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MODEL ANALYSIS FOR THE TREND OF SOME TIME SERIES WHICH ARE DESCRIBING THE ENERGY EFFICIENCY IN THE RAILWAY SUBSTATIONS

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The original aspects of this paper consists in the presentation of the trend model analysis of some time series which are describing the forecast calculation and implicit the energy efficiency in the railway substations. It will be described which method is the most exact one and gives the best results. Those calculations are representing a very important issue in the electrical distribution networks, because only so energy efficiency measures can be taken. The main focus will be to find the exact calculation method in order to forecast the energy consumption in the substations and to optimize the energy efficiency.

Keywords: trend model analysis, time series, forecast calculation, energy efficiency

1. Introduction

The importance of the forecast in the energy efficiency issues grew in the last period exponential because without an exact consumption forecast it not possible to even talk about energy efficiency and optimization. The initiator of the privatisation process of the electricity distribution, the generalization of the dealing on the market, new mechanisms and instruments for the market risk management and the bigger decentralization of the dealing with electric energy are some of the most important aspects in which the forecast studies on short term are very important. The powerful industrial developments have brought important changes in all areas, and this were reflected in the environment and also at the society level. The only possibility for maintain the control on the fast and important changes is the adaptive behaviour against all those changes. This means in the first place to establish a future development and exact appreciation of the influencing factors and in the second place to take the right decisions based on the forecast behalf, in order to meet the purposes goal.

It is self-understood that the forecast process and taking decisions based on it, are processes developed in time, in conditions of aleatoric perturbation [1-3]. Furthermore the adaptation process must be continuous, showed in forecasts

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and rehearses by corrections which will maintain the evolution on the target. Once that we are closer to the specific targets, some other future targets will arise which presumes new forecast horizons and new decisions [4-5].

Following this idea, the next definition for both energy consumption forecast and power: The energy consumption and power forecast is the scientific activity who has the purpose to predict the energy consumption and power, based on different data calculations and analyses, so that will be realised a obvious concordance between estimated consumption and real consumption.

2. Establishing the mathematical model of the consumption

The methodology of forecast study elaboration for the energy consumption has few main steps:

- measurement, selection and analyse of the initial data;
- establishing the mathematical model for the consumption;
- variance analyse which has been obtained for the forecast and establishing the final decision.

For realising a more specific forecast we must use a large data base which should content [6-7]:

- the values for the global energy consumption with their components also (if it is possible), for a long enough period of time (minimum 5 years).
- the developments of the economical, demographical, climatically factors in that certain period of time.

In this forecast stage, it is realised a first data selection and processing, which consists in graphical outputs and than their statistical conversion [9-11].

3. The components for the mathematical model of the energy consumption curve

The consumption curve represents the energy variation in time (or taking into consideration another parameter) and it can be split in several components. Forecast experience of the energy consumption shows the existence of four main components, which establishes the consumption curve (W) (fig.1):

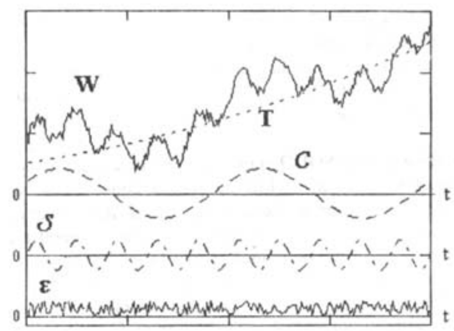

Fig.1. the mathematical model components for the energy consumption curve [1,11]

1. The trend (T) represents the consumptions main compound, establishing the energy consumption behaviour.
2. The cyclic component (C) shows the fluctuant causes with slowly effect like the demand-supply correlation on a period over a year.
3. The seasonal component (S) it is caused by certain parameters which presents seasonal fluctuations (especially climatic changes). This component has a few months variation period and a similar shape for all years.
4. The aleatoric component (ε) represents the stochastic elements and it is normally previously specified.

As a conclusion, the energy consumption is the sum of all elements specified above:

$$W(t)= T(t)+C(t)+S(t)+\varepsilon(t) \quad (1)$$

As a rule, the forecast methods are elaborated for the consumption's components sum. For this reason it becomes a current application and it is necessary in the first stage of the forecast calculation to bring the model at the standard configuration (1) using functions transformations and proper chosen variables. There are two main criteria for choosing the proper transformation:

- viewing the consumption graphics
- the statistics indicators, which can be calculated from the consumptions curve offers relevant information for finding the correct transformations which distinguish the consumptions components and the way they associate.

When the consumptions forecast is made, it is used to estimate separately each consumptions component variation, getting the final result by summing the components forecast results.

4. The description of some mathematical models, often used in forecast studies

The models described below usually reports to the consumptions curve trend component. An exception is made by the events when the aleatoric component is also inserted by the uncertainty factor. In fact, it might be considered if necessary, in same way as other models and adding the uncertainty factor. The econometric models are characterized through the mathematical wording that results after a technical-economical analyze and followed by a statistic check [6-11]. The models which belong to this category are:

- the autonomous extrapolation time is the only variable, chasing the energy consumption variation trend
- conditional adapting

4.1 The extrapolative methods principle

The direct forecast methods are supposing the assumption that the causes[1,5,6,11], the factors and the trends which establish the energy consumption in the past are remaining the same also in the future, without appearing any dramatic and sudden changes during the forecast which will affect the evolution consumption.

This assumption will justify the energy consumptions evolution trend extrapolation from the past for the future period and bring the forecast problem to the analysis of the energy consumption variation law from the past to the future.

The mooted forecast methods are supposing the establishment of a mathematical model likeness a one or more variables function (generally a single variable, time) who fairly estimates the trend on the last period [11]. The estimation of the functions coefficients is making by solving an equations system where the coefficients are calculating means the energy consumptions from the last period.

4.2 The estimation for the model components

It is considered an observed value set yt, of a chronological series [1,5,6,11].

Mathematical shaping can be made using an additive model:

$$yt = Tt + Ct + St + Rt \qquad (2)$$

where: Tt represents the trend (continuous component), Ct represents cyclical component, St represents seasonal components, Rt represents the component due to aleatory variations.

5. Conclusions

Data estimation and forecast can be done by applying more shaping methods. For certain phenomenon categories bounded by season's cyclicity, the classic model is useful and might serve as development base.

The usage of a recursive approximation procedure gave satisfactory results so in great variations conditions it can be developed a model which takes into account the previous data. This techniques application is possible only trough the programming medium MatLab.

It was analysed the possibility of a optimal model for the energy consumption trend in the railway substations. The analysed data was daily measured, during one calendaristic year (Table 2). For this purpose there were use different analyse methods of the stochastic deterministic component.

In order to obtain an analytical expression of the function which describes the temporal series trend from the Table 1, they were used calculation methods like Fourier Sum with 1 till 8 terms, polynomial regressions, classical exponential functions, polynomial functions, sinus sum with 1 to 8 terms, Smoothing Spline, Interpolant-Nearest neighbour, Interpolant cubic-spline and Interpolant Shape-preserving.

In each case were calculated the validation statistic indicators: SSE, R^2 , $\overline{R^2}$, RMSE and the measured data graphically depicted. The graph of the residual series was also drawn in the Figures. In this paper there are represented only the 6 most important solutions. The calculations are made for trusted intervals of 95% and the deliverables are presented in table 1.

Table 1

Modelling type	Ecuation	SSE	R2	$\overline{R^2}$	RMSE
Fourier k=1	(Fig.1)	3.357e+007	0.4227	0.4176	313.8
Fourier k=2	(Fig.2)	3.043e+007	0.4766	0.4689	299.6
Fourier k=8	(Fig.3)	9.825e+006	0.831	0.8222	173.3
Gaussian k=2	(Fig.4)	3.585e+007	0.3835	0.3744	325.2
Gaussian k=5	(Fig.5)	1.043e+007	0.8207	0.8131	177.8
Sum of Sinus k=8	(Fig.6)	8.643e+006	0.8514	0.8407	164.1

From all the trend adjustment methods, it was chosen the analytical method which takes in consideration all the terms of the chronological series (measured daily values) that we have. This method fundaments its calculation on mathematical functions of trend adjustment and general tendency estimation. They will be set usually in consideration with the real tendency of the electricity consumption tendency in time. This is highlighted at the beginning by the graphical depiction. After the adjustment function is chosen, it is necessary to estimate the regression function parameters. The analysis of the general tendency estimation is a problem of statistical decision which becomes necessary when several regressions are tested. In general, the most important statistical parameters are: standard correlation coefficient R^2 and/or adjusted $\overline{R^2}$, the root mean square error RMSE and the summed square of residuals SSE. It is easily seen just from the beginning that the adjustments ”Interpolant-Nearest neighbour”, ”Interpolant Cubic-spline” and ”Interpolant Shape-preserving” can be used only for interpolation purpose or to estimate an absolute trend (in this particular case, the residual series is zero, which determines the impossibility of the analysis of the other 3 factors which are characterising a dynamic series).

It was calculated that for Gaussian functions with one term and with more than 5, the estimation parameter process is not convergent. The same issue was demonstrated by the polynomial regressions higher than power 3.

Notation:
SSE= summed square of residuals
R^2= correlation coefficient
$\overline{R^2}$ = adjusted correlation coefficient
RMSE= root mean square error
The calculations are made for trusted intervals of 95%

Table 2

y(t) =[2.0323 2.0191 2.0368 2.0480 1.9342 1.9629 1.9540 1.9627 1.9408 2.0737 2.186 2.1850
2.1102 2.1017 2.0813 2.0692 2.0984 2.0959 1.9836 2.0876 2.1330 2.1353 2.2134 2.2685 2.2614
2.1511 2.25872.2952 2.2700 2.2783 2.5423 2.3098 2.2222 2.2037 2.2540 2.3251 2.2216 2.2400
2.2455 2.1831 2.1788 2.1709 2.1761 2.1603 2.1512 2.0573 1.9661 1.8736 2.0612 2.1940 2.1453
2.1632 2.1290 1.9791 1.9992 2.0941 2.0824 2.1180 2.1681 2.0936 1.9415 1.9529 2.1637 2.2268
2.1786 2.1431 2.0836 1.8186 1.73601.8637 1.8920 1.8607 1.9058 1.8496 1.7131 1.7420 1.8984
1.9922 1.9594 1.9618 2.0025 1.8225 1.7106 1.8451 1.8689 1.9669 1.8437 1.8156 1.3311 1.4298
1.6524 1.7167 1.8932 1.8800 1.8933 1.6068 1.7287 1.7883 1.7831 1.8588 1.9280 1.7612 1.6672
1.6751 1.6635 1.8662 1.8604 1.9022 1.8435 1.6748 1.6412 1.7744 1.7683 1.9094 1.8273 1.7208
1.6324 1.6013 1.7812 1.7979 1.8327 1.8105 1.7262 1.6541 1.6207 1.7610 1.7899 1.7762
1.77711.7809 1.7249] 1.5767 1.5959 1.6482 1.7632 1.7322 1.6470 1.4662 1.3551 1.5316 1.5327
1.7137 1.7026 1.6985 1.5638 1.5676 1.5665 1.7384 1.7559 1.8328 1.7078 1.5978 1.6303 1.7045
1.8470 1.8354 1.7975 1.7750 1.6080 1.7279 1.7663 1.7918 1.7523 1.8296 1.7433 1.6463 1.6838
1.8151 1.8485 1.81281.8027 1.7447 1.5434 1.7683 1.9094 1.8273 1.7208 1.6324 1.6013 1.7812
1.7979 1.8327 1.8105 1.7262 1.6541 1.6207 1.7610 1.7899 1.7762 1.7771 1.7809 1.7249 2.4989
2.4859 2.4353 2.4395 2.6162 2.5473 2.5382 2.6107 2.3495 2.3958 2.6619 2.5521 2.4689 2.3310
2.4386 2.3617 2.4247 2.4639 2.5034 2.3616 2.6452 2.5381 2.5230 2.3396 2.3072 2.5823 2.6519
2.4862 2.5619 2.6078 2.5238 2.5994 2.5946 2.7008 2.6689 2.6883 2.5124 2.2062 2.4092 2.7727
2.6650 2.7493 2.6249 2.6079 2.5816 2.6422 2.7944 2.8334 2.5605 2.7407 2.7809 2.7014 2.6086
2.4275 2.5919 2.5778 2.8683 2.8489 2.6734 2.7653 2.5621 1.6756 1.5619 1.6581 1.7468 1.7164
1.7425 1.7523 1.7757 1.7204 1.6959 1.8002 1.7822 1.7963 1.8505 1.9791 1.9992 2.0941 2.0824
2.1180 2.1681 2.0936 1.9415 1.9529 2.1637 2.2268 2.1786 2.1431 2.0836 1.8186 1.7360 1.8637
2.5124 2.2062 2.4092 2.7727 2.6650 2.7493 2.6249 2.6079 2.5816 2.6422 2.3499 2.3822 2.2785

2.1290 1.9791 1.9992 2.0941 2.0824 2.1180 2.1681 2.0936 1.9415 1.9529 2.1637 2.2268 2.1786 2.1431 2.0836 1.8186 1.7360 2.2315 2.6559 2.7705 2.8324 2.7943 2.7035 2.6711 2.8006 2.8712 3.0270 3.1334 3.1018 2.8602 2.8311 2.8207 2.8806 2.9979 2.9912 2.9206 2.9038 2.8573 2.8768 2.9364 2.9996 3.0254 3.0194 2.8511 2.9811 2.9740 3.0655 3.1441]

Findings:

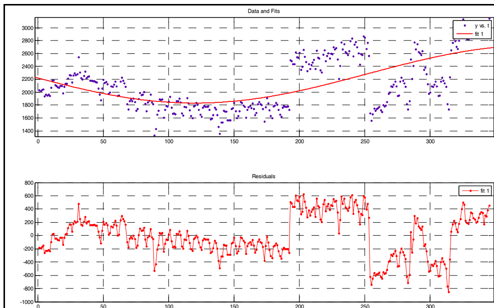

Fig. 2: Fourier Sum for k=1,

$$f(t) = 2281 - 60.65\cos(0.01197t) - 445.5\sin(0.01197t)$$

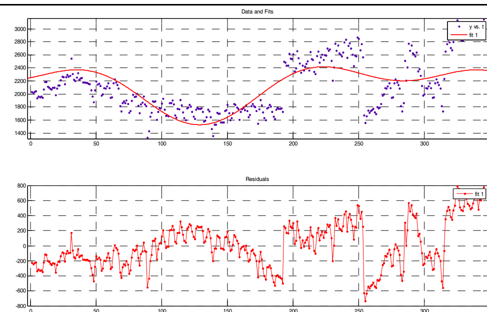

Fig. 3: Fourier Sum for k=2,

$$f(t) = 2100 + 290.9\cos(0.02065t) - 172.9\sin(0.02065t) - 140.4\cos(0.0413t) + 186.9\sin(0.0413t)$$

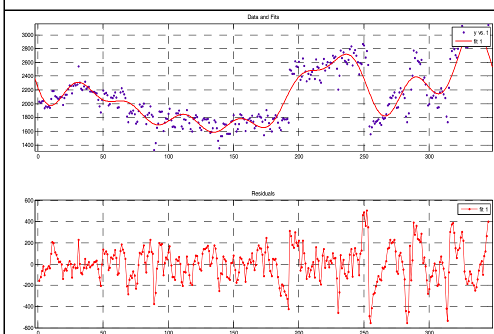

Fig. 4: Fourier Sum for k=8,

$$f(t) = 2135 + 211.9\cos(0.01777t) - 297.9\sin(0.01777t) + 94.73\cos(0.0355t) + 127.5\sin(0.0355t) + 115.9\cos(0.0533t) - 185.6\sin(0.0533t) - 120.4\cos(0.0711t) - 92.56\sin(0.0711t) - 6.748\cos(0.0889t) - 43.52\sin(0.0889t) - 0.3503\cos(0.1066t) - 101.4\sin(0.1066t) - 41.93\cos(0.1244t) - 100.2\sin(0.1244t) - 153.3\cos(0.1422t) - 45.22\sin(0.1422t)$$

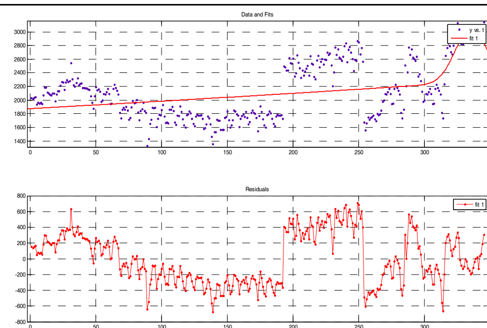

Fig. 5: Gauss Sum for k=2,

$$f(t) = 788.9\, e^{-\left(\frac{t-333.5}{16.48}\right)^2} + (1.099e+017)e^{-}$$

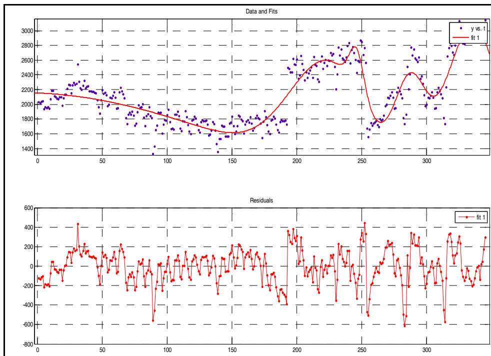

Fig. 6: Gauss Sum for k=5,

$$f(t) = 2608\, e^{-\left(\frac{t-339.4}{82.98}\right)^2} + 580.8\, e^{-\left(\frac{t-244.1}{7.847}\right)^2} + 1257\, e^{-\left(\frac{t-257.8}{17.04}\right)^2} + 1547\, e^{-\left(\frac{t-226}{44.32}\right)^2} + 2158\, e^{-\left(\frac{t+32.87}{278.7}\right)^2}$$

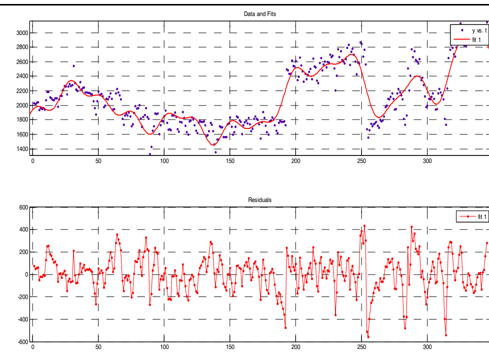

Fig. 7: Sum of Sinus for k=8,

$$f(t) = 4761 \sin(0.005328t + 0.5969) + 2814 \sin(0.007894t + 3.428) + 297.9 \sin(0.03819t - 0.3226) + 182 \sin(0.06155t + 0.3768) + 7622 \sin(0.1415t - 2.595) + 45.94 \sin(0.1057t + 2.624) + 7559 \sin(0.1414t + 0.5529) + 80.34 \sin(0.2584t + 0.6375)$$

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