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Modeling And Forecasting Electricity Consumption And Its Determinants: Evidence From The Kashkadarya Region

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INTRODUCTION & AIM

Currently, the increasing demand for electricity, the depreciation of energy infrastructure, and the necessity of improving energy efficiency have significantly enhanced the importance of scientifically grounded modeling and forecasting of regional electric power systems. In the Kashkadarya region, the volume of electricity consumption is closely associated with economic activity, population growth, income levels, and the condition of the energy infrastructure. Uncertainties in accurately forecasting electricity consumption may result in network overloads, increased energy losses, and inefficient allocation of resources. The main objective of this study is to analyze the socio-economic and technical factors influencing electricity consumption in the Kashkadarya region using econometric and ARIMA time series models, as well as to develop forecast parameters for the period 2025–2030. Within the framework of the study, the relationship between electricity consumption and household income, the regression relationship between subscriber electricity consumption and population size, and the indicators of energy efficiency and network losses were comprehensively evaluated.

METHOD

Research Object and Database: This study focuses on the electric power system of the Kashkadarya region over the period 2010–2024. The research is based on official statistical databases and examines the main technical, socio-economic, and demographic indicators affecting regional electricity consumption and energy system performance. The analyzed variables include electricity losses in the network (EL, %), energy efficiency indicators (EE, %), the technical depreciation level of electricity generation capacities (GA, %), permanent population (POP, thousand people), per capita income (GNI, thousand UZS), household electricity consumption (ECP, million kWh), and electricity consumption by subscribers (ECS, million kWh). These indicators were selected to evaluate the relationships between electricity demand, infrastructure conditions, and socio-economic development within the regional electric power system., as well as the structural forms of the components within the electric motor system. The descriptive statistical characteristics of the variables used in the study for the period 2010–2024 were determined (Table 1).

Table 1. Descriptive statistics of the variables used in the study (2010–2024)

Variable	Mean	Median	S.D.	Min	Max
EL	20.7	20.9	2.64	16.5	24.6
EE	3.28	3.16	0.711	2.39	4.66
GA	42.6	43.6	4.14	37.1	49.2
POP	3089.7	3088.8	290	2616.1	3560.6
GNI	8442.0	6927.8	5665.3	1896.4	19915
ECP	1122.3	1034.2	192.03	923.44	1471.4
ECS	5055.3	5116.1	766.73	3922.4	6554.8

Econometric Modeling: Ordinary Least Squares (OLS) regression models were applied to evaluate the relationship between electricity consumption and socio-economic factors. In addition, elasticity coefficients were estimated to economically assess the impact of explanatory variables on electricity consumption.

Model reliability was assessed using: Variance Inflation Factor (VIF); Durbin–Watson statistic; F-test and Adjusted R^2; AIC/BIC criteria; Statistical significance level: p<0.05

$$\hat{y}_t = \underbrace{\beta_0}_{t;\,p} + \underbrace{\beta_1 * x}_{t;\,p} \quad (1) \qquad E_c = \beta_1 * \frac{\bar{X}}{\bar{Y}} \quad (2)$$

Where: β_0 and β_1-denote the regression coefficients; $\bar{X}$ and $\bar{Y}$-represent the mean values of the independent and dependent variables, respectively; E_c refers to the elasticity coefficient; and , t and p denote the t -ratio and p -value of the estimated coefficients.

Forecasting Methods Based on Time Series Analysis: To forecast the main indicators of the electric power system, ARIMA (p,d,q) time series models based on the Box–Jenkins methodology were applied. The stationarity of the time series was tested using the Augmented Dickey–Fuller (ADF) test. Forecasting accuracy was evaluated using the MAE, RMSE, and MAPE indicators, and models with MAPE<5% were considered highly accurate. The forecasting horizon covered the period 2025–2030, and the forecast results were calculated with a 95% confidence interval.

$$y'_t = c + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \ldots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t \qquad (3)$$

Where: y'_t represents the differenced time series, which may be differenced multiple times if the original series is non-stationary. The right-hand side of the model includes the lagged values of $\mathbf{y_t}$ as well as the lagged values of the error terms [24]. To evaluate the forecasting accuracy and reliability of the model parameters, the following three standard indicators were applied:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \ (4) \quad MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right| * 100\% \ (5) \quad RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2} \ (6)$$

Where: y_t–denotes the actual observed value, $\hat{y}_t$-represents the forecasted value.

RESULTS & DISCUSSION

To quantitatively assess the relationship between ECP and GNI, as well as between ECS and POP in the region, the Ordinary Least Squares (OLS) method was employed.

Table 2. Results of the regression models for ECP and GNI, and ECS and POP, including elasticity estimates.

Mathematical expression of the model			
$ECP = \underbrace{842{,}15}_{t=43{,}77;p=0{,}0001} + \underbrace{0{,}033 * GNI}_{t=17{,}25;p<0{,}0001}$ (7)		$ECS = \underbrace{-2877.05}_{t=-5.191;p=0.0002} + \underbrace{2.567 * POP}_{t=14.37;p<0{,}0001}$ (8)	
Indicators	Values	Indicators	Values
R^2	0.9586	R^2	0.9407
DW	2.08	DW	1.71
RMSE	37.74	RMSE	180.27
MAE	31.09	MAE	135.23
MAPE	2.7061	MAPE	2.5241
$E_c = \beta_1 * \frac{\overline{GNI}}{\overline{ECP}}$	$0{,}033 * \frac{8441{,}96}{1122{,}32} = 0.25$	$E_c = \beta_1 * \frac{\overline{POP}}{\overline{ECS}}$	$2.567 * \frac{3089{,}68}{5055{,}28} = 1.57$

To determine the relationship between electricity losses in the network (EL) and the variables EE and GA, a multiple regression model based on the Ordinary Least Squares (OLS) method was constructed. The mathematical expression of the model, together with the main adequacy indicators and elasticity estimates, are presented in Table 3.

Table 3. Results of the multiple regression model for assessing EL based on EE and GA, Including elasticity estimates

Mathematical expression of the model	
$EL = \underbrace{14.61}_{t=5.28;p=0{,}0002} - \underbrace{2.01 * EE}_{t=-7{,}63;p<0{,}0001} + \underbrace{0{,}297 * GA}_{t=6{,}55;p<0{,}0001}$ (9)	
Indicators	Values
R^2	0.99
DW	2.07
RMSE	0.2
MAE	0.17
MAPE	0.86
$E_c = \beta_1 * \frac{\overline{EE}}{\overline{EL}}$	$-2.01 * \frac{3{,}276}{20{,}68} = -0.32$
$E_c = \beta_2 * \frac{\overline{GA}}{\overline{EL}}$	$0.297 * \frac{42{,}586}{20{,}68} = 0.61$

ARIMA time series models were developed using the Gretl software package to forecast the main electric power indicators of the Kashkadarya region.

Table 4. Time Series Models of Electric Power Indicators

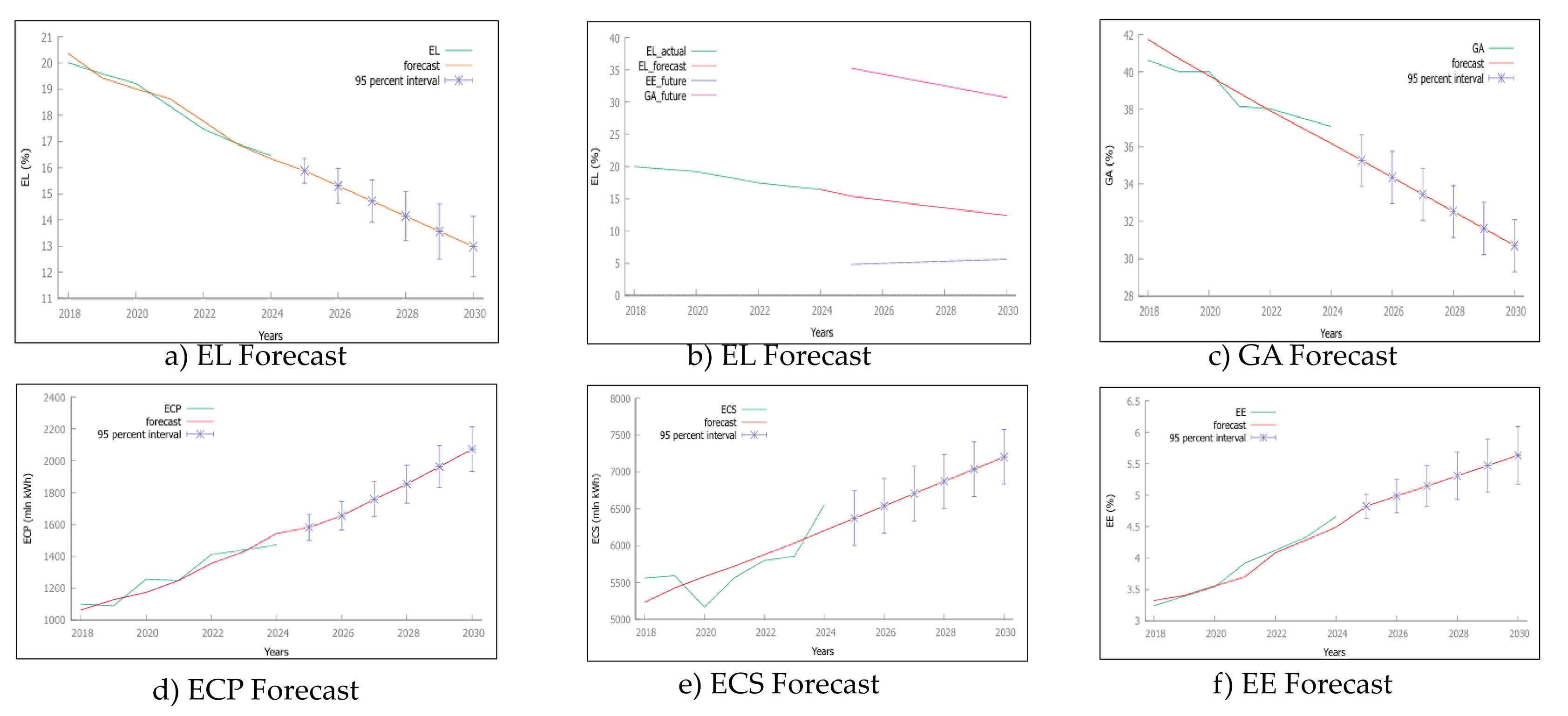
ARIMA	Symbol	Coeffic	Std. Error	z	p-value	R^2	RMSE	MAE	MAPE
$(1-L)EL_t = -0{,}58 + \varepsilon_t$ (10)									
(0.1.0)	const	−0.580000	0.0641256	−9.045	<0.0001	0.99	0.2312	0.1813	0.9
$(1-L)EE_t = 0.16 + \varepsilon_t$ (11)									
(0.1.0)	const	0.162143	0.0255957	6.335	<0.0001	0.99	0.0922	0.0710	2.13
$(1-L)GA_t = -0.91 + \varepsilon_t - \varepsilon_{t-1}$ (12)									
(0.1.1)	const	−0.911536	0.0424801	−21.46	<0.0001	0.96	0.7108	0.64678	1.54
	theta_1	−1.00000	0.249805	−4.003	<0.0001				
$(1-L)^2ECP_t = 5.56413 - 0.59(1-L)^2 * ECP_{t-1} - \varepsilon_{t-1} + \varepsilon_t$ (13)									
(1.2.1)	const	5.56413	1.91684	2.903	0.0037	0.95	42.341	34.629	2.97
	phi_1	−0.595040	0.205930	−2.890	0.0039				
	theta_1	−1.00000	0.260483	−3.839	0.0001				
$(1-L)ECS_t = 166.16 + \varepsilon_t - \varepsilon_{t-1}$ (14)									
(0.1.1)	const	166.161	11.2897	14.72	<0.0001	0.92	188.91	133.93	2.42
	theta_1	−1.00000	0.206545	−4.842	<0.0001				

Based on the developed models, the following forecast parameters were calculated (Table 7).

Table 5. Forecast parameters of electric power indicators in the Kashkadarya region

Indicators		Forecast Years						2030/2024 Ratio (times)	Average Growth Rate (%)
		2025	2026	2027	2028	2029	2030		
EL (%)	9	15.40	14.80	14.20	13.60	13.00	14.42	0.87	2.18
	10	15.88	15.30	14.72	14.14	13.56	12.98	0.79	3.88
EE (%)	11	4,82	4,98	5,15	5,31	5,47	5,63	1.21	3.2
GA (%)	12	35,26	34,35	33,44	32,53	31,62	30,71	0.83	3.1
ECP (mln kWh)	13	1581.9	1654.9	1759.2	1853.7	1962.91	2072.25	1.41	5.9
ECS (mln kWh)	14	6372.8	6538.9	6705.1	6871.2	7037.4	7203.6	1.10	1.59

Figure 1. Forecast results of electric power indicators (2025–2030) with 95% confidence intervals.



a) EL Forecast b) EL Forecast c) GA Forecast

d) ECP Forecast e) ECS Forecast f) EE Forecast

Figure 1. Confidence intervals of forecast results for electric power indicators

CONCLUSIONS

The results of the study confirmed significant relationships between electricity consumption and socio-economic as well as technical factors in the Kashkadarya region. The econometric models showed that increases in household income and population size contribute to higher electricity consumption, while improvements in energy efficiency reduce electricity network losses. Forecasting results based on ARIMA models indicate a stable growth trend in electricity consumption and energy efficiency indicators by 2030, accompanied by a gradual decline in the technical depreciation level of the energy infrastructure. The findings highlight the importance of modernizing outdated power infrastructure, reducing network losses, and implementing smart grid and digital monitoring technologies to improve the efficiency and sustainability of regional electric power systems.

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