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Abstract. Forecasting is a special scientific study, the subject of which is the perspective for the development of the phenomenon. It is of great importance for many scientific and applied fields. This article presents a stochastic model for microgrid load forecasting. Statistical and stochastic methods are used for forecasting.

INTRODUCTION

The forecasting methodology has long been fully integrated into human life, but it is gaining the greatest importance today. This trend is associated with the rapid development of technological processes in the world and the increased uncertainty in the internal and external environment. Numerous crisis phenomena in the economy, politics and social sphere provoke an increase in the risk load in all spheres of activity. The deepening processes of globalization have led to the emergence of systemic global risks, creating a possible domino effect, when the problems in individual corporations or countries have a serious negative impact on the economic and political situation of the entire world community. Risks related to climate instability, major man-made disasters and military-political crises have also increased recently. All this testifies to the special role of forecasting potential global and current individual risk events in the modern world. Effective forecasting of systems meeting current challenges can avoid or reduce the effects of many threats and even transform them into advantages.

Forecasting is a special scientific study, the subject of which is the perspective for the development of the phenomenon. It is of great importance for many scientific and applied fields. In many cases, it is necessary for tasks related to making informed and correct decisions. As the behavior of the modeled system can be very complex, it is necessary to use sufficiently powerful and flexible forecasting methods.

The forecast is the probabilistic description of the possible or the desired.

Research forecasts

- transfer past and present trends into the future;
- answer the question of what is likely to happen provided that existing trends are maintained;
- usually consider different options and determine the probability of each.

Scientific and technical forecasts contribute to:

- the development of science, its structures;
- the comparative efficiency of the different directions of research;
- further development of the scientific staff.

According to J. Armstrong, forecasting methods are divided into two major groups:

- statistical (quantitative);
- expert methods and assessments (assessment, quality, experts are used).

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A conceptual overview of the forecasting methods and models is presented in [1] with the main purpose of determining which model is most suitable for use in a particular case or scenario. More than 113 different cases, reported in 41 academic documents, are used to obtain an assessment. The time frame, inputs, outputs, scale, sample size, type and size of the error are taken into account as the main criteria for the preparation of the comparative analysis. The review shows that despite the relative simplicity of all considered models, regression and/or multiple regression are widely used and proven effective for long-term and very long-term prediction. On the other hand, machine learning algorithms such as artificial neural networks supporting vector machines and time series analysis are preferred for short and very short-term forecasting (including Autoregressive Integrated Moving Mean (ARIMA) and Autoregressive Moving Mean (ARMA)). The most widely used independent variables in forecasting are building and employment characteristics and environmental data, especially when machine learning models are applied. In many cases, time and regression analysis rely only on historical data on electricity consumption, without the introduction of exogenous variables.

In [3] a solution for short-term load forecasting (STLF) in microgrids is given, based on a three-stage architecture, which initially starts with image recognition from a self-organizing map (SOM), continues with grouping the previous partition by k-means algorithm and finally, it ends with a prediction for each cluster with a multilayer perceptron. The validation of the model is done with data from a micro-sieve environment provided by the Spanish company Iberdrola.

A deep repeating neural network with a long-term memory model (DRNN-LSTM) model [4] has been developed to predict the power load from a photovoltaic generator (PV) in a microgrid. The main task in three different planning scenarios is to synthesize an optimal load-sending model for a network-connected common micro-grid consisting of a load of the power supply, PV arrays, electric vehicles (EVs) and an energy storage system (ESS). In order to achieve a balance between the load and the generated power, the stochastics of both the residential load of the electricity and the photovoltaic power are studied on the one hand. This is taken into account in the presented model by integrating the obtained forecast results. Two sets of real data are applied to verify the proposed prediction model, and the results show that the DRNN-LSTM model performs better than the network perception of multilayer networks and a vector support machine (SVM). On the other hand, the particle optimization algorithm (PSO) is most often used to optimize the load sending of the networked microgrid. The presented results show that the power system and the coordinated charging mode of EVs can achieve a shift in the peak load and thus reduce 8.97% of daily costs.

[5] shows a hybrid model for load forecasting, obtained by optimizing the parameters for the purposes of short-term load forecasting of micro-networks, consisting of empirical mode decomposition (EMD), extended Kalman filter (EKF), extreme learning machine with core (KELM) and particle swarm optimization (PSO). The model is constructed as follows: First, the load data presented in time series is decomposed into several components of the internal mode function via IMD. Two typical different forecasting algorithms (EKF and KELM) have been adopted for forecasting different types of IMF components. Particle swarm optimization (PSO) is used to optimize the parameters in the model. Taking into account the limited resources for calculation, an execution mode based on optimization of offline parameters, updating of the parameters of the period and forecasting of the online load is used. Finally, four selected for microcircuits with different users and capacities are used to determine the accuracy and efficiency of the forecasting model display.

A new hybrid evolutionary fuzzy model with parameter optimization is shown in [6]. It is known that finding optimal values for fuzzy rules and weights is in practice a combinatorial task, the optimization of the model parameters is performed by a bio-inspired optimizer, the so-called. GES, which is obtained as a combination of two heuristic approaches, namely the strategies of evolution. and the GRASP procedure. Again, through real data from electrical utilities to individual users, are used to validate the proposed methodology. The presented results show that the proposed methodology is suitable for short-term forecasting of both microgrid networks and large networks. At the same time, the model is able to accurately predict data using short computational times.

The authors of the manuscript [8] propose the use of a hybrid technique for predicting very short-term load in micro-networks. The proposed technique essentially integrates a genetic algorithm, particle swarm optimization and adaptive neurofuzzy inference systems. Also, in [8] the binary genetic algorithm is used to select important indicators that significantly influence the load model among a set of available candidate input variables; On the other hand, the particle swarm optimization algorithm is used to optimize a model of adaptive neurofuzzy inferences for based systems for very short-term load prediction. The effectiveness of the proposed technique is confirmed by using an available data set to predict the load on a microgrid system in Beijing, China.

In [2] a stochastic model for solving the problem of single engagement (SUC) of a hybrid micronetwork for a very short period - 24 hours is presented. The micro grid considered in the problem is a hybrid consisting of a wind turbine (WT), a photovoltaic system (PV), a diesel generator (DE), a microturbine (MT) and a battery energy storage system (BESS). Here, too, the task is solved in three stages. First, based on the historical data on the power demand in the microgrid, an ARMA model is applied to obtain the consumption forecast. Second, the problem with SUC 24 hours ahead is eliminated based on the limitations of generators related to their capacity, the forecast for renewable energy production and consumption and the statistical distribution of the error in forecasting demand. In solving this problem, a rotating is a reserve of renewable sources, which should cover the stochastics in the assessment of demand. In the third stage, after the SUC problem is solved, a real-time procedure is created, and the error in the load estimation is known at all times. Therefore, the goal of this final stage is to determine the generator capacity reserve in an optimal way in order to minimize costs and investments.

In [7], a combined prediction model is proposed in which multivariate linear regression (Multi-LR) with a multi-label based on the K-nearest neighbor (K-NN) and K-means is used. The authors use a multi-label and K-NN algorithm to be able to give a different weight to each cluster to determine the prediction points and thus build Multi-LR models. The test data presented, which include the daily temperature (containing the highest temperature and the lowest temperature) and the power load for a quarter of an hour. It has been shown that compared to the results using only Multi-LR for load prediction, the proposed combined model achieves high accuracy and reduced calculation time.

The present study shows a stochastic model for microgrid load forecasting and follows the plan:

1. Determining and specifying the object of forecasting: part of a photovoltaic station, i.e. microphotovoltaic station;
2. What is the problem that the forecast is trying to clarify: to determine the estimated amount of the studied parameter based on historical data for it;
3. What is the subject of the forecast development, in other words, what aspect of the object of forecasting will be studied: microgrid load;
4. What will be the purpose of the forecast study: to compare by means of an average absolute percentage error the estimated quantities for the researched subject on the proposed cases of forecasting, in order to evaluate the qualities of the proposed models of forecasting;
5. What tasks should be solved with the forecast study:
   - To extract and process the necessary data for the research from a database;
   - To compile forecasting models in the following cases:
   - Forecasting the microgrid load for the current month based on data for the previous three months;
   - Forecasting the microgrid load for the current month based on data for the same months from the previous two years;
   - Forecasting of microgrid load by data seasons for the same seasons from the previous two years;
   - To calculate the average absolute percentage errors for the three cases;
   - To compare for the three cases the obtained average absolute percentage errors and to draw conclusions about the quality of the proposed models;
   - To make a numerical realization in the three cases according to the described methodology in order to validate the obtained results.
6. What will be the methodological tools of the research: Data Mining, statistical and stochastic methods?

FORECASTING METHODOLOGY

From the database for a given object – microgrid with photovoltaic system, for the last three years for each day at each minute the parameters such as microgrid load, generated power, etc., are considered and the data for microgrid load are extracted. The data are processed by consequential reading and extracting the values for each day and each month of the study period (Data Mining).

Let the microgrid load for each month of the given years be set with the following matrix:

$$P = \begin{pmatrix} P_{Y_1,1} & P_{Y_1,2} & \dots & P_{Y_1,12} \\ P_{Y_2,1} & P_{Y_2,2} & \cdots & P_{Y_2,12} \\ P_{Y_3,1} & P_{Y_3,2} & \cdots & P_{Y_3,12} \end{pmatrix}, \tag{1}$$

where $P_{Y_i,j}, i = 1,2,3; j = 1, \dots, 12$, is the microgrid load for the i -th month in year Y_i.

Then for each of the years studied:

$$P_{Y_i} = \begin{pmatrix} P_{Y_i,1} & P_{Y_i,1} & \cdots & P_{Y_i,1} \end{pmatrix}, i = 1,2,3. \tag{2}$$

Three cases of forecasting are considered:

For each of the cases, weights have been introduced, which determine the property of the forecast data to be stochastic.

First Case

Forecast of microgrid load for the current month based on data for the previous three months

Let the weights in this case be $\omega_k, k = 1,2,3$ and be normalized, i.e.

$$\omega_1 + \omega_2 + \omega_3 = 1. \tag{3}$$

Then the estimated quantities of microgrid load for each month of the forecast year Y_3 are:

$$\begin{aligned}
&For\ January: P^*_{Y_3,1} = \omega_1.P_{Y_2,10} + \omega_2.P_{Y_2,11} + \omega_3.P_{Y_2,12}\\
&For\ February: P^*_{Y_3,2} = \omega_1.P_{Y_2,11} + \omega_2.P_{Y_2,12} + \omega_3.P_{Y_3,11}\\
&For\ March: P^*_{Y_3,3} = \omega_1.P_{Y_2,12} + \omega_2.P_{Y_3,1} + \omega_3.P_{Y_3,2}\\
&For\ April: P^*_{Y_3,4} = \omega_1.P_{Y_3,1} + \omega_2.P_{Y_3,2} + \omega_3.P_{Y_3,3}\\
&For\ May: P^*_{Y_3,5} = \omega_1.P_{Y_3,2} + \omega_2.P_{Y_3,3} + \omega_3.P_{Y_3,4}\\
&For\ June: P^*_{Y_3,6} = \omega_1.P_{Y_3,3} + \omega_2.P_{Y_3,4} + \omega_3.P_{Y_3,5}\\
&For\ July: P^*_{Y_3,7} = \omega_1.P_{Y_3,4} + \omega_2.P_{Y_3,5} + \omega_3.P_{Y_3,6}\\
&For\ August: P^*_{Y_3,8} = \omega_1.P_{Y_3,5} + \omega_2.P_{Y_3,6} + \omega_3.P_{Y_3,7}\\
&For\ September: P^*_{Y_3,9} = \omega_1.P_{Y_3,6} + \omega_2.P_{Y_3,7} + \omega_3.P_{Y_3,8}\\
&For\ October: P^*_{Y_3,10} = \omega_1.P_{Y_3,7} + \omega_2.P_{Y_3,8} + \omega_3.P_{Y_3,9}\\
&For\ November: P^*_{Y_3,11} = \omega_1.P_{Y_3,8} + \omega_2.P_{Y_3,9} + \omega_3.P_{Y_3,10}\\
&For\ December: P^*_{Y_3,12} = \omega_1.P_{Y_3,9} + \omega_2.P_{Y_3,10} + \omega_3.P_{Y_3,11}
\end{aligned} \tag{4}$$

Then the average absolute percentage error is:

$$SMAPE = \sum_{j=1}^{12} \frac{2.\left|P_{Y_3,j} - P^*_{Y_3,j}\right|}{\left(P_{Y_3,j} + P^*_{Y_3,j}\right)}.100. \tag{5}$$

Second case

Forecast of microgrid load for the current month based on data for the same months of the previous two years

In this case the weights ω_{Y_1} and ω_{Y_1} are set so that

$$\omega_{Y_1} + \omega_{Y_2} = 1. \tag{6}$$

A microgrid load has been determined for each month of the forecast year Y_3:

$$P^*_{Y_3} = \left(\omega_{Y_1}.P_{Y_1,1} + \omega_{Y_2}.P_{Y_2,1} \quad \omega_{Y_1}.P_{Y_1,2} + \omega_{Y_2}.P_{Y_2,2} \quad \cdots \quad \omega_{Y_1}.P_{Y_1,12} + \omega_{Y_2}.P_{Y_2,12}\right) \tag{7}$$

so, let's

$$P^*_{Y_3,j} = \omega_{Y_1}.P_{Y_1,j} + \omega_{Y_2}.P_{Y_2,j}, j = 1, \dots, 12. \tag{8}$$

Then

$$P^*_{Y_3} = \left(P^*_{Y_3,1}, P^*_{Y_3,2}, \dots, P^*_{Y_3,12}\right). \tag{9}$$

The average absolute percentage error is:

$$SMAPE = \sum_{j=1}^{12} \frac{2.\left|P_{Y_3,j} - P^*_{Y_3,j}\right|}{\left(P_{Y_3,j} - P^*_{Y_3,j}\right)}.100 = \sum_{j=1}^{12} \frac{2.\left|P_{Y_3,j} - \left(\omega_{Y_1}.P_{Y_1,j} + \omega_{Y_2}.P_{Y_2,j}\right)\right|}{\left(P_{Y_3,j} - \left(\omega_{Y_1}.P_{Y_1,j} + \omega_{Y_2}.P_{Y_2,j}\right)\right)}.100. \quad (10)$$

Third case

Forecasting of microgrid load by data seasons for the same seasons from the previous two years

The weights ω_{Y_1} and ω_{Y_2} are set as in the second case, i.e.

$$\omega_{Y_1} + \omega_{Y_2} = 1. \quad (11)$$

The seasons include the following:

$$\begin{aligned} &Winter = \{December, January, February\} \\ &Spring = \{March, April, May\} \\ &Summer = \{June, July, August\} \\ &Autumn = \{September, October, November\} \end{aligned} \quad (12)$$

Then the corresponding quantities of microgrid load by seasons for each of the years $Y_j, j = 1,2,3$, is:

$$\begin{aligned} P_{Winter,Y_j} &= P_{Y_{j-1},12} + P_{Y_j,1} + P_{Y_j,2} \\ P_{Spring,Y_j} &= P_{Y_j,3} + P_{Y_j,4} + P_{Y_j,5} \\ P_{Summer,Y_j} &= P_{Y_j,6} + P_{Y_j,7} + P_{Y_j,8} \\ P_{Autumn,Y_j} &= P_{Y_j,9} + P_{Y_j,10} + P_{Y_j,11} \end{aligned} \quad (13)$$

The estimated quantities of microgrid load by seasons for the year Y_3 is:

$$\begin{aligned} P^*_{Winter,Y_3} &= \omega_{Y_1}.P_{Winter,Y_1} + \omega_{Y_2}.P_{Winter,Y_2} \\ P^*_{Spring,Y_3} &= \omega_{Y_1}.P_{Spring,Y_1} + \omega_{Y_2}.P_{Spring,Y_2} \\ P^*_{Summer,Y_3} &= \omega_{Y_1}.P_{Summer,Y_1} + \omega_{Y_2}.P_{Summer,Y_2} \\ P^*_{Autumn,Y_3} &= \omega_{Y_1}.P_{Autumn,Y_1} + \omega_{Y_2}.P_{Autumn,Y_2} \end{aligned} \quad (14)$$

The average absolute percentage error is:

$$\begin{aligned} SMAPE = \frac{1}{4}.\Bigg(&\frac{2.\left|P_{Winter,Y_3} - P^*_{Winter,Y_3}\right|}{\left(P_{Winter,Y_3} + P^*_{Winter,Y_3}\right)} + \frac{2.\left|P_{Spring,Y_3} - P^*_{Spring,Y_3}\right|}{\left(P_{Spring,Y_3} + P^*_{Spring,Y_3}\right)} + \\ &+ \frac{2.\left|P_{Summer,Y_3} - P^*_{Summer,Y_3}\right|}{\left(P_{Summer,Y_3} + P^*_{Summer,Y_3}\right)} + \frac{2.\left|P_{Autumn,Y_3} - P^*_{Autumn,Y_3}\right|}{\left(P_{Autumn,Y_3} + P^*_{Autumn,Y_3}\right)}\Bigg).100 \end{aligned} \quad (15)$$

NUMERICAL REALIZATION

For the numerical realization an autonomous microgrid system, consisting of PV generator (2,3kW), Hydro Generator (3kW), Diesel Generator (12kW), Hybrid Inverter - Charger - Transfer device (48V DC, 230VAC, 8kVA), battery storage (43,2 kWh), supplying AC load 230V is used (figure 1).

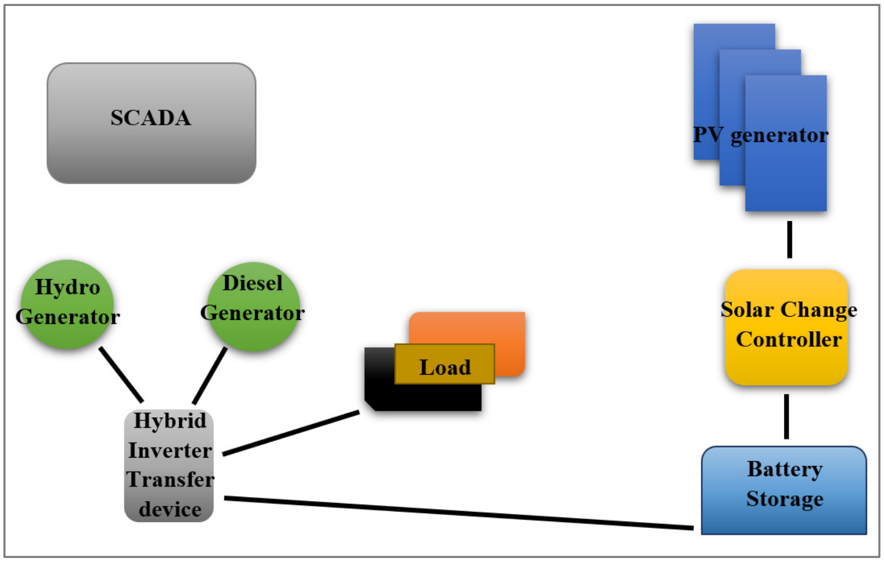

FIGURE 1. Scheme of the autonomous microgrid system

Input Data and Processing

The input data are processed according to the methodology described above and the total microgrid loads [kW] for each month of the given years are found (Table 1).

TABLE 1. Input data [kW]

Month / Year	Jan	Feb	March	Apr	May	June	
2017	18865.56	14209.84	17394.60	15274.32	17665.77	14970.54	
2018	18663.12	19228.73	15418.24	17353.68	15805.79	16509.65	
2019	16942.88	18169.05	14826.96	15346.69	13745.68	12033.19	
Month / Year	**July**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**	**Σ**
2017	15817.60	15324.38	14805.19	17616.73	15624.34	19843.44	197412.31
2018	14892.27	13999.36	12513.87	15506.31	14193.28	17683.84	191768.14
2019	10197.14	15638.28	13983.58	15986.47	17067.71	17444.61	181382.24

Results

The three cases of forecasting described above are realized and the numerical results are presented in Tables 2÷4.

TABLE 2. First case: Stochastic forecast values for microgrid load [kW] for the months of 2019 according to data for the previous three months of at $\omega_1 = 0.17, \omega_2 = 0.33, \omega_3 = 0.50$

Month / Year	Jan	Feb	March	Apr	May	June	
2019	781.10	1449.09	2854.97	942.87	1909.30	2424.64	
Month / Year	**July**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**	**Σ**
2019	2964.47	4231.99	753.74	2100.53	1801.39	1258.01	23472.10

TABLE 3. Second case: Stochastic forecast values for microgrid load [kW] for the months of 2019 according to data for the respective months of the previous two years at $\omega_{Y_1} = 0.33, \omega_{Y_2} = 0.67$

Month / Year	Jan	Feb	March	Apr	May	June	
2019	18729.93	17572.50	16070.44	16667.49	16419.58	16001.74	
Month / Year	**July**	**Aug**	**Sept**	**Oct**	**Nov**	**Dec**	**Σ**
2019	15197.63	14436.62	13270.01	16202.75	14665.53	18396.51	193630.72

TABLE 4. Third case: Stochastic forecast values for microgrid load [kW] for the seasons of 2019 according to data for the respective seasons from the previous two years at $\omega_{Y_1} = 0.33, \omega_{Y_2} = 0.67$

2019	**Winter**	54698.93
	Spring	49157.51
	Summer	45635.99
	Autumn	44138.28
	Σ	193630.72

The calculated mean absolute percentage error in the three cases is presented in Table 5.

TABLE 5. Average absolute percentage error [%]

Case	First	Second	Third
SMAPE [%]	12.56	11.51	9.05

The numerical results for the three cases are presented graphically in Figures 2÷4.

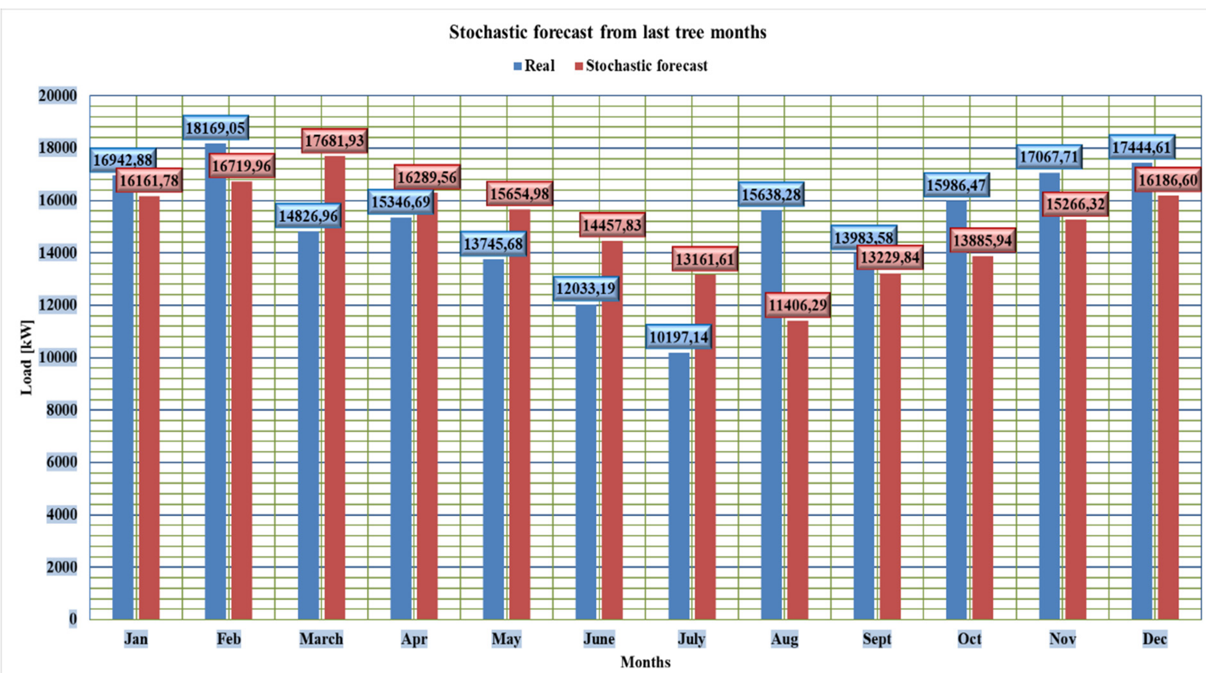

FIGURE 2. Results in First case

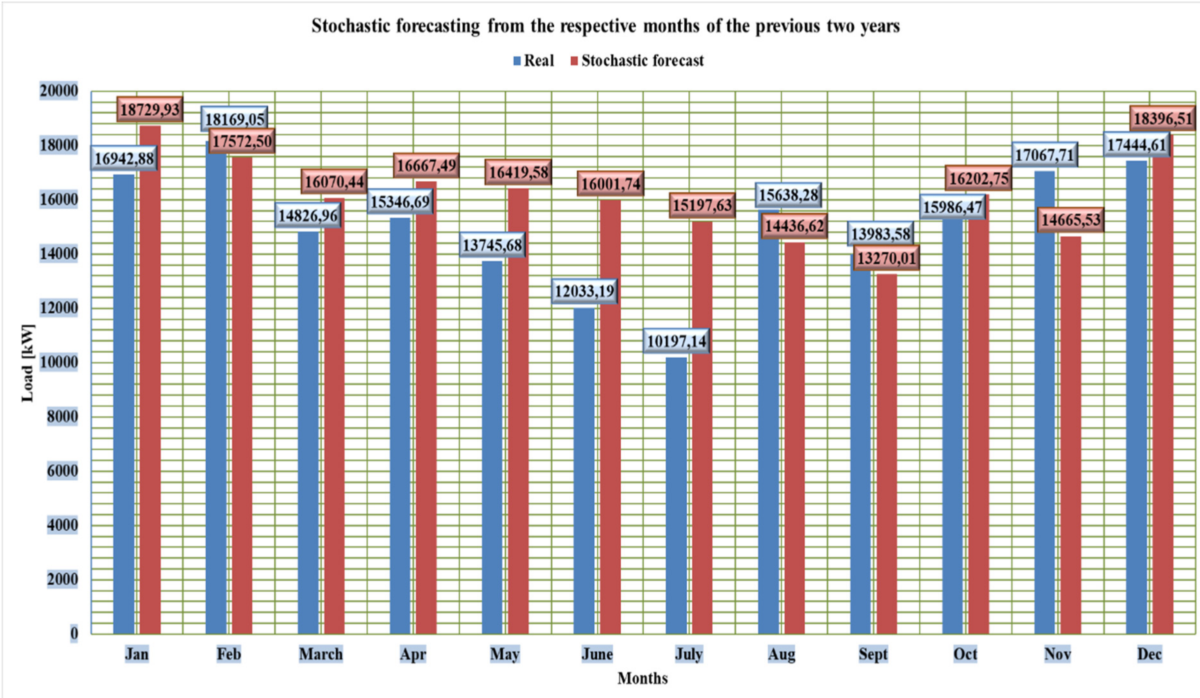

FIGURE 3. Results in Second case

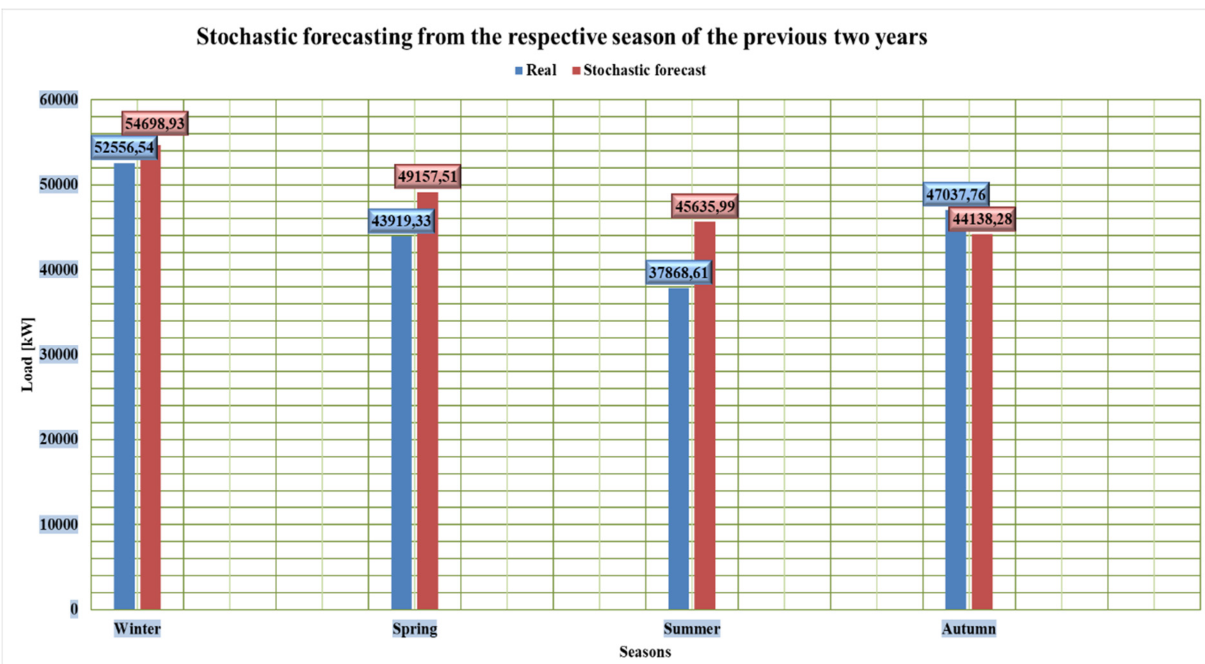

FIGURE 4. Results in Third case

Numerical implementation is carried out in programming environments in Python, Maple, MS Excel.

Discussion on the Results

From the obtained numerical results in the proposed methodology for microgrid load stochastic forecasting the following conclusions can be made:

- The study showed that the best forecast is achieved in seasonal forecasting, where a similar trend of the seasonal amount for microgrid load is observed (Figure 5). This is mainly due to the human factor and weather conditions.

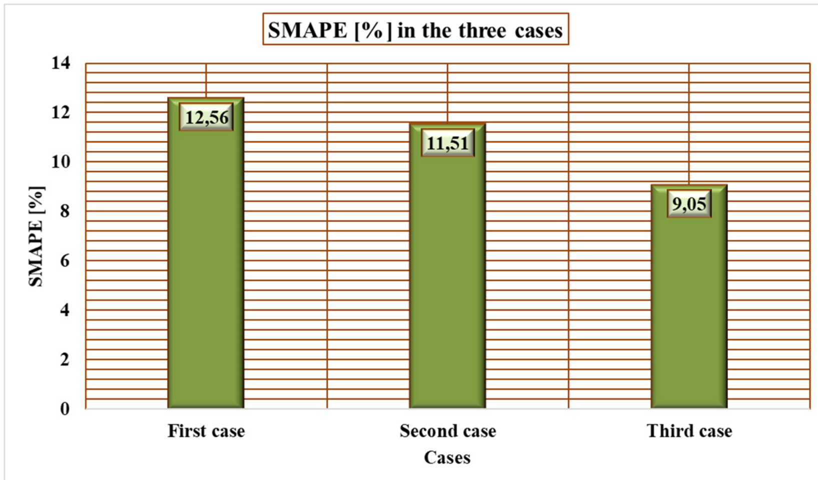

FIGURE 5. SMAPE [%] in the three cases of stochastic forecasting

- Since the stochastic forecast for microgrid load is made only on the basis of historical data for the specified period, the average absolute percentage errors in the three cases obtained in the numerical implementation of the proposed model are not so good (Figure 5). The microgrid load process itself is also influenced by other factors such as ambient temperature, daily duration of sunshine, solar radiation, etc., which are not included and reported in the present study. This will be the work of our further research.

CONCLUSION AND FUTURE WORK

In all modern activities, the processing of information and the extraction of useful results from its analysis is a key process. This fact makes the presented research relevant and significant. The presented stochastic model for microgrid load forecasting shows a predictability that will be relevant to the specific site in terms of planning its future activities. Our future research will focus on forecasting the microgrid load by adding additional factors that influence the process.

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