Pre-forecast modeling of airport electricity consumption time series

Nataliya Sokolova[1], *Dmytro* Bugayko[1], *Sergey* Yekimov[2], *Oleksii* Lobov[1], *and Oleg* Leshchinsky[1*]

[1]National Aviation University, 1, Liubomyra Huzara ave., 03058, Kyiv, Ukraine
[2]Czech University of Life Sciences Prague, Kamycka 129, 16500, Praha - Suchdol, Czech Republic

Abstract. The article analyzes the relevance of pre-forecast modeling of time series of electricity consumption by airports, systematizes the methods and ways of the specified pre-forecast modeling and considers some problems arising in the process of their use. A separate stage of pre-forecast modeling of electricity consumption by the airport is proposed, which contributes, on the one hand, to a fairly quick receipt of primary information about the forecasted object, and on the other hand - to a more effective and adequate final forecast. It is proposed to build a series of neural network models at the stage of preliminary forecasting, including convolutional, recurrence. As a model example, a neural network pre-forecast model of electricity consumption for the Lviv International Airport is built on the basis of statistical data for the period of relatively stable development of the Ukrainian economy. A comparative analysis of the obtained results of the neural network model with the constructed trend-seasonal model using analytical methods was carried out, which gave a positive result. Conclusions are made on the prospects of building pre-forecast models of time series of electricity consumption by the airport using neural networks.

1 Introduction

Building a satisfactory forecast of electricity consumption by an airport remains a relevant task today and requires constant attention. One of the explanations for this is the accounting and calculation of planned costs for the purchase and consumption of electricity. An airport, being a large consumer of electricity, is naturally a participant in the wholesale electricity market, and its purchase is associated with a preliminary analysis of the required volume. Deviations in its further real consumption from the purchased volume to the smaller side give rise to risks of penalties from suppliers, and to the larger side - risks of additional purchase of electricity at a significantly higher (naturally) non-wholesale price. In addition, an overestimated forecast of electricity consumption can contribute to an increase in costs for the inefficient and useless use of already purchased electricity. Therefore, a satisfactory reliability of the forecast of electricity consumption by an airport, the quality of its planning

* Corresponding author: bugaiko@nau.edu.ua

and the efficiency of the discipline of the power supply contribute to effective management of electricity consumption.

Saving electricity, increasing the efficiency of its use directly depend on the quality of the consumption forecast and naturally affect the increase in airport profits.

The process of forecasting electricity consumption by an airport is generally multi-level and multi-stage, and if properly organized, it can become the basis for developing a rational strategy for using electricity by an airport.

One of the stages of this process can be pre-forecast modeling.

The objectives of pre-forecast modeling can be the following:

- determining the presence (absence) of a trend;
- determining the presence (absence) of a cyclic component;
- determining the presence (absence) of a seasonal component;
- identifying and filtering abnormal values of electricity consumption.

Abnormal values of electricity consumption can be observed for technical reasons (errors of the first kind): errors in aggregating and disaggregating indicators, receiving, processing and transmitting information, etc., as well as due to the impact of factors that are objective in nature, but manifest themselves unsystematically, episodically and comparatively very rarely (errors of the second kind), which can be neglected in pre-forecast modeling. Predictive models do not claim to be highly accurate, but only at a primary level study the structure of the feature space, the possible structure and type of the future completed, much more accurate model [1-21].

2 Literature Review

With a fairly rich variety of publications [4-11,14-15] devoted to the use of time series for forecasting electricity, the authors are not fundamental studies that give reason to believe that the main consumer is the airport. Among the modern publications devoted to the methodology for constructing and analyzing forecast time series, the following economic and other indicators can be distinguished. In [12] the authors Laboisiere L.A., Fernandes R.A.S., Lage G.G. The methodology of forecasting the maximum and minimum daily prices of shares of three African energy distribution companies, whose shares are traded on the Sao Paulo Stock Exchange BM&FBovespa, is studied. The authors of this article examine the methodology for constructing a forecast of the closing currency prices of shares of Brazilian electricity distribution companies. As a result of their forecasts, investors have the opportunity to determine threshold values for their transactions using promotional campaigns. The actual forecasting was performed by the authors with artificial neural networks (ANN), the performance was measured by calculating the mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE). They proposed a methodology for solving the problem of forecasting the maximum and minimum daily prices of Brazilian distribution companies, which turned out to be quite effective. The authors managed to achieve this by simultaneously using the results of correlation analysis and artificial neural networks. In [16], the authors Zheng H., Yuan J., Chen L. developed and investigated a hybrid algorithm that selects similar days (SD), empirical mode decomposition (EMD) and neural networks with long and long memory (LSTM). The paper also used the weighted k-means method based on extreme gradient boosting, which was used to assess the similarity between the forecasted and historical days. The EMD method is used to distribute the SD load into multiple good mode functions (IMFs) and residual, LSTM neural networks are used to predict each IMF and residual.

In [17], the authors Lopez M., Sanz S., Valero S. in their studies conducted an empirical comparison of neural network (NN) and autoregressive (AR) models for predicting the conditions of protection determination under which the model shows performance efficiency. The results of their analysis show that the AR model has 0.13% lower error than NN under ideal conditions. With this model, NN works accurately in a sufficient number of portable devices.

In [18], the authors Li M.W., Geng_J., Hong W.C. studied microgrids of electrical load (MEL). According to the authors, their characteristics have independent independence and dependence on many factors with large fluctuations, which leads to difficulties in obtaining more accurate forecast results. To determine the specified characteristics of the MEL time series, the authors used the method of support vectors - least squares (LS-SVR) in combination with metaheuristic algorithms to model the nonlinear time series of MEL, as well as elements of low-level artificial intelligence (FOA swarm intelligence methods) and a quantum computing mechanism. (QCM). From the above, it follows that the time series of electricity consumption depends on a large number of factors, some of which are non-deterministic, so it is poorly formalized. A more significant factor is the time series of constructions using neural networks.

3 The aim and objectives of the study

The purpose of this article was to study a separate experience of pre-forecast modeling of time series of electricity consumption with transport to determine the accuracy of the final forecast and analyze the methodology for its implementation.

The main idea of creating the model was a pre-forecast neural network model of the time series of electricity consumption at the airport, observing its dependence on influencing factors.

To implement the idea and achieve the goal, the following research objectives were formulated:

1) to identify the main features of forecasting the form of electricity consumption along the route using analytical methods;

2) to build a trend-seasonal pre-forecast model of the time series of electricity consumption at the airport of comparative visual and analytical results;

3) to build a neural network pre-forecast model of the time series of electricity consumption at the airport, the observational dependence of the preliminary forecast on passenger traffic, dispatched cargo, the number of flights and the average monthly temperature.

4 Methods

Without claiming to be complete, the classification of the main methods and techniques for pre-forecast modeling of electricity consumption by an airport can be presented as follows (Table 1):

Table 1. Methods and techniques for pre-forecast modeling of electricity consumption by an airport

A clear-cut approach	Fuzzy-valued approach (with possible fuzzification of input data)
Mathematical methods Extrapolation methods Spline extrapolation methods Statistical methods Methods of correlation and regression analysis Methods of constructing time series Spectral analysis and harmonic synthesis Principal component analysis Autoregressive models with moving	Fuzzy mathematical methods Extrapolation fuzzy methods Fuzzy methods of spline extrapolation Methods of fuzzy statistics Fuzzy methods of correlation-regression analysis Methods of constructing fuzzy time series Spectral fuzzy analysis and fuzzy harmonic synthesis Fuzzy method of principal components Fuzzy autoregressive models with moving average residual Methods of fuzzy artificial intelligence

average residual Artificial intelligence methods Neural network methods of pre-forecast modelling Swarm intelligence method Evolutionary methods (genetic algorithm, etc.) Combined methods	Fuzzy neural network methods of pre-forecast modelling Method of fuzzy swarm intelligence Evolutionary fuzzy methods (fuzzy genetic algorithm, etc.) Fuzzy combined methods

Mathematical methods of pre-forecast modeling are characterized by high degrees of complexity and labor intensity of construction. For example, spline approximation methods provide a combination of complementary models of the spline function of the current mode of electricity consumption and the spectral function of the planned consumption for a given period, taking into account seasonal fluctuations in consumption.

Based solely on the available quantitative dependencies and on the hypothesis of the immutability of the trend in the future, formalized extrapolation methods do not contribute to achieving acceptable accuracy of results and can lead to their erroneousness and even to incorrectness.

Statistical methods, generally speaking, are appropriate under the condition of a steadily developing state economy (this, in particular, explains the choice of bench data used by the authors to construct trend-seasonal models in this article), but, even if this condition is met, the correlation-regression technique, for example, is characterized by the inertia of forecasts based on the "prehistory", weak sensitivity to the manifestation of new trends in electricity consumption by the airport. The above also applies to "long" time series of electricity consumption levels and significant factors influencing it. Continuous operation of the airport naturally contributes to the emergence of new information relevant for a certain period of time, requiring transformation and adjustment of the pre-forecast model, which is a rather complex and labor-intensive task with a significant amount of calculations. The above explains, in particular, the inertia of forecasts, their noticeable inaccuracy and inefficiency. Time series describing the volumes of electricity consumption are characterized by heterogeneity of values and the complexity of their practical modeling. Even the models of J.Box and G.Jenkins, which have the well-known abbreviation ARMA ARIMA, using information from the "prehistory" of the constructed pre-forecast time series, have, as a rule, limited algorithmization capabilities, explained by the imperfection of correlation methods for forecasting electricity consumption by the airport. [1-3]

The Ingle (ARCH), Bollersley (GARCH) and Nelson models, which include heteroscedasticity features, are sensitive to future instability. However, their ambiguity and resource intensity, as well as the lack of a method for assessing the optimal amount of initial information, significantly complicate the process of their construction and use (www.tensorflow.org).

5 Results

The time series of electricity consumption generally remains dependent on a number of factors, some of which are not deterministic and are poorly formalized. So, let's generalize the example of a one-dimensional autoregressive model into a multidimensional, even lag model.

$$y(t) = u_0 + \sum_{k=1}^{N} \sum_{i=1}^{P(k)} U_i^k y(t - \tau_i) + e(t), where$$

$y(t)$- current electricity consumption of the airport;

$y(t-\tau_i)$- electricity consumption with step τ_i;
u_0- initial constant;
k- number of time series of the corresponding factor influencing consumption;
N – number of time series in the pre-forecast model;
p(k)- number of retrospective terms of the k-th series taken into account in the model;
i- number of the element of the series;
U_i^k- model parameter at the *i*-th element of the *k*-th series;
e(t)- random component;

does not improve the quality of the preliminary forecast (in particular because adding factors to the preliminary forecast model increases R^2, thereby worsening it.

In addition to the autoregressive modeling technique with moving averages of residuals, in the "classic" modeling there is a compositional approach based on the opinion that, similar to a spatial sample, a dynamic series is considered a sample from an infinite series of indicator values over time. But unlike a spatial sample, the elements of a dynamic series turn out to be statistically dependent and differently distributed values. The values of a time series contain two types of components: systematic and random. The systematic component is the result of the influence of constantly acting factors. As a rule, the following main systematic components are distinguished:

-trend (*x1*);
-cyclicity (*x2*);
-seasonality (*x3*);
-random component reflecting sharp, unexpected influences and dependencies (*x4*).

The additive model of the time series obviously has the form:

$$y_t = \sum_{k=1}^{4} x_k$$

Multiplicative

$$y_t = \prod_{k=1}^{4} x_k$$

To model the cyclical component, fairly large data sets of the studied indicator are required, and therefore the authors of the article, familiar with cyclomatics, decided not to include it in the bench (control) pre-forecast model, choosing the trend-seasonal approach. The authors considered the trend-seasonal time series $\{Y_t\}$, $t = \overline{1,T}$ generated by an additive random process $Y_t = x_1 + x_3 + x_4$, where at the stage of pre-forecast modeling *x4* is not analyzed.

In the process of research related to identifying the trend, the apparatus was used where at the stage of pre-forecast modeling *x4* is not analyzed. In the process of research related to identifying the trend, the apparatus of probability theory and mathematical statistics developed for simple statistical populations was used.

Time series of electricity consumption by international airports Boryspil, Kyiv (Zhulyany), Lviv, Dnepropetrovsk differ from simple statistical populations by a fairly complex dependence of the levels of the time series among themselves. Therefore, the use of theoretical-probability and mathematical statistical conclusions and formulas imply a certain accuracy and attentiveness at the stage of interpreting the results of trend analysis. In the classical theory of forecasting, as a rule, three types of trends are considered:

- the trend of the average level of the time series;
- the trend of dispersion;
- the trend of autocorrelation.

The results of the pre-forecast trend analysis are summarized in the following table (Table 2):

Table 2. Results of the pre-forecast trend analysis

	Airport name	Hypothetical trend equation, not confirmed by t-tests
	Boryspil	y = 6504,3x + 825746
	Lviv	y = -559,08x + 199609
	Zhulyany	y = 1640,5x + 90132
	Dnepropetrovsk	y = -806,64x + 327415

The authors of the article investigated the presence of linear trends in the average level of time series of electricity consumption by the airports of Boryspil, Zhuliany, Lviv, Dnepropetrovsk (hypothetically explained by the corresponding statistical graphs) by checking the differences in average levels.

A model example can be the data on electricity consumption by the airport "Lviv" for the period 2000-2007. (Table 3). The choice of data corresponds (in the opinion of the authors) to a relatively stable period of development of the Ukrainian economy.

Table 3. Statistical data on electricity consumption of the International Airport "Lviv" for the period 2000-2007.

	2000	2001	2002	2003	2004	2005	2006	2007
1	259520	258691	285799	294863	150068	230790	275216	172648
2	277048	274803	222500	208573	234755	261344	238236	192205
3	245913	225040	250526	272493	224851	234214	214566	148124
4	157265	149175	168404	270103	260381	177567	182690	140572
5	90035	84222	114254	139748	277838	147911	95664	95039
6	80755	118475	124401	137111	140232	131721	102098	97606
7	115909	102934	130081	128909	131107	103510	81738	71911
8	116414	109158	137880	127357	128288	94336	75145	86442
9	142774	132565	132974	140169	99406	108331	97616	78004
10	116096	198198	185334	191173	135254	126182	112099	133310
11	200395	209101	241530	277889	201448	203068	149505	183630
12	265103	296675	274581	242704	216147	222509	161234	207238
Total	2067227	2159037	2268264	2431092	2199775	2041483	1785807	1606729

When checking the equality (homogeneity) of the variances of both parts of the series using Fisher's F-criterion, based on a comparison of the calculated value of this criterion,

$$F = \begin{cases} \dfrac{\sigma_1^2}{\sigma_2^2}, \text{given that } \sigma_1^2 > \sigma_2^2 \\ \dfrac{\sigma_2^2}{\sigma_1^2}, \text{given that } \sigma_1^2 < \sigma_2^2 \end{cases}$$

with tabular (critical) value of Fisher criterion F_α был a positive result was obtained: the hypothesis of equality of variances was accepted (F=1,29 $F_\alpha = 1{,}6$),), and a conclusion was made about the possible presence of a linear trend of the average level of the series.

Then the hypothesis about the absence of a trend was tested by Student's *t*-test according to the formula

$$t = \frac{|\overline{y_1} - \overline{y_2}|}{\sigma\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}},$$

$\sigma = \sqrt{\frac{(n_1-1)\sigma_1^2+(n_2-1)\sigma_2^2}{n_1+n_2-2}}$ - −standard deviation of the difference in means

and she was justified ($t_{расч}$=3,2*$10^{-5.}$ $t_{табл}$=1,99), which contradicts the results of the F-criterion test. The resulting contradiction indicates the incomparable complexity of the real time series of electricity consumption relative to the visual perception of the constructed one. The conclusion from the above can be the assumption that the method used by the authors is correct only for time series with a monotonic trend.

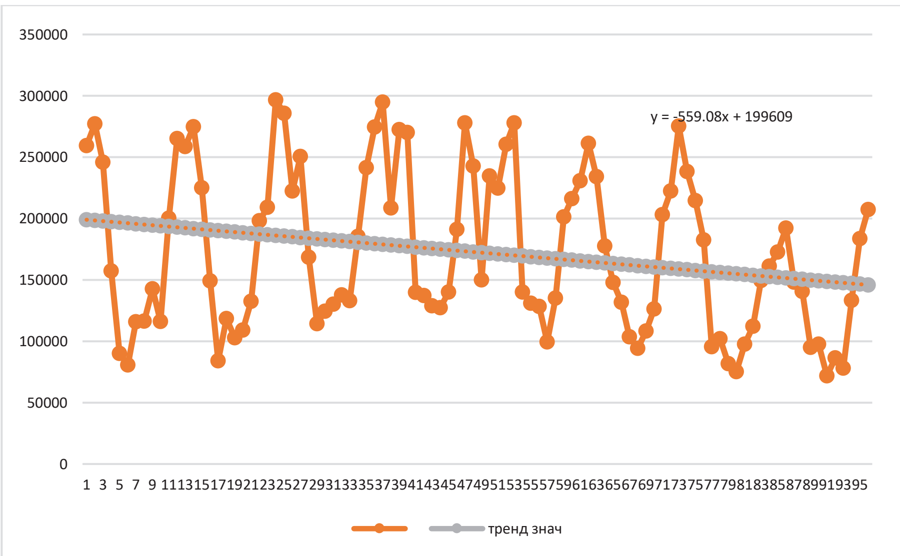

Fig. 1. Time series of electricity consumption at Lviv International Airport for the period 2000-2007 with a hypothetical trend

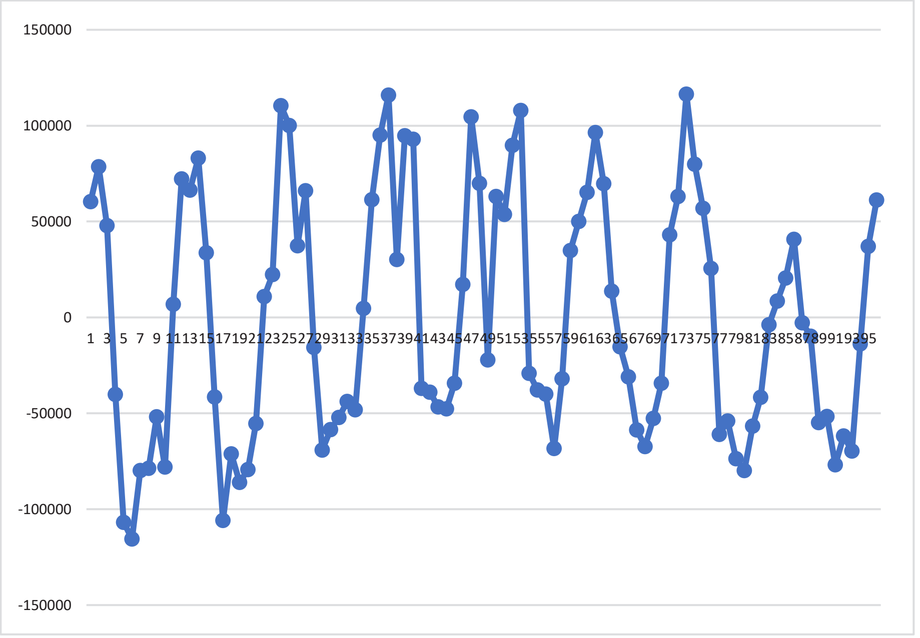

Fig. 2. Time series of electricity consumption at Lviv International Airport for the period 2000-2007 without filtered hypothetical trend

After using the Forster-Stewart method, the results of both methods were similar and the conclusions did not change.

Regarding seasonal fluctuations, it should be noted that they are formed not only under the influence of natural and climatic conditions, but also under the influence of other features of electricity consumption. From the above, it follows that not in all cases seasonality is formed by uncontrollable factors (or almost uncontrollable). In many cases, there is a possibility of their regulation or at least their active consideration, affecting the technological, organizational and management processes that contribute to the rational and efficient consumption of electricity by the airport.

The authors studied the structure of the time series using linear autocorrelation analysis of its levels. Based on the use of the linear correlation coefficient:

$$r_\tau = \frac{\sum_{t=1}^{n-\tau} y_t y_{t+\tau} - (n-\tau)\overline{y_1 y_2}}{\sqrt{\left[\sum_{t=1}^{n-\tau} y_t^2 - (n-\tau)\overline{y_1^2}\right]\left[\sum_{t=1}^{n-\tau} y_{t+\tau}^2 - (n-\tau)\overline{y_2^2}\right]}},$$

$$\tau - \text{order of autocorrelation}$$

the following correlogram was obtained

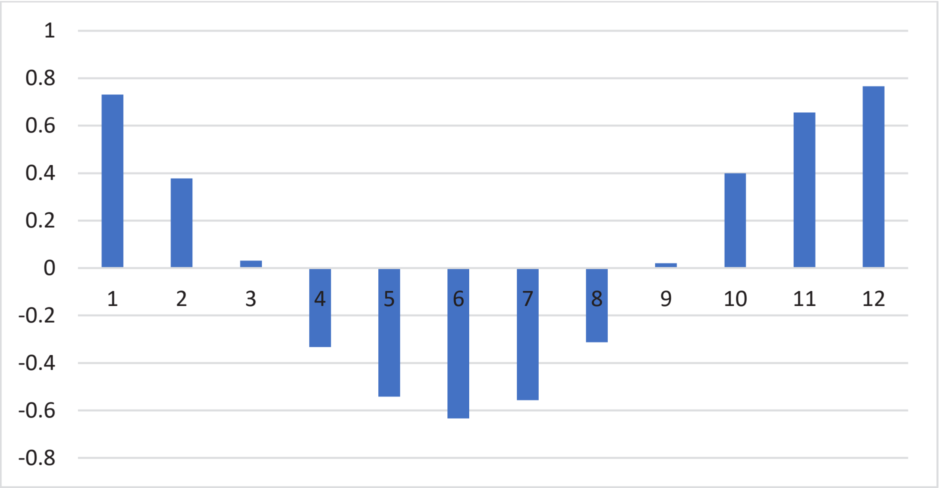

Fig. 3. Correlogram

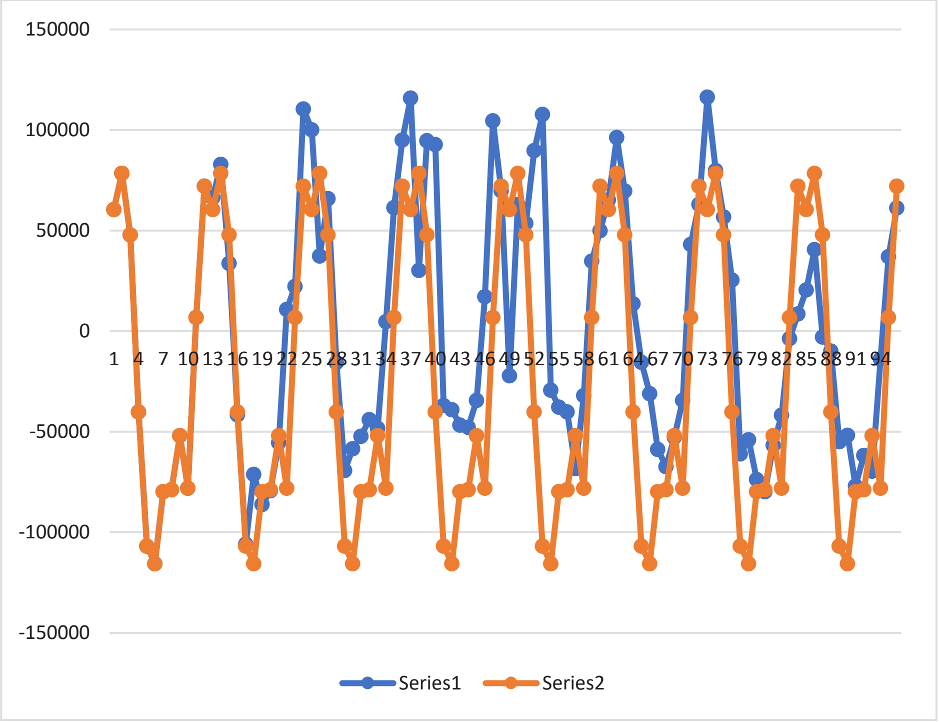

Fig. 4. Time series: - electricity consumption by the Lviv International Airport for the period 2000-2007. (2) - constructed trend of the seasonal model (1)

Considering the well-known fact that with an increase in the order of autocorrelation, the number of correlated pairs decreases and only high coefficients are significant, which distorts the real state of the relationships between the levels of the time series, the authors settled on the value $\tau = 12$.

In the conditions of airport operation, when the air transportation plan for both short-term and long-term perspectives is essentially oriented, a satisfactory model (even a pre-forecast model, not to mention the final forecast) will be one with adequate adaptability and reliability under rapidly changing conditions. According to the authors, such a model can be built using neural network theories [13,20].

For preliminary neural forecasting, the TensorFlow machine learning library [19,21] was used, created for working with neural networks by Google and released under the open Apache 2.0 license. The model was built according to the recommendations of the library developers for working with time series in the Python programming language. The purpose of forecasting was to determine energy consumption for the next month.

For forecasting, 96 statistical data of the Lviv International Airport for the period 01.01.2000-31.12.2007 were used:

- energy consumption volumes;
- passenger traffic;
-shipped cargo;
-number of flights;
-average monthly temperature.

The first five rows of data are given in the following table 4

Table 4. The first five rows of data

Electricity consumption (kW∗hour)	Passenger flow (people)	Quantity of cargo shipped (t.)	Number of flights	T C
259520	1670	2.3	208	-4.1
277048	2065	24.0	302	-3.1
245913	2376	27.2	294	1.3
157265	2644	22.3	272	7.4
90035	3484	6.8	280	13.8

The statistical characteristics of the data are presented in Table 5.

Table 5. The statistical characteristics of the data

Parameter	Quantity	Average	Standard Deviation	Min	25%	50%	75%	Max
Electricity consumption (kW*h)	96	172493	65024	71911	117 959	149786	226477	2966 75
Passenger flow	96	7910	5417	1670	385 7	6304	10530	2737 9
(people)	96	16	26	0.7	2.77 5	5.35	16.85	122
Amount of shipped cargo (t)	96	367	118	208	288	338	449	698
T C	96	6.91	7.08	-7.1	1.3	7	13.6	18.3

The monthly consumption of electrical energy is shown in Fig.5.

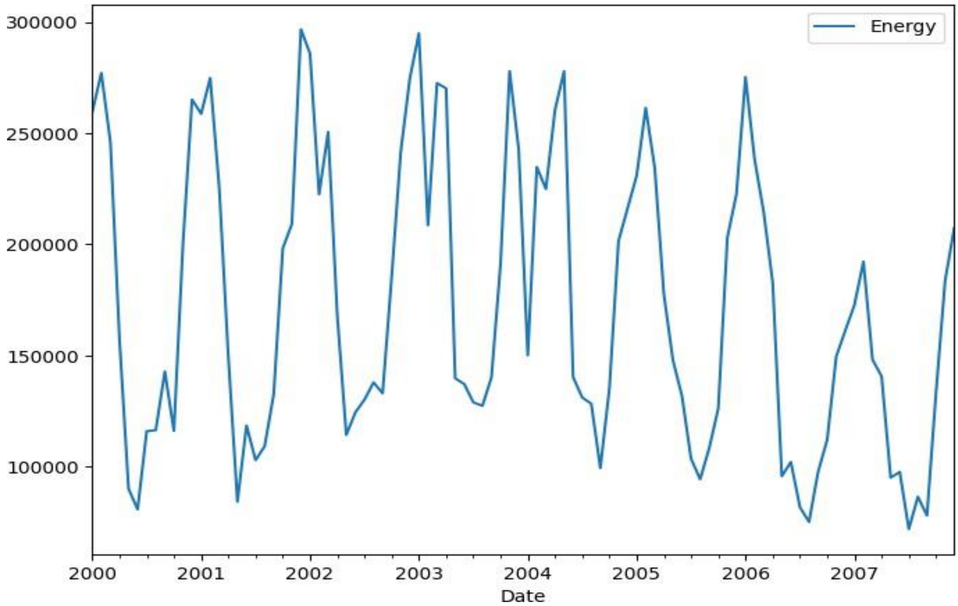

Fig. 5: The graph of monthly energy consumption of the airport

It is obvious that there is a periodic dependence on the season: in winter, energy consumption increases due to heating costs, and in summer, it decreases. The influence of other factors on the periodicity is also obvious.

For a clear definition, the Fourier transform was used (Fig.6.) [21].

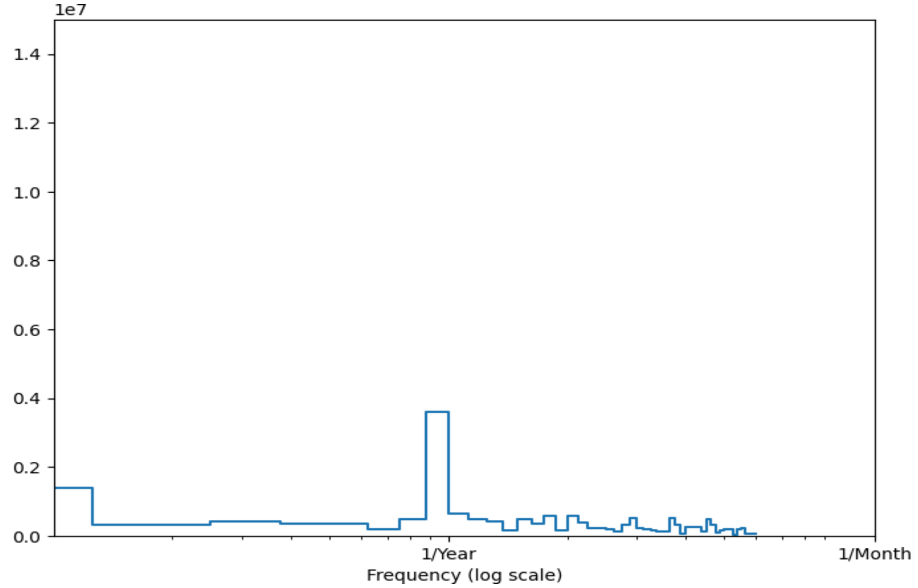

Fig.6. Fast Fourier transform for energy consumption

According to Fig. 6, a clear maximum is observed in the frequency of 1/year. To improve the predicted values, synthetic columns were added according to the formulas:

$sin\_month = sin(\frac{2\pi * month}{12})$ (1)

$cos\_month = cos(\frac{2\pi * month}{12}$ (2)

The calculation results are summarized in Table 6.

Table 6. The calculation results

Electricity consumption (kW∗hour)	Passenger flow (people)	…	Sin_month	Cos_month
259520	1670	…	-0.007431	0.999989
277048	2065	…	0.504286	0.863537
245913	2376	…	0.855976	0.517015
157265	2644	…	0.999949	0.010074
90035	3484	…	0.874686	-0.48469

The next step was to divide the data into three categories:

• training_data - 70% of the data was used to train the neural network (hereinafter referred to as training data);

• validation_data - 20% of the data was used to check the training results (hereinafter referred to as validation data);

• test_data - 10% of the data was used to check the quality of the neural network (hereinafter referred to as test data).

The distribution of data into categories of training verification and neural network quality is associated with the prevention of the fact of possible dependence of neural network training on the data by which the final result is checked.

The data was normalized as follows:

$training\_data = \frac{training\_data - training\_data\_mean}{trainin\_data\_std}$ (3)

$validation\_data = \frac{validation\_data - training\_data\_mean}{training\_data\_std}$ (4)

$test\_data = \frac{test\_data - training\_data\_mean}{training\_data\_std}$ (5)

Normalization prevents working with large numbers.

In formulas 3-5, training_data_mean is the mean value of the training data parameter, training_data_std is the standard deviation of the training data parameter.

The mean value and standard error of the training data were used to normalize the validation and test data.

The data presented below will be relative to the normalized data.

Fig. 3 shows the distribution of parameters taking into account the absence of obvious deviations. Based on the obtained data, subsequent calculations were carried out.

Models. Basic model.

The results were compared with the base model as follows: the current month's data were taken as the predicted values of the next month's electricity consumption. It is obvious from Fig. 7 that if the consumption points of the expected results are shifted to the left by 1 month, they coincide with the current electricity consumption curve.

Linear model

The linear model makes a linear transformation between the input and output values. The following linear model code was obtained in the work:

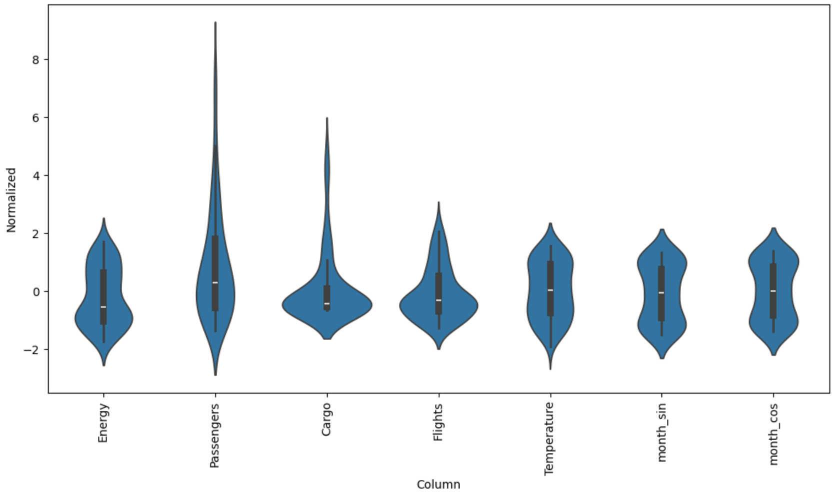

Fig. 7. Normalized parameters

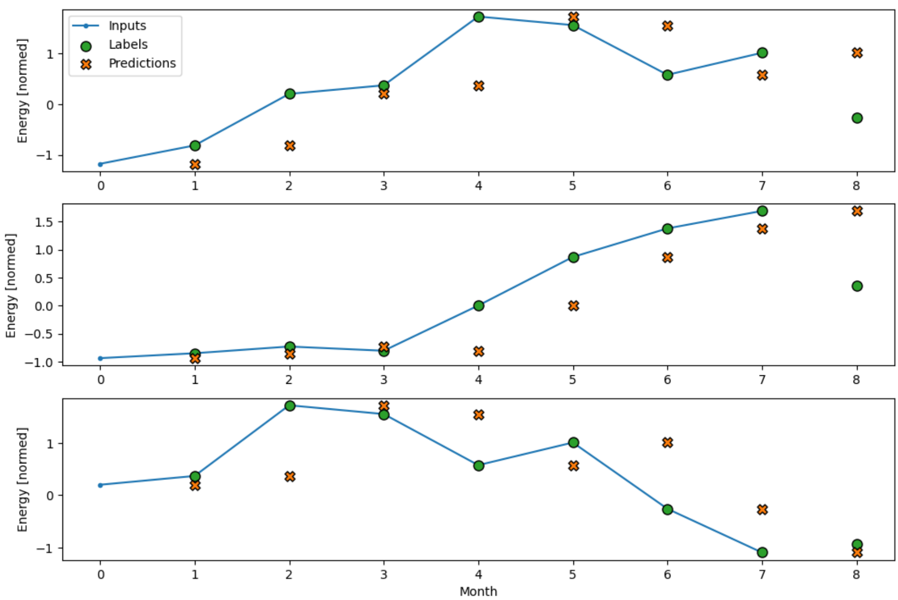

Fig. 8. Forecasting illustrations for the base model

linear = tf.keras.Sequential([
tf.keras.layers.Dense(units=1)

1) The simplicity of the linear model allows us to “increase the weight” for each parameter in Fig. 9.

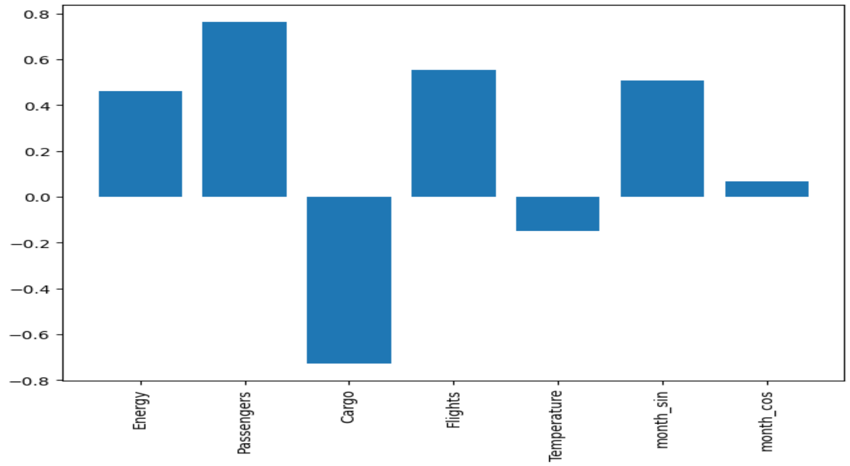

Fig.9. Weight of input parameters of the linear model

Dense model

The difference between the dense model and the linear model is that there are additional layers between the input and output. The model has the following form:

```
dense = tf.keras.Sequential([
   tf.keras.layers.Dense(units=32, activation='relu'),
   tf.keras.layers.Dense(units=32, activation='relu'),
   tf.keras.layers.Dense(units=1)
```

Multistage dense model

The previous models are characterized only by the current input data (there was no tracking of changes over time in the work]. For the multistage model, training data for a period in time, three time data were used - current, previous, pre-previous. The model code is as follows:

```
multi_step_dense = tf.keras.Sequential([
   tf.keras.layers.Flatten(),
   tf.keras.layers.Dense(units=32, activation='relu'),
   tf.keras.layers.Dense(units=32, activation='relu'),
   tf.keras.layers.Dense(units=1),
   tf.keras.layers.Reshape([1, -1]),
```

Convolutional Model

The convolutional model was proposed by Yan Likun in 1988 and is one of the more effective modern models, which has made significant progress in pattern recognition. It is based on the imitation of the biological eye. The essence of the convolutional model is the use of convolutional layers, which use the convolution operation to transfer data to subsequent layers. This model is widely used in medicine, retail, automotive, marketing and computer vision.

The code of the model is as follows,

```
conv_model = tf.keras.Sequential([
   tf.keras.layers.Conv1D(filters=32,
])
2.6
                    kernel_size=(3,),
                    activation='relu'),
tf.keras.layers.Dense(units=32, activation='relu'),
tf.keras.layers.Dense(units=1),
```

Recurrent model

The recurrent model (LTSM) builds parallel connections (orientation graph) and uses long- and short-term memory. This model is used, in particular, in speech recognition. Model code:

```
lstm_model = tf.keras.models.Sequential([
    tf.keras.layers.LSTM(16, return_sequences=True),
    tf.keras.layers.Dense(units=1)
])
```

Comparison of forecasting efficiency

To compare the forecasting efficiency, the values of the average absolute error were used. The results of the comparison are presented in Fig. 10 and Table 7.

Table 7. Comparative analysis of the results of the effectiveness of models

Check	baseline	linear	dense	multistage	convolutional	recurrent
validation	0.4383	2.0863	0.4034	0,5128	0,2949	0,71717
test	0,4007	3,6634	0,5954	0,8844	0,3508	0,7837

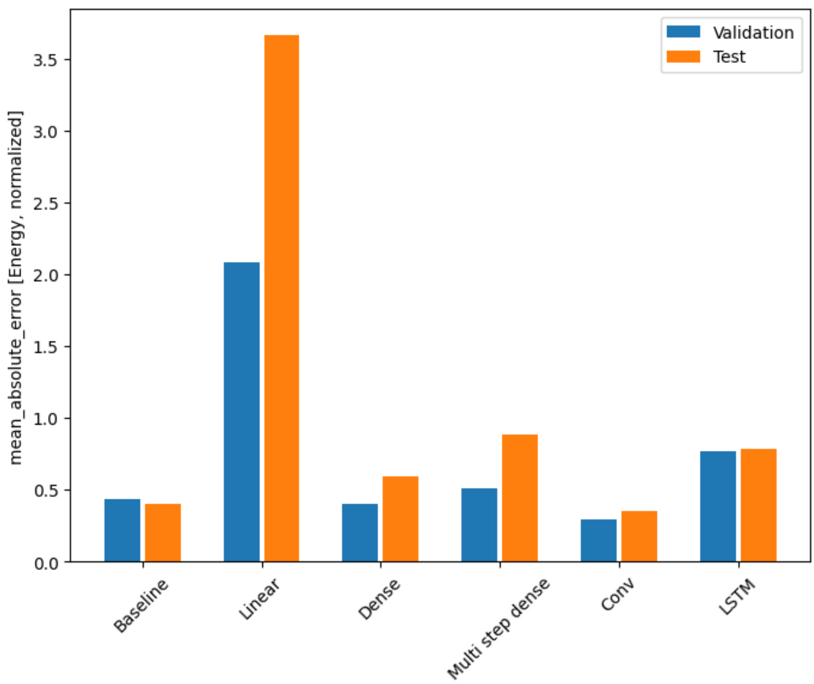

Fig.10 Diagram of the efficiency of the models used

It is obvious that the results of the convolutional model are the most effective. Using standard approaches to neural networks, the authors were able to obtain a model that gives the best forecast, in particular, better than the base model.

In the process of searching for the most effective model, variations of input parameters were used, namely:

-number of training approaches;
-division of training data;
-time range of input data;
-model structure;

-number of input data.

These variations changed the results of model checks (except for the base one), but in general these changes cannot be called significant.

The error result for the recurrent model, which usually gives the best result in forecasting problems, was unexpected. The reason for this may be an insufficient number of input data and parameters.

The result of computer experiments confirms the effectiveness of using neural networks to forecast electricity consumption.

6 Discussion

The efficiency of the method of analyzing information on energy consumption, the objectivity and accuracy of forecasts directly contribute to the adequacy of the applied management and engineering solutions in matters of energy management in general and energy consumption in particular, which in turn determines the successful operation of the airport as a whole and its individual divisions.

The goal of the pre-forecast modeling stage of electricity consumption by the airport may be the identification (or reasoned denial) of a trend, the elimination (if necessary) of abnormal data, and the identification of "seasonal" dependence.

Analytical methods, having obvious positive sides for forecasters, among which are relative knowledge of the toolkit for constructing forecast models, satisfactory clarity of methods, stages, checks, assessments and conditions of applicability and correctness, have a number of negative properties: labor intensity and labor-intensiveness of application, difficulty of application associated with the nonlinearity of real relationships in correlation-regression and autocorrelation tools, inability to process "noisy" and incomplete data, i.e. the need for a sufficiently large set of input data, low adaptability, etc.

An alternative analytical method could be the method of expert assessments, which, in particular, is applicable in cases where analytical, formalized ones are not applicable. However, the significant dependence of the quality of the forecast on the qualifications of experts and the low solvability of issues of computerization of forecast construction make these methods narrowly applicable and uncommon.

Analyzing the goals, objectives and specifics of forecasting electricity consumption in the electricity market by airports, the advantages and disadvantages of methods and ways of pre-forecast modeling, the authors agreed with the prevailing opinion that, in terms of the set of properties for computer implementation of pre-forecast modeling, methods based on the theory of constructing artificial neural networks are satisfactory.

In particular, pre-forecast models for determining the patterns of electricity consumption by an airport and the process of self-improvement directly occur simultaneously at the stage of training the neural network.

7 Conclusions

In this article were:

1. The main features of preliminary forecasting of the amount of electricity consumption by the airport using analytical methods were defined;

2. A trend-seasonal pre-forecast model of the time series of electricity consumption by the airport was built and a comparison of visual and analytical results was made.

3. A neural network pre-forecast model of the time series of electricity consumption by the airport was built, taking into account the dependence of the preliminary forecast on

passenger traffic, dispatched cargo, the number of flights and the average monthly temperature.

References

1. Kendall, Maurice G. (Maurice George), Time series, New York, 1983. 320p.
2. Robert K. Otnes Applied time series analysis, New York, 1982. 430 p.
3. E.J. Hannan Multiple Time Series, 1974. 152 p.
4. Rajan DV, Sourav M., Thakur S.S. International Journal of Engineer Research & Technology . 2012;**3:**1-9.
5. Nur A.A., Maizah H.A., Norizan M //World Applied Sciences Journal. – 2013.- #**22(11).-** P.1540-1543
6. Taylor J.W., McSharry P.E. //IEEE Transactions on Power Systems. – 2007. - #**22(4).-** P.2213-2219.
7. Taylor J.W. //IEEE Transactions on Power Systems. – 2012. - #**27(1).-** P.458-464.
8. P.Han, P.X. Wang, S.Y. Zhand, D.N. Zhu // Mathematical and Computer Modelling. – 2011. - **#51 (11).** P.1398-1403
9. Jakasa T., Adrocec I.,Sprcic P. *Electricity price forecasting ARIMA model approach*// Proc. Of the 8 International Conference on the European Energy Market (EEM) .- Zagreb, 2011. -P.222-225
10. Wang J., Zhou Y., Chen X. *Electricity load forecasting based on support vector machines and simulated annealing particle swarm optimization algorithm* // Proc. Of the IEEE International Conference on Automation and Logistics. – Jinan, 2007.- P.429-435.
11. Laboissiere L.A., Fernandes R.A.S., Lage G.G. // Applied Soft Computing.-2015.-**N 35**.-P.66-74.
12. Pai P.F., Hong W.C: //Energy Conversion and Management. - 2005.- **N 46** (17). P. 2669-2688.
13. .Swingler K. Applying neural networks: a practical guide. - Waltham, Morgan Kaufmann Publishers, 1996.
14. Gao G., Lo K, Lu JF, et al World Journal of Engineering and Technology. 2016;**4**:58-65. doi:10.4236/wjet.2016.43D008
15. Zheng H., Yuan J., Chen L. Energies. 2017; **10**:1-20. Doi: 10.3390/en10081168
16. Lopez M, Sans C, Valero S, et al. Energies. 2018;**11**:-19 doi:10.3390/en1 1082080
17. Li M.W., Geng_J., Hong W.C., et al. Energies. 2018;**11(2226):**1-22. doi:10.3390/en11092226
18. Wang Z, Srinivasan R. Renewable and Sustainable Energy Reviews. 2017; **75**:796-808. doi: 10.1016/j.rser.2016.10.079
19. A Brief Introduction to Neural Networks (D. Kriesel) - Illustrated, bilingual manuscript about articial neural networks; Topics so far: Perceptrons, Backpropagation, Radial Basis Functions, Recurrent Neural Networks, Self Organizing Maps, Hopeld Networks (Posted on 2009)
20. Van Loan, Charles (1992). Computational Frameworks for the Fast Fourier Transform
21. Amita Kapoor, Antonio Gulli, Sujit Pal (2022) Deep Learning with TensorFlow and Keras (Third Edition). Packt Publishing