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EFFECTIVENESS EVALUATION OF DISCRETE MACROMODELLING TO FORECAST POWER CONSUMPTION OF ELECTRIC POWER SYSTEM COMPONENT ELEMENTS

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Abstract: The paper is concerned with a method intended for forecasting electric power consumption using discrete macromodels of daily and annual electric power consumption of defined objects. The method provides the possibility of estimating qualitative characteristics of future electric power consumption based on known prior data. The procedure of development of a mathematical macromodel for the electric power consumption forecasting by using the evolution algorithms is described; it is based on the discrete autonomous macromodels in the form of state equations using “black box” approach. A discrete autonomous macromodel of annual power consumption of a real component element has been developed as a test example for the proposed technique. Effectiveness of the discrete equation apparatus application for power consumption forecasting of electric utilities has been evaluated.

Key words: electric power system, macromodel, forecasting, power consumption, optimization.

1. Introduction

Electric power consumption forecasting is currently one of the main research problems in the electric power industry [3–7]. The greatest interest is attracted by long-term and mid-term forecasting of the world energy consumption in general and individual industrial objects in particular. Besides, the problem of power consumption forecasting has become more complex during several last years due to the requirements of scientific and technical progress and impact of geopolitical factors.

2. Problem statement

The goal of this research is to evaluate the effectiveness of the discrete equation apparatus usage for the purpose of forecasting the power consumption of electric utilities. In order to ensure uninterruptible and economical power consumption, it is necessary to solve the problem of forecasting both short-term (from one up to seven days) and long-term (annual) power consumption. This problem remains a topical issue for the field of electric power engineering [4].

To fulfill the conditions of reliability and adequacy, the mathematical models developed to predict power consumption should take into account:

1) background of the system (information about the state of the system, which predates the modelling process); 2) changes of astronomical factors (fluctuations of the light part of a 24-hour period) causing variations of the astronomical part of the electrical load; 3) influence of external factors and atmospheric phenomena; 4) influence of seasonal network load fluctuations and work day duration; 5) structural changes in the industrial load; 6) social and political factors.

There are many techniques intended for the load forecasting [6], namely:

1) time series models where the load is modelled as a function of its previously registered values. These models include multiplicative autoregressive, dynamic linear or non-linear models, threshold autoregressive models [5] and those based on the Kalman filters [7];

2) cause-consequence models where the load is modelled as a function of some exogenous factors (based on Box-Jenkins transfer functions, optimization models and models with non-parametric regression) [6, 8].

In spite of many types of mathematical models applicable to the solution of the problem stated, the most popular ones are the linear regression models and those allowing for the load to be divided into the basic (regular) and dependent on the weather parts. Nevertheless, they are mainly linear models, while the load series are nonlinear functions of external variables. The research [4] presents the technique of a hierarchical multifactor model of the electric load intended for enhancing the effectiveness of short-term forecasting. This model contributes to more correct consideration of the influence of astronomical and meteorological factors. In recent years owing to the development of the theory of artificial intellect, the problem of power consumption can be solved using models based on neural networks and fuzzy logic [4].

3. Mathematical model

Mathematical macromodelling employing discrete autonomous macromodels in the form of state equations using the “black box” approach can become an alternative way to solve the stated problem. Such a type of mathematical macromodels can be developed based on the registered characteristics of power consumption using homogeneous differential or finite-difference state equations in the following form [1–3]:

$$\begin{cases} \frac{d\vec{x}}{dt} = \vec{f}(\vec{x}) \\ \vec{y} = \vec{g}(\vec{x}) \end{cases} \tag{1}$$

$$\begin{cases} \vec{x}^{(k+1)} = \vec{f}\left(\vec{x}^{(k)}\right) \\ \vec{y}^{(k+1)} = \vec{g}\left(\vec{x}^{(k)}\right) \end{cases} \tag{2}$$

where $\vec{x}$ is the state variables vector, $\vec{y}$ is the vector of output variables; $\vec{f}(\cdot)$, $\vec{g}(\cdot)$ are some vector-functions.

Solution of equations (1, 2) totally depends on the initial values of the state variables $\vec{x}(0) = \vec{x}_0$. Hence, these initial values of the state variables can be interpreted as some disturbances causing a uniquely determined dynamic process $\vec{x}(t)$ or $\vec{x}^{(k)}$ on the basis of which it is possible to identify parameters and a structure of the corresponding systems of equations (1) or (2). Such a dynamic system can be considered as a mathematical model (an autonomous macromodel) suitable for the forecasting of dynamic processes caused by a certain initial state of the corresponding dynamic system. Nevertheless, stability of the system parameters with respect to time constitutes a necessary condition for calculation.

The examples of scientific and technical problems for which the proposed approach to forecasting time characteristics is useful, can be found in different fields of science, technology, and economy. The mathematical modeling approach proposed above can be named autonomous macromodelling and the corresponding models can be named autonomous macromodels. It should be noted that it is not necessary for macromodels of (1) and (2) type to satisfy the stability conditions. Moreover, in many cases, this condition cannot lead to the adequate forecasting. This feature restricts the time period when the prediction of the dynamic system behavior is a certain fact. Therefore, autonomous macromodels are especially effective in cases where the state variables of the system under research have a periodic or quasi-periodic nature (for example, it can be the forecasting of fuel-economic indicators during the year).

Another feature of the autonomous macromodelling is the ability to refine the forecasting results with the additional information received in subsequent time points. This peculiarity stems from the need to determine the initial state of the modeled object to predict the dynamic processes. With new data available, it could be possible to clarify the initial state of the modelled object based on the forecasting results that are more adequate.

Let us consider a case when the initial value of the state variables has a non-zero value. The form of the macromodel description can be written down using the following equation:

$$\begin{cases} \vec{x}^{(k+1)} = \mathbf{F}\vec{x}^{(k)} + \Phi\left(\vec{x}^{(k)}, \vec{v}^{(k)}\right) \\ \vec{y}^{(k+1)} = \mathbf{C}\vec{x}^{(k+1)} \end{cases} \tag{3}$$

The initial state of the modelled object is described by a zero discrete of the state variable vector $\vec{x}^{(0)}$. Therefore, the components of this vector should be added to a set of unknown coefficients of the model $\vec{l}$. But it is impossible to introduce the vector $\vec{x}^{(0)}$ into the set of the model parameters because for each dynamic process we will have the independent value $\vec{x}^{(0)}$. In order to take this fact into account, it is necessary to split the vector of unknown coefficients $\vec{l}$ into two parts. The first part contains coefficients equal for all processes. The second part contains an independent set of elements of the vector $\vec{x}^{(0)}$ for each process that leads to the increasing of unknown number of coefficients and complicates the optimization procedure.

Using the proposed macromodel causes the problem of defining a zero discrete of the vector $\vec{x}$ as the components of this vector, as a rule, are not measured directly during field tests but are defined using some values of the output elements $\vec{y}$. In general, it means that it is necessary to find some linear or nonlinear dependence of the vector $\vec{x}^{(0)}$ as a function of the experimentally measured values $\vec{y}$. Particularly, for the forecasting tasks, this dependence can be built as a function of several first discretes of output values:

$$\vec{x}^{(0)} = \vec{f}\left(\vec{y}^{(1)}, \vec{y}^{(2)}, ..., \vec{y}^{(l)}\right) \tag{4}$$

where l is the number of discretes used for searching a zero discrete of the vector $\vec{x}$.

The optimization approach, owing to its universality, to the form of macromodel representation is quite suitable for searching those additional dependencies. In fact, it means that the elements of the vector $\vec{x}^{(0)}$ added to the set of unknown coefficients $\vec{\lambda}$ should be substituted by the coefficients from the equation (4), i.e. this expression should be introduced into the model. If the model is represented by the equation (3), we obtain:

$$\begin{cases} \vec{x}^{(k+1)} = \mathbf{F}\vec{x}^{(k)} + \vec{\Phi}\left(\vec{x}^{(k)}\right) \\ \vec{y}^{(k+1)} = \mathbf{C}\vec{x}^{(k+1)} \\ \vec{x}^{(0)} = \vec{f}\left(\vec{y}^{(1)}, \vec{y}^{(2)}, ..., \vec{y}^{(l)}\right) \end{cases} \tag{5}$$

An alternative approach to the identification procedure of the dependence (4) is a search for the optimal vector $\vec{x}^{(0)}$ for the available values of $\vec{y}$. This makes it possible to find the optimal initial value of the state variable vector based on actually available data but not the previously defined set. With new data being provided, values of the vector $\vec{x}^{(0)}$ are defined more accurately by using optimization procedures [1] where $\vec{x}^{(0)}$ is the vector of unknown values. The calculation of the goal function is carried out using the available values of the vector $\vec{y}$, the model and its coefficients being unchanged.

3. Test example of the power consumption forecasting

A discrete autonomous macromodel of power consumption of Kyivenergo in 2007 has been created as a test example of the proposed technique. The root-mean-square error of the macromodel developed is equal to 6 %. Fig. 1 depicts the curves of actual annual power consumption and those obtained by the macromodel. The developed macromodel (6) has 19 non-zero coefficients, 4 components of the state variables vector and square non-linearity (Formula 6).

As the process of development of that macromodel has shown, the optimization approach can be effectively used for the autonomous macromodelling. In spite of the presence of a considerable level of noise in the registered input data caused by random factors, the adequacy of emulation of output data by using the developed macromodel is quite high while the procedure of transient process modelling is rather complicated.

$$\begin{cases} \vec{x}_1^{(k+1)} = 0.6166\vec{x}_1^{(k)} + 0.8\vec{x}_4^{(k)} \\ \vec{x}_2^{(k+1)} = 1.001\vec{x}_2^{(k)} - 7.79\cdot 10^{-4}\,\vec{x}_1^{(k)}\vec{x}_3^{(k)} - \\ \qquad - 7.6\cdot 10^{-3}\,\vec{x}_2^{(k)}\vec{x}_4^{(k)} \\ \vec{x}_3^{(k+1)} = 0.3335\vec{x}_3^{(k)} + 1.22\cdot 10^{-3}\left(\vec{x}_2^{(k)}\right)^2 - \\ \qquad - 0.1191\vec{x}_2^{(k)}\vec{x}_4^{(k)} + 0.4745\vec{x}_2^{(k)}\vec{x}_3^{(k)} \\ \vec{x}_4^{(k+1)} = -0.8109\vec{x}_1^{(k)} + 0.6491\vec{x}_4^{(k)} - \\ \qquad - 0.2054\vec{x}_2^{(k)}\vec{x}_3^{(k)} \\ \vec{y}^{(k+1)} = 0.42\vec{x}_1^{(k)} + 1.474\vec{x}_2^{(k)} + 0.8777\vec{x}_4^{(k)} \end{cases}, \quad (6)$$

where $\vec{x}^{(0)} = \begin{pmatrix} 0.25 \\ 1.43 \\ -1.427 \\ 0.215 \end{pmatrix}$

It should be mentioned that the periodical process caused by weekly variations of power consumption is inherent in the process of annual consumption. Therefore, the proposed approach can be used for the development of real autonomous object models and forecasting of their characteristics.

4. Conclusions

Given the obtained forecasting results for the test example of power consumption of a real object and comparing them with the results obtained in the process of approximations, it is possible to make a conclusion concerning the efficiency of the approach proposed. At the same time, using forecasting together with macromodelling makes the process of considering the random factors more complex that is important for the short-term forecasting.

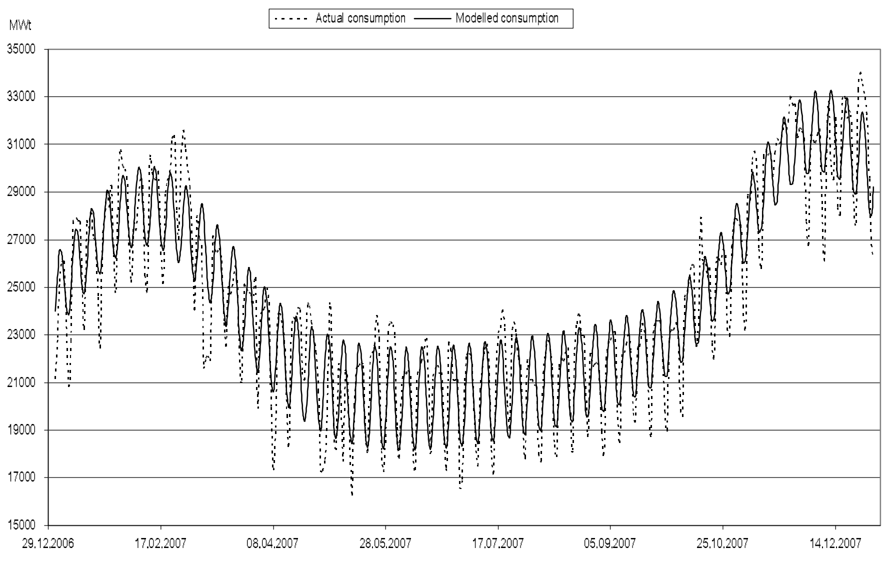

Fig. 1. Actual annual power consumption and its emulation by the developed macromodel.

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ЗАСТОСУВАННЯ ДИСКРЕТНИХ МАКРОМОДЕЛЕЙ ДЛЯ ПРОГНОЗУВАННЯ ЕНЕРГОСПОЖИВАННЯ ОБ'ЄКТІВ ЕЛЕКТРОЕНЕРГЕТИЧНИХ СИСТЕМ

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Запропоновано метод прогнозування добового та річного споживання електроенергії визначених об'єктів з використанням дискретних макромоделей, який дає змогу оцінювати динаміку споживання електричної енергії у майбутньому на основі відомих попередніх даних. Описано процедуру побудови моделі на основі дискретних автономних макромоделей у вигляді "чорної скриньки" для прогнозування енергоспоживання з використанням еволюційного підходу для конкретних об'єктів. Побудовано дискретну автономну макромодель річного енергоспоживання реального об'єкту за один рік як перевірку запропонованого підходу. Оцінено ефективність використання апарату дискретних рівнянь стану для прогнозування енергоспоживання об'єктів енергетики.

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