Forecasting of electricity consumption by industrial enterprises with a continuous nature of production

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Abstract. The development of models for forecasting electricity consumption is a complex process, due to the non-linear dependence of electricity consumption on factors that affect the forecast indicators. Since the current forecasting methods do not take into account this non-linearity, the difference between the actual and forecast indicators of electricity consumption often exceeds the allowable values. To determine the required forecast indicators with high accuracy is the use of artificial intelligence methods. In this paper, when predicting electricity consumption, the method of autoregression of the integrated moving average is used. An enlarged block diagram of the algorithm for predicting power consumption using the ARIMA method has been developed.

1 Introduction

The creation and implementation in practice of forecasting models using the ARIMA method is simple in determining forecast indicators, in particular, in the process of checking the adequacy of the developed model. If the forecast error deviates from acceptable values, the automatic change of ARIMA components allows obtaining high-precision forecast indicators. Point and interval prediction can be performed using any developed model; for these types of forecasting, it is not required to develop separate forecasting models [1, 2, 4].

2 The current state of the investigated problem

It is known that the ARIMA method is part of the ARMA model, in which the autoregressive part has a differentiating component d to transform the time series into a stationary series. To do this, it is advisable to express these polynomials in the form of an operator for calculating the autoregression coefficients. To simplify the calculation and writing expressions in the form of an operator, the following definitions A are introduced [3, 5]:

A-d=0,, A-1=0. A0=-1, A1=a1, …, Ap=ap, Ap+1=0, …, Ap+d=0:

$$-(\sum_{k=0}^{p} A_k L^k)(1-L)\Delta^d y_t = -(\sum_{k=0}^{p} A_k L^k - \sum_{k=0}^{p} A_k L^{k+1})\Delta^{d-1} y_t =$$
$$= -(A_0 L^0 + \sum_{k=1}^{p} A_k L^k - \sum_{k=1}^{p} A_{k-1} L^k - A_p L^{p+1})\Delta^{d-1} y_t =$$
$$= -((A_0 - A_{-1} L^0 + \sum_{k=1}^{p} (A_k - A_{k-1}) L^k + (A_{p+1} - A_p) L^{p+1})\Delta^{d-1} y_t =$$
$$= -\sum_{k=0}^{p+1} (A_k - A_{k-1}) L^k \Delta^{d-1} y_t = -\sum_{k=0}^{p+1} \Delta A_k L^k \Delta^{d-1} y_t . \quad (1)$$

Thus, the difference operator Δ can be transferred from the time series yt on a sequence of coefficients, and the number of non-zero terms will increase by one. Repeating these calculations d times and taking into account that ΔdA0=-1, we get:

$$(1-\sum_{k=1}^{p} \Delta^d A_k L^k) y_t = (1-\sum_{k=1}^{q} b_k L^k)\varepsilon_t . \quad (2)$$

From the analysis (2) it can be concluded that in the structure of the ARMA model, MA is a process of infinite order with restrictions set by the limits. Using this method, it is possible to express a complex damage structure with a small amount of primary data. As mentioned above, this in turn is done by transforming the content of the non-stationary data into stationary data.

An enlarged block diagram of the power consumption forecasting algorithm using the integrated moving average autoregression (ARIMA) method can be represented as shown in Fig. 1. Analysis of the graph shows that power consumption is a non-stationary process [19, 6-15, 17, 20, 18].

The ARIMA prediction model is represented by three components (p, d, q).

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The order of the time series difference – d is calculated as follows.

At the initial stage of creating a forecast model, a differentiation process is performed to obtain a constant time series from a changing time series. At the same time, with the help of formal tests, an assessment of the invariance of the initial time series is made. Since the processes of consumption of electrical energy are not always unchanged, then, with the help of certain transformations, the time series is reduced to a stationary mode. It includes the following parameters [16, 3, 21, 22]:

- finite differences:

$$X_t = \Delta Y_t = Y_t - Y_{t-1} \quad (3)$$

where Xt – primary difference:

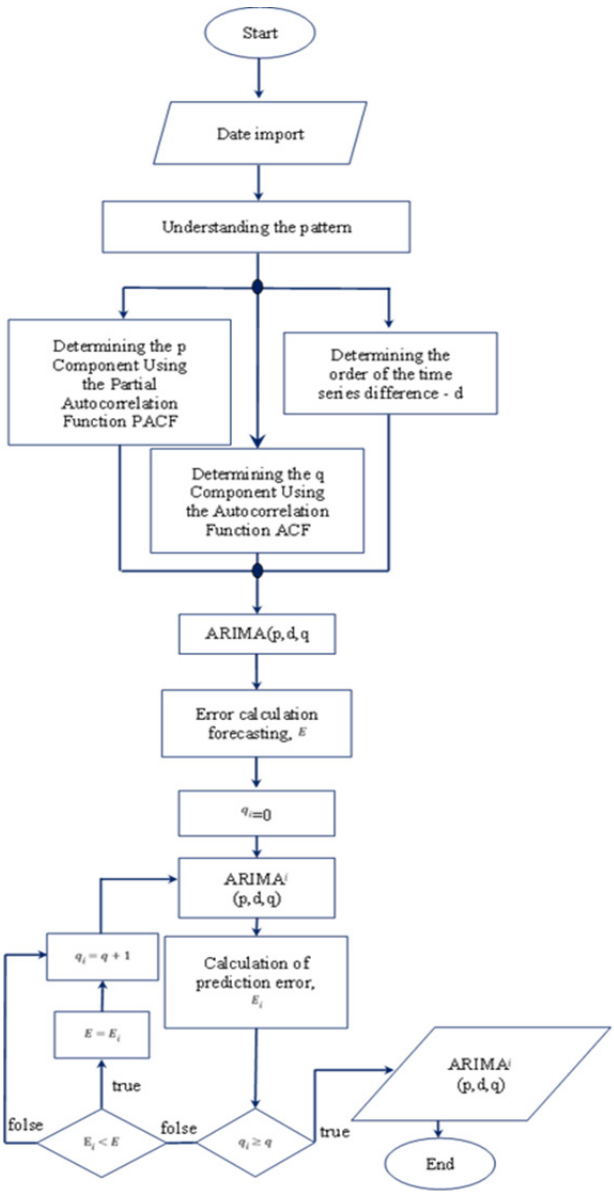

Fig.1. Enlarged block diagram of the algorithm for predicting power consumption using the autoregressive method of the integrated moving average [8]

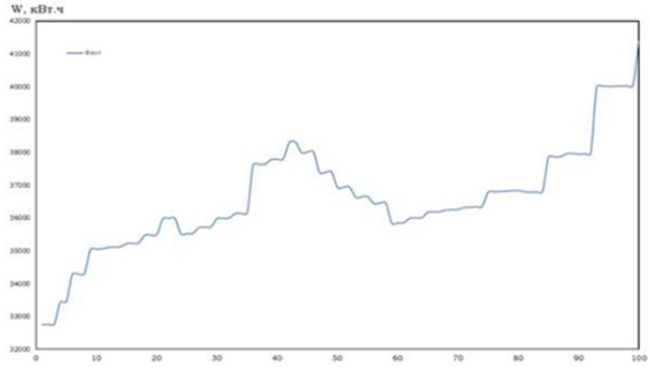

Fig.2. Electricity consumption chart of a metallurgical enterprise

$$Z_t = \Delta X_t = X_t - X_{t-1} = Y_t - 2Y_{t-1} + Y_{t-2} = \Delta^2 Y_t, \quad (4)$$

(Zt – secondary difference);

- logarithmic chain indices of the following form:

$$X_t = \ln(Y_t / Y_{t-1}) = \ln Y_t - \ln Y_{t-1}; \quad (5)$$

- growth rate of the next type:

$$X_t = (Y_t - Y_{t-1}) / Y_{t-1} = (Y_t / Y_{t-1}) - 1; \quad (6)$$

- logarithmic series:

$$X_t = \ln Y_t; \quad (7)$$

- growth rate of the next type:

$$X_t = (Y_t / Y_{t-1}) \quad (8)$$

It should be noted that when determining a stationary time series, it is necessary to take into account the nature of the change in the time series graph *Xt*. In this case, the main criterion for the quality of the process is the fulfillment of the condition *Xt=f(Yt)*≈const.

For the case we are considering, the time series reaches stationarity with two orders of difference, that is, the second order is considered sufficient in our study (Fig. 3) [23, 7, 18].

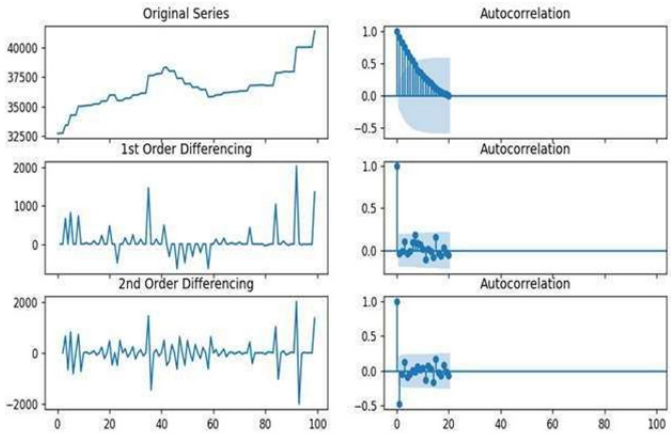

Fig.3. Determining the order of the time series difference – d

In this case, the stationarity of the series is checked first, using the extended Dickey Fuller test (adfuller) from the statsmodels package. If the series is non-stationary, then it is necessary to differentiate it. Otherwise, no difference is required, that is, d = 0. After

that, differentiation is performed and the autocorrelation of the graph is obtained. As a graph line, it is enough to differentiate 1 time, so d is equal to 1.

Autoregressive process to determine autoregressive order - p.

In the autoregressive process, each time series value is the sum of a random relationship and takes previous values into account to predict future values. Any autocorrelation in the stationary series can be corrected by adding AR [7, 8, 24-28, 12]. In this case, the condition is accepted that the number of ARs is equal to the number of lags that cross the significance limit on the PACF graph (Fig. 4).

On fig. 4.4 shows a lagging of 1 PACF as it is well above the significance line. Lag 2 is also significant, but it is in the marginal zone (blue area) and p can be taken tentatively as 1.

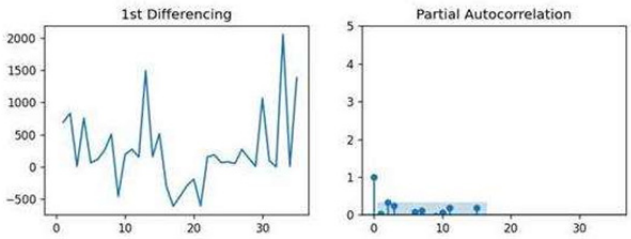

Fig. 4. Partial autocorrelation function PACF

Moving average process to determine the order of the moving average - q.

It is known that the moving average component is required to adjust the time series and the process of forming the adjustment begins with determining the observation window.

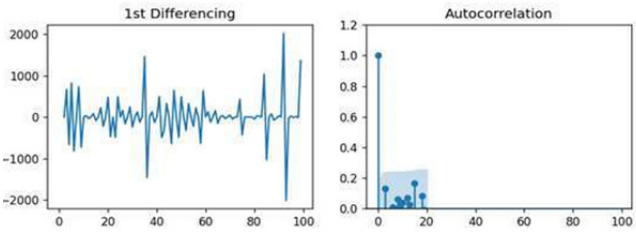

Fig. 5. Autocorrelation function ACF

The autocorrelation function (ACF) shown in Figure 5 allows you to determine the number of MA terms. Figure 4.5 shows that the pair of lags of the ACF autocorrelation function is much higher than the significance line and the dependence does not contain autocorrelation, so it is assumed that the q coefficient is equal to 1.

According to the above calculations for forecasting in the ARIMA model, the main components are determined, and they have the following form: autoregression order p=1; the order of the time series difference d=1; moving average order q=1. In general ARIMA (1, 1, 1).

The next step is to analyze the difference between the actual and forecast values, i.e. balances (imbalances). The assessment of the validity obtained using the ARIMA model is based on a comparison of the actual data with the simulation results. The evaluation results are shown in graphical form (Fig. 6) [14, 22, 15].

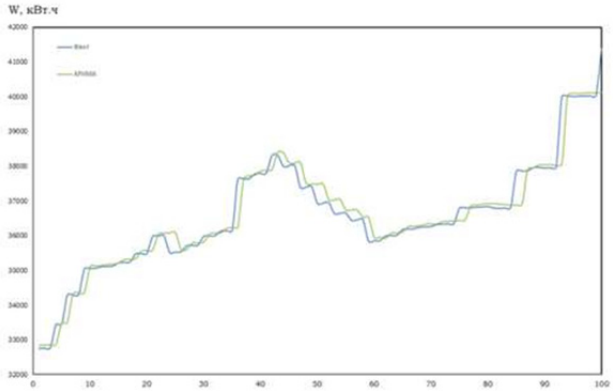

Fig. 6. Comparison of actual and forecast power consumption according to the ARIMA model (1,1,1)

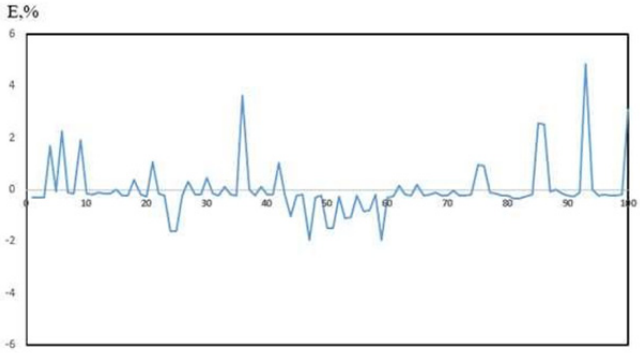

Fig. 7. Graph of the error between the actual and predicted values of power consumption according to the developed model using the ARIMA method

The degree of adequacy of the developed models is substantiated by low absolute and relative errors between actual and forecast data. Analysis of the value of forecasting errors (Fig. 7) of the error shows (6%) that the obtained mathematical models of electrical energy consumption are adequate and therefore they can be used to determine the predicted values of power consumption parameters at ferrous metallurgy enterprises [10].

3 Conclusion

Thus, it can be concluded that the use of models obtained on the basis of the ARIMA method for forecasting power consumption provides high accuracy and adequacy in determining the predicted values of power consumption parameters.

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