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Rolando A. Danao[1] and Geoffrey M. Ducanes[2]

Abstract

This paper presents an error correction model for forecasting electricity consumption in the Philippines based on income, price, and temperature. The empirical evidence shows that there is a long-run positive and inelastic relationship between electricity consumption and income. We find that income, price, and temperature have significant short-run effects. Short-run demand is positive and inelastic with respect to income, negative and inelastic with respect to price, and positive and elastic with respect to temperature. Despite the small sample size, the model passes the standard diagnostic and parameter stability tests and performs well in within-sample and out-of-sample forecasting. It can be used not only for forecasting but also for analyzing, through simulations, the impacts on electricity consumption of changes in income, price, and temperature.

The simulations confirm that, in the long run, electricity consumption is mainly driven by economic growth. Increasing GDP growth rate from 6% per year to 7% could increase electricity consumption at the end of 15 years by 10%. Although the effect of electricity price on electricity consumption is small (because of low price elasticity in absolute terms) and the effect of temperature change is also small (because annual average temperature change is small), their combined effects could add up and our simulation indicates that under very conservative assumptions, electricity consumption at the end of 15 years could rise further by 2%. Thus, it is important to include these variables in the simulations in order to account for their combined effects.

JEL Classification: C53

Key words: Electricity consumption, forecasting, error correction model

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AN ERROR CORRECTION MODEL FOR FORECASTING PHILIPPINE AGGREGATE ELECTRICITY CONSUMPTION

1. Introduction

Electricity is linked to practically all aspects of national development (industrial production, agricultural production, education, health, etc.) that forecasting the country's future electricity demand has become crucial to energy planning and management. Government planners rely on sound and reliable electricity demand projections in their development planning and forecasts that are way out of line can have serious economic consequences. The objective of this study is to develop a forecasting model for aggregate electricity demand in the Philippines. Specifically, we develop an error correction model (ECM) where electricity demand is related to economic and climatic variables. We believe this is the first time an error correction model is used for forecasting electricity consumption in the Philippines. It is also the first time that a Philippine model for electricity consumption includes temperature as an explanatory variable.

2. Demand for Electricity

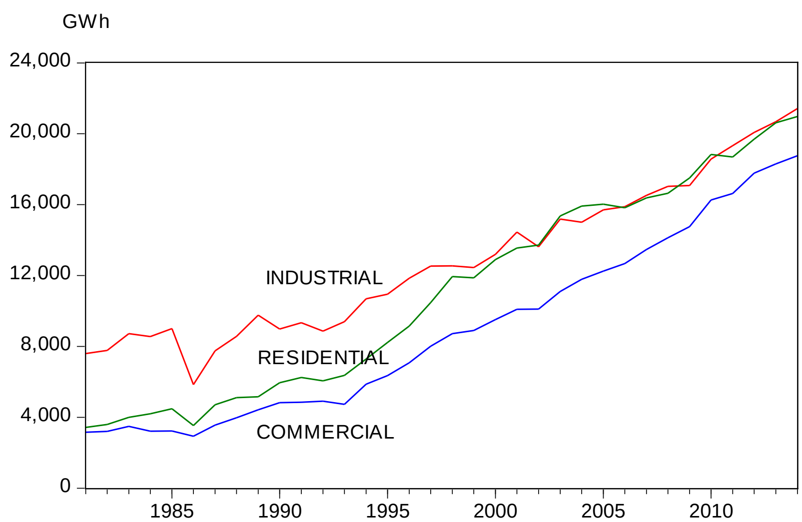
Electricity consumption in the Philippines grew by 4.4% per year between 1981 and 2014 and reached 77,261 GWh, a fourfold increase. Table 2.1 presents the trends in electricity consumption from 1981 by type of use. It shows that in 1981 the residential and commercial sectors had almost equal shares while the industrial sector had more than the share of the commercial and residential sectors combined. Although the industrial sector historically had the highest consumption levels, it had the lowest growth rate because of its marked decline in electricity consumption, relative to the other sectors, brought about by the economic crisis in 1984 -1985 (Figure 2.1). These trends in electricity consumption are shown in Figure 2.1. The graph clearly shows the dampening effects on electricity consumption of the power shortage crisis in the early 1990s. The government's response to the crisis was to enact the Electric Power Crisis Act of 1993 (approved April 2, 1993) which authorized the President to negotiate IPP (Independent Power Producer) contracts on a fast track basis.

Table 2.1. Electricity Consumption by Type of Use: Philippines, 1981 and 2014

	1981		2014		Annual Growth Rate (%)
	GWh	% Share	GWh	% Share	1981-2014
Total Consumption	18,583	100	77,261	100	4.41
Type of Use					
Industrial	7,597	40.88	21,429	27.74	3.19
Residential	3,424	18.42	20,969	27.14	5.65
Commercial	3,157	16.99	18,761	24.28	5.55
Power Loss	2,150	11.57	7,270	9.41	3.76
Utilities Own Use	1,157	6.23	6,646	8.60	5.44
Others	1,098	5.91	2,186	2.83	2.11

Source: Philippine Statistical Yearbook, 2014

Figure 2.1. Electricity consumption (GWh) by type of use, Philippines: 1981-2014



The IPP contracts increased generation capacity resulting in a 14.6% jump in power generation from 1993 to 1994 (PSY [1995]). This, in turn, resulted in electricity consumption increases: industrial by 14%; commercial by 24%; and residential by 14% (Philippine Power Statistics [2015]). The residential sector consumption showed a sustained growth with annual rates ranging from 11.3% to 14.5% during the years 1993 to 1998 (Figure 2.1). With the National Electrification Administration's focus on rehabilitation of lines, line expansion, and energization of isolated islands, access to electricity in the rural population increased by 26.4 percentage points from 1990 to 2010 (Table 2.2). Residential consumption continued to grow and by 2014, the industrial and residential sectors had almost equal shares at 27.74% and 27.14%, respectively.

Table 2.2. Access to Electricity (% of population)

Year	Rural	Urban	All
1990	46.4	84.0	65.4
2000	51.9	91.0	71.3
2010	72.8	94.4	83.3

Source: Index mundi, sourced from World Bank Sustainable Energy for All, Global Electrification data base.

The evolution of electricity consumption in the Philippines is closely related to that of real gross domestic product (see Figure 2.2). In fact, the correlation coefficient between these two variables is 0.98. This strong positive relationship is graphically shown in Figure 2.3. But in terms of growth rates, electricity consumption outpaced real GDP by a factor of 1.3. (The average annual growth rate of real GDP for the period 1981-2014 was 3.42%.)

Figure 2.2. Total electricity consumption (GWh) and real gross domestic product (billion pesos at 2000 constant prices), Philippines: 1981-2014

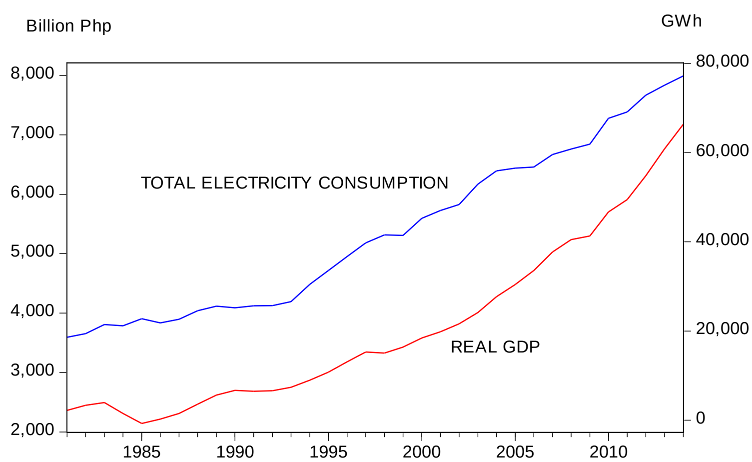
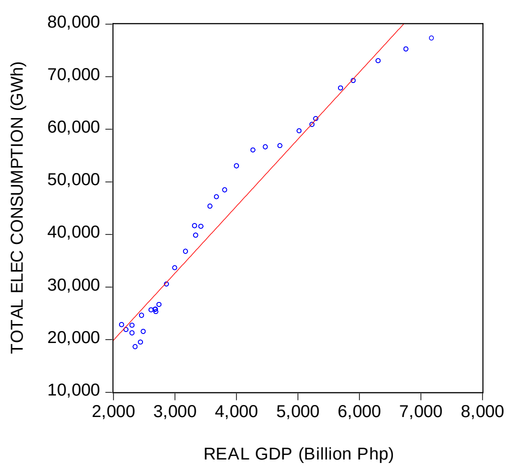


Figure 2.3. Total electricity consumption vs real gross domestic product



3. Model Framework

From the point of view of economic theory, demand for electricity is a function of income and price of electricity. In recent years, an increasing number of researchers have included weather variables among the factors affecting electricity consumption (Lam et al. [2008]; Zachariadis [2010]; Goel and Goel [2014]). Obviously, climate change such as increasing temperature will increase electricity demand related to cooling requirements.

We begin with a basic relationship between electricity consumption (y) and real gross domestic product (x) and electricity price (p) given as an autoregressive distributed lag (ARDL) model,

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 p_t + \beta_4 p_{t-1} + \beta_5 y_{t-1} + \varepsilon_t \qquad (3.1)$$

where y_t, x_t, and p_t are in natural logarithms and, for stability, $|\beta_5| < 1$. (We follow the convention that lower case italics denote variables in natural logarithms.) In long-run equilibrium, $y_t = y_{t-1}$, $x_t = x_{t-1}$, and $p_t = p_{t-1}$. Hence, from (3.1),

$$(1 - \beta_5) y_t = \beta_0 + (\beta_1 + \beta_2) x_t + (\beta_3 + \beta_4) p_t + \varepsilon_t \qquad (3.2)$$

Thus, the long-run equation is

$$y_t = \frac{\beta_0}{1 - \beta_5} + \frac{\beta_1 + \beta_2}{1 - \beta_5} x_t + \frac{\beta_3 + \beta_4}{1 - \beta_5} p_t + u_t \qquad (3.3)$$

where $u_t = \frac{\varepsilon_t}{1-\beta_5}$. The short-run dynamics is introduced by subtracting y_{t-1} from both sides of (3.1) and adding and subtracting $\beta_1 x_{t-1}$ and $\beta_3 p_{t-1}$ on the right-hand side, resulting in the following equation:

$$\Delta y_t = \beta_1 \Delta x_t + \beta_3 \Delta p_t + (\beta_5 - 1) \left[y_{t-1} - \frac{\beta_0}{1 - \beta_5} - \frac{\beta_1 + \beta_2}{1 - \beta_5} x_{t-1} - \frac{\beta_3 + \beta_4}{1 - \beta_5} p_{t-1} \right] + \varepsilon_t \quad (3.4)$$

In equation (3.4), the expression in square brackets is the error term u_{t-1} of the long-run equation (3.3) and is called the error-correction term. Equation (3.4) is the Error Correction Model (ECM) formulation of equation (3.1). Thus, ECM links the short-run dynamics and the long-run equilibrium. The coefficient, $(\beta_5 - 1)$, of the error correction term measures the speed of adjustment to long-run equilibrium after a deviation. Note that the speed of adjustment is negative.

4. ECM Empirical Specification and Data for an Annual Model

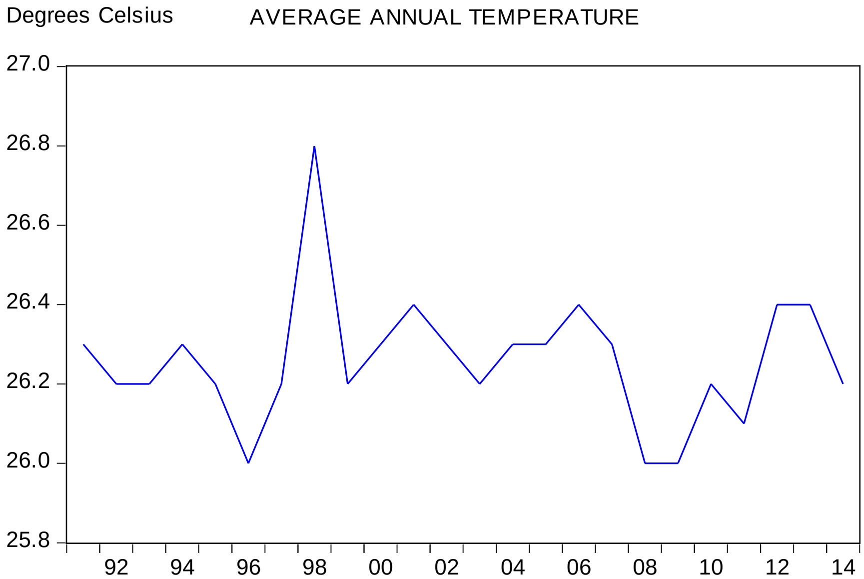
Specifying an electricity demand function is complicated by the existence of block pricing in some distribution utilities in which prices differ in each block. From economic theory, the appropriate price variable is marginal price. But Taylor [1975] argued that to use only the marginal price in this case neglects the income effect of the intramarginal prices and introduces biases in the parameter estimates. However, Berndt [1984] estimated these biases and found them to be negligible.

At a highly aggregated level of data (national level), electricity consumption under differing block pricing structures make it impossible to determine marginal price. Thus, as a measure of electricity price, we use the ex post average price, computed as total expenditure on electricity divided by total kilowatt hours consumed. Van Helden et al. [1987] estimated residential electricity demand functions using different price variables and found support for using average price in the demand function for electricity.

In the empirical specification of the ECM, the practice is to include other exogenous variables and allow a richer dynamic structure by including lags of the short-run terms. However, since the number of lags to include is unknown, it has to be empirically determined and the suggested procedure is to "test down" the lagged terms and produce a parsimonious model without violating the usual diagnostic tests.

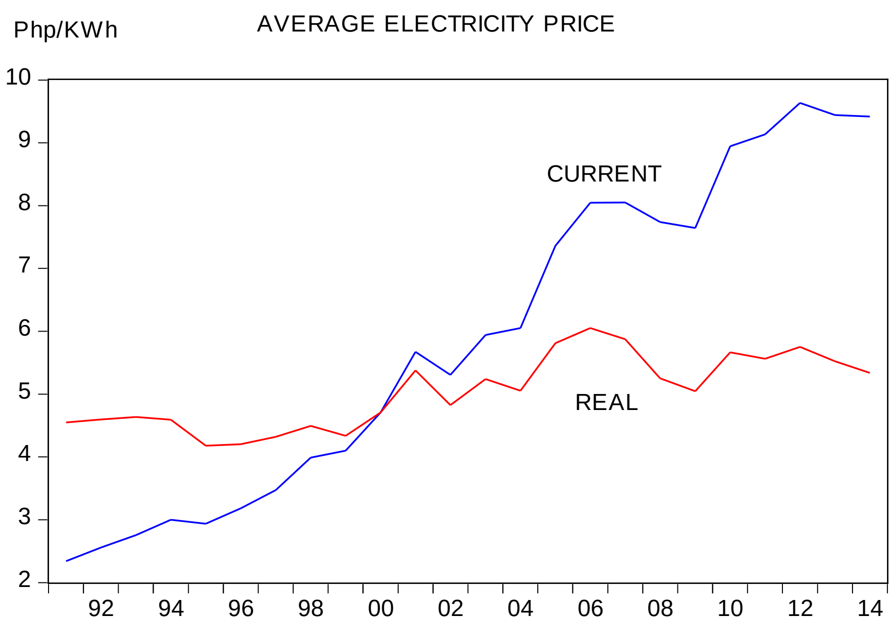
In addition to real GDP and electricity price, we include temperature as an exogenous variable that affects electricity consumption in the short run. Thus, the variables used in the model are (a) total electricity consumption (Y, in GWh), (b) real gross domestic product (X, in 2000 pesos), (c) real electricity price (P, in 2000 pesos/KWh), and temperature (Z, in degrees Celsius). Real gross domestic product data was obtained from the Philippine Statistical Authority, total electricity consumption was obtained from the Department of Energy, and temperature was obtained from the Climate Research Unit of the University of East Anglia (graph of temperature is shown in Figure 4.1). Meralco average price was used as a proxy for electricity price. Meralco is the largest distribution utility, accounting for 55%-60% of total electricity sales during the last decade. Figure 4.2 shows the movement of the current and real prices, where the latter was obtained by using the GDP deflator.

Figure 4.1. Temperature



Source of basic data: Climate Research Unit, University of East Anglia

Figure 4.2. Electricity Price



Source of basic data: Current price provided by Meralco. Real price obtained by deflating current price by the GDP deflator.

Unit Root Tests and Cointegration

Error-correction modeling requires determining the order of integration of each variable and is done by testing for the presence of a unit root. If a series has a unit root and its first difference is stationary or I(0), the series is integrated of order 1 or I(1). Testing for a unit root may be accomplished by using the Augmented Dickey-Fuller (ADF) Test (Dickey and Fuller [1979]). The null hypothesis in an ADF test is that the series under consideration has a unit root. The ADF tests showed that $y_t, x_t,$ and p_t are I(1) while z_t is I(0) (Table 4.1).

Table 4.1. Summary of ADF Tests

Variable	Symbol	Exogenous regressors	t-Statistic	p-value*	Order of integration
log(electricity consumption)	y	Constant, linear trend	-2.0503	0.5433	I(1)
	Δy	Constant	-3.9126	0.0076	I(0)
log(real GDP)	x	Constant, linear trend	-1.0151	0.9210	I(1)
	Δx	Constant	-4.1571	0.0045	I(0)
log(price)	p	Constant, linear trend	-2.4878	0.3300	I(1)
	Δp	Constant	-5.1859	0.0005	I(0)
log(temperature)	z	Constant	-4.0999	0.0048	I(0)
	Δz	Constant	-5.7135	0.0002	I(0)

*MacKinnon one-sided p-value.

The next step is to determine if the economic variables, which are all I(1), are cointegrated, i.e., there is a long-run relationship among them given by the equation (cointegrating equation)

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 p_t + \varepsilon_t \tag{4.1}$$

where ε_t is the error term. A number of cointegration tests are available including the residual-based Engle-Granger [1987] test, the Hansen [1992] parameter instability test, and the error correction test (Enders [2010]; Kremers et al. [1992]). Although the Engle-Granger test is popular, it has some problems such as the common factor restrictions problem, its low power, and small sample bias (Harris [1995]). Hansen's test is based on the notion that parameter instability arises when there is no cointegration. It is implemented by estimating the cointegrating equation by the Fully Modified Ordinary Least Squares (FMOLS) procedure [Phillips and Hansen [1990]). The error correction test, suggested by Kremers et al. [1992]), tests the null hypothesis that the coefficient of the error correction term is equal to zero. If the null hypothesis is true, then there is no cointegration; otherwise, cointegration is indicated.[3] Kremers et al. [1992] showed that this test is more powerful than the Augmented Dickey-Fuller test because no common factor restrictions are imposed.

Equation (4.1) was estimated using the COINTREG command in EViews 9 and the result is presented in Table 4.2. The Hansen cointegration test is shown in Table 4.3. With a p-value of 0.125, the null hypothesis of cointegration cannot be rejected.

Table 4.2. Estimation output for equation (4.1)

Dependent variable: y

	Coefficient	Std. Error	t-Statistic	p-value
x	0.959	0.119	8.028	0.0000
p	0.258	0.295	0.874	0.3930
constant	2.389	0.7001	3.409	0.0029
$R^2 = 0.94$				

Table 4.3. Cointegration Test – Hansen Parameter Instability

Equation	Cointegrating Equation Deterministics	Null Hypothesis	L_c Statistic	p-value
Equation (4.1)	Constant	Series are cointegrated	0.341	0.125

Although the variables are cointegrated, electricity price p has a positive sign. As this does not conform to economic theory, the price variable was dropped from equation (4.1) resulting in the potential long-run relationship between electricity consumption and real gross domestic product:

$$y_t = \beta_0 + \beta_1 x_t + u_t \tag{4.2}$$

This new cointegrating equation was estimated by COINTREG; the regression output is shown in Table 4.4 and the Hansen cointegration test result presented in Table 4.5. With a p-value greater than 0.2, we cannot reject the null hypothesis that the variables y and x are cointegrated. This result is confirmed in the next section where it is shown that these two variables have an error correction representation, a necessary and sufficient condition for cointegration by virtue of the Granger representation theorem.

[3] This follows from the Granger representation theorem which states that a set of I(1) variables are cointegrated if and only if they have an error correction representation (Enders [2010]).

Table 4.4. Estimation output for equation (4.2)

Dependent variable: y

	Coefficient	Std. Error	t-Statistic	p-value
x	1.014	0.174	5.842	0.0000
constant	2.343	1.452	1.614	0.1223
$R^2 = 0.94$				

Table 4.5. Cointegration Test – Hansen Parameter Instability

Equation	Cointegrating Equation Deterministics	Null Hypothesis	L_c Statistic	p-value
Equation (4.2)	Constant	Series are cointegrated	0.173	> 0.2

5. Estimation of the ECM and Statistical Tests

With the long-run relationship in equation (4.2), we specify an Error Correction Model that captures the short-run dynamics involving not only the short-run effects of real GDP but also of electricity price and temperature. After experimenting with different lag structures, we came up with the following single-equation ECM:

ECM1: $$\Delta y_t = \alpha_1 \Delta x_t + \alpha_2 \Delta p_{t-1} + \alpha_3 \Delta z_t + \lambda(y_{t-1} - \beta_0 - \beta_1 x_{t-1}) + v_t \qquad (5.1)$$

We note that the single-equation ECM can be used only when the cointegrating vector is unique and the variables on the right-hand side are weakly exogenous (Harris [1995]). The uniqueness of the cointegrating vector follows from the fact that the cointegrating equation has only two variables. Weak exogeneity is established by showing that Δx_t, Δp_{t-1} and Δz_t do not depend on the long-run disequilibrium represented by $\hat{u}_{t-1}$ in equation (4.2) (Harris [1995], Enders [2010]):

$$\hat{u}_{t-1} = y_{t-1} - \hat{\beta}_0 - \hat{\beta}_1 x_{t-1}$$

Obviously, temperature does not depend on the disequilibrium but we need to test the weak exogeneity of real gross domestic product and price. We do this by regressing Δx_t and Δp_{t-1} on $\hat{u}_{t-1}$ and determining if the coefficient of $\hat{u}_{t-1}$ is not significantly different from zero using the t-test. The t-test is applicable since the variables in the regression are I(0). The results of the tests are reported in Table 5.1.

Table 5.1. Tests of Weak Exogeneity

	Δx_t	Δp_{t-1}
Constant	0.0444	0.0043
t-value	(10.5520)	(0.2699)
p-value	(0.0000)	(0.7902)
$\hat{u}_{t-1}$	0.0079	0.3252
t-value	(0.1500)	(1.4698)
p-value	(0.8823)	(0.1580)
F	0.0225	2.1604
p-value	(0.8822)	(0.1579)
R^2	0.0011	0.1021

The test equations in Table 5.1 pass the standard diagnostic tests. Since the coefficients of $\hat{u}_{t-1}$ are not significantly different from zero, we conclude that real gross domestic product and electricity price are weakly exogenous.

Model (5.1) may be estimated by the two-step residual-based Engle-Granger method (Harris [1995]) but the recommended approach is to estimate the long-run relationship jointly with the short-run dynamics as given in model (5.1). This approach is preferred because estimating the cointegrating equation (4.2) separately results in considerable small-sample bias (Kennedy [2003]; Banerjee et al. [1993]; Inder [1993]). Moreover, Bewley [1979] showed that simultaneous estimation results in more efficient estimates of the long-run parameter. To estimate model (5.1), we rewrite it as

$$\Delta y_t = \alpha_0 + \alpha_1 \Delta x_t + \alpha_2 \Delta p_{t-1} + \alpha_3 z_t + \lambda y_{t-1} + \gamma x_{t-1} + \nu_t \qquad (5.2)$$

where $\alpha_0 = -\lambda\beta_0$ and $\gamma = -\lambda\beta_1$. Note that the long-run parameters β_0 and β_1 are identified since $\alpha_0, \lambda,$ and γ are estimated in (5.2). Model (5.2) was estimated using data for the period 1992-2014 and the regression results are shown in Table 5.2.

Table 5.2. Estimated ECM1: Annual Electricity Consumption

Dependent variable: Δy

	Coefficient	Std. Error	t-Statistic	p-value
Constant	1.164	0.163	7.142	0.0000
Δx	0.937	0.212	4.422	0.0005
Δp_{-1}	-0.132	0.054	-2.470	0.0260
Δz	1.417	0.414	3.417	0.0038
y_{-1}	-0.188	0.055	-3.413	0.0039
x_{-1}	0.105	0.060	1.751	0.1003
$F = 16.94$				0.0000
$R^2 = 0.85$	$DW = 1.25$			

The estimated equation passes Ramsey's RESET test for specification error, Breusch-Godfrey Serial Correlation LM Test, Breusch-Pagan-Godfrey Heteroskedasticity Test, the Jarque-Bera Normality of Residuals Test, the CUSUM Test and the CUSUM of Squares Test for parameter stability (Vogelgang [2005])[4]. A summary of these test results is given in Table 5.3 and in Figure 5.1 and Figure 5.2.

Table 5.3. Summary of Statistical Diagnostic Tests for ECM1 (Table 5.2)

Test	H_0	Statistic	p-value
Ramsey's RESET	No specification error	0.6625	0.4293
Breusch-Godfrey Serial Correlation LM Test	No serial correlation	5.6834	0.1280
Breusch-Pagan-Godfrey Heteroskedasticity Test	No heteroskedasticity	4.9300	0.4245
Jarque-Bera Normality Test	Normal residuals	0.2916	0.8643

[4] Because of the small sample size, these tests are indicative rather than exact tests.

Figure 5.1. The CUSUM TEST

The graph of the CUSUM Test statistic is inside the 5% significance level bounds; hence, the parameters are stable.

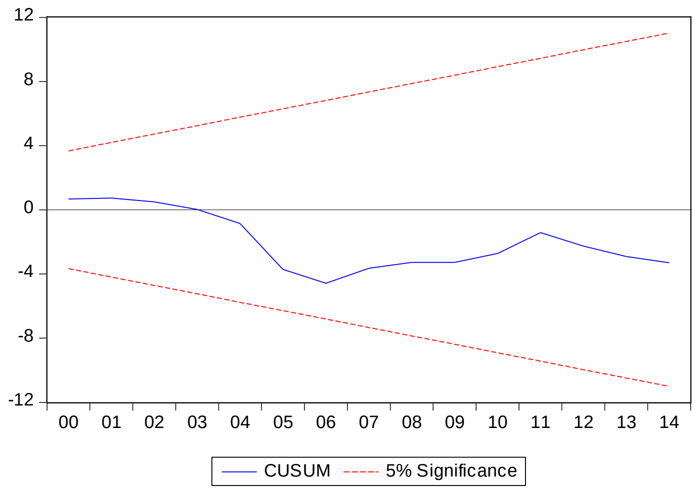
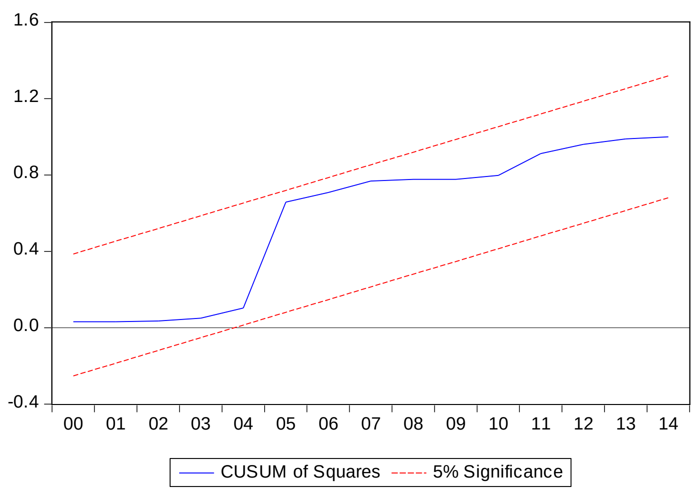


Figure 5.2. CUSUM OF SQUARES TEST

The graph of the CUSUM of Squares Test statistic is inside the 5% significance level band; hence, the parameters are stable.



The estimated equation is written in ECM equation form (5.1) as

$$\Delta y_t = 0.937\Delta x_t - 0.132\Delta p_{t-1} + 1.417\Delta z_t - 0.188(y_{t-1} - 6.191 - 0.558x_{t-1}) \qquad (5.3)$$

The results show that short-run changes in real gross domestic product and temperature have significant positive effects on electricity consumption while short-run changes in price have significant negative effects. The speed of adjustment, denoted by λ in equation (5.1) and whose estimate is -0.188, has the correct sign in accordance with convergence toward long-run equilibrium. Moreover, it is significantly different from zero, indicating that an error correction representation exists, thereby confirming, by the Granger Representation Theorem, the earlier result that electricity consumption and GDP are cointegrated. It says that about 19% of the discrepancy between actual and equilibrium value of electricity consumption is corrected every year.

The short-run price elasticity of -0.13 is significant and conforms to the common finding that in the short run, electricity demand has a low sensitivity to price (Zachariadis [2010]; Galindo [2005]; Hunt and Manning [1989]; Bianco et al. [2010]).

The model estimates a short-run income elasticity of 0.94 which is higher than the estimated long-run income elasticity of $0.105/0.188 = 0.56$. This result, where short-run income elasticity is higher than long-run income elasticity, has also been observed in other countries (Hunt and Manning [1989] for UK and Amarawickrama and Hunt [2008] for Sri Lanka). They argued that an increase in income causes "an immediate increase in derived demand for energy in the short-term, but this derived demand is reduced in the longer-term as more energy efficient machines are installed" (Hunt and Manning [1989]). In the Philippines, some indication of energy efficiency can be observed during the period 2003-2014, coinciding with the second half of the estimation period. Energy efficiency may be measured by energy intensity, defined as electricity consumption per unit of output. Energy intensity steadily declined from 13.21 GWh/billion pesos in 2003 to 10.78 GWh/billion pesos in 2014 or an average decline of 1.8% per year. This suggests that, during the 2003-2014, the Philippines was producing more output with less energy.

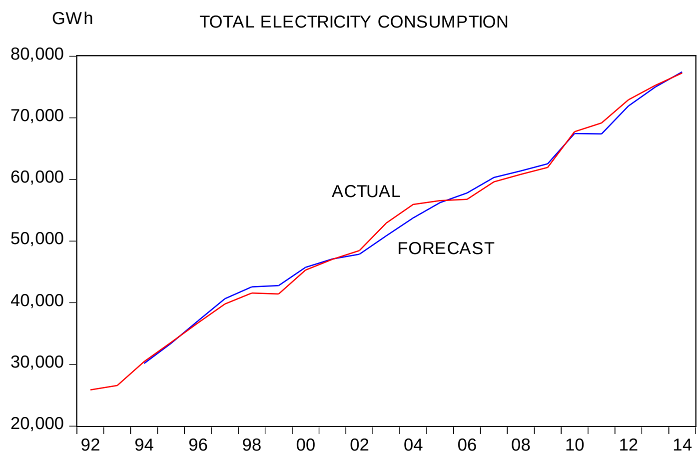
6. Model Forecasting Performance

The forecasting performance of models is usually measured by the accuracy of the model's forecasts. The most widely used measure of accuracy is the mean absolute percent error (MAPE)[5] which has the advantage of being dimensionless. The estimated model performed well in historical simulation with an MAPE of 1.47%. In addition, the Theil inequality coefficient of 0.009 is close to zero, where zero indicates a perfect forecast

[5] $\mathrm{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t-\hat{y}_t}{y_t}\right| \times 100$, where y_t is the actual value of the dependent variable and $\hat{y}_t$ is the predicted value.

(Vogelvang [2005]). The actual and forecasted electricity consumptions for the estimation period are graphically shown in Figure 6.1.

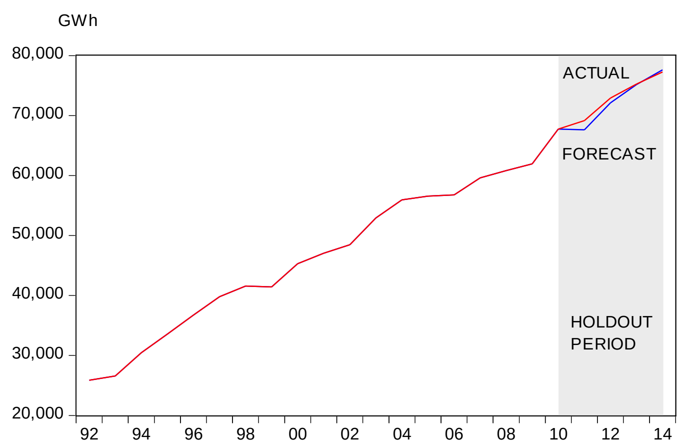
Figure 6.1. Historical Simulation: 1992-2014



Out-of-Sample Forecast Performance

Besides model performance “within-sample”, as was done above, the model is also tested “out-of-sample”, where forecasts are made ex post (i.e., forecasts for which actual values are known but are outside the estimation period). For this purpose, the model was reestimated over the sample period 1992-2010, making 2011-2014 the holdout period. The reestimated model’s forecast in the holdout period had an MAPE of 0.97% and a Theil inequality coefficient of 0.006. These results validate the within-sample performance of the model. The graphs of the out-of-sample forecast together with the actual values are shown in Figure 6.2.

Figure 6.2. Out-of-Sample Forecast



A Comparison with Other Models

It would be interesting to see if the presence of drivers of electricity consumption other than GDP, as in ECM1, improves the forecasting ability of the error correction model. So we construct another ECM, denoted as ECM2, with real GDP as the only explanatory variable. We also present the forecasting performance of an elasticity-based model (where elasticity is the elasticity of electricity consumption with respect to real GDP). This is a commonly used forecasting method in the absence of an econometrically developed model because it is simple, can be done quickly, and does not require a sophisticated forecaster to implement. These models are presented below.

(a) ECM2: ECM with GDP as the only explanatory variable

Table 6.1. Estimation of ECM2

Dependent variable: Δy

	Coefficient	Std. Error	t-Statistic	p-value
Constant	0.927	0.226	4.095	0.0007
Δx	1.002	0.340	2.949	0.0086
y_{-1}	-0.133	0.075	-1.783	0.0914
x_{-1}	0.062	0.085	0.727	0.4764
$F = 6.35$				0.0040
$R^2 = 0.51$	$DW = 2.20$			

(b) Elasticity-based model

In income elasticity-based forecasting we use the following definition of income elasticity of demand (η_t):

$$\eta_t = \frac{(Y_t - Y_{t-1})/Y_{t-1}}{(X_t - X_{t-1})/X_{t-1}},$$

where Y_t is total electricity consumption and X_t is real GDP. Solving for Y_t, we get

$$Y_t = Y_{t-1}\left(\eta_t \frac{X_t - X_{t-1}}{X_{t-1}} + 1\right). \tag{6.1}$$

A historical value of η is obtained and assumed to remain constant in the forecast horizon. Y_t is forecast given a starting value Y_0 and the assumed values of X_t in the forecast horizon. For our purpose, we use $\eta = 1.016$, the average of the yearly income elasticities for the period 2007-2010, the four years prior to the holdout period 2011-2014.

The three models are compared with respect to their out-of-sample MAPEs and Theil inequality coefficients. These are presented in Table 6.2. The results show that ECM1 outperforms the other models. Thus, the presence of drivers of electricity consumption other than GDP appears to improve the forecasting performance. It is also worth noting that ECM2 outperforms the non-ECM elasticity-based model.

Table 6.2. Forecasting Performance of Three Models

Model	Out-of-Sample Performance	
	MAPE	THEIL
ECM1 (Table 5.1)	0.97%	0.006
ECM2 (Table 6.1)	1.62%	0.012
Elasticity-based model	2.55%	0.014

7. Forecasting: A Scenario Analysis

This section presents the results of simulations for the forecast horizon 2015-2030. We stipulate a baseline forecast where the drivers of electricity consumption in ECM1 (real GDP, electricity price, and temperature) follow historical trends. Several alternative scenarios examine how changes in these drivers affect electricity consumption over the next 15 years when compared with the baseline forecast.

The baseline forecast assumes the following: real GDP grows at a rate of 6% per year, the growth rate during the last five years (2010-2014) of the estimation period; electricity price and temperature follow their historical trends. The results are given as Scenario 1 (Baseline) in Table 7.1. Under the baseline forecast, electricity consumption will grow at an average annual rate of 3.41% from 80,542 GWh in 2015 to 133,193 GWh by 2030, an increase of 65%.

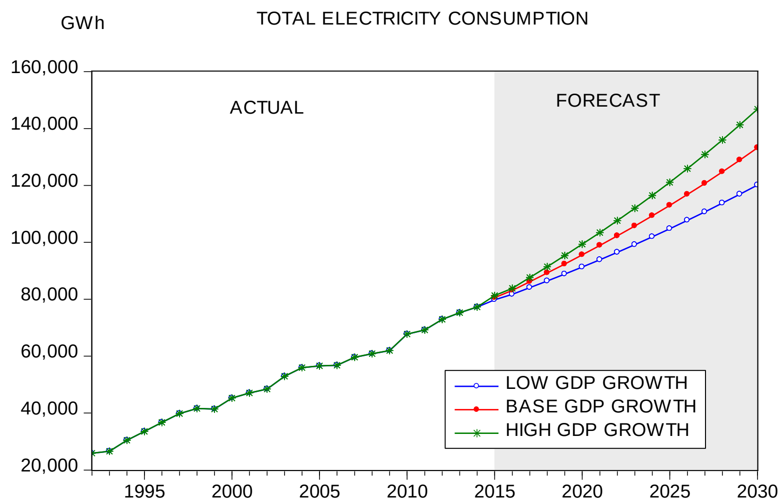
Table 7.1. Simulated Effects of Alternative Scenarios

Scenario Number	Assumptions	Forecast Annual Growth Rate: 2015-2030	Forecast for 2030 (GWh)	% Increase over base case
1. Baseline GDP Growth	GDP annual growth rate: 6% Price: historical trend Temp: historical trend	3.41%	133,193	
2. High GDP Growth	GDP annual growth rate: 7% Price: historical trend Temp: historical trend	4.02%	146,715	10.15
3. Low GDP Growth	GDP annual growth rate: 5% Price: historical trend Temp: historical trend	2.76%	120,146	- 9.80
4. Price Reduction	GDP annual growth rate: 6% Price: reduction by 1%/year Temp: historical trend	3.45%	133,989	0.60
5. Temp. Increase	GDP annual growth rate: 6% Price: historical trend Temp: 0.05°C increase/year	3.79%	135,016	1.37
6. Combined Changes	GDP annual growth rate: 7% Price: reduction by 1%/year Temp: 0.05°C increase/year	4.20%	149,617	12.33

The Impact of High and Low GDP Growth Rates

The high GDP growth rate (Scenario 2) assumes a growth rate of 7% per year while the low GDP growth rate (Scenario 3) assumes 5% per year. Electricity price and temperature follow their historical trends. The results are given in Table 7.1. Under the high GDP growth scenario, electricity consumption will grow at the rate of 4% per year and by 2030, electricity consumption will reach 146,715 GWh, about 10% higher than under the baseline scenario. This will require an additional generation capacity of about 1,540 MW. On the other hand, under the low GDP growth scenario, electricity consumption will grow at 2.76% per year and by 2030, electricity consumption will reach 120,146 GWh which is 9.8% lower than under the baseline scenario. The three scenarios are graphed in Figure 7.1.

Figure 7.1. Electricity Consumption Forecasts Corresponding to Low, Baseline, and High GDP Growth Rates



The Impact of a Price Decrease

In this forecast (Scenario 4) we assume the baseline scenario for GDP growth (6%), a 1% per year decline in real electricity price, and a temperature that follows its historical trend. The effect is to increase the growth rate of electricity consumption from 3.41% to 3.45% and by 2030, electricity consumption will reach 120,146 GWh, just about 0.6% higher than under the baseline scenario. This small effect is expected because of the low price elasticity in absolute terms.

The Impact of a Temperature Increase

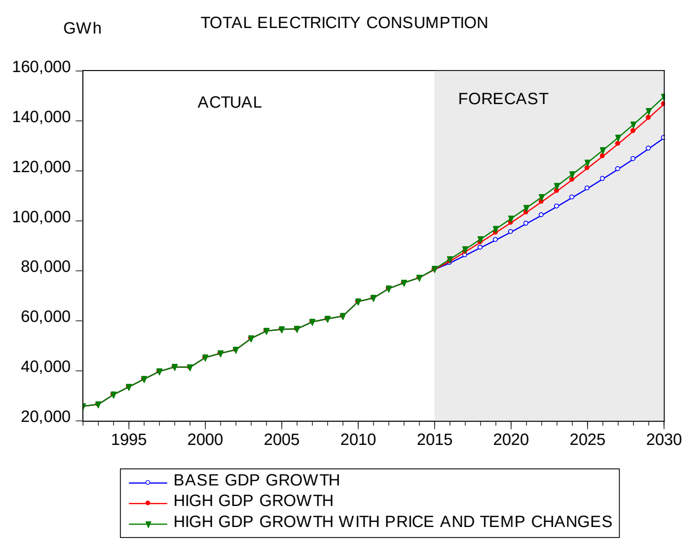
In this scenario (Scenario 5), we assume that GDP grows at 6% per year, electricity price follows its historical trend, and temperature increases at the uniform annual increment of 0.05°C from 26.2°C in 2014 to 27.0°C in 2030.[6] Although the temperature elasticity of demand is greater than 1, the increase in consumption is not large because the projected temperature increase by 2030 is only 0.8°C. Electricity consumption will reach 135,016 GWh by 2030, 1.37% higher than the baseline.

[6] Temperature is projected to increase between 0.9°C and 1.1°C from 2000 to 2020 (Cinco et al. [2013]). Taking the midpoint projection at 1°C and dividing by 20 years, we get 0.05°C per year. This projection was extended to 2030.

The Impact of Combined Changes in the Explanatory Variables

Besides looking at the impact of each explanatory variable separately, it is also useful to look at the impact of the combined changes of the explanatory variables. This simulation (Scenario 6) combines the assumptions of the previous simulations: (a) high GDP growth of 7%, (b) a 1% per year decline in electricity price, and (c) a uniform increase in temperature of 0.05°C per year up to 2030. As expected, electricity consumption and its growth rate are higher. Under this scenario, electricity consumption will reach 149,617 GWh by 2030, 12.33% higher than under the baseline scenario. Compared with the high growth scenario (Scenario 2), this is higher by 2,902 GWh. Thus, the effect of including price and temperature changes to changes in GDP is to increase electricity consumption by about 2%.

Figure 7.2. Result of Simulation with Combined Changes in All Explanatory Variables



8. Concluding Remarks

The aim of this paper is to construct an error correction model for forecasting electricity consumption in the Philippines based on income, price, and temperature. The empirical evidence shows that there is a long-run positive and inelastic relationship between electricity consumption and income. We find that income, price, and temperature have significant short-run effects. Short-run demand is positive and inelastic with respect to income, negative and inelastic with respect to price, and positive and elastic with respect to temperature. Despite the small sample size, the model passes the standard diagnostic and parameter stability tests and performs well in within-sample and out-of-sample forecasting. It can be used not only for forecasting but also for exploring, through simulations, how changes in income, price, and temperature affect future electricity consumption.

The simulations confirm that, in the long run, electricity consumption is mainly driven by economic growth. If GDP growth rate increases from 6% per year to 7%, electricity consumption grows by 82% from 80,542 GWh in 2015 to 146,715 GWh in 2030, the latter increasing the baseline by 10%. Although the effect of electricity price on electricity consumption is small (because of low price elasticity in absolute terms) and the effect of temperature change is also small (because annual average temperature change is small), their joint effects could add up and our simulation indicates that under very conservative assumptions, electricity consumption at the end of 15 years could rise further by 2%. Thus, it is important for planners to know the likely directions that the driver variables will take in order to account for their combined effects. This will provide a more accurate forecast of electricity demand and consequently, a more accurate determination of the generation capacity needed to meet the demand.

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