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Modelling the Torque with Artificial Neural Networks on a Tunnel Boring Machine

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Abstract

The performance of earth pressure balanced tunnel boring machines (EPB-TBM) is dependent of a variety of parameters. Moreover, these parameters interact in a rather challenging way, making it difficult to adequately model their behaviour. Artificial neural networks have the aptitude to model complex problems and have been used in a variety of construction engineering problems. They can learn from existing data and then be used to predict the results, which makes them adequate for modelling problems where large amount of data is generated. In this work, a multilayer feedforward artificial neural network has been used to predict the torque at the cutter head of an EPB-TBM. A time series neural network has been used, where torque was predicted as a function of the measured torque and the volume of the injected foam on previous time steps. Results indicate that feedforward artificial neural network can be used to predict the torque at the cutter head in a EPB-TBM

Keywords: *artificial neural networks, tunnelling, TBM, EPB, foam*

1. Introduction

In earth pressure balanced (EPB) tunnelling, the excavated soil is used to support the tunnel front at the same time as it is being mixed with foams or slurry and other additives. Foam is used to improve the soil conditions in the mixing chamber of the TBM, so that it equilibrates the pressure of the surrounding soil. The amount of soil in the mixing chamber is controlled with the aid a screw conveyor that extracts the soil. Foam improves the soil conditions through three different mechanisms: 1) it increases the porosity between the soil grains, leading to negligible effective stresses between the grains, thus reducing the torque in the cutter head; 2) it reduces the permeability and 3) it increases the compressibility, allowing that the pressure in the mixing chamber could be kept approximately constant while the screw conveyor controls the soil extraction in the EPB shield (Bezuijen, 2006).

The performance of a TBM can be measured by the advance rate, which can be controlled by the TBM operator, considering some limiting variables such as the torque on the cutter head, the capacity of the screw conveyor and the thrust force on the jacks. The torque in the cutter head is, fundamentally, a function of the shear strength of the soil in front of the cutter head, the friction between the muck and the cutter head in the mixing chamber, which are both to some extend influenced by the pressure in the excavation chamber and of the thrust applied (Mori, 2016). The injection of foam, acting on the soil as described, can reduce the required torque and consequently improve the TBM performance. However, there is no simple relation between the injected foam and the torque at the cutter head because there is a variety of factors that affect this relation. The most important being the shear strength of in-situ and conditioned soil, the friction between the moving TBM parts and the soil, the pressure in the chamber, and the thrust applied to the face. Some physical and empirical models have been proposed and are commonly used to estimate the required torque (Godinez *et al*., 2015; Reilly, 1999; Shi *et al.*, 2011; Wang *et al.*, 2012). The most important soil parameters considered are shear strength and friction, where the foam addition is indirectly taken into account by considering the modified soil parameters. These models, although very useful and capturing the main influences in the torque, do not give accurate estimations of the torque when the TBM is working.

Artificial neural networks (ANN) are computational models where the main feature is their ability be trained from examples, rather than explicitly programmed, and they have, consequently, the capacity of approximation of any arbitrary function. As with any approximation method, the extrapolation ability can be limited but, because ANN can learn from data, new results can be added to the dataset so that the network can continuously evolve and adjust to new results. In geotechnical engineering,

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ANN have been used to model a variety of problems, such as, soil properties and behaviour, tunnelling, pile capacity, foundation settlement, liquefaction or slope stability (Goh, 2001; Shahin *et al*., 2008, 2001; Sulewska, 2011; Xiangjun and Zhanfeng, 2007). In the specific case of tunnelling, ANN have been used for very different situations, including the prediction of ground surface settlement (Kim *et al*., 2001; Neaupane and Adhikari, 2006; Suwansawat and Einstein, 2006), TBM performance (Alvarez Grima *et al*., 2000; Benardos and Kaliampakos, 2004), inverse back analysis (Gao, 2016) or the prediction of air chamber pressure (Zhou *et al*., 2013).

The aim of this article is to present the possibility of the use of artificial neural networks for the prediction of the torque of an EPB-TBM. The idea is to keep the model as simple as possible, using a minimum set of variables as a base. For this, data collected from the construction of the Botlek Rail Tunnel in The Netherlands was used. Feedforward ANN with resilient propagation were used, and it was observed that ANN provide an efficient tool to model the torque of an EPB-TBM.

2. Artificial Neural Networks

Artificial neural networks (ANN) are a computational model, which operation look like a network of biological neurons. ANN are composed of a system of neurons that are interconnected by weighted links. The outcome of the ANN is changed by modifications of the weights of the links. Data is provided to the input layer and the result of the network is displayed by the output layer. The input neurons represent the base variables that are used for predicting the dependent variables, that is, the output neurons.

In this work, a feedforward artificial neural network (FFANN) is used. In a FFANN, the connections between the neurons do not form a cycle. This type of networks was the first and the simplest type of ANN. Usually, in FFANN, neurons are organized in layers. In each layer, there are no connections between the neurons of the layer. However, each neuron of a layer is connected to all the neurons of the preceding layer (the inputs for the layer) and to all the neurons of the succeeding layer (through the outputs of the layer). A FFANN must have, at least, three different layers: 1) one input layer; 2) one output layer; and 3) one (or more) hidden layer(s). Fig. 1 illustrates a scheme of a FFANN with two hidden layers.

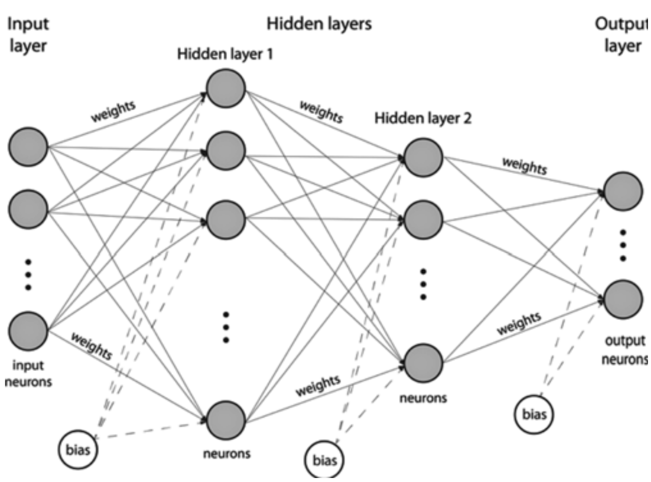

Fig. 1. Scheme of a FFANN

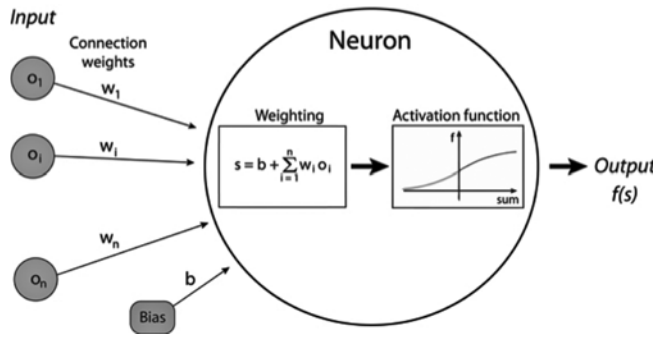

Fig. 2. Calculation Scheme in a Neuron

In a FFANN, each neuron of the input layer gets information from operation, test data or other models. This information is the output of the input layer and the input for the next layer (the first hidden layer). Each neuron of the next layer gets the outputs of the precedent layer. At each layer, starting in the first hidden layer, each neuron receives as input a weighted sum of the neurons of the preceding layer passed through an activation function (see Fig. 2). This procedure runs through all the neurons and all the layers of the network. A bias neuron is often introduced in the calculations as shown in Figs. 1 and 2.

There are different functions commonly used as activation functions. One of the of the most used, is the bipolar sigmoid function:

$$f(s_j) = \frac{2}{1+\exp(-\alpha s_j)} - 1 \tag{1}$$

where the rate of variation of the function is controlled by the parameter α. As α increases, also increases the rate of variation. Commonly used values for α are 1 and 2. When α = 2, this function becomes the hyperbolic tangent function. Another function that can be used as activation function is the logarithmic function. This function can be useful to prevent saturation that is, when the output for a given set of inputs is approximately 1 or -1 in most cases. The logarithmic activation function reads:

$$f(s_j) = \begin{cases} -\log(1-\alpha s_j), s_j < 0 \\ \log(1+\alpha s_j), s_j < 0 \end{cases} \tag{2}$$

Again, the rate of variation of the function is controlled by the parameter α. When α = 1, the two presented functions are relatively similar in the range [-1.5, 1.5].

2.1 Time Series using a FFANN

A neural network can be used to predict future values using its input to accept information about current data and its outputs to predict future data. A predictive neural network uses two time windows, a future time window and a past time window. Both time windows must have a window size that represents the amount of data that is either predicted or that is needed to predict. To illustrate how a FFANN can be used for prediction, consider s_{pw} the size of the past window and s_{fw} the size of future window, and a dataset with n_i input variables and n_o output variables. In a time series FFANN, the output variables can also be input variables. The number of input neurons of the resulting network will be $s_{pw}n_i$, and the number of output neurons will be $s_{fw}n_o$. To create the dataset for the FFANN the first $s_{pw}+ s_{fw}$ points will be the first data points and to obtain additional data, both windows are simply slid forward one point at a time. Both past and future time windows would continue sliding forward through the existing points.

2.2 Definition and Training of the FFANN

There is no reliable method to define the number of hidden layers of a network, neither the number of neurons in each layer, meaning that the definition of the number of hidden layers and of the number of neurons in each hidden layer should be carried out by trial-and-error, searching for a network configuration that provides the best results. Nevertheless, as the number of input and output parameters increases, also the number of hidden layers and neurons increased.

For numerical and practical reasons, input and output variables are normalized before running the network, usually to the ranges [0, 1] or [-1, 1], depending on the activation function. To avoid numerical issues and saturation ranges [0.1, 0.9] or [-0.9, 0.9] are commonly used. With activation functions described by Eqs. (1) and (2) the used range is [-1, 1].

The propagation learning algorithm for the network will adjust the weights of the connections between neurons in different layers. Starting from a random set of weights, the propagation training algorithms used for supervised training, iterate through all points of the training set in a forward and backward pass. In the forward pass, the algorithm calculates the error between the outputs generated by the current network. In the backward pass, starting from the output layer, the error is distributed by the different neurons. Weights are adjusted in each layer by learning strategies that reduce the final error, depending on the algorithm used. Because the algorithms use the derivative of the activation function, propagation learning can only be used with activation functions that actually have a derivative function. Resilient propagation, is a learning, first-order, algorithm, commonly used for training FFANN. Resilient propagation, takes into account only the sign of the partial derivative over all patterns (not the magnitude), and acts independently on each weight. One advantage of this algorithm over other backpropagation algorithms, is that there are no parameters that need to be defined for setting it up.

2.3 Quality of the Results of the ANN

The network error and accuracy can be evaluated by using several strategies. Error measures compare the differences between the predictions of the network with data. Two common error measures, the Root Mean Square Error (RMSE) and the Mean Absolute Error (MAE), are shown in following equations:

$$RMSE = \sqrt{\frac{1}{p}\sum_{i=1}^{p}\left(t_i - o_i\right)^2} \tag{3}$$

$$MAE = \frac{1}{p}\sum_{i=1}^{p}\left|t_i - o_i\right| \tag{4}$$

where t_i is the expected result, o_i is the output, as predicted by the network, and p is the number of points under consideration. The RMSE measures the square root of the average of the squares of the difference between each predicted and expected result. The MAE is simply the average of the absolute difference between each predicted and expected result. Besides those error measures, accuracy of the network can also be assessed by the coefficient R^2, as described by Eq. (5)

$$R^2 = 1 - \frac{\sum_{i=1}^{p}\left(t_i - o_i\right)^2}{\sum_{i=1}^{p}\left(t_i - \bar{t}\right)^2} \tag{5}$$

These error and accuracy measures can be used to assess the network results during the training process or during testing process. Testing of the network should be done on a subset of data not used for the training process.

3. Data from TBM

Data collected by the TBM on the Botlek Rail Tunnel, included some 180 plus variables recorded approximately every 5 seconds. In this work, data from ten rings from two different sets was used (rings R342 to R346 and R618 to R622). These rings were chosen for being the ones with more available data. This huge amount of data for each ring provides information that could be worked so that some relations between variables could be found. As mentioned previously, torque of the cutter head plays an important role on the performance of the TBM and it could be interesting if it could be modelled or predicted based on other measured parameters.

Some reference parameters that characterize the TBM behaviour include the advance rate (AR), the thrust (FT), the torque on the screw conveyor (Tsc), the torque on the cutter head (Tch) and the foam injection ratio (FIR). The evolution of these parameters during the excavation of a ring is complex as can be seen on Figs. 3 to 5, where these variables for ring 342 are plotted.

It is possible to observe in the figures that some degree of correlation exists between some of the observed variables. Preliminary attempts using ANN were made to model these variables in time. These attempts include the use of different variables, but it was concluded that FIR and torque in the cutter head were the more relevant and sufficient and were, subsequently, considered in in this study. These two parameters should have some degree of relation, since the injection of foam, in principle,

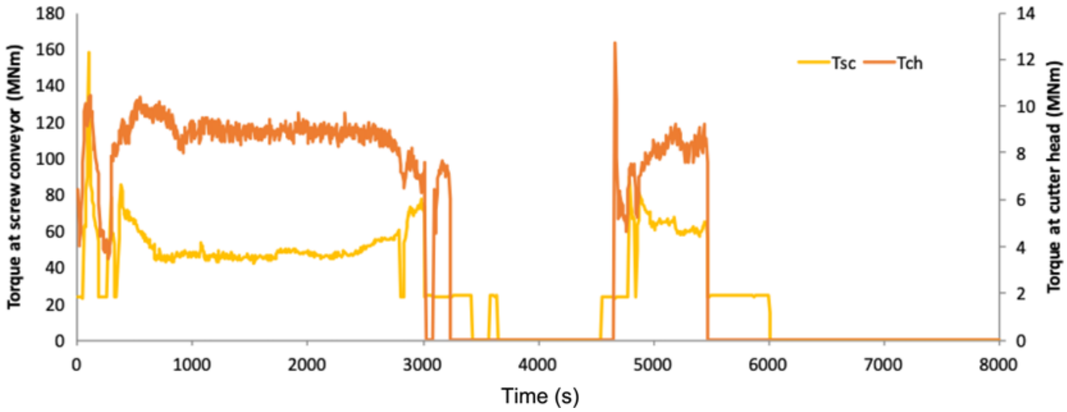

Fig. 3. Example of Tsc and Tch Evolution during One Ring Excavation (R342)

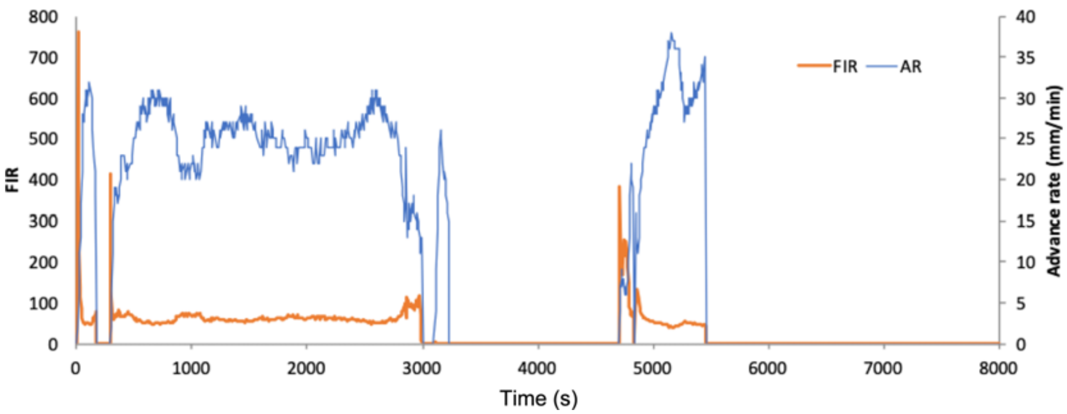

Fig. 4. Example of AR and FIR Evolution during One Ring Excavation (R342)

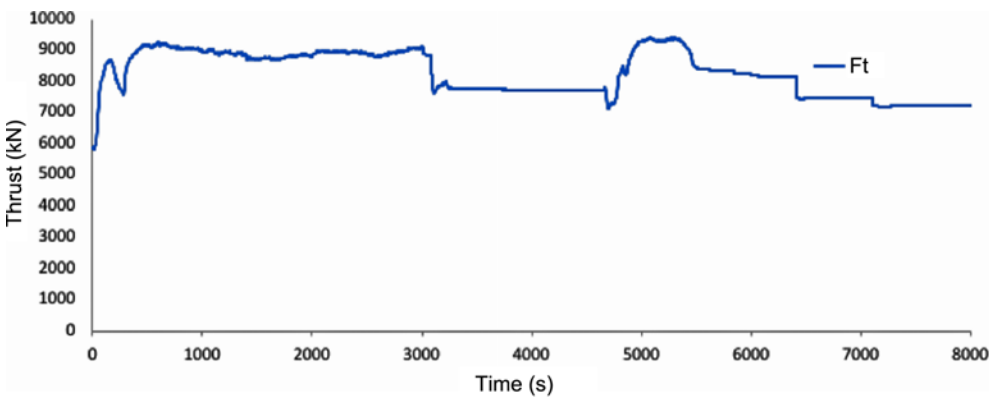

Fig. 5. Example of Force Evolution during One Ring Excavation (R342)

facilitates the advance of the TBM, reducing the torque in the cutter head. However, there is no simple or immediate relation between these two variables, FIR and torque.

4. Modelling Torque on a TBM using a Time Series ANN

As ANN in the current work, Encog machine learning framework (Heaton, 2015) has been used. Encog supports a number of advanced algorithms, as well as support classes to normalize and process data. It is open source and is available in Java and c#. Machine learning algorithms supported in Encog include Support Vector Machines, Artificial Neural Networks, Bayesian Networks, Hidden Markov Models, Genetic Programming and Genetic Algorithms. In this work, the c# version was used, and a user interface was developed to work with Encog.

For training the networks, the resilient propagation algorithm was used since it is one of the most efficient training algorithms for supervised learning in feedforward neural networks. As mentioned before, one actual advantage to this algorithm is that there are no parameters that need to be defined for setting it up.

The possibility of using an ANN for modelling the Tch on a TBM based on FIR and Tch has been investigated using time series ANN. In both cases a time series ANN based on FIR and

Tch to predict the Tch have been used. In the first approach, a significant number of FIR and Tch values of one ring have been used to train the network and then the resulting network has been tested to predict Tch values in other rings. In the second approach a reduced number of FIR and Tch values have been used to train the network, but the network is constantly being trained as new values are being predicted and measured.

4.1 Single Time Series ANN

For the single time series ANN, the variables considered were, as mentioned, the FIR and the Tch. A lag window of five previous observations has been used as input and a lead prevision of one.

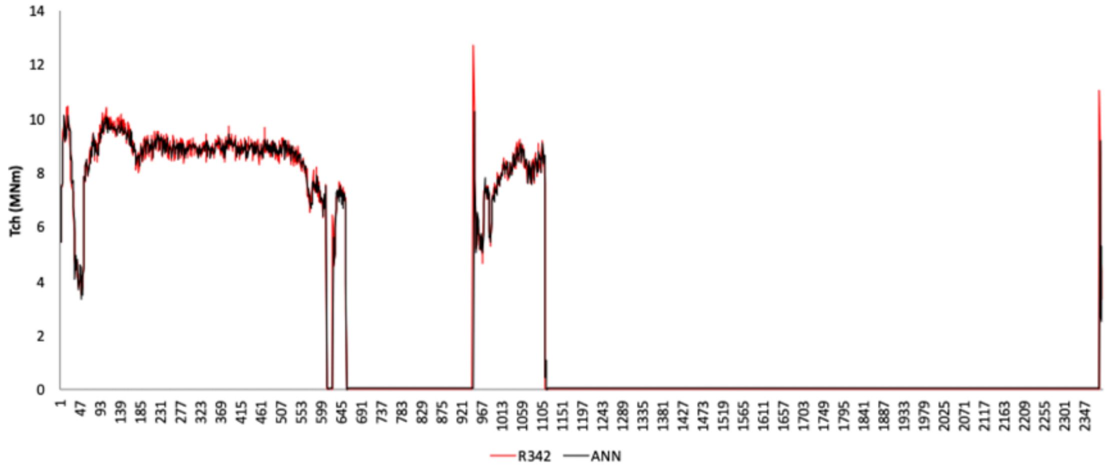

Fig. 6. Comparison of ANN Results with Acquired Data for Ring R342

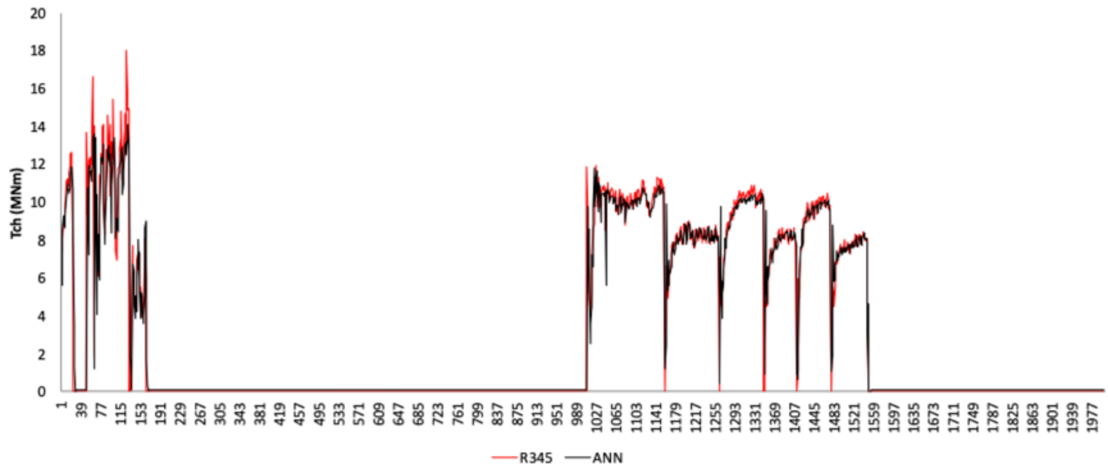

Fig. 7. Comparison of ANN Results with Acquired Data for Ring R345

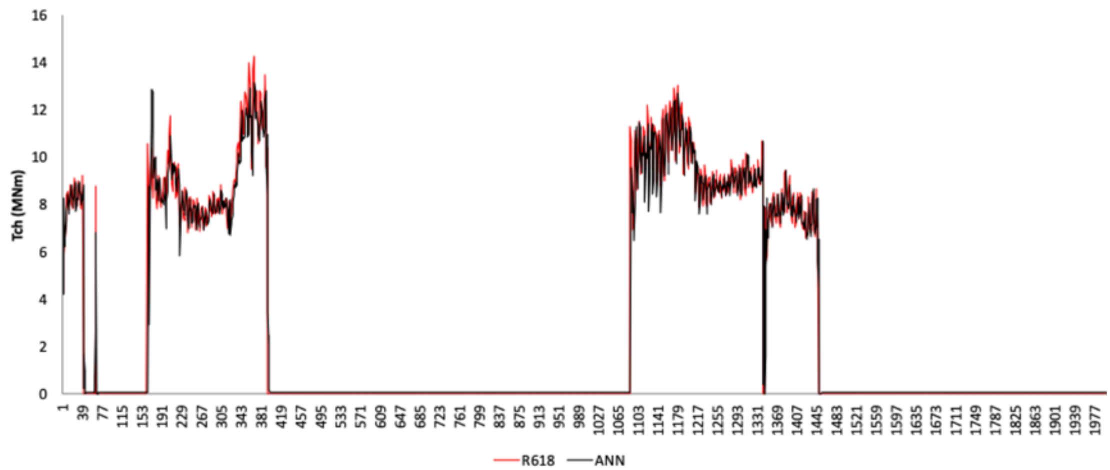

Fig. 8. Comparison of ANN Results with Acquired Data for Ring R618

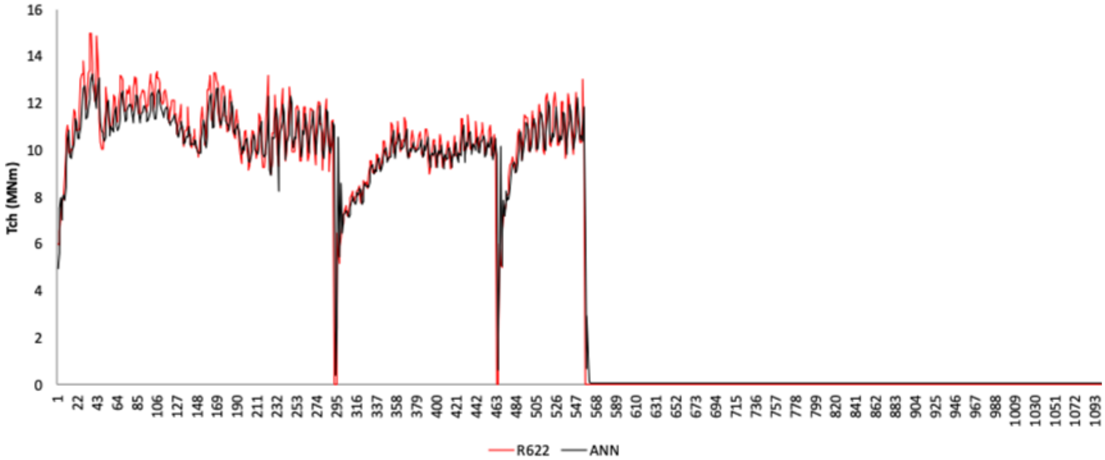

Fig. 9. Comparison of ANN Results with Acquired Data for Ring R622

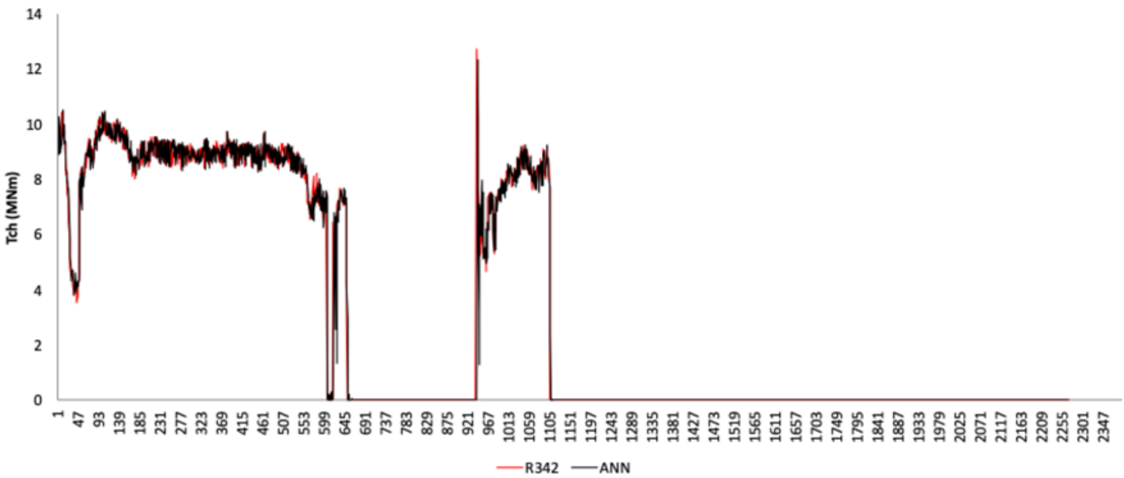

Fig. 10. Comparison of ANN Results with Acquired Data for Ring R342

Both FIR and Tch has been used as inputs, while Tch has been used as output. The analysed ANN has therefore ten input neurons and one output neuron. A hyperbolic tangent activation function has been used, with values normalized in the range [-0.9, 0.9], to prevent eventual saturation near the limits and to allow extrapolation beyond the limits of the first ring.

After several trials, the chosen ANN has two hidden layers, with twenty neurons in the first layer and fourteen neurons in the second layer. A bias neuron has been used in all the layers. The ring used for training was R342. The total number of observations in R342 was 2372 points, from which the first 1,000 points were selected to train the ANN. In Figs. 6 to 9, the comparison of predictions using the ANN, for the relation of FIR and Tch, with acquired data is shown for rings R342, R345, R618 and R622. As can be observed a good prediction was obtained.

4.2 Moving Time Series ANN

For the moving time series ANN, the variables considered were also the FIR and the Tch. A lag window of five previous observations has been used as input and a lead prevision of one. Both FIR and Tch has been used as inputs, while Tch has been used as output. The analysed ANN has therefore ten input neurons and one output neuron. A hyperbolic tangent activation function has been used, with values normalized in the range [-0.9, 0.9].

In this procedure, twelve points are used to train the network in eah loop. After convergence, the next Tch read from the TBM is added to the training points and the first of the previous twelve training points discarded. In this way, the results obtained for Tch are the result of a training process using the previous points. Bigger number of points for network training has been tested but the results do not significantly improve, so the number of twelve points was considered appropriate.

After several trials, the ANN used has two hidden layers, with ten neurons in the first layer and eight neurons in the second layer, with a bias neuron used in all the layers. In Figs. 10 to 13, the comparison of predictions using the ANN with acquired data is shown for rings R342, R345, R618 and R622.

4.3 Comparison of Results

In previous sections the results of the use of a simple and a moving time series for the prediction of Tch has been presented.

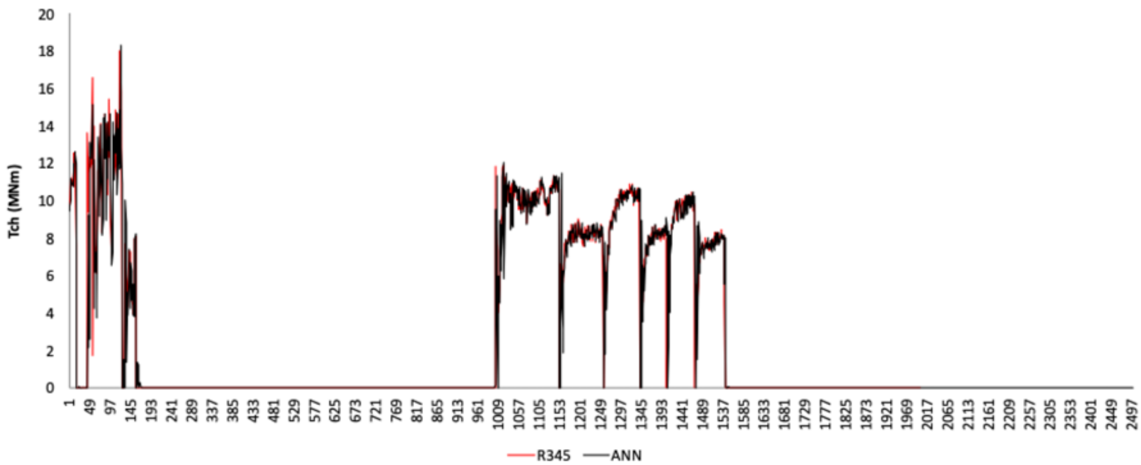

Fig. 11. Comparison of ANN Results with Acquired Data for Ring R345

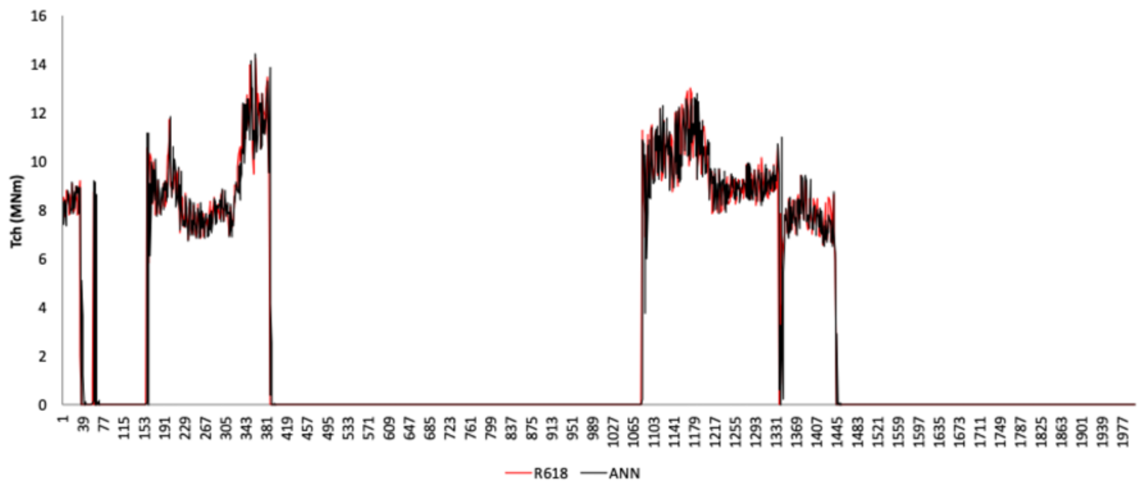

Fig. 12. Comparison of ANN Results with Acquired Data for Ring R618

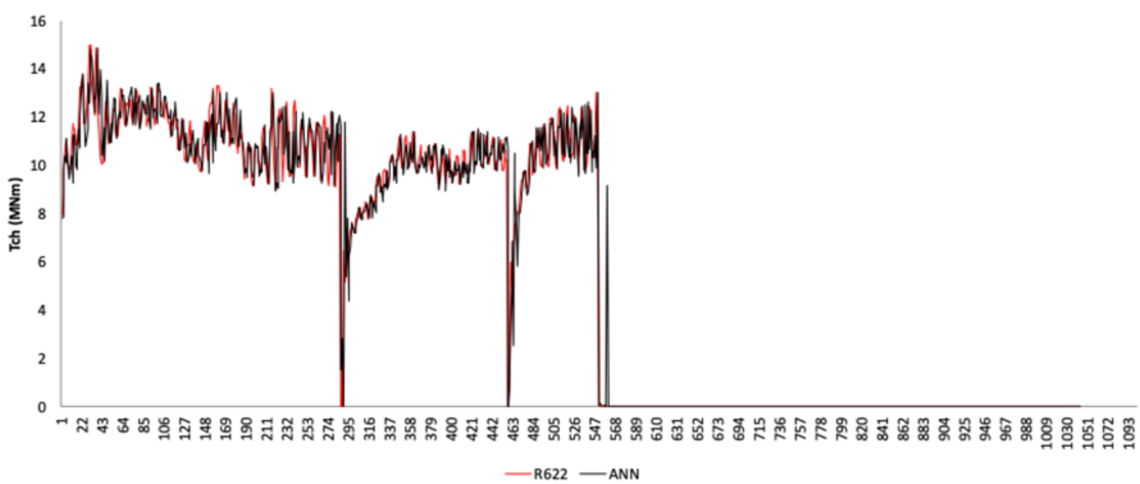

Fig. 13. Comparison of ANN Results with Acquired Data for Ring R622

It is apparent from the graphs that both approaches provide good results. Error and accuracy measures for both cases are presented in Table 1. Results for ring R342 cannot be directly compared with results of other rings in the case of simple time series because they have been used, partially, to train the network. One important feature to be observed is that the R^2 values for all tested cases are above 0.93, which indicate a reasonably good correlation. Also, the MAE and RMSE are relatively small. Nevertheless, there are some points where the differences between the predicted and measured values are big.

Looking at the MAE and RMSE values, in both approaches, it is apparent that RMSE is much bigger than MAE. Due to the

Table 1. Error and Accuracy Measures for ANN

Ring	Simple time series			Moving time series		
	MAE	RMSE	R^2	MAE	RMSE	R^2
R342	0.137	0.434	0.9884	0.146	0.496	0.9852
R345	0.251	0.881	0.9526	0.246	1.007	0.9396
R618	0.205	0.645	0.9727	0.192	0.776	0.9615
R622	0.338	0.744	0.9811	0.380	0.923	0.9711

nature of these measures, this indicates that there are some predicted values that differ significantly from the observed ones. This can be observed on Figs. 14 and 15 where scatter plots of measured and predicted values of Tch for rings R342 and R345 are shown. These rings were chosen because they represent the biggest and smallest R^2 values, respectively. It is clear that in the case of R342, which basically represents the training set, with a few exceptions, results are quite near the equality line. Most of these readings correspond to points where a sudden start or stop of the torque occurs and the ANN can only detect it afterwards. This is particularly more relevant on the moving time series approach.

The values of the coefficient of determination, R^2, are all above 0.96, except for the ring R345 that, as can be observed in Fig. 7 and Fig. 11 has an initial quite inconstant behaviour. These high values of R^2 indicate that both models can accurately predict the Tch behaviour during excavation on sands with an EPB-TBM. It is quite interesting to note that the single time series approach behaves well through all the analysed rings, despite the fact that it has been trained with results of just the first ring.

Comparing the results of the two approaches seems to indicate that the single time series performs better than the moving time series, showing lower RMSE and R^2 values for all the four rings. MAE values are smaller in the moving time series approach in the case of rings R345 and R618. Comparing both approaches, it is apparent that the single time series approach leads to a small dispersion of points around equality line for both rings. It is also visible that the predicted values of Tch are distributed above and below the equality line in a more or less uniform way.

Comparison of rings at different locations using the models calibrated for a particular ring, gives good indication that the ANN models are capable of predicting the Tch values based on the FIR and Tch of previous readings. This is a promising method to, eventually, extend to other variables so that some

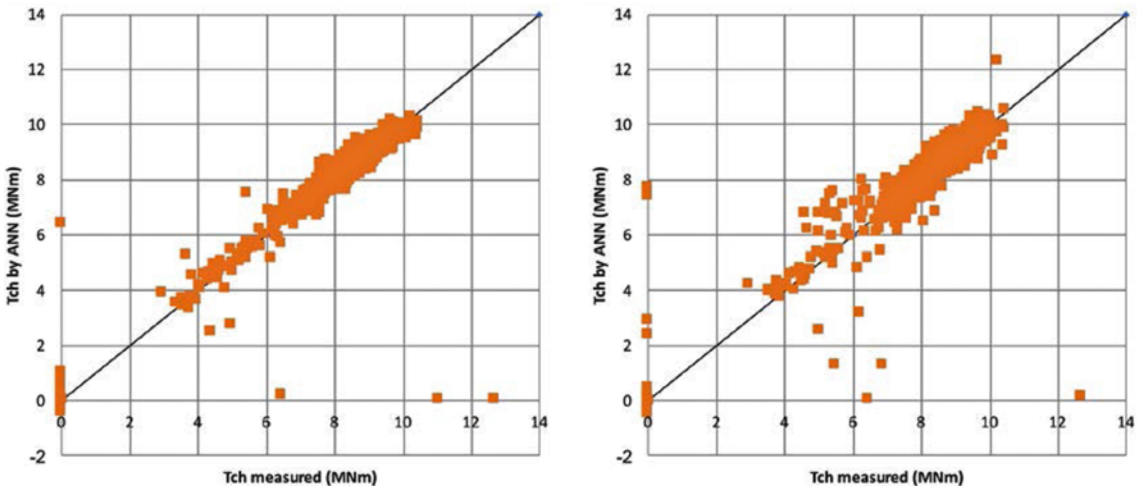

Fig. 14. Comparison of Measured and Predicted Tch for Ring R342: (a) Single Time Series, (b) Moving Time Series

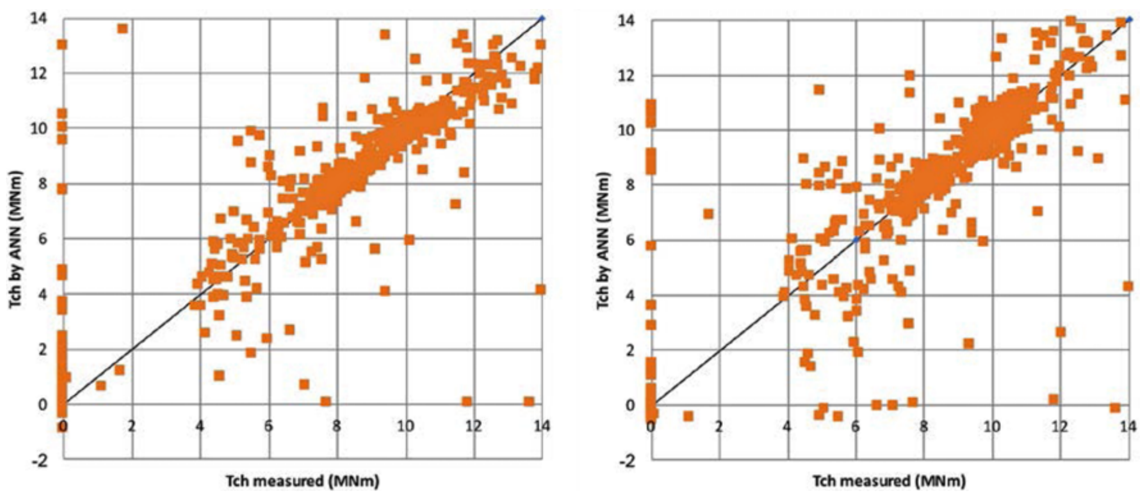

Fig. 15. Comparison of Measured and Predicted Tch for Ring R345: (a) Single Time Series, (b) Moving Time Series

parameters can be predicted based on previous readings, allowing a better control of the tunnelling TBM operating procedure.

5. Conclusions

Artificial neural networks are a powerful tool to solve complex engineering problems. In this article, a FFANN was used to predict the torque at the cutter head in a EPB-TBM, based on FIR. Results of the ANN were compared with experimental data obtained from different rings of the excavation of a tunnel in The Netherlands. Time series ANN have been used with prediction of the torque based in the last five observations. Two different approaches have been used. The first approach, named single time series, trains the network with data from the first ring and then applies the results for prediction of the torque in the other rings. The second approach, named moving time series, uses the last points of excavation data to train the network and predict the torque. Results obtained show that:

1. The use of FFANN with time series can be used to predict the torque at the cutter head in an EPB-TBM;
2. Single time series give, in general, better results than those obtained with the moving time series;
3. Moving time series approach may be better suited to be incorporated into a control procedure of a TBM, since it uses the last points acquired by the machine;
4. It was observed in this study that the models can be used to study dependencies between different variables and by simulation of different FIR and Tch variations, the model could be also used to optimize the TBM process.

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