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Comparing energy consumption for rail transit routes through Symmetric Vertical Sinusoid Alignments (SVSA), and applying artificial neural networks. A case study of Metro Valencia (Spain)

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Abstract
This paper presents the training of an artificial neural network using consumption data measured in the metropolitan network of Valencia, Spain, to estimate the energy consumption of a metro system. After calibration and validation of the neural network, the results obtained show that it can be used to predict energy consumption with high accuracy. Once fully trained, the neural network is used for testing hypothetical operational scenarios aimed to reduce the energy consumption of a metro system. These operational scenarios include different vertical alignments that prove that Symmetric Vertical Sinusoid Alignments (SVSA) can reduce energy consumption by 18.41% in contrast to a flat (0% gradient) alignment.

Keywords: Symmetric Vertical Sinusoid Alignments (SVSA); gradient; energy consumption; artificial neural networks; metro system.

Comparando el consumo energético para rutas de tránsito ferroviario mediante Alineamientos Verticales Sinusoidales Simétricos (SVSA), y aplicando redes neuronales artificiales. Un estudio de caso de MetroValencia (España)

Resumen
Este artículo presenta el entrenamiento de una red neuronal artificial usando el consumo energético medido en la red metropolitana de Valencia, España, para estimar el consumo energético de un sistema metro. Después de la calibración y validación de la red neuronal, los resultados obtenidos muestran que esta puede ser utilizada para predecir el consumo energético con una gran precisión. Una vez entrenada, la red neuronal es utilizada para probar diferentes escenarios de operación hipotéticos con el objetivo de reducir el consumo energético de un sistema metro. Estos escenarios de operación incluyen diferentes trazados verticales que prueban que los Alineamientos Verticales Sinusoidales Simétricos (SVSA, por sus siglas en inglés) pueden reducir el consumo energético en un 18.41 % en contraste con un alineamiento plano (pendiente del 0%).

Palabras clave: Alineamientos Verticales Sinusoidales Simétricos (SVSA, por sus siglas en inglés); pendiente; consumo energético; redes neuronales artificiales; sistema metro.

1. Introduction

There is no doubt that the transport sector contributes so vastly to total energy consumption that according to the International Energy Agency [1], the world's overall energy consumption in 2013 was a whopping 2.56 Billion Tonnes of Oil Equivalent (Mtoe) - and 27.6% of it is from the transport sector.

Railways are generally much more efficient in terms of energy consumption than road transport systems in transporting both freight and passengers [2-4]. Despite this advantage, it is still necessary to reduce its energy

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consumption to improve competitiveness and contribute to a more sustainable world. For this reason, many strategies are nowadays being implemented to reduce energy consumption in railways and they include strategies that involve line design, rolling stock and operations [5].

To optimize many aspects of this mega transport system, some researchers have modelled electric train energy consumption [6], while other authors have estimated its energy consumption and explored improvements in rail transport through track layout optimisation using Geographic Information Systems (GIS) [6,7]. There are also other authors that have used genetic algorithms to optimise different aspects of the said transport system, such as its track alignments, operators, user costs for rail operation [6-8] and crew scheduling [9,10]. There are also methods created that aim to optimise travel time and coasting points by using models based on artificial neural networks and genetic algorithms [11]. These methods, however, do not include gradient or real time measured energy consumption as data.

Kim and Schonfeld [12] introduced the Dipped Vertical Alignment (DVA) concept for urban rail systems. They considered Symmetric Vertical Sinusoid Alignment (SVSA) profiles (Fig. 1) which is a function of the total curve length *S* and the maximum depth *d* halfway between two stations having the same elevation. There are three sections in the SVSA between two stations:

- Section 1: The train must accelerate upon leaving the station, and in this case, it will find a slope and, using gravity, the train will reach an adequate rate of acceleration easier than that in a flat alignment. Here, acceleration and slope resistances are reduced - which leads to a reduction in the power requirement.
- Section 2: The train reaches its cruising speed (optimum speed between two points).
- Section 3: The train is coasting, and the existence of an uphill section in the part where it must decelerate to stop means requiring less power to brake, which in turn, is equivalent to less energy dissipation. This translates to energy advantage when a station is located at a relatively higher elevation than adjacent sections.

They compared the alignment below to flat alignments and identified its significant potential benefits in energy consumption. Their equations for the DVA are shown in eq. (1) [12].

$$
\begin{aligned}
y_1 &= -\frac{12\delta}{S^2}x^2 && For\ 0 \le x \le \frac{S}{6} \\
y_2 &= \frac{6\delta}{S^2}x^2 - \frac{6\delta}{S}x + \frac{\delta}{2} && For\ \frac{S}{6} \le x \le \frac{5S}{6} \\
y_3 &= -\frac{12\delta}{S^2}x^2 - \frac{24\delta}{S}x - 12\delta && For\ \frac{5S}{6} \le x \le S
\end{aligned}
\qquad (1)
$$

where:

- y_1, y_2, y_3: Difference in elevation relative to the initial station [m].
- x: Horizontal distance from the center of the initial station [m].
- δ: Maximum depth at the intermediate of the two stations [m].
- S: Total length between the two stations [m].

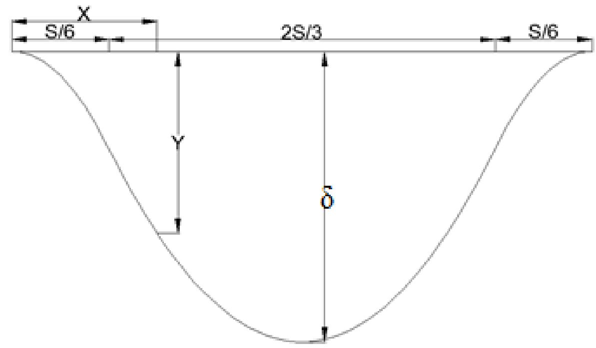

Figure 1. SVSA at the same station elevations
Source: Adapted from [12]

It is important to note that there is no trace of studies of this nature - one with a certain capacity of validation for a model with real data of operation in a metropolitan line, and a posterior application of energy consumption saving methods for railways.

This paper thus aims to develop, train and validate a neural network to simulate the energy consumption of a metropolitan line using measured empirical data, and use the neural network to predict the energy consumption at each instant. Finally, the neural network will be used to compare different vertical alignments to improve or reduce energy consumption between two stations with the same elevation.

2. Methodology

2.1. Data gathering and processing

In order to check the energy consumption of one train, three MSAVDC meter devices, manufactured by Mors-Smitt, were installed in the front car of the train: one in the pantograph (circuit breaker), another in the auxiliary converter input, and the third in the braking resistors. These devices will allow the measurement of not only the overall train energy consumption in real time, but also the energy consumed by each subsystem: traction, auxiliary devices and rheostatic brake.

The train's speed was measured by a Knorr sensor (model BB0457681100), fed by a phonic wheel on one axis of another car of the train.

After verifying the correct functionality of all the devices, measurements were made on August 4th, 2014 with passengers on board. Twelve trips were measured in line 5 of MetroValencia, between Marítim-Serrería and

Alameda stations; six trips towards Alameda and six trips towards Marítim-Serrería.

2.2 Neural networks

The structure chosen to accomplish this objective is a two-layer *feed-forward* neural network because it is a common and a tested scheme, with great ability to adjust functions [14,15]. In addition, these networks are known by its classification in layers and connections between the units strictly forward, and do not form cycles or loops in the network. *Feed-forward* neural networks are the most commonly used in practical applications that use neural networks, obtaining very satisfactory results, fundamentally as pattern classifiers and function estimators.

The first layer, called the *hidden layer*, has a number of neurons that it is necessary to define. The second layer (*the output layer*) has a single neuron with a linear transfer function. Eq. (2) shows the formula of the network:

$$O_k = \tilde{g}(\sum_{j=0}^{M} w2_{kj} \cdot g(\sum_{i=0}^{N} w_{ji} \cdot I_i)) \qquad (2)$$

where O_k is the network output, M is the number of output elements, I_i is the input data, N is the number of input variables, w_{ji} is the synaptic weight of the first layer and $w2_{kj}$ is the synaptic weight of the second layer. The synaptic weight w_{ji}, for example, defines the strength of a synaptic connection between two neurons, the presynaptic neuron j and the postsynaptic neuron i. This structure can identify non-linear relations between *input* and *output* data [14] using the Log-Sigmoid function as a transfer function between the hidden layer and the output layer.

The training method used is called the *Back-Propagation*, where the network is evaluated, the results are checked based on certain criteria, and the synaptic weights are changed in an iterative loop [14]. The chosen calibration criterion is the minimization of the Mean Square Error (MSE) between the network *output* and the *target* data, which is verified by deriving the MSE with respect to the network synaptic weights. The specific training algorithm used is called the *Levenberg-Marquardt* algorithm, which is very efficient and widely checked [14].

The neural network presented in this paper uses speed, acceleration, gradient and traction effort as *input* data and measured empirical energy consumption as *target* data. These input data provide good accuracy, thus making it unnecessary to consider another input data to calibrate on energy consumption. Once trained, the neural network may predict the train's energy consumption (*output*) data with high accuracy, as proven when compared to the measured empirical data (*target data*).

2.3. Simulation model development

After training the neural network, hypothetical vertical alignments are specified with their respective speed profile, considering the optimal indications for efficient driving between two stations [14-16]:

- To accelerate to maximum acceleration, to maintain maximum speed, and to reduce speed in coasting before each of the points in which it is necessary to reduce speed.
- The same strategy as above, but with the difference of the coasting not occurring until minimum speed (or until a stop), but until a greater speed to this one below which the service brake is applied to reduce speed.
- Accelerating to the maximum acceleration to recover the maximum speed and so on.

Once the hypothetical vertical alignments have been determined, the trained neural network is applied to achieve the energy consumption (*output*) verifying them in each alignment, comparing them and obtaining the vertical alignment with the lowest energy consumption. It is necessary to clarify that speed optimization was not considered in this paper, but for each alignment, it was verified that the travel time between both stations were the same.

The following assumptions used by Yeh [17] are considered in this simulation:

- The vertical track profile is symmetrical regarding to a central axis.
- Parabolic curvatures are applied to the vertical curves while the gradient cannot exceed the maximum climbing ability of the train.
- Horizontal curvatures are negligible for this analysis.
- A concentrated mass is used to represent trains in motion.
- A train accelerates to its full power unless it exceeds the comfort-limited acceleration.
- The braking system can provide the maximum allowable comfort-limited deceleration rate.

3. Case study

3.1. Introduction

MetroValencia has six subway lines and three tram lines. It also has 132 stations with a total length of 146.8 km and has 121 trains [18]. Trips along line 5 were analysed, between Marítim-Serrería and Alameda stations. As for the traction and power systems of the network, there is only a single input voltage to the substations with a magnitude of 20 kV AC. There are, however, two different output voltages: 1,500 V DC, (used in all six subway lines) and 750 V DC (used in all three tram lines), with an annual energy consumption of around 64.4 GWh and 18.1 GWh, respectively. This energy is consumed by all elements and systems of MetroValencia. Considering the energy consumption of each network component, 70% of the overall energy goes to traction (53 GWh) while 24% goes to stations. Other power consumptions from the remaining elements are negligible [19].

3.2. Input data

Four variables were chosen as *input* data (gradient, speed, traction effort and acceleration). During the neural network training, all *input* variables and their combinations were tested until the one that provided the best fit with the *target* data was chosen.

Focusing on Line 5 of MetroValencia, particularly between the chosen stations, it is important to consider that there are three stations in between them, namely: Ayora, Amistat and Aragón. They have a total length of 2,720 m and the chosen route has four stops. There is a maximum gradient of 2% in this route. Fig. 2 shows a diagram of the vertical track layout of the studied route, indicating the gradient profile along the five stations of Metro Valencia's line 5.

Speed was measured using an odometer placed in one of the wheels of the monitored train. Acceleration is directly derived from the speed. Fig. 3 shows these two variables of the first trip.

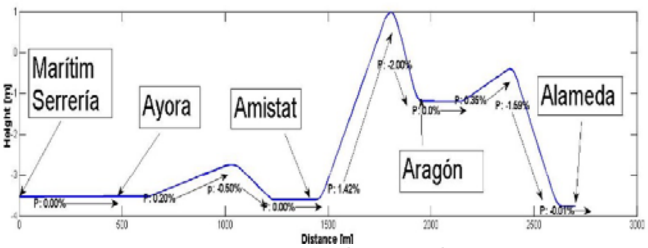

Figure 2. Vertical layout between Marítim Serrería and Alameda and the stations (stops) in between them.
Source: The authors

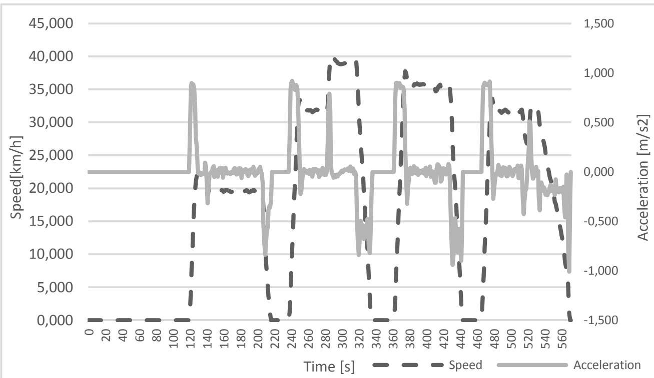

Figure 3. Speed (blue) and acceleration (orange) of the first trip between Marítim-Serrería and Alameda
Source: The authors

3.3. *Target data*

The monitored train was a Metro Series 4300 (Vossloh) with 4 cars, a maximum speed of 80 km/h, a nominal tension of 1,500 V DC and a power of 1,480 kW.

The energy consumption in the pantograph (measured in the circuit breaker) was monitored real time while the train performed conventional services with passengers on board. The measured energy consumption was used as *target* data.

The measuring devices provide the energy consumption measured in the circuit breaker of the train every second, as shown in Fig. 4. The Fig. 4 represents the training *target* of the neural network on the first trip.

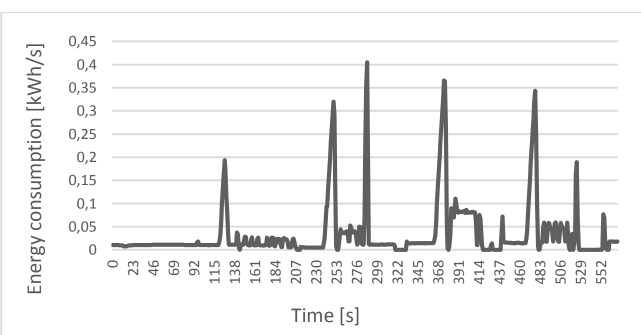

Figure 4. Example of the energy consumption measured in the circuit breaker on the first trip between Marítim-Serrería – Alameda stations
Source: The authors

4. Results and discussion

4.1. *Training of the Artificial Neural Network*

Two different criteria were used to assess the performance of the network and to decide whether its training was successful. The first of which was the Pearson correlation coefficient (R) between the neural network *output* (modelled energy consumption) and the *target* data (measured energy consumption), which needs to be equal or greater than 90% for all the three subsets (training, validation and testing).

The second criterion was the relative Mean Square Error (rMSE), which is defined as follows in eq. (3):

$$rMSE = \frac{MSE}{Var(Q)} \leq 0.2 \qquad (3)$$

where MSE is the Mean Square Error, and Var(Q) is the variance of the measured consumption data (*target*). The rMSE needs to be lower than 20% of the variance of the data for all three subsets (training, validation and testing) [20], in order to control the dependence of the neural network to the specific data used for training. The process of the creation, training, and validation of the neural network was performed using the Neural Fitting Tool, from MATLAB R2014a (The MathWorks, Inc.)

Different tests were performed by combining the four input variables previously defined so as to identify which fits the energy consumption data better. If the input variables are speed, acceleration, gradient and traction effort, the neural network satisfies all the criteria; with the rMSE being lower than 20% and the R coefficient being greater than 90% [21]. Those input variables were, therefore, chosen for the analysis due its significant impact on energy consumption.

The results (Fig. 5) show an average measured energy consumption of 7.29 kWh per km, while the network estimated an energy consumption of 7.11 kWh per km, which has a small deviation of 0.176 kWh per km (2.42%). Every trip was the same: each with four stops between the first station and the last, and in terms of train load.

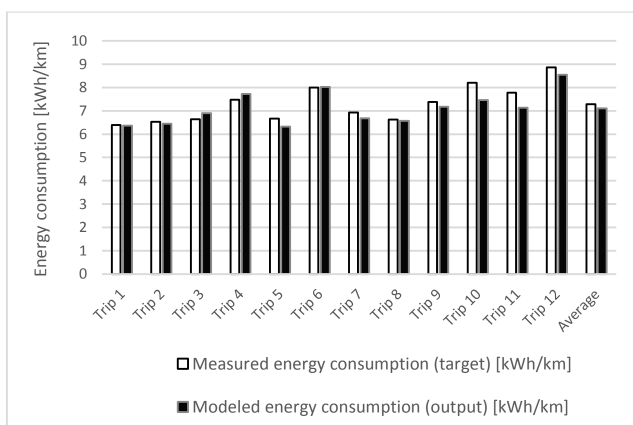

Figure 5. Energy consumption by trip
Source: The authors

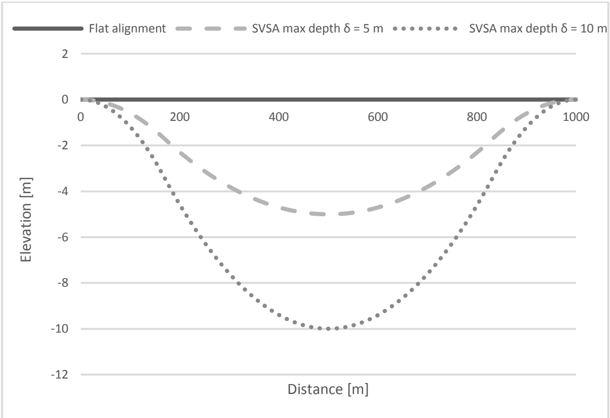

Figure 6. Hypothetical scenarios of vertical alignments between two stations oft the same elevation
Source: The authors

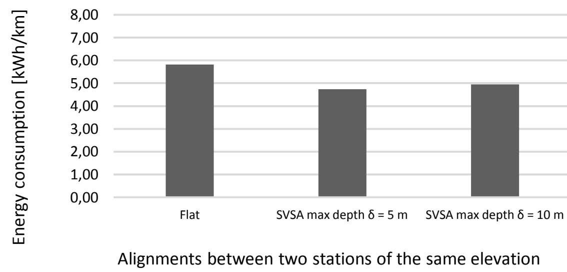

Figure 7. Total energy consumption in the hypothetical vertical alignments
Source: The authors

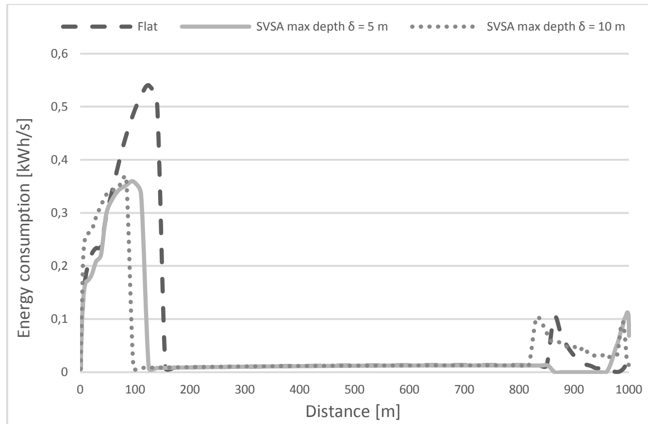

Figure 8. Energy consumption in the hypothetical alignments in every step
Source: The authors

4.2. Application of artificial neural networks on hypothetical vertical alignments

For applying the trained artificial neural network on alignments, three hypothetical vertical alignments scenarios between two stations with a length of 1,000 m were considered: the first scenario is a flat alignment; the second is the SVSA profile with a maximum depth *d* halfway between two stations of δ = 5 m (0.5% of total length) having the same elevation. The last is the SVSA profile with a maximum depth *d* halfway between two stations of δ = 10 m (1.0% of total length) having the same elevation. Fig. 6 shows the three hypothetical scenarios.

After which, the trained neural network was implemented to estimate the energy consumption for every case using the *input* variables for each hypothetical scenario.

The results show a total energy consumption of 5.81 kWh per km for the flat alignment between two stations, 4.74 kWh per km for the SVSA with a maximum depth of δ = 5 m between two stations, and 4.94 kWh per km for the SVSA with a maximum depth of δ = 10 m between two stations. It was observed that the SVSA with a maximum depth of δ = 5 m between two stations recorded the lowest energy consumption, reducing it by 18.41% in comparison to the flat alignment (Fig. 7). Each trip had a duration of 86 seconds, which did not affect the travel time element of one trip from the other.

Fig. 8 shows the energy consumption estimated by the neural network for the three cases in every location in the alignment.

4.3. Discussion

Fig.5 shows that the network adjusts the energy consumption, measured in the circuit breaker, reasonably well, reproducing the peaks from traction and valleys, where the train is coasting. However, the network omitted small oscillations in consumption, and indeed shows small oscillations and negative peaks that do not correspond to the registration. This shows that there is still room to further refine the training of the network, possibly with a post-processing of the output.

In any case, the trained network as shown above, with four input variables, provides a good estimation of the energy consumption of the train, and since it is always within the range considered for every variable, the network could be used to test other alternatives like other hypothetical vertical alignments so as to reduce energy consumption and improve efficiency.

The results of applying the neural network on the hypothetical vertical alignments scenarios between two stations oft the same elevation, with a length of 1,000 m, show that the SVSA with a maximum depth of δ = 5 m between two stations yields the lowest energy consumption, reducing it by 18.41% as compared to a flat alignment. This technical advantage is facilitated by gravity, both as the train accelerates at the first station and as it decelerates at the steep final station.

As for the flat alignment, Fig. 8 shows a peak of energy consumption at the beginning of the route when the train accelerates to reach cruising speed. Then, when the train coasts, energy consumption is reduced. Finally, when service brake is applied, a traction energy consumption of almost zero results.

As for both SVSA alignments, Fig. 8 shows a peak of energy consumption at the beginning of the route when the train accelerates to reach cruising speed. Then, when the train coasts, energy consumption is reduced. Later, while the train is coasting, it arrives to a slope which gradually increases energy consumption. Finally, there is a point where energy consumption presents another peak just before service brake is applied to stop at the next station.

5. Conclusions

This paper describes the training and validation of a neural network to model the energy consumption of a metro line in Valencia's metro network operated by Metro Valencia. Actual energy consumption was measured using a monitored train operating normally along line 5 of the metro network. This data was analysed and used to train and validate the neural network. Four *input* variables were chosen: speed, acceleration, gradient and traction effort. These combined *input* variables predict energy consumption with high accuracy, proving that just one variable cannot explain this phenomenon by itself.

Total energy consumption shows an average measured energy consumption of 7.29 kWh per km, while the trained neural network estimates an energy consumption of 7.11 kWh per km, having a small deviation of 0.176 kWh per km (just 2.42%).

A fully trained neural network is a useful tool in studying the energy consumption of the metro system. The advantages of this method lie in its adjustment of speed and simulation, and, particularly, in the fact that the neural network may function as a virtual laboratory where it is possible to test hypothetical scenarios, modify variables such as track layout and train driving style in order to reduce a train's energy consumption.

Three hypothetical vertical alignments scenarios between two stations were considered for the application of the trained artificial neural network, the first scenario was a flat alignment; the second was the SVSA profile with a maximum depth *d* halfway between two stations of $\delta = 5$ m having the same elevation, the third was the SVSA profile with a maximum depth *d* halfway between two stations of $\delta = 10$ m having the same elevation. After which, the trained neural network was implemented to estimate the energy consumption for every case using the *input* variables for each scenario.

The model results show an energy consumption of 5.81 kWh per km for the flat alignment between two stations, 4.74 kWh per km for the SVSA with a maximum depth of $\delta = 5$ m between two stations, and 4.94 kWh per km for the SVSA with a maximum depth of $\delta = 10$ m between two stations. Results show that the SVSA with a maximum depth of $\delta = 5$ m between two stations yielded the lowest energy consumption, reducing it by 18.41% as compared to the one with flat alignment.

These results highlight the importance of designing energetically efficient geometric alignments. As this strategy already allows obtaining significant energy consumption reduction, it can be accompanied by other strategies such as economic driving to come up with a better and efficient transport system in terms of energy consumption.

The next step of research will involve an analysis on how the model can be improved if energy recuperation is included, so as to use it to test hypothetical operation and construction scenarios, with the aim of minimizing the energy consumption of the system.

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