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The planning of electricity: Forecasting using the ARMAX model based on consumption and taking into account relative humidity

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Abstract

Effective energy demand forecasting for grid stability and resource management is essential, especially in regions facing extreme climate turmoil. This study discusses the challenge of high electricity consumption in Babylon, Iraq. In Babylon's climate, forecasting models seldom account for the impact of relative humidity. Although earlier studies have addressed temperature, the impact of humidity on power load remains poorly studied in this region. Given these conditions, an ARMAX model is imperative. To address this, we developed an ARMAX (Autoregressive Moving Average with eXogenous input) model using daily relative humidity from March to June 2024. We evaluated the model using AIC, BIC, and RMSE. We estimated the model parameters using least squares, maximum likelihood, and RLS-KF. The results show that incorporating humidity as an external variable improves forecasting considerably compared with univariate models. The findings provide practical insights for regional policymakers to enhance short-term energy planning and reduce resource allocation inefficiencies in climate-sensitive regions. The ARMAX model uses historical time-series data and the influence of other variables to improve forecasting accuracy and better understand the causes of fluctuations in greater detail. The need for intelligent forecasting tools is growing to tackle climate change, energy efficiency, economic impact, and more.

Keywords: ARMAX model; exogenous inputs; Forecasting; relative humidity; electricity consumed

1. Introduction

The global transition toward sustainable energy systems necessitates highly accurate load forecasting to balance supply and demand. In developing economies, the pressure on aging electrical grids is exacerbated by rapid urbanization and unpredictable climatic shifts (El-Khozondar, H. et al., 2024)

Studying the relationship between electricity and relative humidity is vital in many fields, such as energy planning, electrical energy management, and environmental protection. Electricity plays a pivotal role in determining electricity demand, especially in areas with extreme climates, where high electricity demand affects air conditioner use. In contrast, low electricity demand affects the use of heating devices. (Nayyar et al., 2022).

In this context, studying the relationship between electricity and relative humidity in the city of Babylon, Iraq, is particularly important. Babylon has a continental desert climate, with high electricity demand in summer and a noticeable decrease in winter.(Manii, J. K.etl (2021)

In this study, ARMAX (AutoRegressive Moving Average with eXogenous inputs) models were used to analyze the relationship between electricity and electricity consumption in Babylon city, Iraq. ARMAX models account for the mutual effects between the independent variable (electricity) and the dependent variable (relative humidity), in addition to accounting for random factors.

Researchers have used ARMAX models to analyze electricity data and relative humidity in different countries with different climatic conditions and environments. Studies have focused on evaluating the impact of external variables such as urban heat islands, land-use patterns, and weather dynamics on electricity data and consumption.

In our paper, we analyze whether adding public mood information derived from Twitter posts can improve predictions of electricity data and electricity consumption in Babylon. To estimate weather conditions and electricity consumption, we analyzed the frequencies of 120 Daily electricity measurements and the daily amount of relative humidity from March 1, 2024, to June 29, 2024.

2. Research problem

Iraq is a critical case study because of its extreme summer conditions. However, most existing frameworks focus primarily on temperature and often neglect relative humidity, which plays a silent yet substantial role in increasing the 'real-feel' heat index and, consequently, cooling demand.

3. Previous studies

Past research on applying ARMAX models to electricity data or electricity consumption has focused on applications in meteorology, environmental monitoring, renewable energy forecasting, and related areas. A few findings and studies include.

Sarlin and Ntoumos in 18 - In this paper, the ARIMAX model was applied to forecasting wind speed for wind energy applications. A study found that introducing exogenous variables like electricity and pressure could improve wind-speed forecasting accuracy.

Azodi and others (2019) researched the relationship between humidity and electricity (in urban areas) using ARMAX models. The findings suggest that considering exogenous variables such as urban heat island intensity improves understanding of these changes.

Hary et al. (2020) used ARMAX models to predict humidity with independent variables such as rainfall and wind direction. The results showed that these factors improved humidity forecast accuracy.

Liu et al. (2017) investigated ARMAX models to predict humidity for irrigation planning. Including soil moisture content as an exogenous predictor helped the model forecast humidity more accurately.

Porshnev et al. (2016) used frequencies of emotional tags in tweets (words, symbols, and abbreviations) to improve stock market indicator predictions based on Twitter by estimating average

mood. They analyzed 175 tweets from 2 billion tweets between February 13, 2013, and April 22, 2015. The Granger test shows that stock market index returns and the range of emotional signs are causally related. This is because 17 emotional signs caused changes in returns. The study's findings indicated that the additional information from Twitter data improved prediction.

with the ARMAX (GARCH) model. For tweets, the assessment used the BIC criterion.

According to Zhao et al. (2015), a research study tackled the (ARMAX - GARCH) model in order to predict flood flow coming out from the Liu - Jiang River in southern China based on annual rainfall data taken from 18 rainfall stations in the land surrounding this river where this model was built. Using yearly data from 2004 to 2002, the model was applied to 2005 data to test its forecasting performance. The results indicated that ARMAX(1, 1, 1)–GARCH(1, 1) was the optimal model for forecasting flood cases on this river because it had the lowest values for each forecast accuracy criterion (MAPE, RMSE).

Kazumi and others

Previous studies have shown the effectiveness of ARMAX models in analyzing and predicting electricity data. Researchers have studied electricity consumption with exogenously introduced variables. Research in this area can also optimize model parameters, examine additional exogenous variables, and improve the overall accuracy of weather forecasting.

There may not be much literature on ARMAX models and weather conditions in Babylon, Iraq. However, studies have used ARMAX models to analyze climate data and forecast. In time series analysis and forecasting, ARMAX models are frequently used to study electricity and humidity variation. Below are some literature references that display the application of ARMAX models in climate change research:

4. Autoregressive Moving Average with Exogenous Inputs (ARMAX)

Definition:

AutoRegressive Moving Average with eXogenous inputs (ARMAX) is a statistical model used for time series analysis and forecasting. It extends the Autoregressive Moving Average (ARMA) model by including additional explanatory variables, also known as exogenous inputs or independent variables.

The ARMAX(n_p, n_q, n_b) model is formulated as:

$$y(t) = \alpha + \sum_{i=1}^{n_p} \varphi_i y(t-i) - \sum_{k=1}^{n_q} \theta_i \varepsilon(t-k) + \sum_{j=1}^{n_b} \Phi_i x(t-j) + \varepsilon(t) \dots (1)$$

where:

- y(t) is average parameters
- $\varepsilon(t)$ is the error term at time the observed value of the time series at time t
- α is a constant term
- φi are the autoregressive parameters
- θi are the moving coefficients at time t
- x(t) is the vector of exogenous variables at time t
- Φ_i are associated with the exogenous variables.

Certain mathematical formulas ($ARMAX(n_p.n_q.n_b)$) can be defined as follows:

$y(t) = \alpha + \varphi_1 y(t-1) + \Phi_1 x(t-1) - \theta_1 \varepsilon(t-1) + \varepsilon(t)$. (2 (Csala, D.etl 2022).

The ARMAX model is typically estimated using methods such as maximum likelihood estimation. Model orders (p, q, and x) can be selected using statistical techniques such as the Akaike information criterion (AIC) or the Bayesian information criterion (BIC). (Singh et al., 2023)

ARMAX models are particularly useful when the time series data exhibit both autocorrelation and a relationship with external factors. By including exogenous variables, we can capture the additional information they provide and potentially improve forecast accuracy.(Majka, M. etl 2024).

ARMAX models (AutoRegressive Moving Average with eXogenous inputs) are commonly used in time series analysis to predict future values based on past values and external factors. One practical application where ARMAX models can be useful is in forecasting stock prices. (Csala, D. et al., 2022).

4.1. Order determination

Because electricity consumption is sensitive to weather variables, this paper uses an ARMAX model to forecast electricity values under the influence of humidity (an exogenous variable). The form of the ARMAX model can be expressed as follows:

$$X_{(p)}Q(t) = Y_{(p)}r(t) + Z_{(p)}s(t) \quad \dots (3)$$

Where $Q(t)$ is the electricity consumption at time t, $r(t)$ is the exogenous humidity variable at time t, $s(t)$ is the white noise at time t, and p is the back-shift operator. $X_{(p)} = 1 + x_1p^{-1} + \cdots + x_np^{-n}, x_1, x_2, \dots, x_n$ are parameters of the autoregressive (AR) part, n is the AR order, $Y_{(p)} = y_1 + y_2p^{-1} + \cdots + y_mp^{-m+1}, y_1, y_2, \dots, y_m$, are the parameters of the exogenous (X) input part, m is the input order, $Z_{(p)} = 1 + z_1p^{-1} + \cdots + z_dp^{-d}, z_1, z_2, \dots, z_d$, are parameters of the moving average (MA) part, and d is the MA order. (Yager, R. R. et al., 2014).

At the order-determination stage, the sample autocorrelation function (ACF), sample partial autocorrelation function (PACF), cross-correlation function (CCF) (Box, 1976), and the AIC, BIC, and FPE criteria are used to select a suitable ARMAX model. (Singh et al., 2023)

4.2. Parameter estimation

After determining the model order, we need to derive efficient parameter estimates. These parameters are estimated to ensure that the gradient of the forecasting errors with respect to the electricity consumption data equals zero. (Banga, J. R. et al., 2015).

The parameter values that minimize forecasting error are considered the primary criterion for selecting both the model order and its parameters. Because the mean square forecasting error function has several local minima, a zero-gradient point does not necessarily indicate a global optimum. (Grunske, L. et al., 2014) Therefore, an alternative method for finding the global optimal solution is needed. In this study, we use different methods to estimate ARMAX model parameters, such as Maximum Likelihood Estimation (MLE), ordinary least squares (OLS), and the Recursive Least-Squares Kalman filter algorithm (RLS-KF). AL (Mohana, F. A. M. et al., 2025).

5. Numerical results

5.1. Data sets in the experiment

In this study, the data represent two time-series datasets of electricity consumption and relative humidity in Iraq (Babylon), with monthly measurements from March 1, 2024 to June 29, 2024. collected to investigate the performance of the ARMAX model in forecasting.

5.2. Empirical results of real data

In this study, real data were used to represent 120 observations of daily electricity consumption and relative humidity measurements during the period from March 1, 2024 to June 29, 2024 to build the ARMAX (Autoregressive Moving Average with exogenous inputs) model, which combines bivariate time-series data of the electricity consumed and the relative humidity (external variables). We used the ARMAX model to analyze and forecast this data.

Figure 1 shows two plots illustrating the behavior of electricity consumption and relative humidity over the specified date range. The top plot shows the daily electricity from March 1, 2024, to June 29,

2024. Electricity fluctuates, with variations that could reflect seasonal changes. The bottom plot shows the actual relative humidity.

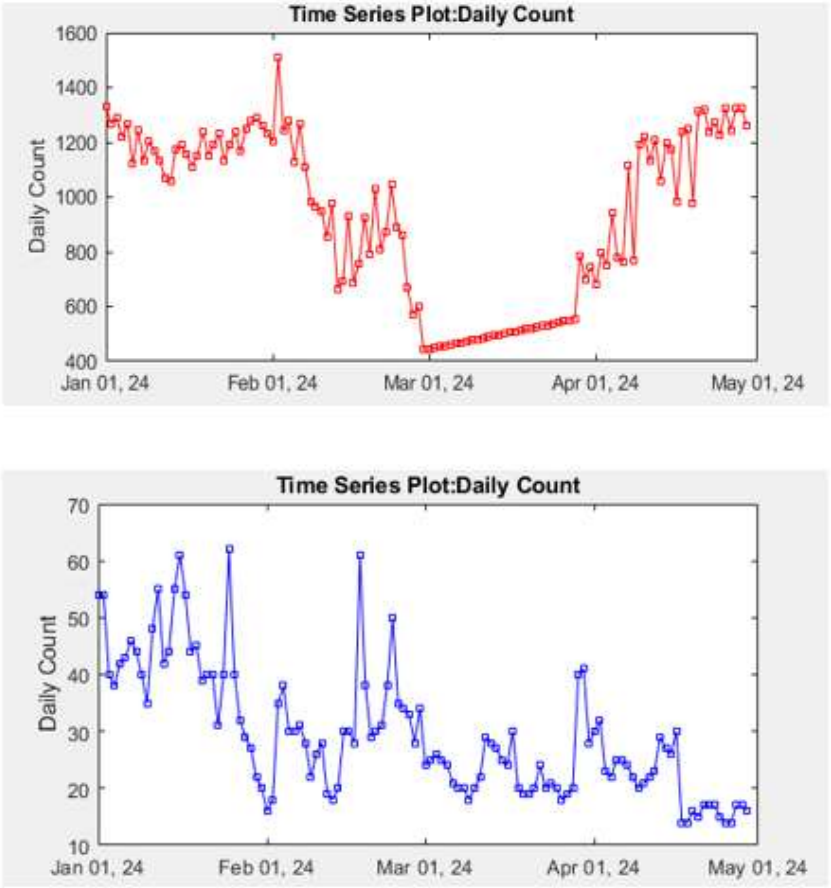


Fig. 1. The daily electricity and relative humidity for the original series (March 1, 2024 to June 29, 2024)

5.3. Fitting of the ARMAX(n_p. n_q. n_b) Models

In this study, the best ARMAX model is chosen based on minimum AIC, BIC, and FPE criteria; consequently, the ARMAX (1,1,1,0) model is selected to model the dynamic relationship between electricity and relative humidity observations. The figure and table below show some AIC, BIC, and FPE results, along with the ACF and PACF, for selecting different ARMAX model permutations. (Amaefula Chibuzo, G. 2023).

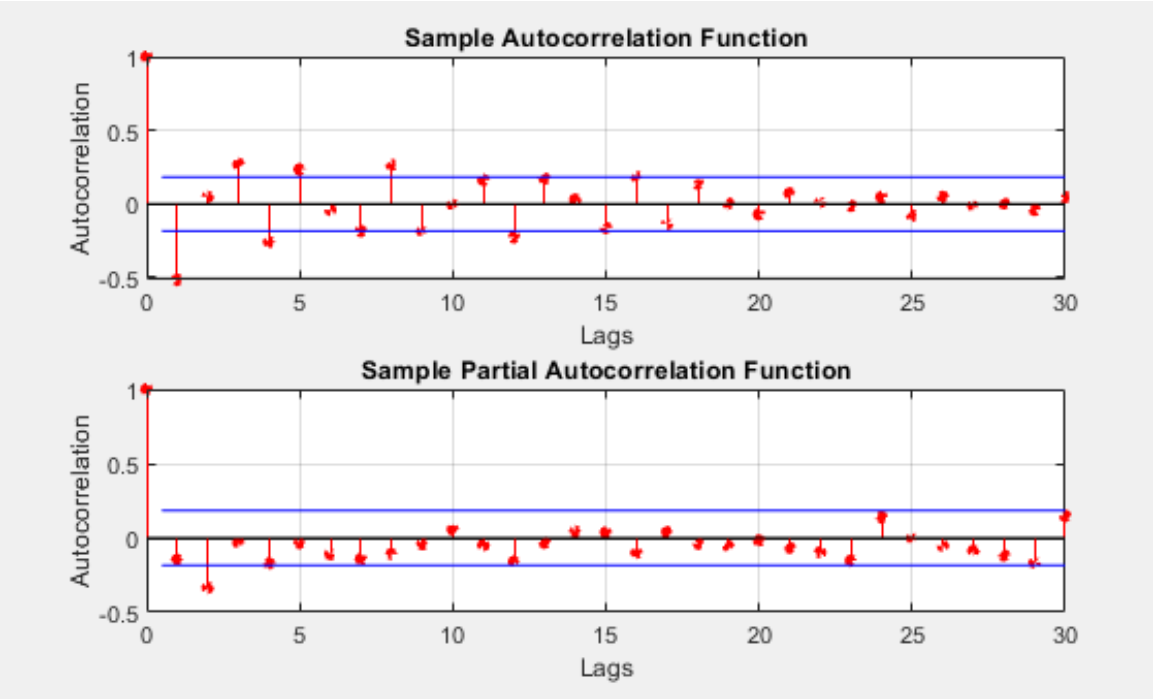


Fig. 2. ACF and PACF for daily electricity and relative humidity for difference series

The AIC, BIC, and FPE criteria are represented in the following table :

Table 1. Results of criteria for different permutation ranks for ARMAX model

Models	AIC	FPE	BIC
ARMAX (0.1.1.0)	0.4226	1.1320	0.6421
ARMAX (0.1.2.0)	0.5363	1.2140	0.5541
ARMAX (1.0.1.0)	0.4121	1.1205	0.5001
ARMAX (1.0.2.0)	0.3132	2.001	0.4102
ARMAX (1.0.3.0)	0.5143	1.004	0.1940
ARMAX (1.1.1.0)	0.2147	1.004	0.1310
ARMAX (1.1.2.0)	0.5600	1.1213	0.321
ARMAX (1.2.3.0)	0.5101	2.0006	0.6321
ARMAX (2.0.1.0)	0.4978	1.3160	0.4321
ARMAX (2.0.2.0)	0.6543	1.2430	0.5321
ARMAX (2.0.3.0)	0.6363	1.2208	0.4536
ARMAX (2.1.1.0)	0.4233	1.3655	0.3292

From the table above, the ARMAX (1,1,1,0) model best represents the relationship between electricity and relative humidity, based on the lowest comparison-criteria values.

5.4. Parameter estimation

After selecting the best ARMAX model in Section 5.3, the parameters of the ARMAX (1,1,1,0) model are estimated using (MLE), (OLS), and (RLS-KF) methods. The table below presents the model parameter estimates, along with the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) for each method. (AL Mohana, F. A. M. 2025).

Table 2. Results of ARMAX (1,1,1,0) prediction model parameter estimation

Method	φ_1	θ_1	ϕ_1	RMSE	MAE
MLE	0.1075	0.5211	0.5799	0.5871	0.3145
OLS	0.8822	0.6329	0.4616	0.1277	0.4832
RLS-KF	0.5211	0.4329	0.1221	0.1182	0.2160

From Table 2, and based on the minimum RMSE (0.1182) and MAE (0.2160), we conclude that the Recursive Least Squares method with Kalman forgetting factor (RLS-KF) is the best estimation method compared with the MLE and OLS methods.

shows metrics related to the effectiveness of the model used in forecasting electricity consumption

The table below shows estimates of statistical parameters related to the effectiveness of the ARMAX (1,1,1,0) model used to forecast electricity consumption, including values and relevant information such as standard error (SE), t-value, and probability value (p-value), using the RLS-EF method. 3 below: -

Table 3. Significance of ARMAX (1,1,1,0) prediction model parameters

estimate	$AR_1\varphi_1$	$MA_1\theta_1$	$x_1\phi_1$
SE	0.1075	0.5211	0.5799
t-value	4.8474	0.8307	0.2088
p-value	0.00001	0.0000	0.00012

We conclude that all p-values (< 0.05) for each parameter are significant. The output shows the results of fitting the ARMAX (1,1,1,0) model to the data, specifically the relationship between electricity consumption (y) and relative humidity (x).

The mean equation discussed in Section 4 follows the ARMAX (1,1,1,0) model used in forecasting electricity consumption and can be written from Table 2 as :

$$y_t = 0.5211\, y_{t-1} + 0.4329\varepsilon_{t-1} + 0.1221 x_{t-1} + \varepsilon_t$$

The equation above represents the ARMAX (1,1,1,0) model used to forecast electricity consumption.

5.5. Forecasting evaluation

The ARMAX(1,1,1,0) model predicted electricity consumption for the last 5 observations of June 2024, used as the test set, to obtain the out-of-sample forecast. These values are represented in Table (4) below.

Table 4. Actual and forecast electricity values of the ARMAX model

electricity degrees	Predicted electricity consumption
1324	1298
1245	1199
1323	1278
1322	1451
1262	1100

These values represent the predicted electricity consumption based on the fitted ARMAX model for future electricity values.

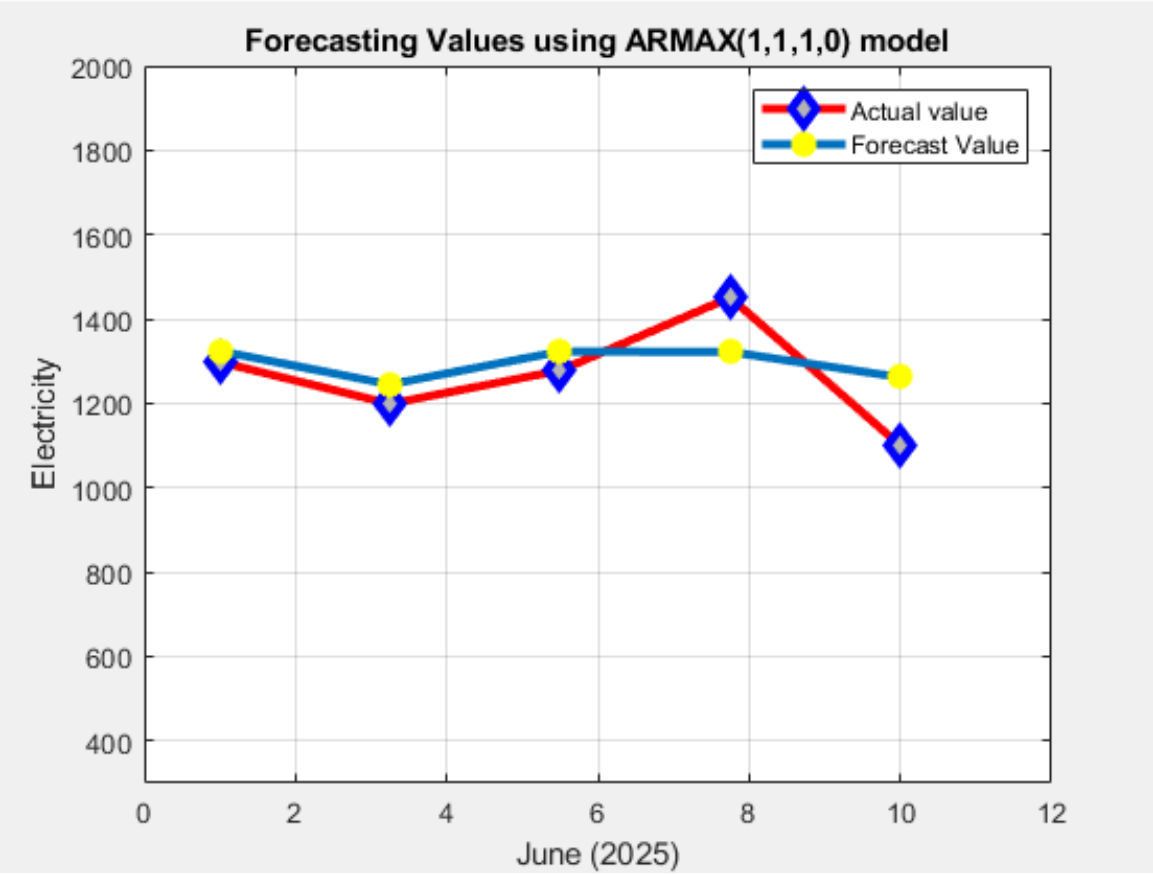


Fig. 3. Actual and forecast values of fitted ARMAX (1,1,1,0) model

6. Results and conclusions

This study will not only help predict future power and energy consumption, but also assess the impact of various factors. Using synthetic data, we can implement diverse scenarios to enhance models and obtain accurate forecasts. This can support regional energy management. Lower AIC, BIC, and FBE values indicate a better ARMAX model. However, these are relative measures compared with other competing models. The research employed a linear regression to model pollution levels in London and proposed various control measures. It showed overall accuracy, but some beta coefficients were not statistically significant; the model could have been improved. We recommend that future studies use larger datasets and add other models to compare with ARMAX models. (Byun, Y. C. et al., 2023).

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