Public Transportation Energy Consumption Prediction by means of Neural Network and Time Series Analysis Approaches

CLAUDIO GUARNACCIA, JOSEPH QUARTIERI, CARMINE TEPEDINO
Department of Industrial Engineering
University of Salerno
Via Giovanni Paolo II 132, Fisciano (SA)
ITALY
cguarnaccia@unisa.it , quartieri@unisa.it , ctepedino@unisa.it

SVETOSLAV ILIEV, SILVIYA POPOVA
Department of Bioengineering and Unique Instruments, Components and Structures
Institute of System Engineering and Robotics
Bulgarian Academy of Sciences
Sofia 1113, Akad. G. Bonchev str. bl 2
BULGARIA
sd_iliev@abv.bg , popova_silvia2000@yahoo.com

Abstract: - Effective management of modern electrical transport systems is a very important and difficult task. Much of the transport of passengers in cities is based on electric vehicles. Tram and trolley transport in Sofia is quite largely developed. It is one of the largest consumers of electricity in the city, which makes the question of electricity prediction very important for its operation. The paper presents two models predicting electricity consumption. One model is based on Artificial Neural Networks (ANN), and the other on Time Series Analysis (TSA). The purpose of this paper is to compare the two models in certain indicators to determine and to identify their advantages and disadvantages. The main conclusion will be that the ANN model is much more precise but requires more inputs and computational efforts, while the TSA model, against some errors, shows a low demanding input entries and an easy computational approach. In addition, the ANN model has a lower range of prediction, since it needs many recent inputs in order to produce the output. On the contrary, the TSA model prediction, once the model has been calibrated on a certain time range, can be extended to any time, of course losing precision in the forecast.

Key-Words: - Neural Network, Time Series Analysis, Electricity consumption prediction, Public transportation

1 Introduction

Public transportation is a relevant issue to be considered in urban planning and in transportation network design.

Many countries adopt electrical systems for public transportation and, in this case, they are required to notify the energy provider about the expected energy consumption for a given time range. Of course, if the prediction is far from the real consumption, there are management and economical disadvantages.

Different predictive models can be found in literature, based on various approaches, such as Neural Networks, Support Vector Machines, Fuzzy logic, statistical tools, etc. [1-6].

In this paper, two models are presented and compared in terms of predictive performances and error distributions: one is based on Artificial Neural Networks (ANN) and the other on Time Series Analysis (TSA) methods. They will be applied to the energy consumption related to public transportation, observed in Sofia, Bulgaria, during 2011, 2012 and 2013.

The effectiveness and versatility of ANN and TSA models will be analyzed and discussed in terms of time history plot and error distributions comparison in four test datasets, related to four different months (January, May, July and November 2013).

2 Models Presentation

In this section, the ANN and TSA models will be shortly presented and discussed.

The dataset is related to energy consumption in 2011, 2012 and 2013. The first two years (2011 and 2012) are used for training and calibration of the

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models, while some intervals of 2013 (January, May, July and November) are used for testing, i.e. comparison between real and predicted data.

2.1 Artificial Neural Network model

Artificial neural networks (ANN) have been applied successfully to a large number of engineering problems. The great advantage of ANN is that they impose less restrictive requirements with respect to the available information about the character of the relationships between the processed data, the functional models, the type of distribution, etc. They provide a rich, powerful and robust non-parametric modelling framework with proven efficiency and potential for applications in many fields of science. The advantages of ANN encouraged many researchers to use these models in a broad spectrum of real-world applications. In some cases, the ANNs are a better alternative, either substitutive or complementary, to the traditional computational schemes for solving many engineering problems. The approach based on ANN has some significant advantages over conventional methods, such as adaptive learning and nonlinear mapping.

In many engineering and scientific applications a system having an unknown structure has measurable or observable input or output signals. Neural networks have been the most widely applied for modelling of systems [1, 7-13]. Artificial neural networks, coupled with an appropriate learning algorithm, have been used to learn complex relationships from a set of associated input-output vectors.

There are four reasons for using neural network for electricity consumption prediction in tram and trolleybus transport:

1. The dependence between input and output data is nonlinear and the neural networks have ability to model non-linear patterns.
2. The neural network learns the main characteristics of a system through an iterative training process. It can also automatically update its learned knowledge on-line over time. This automatic learning facility makes a neural network based system inherently adaptive.
3. ANN can be more reliable at predicting. It is well-known that forecasting techniques based on artificial neural networks are appropriate means for prediction from previously gathered data. The neural networks make possible to define the relation (linear or nonlinear) among a number of variables without their appropriate knowledge.
4. There is a big number of data available. The neural network, trained with these data, adjusts the weights and predicts output with small error when working on new data with the same or similar characteristics of the input data.

2.1.1 ANN Model Details

Two-layer network with “error back propagation training algorithm” is used to predict electricity consumption. The network has one hidden layer with forty-three neurons and an output layer with one neuron. The sigmoid *tansig* transfer function is used for the hidden layer and for the output layer the activation function is the linear function *purelin.* Six input factors: mileage, air temperature, time of day, weekday or holiday, month, schedule (summer / winter).

Training data for 2011 and 2012 years with a total of 17496 items were used. The best result in the training of the network is achieved after 158 iterations, as mean square error (performance) is 0,0776 .

In Fig. 1 the multiple-correlation coefficients and comparison between linear regression and ANN for training, validation and testing are shown, while in Fig. 2, the error histogram in the complete training process is reported.

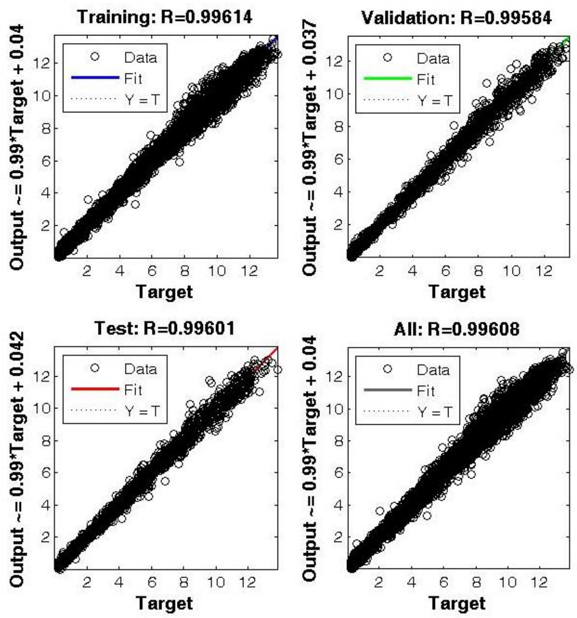

Fig. 1: Comparison between linear regression and ANN model results plotted versus the observed values for training, validation and testing.

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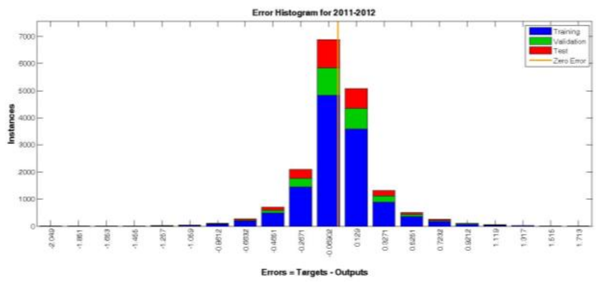

Fig. 2: Error histogram in the ANN training process.

2.2 Time Series Analysis model

Time Series Analysis models are mathematical models able to highlight the intrinsic features of a certain time dependent observable and exploit them for prediction [14-26].

They are largely used in Economics, for instance to predict the index of stock exchange or to evaluate the production need of a certain product, based on the demand of the market.

There are different kind of models based on Time Series Analysis, each of them characterized by a different approach in estimating the parameters of the model. One of the most general class is the ARIMA (AutoRegressive Integrated Moving Average) model, that can include also a seasonal predictor (SARIMA). The most simple method, instead, is to evaluate the trend and the seasonal component of the series, respectively by means of regression methods and autocorrelation evaluation, and to compose these parts in additive or multiplicative way. For instance, in [14-17], some mixed models (multiplicative between trend and seasonality, and additive with respect to the error component) are applied to acoustical noise and to CO concentrations.

In [26], a mixed model is applied to the energy absorption of public transportation in Sofia, Bulgaria. The introduction of a "monthly" seasonal component, in addition to the daily and the weekly ones, give very good results in terms of predictive performances and error (difference between actual and predicted data).

In this paper, the model presented in [26] is compared with the Neural Network model presented in [13] and resumed in Section 2.1. The formula of the TSA model is:

$$F_t = T_t \,\bar{S}_{1,i}\, \bar{S}_{2,j}\, \bar{S}_{3,h} + m_e \ , \qquad (1)$$

where F_t is the forecast of the TS model at time t, T_t is the trend, $\bar{S}_{1,i}$, $\bar{S}_{2,j}$ and $\bar{S}_{3,h}$ are the seasonal coefficients, and m_e is the mean of the error evaluated by a statistical analysis on the error, defined as observed value (A_t) minus forecast (F_t) in the calibration phase:

$$e_t = A_t - F_t. \qquad (2)$$

2.2.1 TSA Model Details

The TSA model presented above has been calibrated on data related to 2011 and 2012.

The two major periodicities are evaluated according to the maximization of autocorrelation function, obtaining a daily (24 hours) and weekly (168 hours) lag. The third coefficient, related to "monthly" seasonal component has been calculated as the ratio between the mean of observed values and the mean of the trend, for each month (for further details see [26]).

3 Comparison of the models

Of course, since the models are deeply different, the comparison must be carefully performed. In fact, it is easy to foresee that the ANN model will be much more efficient with respect to TSA. This is due to the bigger number of parameters (day of the week and of the month, hour, kilometers run, temperature, etc.) and to the complexity of the ANN model, that is designed to "learn" and "understand" the context in which it is applied. On the contrary, the TSA model has a very low number of inputs (only the data in a certain past time range) and does not consider many variables.

Thus, in the comparison, the authors will underline that the choice of the proper predictive model must be performed according to the needs of the user: when a large accuracy is needed and there are good computing platforms at disposal, the ANN should be preferred, keeping in mind that, in order to be used, it needs also information about temperature, kilometers run, day of the week, etc.. On the contrary, if an average prediction is satisfactory and the operator does not know all the parameters needed for ANN model application, the TSA model can give a good estimation, with low mean error and standard deviation.

The datasets used to compare the models are four months of 2013, in particular January, May, July and November. The statistics of the electricity consumptions observed in these months and the skewness and kurtosis of the distributions are resumed in Table 1. In Fig. 3, the boxplot of the consumptions is reported. The 25 (lower bound of the box), 50 (solid line), 75 (upper bound of the box) percentiles are plotted, together with minimum and maximum value per each month of comparison.

Tab. 1: Summary of statistics of the 2013 validation data.

	Mean [MWh]	Std.dev [MWh]	Median [MWh]	Skew	Kurt
January	6,62	3,43	6,84	-0,22	-1,19
May	4,01	2,38	3,89	-0,19	-1,29
July	3,58	2,01	3,72	-0,39	-1,18
November	5,20	3,09	5,17	0,1	-0,82

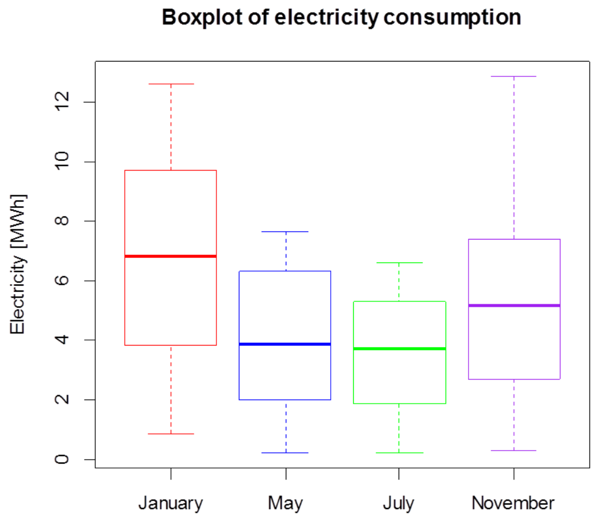

Fig. 3: Boxplot of the 2013 validation datasets.

3.1 Time history plot comparison

A first comparison that can be pursued regards the plot of the time histories observed and simulated. The agreement or disagreement between the curves will give interesting information about the performances of the models, especially in certain days in which unusual consumptions are observed.

In Fig. 4, the plot of January 2013 is reported for observed data and predictions made by ANN and TSA models.

It can be noticed that on the 1st of January, the TSA model overestimates the absorption because it treats that day as a working day, instead of ANN model that knows in input that it is a holiday.

In Fig. 5, the observed and predicted absorption values are reported for May 2013.

It is easy to notice that the TSA model overestimates the absorption in the first days of May 2013. This is due to the fact that it was the week of the Work Holiday (1st of May), the Orthodox Easter celebration (on Sunday, the 5th of May) and the Day of Bulgarian army (Monday the 6th of May). During these holidays, a lower absorption is observed, with respect to usual working days.

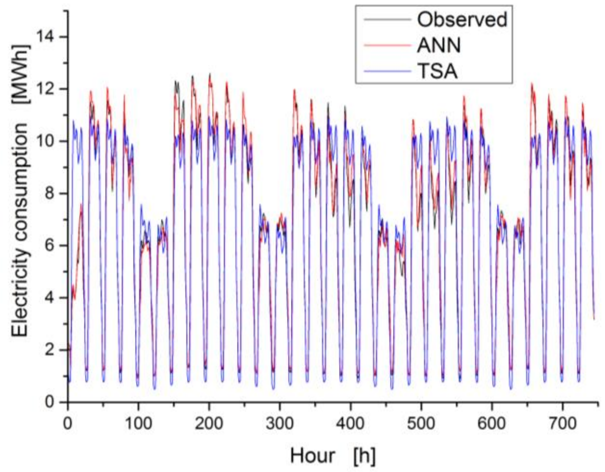

Fig. 4: Time history comparison between real data (black line), ANN predictions (red line) and TSA predictions (blue line) in January 2013.

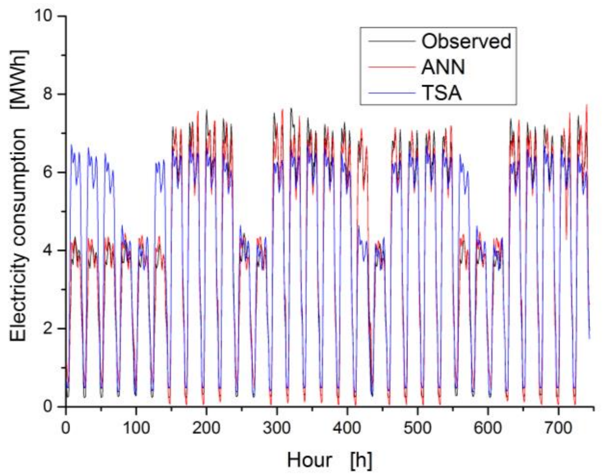

Fig. 5: Time history comparison between real data (black line), ANN predictions (red line) and TSA predictions (blue line) in May 2013.

The same happens on Friday the 24th of May, Day of the Public Education and Culture, that is holiday but the model treats as a working day.

This bug does not occur in the ANN model because this model has as input the "weekday or holiday" flag and the schedule of the vehicles, so it is able to understand if the consumption is affected by the work and schools vacation.

A strange behavior is observed on Saturday the 18th of May, in which a higher absorption, with respect to usual Saturdays, is observed. This is due to the fact that the 18th of May was a working day. Of course the TSA model cannot predict this behavior and treats the Saturday as a holiday. The ANN model, instead, is able to follow all the variations from the usual slope, thanks to the working day / holiday input parameter.

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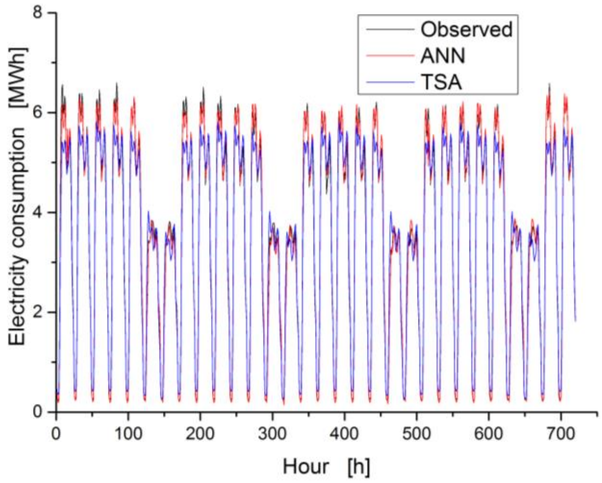

Fig. 6: Time history comparison between real data (black line), ANN predictions (red line) and TSA predictions (blue line) in July 2013.

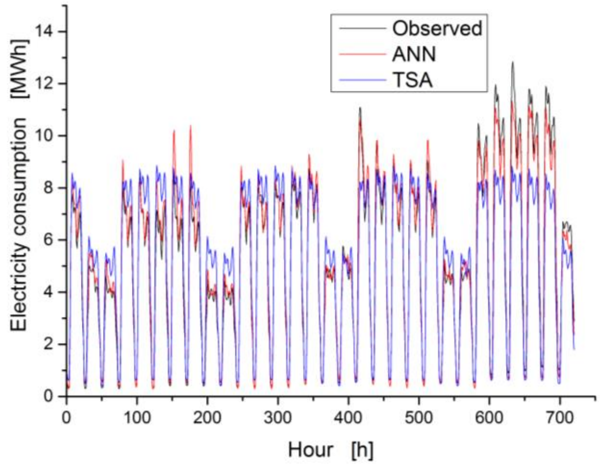

Fig. 7: Time history comparison between real data (black line), ANN predictions (red line) and TSA predictions (blue line) in November 2013.

In Fig. 6, the plot related to July 2013 is reported. No strange behaviors occur and a strongly periodic pattern is evidenced. Both models follow very well the observed curve.

In Fig. 7, concerning November 2013, there are two events to be underlined. In the first week there are some overestimations of ANN with respect to observed consumptions. On the contrary, in the last week, a big electricity consumption is observed, larger than previous weeks, probably related to the lowering of temperature and to a larger use of heating system. This variation is quite well explained by ANN model, in spite of some underestimations. TSA model, instead, cannot take into account this growth and it strongly underestimates the absorption.

3.2 Error Evaluation

The error of the models can be evaluated simply according to the difference between observed and predicted values in each time period, as in formula (2).

The statistics of the error are reported in Tables 2-5 for the four months of 2013 (January, May, July and November) used to evaluate the performances of the models.

Tab. 2: Error resume for January 2013.

	Mean [MWh]	St Dev [MWh]	Sum of absolute error [MWh]	Predicted consumption for month [MWh]	Real consumption for month [MWh]
ANN	-0,076	0,361	204,81	4981,7	4924,7
TSA	-0,04	1,16	607,96	4952,0	

Tab. 3: Error resume for May 2013.

	Mean [MWh]	St Dev [MWh]	Sum of Absolute error [MWh]	Predicted consumption for month [MWh]	Real consumption for month [MWh]
ANN	0,017	0,3146	187,5	2969,6	2982,2
TSA	-0,06	0,93	476,8	3027,9	

Tab. 4: Error resume for July 2013.

	Mean [MWh]	St Dev [MWh]	Sum of Absolute error [MWh]	Predicted consumption for month [MWh]	Real consumption for month [MWh]
ANN	0,004	0,143	73,21	2572,9	2575,6
TSA	0,06	0,35	189,61	2533,5	

Tab. 5: Error resume for November 2013.

	Mean [MWh]	St Dev [MWh]	Sum of absolute error [MWh]	Predicted consumption for month [MWh]	Real consumption for month [MWh]
ANN	-0,077	0,48	260,3	3803,1	3747,5
TSA	-0,09	1,21	645,1	3809,2	

It can be noticed that the mean of the error is close to zero for both models, in almost all the datasets considered. Except for January, the ANN model gives always a lower mean error.

The standard deviation is always very low for the ANN model, while for TSA in two cases is higher than 1 MWh. This is due to a broader error distribution, with respect to ANN. The sum of absolute error confirms that in all cases the ANN model is closer to observed values than TSA.

The comparison between the observed and predicted total consumptions shows that the two models have very slight differences between each other, confirming that on an average base, the TSA gives performances very close to the ANN, that, on

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the contrary, is more precise on a local (single data) base. With respect to the real consumption, in January and November the two models give an overestimation, while in July they both give a small underestimation. May is the only case in which ANN overestimates and TSA underestimates the consumption. These results are confirmed by the sign of the mean error.

4 Conclusions

The problem of predicting the energy consumption of public transportation in Sofia has been considered.

Two models have been proposed and compared: one is based on Artificial Neural Network (ANN) and the other is based on Time Series Analysis (TSA) approach.

The ANN resulted to be much more precise and with a very low mean error and narrow error distribution, but it needs a large vector of input, containing data related to time periods close to the one to be predicted.

The TSA, instead, has a lower precision and a larger range of errors, even if the mean error is close to zero. The main advantage of TSA is that it needs as input only the values of the observable under study (i.e. the energy absorption) in a certain "calibration" dataset.

Thus, the choice of the proper predictive model must be performed according to the needs of the user: when a large accuracy is needed, many input data are known and there are good computing platforms at disposal, the ANN model should be preferred, keeping in mind that, in order to be used, it needs also information about temperature, kilometers run, weekday or holiday, bus schedule, etc.. On the contrary, if an average prediction is satisfactory and the operator does not know all the parameters needed as input for ANN model application, the TSA model can give a good estimation, with low mean error and standard deviation.

In addition, the ANN can predict on a given range, say for instance one week or one month, according to the available inputs or to the models used to predict them, while the TSA, in principle, has no limitation on this point, since it can predict at any time just after calibrating on a sufficiently large dataset. This process does not degrade the efficiency of TSA, thanks to the implementation of the proper periodicities. The error, in fact, does not significantly increase when moving far from the calibration dataset, i.e. when validating in July and November.

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