20th International Symposium INFOTEH-JAHORINA, 17-19 March 2021

Classical Approach For Forecasting Temperature In Residential Premises

Part 1

Snezhinka Lubomirova Zaharieva
Department of Electronics
University of Ruse "Angel Kanchev"
Ruse, Bulgaria
szaharieva@uni-ruse.bg

Ivan Radoslavov Georgiev
Department of Applied Mathematics and Statistics
University of Ruse "Angel Kanchev"
Ruse, Bulgaria
irgeorgiev@uni-ruse.bg

Adriana Naydenova Borodzhieva
Department of Telecommunications
University of Ruse „Angel Kanchev"
Ruse, Bulgaria
aborodzhieva@uni-ruse.bg

Valentin Angelov Mutkov
Department of Electronics
University of Ruse "Angel Kanchev"
Ruse, Bulgaria
vmutkov@uni-ruse.bg

2021 20th International Symposium INFOTEH-JAHORINA (INFOTEH) | 978-1-7281-8229-2/20/$31.00 ©2021 IEEE | DOI: 10.1109/INFOTEH51037.2021.9400519

Abstract—**This paper presents classical approach for modelling based on time series used as a tool for predicting temperature changes in residential premises. Based on calculations in MATLAB, temperatures are predicted at six points, which are located symmetrically three by three, opposite each other. The forecasting aims to reduce the cost of electricity in a household.**

Keywords-classical approach; time series; temperature; prediction.

I. Introduction

The main function of a sensor is to convert a physical quantity into numerical data. Sensor node represents one or more different types of sensors integrated into a single data acquisition device for measurement of different physical quantities. When many sensor nodes are organized in a distributed network to collect data from a large environment, it is already referred to as a sensor network. A communication link is established via wires to transmit the measured data from each node to a central data collection node. Nowadays, the use of wires is considered as a primitive technology, which has proved cumbersome for sensor nodes located far from the user. Therefore, other solutions and technologies are being sought, such as WiFi, Bluetooth and others.

An electronic system for management of energy flows in residential premises has been developed and is installed in a laboratory at the University of Ruse "Angel Kanchev" [1]. The system measures and collects, and records data for various microclimatic parameters (temperature, humidity, light and barometric pressure), based on multifunctional modules representing sensor nodes built using WiFi SoC ESP8266 [2].

Fig. 1 presents the location of the modules integrated in the system for measurements and control of the energy flows, such as inside a room used six modules, which are arranged symmetrically opposite each other – points 2, 3, 4, east wall and 6, 7, 8, west wall.

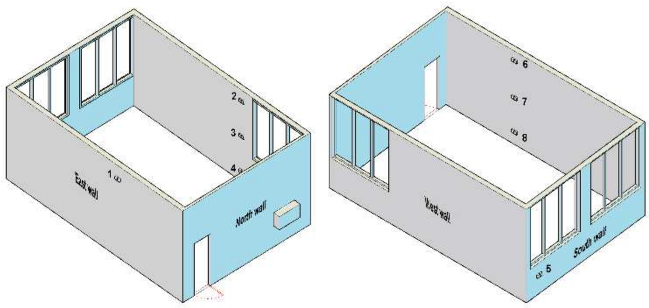

Figure 1. Digital temperature sensors West wall and East wall

Every multifunctional measurement module consists of eight digital sensors for measurement of temperature. The number of temperature measurements of each module are reduced after statistical evaluation of gross errors and subsequent evaluation of the synchronization of the results obtained amongst their readings [3, 4].

The purpose of this paper is to present an approach for prediction the temperature in the living room, using classical approaches for time series models, as the forecasting is based on the geometric arrangement of the six multifunctional modules for measurement of microclimatic parameters, i.e. six points. The main expectation is to reduce the level of used energy in residential premises.

The paper presents results from Project 2021 - FNI - FEEA, "Development and analysis of electronic modules for remote management of objects ", with financial support of the National Science Fund of University of Ruse.

978-1-7281-8229-2/21/$31.00 ©2021 IEEE

II. Theoretical Justification of the Classic Approach for Forecasting Temperature in Residential Premises

In order to ensure energy optimization in residential premises, it is necessary to predict the temperature fluctuations. In this regard, the information about the measured temperature with the developed electronic system for control of energy flows in residential premises is obtained at intervals of ten minutes, twenty-four hours a day.

The time series is a set of statistical observations arranged in chronological order of a physical quantity, such as temperature, humidity, barometric pressure and many others [2, 5].

Classical analysis of time series is a method where the studied order is presented as composed of individual components, representing the various effects of grouping and the influence of factors [6, 7].

A. Components of time series:

- Trend (long term direction) – *T*;
- Cyclical (regular or periodic) effects – *C*;
- Seasonal effects (systematic, calendar related movements) – *S*;
- Irregular effects (unsystematic, short term fluctuations) – *I*.

B. Classical models of time series:

- Additive model;
- Multiplicative model;
- Hybrid model.

For the purposes of the study, an additive time series model is used, which is the sum of the components of the time series. The advantage of this model is that the analysis of the time series is performed relatively easily, decomposing into its individual components. This is the reason that the possibility of converting other models to this type is usually sought. The model has the form:

$$\tilde{Y} = T + C + S + I \tag{1}$$

where: *T*, *C*, *S* and *I* are the components of the time series.

This model represents the sum of the components of the time series. If for some reason one of the components is not in the time series, then it is considered equal to zero.

C. Analysis of the components of the time series:

- Trend analysis;
- Determination of cyclical effects;
- Determination of seasonal effects;
- Removal of irregular effects.

III. Results of the Classic Approach for Forecasting Temperature in Residential Premises

The object of prediction using the model are the measured temperatures (°C) with the developed electronic system for control of energy flows in residential premises from 08.01.2018 to 10.01.2018. These three days were chosen because the measured temperatures in the room were approximately close and during this period the room was not occupied. In this way the subjective factors that would influence the obtained temperatures are avoided.

For the needs of the research, the arithmetic mean values of the readings of the digital temperature sensors, integrated in the six multifunctional modules for the determined period, were calculated. The software product MATLAB was selected for the calculation of the results. For this reason, time intervals of ten minutes to twenty-four hours of the day are converted to numerical values for the entire period.

Due to the uniformity of the model for forecasting the temperature in the residential premise, in this paper the results will be presented only for point 1. The same analysis is applied for all the points where the multifunctional measuring modules are placed.

A. Temperature changes during the period that is the subject of research

Fig. 2 presents the temperature changes for the period from 08.01.2018 to 10.01.2018 (the ordinate of the graph) and the converted time intervals into numerical values (the abscissa of the graph) for point 1.

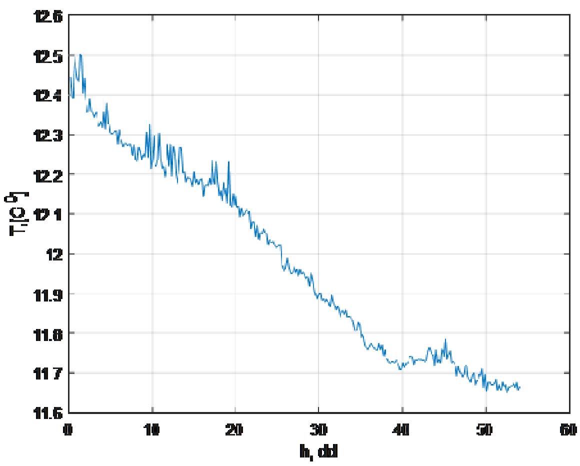

Figure 2. Temperature changes during the period, subject of research

From the results obtained during the analysis it can be concluded that the temperature in the room for the determined period decreases by approximately 0,85^{0}C, i.e. the measured temperatures are approximately close to the values mentioned above.

B. Trend modeling

Different models calculated by the least squares method were used to model the trend of temperature change in the time series.

Using the toolbox "cftool" in MATLAB, the coefficients and the main statistical characteristics of the trend of the time series are calculated.

Fig. 3 presents the graphical interpretation of the calculations obtained in MATLAB. The first used model is based on a linear trend. It is usually used where there are no large fluctuations in the data, and especially where no significant changes in the process are observed.

- Linear trend:

$$f(x) = p_1.x + p_2 \tag{2}$$

p_1 = -0.01537 (-0.01569, -0.01505)

p_2 = 12.4 (12.39, 12.41)

where: x – time, $f(x)$ – temperature, p_i – the required coefficients in the model.

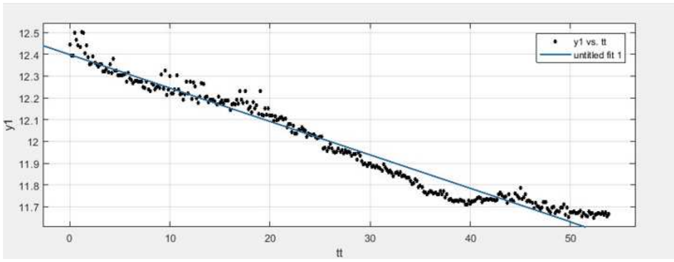

Figure 3. Real data and linear trend

The values in parentheses in equation (2) represent the confidence intervals guaranteed with a probability $\gamma = 0.95$. One way to check the statistical significance of these coefficients is whether their confidence intervals contain the number zero. If the confidence interval of a coefficient contains the number zero, then this coefficient is statistically insignificant and can be removed from the model.

From Fig. 3 it can be seen that the trend is negative and with increasing time of day, the temperature decreases. The resulting coefficient of determination is $R^2 = 0.9654$, i.e. this model can explain 96% of the fluctuations in the error.

In order to improve the models, the quadratic model of the trend is used, Figure 4.

- Square trend:

$$f(x) = p_1.x^2 + p_2.x + p_3 \tag{3}$$

p_1 = 0.0001044 (8.453e-05, 0.0001243)

p_2 = -0.02099 (-0.0221, -0.01989)

p_3 = 12.45 (12.44, 12.46)

The coefficient of determination obtained from the quadratic model is $R^2 = 0.9739$, i.e. the model can explain 97.4% of the fluctuations in the error.

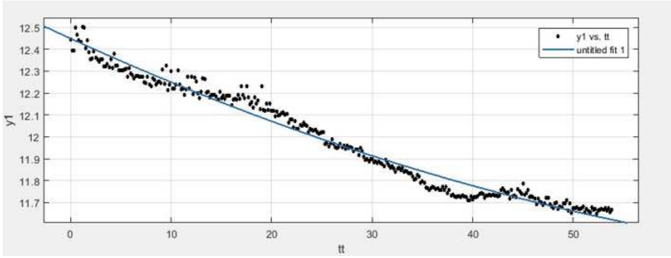

Figure 4. Real data and square trend

After removal of the errors (filtration) of the trend, the graph is presented in Fig. 5.

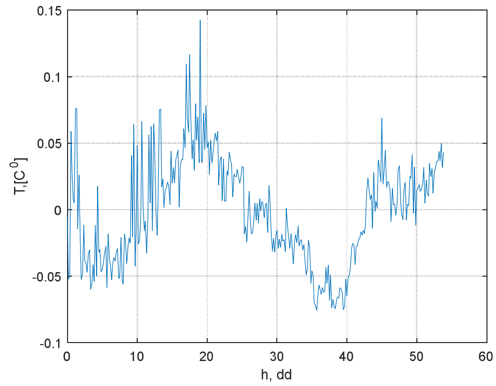

Figure 5. Clearing (Filtering) the trend with a quadratic model

The results from the analysis present that the temperature differences in the determined period are in the range from -0,75°C to +0.15°C.

C. Cyclicality

To clear the cyclicality, it is appropriate to choose periodic functions for models. This can be done through a linear and sometimes non-linear combination of standard trigonometric functions. If possible, a relatively elementary model is sought, but satisfactorily approximating the data.

After filtering the trend, four different periodic models were tested. The model is shown, followed by the values of the coefficients. Next to each coefficient the corresponding confidence interval is placed and the model is drawn with the exact values.

The values of one of the main statistical characteristics are presented in graphical form, namely the determinant of each different model for periodicity.

Models describing cyclicality:

- General model Fourier 1, Fig. 6:

$$f(x) = a_0 + a_1.cos(x.w) + b_1.sin(x.w) \tag{4}$$

$a_0 = 0.0001099$ (-0.002792, 0.003012)

$a_1 = -0.03844$ (-0.04368, -0.03321)

$b_1 = -0.01599$ (-0.02413, -0.007862)

$w = 0.184$ (0.1772, 0.1908)

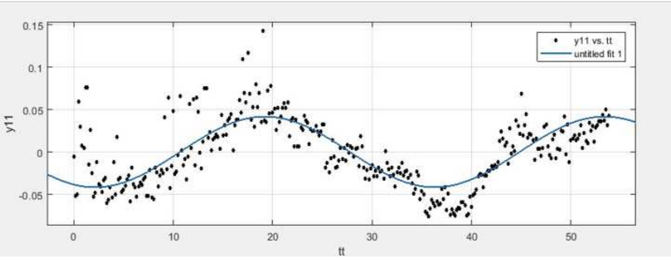

Figure 6. General model Fourier 1

- General model Fourier 2, Fig. 7:

$$f(x) = a_0 + a_1.cos(x.w) + b_1.sin(x.w) + \\ + a_2.cos(2.x.w) + b_2.sin(2.x.w) \quad (5)$$

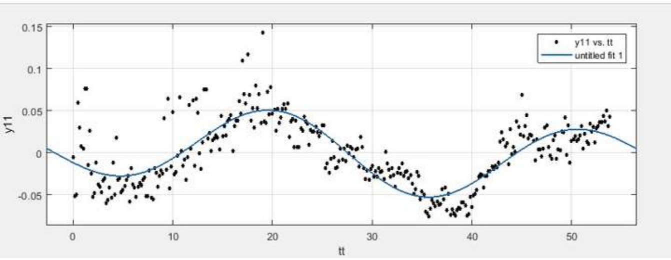

Figure 7. General model Fourier 2

$a_0 = -0.0006419$ (-0.003319, 0.002035)

$a_1 = 0.004199$ (-0.0002856, 0.008684)

$b_1 = 0.01648$ (0.01152, 0.02144)

$a_2 = -0.01544$ (-0.02522, -0.005663)

$b_2 = -0.03614$ (-0.04103, -0.03125)

$w = 0.1063$ (0.1017, 0.111)

- General model Sin 2, Fig. 8:

$$f(x) = a_1.sin(b_1.x + c_1) \; + \; a_2.sin(b_2.x + c_2) \quad (6)$$

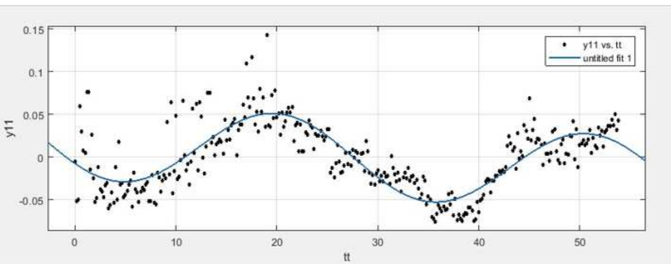

Figure 8. Sine model 2

$a_1 = 0.04574$ (0.03546, 0.05601)

$b_1 = 0.2037$ (0.1861, 0.2214)

$c_1 = 3.796$ (3.286, 4.306)

$a_2 = 0.05401$ (-3.35, 3.458)

$b_2 = 0.01443$ (-0.9233, 0.9522)

$c_2 = 2.759$ (-22.07, 27.58)

- General model Sin 4, Fig. 9:

$$f(x) = a_1.sin(b_1.x + c_1) + a_2.sin(b_2.x + c_2) + \\ + a_3.sin(b_3.x + c_3) + a_4.sin(b_4.x + c_4) \quad (7)$$

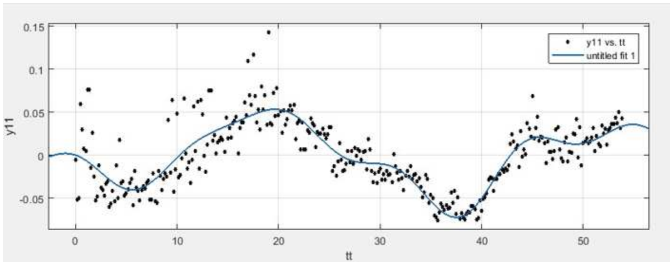

Figure 9. Sine model 4

$a_1 = 0.04075$ (0.02698, 0.05452)

$b_1 = 0.2004$ (0.1822, 0.2187)

$c_1 = 3.852$ (3.268, 4.436)

$a_2 = 0.01297$ (0.002343, 0.0236)

$b_2 = 0.1004$ (0.006075, 0.1948)

$c_2 = 0.5667$ (-2.18, 3.313)

$a_3 = 0.01165$ (0.008015, 0.01528)

$b_3 = 0.436$ (0.4107, 0.4614)

$c_3 = 0.8822$ (0.106, 1.658)

$a_4 = 0.01132$ (0.007983, 0.01465)

$b_4 = 0.5683$ (0.5446, 0.5919)

$c_4 = 1.919$ (1.199, 2.639)

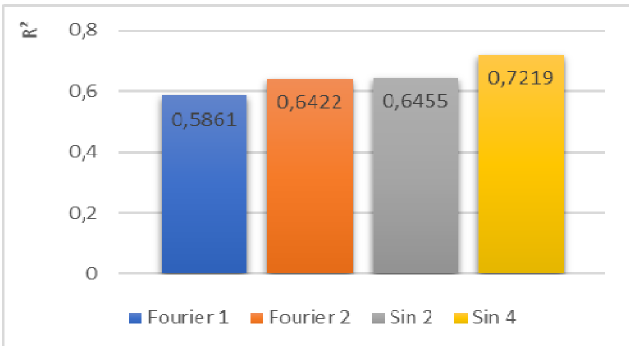

Figure 10. Determinants of different periodicity models

Fig. 10 presents the determinants of the proposed four models. The cyclicality is best described by the last, dependence (6) describing Sine model 4.

The coefficient of determination is $R^2 = 0.7219$, which means that approximately 72.2% of the errors in the data are explained by the model. This is much better than the previous proposed models, but there is still room for more precise research.

Taking into account the equations of trend and cyclicality, the generalized model acquires the form:

$$\tilde{Y} = p_1 t^2 + p_2 t + p_3 + a_1 \sin(b_1 t + c_1) + \\ + a_2 \sin(b_2 t + c_2) + a_3 \sin(b_3 t + c_3) + a_4 \sin(b_4 t + c_4) \quad (8)$$

D. Approximating function with included trend and cyclicality

Taking into account the quadratic trend and the periodic cyclicality to approximate the time trend, equation (8) is formed. Fig. 11 presents the graphs of the approximating function (8) and the real data. It is evident that some of the data are relatively well approximated by the constructed model. There are also data that differ slightly from the totality and from the prediction of the model.

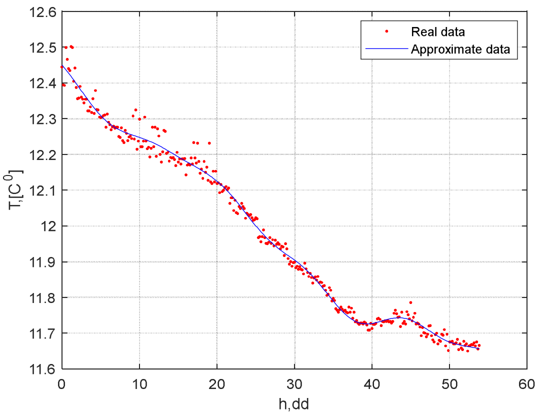

Figure 11. Approximating function with included trend and ciclicality

Random changes are difficult to determine precisely because of their random nature. As a rule, they are less often modelled in the form of an explicit equation. Rather, they are simulated by pseudo-random number generators. Their characteristics are usually described by means of standard statistics. The random changes will be limited by ignoring them.

Following remarks on seasonal variations and random changes in the presented model, the final model remains equation (8).

E. Validation of the model

In order to validate the proposed model, the last six values from the real data are used to evaluate the model and its predicted values. The original model was built without the last six values (in one hour, every ten minutes). Based on the model, these six values are predicted and then compared with the real data. If errors are allowed, the coefficients in the model are recalculated, with the last six real values already added. The model thus obtained serves to predict future values. Fig. 12 presents the real and approximate values during the model validation.

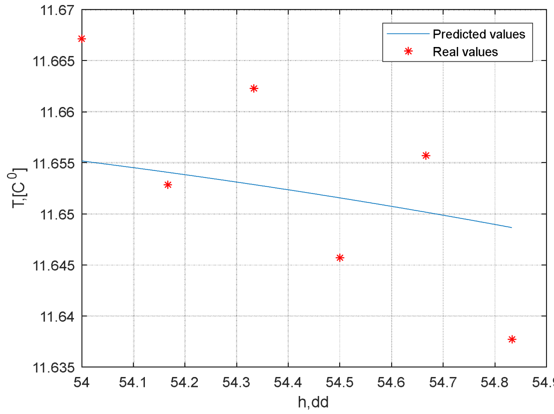

Figure 12. Real and aproximated values during the validation of the presented model

F. Correlogram of the real and predicted values of the room temperature

The correlogram also serves as a good tool for assessing the adequacy of the model. The real values are located on one axis and the approximate ones on the other. With absolute equality of real and approximate values, all points will lie on a line bisecting the first quadrant. Thus, the scattering around the lines is an indicator of the accuracy of the model.

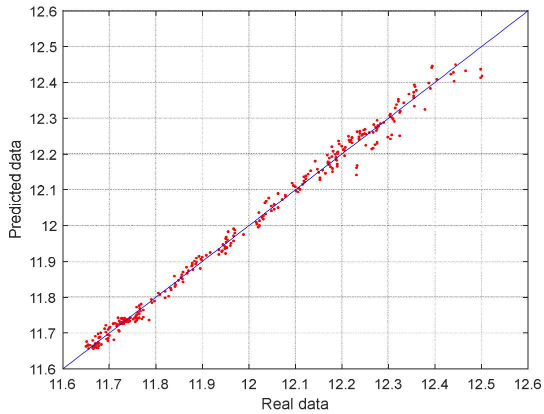

Figure 13. Correlogram of the real and predicted values of the room temperature

From Fig. 13 it can be seen that the model again behaves adequately and the scattering around the lines shows this.

Fig. 14 and Fig. 15 show the errors of the approximated data in absolute and relative values during the validation of the model. From the obtained results it can be concluded that the relative error between real and approximate data is of the order of ± 0.1%, which shows that the model behaves adequately.

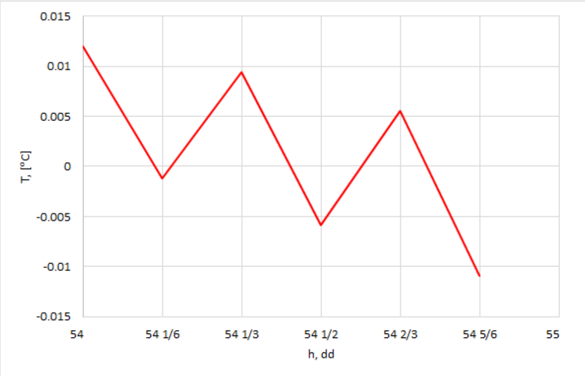

Figure 14. Absolute errors

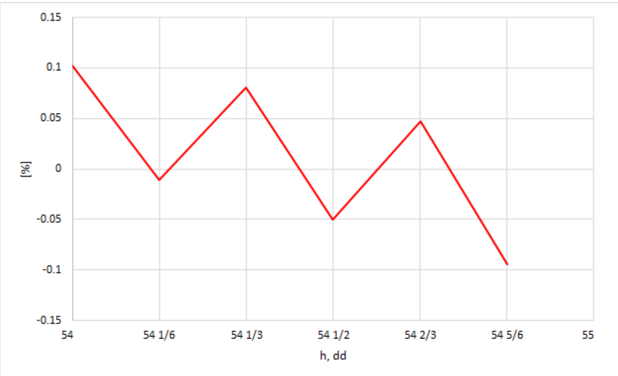

Figure 15. Relative errors

IV. Conclusion

The presented classical approach for forecasting time series predicts the temperature changes in residential premises. The choice of a specific model from four different models is done on the basis of decomposition of the time series in components.

The first component to be evaluated is the trend. The trend is constant so as to describe the process adequately, while being the most elementary. After filtering the trend, the cyclicality of the process is modelled, and again the priority is the adequate description of the process with the most elementary periodic functions possible. The equations of the functions approximating the trend and the cyclicality in an interval of one hour, every ten minutes are constructed using MATLAB. After validation, the relative errors in the model are of the order of ± 0.1%, indicating that the selected model is adequate.

Based on the obtained results, the temperature in time is predicted, through which the moment when the heating unit is switched on can be optimized in order to achieve the desired comfort temperature at minimal energy costs.

References

[1] I. Stoev and V. Mutkov, "Microclimatic data collection multisensor system for design of energy model in residential buildings," 2018 20th International Symposium on Electrical Apparatus and Technologies (SIELA), Bourgas, 2018, pp. 1-3, doi: 10.1109/SIELA.2018.8447124.

[2] V. Pencheva, A. Sladkowski, A. Asenov, I. Georgiev, I. Beloev, K. Ivanov, “Modelling of the Interaction of the Different Vehicles and Various Transport Modes Chapter: The Danube River, Multimodality and Intermodality. Switzerland AG”, Springer International Publishing, 2019, pp. 527, ISBN 978-3-030-11511-1.

[3] I. Stoev, S. Zaharieva, V. Mutkov, “Evaluation of Gross Errors in Measured Temperature with an Electronic System for Management of Residential Energy Systems.”, 27th Telecommunications Forum TELFOR 2019, 26-27 November 2019, Belgrade, Serbia, 2019, pp. 454-457, ISBN 978-1-7281-4790-1.

[4] I. Stoev, S. Zaharieva, A. Borodzhieva. “An Approach for Assessment of the Synchronization Between Digital Temperature Sensors”, 27th Telecommunications forum TELFOR 2019, Serbia, Belgrade, November 26-27, 2019, pp. 458-461, ISBN 978-1-7281-4790-1.

[5] S. G. Gocheva, Lectures on econometrics, Time series, http://www.fmi-plovdiv.org/evlm/DBbg/database/courses_Ikono_BM/6-8%20lekcii%20ikonometriq.pdf, (in Bulgarian)

[6] P. M. Ferreira, A. E. Ruanoac, S. Silva, E. Z. E. Conceiçãoa, “Neural networks based predictive control for thermal comfort and energy savings in public buildings”, Energy and Buildings,Volume 55, December 2012, pp. 238-251.

[7] Rok Krˇsmanc,a* Alenkaˇ Sajn Slakaand Janez Demˇsarb, “Statistical approach for forecasting road surface temperature”, Meteorological applications meteorol. 2013, pp. 439–446.