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MACROMODELING FOR THE FORECASTING OF LOCAL ENERGY SUPPLY SYSTEMS BALANCE, APPLYING FRACTAL PROPERTIES OF LOADING AND GENERATION GRAPHS

Method for the forecasting of the energy consumption balance of the urban civil development objects using discrete macro-models has been suggested. Energy supply system (ESS) of the district is considered, characteristic feature of the system is energy consumption from the electric public grids and which has own source of electric energy generation from the renewable sources of energy (RSE). Such local electric energy system (LES) at certain conditions can operate as an independent balanced energy object. For optimal operation of LES in such conditions the graphs of its energy consumption must be forecast.

The suggested method of macro modeling enables to develop with the needed accuracy the determined models of energy consumption, based on the retrospective information without using the procedures of the preliminary data processing. The solution of the problem of energy consumption graphs forecast is simplified as a result of using in the process of model construction only the basic or determining characteristics. They comprise fractal properties of the graphs of ESS loading. The essence of the alternative forecasting on the base of macro modeling is the process of construction of energy consumption model by stages. At the first stage of the analysis procedure realization the collection and processing of the data regarding energy consumption of the investigated real object is provided, the second stage includes the selection of mathematical model, further improvement of the mathematical model parameters and testing.

The performance of the suggested method was verified by means of construction the macro model of daily energy consumption of 9-story 216-apartment residential building. For this purpose input data of average daily energy consumption and week average consumption were used. The results obtained showed that using ASCAE (Automatic system for commercial accounting of power consumption) information it is possible to obtain a number of obvious daily graphs of electric loading and generalize them for further usage. As a result of the application in the process of macro modeling the fractal properties of LES loading graphs the accuracy of the energy consumption forecast improves and the term of the satisfactory forecast increases.

Key words: *energy supply system, forecast, energy consumption, macro modeling, fractal properties, renewable sources of energy, local energy system.*

Introduction

Macro modeling in energy branch of national economy enables to perform large scale analysis and forecast of electric energy systems operation. This may include such aspects as generation, transmission and distribution of electric energy.

Macro modeling can serve as a useful tool for decision-making concerning the development and control of electric energy system, provision of the stability and reliability of energy supply as well as for the analysis of the impact of various factors such as growth of energy consumption, changes in energy technologies, etc. For the assessment of complex systems, including energy supply system (ESS) macro modeling is also used [1 – 3]. These models of ESS differ in that they describe only external characteristics of the modeled system and are intended for its general assessment. The solution of the problems in this case is simplified, without losing adequacy, as a result of using in the process of model construction, only basic or determining characteristics [1]. The characteristics, describing the loading graphs of ESS comprise their fractal properties [4 – 6]. That is, self-affine structures – fractals are used, each part of fractal repeats in its development the development of the whole model. This means that they have similar structural properties at different levels of detailing. Such models are useful for obtaining the preliminary assessment of the system, for instance, during the preprojective solutions. However, the problem is that the forecasting of powerful energy systems, industrial enterprises does not provide the possibility to take into consideration the composition, specific features and technological peculiarities of the operation modes of electric receivers and energy consumption of the urban development objects. That is why, t**he objective of the paper** is the development of the efficient, rather accurate for practical application method of forecasting, using fractal properties for ESS of the urban development.

Highlighting of the basic properties of ESS in the technique of macro modeling

Energy consumption in the residential buildings may vary, depending on the day, season, year. Volume of energy consumption is influenced by the usage of various electric devices, weather conditions, daily activity of the inhabitants, etc. Besides, in local ESS instability of RSE generation should be taken into account as RSE are the part of energy supply. These factors create problems, dealing with the forecasting of ESS energy consumption graphs. Thus, determination of the forecast electric loading is the basic for urban grids design.

Main group of the consumers in the residential areas are residential buildings. Behavior of the inhabitants influences the energy consumption. Form of electric appliances usage, lightening, heating and air conditioning may change in time. Volume of electric energy consumption is influenced by powerful electric receivers (air conditioners, washing machines and dish washers, electric heating devices such as boilers, electric ovens, heating systems, etc.).

Fig. 1 shows the structural diagram of the models, intended for the forecasting of the electric energy consumption by the civil objects of the urban development.

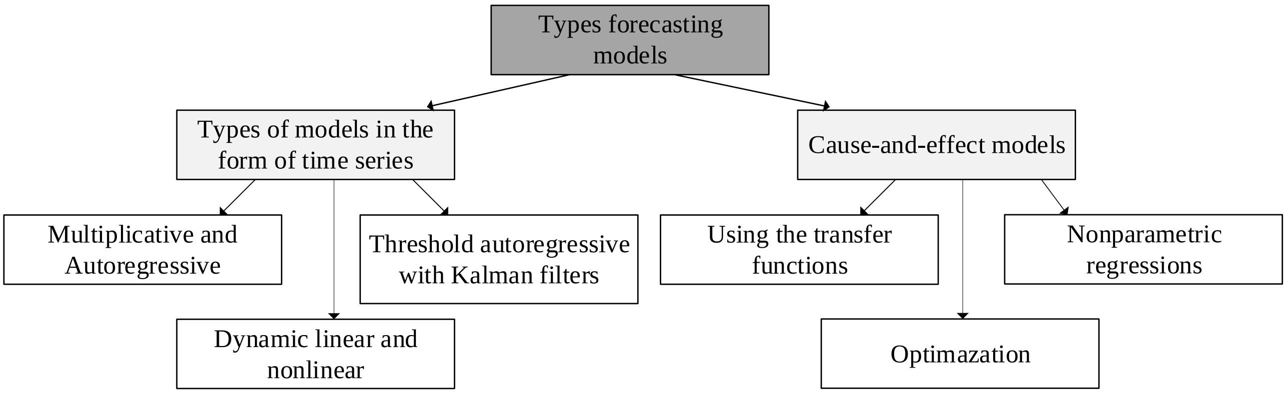

Fig. 1. Type of the models of electric energy consumption forecast

Autoregression models are the models of the time series, where the value of the time series at the given moment is linearly dependent on the previous values of the same time series. Autoregression process of p order is determined as:

$$X_t = c + \sum_{i=1}^{p} a_i X_{t-i} + \varepsilon_t , \tag{1}$$

where α_i – are the parameters of the model (autoregression coefficients); c – is constant (often to simplify is taken to be equal zero); ε_t – is white noise.

By means of autoregression models the seasonality can be modeled, in this case the number of model coefficients will correspond to the number of factors, that change cyclically and are taken into consideration.

1) In order to forecast consumption the following form of autoregression model can be applied:

$$L(t,d) = \sum_{k=1}^{4} a_k L_k(t,d), \tag{2}$$

where a_k – are linear weights, which provide the optimal combination of four separate forecasts; $L1\ (t, d)$ – is forecast $L\ (t, d)$ on the base of autoregressive model of the first order with one hour of delay; $L2\ (t, d)$, $L3\ (t, d)$, $L4\ (t, d)$ –is the same with day, week and year of delay, correspondingly.

2) Generalized exponential, smoothing which could be applied for the forecast of the total hourly energy consumption:

$$L(t) = a^T f(t) + \varepsilon(\mathrm{t}), \tag{3}$$

where a^T– is the vector of exponentially smoothed weights, being transposed; $f(t)$ – is the vector of smoothing functions.

Smoothing functions is the decomposition in Fourier transform for one week period.

3) Neural networks and fuzzy logic – it is one of new approaches, used for the solution of the forecasting problem on the base of fuzzy logic and neural networks. Method provides the usage of the a priori information, enables to use new information in the process of construction and take into account the properties of the process being modeled. Previously known information, used for model teaching and is visible for the observer can be used. Neural networks are able to determine complex dependences between input and output data and perform generalization of the available, although hidden properties and interactions. It follows from this the ability of the taught neural network to forecast, predict future value of the certain sequence on the base of several previous values or factors, existing at a given moment.

Modeling, using fuzzy sets is expedient in case of studying very complex technical system or process.

Modern mathematical statistics, which was the basic tool for data analysis does not always suitable for the solution of the real life problems. This happens as the averaged characteristics of the sample are used, they are often turn out to be fictitious values. That is why, the methods of mathematical statistics are useful for the verification of preformulated hypotheses.

Construction of forecast macro model

The essence of the alternative forecasting on the base of macro modeling is the process of the construction of energy consumption model by the stages, presented in Fig. 2.

At the first stage of the analysis procedure execution the collection and processing of the data, regarding energy consumption of the investigated real object is provided. System of the organization of the collection and registration of energy loading data of the object is performed by means of automated system of the commercial account of electric energy (ASCAE). Electricity meters in the residential buildings, public buildings and their complexes are recommended to connect to ASCAE system, this will promote the usage of the given system as a tool of energy audit and monitoring of energy resources saving, introducing the corresponding measures [7]. Application of ASCAE will promote energy resources saving as a result of the careful monitoring of electric energy consumption and elaboration of the corresponding measures.

The collected information is represented in the form of continuous graphs (Fig. 3) or in digital form. Maximum electric loading is determined according to the obtained information (in the graphs of Fig. 3 this loading is 95 kW). Graphs of electric loading are of probabilistic character and change during a day, they have maxima from 7 am to 9 am and from 19 pm to 23 pm, this is stipulated by the operation modes of various electric devices.

Preliminary processing of the data provides the selection of the period of time, for which the forecast is performed and the period of further verification of the data. Filtration of the given volume of information regarding energy consumption is carried out in order to select the form of the model and simplification of the forecasting procedure.

In the process of the model form selection mathematical macro modeling, using discrete autonomous macro models in the form of "black box" may emerge. The process occurs on the base of the registered characteristics of electric energy consumption, using homogeneous differential or difference equations of the state in the following form:

$$\begin{cases} \dfrac{d\vec{t}}{dt} = \vec{f}(\vec{x}) \\ \vec{y} = \vec{g}(\vec{x}) \end{cases}, \tag{4}$$

$$\begin{cases} \vec{x}^{(k+1)} = \vec{f}\left(\vec{x}^{(k)}\right), \\ \vec{y}^{(k+1)} = \vec{g}\left(\vec{x}^{(k)}\right) \end{cases} \tag{5}$$

where $\vec{x}$ – is a vector of variable states; $\vec{y}$ – is a vector of the output variables; $\vec{f}(\cdot), \vec{g}(\cdot)$ – are vector function, chosen by means of optimization algorithms.

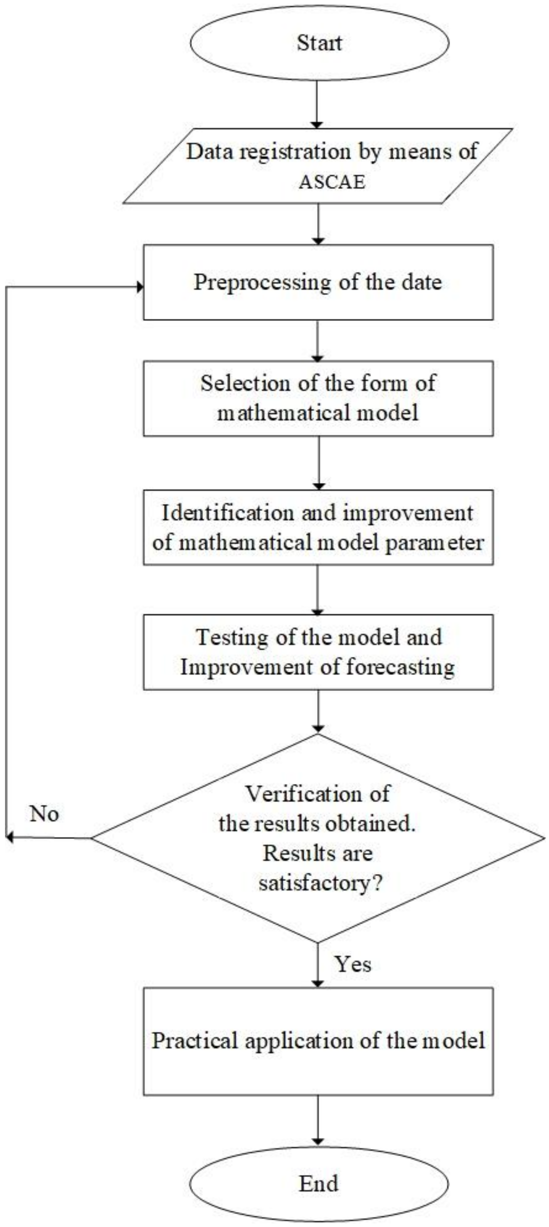

Fig. 2. Stages of forecasting macro model construction

As during the construction of electric energy consumption model the vector of the input variables is missing, we will consider the case, when the initial value of the variables of the modelled object state is zero. The form of macro models description will be selected in the following form:

$$\begin{cases} \vec{x}^{(k+1)} = \mathbf{F}\,\vec{x}^{(k)} + \Phi\left(\vec{x}^{(k)}, \vec{\nu}^{(k)}\right) \\ \vec{y}^{(k+1)} = \mathrm{C}\left(\vec{x}^{(k+1)}\right) \end{cases}.$$

(6)

Initial state of the object being modelled is described by zero discrete of the vector of state variables $\vec{x}^{(0)}$. That is why, the components of this vector must be added to the set of the unknown coefficients of the model.

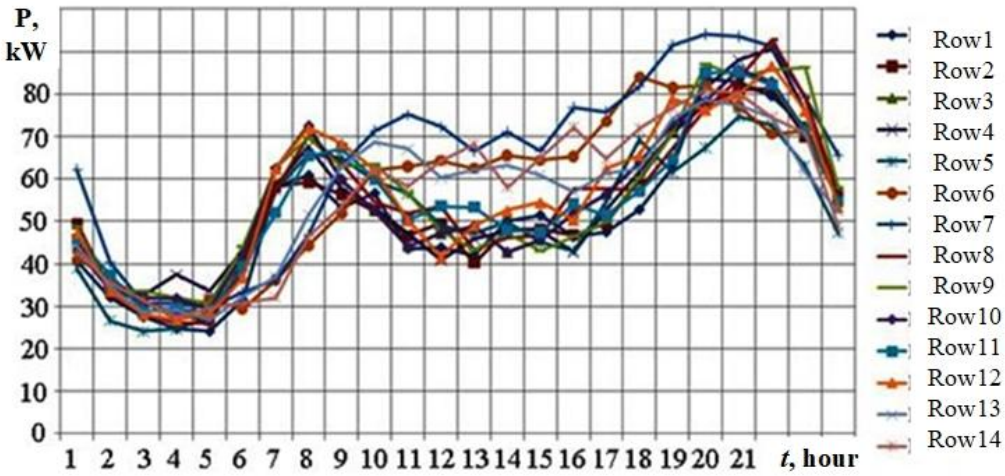

Fig.3. Example of the graphs of the daily electric loading of the residential building (day of the month coincides with the number of the row)

However, $\vec{x}^{(0)}$ can not be simply included in the set of model parameters, as for each dynamic process, there will be its independent value of $\vec{x}^{(0)}$. To take into account this fact, it is necessary to divide the vector of the unknown coefficients $\vec{\lambda}$ into two parts: the first, comprising the coefficients, identical for all the processes and the second – with the independent set of the vector $\vec{x}^{(0)}$ elements for each process, that increases the unknown amount of the coefficients and complicates the optimization task.

During the usage of the suggested macro model there appears the problem, dealing with the determination of zero discrete of the vector $\vec{x}$, since the components of this vector, as a rule are not measured experimentally but are determined by means of certain values of the output elements $\vec{y}$. In general case, this means, that it is necessary to find additionally linear or nonlinear dependence $\vec{x}^{(0)}$ on the experimentally measured values $\vec{y}$.

In particular, in the problems of the forecast this dependence is constructed as the function of several first discrets of the output values:

$$\vec{x}^{(0)} = \vec{f}\left(\vec{y}^{(1)}, \vec{y}^{(2)},..., \vec{y}^{(l)}\right), \tag{7}$$

where l – is the number of discretes, used for determining zero discrete of the vector $\vec{x}$.

Optimization approach can be used for finding the additional dependences due to the universality of the macro models presentation form. This means, that the elements of the vector $\vec{x}^{(0)}$, added to the unknown coefficients $\vec{\lambda}$ should be replaced by the coefficients of the expression (3), i. e., actually introduce this expression in the model itself.

If the model has the form (7), then we obtain:

$$\begin{cases} \vec{x}^{(k+1)} = \mathbf{F}\,\vec{x}^{(k)} + \Phi\left(\vec{x}^{(k)}\right) \\ \vec{y}^{(k+1)} = \mathbf{C}\,\vec{x}^{(k+1)} \\ \vec{x}^{(0)} = \vec{f}\left(\vec{y}^{(1)}, \vec{y}^{(2)}, \dots, \vec{y}^{(l)}\right) \end{cases}, \tag{8}$$

that will promote the approbation of energy consumption macro model.

In order to verify the performance of the suggested approach, macro model of daily energy consumption of 9-story 216 apartment residential building was constructed, for this purpose input data, regarding average daily and week energy consumption are used (Fig. 4 and 5).

Discrete macro model of the residential building energy consumption is created in the form of the following relation:

$$\begin{cases} \vec{x}^{(i+1)} = \mathbf{F}\,\vec{x}^{(i)} \\ \vec{y}^{(i+1)} = \mathbf{C}\,\vec{x}^{(i+1)} \end{cases}. \tag{9}$$

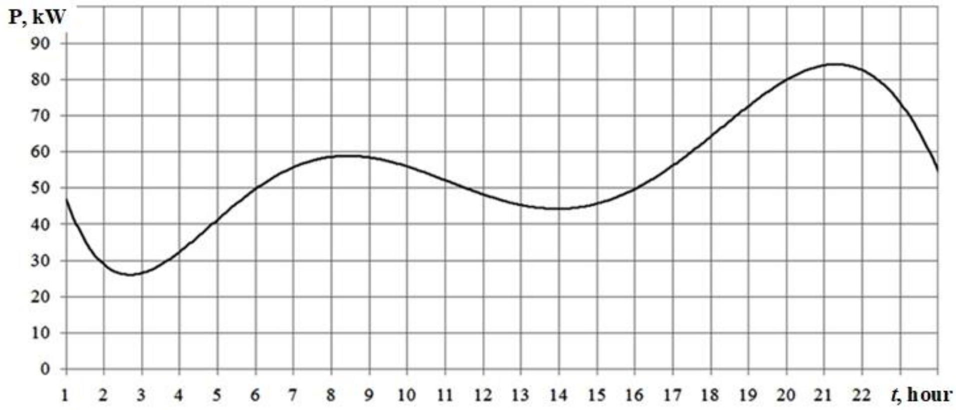

Fig. 4. Dynamics of average daily energy loading of the residential building

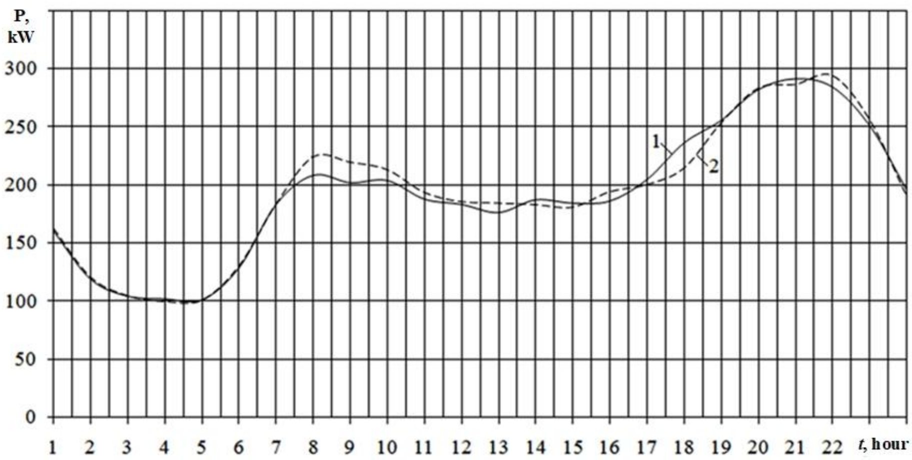

Fig. 5. Input data of energy consumption of the residential building during the first and second weeks, curves 1 and 2 correspondingly

For the construction of the macro model input data of daily energy consumption during the first and second weeks are used. Initial value of the state variables was determined on the base of the linear dependence on the level of electric energy consumption at randomly chosen time, namely, at 9am, 20pm and 22pm:

$$\vec{x}^{(0)} = S\begin{pmatrix} y_9 \\ y_{20} \\ y_{22} \end{pmatrix}. \tag{10}$$

Verification of the autonomous macro model was carried out on the independent set of data. For this purpose the input data of the residential building energy consumption for the third week and created macro model of energy consumption for the third week were used (Fig. 6).

Comparison of root mean square error of the forecast by the regression forecast model of the residential building energy consumption and by means of the neural network showed the following.

According to the retrospective information of the residential building energy consumption regression model for the forecast has the following form:

$$w = 55t + 4562\,. \tag{11}$$

Root mean square error of electric energy consumption forecast by the regression model was 6.0 %.

Fig. 6. Input data (curve 1) and reaction of the macro model at the 3rd week (curve 2)

Comparing the actual value of energy consumption by the residential building during the 3rd week of October with its value according to macro modeling, root mean square error of the forecast is approximately 3.1 %. Thus, the forecasting according to macro modeling better approaches to the adequacy of the process than according to regression model.

Conclusions

The suggested method of forecasting allows to develop with sufficient accuracy the determined models of energy consumption, based on the retrospective data without using the procedures of the preliminary processing of the data, typical for other methods. Forecast of LES energy consumption graphs is simplified due to the application in the process of macro model construction only basic and determining characteristics. These characteristics comprise fractal properties of ESS loading graphs.

On the example of energy consumption forecast of the residential building it was shown that the approach of the autonomous macro modeling, efficiently using a priori information, enables to learn and at the output provide visual and adequate information, concerning the process of energy consumption by LES. Using the information of ASCAE (Automatic system for commercial accounting of power consumption) it is possible to obtain a number of visual daily graphs of electric loading and generalize them for the future. As a result of using in the process of macro modeling the fractal properties of LES loading graphs the accuracy of energy consumption forecast improves and the term of the satisfactory forecast increases.

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Editorial office received the paper 20.09.2023.
The paper was reviewed 27.09.2023.

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