

THE AUTOMATIC VEHICLE MONITORING TO IMPROVE THE URBAN PUBLIC TRANSPORT MANAGEMENT

L. La Franca, M. Migliore, G. Salvo

Dipartimento di Ingegneria Aeronautica e dei Trasporti, Università degli Studi di Palermo, ITALIA

F. Carollo

AMAT, Palermo, ITALIA

ABSTRACT: In order to improve efficiency of the public transport system, the technological evolution has allowed the employment of innovative solutions for the automation of remote control systems of the bus fleet on the road network. These systems, said "AVM" (Automatic Vehicle Monitoring) and introduced in the urban transport network, allow to offer the maximum levels of availability of the lanes, to improve the quality of the service (commercial speed, regularity of the transport, etc) and the information to the user.

The recorded data about the vehicular fleet position can be also used for off-line optimising of the urban public transport routes and frequencies.

In this work the recorded data about the vehicular fleet position of the public transport firm of Palermo (the main town of Sicily) have been elaborated using neural networks in order to calibrate a multidimensional function among independent variables and the value of commercial speed in a medium working day and for different traffic conditions (rush hour or non congested conditions) in different links of the transport network. A sensitivity analysis has been also carried out in order to determinate the importance of each variable in the commercial speed estimation.

The calibrated model has been tested on different links (unseen from the neural network in the calibration process) of the public transport network of Palermo producing good results in the comparison between estimated and observed data.

RÉSUMÉ : Pour améliorer l'efficacité du système de transport public, l'évolution technologique a permis l'emploi de solutions innovantes pour l'automatisation des systèmes de télécommande de la flotte d'autobus sur le réseau routier. Ces systèmes, appelés "CAV" (Contrôle Automatique du Véhicule) et introduits dans le réseau urbain de transport, permettent d'offrir les niveaux maximum de disponibilité des voies, d'améliorer la qualité du service (la vitesse commerciale, la régularité du transport, etc) et l'information à l'utilisateur.

Les données enregistrées quant à la position de la flotte des véhicules peuvent aussi être utilisées pour l'optimisation autonome des itinéraires et des fréquences des transports publics urbains.

Dans ce travail, on a donné les détails des données enregistrées quant à la position de la flotte des véhicules de la société de transport public de Palermo (ville principale de la Sicile) en utilisant des réseaux neuronaux pour calibrer une fonction multidimensionnelle parmi des variables indépendantes et la valeur de vitesse commerciale dans un jour ouvrable moyen et dans des conditions de trafic différentes (des heures de pointe ou des conditions fluides) dans les liaisons différentes du réseau de transport. On a également effectué une analyse de sensibilité pour déterminer l'importance de chaque variable dans l'évaluation de la vitesse commerciale.

Le modèle calibré a été évalué sur des liaisons différentes (invisible du réseau neuronal dans le processus de calibrage) du réseau de transport public de Palermo produisant de bons résultats dans la comparaison entre les données estimées et observées.

1 INTRODUCTION: THE AUTOMATIC VEHICLE MONITORING SYSTEM

The public transport market is undergoing a transformation of rules and law (deregulation, privatisation).

In order to compete in a deregulation market, the firm should optimise internal resources (drivers, buses, etc), taking into account the customer satisfaction (regularity, comfort, etc.) to increase its transport demand.

The information system technologies could support the transport supply management.

The AVM (Automatic Vehicle Monitoring) systems are based on the real time knowledge of each vehicle of fleet. Fleet management includes location monitoring, collected by GPS (Global Position System), load condition (passengers on board) and vehicle conditions (check of engine and electrical parts).

The analyse of all data collected makes possible to improve the transport service planning.

AVM supports in fact firm management in production process to take a decision based on on-line data taking corrective actions, or managing in real time the emergencies and the danger situations, with the least discomfort for the passengers.

The AVM system includes, in addition to technological tools, a dynamic database with the real time transit data (vehicle position of each bus). By analysing vehicle position and transit time it is possible to evaluate the commercial speed of each bus transiting on each link of the network.

All information can be saved and then used to plan urban public transport.

Beginning from data analysis, described in the next paragraph, it is possible to study the speed along on single link of the transport network, concerning different configurations of the road network.

The knowledge of commercial speed allows to plan the maximum levels of service, according to the adopted safety system, in order to improve quality indexes of the service (efficiency, regularity of the courses, etc.) to the maximum levels.

An other objective is the passenger information, such as the transit time at the bus stop, the number of lines and the time scheduled of next buses approaching and the possibility of direct connection between the user and the control centre.

2 THE ESTIMATION OF THE PUBLIC TRANSPORT COMMERCIAL SPEED

In this work the recorded data in a week about the vehicular fleet position of the public transport firm of Palermo have been elaborated in order to calibrate a multidimensional function among independent variables (presence of public transport reserved lane, number of intersections with traffic lights per kilometre, number of secondary intersections without traffic lights per kilometre, number of pedestrian crossing per kilometre, number of bus stops per kilometre, legal or illegal parking on the way, trade area, rate flow/capacity) and the value of commercial speed in a medium working day and for different traffic conditions (rush hour or non congested conditions) in different links of the transport network.

In particular, a statistical data handling (*pre-processing data*) has been carried out in order to put

out the outliers from the database useful for the estimation of the public transport commercial speed.

Neural networks have been used in order to calibrate the multidimensional function.

Neural networks are composed of many simple elements operating in parallel, taking inspiration from biological nervous system, whose operation is determined largely by the connection between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections between elements (Cammarata, 1990), (Rizzo, 1994).

Neural networks have been trained to perform complex functions in various application fields.

Training and production are the essential phases of a neural network application. (figure 1).

In the first phase, the neural network is trained by using an error minimising algorithm for calibrating the connection weights.

In the second phase, it is possible to run the neural network, obtaining outputs also for data sets unseen.

The neural network generally includes different neural layers (input layer, output layer and hidden layers), as showed by the figure 2.

The two-layer sigmoid/linear (as activation functions for neurones in each layer) network can represent any functional relationship between inputs and outputs if the sigmoid layer has enough neurones (Hornik, 1989).

The backpropagation algorithm can train multi-layered feed-forward networks (where a neurone in a layer is linked only with the other neurones of a successive layer) with differentiable activation functions to perform function approximation.

In particular for backpropagation, the training continues until the MSE (mean-square-error) designed for outputs (difference between predicted value and real value) is met, or the prefixed number of epochs has occurred.

Figure 1: The essential phases of a neural network application: training and production

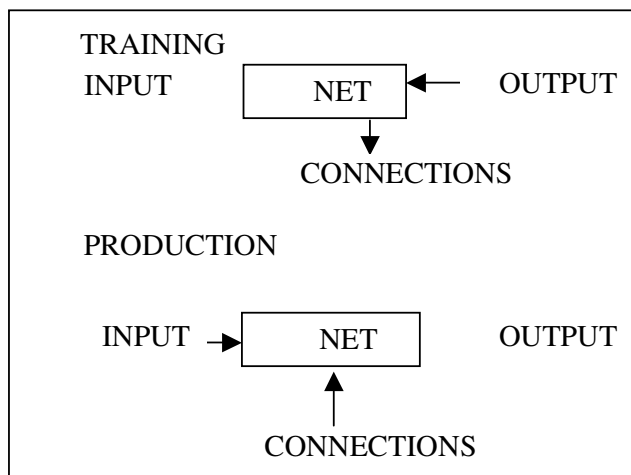
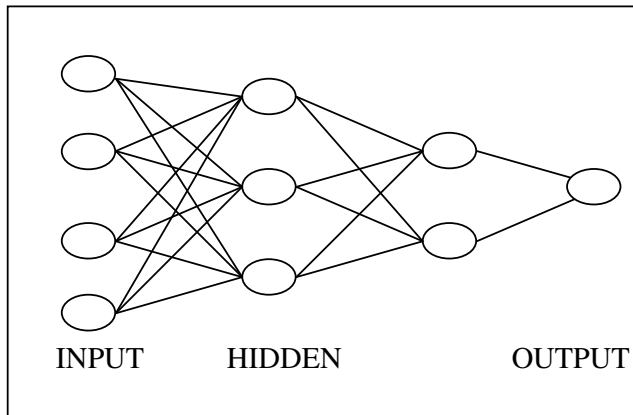


Figure 2 : The architecture of a multi-layered feed-forward neural network.



The architecture of a backpropagation network is not completely constrained by the problem to be solved. The number of inputs to the network is constrained by the problem, and the number of neurones in the output layer is constrained by the number of outputs required by the problem.

However, the number of layers between network inputs and the output layer and the sizes of the layers depend on the designer's decision (using a test set for the calibration of the network architecture and the weights of the network).

In the training of the network is important to compare the forecast performance on the test set to exclude an overfitting to the training set and, then, to test the capability of the network to generalise the results (Bishop, 1995).

The *early stopping* method has been used in this work in order to solve the over fitting problem and improve the generalisation.

It was defined a test set in 20% of the total amount of the data samples. It was partitioned randomly the data set into a training set and a test set. The training set was further partitioned into two subsets: a subset used for the estimation of the model (training) and a subset used for the evaluation of the performance of the model (validation data set for the early stopping method).

The numerical variables were normalised (both inputs and targets) in order to homogenise mean level and variance of all variable distributions.

A tan-sigmoid transfer function was chosen for both the layers. A tan-sigmoid transfer function was used to constrain the output of the network between -1 and 1 . They were used 16 data for test, 16 for validation and 80 for training.

The optimal structure, found pruning step by step the neurones of the hidden layer until to minimise the MSE function on the test set, was a network with a single hidden layer of 2 neurones, an input layer with 10 neurones (one for each variable), one output layer with one neurone.

The Levenberg-Marquardt (AA.VV., 2000) function has been used for the neural network training. The %RMSE on the test set was about 16 %.

One of the major limits of neural network is the fact that it is difficult to interpret, in terms of the weights, the relationships between neurones and, therefore, the relationship between inputs and outputs.

To overcome this limitation, it was possible to consider the network like a black box and examine its answers to small perturbations operated in the inputs layer (Dougherty, 1998).

By increasing every parameter in steps of 1%, the sensitivity was evaluated according to the following formula:

$$S_{ij} = \Delta_{ij} / \delta_{ij}$$

where:

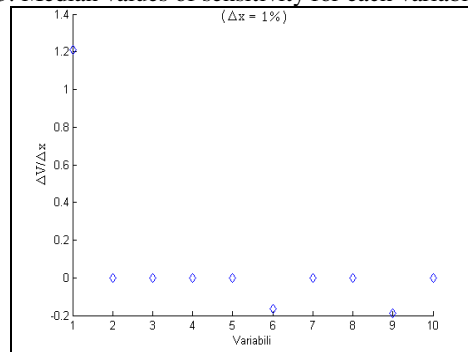
Δ_{ij} = variation in the network's output after increasing of the i^{th} input for the j^{th} record.

δ_{ij} = perturbation of the i -th input for the j -th record.

Once the sensitivity for each variable and for each record was calculated, the medians for each sensitivity vector were computed.

The highest values of sensitivity have been found for: the presence of public transport reserved lane, the number of pedestrian crossing per kilometre, the presence of a trade area (figure 3).

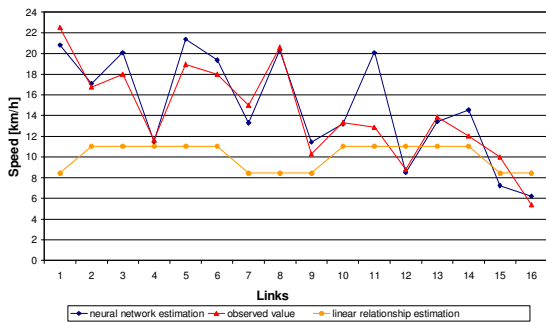
Figure 3: Median values of sensitivity for each variable



These variables represent the most significant factors that influence the public transport commercial speed in Palermo.

In the figure 4 is showed a comparison, carried out using the test set data (unseen from the neural network in the calibration process), among the observed values of the public transport commercial speed in different links and in different hours of a working day, the estimations by using the calibrated neural network and the estimations by using a linear relationship based on a medium commercial speed calculated on large periods of time (6 – 9 a.m., 5 – 7 p.m.).

Figure 4: Comparison among observed values of the public transport commercial speed in different links and in different hours of a working day and the estimated values by using the calibrated neural network and a linear relationship.



In the figures 5 – 10 are showed the comparisons between the observed values of the public transport commercial speed and the estimations by using the calibrated neural network in different hours of a working day and in different links of the public transport network of Palermo where the AVM system does not work.

Figure 5: Comparison between observed values (red colour) of the public transport commercial speed and the estimated values (blue colour) by using the calibrated neural network.

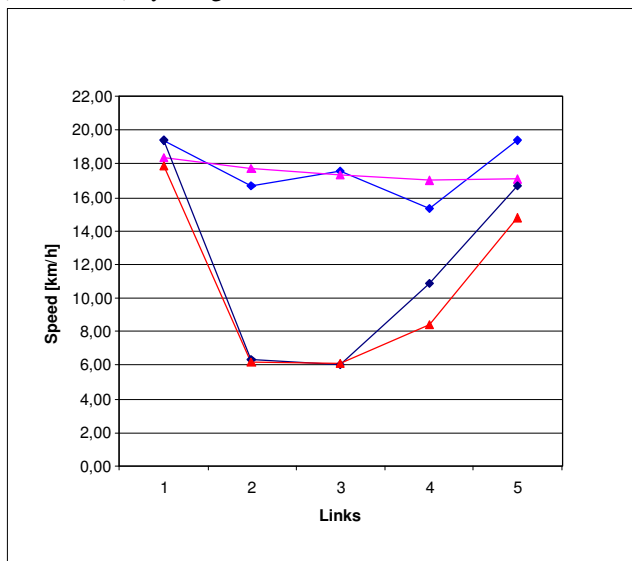


Figure 6: Comparison between observed values (red colour) of the public transport commercial speed and the estimated values (blue colour) by using the calibrated neural network.

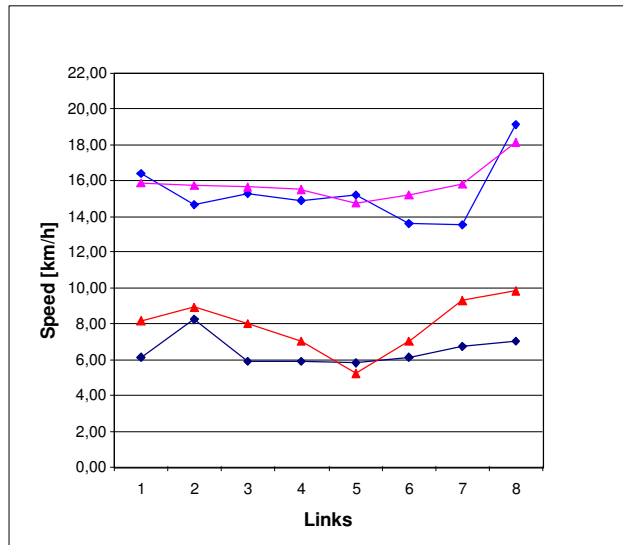


Figure 7: Comparison between observed values (red colour) of the public transport commercial speed and the estimated values (blue colour) by using the calibrated neural network.

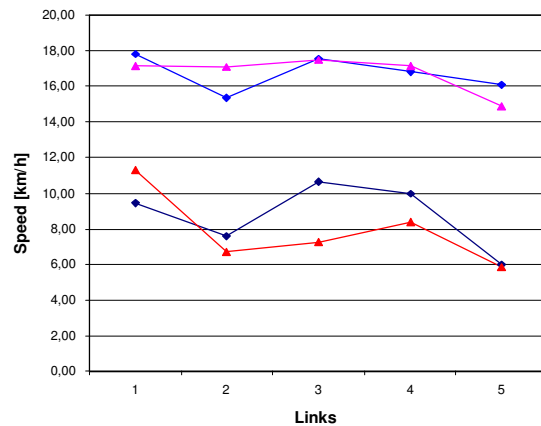


Figure 8: Comparison between observed values (red colour) of the public transport commercial speed and the estimated values (blue colour) by using the calibrated neural network.

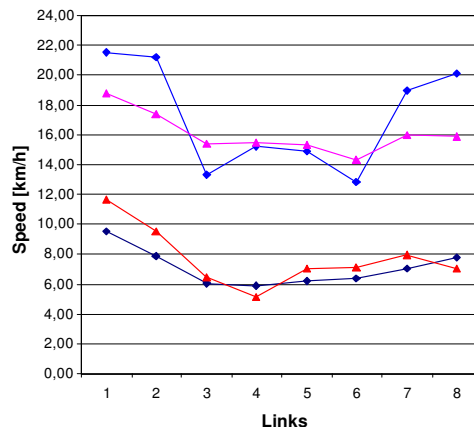


Figure 9: Comparison between observed values (*red colour*) of the public transport commercial speed and the estimated values (*blue colour*) by using the calibrated neural network.

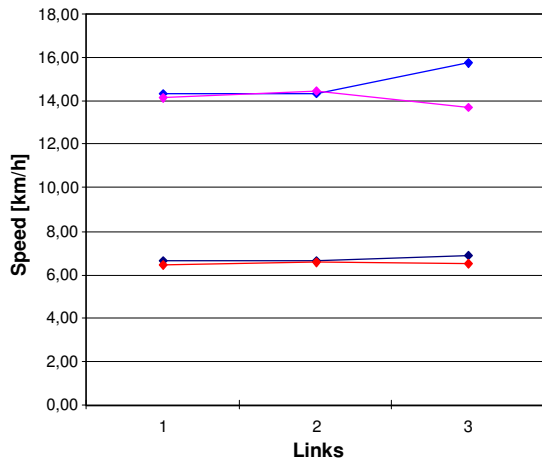
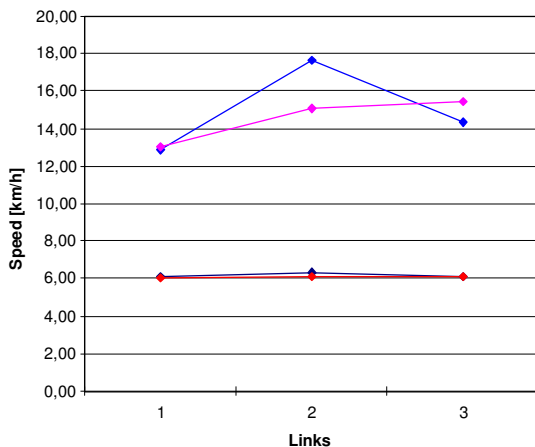


Figure 10: Comparison between observed values (*red colour*) of the public transport commercial speed and the estimated values (*blue colour*) by using the calibrated neural network.



The results of the showed comparisons encourage us to persevere the work extending, in particular, the database to different conditions and elaborating data about a longer period of time than a week.

3 CONCLUSIONS

In this paper has been showed a methodological process to set-up and calibrate a neural network to estimate the value of commercial speed in a medium working day in different links of the urban public transport network and for different traffic conditions.

At the end of the training, the sensitivity analysis for each variable has been calculated to evaluate the most important elements that have influenced the commercial speed. They were: public transport re-

served lane, the number of pedestrian crossing per kilometre, the presence of a trade area.

Good results have been found comparing the observed values of the commercial speed, in different links and for different traffic conditions, and the estimated values by using the calibrated neural network.

The goodness of the results lets think that the neural network has succeeded in calibrating and could be used from the management of the firm to improve supply and to plan the runs of new lines.

Neural network tools could allow:

- to check and eventually to correct, in planning phase, the temporal distances between two following stops,
- to check and eventually to correct line frequencies and the bus departure schedules because real time of turn is well-know during a medium working day,
- to optimize the resources assigning to every line an appropriate number of buses and drivers.

All these possibilities allow to schedule supply in such to make it more adherent to the network conditions under which the supply is developed.

The calibrated neural network has a good capability of generalization and is able to estimate commercial speed in different links and for different traffic conditions. It could be useful then to plan new lines that include roads in which commercial speed is not well-know.

REFERENCES

- AA.VV. (2000) *Neural Network Toolbox* for use with MATLAB®, Reference Guide (The Math Works Inc.).
- Bishop C. M. (1995), *Neural Network for Pattern Recognition*, Oxford University Press, Oxford.
- Cammarata S., *Reti neurali*, Etaslibri, Sonzogno, 1990.
- Dougherty M S (1998) Exploring traffic systems by elasticity analysis of neural networks. In: Himanen, V., Nijkamp, P. and Reggiani, A. (eds), *Neural networks in transport applications*. (Ashgate)
- La Franca L, Salvo G, Amenta S (2002) A real-time information system for urban bus service management, *II International Conference Transport System Telematics (TST 2002)* Katowice (Poland)
- Hornik K., Stinchcombe M., White H. (1989), Multilayer feed-forward networks are universal approximators, *Neural Networks*, 2(5), pp. 359-366.
- Rizzo R.(1994), *I sistemi neurali*, Pubblicazione n° 90, collana CERISEP, Palermo.