Estimation of the error in forecasting the consumption of the natural gas of the freight schedule per subscriber according to the seasons

Cite as: AIP Conference Proceedings **2333**, 090019 (2021); https://doi.org/10.1063/5.0041824
Published Online: 08 March 2021

Silvia Baeva, and Ivelina Hinova

Estimation of the Error in Forecasting the Consumption of the Natural Gas of the Freight Schedule per Subscriber According to the Seasons

Silvia Baeva [a] and Ivelina Hinova [b]

Technical University of Sofia, Bulgaria

[a] Corresponding author: sbaeva@tu-sofia.bg
[b] ihinova@tu-sofia.bg

Abstract. This article offers estimation of the error in forecasting the consumption of the natural gas of the freight schedule per subscriber according to the seasons. Statistical and stochastic methods are used for the analysis and forecasts.

INTRODUCTION

The Energy sector is developing more efficient analyzes and forecasts of freight scheduling, which lead to more efficient management of the resources associated with their use and the cost of their delivery.

Statistical forecasting methods are one of the most popular. The least squares method is the basis for determining the structure and parameters of forecasting systems. This method restores the linear dependence of the current values of time series, based on the accumulated history. There are different variants of the "automatic regression with moving averages" model. These models are not actively used in practice because scientific competence is required. Such extrapolation models have the disadvantage of low accuracy in case of uncertainty.

Currently, neural networks and decision trees (classification-based methods) are yielding good results. Only well-trained professionals can handle forecasting, although there are applications that automate the formation of such models.

A systematic and critical review of the forecasting methods used in 483 EPMs is presented by the authors in [4]. The methods are analyzed for forecasting accuracy; applicability for time and space forecasts; and relevance to planning and policy purposes. Fifty different methods have been identified for forecasting. The most widely used method is the artificial neural network (ANN), which is used in 40% of the examined EPMs. In descending order, the other popular methods are: support vector machine (SVM), autoregressive integrated moving average (ARIMA), fuzzy logic (FL), linear regression (LR), genetic algorithm (GA), particle swarm optimization (PSO) , gray prediction (GM) and autoregressive moving average (ARMA). Computational intelligence (CI) methods demonstrate better results than statistical ones in terms of accuracy with parameters with greater variability in the original data. Hybrid methods give better accuracy than stand-alone ones. Statistical methods are used for short and medium range forecasting. For all prediction time ranges (short, medium and long), CI methods are preferred. Most EPMs focus on forecasting energy consumption and load. The largest number of EPMs are developed in China, in terms of geographical coverage.

In [5] the optimal forecasting of the volumes of electricity consumption by an industrial enterprise is considered, based on a method for multilevel rationing. Empirical dependencies based on the specific energy consumption of the quantity of products produced are used for forecasting for the individual production sites. Errors are minimized when compiling the balance of electricity consumption by the whole enterprise. Using the results obtained by applying measuring instruments at the appropriate levels, an algorithm is created to coordinate solutions to problems of lower and higher levels. The developed algorithms are tested with real data obtained from power plants of industrial

Applications of Mathematics in Engineering and Economics (AMEE'20)
AIP Conf. Proc. 2333, 090019-1–090019-12; https://doi.org/10.1063/5.0041824
Published by AIP Publishing. 978-0-7354-4077-7/$30.00

enterprises. It is possible to predict the energy consumption of an entire enterprise with an accuracy of 1% using the proposed method.

Forecasting of energy consumption from private production areas of a large industrial facility, as well as from the facility itself is discussed in [6]. Based on empirical dependences on the specific energy consumption and the produced production, the forecast for the production areas is made. Minimization of the error in forecasting the energy consumption is based on the correction of the actual values of the energy consumption estimated with the measuring device and the total design energy consumption in separate production zones of the facility. From the actual data on the main production and energy consumption of a group of workshops and power plants of large iron and steel facilities, the optimal energy consumption is tested. Using this procedure, the test results give an average accuracy of forecasting energy consumption for winter 2014 of 0.11% for the group of workshops and 0.137% for power plants.

The LS-SVM [1] is used to forecast electricity consumption in Turkey. Artificial neural networks are considered in addition to traditional regression analysis. Gross electricity generation, installed capacity, total subscription and population based on historical data from 1970 to 2009 are used as independent variables in the models. Using different efficiency criteria, the forecast results are compared with each other in this study. To determine the specificity and sensitivity of the empirical results, an analysis of the operational characteristics of the receiver is performed. The proposed LS-SVM model is an accurate and fast method of forecasting, as evidenced by the results of this study.

Modeling, neural forecasting and optimal sizing for hybrid energy systems are presented in [2], which are proposed to reduce both total annual costs and the use of conventional sources, which in turn represents a reduction in pollutant emissions. A high-order neural network trained with an extended Kalman filter is envisaged in the use of renewable sources, along with differences in load demand. A clonal selection algorithm and a genetic algorithm are used in calculating the optimal sizing. The simulation with results showing the effectiveness of the two algorithms for optimizing the calculation of the optimal sizing of the hybrid system, which ultimately represents an optimal cost-effective system, illustrates the efficiency of using neural prediction data.

A prediction model that combines data transformation for the original data sequence and combined interpolation of GM background value optimization (1,1) is proposed by the authors in [3], so it is called DCOGM (1,1). The simulation and prognostic efficacy of DCOGM (1,1) is evaluated by considering two cases. In terms of prediction accuracy, DCOGM (1,1) outperforms most existing improved gray models, as evidenced by the results. The total electricity consumption in the city of Shanghai in China from 2017 to 2021 is projected using DCOGM (1,1). Compared to the traditional GM model (1,1) and other gray model modifications, the results show that DCOGM (1,1) performs well.

In order to categorize the sample data for WWTPs and analyze the relationship between energy consumption and the factors of influence in different categories in [7], the fuzzy clustering method is used. Energy efficiency in different categories varies and the same impact factors in different species have different intensities of influence found by the study.) The Radial Basis Function (RBF) neural network is used to predict energy consumption. The model is tested and trained with data from the full set and categories. Compared to the multivariate linear regression (MLR) model, the RBF model using the date from the subset has better performance. The data from this study are a theoretical basis for energy saving in WWTPs.

The topic of forecasting energy consumption is relevant and not exhaustive. The power of models is used differently by each author to interpret inputs and outputs, as well as their impact on the consumption process.

This study offers estimation of the error in forecasting the consumption of the natural gas of the freight schedule per subscriber according to the seasons. Statistical and stochastic methods are used for the analysis and forecasts.

DESCRIPTION OF THE STUDY METHODOLOGY

This study is for a specific subscriber of a natural gas company for the four seasons:

- Spring;
- Summer;
- Autumn;
- Winter.

Each season includes three months:

- Spring - March, April, May;
- Summer - June, July, August;
- Autumn - September, October, November;
- Winter - December, January, February.

Factors that are provided in this study and influence forecasting consumption representing consumers are:

- previous and forecast average daily temperatures;
- previous and forecast daily temperature amplitudes;
- workdays or holydays;
- previous subscriber daily consumption.

For each day of the previous year are given:

- average daily temperature;
- daily temperature amplitude;
- workday or holyday;
- subscriber daily consumption.

The aim of the study is to estimate the error in forecasting the consumption of the load schedule per subscriber according to the seasons.

To achieve this aim, the following problems have been set:

- Forecasting the natural gas consumption of a subscriber for each season;
- Estimating the error in forecasting consumption by season.

REALIZATION OF THE DESCRIBED METHODOLOGY

Forecasting the natural gas consumption of a subscriber for each season

The input data for the subscriber survey are presented in the following tables 1÷4.

TABLE 1. Input data - Spring

March 2018	**Average daily temperature (°C)**	**Daily temperature amplitude (°C)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{March,1}$	$a_{March,1}$	W	$C_{March,1}$
2	$t_{March,2}$	$a_{March,2}$	W	$C_{March,2}$
…	…	…	…	…
31	$t_{March,31}$	$a_{March,31}$	H	$C_{March,31}$
April 2018	**Average daily temperature (°C)**	**Daily temperature amplitude (°C)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{\mathrm{April},1}$	$a_{\mathrm{April},1}$	H	$C_{\mathrm{April},1}$
2	$t_{\mathrm{April},2}$	$a_{\mathrm{April},2}$	W	$C_{\mathrm{April},2}$
…	…	…	…	…
30	$t_{\mathrm{April},30}$	$a_{\mathrm{April},30}$	W	$C_{\mathrm{April},30}$
May 2018	**Average daily temperature (°C)**	**Daily temperature amplitude (°C)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{\mathrm{May},1}$	$a_{\mathrm{May},1}$	W	$C_{\mathrm{May},1}$
2	$t_{\mathrm{May},2}$	$a_{\mathrm{May},2}$	W	$C_{\mathrm{May},2}$
…	…	…	…	…
31	$t_{\mathrm{May},31}$	$a_{\mathrm{May},31}$	W	$C_{\mathrm{May},31}$

TABLE 2. Input data - Summer

June 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{\text{June},1}$	$a_{\text{June},1}$	W	$C_{\text{June},1}$
2	$t_{\text{June},2}$	$a_{\text{June},2}$	H	$C_{\text{June},2}$
…	…	…	…	…
30	$t_{\text{June},30}$	$a_{\text{June},30}$	H	$C_{\text{June},30}$
July 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{\text{July},1}$	$a_{\text{July},1}$	H	$C_{\text{July},1}$
2	$t_{\text{July},2}$	$a_{\text{July},2}$	W	$C_{\text{July},2}$
…	…	…	…	…
31	$t_{\text{July},31}$	$a_{\text{July},31}$	W	$C_{\text{July},31}$
August 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{\text{August},1}$	$a_{\text{August},1}$	W	$C_{\text{August},1}$
2	$t_{\text{August},2}$	$a_{\text{August},2}$	W	$C_{\text{August},2}$
…	…	…	…	…
31	$t_{\text{August},31}$	$a_{\text{August},31}$	W	$C_{\text{August},31}$

TABLE 3. Input data - Autumn

September 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{\text{September},1}$	$a_{\text{September},1}$	H	$C_{\text{September},1}$
2	$t_{\text{September},2}$	$a_{\text{September},2}$	H	$C_{\text{September},2}$
…	…	…	…	…
30	$t_{\text{September},30}$	$a_{\text{September},30}$	H	$C_{\text{September},30}$
October 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{\text{October},1}$	$a_{\text{October},1}$	W	$C_{\text{October},1}$
2	$t_{\text{October},2}$	$a_{\text{October},2}$	W	$C_{\text{October},2}$
…	…	…	…	…
31	$t_{\text{October},31}$	$a_{\text{October},31}$	W	$C_{\text{October},31}$
November 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**Workday or Holyday**	**Daily consumption (m³)**
1	$t_{\text{November},1}$	$a_{\text{November},1}$	W	$C_{\text{November},1}$
2	$t_{\text{November},2}$	$a_{\text{November},2}$	W	$C_{\text{November},2}$
…	…	…	…	…
30	$t_{\text{November},31}$	$a_{\text{November},31}$	W	$C_{\text{November},31}$

TABLE 4. Input data - Winter

December 2018	Average daily temperature (ºC)	Daily temperature amplitude (ºC)	Workday or Holyday	Daily consumption (m^3)
1	$t_{\text{December},1}$	$a_{\text{December},1}$	H	$C_{\text{December},1}$
2	$t_{\text{December},2}$	$a_{\text{December},2}$	H	$C_{\text{December},2}$
…	…	…	…	…
31	$t_{\text{December},31}$	$a_{\text{December},31}$	W	$C_{\text{December},31}$
January 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	$t_{\text{January},1}$	$a_{\text{January},1}$	H	$C_{\text{January},1}$
2	$t_{\text{January},2}$	$a_{\text{January},2}$	W	$C_{\text{January},2}$
…	…	…	…	…
31	$t_{\text{January},31}$	$a_{\text{January},31}$	W	$C_{\text{January},31}$
February 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	$t_{\text{February},1}$	$a_{\text{February},1}$	W	$C_{\text{February},1}$
2	$t_{\text{February},2}$	$a_{\text{February},2}$	W	$C_{\text{February},2}$
…	…	…	…	…
28	$t_{\text{February},28}$	$a_{\text{February},28}$	W	$C_{\text{February},28}$

The predicted values of average temperature and temperature amplitude for each day from each of the seasons are given in following tables 5, 6.

TABLE 5. Estimated values – Spring and Summer

Spring			Summer		
March 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**June 2018**	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**
1	$t^*_{March,1}$	$a^*_{March,1}$	**1**	$t^*_{\text{June},1}$	$a^*_{\text{June},1}$
2	$t^*_{March,2}$	$a^*_{March,2}$	**2**	$t^*_{\text{June},2}$	$a^*_{\text{June},2}$
…	…	…	**…**	…	…
31	$t^*_{March,31}$	$a^*_{March,31}$	**30**	$t^*_{\text{June},30}$	$a^*_{\text{June},30}$
April 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**July 2018**	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**
1	$t^*_{\text{April},1}$	$a^*_{\text{April},1}$	**1**	$t^*_{\text{July},1}$	$a^*_{\text{July},1}$
2	$t^*_{\text{April},2}$	$a^*_{\text{April},2}$	**2**	$t^*_{\text{July},2}$	$a^*_{\text{July},2}$
…	…	…	**…**	…	…
30	$t^*_{\text{April},30}$	$a^*_{\text{April},30}$	**31**	$t^*_{\text{July},31}$	$a^*_{\text{July},31}$
May 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**August 2018**	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**
1	$t^*_{\text{May},1}$	$a^*_{\text{May},1}$	**1**	$t^*_{\text{August},1}$	$a^*_{\text{August},1}$
2	$t^*_{\text{May},2}$	$a^*_{\text{May},2}$	**2**	$t^*_{\text{August},2}$	$a^*_{\text{August},2}$
…	…	…	**…**	…	…
31	$t^*_{\text{May},31}$	$a^*_{\text{May},31}$	**31**	$t^*_{\text{August},31}$	$a^*_{\text{August},31}$

TABLE 6. Estimated values – Autumn and Winter

Autumn			Winter		
September 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**December 2018**	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**
1	$t^*_{\text{September},1}$	$a^*_{\text{September},1}$	**1**	$t^*_{\text{December},1}$	$a^*_{\text{December},1}$
2	$t^*_{\text{September},2}$	$a^*_{\text{September},2}$	**2**	$t^*_{\text{December},2}$	$a^*_{\text{December},2}$
…	…	…	**…**	…	…
30	$t^*_{\text{September},30}$	$a^*_{\text{September},30}$	**31**	$t^*_{\text{December},31}$	$a^*_{\text{December},31}$
October 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**January 2018**	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**
1	$t^*_{\text{October},1}$	$a^*_{\text{October},1}$	**1**	$t^*_{\text{January},1}$	$a^*_{\text{January},1}$
2	$t^*_{\text{October},2}$	$a^*_{\text{October},2}$	**2**	$t^*_{\text{January},2}$	$a^*_{\text{January},2}$
…	…	…	**…**	…	…
31	$t^*_{\text{October},31}$	$a^*_{\text{October},31}$	**31**	$t^*_{\text{January},31}$	$a^*_{\text{January},31}$
November 2018	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**	**February 2018**	**Average daily temperature (ºC)**	**Daily temperature amplitude (ºC)**
1	$t^*_{\text{November},1}$	$a^*_{\text{November},1}$	**1**	$t^*_{\text{February},1}$	$a^*_{\text{February},1}$
2	$t^*_{\text{November},2}$	$a^*_{\text{November},2}$	**2**	$t^*_{\text{February},2}$	$a^*_{\text{February},2}$
…	…	…	**…**	…	…
30	$t^*_{\text{November},31}$	$a^*_{\text{November},31}$	**28**	$t^*_{\text{February},28}$	$a^*_{\text{February},28}$

Data processing is done as follows:
Each estimated value t^* and a^* falls into one of the cases in next table 7.

TABLE 7. Cases arising from average daily temperature and daily temperature amplitude forecasts

Amplitude intervals (ºC) / **Average temperature intervals (ºC)**	$\boldsymbol{a_1}$	$\boldsymbol{a_2}$	**…**	$\boldsymbol{a_N}$
$\boldsymbol{t_1}$	ta_{11}	ta_{12}	…	ta_{1N}
$\boldsymbol{t_2}$	ta_{21}	ta_{22}	…	ta_{2N}
…	…	…	…	…
$\boldsymbol{t_M}$	ta_{M1}	ta_{M2}	…	ta_{MN}

Behind each $ta_{mn}, m = 1, \ldots, M; n = 1, \ldots, N$, there is a corresponding input data processing, as shown in table 8.

TABLE 8. Forecasting the average expected daily consumption of a particular subscriber under the cases

Day	Consumption (m³)		Weight	
$\boldsymbol{d_1}$	C_1		$w_1 = \frac{1}{\sum_{l=1}^{L} l}$	$C_1.w_1$
$\boldsymbol{d_2}$	C_2		$w_2 = \frac{2}{\sum_{l=1}^{L} l}$	$C_2.w_2$
…	…		…	…
$\boldsymbol{d_L}$	C_L		$w_L = \frac{L}{\sum_{l=1}^{L} l}$	$C_L.w_L$
		Σ	$\boldsymbol{\sum_{l=1}^{L} w_l = 1}$	$\boldsymbol{\sum_{l=1}^{L} C_l w_l}$

Enter weights with normalized:

$$\sum_{l=1}^{L} w_l = 1. \tag{1}$$

Then the predicted subscriber consumption for the relevant day is:

$$C_{s,k}^{*} = \sum_{l=1}^{L} C_l w_l\,, s = \text{January, February,…, December; } k=1,…,31. \tag{2}$$

Estimation of Error in Forecasting Natural Gas Consumption by Season

As much as the deviations for each day $\left|C_{s,k} - C_{s,k}^{*}\right| = c_{s,k}, s =$ January, February,…, December; k=1,…,31, are less (close to zero), then the projected amount of natural gas consumption is closer to the real one.

The standard error of projected consumption by season is:

$$SD_h = \sqrt{\frac{\sum_{l=1}^{L} \left|C_{h,k} - c_{h,k}\right|^2}{L}}, \tag{3}$$

where:

$$h = \left\{Spring = \begin{pmatrix} March \\ Aprils \\ May \end{pmatrix}\right\}; \left\{Summer = \begin{pmatrix} June \\ July \\ August \end{pmatrix}\right\}; \left\{Autumn = \begin{pmatrix} September \\ October \\ November \end{pmatrix}\right\}; \left\{Winter = \begin{pmatrix} December \\ January \\ February \end{pmatrix}\right\};$$

L is number of days in each of the seasons,$l = 1, \dots, L$.

Once the standard errors for projected natural gas consumption by season have been found, an estimate of the error can be made.

The input data are discrete variables and statistical and stochastic methods are used to process them.

NUMERICAL REALIZATION

Input Numerical Data

The input numerical data for the subscriber survey are presented in following tables 9÷12.

TABLE 9. Input numerical data - Spring

March 2018	**Average daily temperature (^{o}C)**	**Daily temperature amplitude (^{o}C)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	-5.5	8.5	W	20775
2	-2.7	9.2	W	18935
…	…	…	…	…
31	12.1	8.6	H	8296
April 2018	**Average daily temperature (^{o}C)**	**Daily temperature amplitude (^{o}C)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	13.9	10.0	H	5720
2	13.2	6.0	W	9567
…	…	…	…	…
30	17.2	12.3	W	6014
May 2018	**Average daily temperature (^{o}C)**	**Daily temperature amplitude (^{o}C)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	20.0	11.9	W	5524
2	18.3	10.1	W	7445
…	…	…	…	…
31	21.0	13.7	W	3650

TABLE 10. Input numerical data - Summer

June 2018	**Average daily temperature (^{o}C)**	**Daily temperature amplitude (^{o}C)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	23.2	15.9	W	4656
2	22.7	11.4	H	1349
…	…	…	…	…
30	20.7	8.7	H	1654
July 2018	**Average daily temperature (^{o}C)**	**Daily temperature amplitude (^{o}C)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	22.5	11.9	H	1474
2	22.7	11.7	W	2836
…	…	…	…	…
31	22.8	8.3	W	2109
August 2018	**Average daily temperature (^{o}C)**	**Daily temperature amplitude (^{o}C)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	23.6	11.4	W	2318
2	24.7	9.7	W	2486
…	…	…	…	…
31	23.2	13.4	W	4700

TABLE 11. Input numerical data - Autumn

September 2018	Average daily temperature (^oC)	Daily temperature amplitude (^oC)	Workday or Holyday	Daily consumption (m^3)
1	22.6	17.9	H	2305
2	23.6	19.3	H	1733
…	…	…	…	…
30	12.0	4.9	H	3144
October 2018	**Average daily temperature (^oC)**	**Daily temperature amplitude (^oC)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	13.1	3.8	W	4714
2	15.7	11.7	W	3749
…	…	…	…	…
31	18.0	14.8	W	5785
November 2018	**Average daily temperature (^oC)**	**Daily temperature amplitude (^oC)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	16.4	15.5	W	4100
2	13.5	9.7	W	5189
…	…	…	…	…
30	-0.7	4.6	W	19167

TABLE 12. Input numerical data - Winter

December 2018	Average daily temperature (^oC)	Daily temperature amplitude (^oC)	Workday or Holyday	Daily consumption (m^3)
1	-0.6	2.5	H	16028
2	4.4	9.7	H	17960
…	…	…	…	…
31	5.4	12.6	W	19319
January 2018	**Average daily temperature (^oC)**	**Daily temperature amplitude (^oC)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	5.4	13.4	H	10341
2	6.2	8.1	W	19114
…	…	…	…	…
31	9.6	11.3	W	13006
February 2018	**Average daily temperature (^oC)**	**Daily temperature amplitude (^oC)**	**Workday or Holyday**	**Daily consumption (m^3)**
1	6.7	11.0	W	13424
2	8.2	8.3	W	12417
…	…	…	…	…
28	-3.8	8.7	W	20788

Numerical Data Processing

The input data are processed according to the methodology described above. For their processing is used specialized software in software environments for Data Mining, Maple, MatLab.

Numerical Results

The numerical results are presented in the following graphs – figures 1-4.

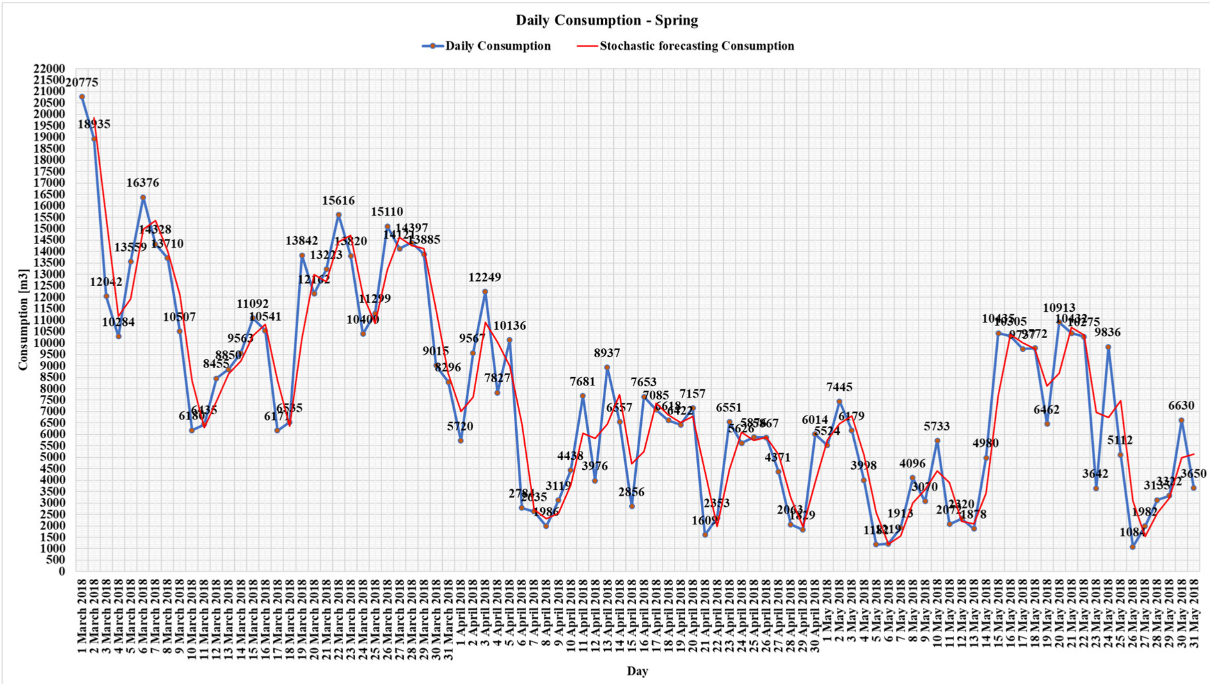

FIGURE 1. $\boxed{SD_{Spring} = 1.3\%}$

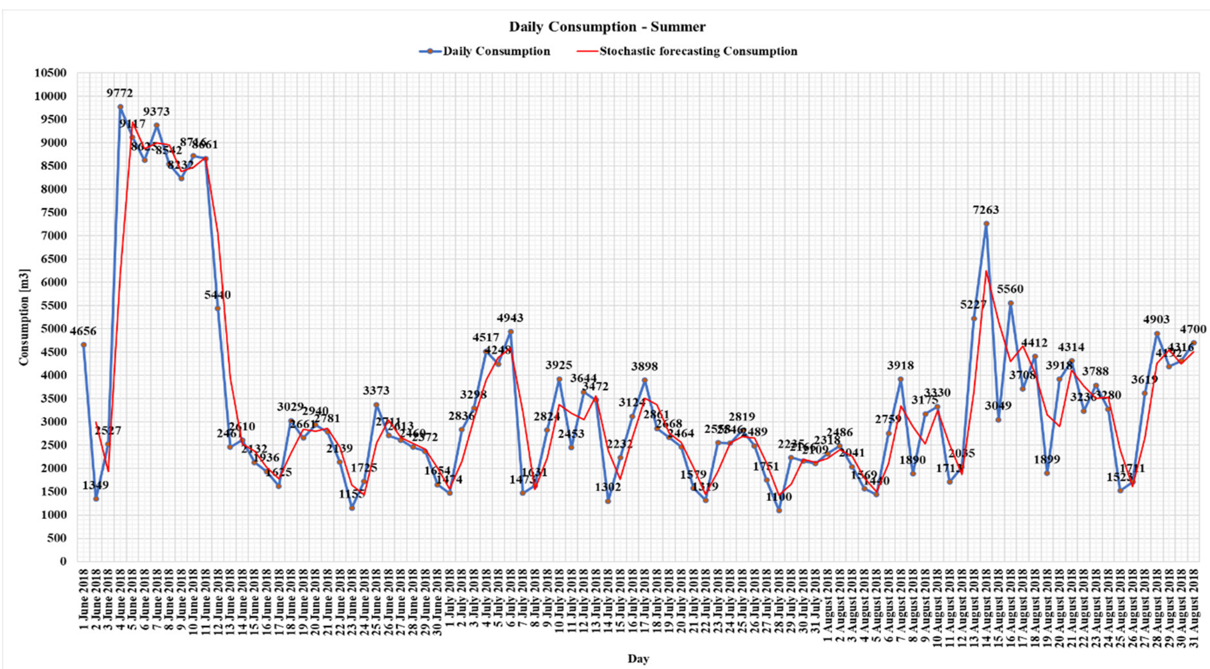

FIGURE 2. $\boxed{SD_{Summer} = 0.65\%}$

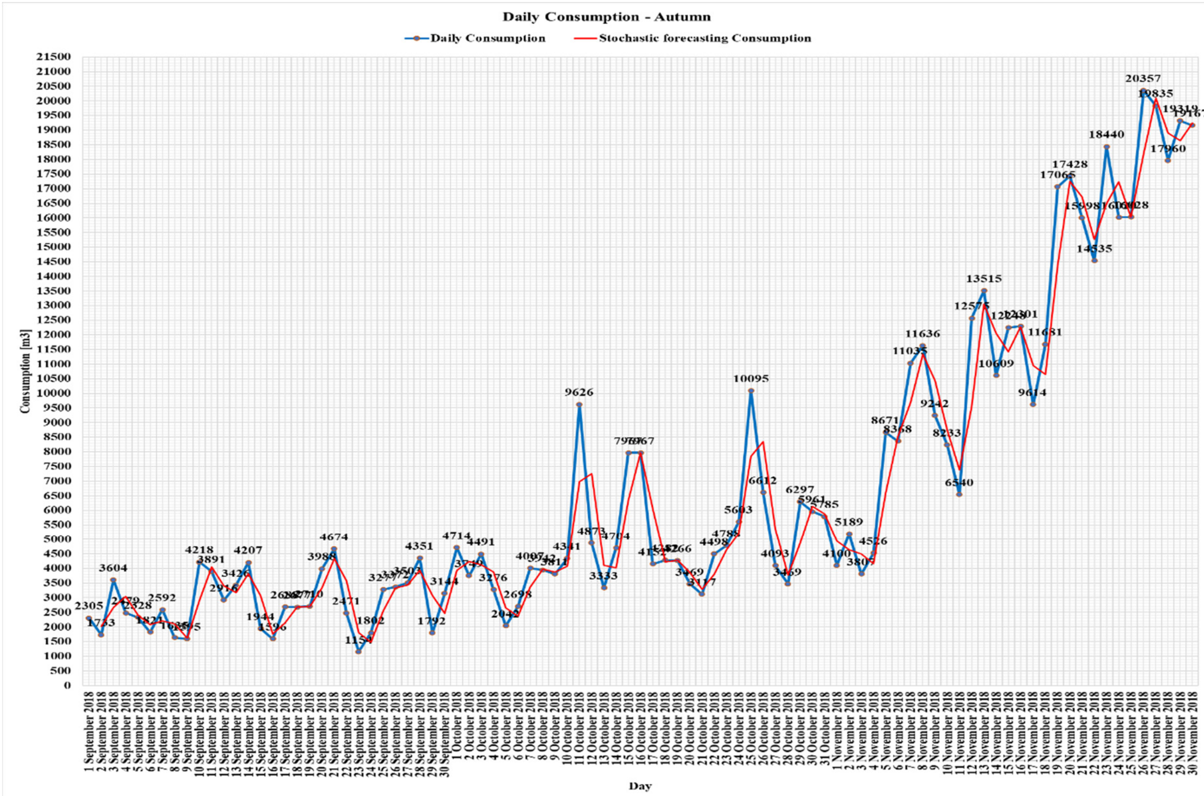

FIGURE 3. $\boxed{SD_{Autumn} = 1.02\%}$

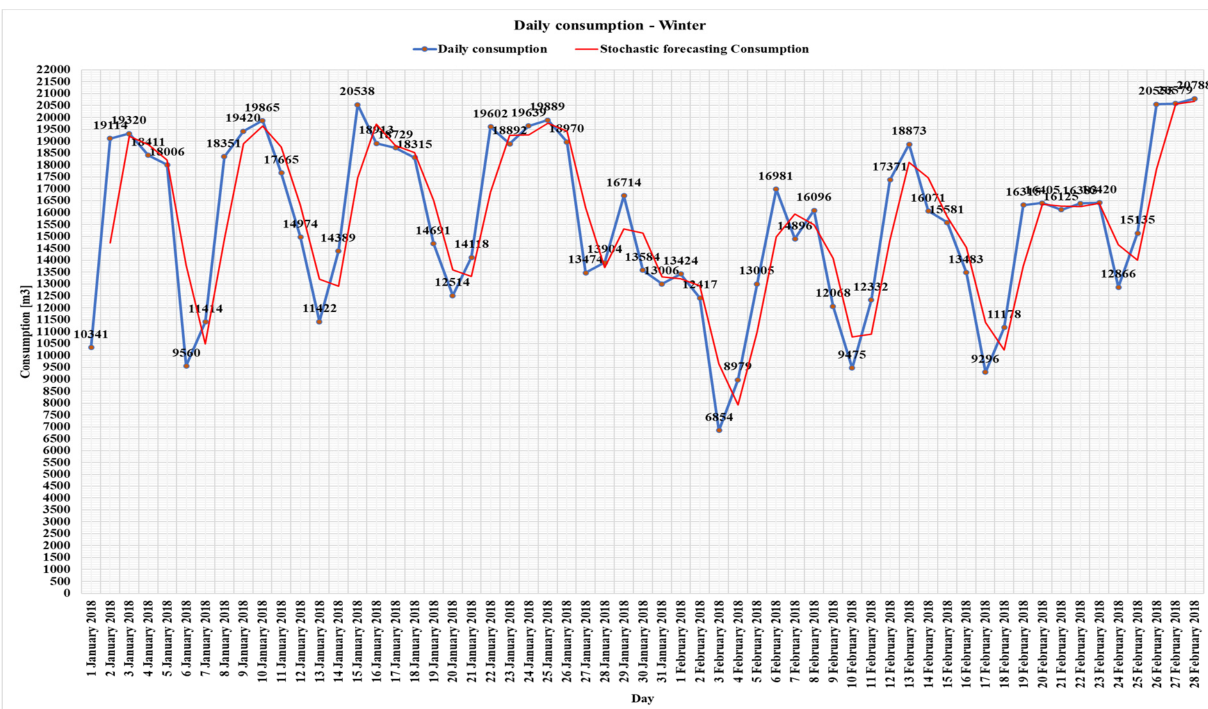

FIGURE 4. $\boxed{SD_{Winter} = 0.89\%}$

Discussion of the Numerical Results

From the numerical results for the error in the proposed methodology for seasonal forecasting of natural gas consumption per consumer and the obtained graphs the following conclusions can be made:

- The proposed methodology turns out to be quite reliable, but there is much to be desired in this direction. The stochastic nature of the conditions of environmental uncertainty will always govern the forecasting process, and hence the deviations in the forecast.
- Additional factors significantly influencing the process of forecasting a high error value are related to unstable political and economic conditions (for example: the global financial crisis in 2007-2008) and/or natural and/or biological disasters (for example: floods, earthquakes, fires, SARS, EBOLA, COVID 19).
- It is observed that the error in forecasting during the transition seasons - Spring and Autumn, is greater. This is due to the large dynamics not so much of the average daily temperature, but of the daily amplitude temperature.

CONCLUSION AND FUTURE WORK

Practice shows that in order to obtain practically significant forecasts, we must not only use software products (as a basis), but also necessarily take into account the opinion of experienced experts. We should not trust the built systems too much, but we should not deprive ourselves of the results we can have thanks to the achievements in the field of applied mathematics, because we can miss an emerging important trend.

Our future work will focus on developing an analytical platform and modern technologies for data analysis, forecasting, visualization and presentation of finished results of one of the main tasks in energy - forecasting consumption to optimize the load schedule through an appropriate choice of technologies and algorithms in a software solution.

REFERENCES

1. Fazil Kaytez, M. Cengiz Taplamacioglu, Ertugrul Cam, Firat Hardalac, *Forecasting electricity consumption: A comparison of regression analysis, neural networks and least squares support vector machines*, International Journal of Electrical Power & Energy Systems, https://doi.org/10.1016/j.ijepes.2014.12.036, 2015.
2. K. J. Gurubel, V. Osuna-Enciso, J. J. Cardenas, A. Coronado-Mendoza, M. A. Perez-Cisneros, and E. N. Sanchez, *Neural forecasting and optimal sizing for hybrid renewable energy systems with grid-connected storage system*, AIP of Journal of Renewable and Sustainable Energy 8, 045303, 2016.
3. Kai Li, Tao Zhang, *Forecasting Electricity Consumption Using an Improved Grey Prediction Model*, Information 2018, 9, 204; https://doi.org/10.3390/info9080204, 2018.
4. Kumar Biswajit Debnath, Monjur Mourshed, *Forecasting methods in energy planning models*, International Journal of Renewable and Sustainable Energy Reviews, https://doi.org/10.1016/j.rser.2018.02.002, 2018.
5. L. S. Kazarinov, T. A. Barbasova, O. V. Kolesnikova, and A. A. Zakharova, *Method of Multilevel Rationing and Optimal Forecasting of Volumes of ElectricEnergy Consumption by an Industrial Enterprise*, Automatic Control and Computer Sciences, Vol. 48, No. 6, pp. 324–333, 2014.
6. Tatyana Aleksandrovna Barbasova, Lev Sergeevich Kazarinov, Olga Valerevna Kolesnikova, Aleksandra Aleksandrovna Filimonova, *Energy Consumption Forecast Procedure for an Industrial Facility*, World Academy of Science, Engineering and Technology, International Journal of Economics and Management Engineering Vol.9, No.12, 2015.
7. ZhenHua Li, ZhiHong Zou, LiPing Wang, *Analysis and Forecasting of the Energy Consumption in Wastewater Treatment Plant*, Research Article, Hindawi, https://doi.org/10.1155/2019/8690898, Mathematical Problems in Engineering, Volume 2019.