Energy Consumption Forecasting Using ARIMA and Neural Network Models

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***Abstract*—Energy forecast is essential for a good planning of the electricity consumption as well as for the implementation of decision support systems which can lead the decision making process of energy system. Energy consumption time series prediction problems represent a difficult type of predictive modelling problem due to the existence of complex linear and non-linear patterns. This paper presents two approaches for energy consumption forecast: an autoregressive integrated moving average (ARIMA) model and a non-linear autoregressive neural network (NAR) model. The two models are deeply described and finally compared in order to evaluate their performance.**

Keywords*—*forecasting, energy consumption, artificial neural networks, arima, time series

I. Introduction

Addressing present and future global energy challenges assumes a growing role of intelligent information and communication technologies on both supply and demand sides. Among the objectives lay a secure and continuous energy supply, grid balancing through growing integration of variable renewable energy sources and more important making efficient use of energy in all its forms. Underlying the last goal arises the stringent need of modelling and forecast of the energy consumption. This goal can be achieved through modern equipment use and the relying on extensive information processing.

The efficient usage of the energy consumption for a given activity is a requirement nowadays for the industry, commercial and housing sector. With increased electricity costs, the energy consumption modelling and forecast has become an important issue. Energy consumption is growing steadily and we need quantitative and qualitative knowledge about this development, which involves a mathematical model of energy consumption to understand future needs. Consumption monitoring systems are of great interest to power companies and consumers also [1].

In recent years, energy consumption forecast has become a hot topic for the academia and an interesting subject for the industry. Mathematical models of energy consumptions were obtained using different solution techniques as shown below. As shown in [2], prediction methods of electrical consumption can be categorised into three categories:

- *Traditional approaches:* autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA) Box-Jenkins models, seasonal ARIMA models (SARIMA) [3], autoregressive moving average with exogenous inputs (ARMAX) models state-space representation models, and linear regression models.
- *Artificial intelligence approaches:* knowledge based expert system (KBES) models, artificial neural network (ANN) and fuzzy logic models [4].
- *Support vector regression approaches:* support vector regression (SVR) model and its associated hybrid/combined models [4], [5], [6].

Recent studies focuses on forecasting the energy (electrical and thermal) consumption of modern, highly instrumented building. The research employ extensive methods for energy consumption forecasting which use the structural properties of buildings, their thermal dynamics equations and also informations from the environment such as: weather conditions, occupants, their activities and heating ventilation and air conditioning (HVAC) system parameters. These methods need information about the structural and thermal parameters of buildings, data that are not always available or easy to acquire and they also depend on intricate physical principles which demand a high level of expertise to develop the models [7], [8], [9].

The literature review offers different methods used for energy consumption forecast, but the disadvantage of this techniques are the large number of inputs used to compute the model. To reduce the complexity of the methods that use wide and detailed information about the analysed system, we have been proposed, in this paper, a more simple methods which use only the available data on energy consumption. In this paper, the ARIMA and ANN models are used to forecast samples framed in a one-dimensional time series containing active energy consumption data.

The outline of the paper is the following: Section II presents the system hardware architecture used for monitoring of the energy consumption. Section III introduces the methodology employed for the forecast, depicting the theoretical aspects of both the ARIMA model and the ANN model. Finally, in Section IV the two mathematical models are presented. Each model is validated using real acquired data and the performance of the algorithms are compared using statistical tests. Conclusions are depicted in the last section of the paper.

II. The Monitoring System Hardware Architecture

A monitoring system is a particular case, which must correspond to the actual requirements of the various installations to be monitored. To implement such an application, usually it is started from a 'standard' monitoring system, containing various basic modules, hardware and software, and the study it is carried out within the perimeter of the real equipment/installations specific to an industrial consumer or householder.

The employed monitoring system hardware architecture consists of several industrial equipment produced by Siemens. The system it is composed of a programmable logic controller (PLC) [10] and a dedicated module for the energy metering and monitoring function. The energy metering module is designed for machine-level implementation using a PLC system. The metering module can record over 200 different energy-specific measurement values (voltages, currents, powers, energies, power factor, frequency, phase angle, etc.). Using the measured values provided by the module, power consumption and forecast can be determined. Monitoring of power and energy values is relevant for customer energy management and equipment maintenance. Because visualization has become a standard component for most industrial applications, we have also used a human machine interface (HMI) [11] panel that offers basic operations to control and monitor various tasks.

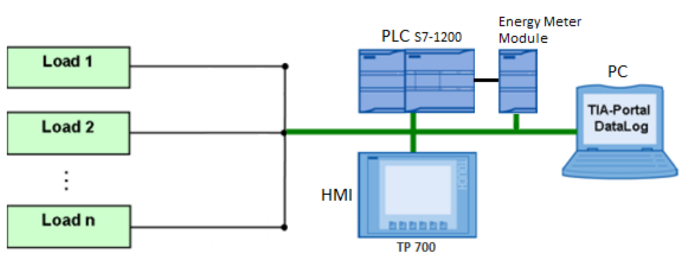

Fig. 1: Diagram of the monitoring system

Fig. 1 presents a schematic diagram of the architecture of the electrical system monitoring. The configuration and programming of the devices was done in a specific Siemens industrial programming environment. Following this, the energy consumption forecast methods implementation were carry out on a study case. The monitoring system was installed at an industrial consumer (e.g. small production aria of a company which produces automation equipment). All data was acquired and provided for several weeks monitoring.

III. Methodology

The development of the current study was done in three stages. First stage: the data acquisition and data pre-processing; second stage: ARIMA and NAR modelling and third stage: the assessment of performance and analogy between two distinctive forecasting models: ARIMA and NAR.

The acquired data used to obtain the two forecasting models represents the active energy consumption and the dataset contains 59.915 values, collected at a sampling time of 10 seconds, over a 7-day period in a hall with moderate production activity of automation equipment.

A. The ARIMA model

Known as Box and Jenkins methodology, the ARIMA model was one of the most popular procedures for forecasting. In an ARIMA model, it is assumed that the future value of a time series is a linear function of multiple previous values of the original series and random errors. The process that generates the predicted time series has the following form:

$$\begin{aligned} y_t = \theta_0 - \varphi_1 y_{t-1} - \varphi_2 y_{t-2} - \dots - \varphi_p y_{t-p} \\ +\epsilon_t - \theta_1 \epsilon_{t-1} - \theta_2 \epsilon_{t-2} - \dots - \theta_q \epsilon_{t-q} \end{aligned} \tag{1}$$

where y_t and ϵ_t are the actual value and the random error of the time series at time t; $\varphi_{1,\dots,p}$ and $\theta_{1,\dots,q}$ are model parameters, p and q represent the autoregressive and moving average orders, respectively [12], [13].

Equation (1) involves some special cases of the ARIMA models family. If $q = 0$, then (1) becomes an AR model of order p. When $p = 0$, the model is reduced to an MA model of order q.

B. The ANN model

Considering the outstanding results and the exceptional performances attained in cases of real applications, artificial neural networks (ANN) are considered one of the most popular methods of identifying different predictive models. One of the considerable benefits of artificial neural networks is their capacity to model non-linear data relationships. In most situations, time series applications are defined by large alterations and transitory periods. This makes it hard to model time series using a linear model, hence, should be proposed a non-linear approach .

A non-linear autoregressive neural network (NAR), applied to the prediction of time series, characterize a discrete, non-linear autoregressive model that can be defined as follows:

$$y_t = f(y(t-1), y(t-2), \dots, y(t-p) + \epsilon(t) \tag{2}$$

The equation define how the network is used to forecast the value of a time series y at time t, $y(t)$, using the p past values of the series. $\epsilon(t)$ represents the error of the approximation of the series y at time t [14].

IV. Application of the Models to Energy Forecasting Consumption

A. ARIMA modelling

Based on the theoretical considerations mentioned in subsection II.A, starting from the data set containing the measured active energy values at a 10-second sampling period, an ARIMA mathematical model was identified. Since a very important requirement of a model identification process is that the data set used to validate the identified model is different from the one used for the estimation, the first step was to divide the data set into two different sets, one being used for model estimation, and second for validation of the model.

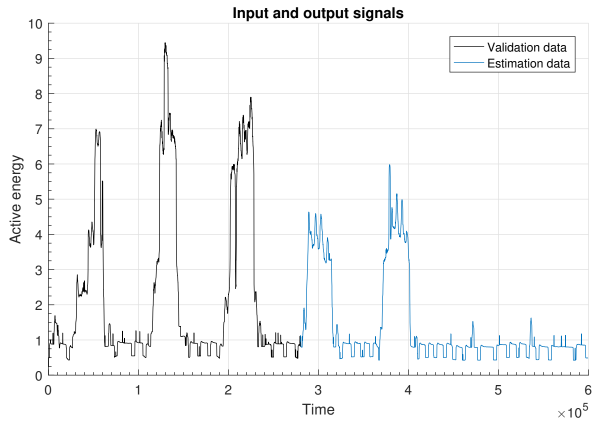

Fig. 2: Data set used for ARIMA model estimation and validation

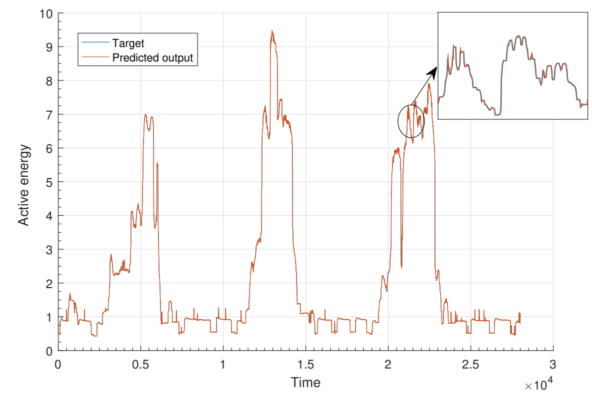

Fig. 3: Prediction result by ARIMA model.
Black line is real data and red line is prediction result

An ARIMA model is described by the following equation:

$$ARIMA[na, nc] : A(z^{-1})y[n] = \frac{C(z^{-1})}{1 - z^{-1}}e[n], \forall n \in \mathbb{N} \quad (3)$$

In order to choose the optimal structural index $n\theta$, a Predictive Error Method (PEM) was used and the criterion used was Akaike's Final Prediction Error (FPE). The criterion is defined by the following equation:

$$FPE = V_n(1 + \frac{2d}{N - d}) \quad (4)$$

where, d is the number of estimated parameters, N represents the number of values in the estimation data set and V_n is the cost function defined by the following formula:

$$V_n = det(\frac{1}{N}\sum_{1}^{N}\epsilon(t, \theta_N)(\epsilon(t, \theta_N))^T \quad (5)$$

where $\epsilon(t)$ represents the prediction error vector and θ_N the estimated parameters.

On the basis of above mentioned criterion, the optimal degrees were obtained: $na = 4$, $nc = 3$. The polynomial coefficients associated with the model are:

$$\begin{aligned} A(z^{-1}) &= 1 - 1.321z^{-1} + 0.2778z^{-2} + 0.01317z^{-3} \\ &\quad + 0.04068z^{-4} \quad (6) \\ C(z^{-1}) &= 1 - 0.39z^{-1} - 0.692z^{-2} + 0.1343z^{-3} \end{aligned}$$

Fig. 2 shows that the degree of matching of real values measured with predicted values is 99.45% for one step predicted output and it indicates that ARIMA model has a good prediction performance.

B. NAR modelling

A standard two-layer feed-forward neural network was developed for the prediction of energy consumption and for training the network it was used Levenberg - Marquardt (LMBP) back-propagation learning algorithm. The training process is controlled by a cross-validation technique that consists in randomly dividing the initial set of data into 3 subsets. The first subset, comprising 70% of the data, was used for training the NAR. The second subset, comprising 15% of the data, was used for validation, and the last 15% was used for testing the model. The 7-day energy consumption data set was used for the time series modelling.

The number of neurons in the input and output layers have been set as 10 and 1 respectively. The prediction model and experimental data is shown in Fig. 4.

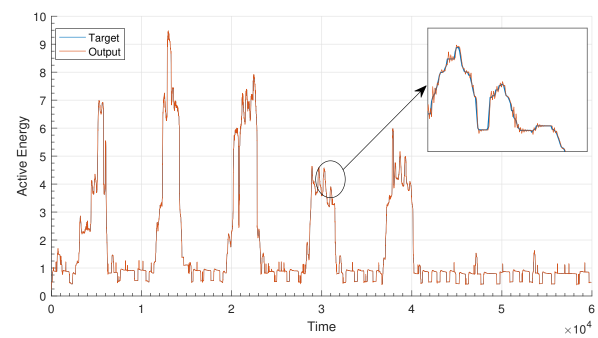

Fig. 4: Prediction result by NAR model.
Blue line is real data and red line is prediction result

The quality of the model approximation was assessed by: the mean square error (MSE) and the correlation coefficient between the actual values specified in the training set and the values produced by the network (R). The MSE values for the learning, validation and testing data sets are: $1.15193 * 10^{-4}$, $8.0697 * 10^{-5}$ and $1.06473 * 10^{-4}$, respectively and the R values are: 0.99983, 0.99988 and 0.99984. It can be seen that the MSE values are close to 0 and the R values are close to 1 which means the model has a good approximation.

C. Models performance comparison

In terms of methods of performance evaluation of the two models, four criteria were used to measure prediction performance, namely: Mean Squered Error (MSE), Root Mean Squared Error (Root Mean Squared Error) RMSE), Average Absolute Error (MAE), and Mean Absolute Percentage Error

(MAPE). They are described by the following formulas:

$$MSE = \sum_{1}^{n} \frac{(Y_t - Yp_t)^2}{n}$$
$$RMSE = \sqrt{\sum_{1}^{n} \frac{(Y_t - Yp_t)^2}{n}} \quad (7)$$
$$MAE = \sum_{1}^{n} \frac{|Y_t - Yp_t|}{n}$$
$$MAPE = \frac{\sum_{1}^{n} |\frac{Y_t - Yp_t}{Yp_t}|}{n} 100\%$$

where Y_t and Yp_t are the vector of the actual values and predicted values, respectively.

In Table 1 are shown the values of these errors for each model.

TABLE I: Forecasting performance of each model

	ARIMA	NAR
MSE	$7.0576 * 10^{-5}$	$1.0871 * 10^{-4}$
RMSE	0.0084	0.0104
MAE	0.0017	0.0027
MAPE	0.1457	0.1887

From Table 1, it can be noticed that the ARIMA model error rates are lower than in the other case, which leads us to conclude that the ARIMA model is more adaptable and therefore produces better results. Thus, it can be argued that the performance of the NAR model is less good than the ARIMA model in terms of forecasting accuracy using MSE, RMSE, MAE and MAPE. However, prediction error is very small for both models, so we conclude that any model can be used to predict energy consumption within the specified perimeter.

V. Conclusion

Energy consumption is a topic of great interest for both the power companies and consumers which desire an accurate profile for understanding future needs and development of the current system. In this paper a monitoring and forecast system was developed.

Two approaches, statistical networks and neural networks have been implemented to identify patterns for time series. Actual values recorder from the monitoring system installed in industrial consumer (e.g. small production aria of a company which produces automation equipment) were used to design and validate the two developed forecast methods. This study includes the empirical results obtained on the performance of two ARIMA and NAR models in predicting energy consumption in a given perimeter over a period of time. The comparison was made to highlight which of the two methods is more accurate in the context presented.

The performance of the NAR model has been compared to that of the ARIMA model, which is commonly used for time series analysis. We note that both the ARIMA model and the NAR model can obtain good forecasts and can be used effectively for energy forecasting. Although the performance of the ARIMA model is better than the NAR model, as observed by comparing the predictive error values. In the forecasting process, the application of the parsimony principle is also an important aspect to find the best model. As it can be seen, the two models are equal in terms of performance, but the ARIMA model can be considered the more appropriate model than the NAR also for the simplicity of its structure.

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