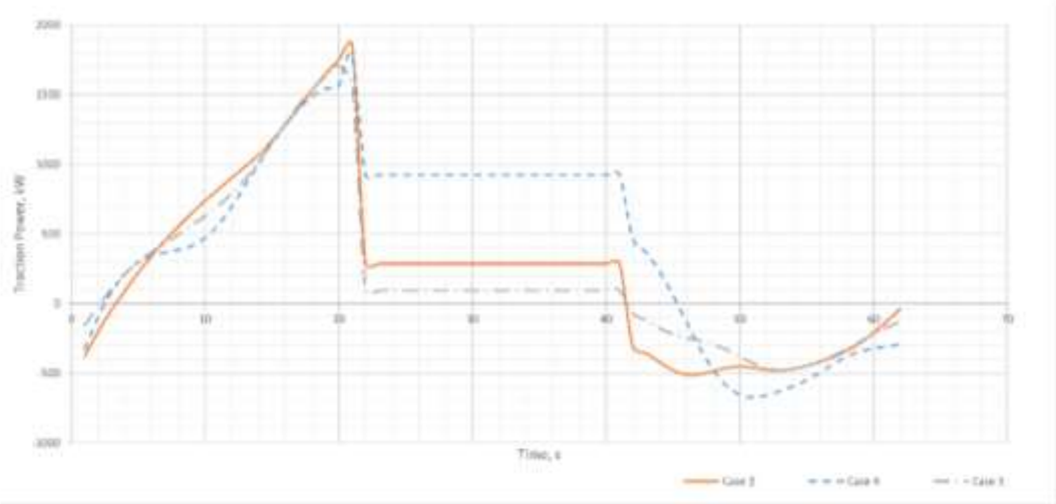


Figure 8. Traction power modelled by the trained network for tests 3 to 5.

The second stage, which corresponds to the train running at constant speed, yields a constant traction power which is clearly higher when running uphill (case 4) than downhill (case 5). The traction power required to maintain speed on a flat track (case 3) is in between the other two, as expected. Finally, some energy is regenerated during braking, and the highest peak occurs when running uphill, although the highest amount of energy regenerated occurs in case 3 (flat track). This result does not correspond to the expected outcome (although the differences are minimal, as shown in Table 2), and again points out that the NN performance during braking events is not as good as during traction. Nevertheless, the global energy consumption for each case study is reasonable, with case 4 (uphill track) having the higher value, followed by case 3 (flat track) and case 5 (downhill track).

Taking into account the results obtained for the five case studies, the NN has apparently learned certain consumption trends such as the influence of the slope and correctly models accelerating and braking stages, particularly the former.

3.6. Limitations and future work

According to the results obtained, the trained NN provides a reliable estimation of the energy consumed by a metro train when traveling along the Valencia Metro Network. There are, however, a couple of limitations that should be taken into account.

The first one is inherent to any function-fitting NN and the theory they are based on: They provide good results when interpolating within the conditions used for their training, but they are unreliable when extrapolating beyond those limits. Therefore, the trained NN should only be applied to settings where each of the variables considered (speed, acceleration, slope, curvature and traction power) are within the ranges used for training. This puts a limit on the scope of scenarios that may be modelled by the NN without further training. However, as a metro network is a rather closed environment where changes in layout, rolling stock or operation conditions are relatively constrained, the obtained NN will be still useful to assess rather diverse scenarios.

The second limitation is particular to this case, and is the already discussed underperformance with regard to braking and regeneration. This may be due to the signal noise aforementioned (noise that has been only partially filtered), which may in turn be caused by certain aspects (such as the actual, detailed composition of the train's braking system) that have not been taken into account. In any case, despite barely affecting the overall NN performance, this drawback may hamper its capability to accurately model the energy consumption under certain circumstances. This issue may be addressed by expanding the training dataset, by more thorough data filtering or by using a combination of NN instead of a single one (e.g. one for traction and one for braking). Combining NN with other methods such as fuzzy logic may also contribute to a more accurate estimation of the energy consumed and regenerated.

In any case, the trained NN may be now used as a tool for further research on the optimisation of the energy consumption in the Valencia Metro Network. For instance, the NN may be used to compare the energy consumed by different driving styles in order to choose the most energy efficient (eco-driving), or to analyse the energy savings obtained by modifying the track layout (efficient track profile, design of new lines). Furthermore, as the Valencia Metro Network does not have, at present, any equipment available to make the most of the regenerated energy, the NN could be used to accurately quantify said energy and to assess whether an investment on reversible substations or on-board storage systems is feasible.

4. Conclusions

The main aim of this study is to develop and train a neural network (NN) capable of modelling the energy consumption of electric metro trains. The development of this tool represents the first stage of a research project whose purpose is to model, analyse and optimise the energy consumption of the Metro Network of Valencia (Spain). The NN has been trained using a comprehensive experimental dataset gathered by means of an instrumented metro train. The developed NN has four input variables (train speed, train acceleration, track slope and track curvature), one output variable (traction power) and 60 neurons in the hidden layer. After extensive, systematic training, the NN provides a good agreement with the target data, (rMSE ≈ 21%) as well as with an independent dataset used as a secondary performance test (rMSE ≈ 16%). The trained NN has been applied to five simple case studies, and has proven to correctly model the traction power during acceleration stages and to include the influence of the track slope. The NN is also capable of modelling the regenerated power during braking events, although it tends to underestimate regenerative energy peaks. Overall the NN provides a reliable estimation of the traction power and the global energy consumption of metro trains, and thus may be used as a modelling tool during further stages of research. Nevertheless, certain improvements may be carried out to enhance the NN performance, particularly with regard to braking and regeneration. Developing and training two different NN (one for traction and one for braking), a more thorough data filtering and the inclusion of fuzzy logics or stochastic methods are a few possible options to increase the reliability of the simulation.

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Declaration of Conflicting Interests

The Authors declare that there is no conflict of interest.

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