Time Series Analysis and Forecast of the Electricity Consumption of Local Transportation

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Abstract: - Electricity consumption due to transportation systems is a very important parameter to be monitored and studied in large cities, in order to optimize the energy management. Additional economic and environmental benefits can be obtained if a proper and reliable description and forecast of energy absorption is available. In this paper, a Time Series Analysis Model is presented and applied to the electricity consumption of public transportation in Sofia (Bulgaria). This method is able to consider the trend, the periodic and the random components of a certain set of data varying over the time, with the aim of forecasting future slope of the data. The strong periodic feature of the dataset will allow to build a good predictive model, thanks to the implementation of multiple seasonality in charge to reconstruct the daily, weekly and monthly periodicities. The triple seasonality model will show better performances with respect to the double seasonality one, in terms of error statistics, distribution and randomness. In addition, a proper interpretation of the model coefficients will open the way to the implementation of improved energy management processes.

Key-Words: - Electricity consumption, Time Series, Multiple seasonality, Error analysis.

1 Introduction

Nowadays, efficient energy management is extremely important in large cities. There are several benefits that can derive from an accurate description and forecasting of electricity consumption. The first relates to the management of the energy system of the city. The energy provider requires each large consumer prior to declare needed energy for a given period of time. The second benefit is economic. The cost of energy expended above a stated amount is much higher than the primary. Incorrect queries lead to economic losses for the transport company. The third is the ability to use the model for the development of various business strategies, such as to provide energy consumption when changing routes and number of vehicles.

It is important to highlight that in many advanced countries, in order to improve energy management in the electrical grid, some relevant energy consumers have the possibility to split their loads in a continuously necessary part and in a detachable part. In the transportation case, for instance, the electrical engine of buses requires continuous energy availability, but the electrical energy used for heating systems is a detachable load. If the bus company knows the correct amount of the two load types and can forecast the two types of absorption, it can participate on a smart grid in a Demand Response Resource (DRR) system [1, 2]. Demand response programs are being used by electric system planners and operators as resource options for balancing supply and demand. Demand response provides an opportunity for consumers to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage during

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peak periods in response to time-based rates or other forms of financial incentives [3].

DRRs are demand–side entities which actively participate in the markets as both buyers of electricity and sellers of load curtailment services. The objective of demand response is to make the load an active participant in balancing electricity supply and demand around the clock via side-by side competition with supply-side resources. DRRs curtail their loads in response to incentive payments to lower electricity consumption at specified times. For this reasons, a reliable prediction can be extremely useful to design and perform DRRs.

In general, several predictive models for energy consumption are present in literature and are based on different approaches, such as Neural Networks, Support Vector Machines, Fuzzy logic, statistical tools, etc. [4-9].

Time Series Analysis (TSA) models are able to consider the trend, the periodic and the random components of a certain set of data varying over the time. They have been adopted for the prediction of road traffic noise [10, 11]. The comparison with other traffic noise models ([12-24]) showed good performances, both in the case of single seasonal coefficient and in the case of double periodicity. Another application of TSA model can be the prediction of air pollution components time evolution. For instance, in [25] the hourly ozone concentration in Monterrey area (Mexico) is modelled by means of a TSA model. In this case, the general trend was achieved, while the local oscillations were roughly predicted.

In this paper a multiple seasonality TSA model is presented and applied to the electricity consumption of local transportation in Sofia (Bulgaria). The goal is to obtain an adequate model describing the process, to be used to predict the electricity required for a given future period.

2 Methods

2.1 Model presentation

The Time Series Analysis (TSA) model adopted in this paper is largely used in several domains, such as Economics, Physics, Engineering, Mathematics, etc. (see for instance [26-30]). In particular, the authors applied these techniques to road traffic noise prediction [10, 11] and to air pollution [25], obtaining good predicting performances.

The general idea of these TSA models is to reproduce the behavior of the data and to predict the future slope, by composing the trend and the periodicity of the time series, and by adding an error component obtained analyzing the residuals in the calibration phase. The latter component is in charge of compensating the oscillations due to the random part of the time series (background noise). The way these three parts are composed define a multiplicative, additive or mixed model.

The detailed description of the TSA model procedure, with single seasonality pattern, can be found in [10]. The formula of the forecast F_t is:

$$F_t = T_t \bar{S}_i \quad , \tag{1}$$

where T_t is the trend, $\bar{S}_i$ is the seasonal coefficient.

The trend is calculated as a linear regression on the observed data.

It is important to underline that the more periodic is the time series, the more precise will be the model prediction. When two periodicities are present in the data (such as in [11]), it is necessary to use two seasonal coefficients. The forecast formula of the Double Seasonality TSA model (DSM) is:

$$F_t = T_t \, \bar{S}_{1,i} \, \bar{S}_{2,j} \quad , \tag{2}$$

where $\bar{S}_{1,i}$ and $\bar{S}_{2,j}$ are the two different coefficients.

In order to remove the effects of short period seasonality from the data, a centred moving average with width k_1 (first lag detected) can be used. Then, it is possible to evaluate the recurring effect, $S_{1,t}$, on the single hour by the ratio between the actual data at time t and the centred moving average at the same t :

$$S_{1,t} = \frac{A_t}{M_{(k_1)t}} \quad , \tag{3}$$

where $M_{(k_1)t}$ is the centred moving average with width k_1 , at the period t.

Finally, evaluating the mean of these effects $S_{1,t}$ on $m_{1,i}$ homologous periods (that are the same hours of each day), the seasonal coefficient $\bar{S}_{1,i}$ is obtained:

$$\bar{S}_{1,i} = \frac{\sum_{l=0}^{m_{1,i-1}} S_{1,i+lk_1}}{m_{1,i}} \quad . \tag{4}$$

At this point, it is possible to clean up the values of the first moving average from the effect of the second seasonality with lag k_2. That is done using a second centred moving average process, with width k_2 (second lag detected). As in the previous step, the effect of the second seasonality for each period ($S_{2,t}$)

can be calculated, and a second seasonal coefficient can be evaluated with a mean on $m_{2,j}$ homologous periods:

$$S_{2,t} = \frac{M_{(k_1)t}}{M_{(k_2)t}} \ , \tag{5}$$

$$\bar{S}_{2,j} = \frac{\sum_{l=0}^{m_{2,j}-1} S_{2,j+lk_2}}{m_{2,j}} , \tag{6}$$

where $M_{(k_2)t}$ is the centred moving average with width k_2 , at the period t.

In our case, as it will be described in the next sections, the Double Seasonality Model (DSM) fails in following the winter/summer changes in the electricity consumption. Thus, a third coefficient is introduced by means of a corrective term, obtained dividing the average value of the measured electricity consumption in the h-th month (with h varying from 1 to 12) by the average value of the estimated trend line in the same month:

$$\bar{S}_{3,h} = \frac{\sum_{t=a_h}^{b_h} A_t}{\sum_{t=a_h}^{b_h} T_t} \ , \tag{7}$$

where a_h and b_h are the progressive number of the first and the last hours of the h-th month in the considered dataset.

Therefore, the forecast formula of the resulting Triple Seasonality TSA model (TSM) is:

$$F_t \ = \ T_t \, \bar{S}_{1,i} \, \bar{S}_{2,j} \, \bar{S}_{3,h} \ . \tag{8}$$

After the calibration phase on a given dataset, the forecast can be performed by means of a final extended formula:

$$F_t \ = \ T_t \, \bar{S}_{1,i} \, \bar{S}_{2,j} \, \bar{S}_{3,h} + \ m_e \ , \tag{9}$$

that includes also m_e , 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:

$$e_t = A_t - F_t. \tag{10}$$

2.2 Linearity tests

A Time Series is linear if it can be expressed as a linear combination of Z_t independent random variables, with ψ_j unknown constant parameters [31]:

$$X_t = \sum_{j=-\infty}^{+\infty} \psi_j Z_{t-j} \ . \tag{11}$$

When this condition is not verified, the time series is non-linear. The non-linearity implies that the usual regressive model adopted in TSA cannot be applied. In order to check the linearity presence, some proper tests can be performed. In this paper, the authors adopt the Lee-White-Granger (LWG) test [32] and the Terasvirta-Lin-Granger (TLG) test [33].

3 Case study

Electricity consumption of the local transportation in Sofia (Bulgaria) is considered as a case study.

In the hauler “Transenergo”, the Power Engineer has to declare necessary electricity consumption for every hour of the following week. The incorrect request affects the price of the electricity. Electricity consumption is a random process which depends on many factors. The Power Engineer has information for the following data: kilometers run, temperature, the kind of day and from this information has to declare the necessary electricity consumption [4].

The data of consumption, in MWh, are provided by an electronic energy meter that measures the hourly electricity consumption during night and daytime. The dataset is related to 2011 year, i.e. period that goes from the 1st of January 2011 to the 31st of December 2011.

The electrical transport in Sofia has started in 1901. Currently in Sofia electrical trams and trolleybuses are a relevant part of the public transportation, carrying each year, millions of passengers. In 2008, for instance, over 198 million of passengers have been transported [34].

Power is delivered by 24 rectifier stations with a total installed capacity of over 125950 kW. The network consists of over 263 km tram tracks and 257 km trolley tracks, and the cable network is more than 740 kilometers [34].

Since summer and winter exploit a strong variation in average temperatures, with a consequent different usage of electrical heating system, and since in summer transportation schedule a smaller number of vehicles is used, a seasonal variation in electricity consumption is expected. The same occurs for week (working) days and weekend days (and public holidays), such as for day and night variations. This suggests weekly and daily periodicities.

In general, in the last decades, electricity consumption in Bulgaria has been growing but, thanks to the operating nuclear plants, the country satisfied the internal request and was able to export part of the produced electrical power. However, since 2006, the export of electricity have been

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reduced because of the closing of two older nuclear units. This energy production changes requires a more effective management of local consumptions.

4 Data analysis and results

The first step, in order to build the model, is to analyse the dataset to be used in the calibration phase. The choice was to consider the hourly electricity consumption, measured during all the year 2011.

The calibration dataset is made of 8760 hourly electricity consumptions, measured in MWh, and the summary statistics are resumed in Table 1.

As it can be noticed from skewness and kurtosis values, the distribution is normal. In addition, the high value of standard deviation with respect to the mean, together with the maximum and minimum values, exploits a very spread distribution.

The load duration curve, i.e. the plot of energy consumption (sorted in descending order) versus the number of hours in which that value of consumption is obtained and surpassed, is reported in Fig. 1.

Table 1: Summary of statistics of the calibration data set, 8760 data, in Megawatt hour.

Mean [MWh]	Std.dev [MWh]	Median [MWh]	Min [MWh]	Max [MWh]	skew	kurt
5.14	3.12	5.28	0.22	12.62	0.17	-0.75

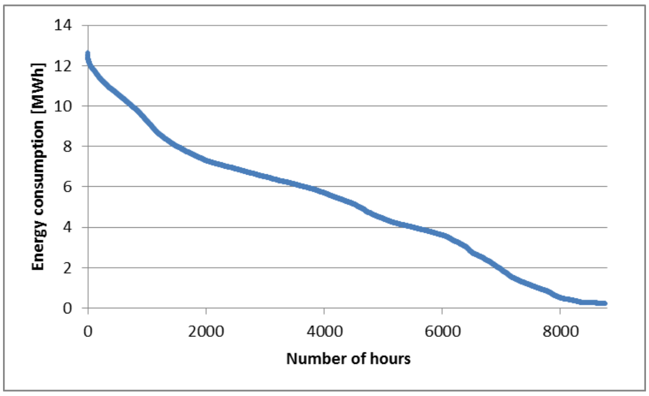

Fig. 1: Electricity consumption sorted by descending order of magnitude. The *x* axis reports the number of hours in which the corresponding electrical consumption is exceeded.

Table 2: Ljung-Box and Box-Pierce tests performed on the 8760 measurements of the calibration dataset.

Test	χ^2	*h*	*p*-value
Ljung-Box	53542.33	30	< 2.2e-16
Box-Pierce	78500.02	50	< 2.2e-16

Table 3: Lee-White-Granger (LWG) and Terasvirta-Lin-Granger (TLG) tests for linearity performed on the 8760 measurements of the calibration dataset.

Test	Statistic of the test	*df*	p-value
LWG	37.4105	2	7.524e-09
TLG	35.4774	2	1.978e-08

In the previous section, it has been discussed the probable presence of three periodicities, a daily one, a weekly one and a seasonal one, that will be implemented on a monthly base. In order to check if the data are autocorrelated or not, the Ljung-Box (LB) and Box-Pierce (BP) tests have been performed. Results are reported in Table 2, in which the small *p*-values in both tests, i.e. the very small probability to observe the sample if the null hypothesis is true, indicates that the hypothesis of absence of autocorrelation in the data can be rejected.

The linearity tests proposed in the section II, are performed on the time series under study, in the “R” software framework. The resulting very low probability values, reported in Table 3, suggest to reject the null hypothesis, i.e. the linearity of the time series. The tests result and the good performances of the model presented in this section highlight its capability of reproducing the non-linear feature of the time series.

The autocorrelation of the data has been evaluated by means of an autocorrelation plot (correlogram), reported in Fig. 2. It is evident the presence of several periodicities. In particular the maximum values of the autocorrelation are obtained in correspondence of a lag (period) of 24 hours (daily periodicity) and 168 hours (weekly periodicity). The latter periodicity is confirmed by the highest autocorrelation value in the correlogram of the first moving average data, calculated with 24 hours span (Fig. 3).

Figures 4, 5 and 6 report the auto dispersion plots of three different datasets: in all cases that data are clustered around the bisector, confirming the presence of the presumed lag. Figure 4 reports the observed dataset and it is plotted as a function of the same data shifted by 24 hours. Two patterns are evident out from the bisector line, showing that more periodicities are present. Figure 5 reports the auto dispersion of the observed dataset as a function of the same data shifted by 168 hours, i.e. one week. Again, the data follow the bisector, but still some of them seem to be not randomly distributed. Figure 6,

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instead, reports the centred moving average data (span 24), plotted versus the same data shifted by 168 hours (one week). The plot shows a general gathering along the bisector line, with some variations that are mostly symmetric with respect to the bisector. This result confirms the presence of a further periodicity, with low frequency.

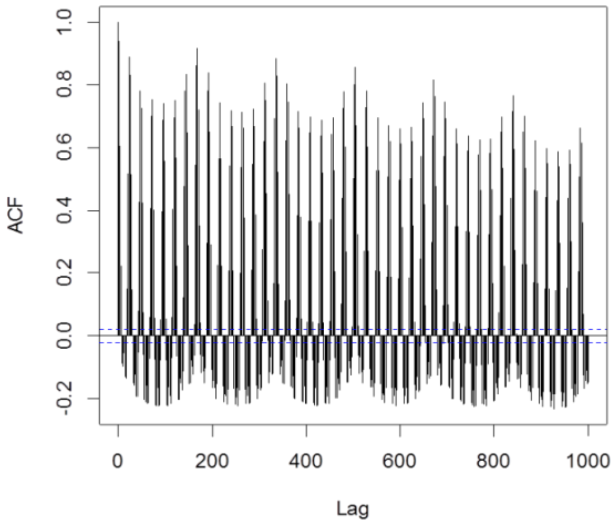

Fig. 2: Autocorrelation plot (correlogram) of the data as a function of the lag (periodicity).

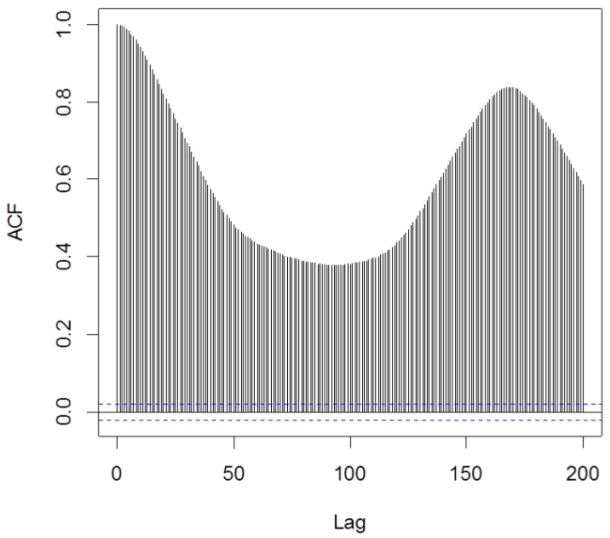

Fig. 3: Correlogram for the first centred moving average data. The value of autocorrelation coefficient is plotted as a function of the lag.

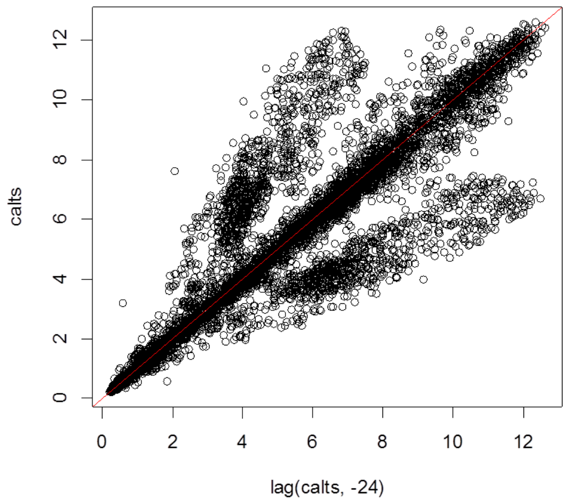

Fig. 4: Auto dispersion plot of the electricity consumption dataset plotted as a function of the same data shifted by 24 hours.

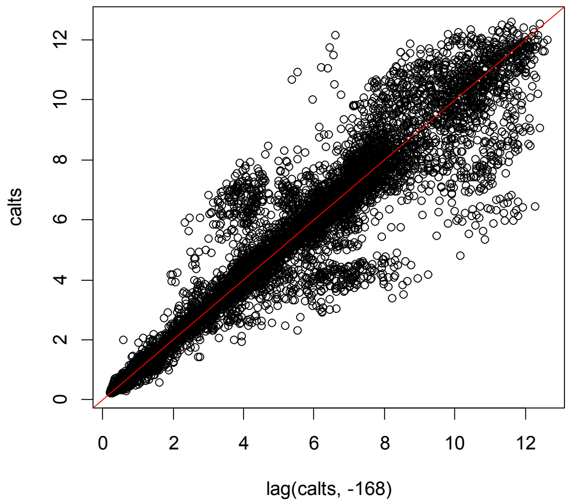

Fig. 5: Auto dispersion plot of the electricity consumption dataset plotted as a function of the same data shifted by 168 hours.

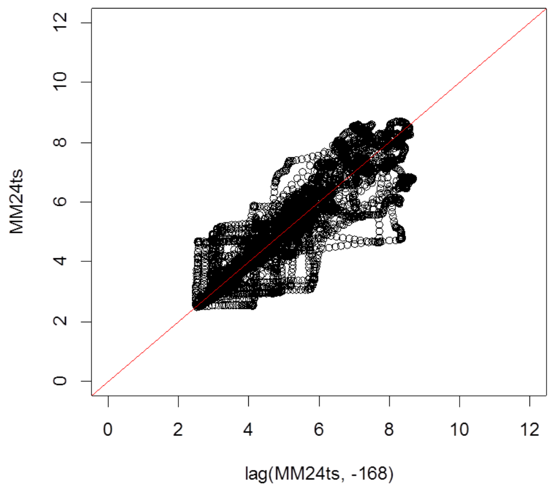

Fig. 6: Auto dispersion plot of the moving average with span 24 plotted as a function of the same moving average data shifted by 168 hours.

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Once the periodicities have been detected, the model has been built as described in Section II. The moving averages are plotted in Figure 7, together with the trend line.

The set of TSA model parameters, that are trend line parameters and 24 first seasonality (daily) coefficients, is reported in Table 4, while the 168 second seasonality (weekly) coefficients are plotted in Figure 8.

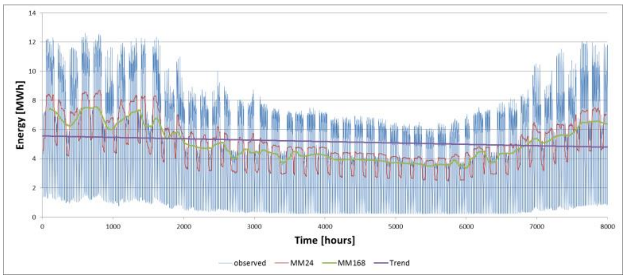

Fig. 7: Plot of the two centred moving averages and of the trend line. In blue the actual data, in violet the trend line, in red the first moving average (span 24), in green the second moving average (span 168).

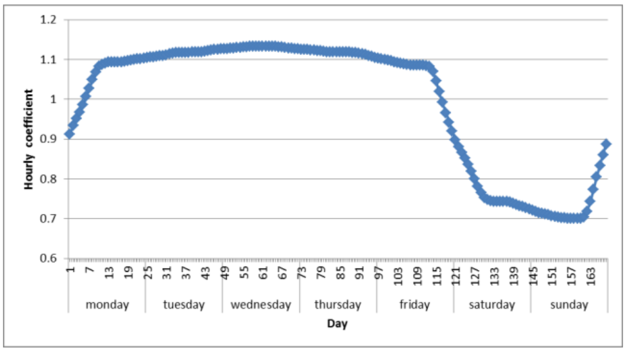

Fig. 8: Hourly coefficient used by the model to reconstruct the weekly periodicity in the dataset.

With this procedure, a Double Seasonality TSA Model (DSM) has been built. The result of the forecast of the DSM are shown in Figure 9, together with the observed values dataset. It is easy to notice that even if the model forecasts follow the local (daily and weekly) oscillation, there is a long term (low frequency) periodicity to be still included. As reported in section II, a third coefficient, in charge of describing the monthly seasonal behavior of the data, is introduced. This corrective coefficient is calculated according to formula (7), i.e. dividing the average value of the measured electricity consumption in each month by the average value of the estimated trend line in the same month.

Table 4: Model parameters estimated on the 2011 electricity consumption data. b_0 and b_1 are respectively the intercept and the slope of the trend line, while $\bar{S}_i$ is the hourly coefficient, to reconstruct the daily periodicity, in the time range from *i*-1 to *i* hour.

Time Series Model parameters			
b_0	5.55998	b_1	0.0000957
$\bar{S}_1$	0.14318	$\bar{S}_{13}$	1.38711
$\bar{S}_2$	0.10604	$\bar{S}_{14}$	1.28621
$\bar{S}_3$	0.10540	$\bar{S}_{15}$	1.22370
$\bar{S}_4$	0.11779	$\bar{S}_{16}$	1.26628
$\bar{S}_5$	0.42944	$\bar{S}_{17}$	1.28007
$\bar{S}_6$	0.97802	$\bar{S}_{18}$	1.35565
$\bar{S}_7$	1.26947	$\bar{S}_{19}$	1.41998
$\bar{S}_8$	1.47812	$\bar{S}_{20}$	1.39447
$\bar{S}_9$	1.43660	$\bar{S}_{21}$	1.22622
$\bar{S}_{10}$	1.36739	$\bar{S}_{22}$	0.80087
$\bar{S}_{11}$	1.38302	$\bar{S}_{23}$	0.60751
$\bar{S}_{12}$	1.41843	$\bar{S}_{24}$	0.46727

These 12 ratios are able to describe the long term variations of the time series. The resulting monthly coefficients are plotted in Figure 10 and exploit the higher electricity consumption observed during cold months, probably due to higher number of vehicles running and to heating systems.

The application of the third seasonal coefficient to the DSM, produce a Triple Seasonality TSA Model (TSM) whose forecasts are plotted in Fig. 11 together with the observed data.

In order to better depict the improvement produced by the third seasonal coefficient, a plot of the DSM and TSM forecasts and of the observed data, in the summer time range (from 4000 to 4500 hours), is reported in Figure 12.

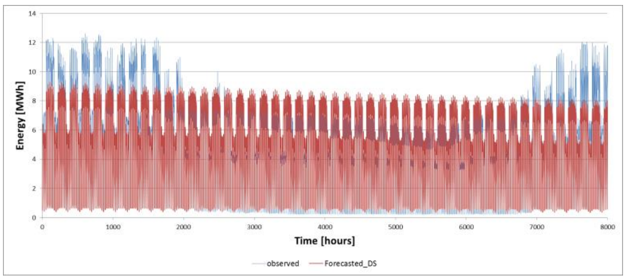

Fig. 9: Observed electricity consumption and Double Seasonality TSA model results, plotted in 2011 time range.

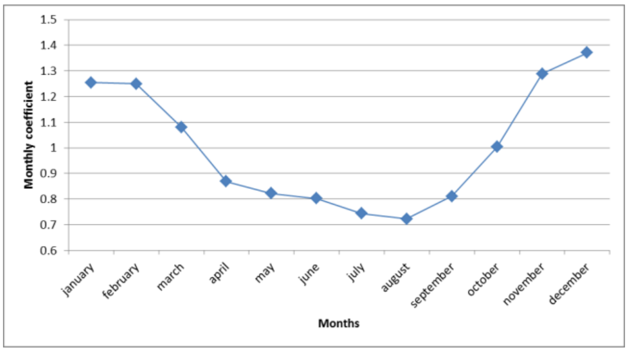

Fig. 10: Monthly coefficient used by the model to reconstruct the third seasonal behaviour of the electricity consumption.

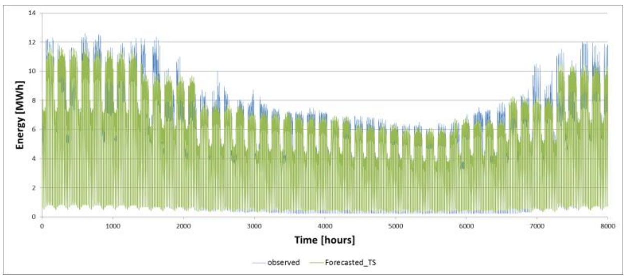

Fig. 11: Observed electricity consumption and Triple Seasonality TSA model, plotted in 2011 time range.

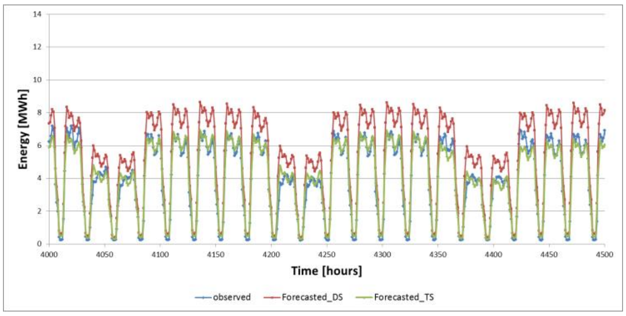

Fig. 12: Observed (blue line) and predicted electricity consumption according to DSM (red line) and TSM (green line), during 2011: zoom on the time range from 4000 to 4500 hours.

The TSM better agrees with the observed data in quite all the range, while the DSM model underestimates during winter time and overestimate in summer months. Few local oscillations are lost.

In order to quantify the performances of the complete model (TSM), an error analysis has been done both on DSM and TSM. Comparing the error statistics of both models (Table 5), it can be noticed that the standard deviation strongly decreases when moving from double to triple seasonality. Also the median and the spread between minimum and maximum error improve when introducing the monthly periodicity.

Table 5: Summary of statistics of the error distribution in the Double Seasonality Model (DSM) and Triple Seasonality Model (TSM), evaluated on the calibration dataset; results are given in MWh.

Model	Mean [MWh]	Std.dev [MWh]	Median [MWh]	Min [MWh]	Max [MWh]
DSM	0.02	1.49	-0.25	-4.86	4.92
TSM	0.02	0.81	0.03	-3.99	3.6

In DSM case, the histogram of errors (Figure 13) is right skewed, while in TSM case the distribution (Figure 14) is more Gaussian-like, suggesting that after introducing the third coefficient the errors are randomly distributed.

Finally, in Figures 15 and 16 respectively the correlogram of the DSM and the TSM errors are reported. It is evident that in the DSM case the errors are still strongly autocorrelated, while in TSM, thanks to the adoption of the third seasonal coefficient, this effect is clearly reduced.

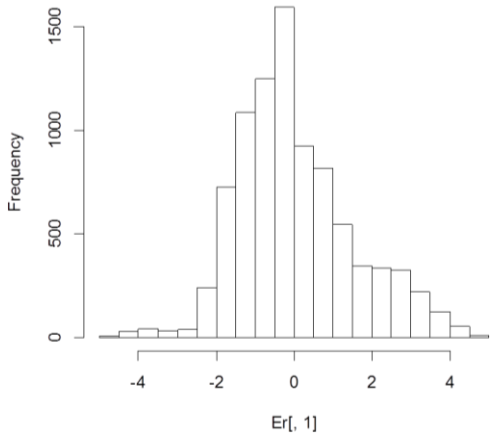

Fig. 13: Frequency histogram of the errors calculated on the Double Seasonality Model, performed on the 8760 calibration data.

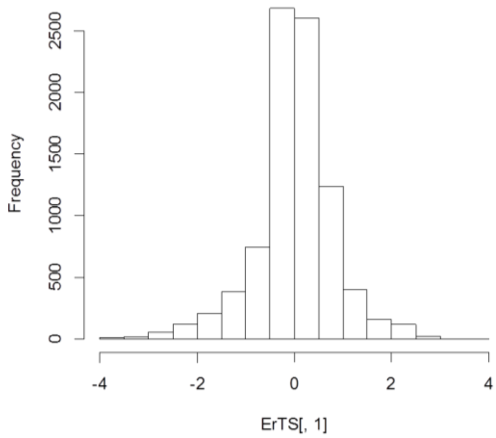

Fig. 14: Frequency histogram of the errors calculated on the triple seasonality model, performed on the 8760 calibration data.

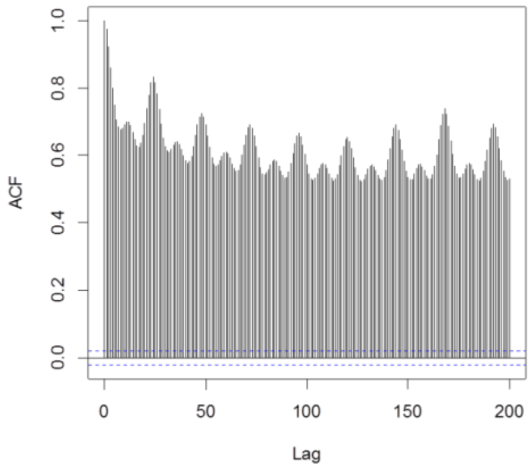

Fig. 15: Correlogram for the errors, Double Seasonality Model . The value of autocorrelation coefficient is plotted as a function of the lag.

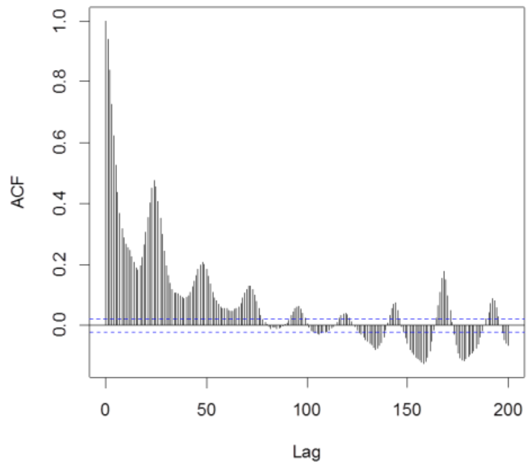

Fig. 16: Correlogram for the errors, Triple Seasonality Model. The value of autocorrelation coefficient is plotted as a function of the lag.

5 Conclusions

The implementation of a Time Series Analysis model to electricity consumption of public transportation in Sofia (Bulgaria) is presented.

With respect to previous applications of this model, a multiple seasonality is present in the data and a third seasonal coefficient is introduced. In this way, the daily, weekly and monthly periodicities are reproduced by the Triple Seasonality TSA Model (TSM). A comparison between a Double Seasonality Model (DSM) is performed by means of error distribution analysis, i.e. the analysis of the difference between observed values and forecasts. The improvement of error statistics and distribution is obtained with TSM and the strong reduction of autocorrelation in the error dataset is achieved with respect to DSM case.

Finally, the presented model fully achieved the aim of reproducing the behavior of the data used in the calibration, in terms of general trend and periodicities.

In addition, besides the good prediction performances of the model, its coefficients can be used to better understand the consumptions behavior in different seasons and conditions. For instance, regarding the raise of consumption during winter time, the percentage of absorption due to heating system can be studied according to the monthly coefficients, in order to understand if a load curtailment process can be performed.

Further studies could be the comparison of the presented model results with other models, such as, for instance, neural network models.

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