Neural Network and Time Series Analysis Approaches in Predicting Electricity Consumption of Public Transportation Vehicles

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Abstract: - Public transportation is a relevant issue to be considered in urban planning and in network design, thus efficient management of modern electrical transport systems is a very important but difficult task. Tram and trolley-bus transport in Sofia, Bulgaria, is 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. In fact, they are required to notify the energy provider about the expected energy consumption for a given time range.
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, during 2011, 2012 and 2013.
The main conclusion will be that the ANN model is much more precise but requires more preliminary information and computational efforts, while the TSA model, against some errors, shows a low demanding input entries and a lower power of calculation. In addition, the ANN model has a lower time 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 at any time period.

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

1 Introduction

In many big European cities, a large amount of resources is adopted to develop an efficient network of public transportation. The growing number of inhabitants in urban areas leads to the necessity to control the vehicular traffic due to private transportation. For this reason, electrical tram and trolley bus are preferred. The reduction of combustion engines usage allows to reduce physical and chemical polluting agents in highly populated areas. Electrical engines are also very quiet, from the acoustical point of view, and contribute to a reduction of noise due to vehicular road traffic [1-13].

Sofia, the capital of Bulgaria, has a very developed network of electrical public transportation vehicles. Anyway, the high electricity absorption must be carefully monitored, both for cost and electrical network stability reasons. Different predictive models can be found in literature, based on various approaches, such as Neural Networks, Support Vector Machines, Fuzzy logic, statistical tools, etc. [14-20].

In this paper, the predictive performances of two different modelling techniques are compared. The first method is based on an Artificial Neural Network (ANN) of the multilayer perceptron typology, thus able to extract the non-linear relations in a data matrix. The second technique makes statistical inference using the time periodicity of the electrical absorption, by means of a model based on Time Series Analysis (TSA).

After having presented the models, they will be tested on 4 different datasets, that are four months of 2013. The differences between results obtained with the two models will be highlighted in terms of error evaluation and analysis.

The ANN model ensures a more accurate mean prediction, but it needs more input information, higher elaboration and computation abilities and input data measured closer to the periods that are under prediction. The TSA model is slightly less precise in the prediction but needs as input only the energy consumption registered in a sufficient number of previous time periods. In addition, the TSA model requires a low computing power and it is able to provide reliable predictions even in time periods far from the data used in the calibration and in the parameters evaluation.

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 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 [14, 21-27]. 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.

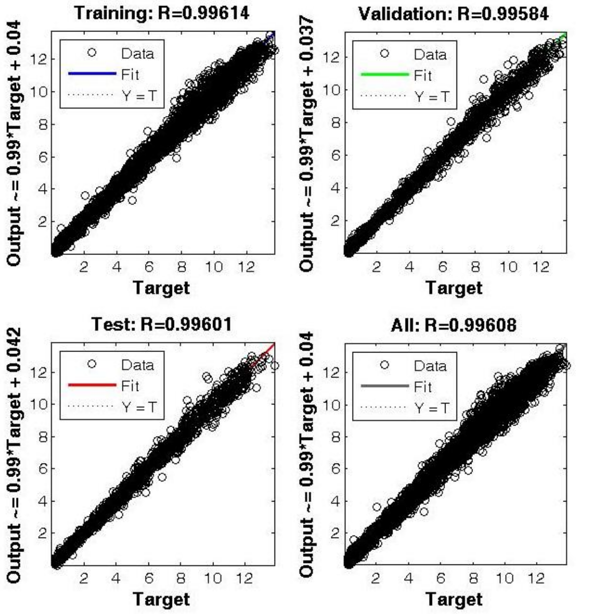

Fig. 1: Comparison between linear regression and ANN model results plotted versus the observed values for training, validation and testing.

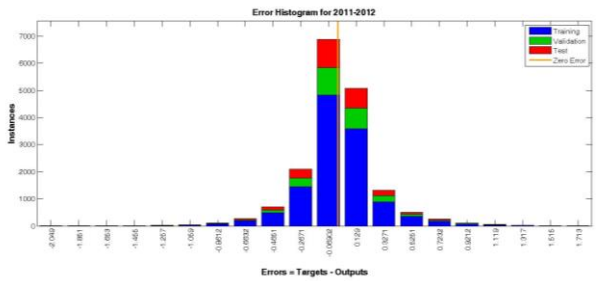

Fig. 2: Error histogram in the ANN training process.

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 [28-40].

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 (Auto Regressive 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 [28-31], 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 [40], 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 [40] is compared with the Neural Network model presented in [27] 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 [40]).

2.3 Error metrics

Two error metrics, already adopted in [28-30], are used to evaluate the model performances: the Mean Percentage Error (MPE) and the Coefficient of Variation of the Error (CVE).

These indexes are used together because the MPE gives a measurement of the error distortion, i.e. is able to describe if the model overestimates or underestimates the observed data, while the CVE considers the variation from the observed data in absolute value. In other words, it provides the error dispersion.

The two metrics are evaluated according to the following formulas:

$$MPE = \frac{\sum_{t=1}^{n}\left(\frac{A_t - F_t}{A_t}\right)100}{n} \tag{3}$$

and

$$CVE = \frac{\sqrt{\frac{\sum_{t=1}^{n}(e_t)^2}{n-1}}}{\bar{A}} \quad , \tag{4}$$

where A_t, F_t and e_t are the same as in formula (2), $\bar{A}$ is the mean value of the actual data in the considered time range, n is the number of data.

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

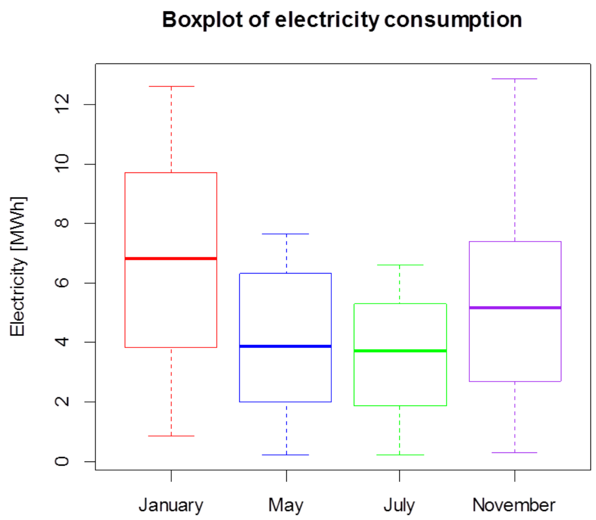

Fig. 3: Boxplot of the 2013 validation datasets.

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.

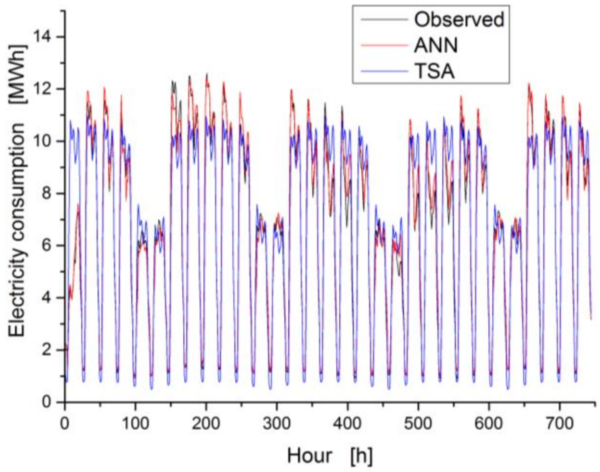

Fig. 4: Time history comparison between real data (black line), ANN predictions (red line) and TSA predictions (blue line) in January 2013.

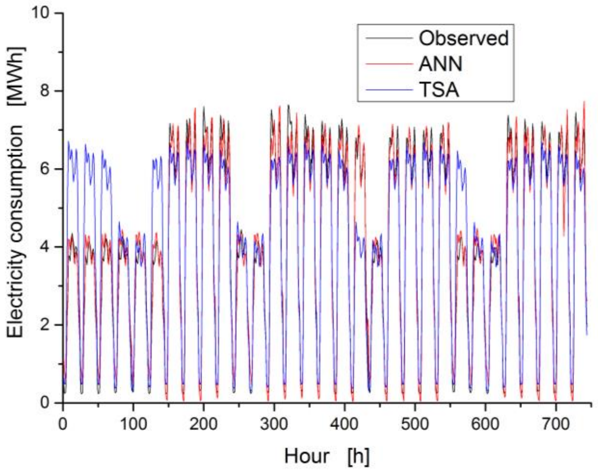

Fig. 5: Time history comparison between real data (black line), ANN predictions (red line) and TSA predictions (blue line) in May 2013.

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.

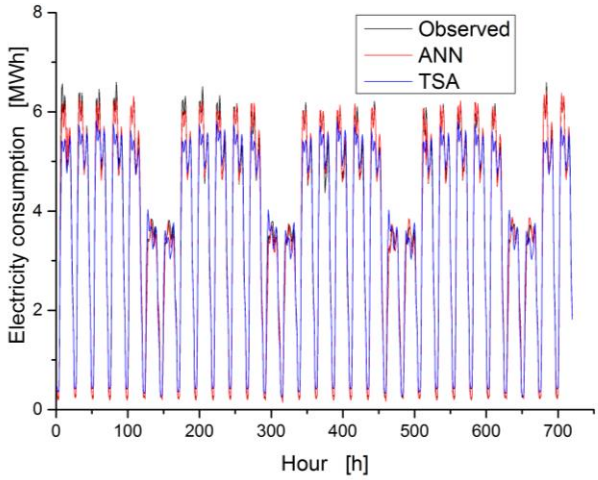

Fig. 6: Time history comparison between real data (black line), ANN predictions (red line) and TSA predictions (blue line) in July 2013.

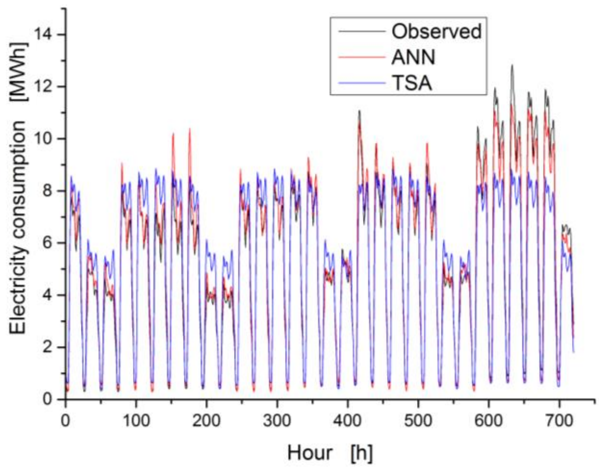

Fig. 7: Time history comparison between real data (black line), ANN predictions (red line) and TSA predictions (blue line) in November 2013.

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 and analysis

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 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.

The histograms of the errors related to the first testing dataset (January 2013) are reported in Fig. 8. In this figure, the higher spread of the results obtained with the TSA model, with respect to the ANN one, is confirmed. Also in the other months, figures 9, 10 and 11, the error distributions are quite normal when using the ANN model and the spreads of the errors are bigger in the histograms related to the TSA model.

In Figg. 12-15, the Q-Q plots are reported for both models and for the four test datasets. This kind of plot compares the sample quantiles with the theoretical ones, that are the quantiles of the Gaussian distribution. When the points approach the bisector, the observed distribution approaches the normal one.

In both cases, ANN and TSA models, the Q-Q plots related to the error distributions show small variations from the theoretical quantiles, but sometimes the points of tails are quite distant from the bisector.

The autocorrelation of the errors has been evaluated by means of autocorrelation plots (correlograms), reported in Figg. 16-19. This test verifies if the data (in our case, the error) have an autocorrelation and, if so, if the presence of fully random data fluctuations may be excluded. In other words, this test shows if the models adopted are able to extract all the information about time dependence from the dataset.

The autocorrelation function, computed in the "*R*" software framework, is evaluated according to the following formula:

$$r(k) = \frac{\sum_{t=1}^{n-k}(x_t-\bar{x})(x_{t+k}-\bar{x})}{\sum_{t=1}^{n}(x_t-\bar{x})^2}\ , \qquad (5)$$

where x_t is the data in each period t, $\bar{x}$ is the mean of all the data, n is the total number of periods, k is the lag hypothesis under test.

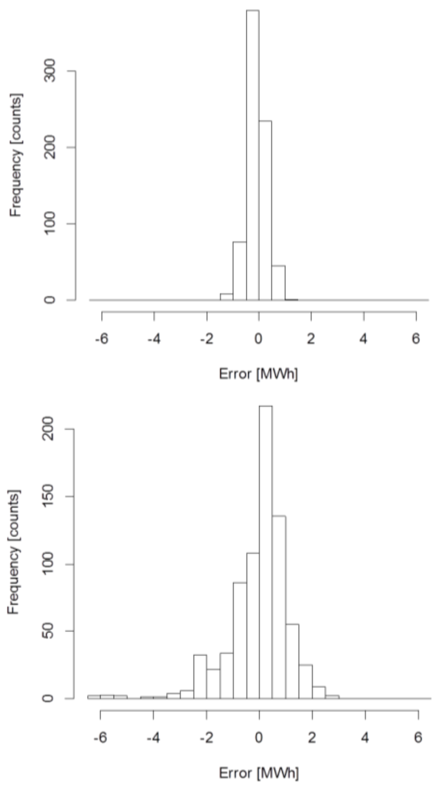

Fig. 8: Frequency histogram of the errors calculated on the ANN model (up) and TSA model (down) testing dataset, performed on the 744 January data.

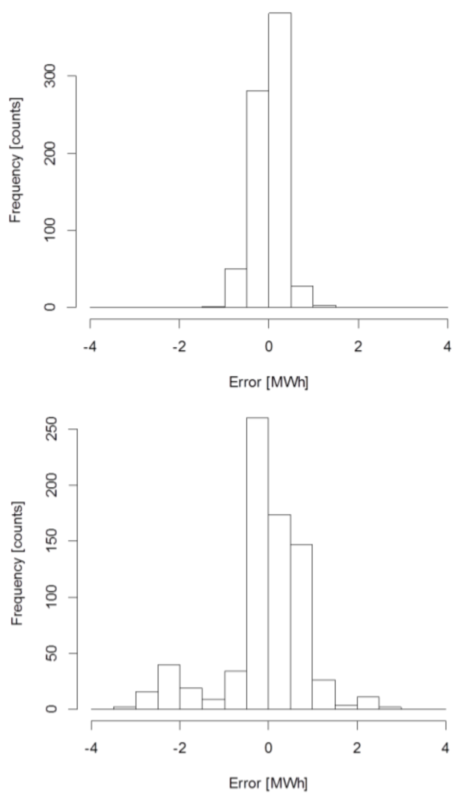

Fig. 9: Frequency histogram of the errors calculated on the ANN model (up) and TSA model (down) testing dataset, performed on the 720 May data.

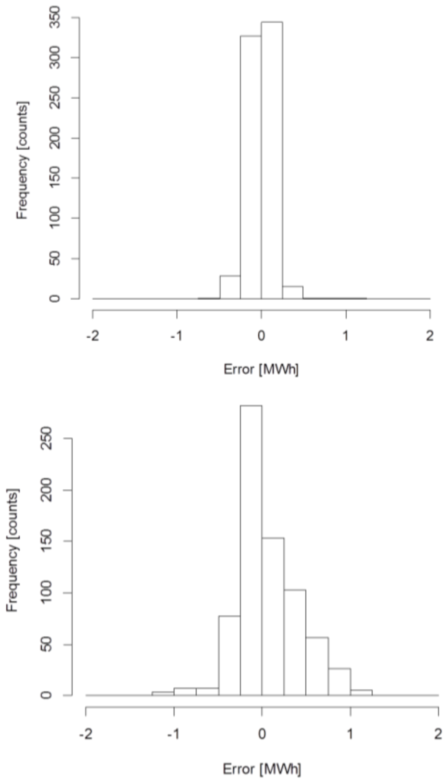

Fig. 10: Frequency histogram of the errors calculated on the ANN model (up) and TSA model (down) testing dataset, performed on the 720 July data.

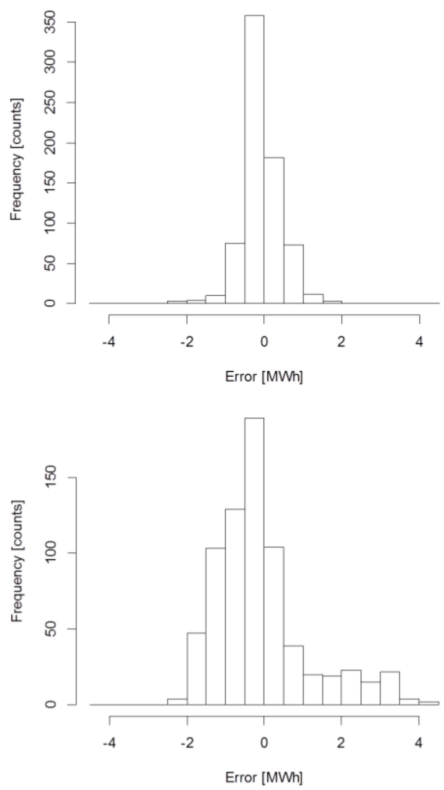

Fig. 11: Frequency histogram of the errors calculated on the ANN model (up) and TSA model (down) testing dataset, performed on the 744 November data.

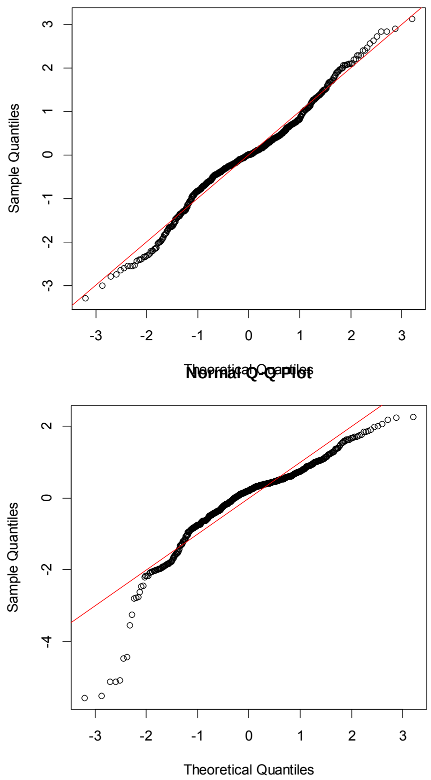

Fig. 12: Normal probability plot that describe error behaviour of the ANN model (up) and TSA model (down) applied to the 744 testing data of January 2013.

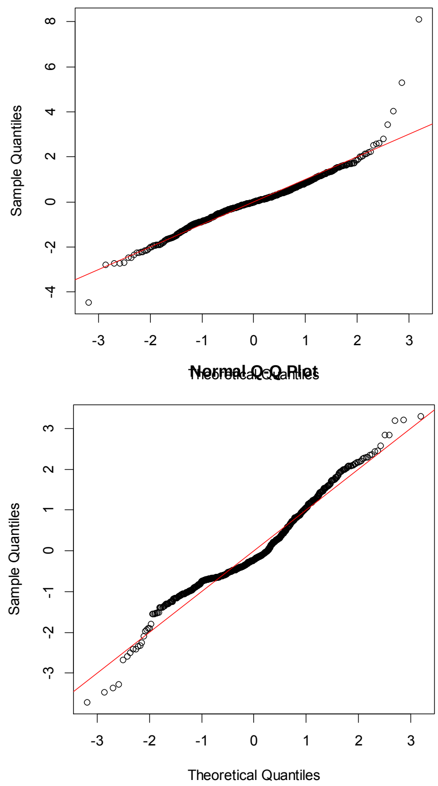

Fig. 14: Normal probability plot that describe error behaviour of the ANN model (up) and TSA model (down) applied to the 720 testing data of July 2013.

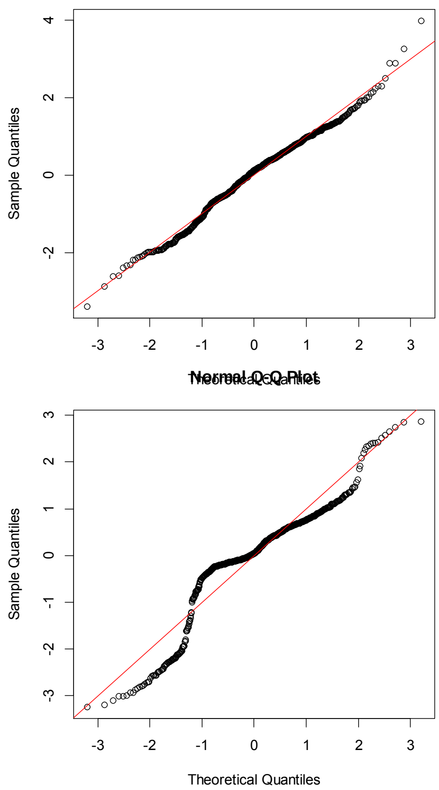

Fig. 13: Normal probability plot that describe error behaviour of the ANN model (up) and TSA model (down) applied to the 720 testing data of May 2013.

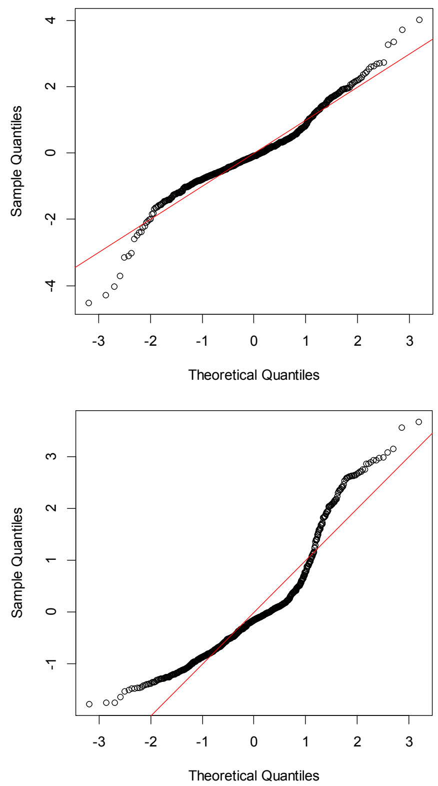

Fig. 15: Normal probability plot that describe error behaviour of the ANN model (up) and TSA model (down) applied to the 744 testing data of November 2013.

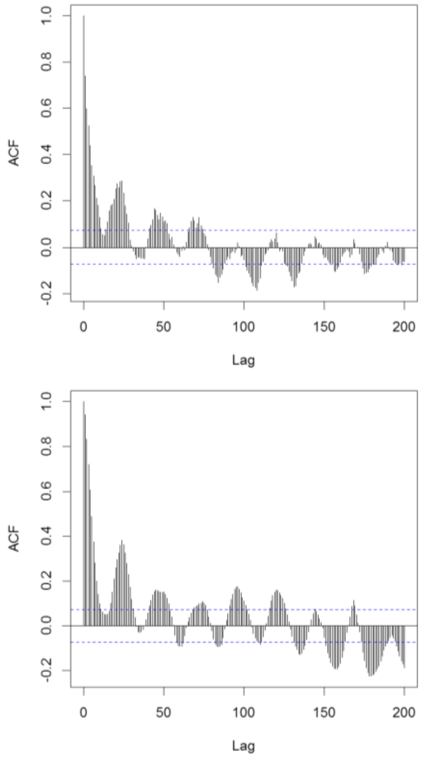

Fig. 16: Correlogram plot for the errors, evaluated in the testing phase (January 2013), of the ANN model (up) and TSA model (down). The value of autocorrelation coefficient is plotted as a function of the lag.

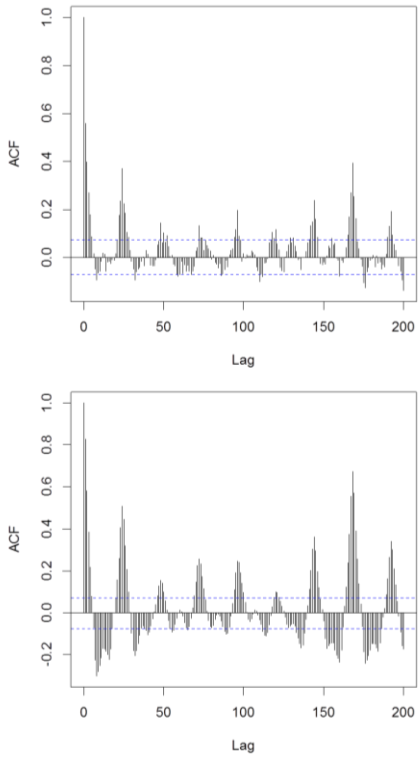

Fig. 17: Correlogram plot for the errors, evaluated in the testing phase (July 2013), of the ANN model (up) and TSA model (down). The value of autocorrelation coefficient is plotted as a function of the lag.

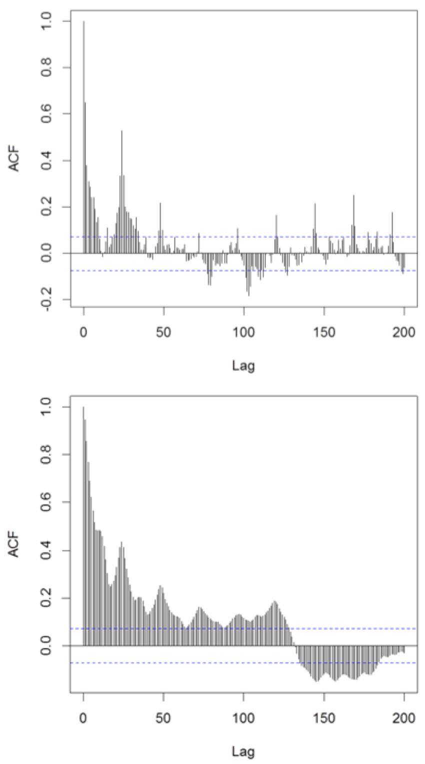

Fig. 1716: Correlogram plot for the errors, evaluated in the testing phase (May 2013), of the ANN model (up) and TSA model (down). The value of autocorrelation coefficient is plotted as a function of the lag.

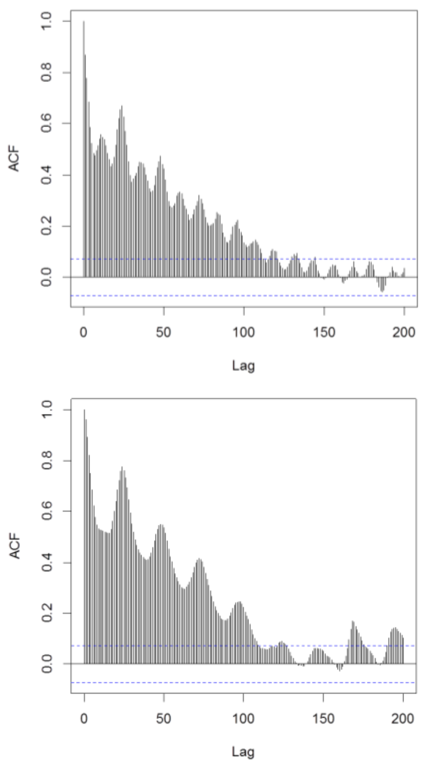

Fig. 18: Correlogram plot for the errors, evaluated in the testing phase (November 2013), of the ANN model (up) and TSA model (down). The value of autocorrelation coefficient is plotted as a function of the lag.

Tab. 6: Values of the autocorrelation function in the errors dataset. The function is evaluated for the most representative lags: 24 and 168 hours.

	January	May	July	November
ANN lag 24	0.288	0.530	0.372	0.671
TSA lag 24	0.382	0.437	0.509	0.777
ANN lag 168	0.033	0.251	0.394	0.062
TSA lag 168	0.115	-0.137	0.674	0.169

In general, both the models show an high value of residual autocorrelation that implies the partial capability of the adopted techniques to produce a randomly distributed error. The presence of some relative maximum points of the functions highlights that the errors present some periodicities. In particular, the maximum values of the autocorrelation are obtained in correspondence of a lag of 24 hours (daily periodicity) and 168 hours (weekly periodicity). Values of the autocorrelation function in the errors dataset, in correspondence of these two lags, using the two different models are reported in table 6.

The MPE and CVE results, reported in Table 7, confirm the better performance of ANN model in all the months used to test these two technique.

Tab. 7: MPE and CVE (error metrics) values, calculated in the testing phases, for the two different models.

Dataset	Model	MPE	CVE
January	ANN	-2.3	0.056
	TSA	2.9	0.175
May	ANN	-5.4	0.079
	TSA	-14.9	0.233
July	ANN	1.3	0.040
	TSA	-6.6	0.098
November	ANN	-3.4	0.093
	TSA	-7.6	0.233

4 Conclusions

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

The aim of this work has been to compare different tools able to provide forecasting of electrical absorption. These tools are helpful for the energy providers and the large consumers to pursue a better management and an optimal energy consumption.

Two different techniques have been implemented and compared: one is based on Artificial Neural Network (ANN) and the other is based on Time Series Analysis (TSA) approach. The models have been calibrated on 2011 and 2012 data and the comparison has been performed using four different testing data sets, that are four months of the 2013, not used in the calibration.

The comparison was implemented by graphical techniques, such as plots of the observed and predicted absorptions, and also by a detailed qualitative and quantitative analysis of the error evaluated in the testing phase.

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. Thus, 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.

The TSA, instead, has a lower precision and a larger range of errors, even if the mean error is still 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. In principle, once the model has been calibrated on a sufficiently large dataset, it has no limitation on time range of prediction. 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 2013.

The error behaviour was inspected by the evaluation of the autocorrelation function. The high value of this index, both using the ANN model and the TSA one, opens the way to future studies, for instance enforcing an hybrid model. This new model could adopt the TSA technique and an ANN used in cascade.

Finally, 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, there are good computing platforms at disposal and a short time range is investigate, the ANN model should be preferred, keeping in mind that, in order to be used, it needs also information about temperature, kilometres 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 of the variable, with low mean error and standard deviation, and with the possibility to extend the prediction to time intervals far from the calibration dataset.

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