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CLASSICAL AND MODERN METHODS USED IN ELECTRICAL ENERGY MANAGEMENT SYSTEM

Empirical study

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Abstract

The forecast can be defined like approximately of the unknown events from the future; this thing is necessary because of the existence of some unknown events, but this events play an important role in taking some decisions. It is obvious that the uncertainty's elimination is not possible, so the forecast is a tool who tries to minimalize this uncertainties. The forecast's importance in the electrical energy management is very important. The forecast of the energy's request presumes the estimation of this request's characteristics: size, time evolution, the request's structure, and so on. The forecast of the electrical charge is a tool of a modern EMS.

1. Foreword

The forecast importance in electrical energy management is fundamental. The forecast of energy demand, involves the estimation of the characteristics of this application: size, time development (load curve form), the demand's structure (on consumer categories), etc.

There are at least two purposes of electrical energy management. On one hand, electrical energy management is the mean which is producing significant economical benefits in the functioning of the plants and power grids and necessary investments in new plants and lines. To achieve these goals, the power supply company has to try to have a flat load curve, or, in some cases, e.g. hydro power plants, to adjust the load curve to curve of the water flow. This form of management can lead to:

- investment savings in the production and transport of the electricity;
- better utilization of power plants:
  - better use of the power plants;
  - fewer starts and stops of the electrical generators;
  - longer running at optimal running parameters.
- reducing the transport costs.

Another purpose of the electrical load management is to avoid the spread of the state of emergency in situations like:

- imbalance between generated and consumed load in real-time in the system;
- overcharging of certain equipment in certain parts of the system;
- unforeseen future imbalance between supply and demand.

All the control functions that allow a safe and economically efficient production, transport and distribution of electricity are grouped in the Energy Management System (EMS).

The load forecast is mainly based on previous data regarding load variation,that is systematically recorded and processed by specific methods.

Electrical load forecast is an instrument of a modern EMS. To be cost effective and to ensure an effective control of the power system, this forecast should be conducted on a wide range of time intervals:

- short term forecast, from several seconds to several hours;
- short-term forecast, from several hours to one week;
- medium-term forecast, from several weeks to one year;
- long-term forecast, from one year to twenty years.

Each of these types of forecasting has a specific purpose and has important influences on economic parameters of companies in the energy sector.

Short term forecast provides information to Commercial Operator and System Operator to cover the load curve during the day/ next days. It is generally an operative forecast, characterized by relatively small deviations from the values achieved.

Medium term forecast provides the necessary information for production planning, establishing normal working schemes in transport and distribution sector, evaluation of the reserve management, planning maintenance works.

Long-term forecast is the base for tactical decisions regarding the rehabilitation, the acquisition of new equipment and structural changes in transport and distribution system.

Very long term forecast provides the necessary data to strategic decision-making on the building of new power plants, changing the structure of electricity generation, energy field policy elaboration, designing new ways of providing primary energy resources.

Although in the forecasts a large number of parameters are included, their primary objective is to obtain reduced errors:

- on a consumption under-evaluation, the risk of the inability to cover it, accompanied by high costs for covering the loss for non supplying the consumers or high costs for purchasing electricity from other sources;

- on a over-evaluation of consumption, loss is resulting from the blocked funds in production capacity, investment in transport and distribution networks, in primary energy sources, in fuel exaggerated reserves.

Important economic implications of errors in the electricity consumption forecast, determined the seeking of ways to provide information with as high as possible confidence level. Made until now largely based on expert human intuition, current methods of forecast rely on increasingly more and more on elaborated mathematical models that allow a parametric analysis, based on a important database.

The forecast in the energy sector must estimate both electricity consumption as well as the losses in the power networks, variation in time of the power required – load curves – consumption structure.

The models used to forecast electricity consumption are based on information regarding the main factors that determine the modification and evolution of load:

- economic factors, taking into consideration the economical development, the policy regarding the development of some industrial sectors, their modernization processes, the level of population household ownership;
- demographic factors that take into account both population growth and changes in territorial arrangement determined by state

policy in this area, with influences particularly on long-term forecast;

- environmental aspects – the policy of using the fuel sources, in terms of effects on the environment – with major influences on the long-term forecast;
- seasonal and local climatic factors, determined by variations in specific sizes (average temperature of day, cloudiness level, wind speed, duration of sun covering etc.) and long-term climate changes;
- temporal factors determined by the differences between weekdays and holidays, particularly influencing the short-term forecast;
- technological factors which include efforts to develop technologies with reduced power demands and measures adopted to increase efficiency in the use of electricity, with influences particularly on long-term and very long forecast;
- pricing policies -with influences especially on medium-term forecast;
- specific events - sport events or large public gatherings, planned strikes – with particularly effects on short-term forecast;
- random factors, unpredictable, which cause changes in electricity consumption.

In the forecast of the electricity consumption, the general trend of increasing electricity consumption with the development of society must be taken in account but also the concerns for a greater efficiency in the use of electricity as well as the development of technologies with low power consumption. In this way, it is possible that, although the number of electricity consumers is increasing, the electricity consumption to have a lower growth rate or even remain constant.

For short and medium-term forecast, a particular interest is showed by the assessment of load curve and how to cover it, and for long and very long term forecast, the interest is especially taken by electricity consumption forecast.

Used for all types of forecasting, the human expert method is based on extensive field experience of specialists who have accumulated a large amount of information in the past and have sufficient knowledge of the future development of society. On long-term and very long term forecasts, the evaluation team, which includes both energy specialists and economists, politicians and financiers, enable the main coordinates of the energy sector development in conjunction with the general development of society and in correspondence with the long term priorities of the society.

2. Load curves forecast

The forecast of the load curves, on short and medium term, has an important role in a company in the electrical energy sector, providing the data needed for programming the operation of dispatchable generation units, determining the order of merit and the system marginal price. It also provides data for studies of network load degree and possible contingencies that might arise in the operation of the network. There are a variety of methods for making these forecasts, some based on static, others on dynamic models. To forecast load curves, the most common methods are:

- intuitive methods (method of human expert);
- time series analysis method;
- spectral methods;
- methods based on artificial intelligence.

2.1 Intuitive forecasting methods (method of human expert)

The method is based on specialists' extensive experience in energy field that, based on data from the past, knowledge of how the various factors are influencing hourly electricity consumption and timing estimate of the specific conditions for which the forecast is made, are assessing the load curve. A specialist with great experience, can provide forecasting errors below 2%.

2.2 The time series analysis method

The method is used primarily to forecast load curves represented as a sequence in time of fair values (generally hourly values). Failure to analytically represent the load curves, determines the need to assess numerical values corresponding to the forecasted load curve.

his method enables the evaluation of a size P (t), variable in time, on a moment t based on the analysis of data from its history

$$P(t) = f(P_{t-24}, Y_{t-48}, ..., Y_{t-n\cdot 24}, t) \quad (2.1)$$

where in corresponds to the first of the previous size that are taken in account.

In principle, the method of time series seeks to establish a mathematical relationship that must ensure the best possible approximation of the data in the process.

Existing data allow the establishing of a mathematical relationship to further approximate the size variation.

Specific to electricity consumption is that the time series method can be used to forecast consumption at a specific time based on relevant data, at the same time in the previous days and previous years. The resulting forecast is corrected based on an analysis of the likely effect of predictable events such as weather forecasting data, daily changing of the times of sunrise and sunset, the profile of atypical days, information on consumer disfunctionalities etc.

The method is used mainly for short and medium-term forecasts, where the previous behavior of the size is a real indicator of its future values, the system showing slow variations in time.

The making of the mathematical model requires:

- the availability of data from previous days and years;
- the knowledge of specific aspects of the process (mode of occurrence of the values of the time series);
- the acquisition of data defining the process;
- the elaboration and validation of the mathematical model.

Establishing the structure of the mathematical model is based on a function which best approximates the evolution of existing data. The mathematical model parameters are determined by classical methods of analysis of "closeness" of the known data points in the history of the process. Usually, the method of smallest squares, provides the information necessary to establish the mathematical model.

The accuracy of the model is validated by checking it for known values.

In general, the mathematical models used to forecast the load curve are using linear functions. Although it does not provide a perfect approximation of the reality, their relative simplicity and the fact that the theory of linear systems provides effective means of analysis and research, is leading to a widespread use of this model.

The mathematical models based on nonlinear functions can provide a much better approximation than the model using linear functions, but the nonlinear systems theory, however, most often does not lead to concrete solutions, leading to a part linearization.

The reduction of forecast errors can be done by decomposing the consumption on type of consumers with similar characteristics. So, the industrial consumers consumption curve is mainly influenced by the following factors:

•• the number of shifts and the work mode (continuous, temporarily, only on weekdays);

•• the intensity of the activity during the week (usually the days at the beginning and the end of week show lower intensity activity);

•• the type of activities in weekends;

•• the type of activities on holidays.

In general, for industrial activities, the climate factors (temperature, cloudiness) have a very low share.

On domestic consumers the climatic factors and predictable events (holidays, sporting events and big artistic events) have an important influence on the consumption curve.

On the service consumption sector (public transportation, trade and public food companies etc.), factors that are substantially influencing the consumption curve, can be set.

The forecast is used primarily for operative management of the system, being the programming basis of the energy producers to cover the load curve.

2.3 Spectral methods

Considering the load curve as a periodic function P(t), its analysis and the short and medium term forecast can be made in frequency domain, by decomposing the function, using the Fourier transformation. In this case, the function can be written as

$$P(t) = a_0 + \sum_{k=1}^{N} a_k \cdot \cos\frac{2 \cdot k \cdot \pi}{T} \cdot t + \sum_{k=1}^{N} b_k \cdot \sin\frac{2 \cdot k \cdot \pi}{T} \cdot t$$

(2.2)

where a_0 is the mean value of the function P(t), a_k and b_k – the coefficients of Fourier decomposition for k level harmonic, N – number of harmonics taken in account, T – the period of the analyzed process.

Using the decomposition (2.2), the forecast of the load curves is reduced to the forecast of the coefficients a_0 , a_k and b_k by linear or non-linear correlation methods with sizes known for the forecast period, e.g. the daily mean power. Also, artificial intelligence techniques can be used.

The establishing of the harmonics N number taken into account in making the forecast depends by the exactity desired and the complexity of the model. As the number of the harmonics is smaller, the forecast procedure is easier to apply and the model used is simpler.

The forecast errors can be reduced a lot by compensating the ones that came in the modeling process by using fuzzy errors weighting techniques from the previous days of the same type.

2.4 Methods based on artificial intelligence

Artificial intelligence methods are used more and more to solve the problems related to forecast the electricity consumption. The quality of forecasts made using artificial intelligence techniques depends largely on the amount and quality of data entry, the provider's database development. On very short-term and short term forecasts, the techniques based on artificial neural networks (ANN) have a wide application, with some additional improvements by using supplemental fuzzy techniques. It is very important to know the evolution of the load curve for a long time to ensure proper planning and effective decision making.

The prediction is based on past trend extraction and translating it in to the future, thus making a very useful ANN from at least two reasons:

- First, it was shown that ANN is capable of a numerical approximation of any continuous

function, with desired accuracy. ANN can be considered a nonlinear method with multiple variables, and nonparametric;
- Secondly, ANN uses the data-drive method. This eliminates the need for a laborious mathematical model and parameter estimation. Starting from a pair of input-output vectors, ANN is able to make a recurrence relationship between input and output, and storage in neurons. Effective use of ANN for making a forecast for the load curves, requires a rich database, built with the information regarding the daily load curves made and special features of each day (workday, holiday, temperature variation during the day, humidity variation during the day, other particularities of the day).

In this way, for estimating the electrical load on t moment, for ANN training, the known powers at moments t – 1; t – 2; t – 3; t – 24; t – 168; t – 192, corresponding temperatures and humidity, forecast day characteristics, can be used. In figure 2.1, the simplified structure of a neural network for forecasting the power P_t, on t hour is shown, on the basis of data from early hours P(t–1), P(t–2), P(t–3), on according temperatures, on day type, as well as the information regarding the power realized on the same hour on the previous day and the powers on the same hour and previous hour from the week before. On ANN input are also sent the forecasted data for t hour, by using some delay blocks, according to the hour of the power made before.

The data on ANN input from the figure 2.1 can be completed with information regarding the humidity on previous hours, meteorological conditions from the previous week, the forecast values of the temperature and humidity for t hour, as well as information regarding specific events that can take place at t hour. Increasing the number of information at ANN input ensures a low deviation of the values predicted from the values made.

To ensure the load curve forecast for a day, 24 copies of the network in Figure 2.1 are used. The performance of ANN is checked by a data set not used in the training process. In choosing an ANN structure the following aspects have to be considered:
- ANN structure must take in account the application aspects
- ANN structure should be simple for the following reasons: simple structures show better generalization capability and a learning process faster than complex ANN
- A flexible neural structure allows adaptation to particular cases
- For an easy forecast, the ANN input data should be easy to obtain, based on measurements and must not contain estimates. As a result, input data, within a previous month, without taking into account the demographic and economic climate indices, influence the evolution;
- Climatic factors have a great influence in evolution, but their actual estimation is difficult. However these factors influence the evolution of the cyclical component, thus being taking into account automatically;
- Artificial neuron is perfectly capable of shaping the monthly trend for a given month. AN (artificial neural) is trained using the learning dataset for a specific month in previous years;
- The data of the previous month for a particular month are considered the neuron inputs. From simplicity requirement, the number of entries is limited to 4. ANN structure flexibility is ensured by the possibility of choosing the number of neurons' input for each alternative forecasting;
- The neurons corresponding to a month in a year must be combined in a recurrent structure where the inputs of a given month are substituted by previous month outputs, when the forecast is designed for an entire year (medium-term prediction).
- ANN is composed of nodes that operate in parallel and communicate with each other through synaptic connections. The great advantage of the neural network is the ability to model complex nonlinear relationship without a prior assumption of the nature of the relationship.

2.5 Econometric methods

Some forecasting methods assume that it is possible to identify the main factors that may influence the variables that are forecasted. Thus, the prediction of the influence of the variables can be used in forecasting.
- Regression analysis using the linear and nonlinear regression
- The auto-regressive model with mobile mean (ARMA);
- The integrated autoregressive model with mobile mean (ARIMA). Example: Box-Jenkins
- Econometrics.

The general form of the autoregressive model is given by the recurrence relationship:

$$x_t = a_1 x_{t-1} + ... + a_p x_{t-p} + £_t \qquad (2.3)$$

where the x_t current value is associated to a weighted sum of previous values and a white noise $£_t$. So, x_t may be considered as a regression on p previous values of the $x(\bullet)$ variable.

Applying the Z transform, the equation becomes :

$$A(z^{-1})x_t = £_t \quad \text{where}$$

$$A(z^{-1}) = 1 - a_1 z^{-1} - ... - a_p z^{-p} \qquad (2.4)$$

The ARMA(p,q) model is obtained by combining the models AR(p) and MA(q) :

$$x_t = a_1 x_{t-1} + ... + a_p x_{t-p} + £_t + c_0 £_t + ... + c_q £_{t-q}$$
(2.5)

$$x_t = \sum_{m=1}^{p} a_m x_{t-m} + \sum_{n=0}^{q} c_n \pounds_{t-n} \qquad (2.6)$$

The ARIMA model is the integrated ARMA model. For non-stationary time series, the x_t and u_t inputs (the exogenous variable), are replaced by their differences $\Delta x_t = x_t - x_{t-1}$ and $\Delta u_t = u_t - u_{t-1}$, respectively.

Box-Jenkins approach

The ARMA BJ model is a combination between AR and MA models. Thus, the ARMA processes, are autoregressive $\{X_t\}$ processes of *p* degree with mobile mean cu residues of q degree, that verifies the relationship

$$X_t + \sim_1 \cdot X_{t-1} + \mathrm{L} + \sim_p \cdot X_{t-p} = Z_t + {}_1 \cdot Z_{t-1} + \mathrm{L} + {}_q \cdot Z_{t-q} \qquad (2.7)$$

where the Z_t s are *q* mobile mean degree residues.

The Box-Jenkins model assumes a stationary time series. Box and Jenkins recommend to differentiate the non-stationary series each time is needed, to reduce it to stationary. This results in an ARIMA model. Some formulations transform the series, extracting the mean of the series at each point. This leads to a series with zero average. Whether this operation is necessary or not, it depends on the software used to estimate the model.

The Box-Jenkins model can be extended to include seasonal autoregressive terms and seasonal slide average. While this complicates the notation and model structure, the fundamental concept for seasonal terms is similar to the non-seasonal terms (autoregressive and mobile mean).

The most general Box-Jenkins model includes different operators, autoregressive terms, mobile means, seasonal autoregressive terms and seasonal mobile means.

The primordial steps in building a model of time series Box-Jenkins are:

1. Identify the model;
2. Estimate the model;
3. Validation of the model.

The Box-Jenkins model is flexible due to the inclusion of autoregressive and mobile mean terms.

According to the decomposition theorem, any stationary process can be approximated by an ARMA model.

The Box-Jenkins standard analysis involves transforming data through various seasonal and non-seasonal differences to achieve a stationary series. A stationary series has a random fluctuation with a constant variation around the mean.

CONCLUSIONS

The usefulness of these analytical methods consist in identifying common criteria that characterize classic products, consumer goods or services and electricity. Using the same thinking should find that product management, production management as a whole activity and electrical energy management are concepts with common connotations.

It is important for companies involved in distribution and supply of electricity to develop the demand of electricity in such way so its acquisition to be made with minimum costs.

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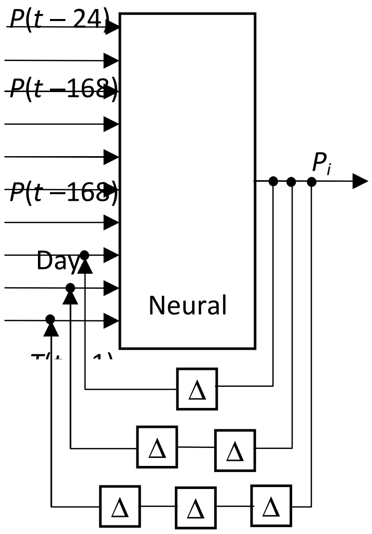

Fig. 2.1. RNA architecture for realizing the forecast for *t*