FORECASTING RESIDENTIAL ELECTRICITY CONSUMPTION IN INDONESIA

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ABSTRACT

Macro indicators impact towards electricity consumption in the residential sector was considered prominent to be investigated in relation to the energy policy planning. The research objective includes establishment of appropriate model containing macro indicators as the variables through the utilization of econometric method. The study period was 1990 – 2010. In addition, the forecasting model for household electricity consumption is also developed using econometric method. The forecasting result showed important findings in terms of supply capacity that should be prepared by the government. Those macroeconomic indicators such as GDP and inflation are confirmed to have a long term effect on residential electricity consumption particularly. The government should be able to predict the demand side along with the supply side of electricity. As one of the important energy, electricity should be intensively preserved as the primary energy that affecting the aggregate economy such as consumption, production, and also investment in the long term relatively to the other energy.

Keywords: *forecasting, autoregressive moving average, conditionally heteroscedastic models, residential electricity consumption*

INTRODUCTION

Indonesian power sector consumer is divided into four major segments, namely residential or household, industrial, commercial, and public sector. As reported by PLN on their 2010 annual report (PLN, 2011), commercial sector rank first with average growth of 10.45% on 2006 – 2010 electricity sales, followed by residential and industrial, with 9.14% and 3.86%, respectively. In 2010, the largest source of the electric power sales revenue still comes from the group of industrial and residential tariffs. In 2010 total revenue from electricity sales increased by 14.20% to Rp102,974 billion, from Rp 90,712 billion in 2009. This increase was due to the increase of electricity tariff which came into effect on July 1, 2010. Based on this fact, the power sector management and its implications are believed to have strong interrelated between PLN as power sector operator and government as the regulator. Regarding to the economic growth impact towards power sector development, the electricity consumption growth at residential sector shall be seen to closely affect by it.

The needs of having a clear understanding on how sectoral electricity consumption developed in Indonesia is unavoidable due to global economic competition. Resources scarcity is one of prominent driving factor that spur efficiency in using resources on power sector. Regarding to this condition, there are at least two implications to follow; firstly, policy on power sector expansion should be made accordingly, by looking into other macro condition so that electricity growth can be controlled and matched with available resources. Secondly, the importance of achieving the predetermined electrification ratio, as it reflects part of millennium development goal, has been unavoidable. Hence, government should pay more attention to provide electricity across the country, particularly to areas unreachable by utility grid. In more extensive way, government has tried to meet the electrification ratio target by conducting development of small power generation plants spread out in the remote areas. Based on the Electricity Law No. 30/2009, private sector is encouraged to be involved in the power sector infrastructure provisioning, particularly in the generation sector. They are becoming a PLN partner to develop distributed generation for which the generated electricity is supplied to the PLN mini grid. The ultimate objective is to increase the electrification rate coming from rural areas contribution.

It is believed that there is close relationship between good economic growth with power sector development in terms of macro indicators impact towards sectoral electricity consumption growth. The immediate impact is then how to allocate sufficient resources to powering the needs of electricity demand, which is in turn supporting economic growth. Which indicator contributes as dominant driver to construct the demand growth should be taking care of could be another important issue. The appropriate policy could be ascertained to match the needs if the indicator's effect towards the demand growth could be revealed. In viewing to these important implications to Indonesian power sector development, an investigation on residential electricity consumption pattern is proposed through this research. The focus of this research is to analyze the interrelation between macro indicators that built a pattern of residential electricity consumption for 1990–2010 through a model as empirical representation to the residential electricity consumption condition. In addition, a forecasting model based on econometric method is then developed to provide insight on the development of residential electricity consumption beyond the study period.

This report is organized as follows. Section 2 briefly reviews the literature. Section 3 describes research objectives and benefits. Section 4 decribes method used to construct residential electricity consumption model and its forecasting model. Section 5 presents analysis results and discussion. The report is finalized with conclusion and recomendations in the last section.

LITERATURE REVIEW

Modeling Using Econometric Method

Literally interpreted, *econometrics* means “economic measurement.” Econometrics is an amalgam of economic theory, mathematical economics, economic statistics, and mathematical statistics (Gujarati, 2004). Econometric analysis uses a mathematical model. A model is simply a set of mathematical equations. If the model has only one equation, it is called a single-equation model, whereas if it has more than one equation, it is known as a multiple-equation model. An anatomy of econometric modeling is given in Fig. 1 below.

Linear-regression model and Multiple-regression model are examples of econometric model. Multiple-regression model is derived from Linear-regression one. Up to today, regression analysis is the main tool of statistical techniques used to obtain the estimates (Gujarati, 2004). The model primarily explains the linear relationship between dependent variable and independent variable(s) or explanatory variable(s). In Multiple-regression model, the explanatory variable consists of more than one variable to affect to the changes of dependent variable. To construct the model mathematically, certain functional form should be specified in the equation, giving certain relationship between dependent variable and explanatory variable(s). Some types of Multiple-regression model according to its functional form are: Linear model, the Log-linear model, Lag-linear model, Reciprocal model, and the Logaritmic reciprocal model (Gujarati, 2004). Example on Linear model on Multiple-regression is given below.

$$Y_{it} = c + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \beta_n X_{nit} \tag{1}$$

where Y_{it} is dependent variable for sector *i* in period *t*, *c* is constant of the model, $\beta_1, \beta_2, \ldots, \beta_n$ is regression coefficient of explanatory variable(s), X_{it} is explanatory variable of sector *i* for period *t*, *i* is sector, *t* is period (e.g. year).

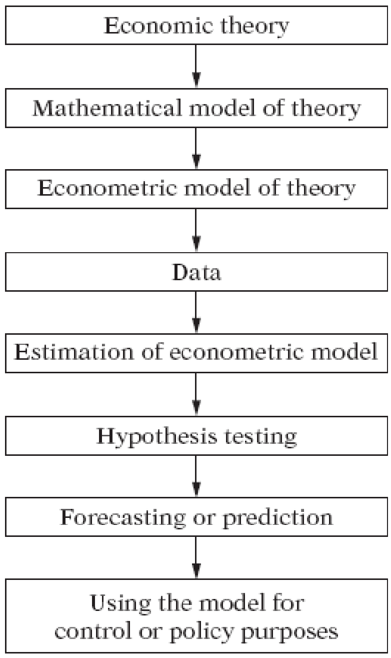


Figure 1. Anatomy of econometric model
Source: Gujarati, 2004

Regression analysis is dealt with the analysis of the dependence of the dependent variable on the explanatory variable(s). The study evaluates some statistical indices to be measured in the regression model, involves measurement on how success the model in predicting the dependent variable and some testing. In the analysis, the term R-square or coefficient of determination measures the portion of explained total sum of square by dividing explained deviation by total deviation. In other word, it measures how much fraction of dependent variable can be explained by explanatory variable. The ratio closer to 1 meaning the model is better in fitting the available data. Meanwhile, the adjusted R-square is the corrected measure of R-square since R-square would remain the same whenever additional explanatory variable is added to the equation. The value of adjusted R-square can be less than that of R-square if any additional explanatory variable do not contribute to the explained deviation of the model.

Several testing can be performed to check validity of the model with specific purposes. Hypothesis testing is conducted to test whether there is any relationship between dependent and explanatory variable. The level of significance T is the critical limit either to accept or to reject the null hypothesis. Another test is F-test of F-statistic, of which obtained from the hypothesis test for all of the slope coefficients, except the constant, are zero. Accordingly, the *p-value* or Probability (Fstatistic) is measuring the marginal significance level of the F-test. Comparing T and *pvalue*, if T is higher than *p-value*, then the null hypothesis should be rejected. T-test is performed to check the significance of independence variables that build up the model. Here, independence variable is said to be significant if the T-test value fall within the critical region based on α and degree of freedom used in the model.

There are four assumptions in the Least Squares Method which is utilized in the Multiple Regression (Stock and Watson, 2007). First, the conditional distribution of u_i given X_{1i}, X_{2i} ,..., X_{ki} has a mean of zero. Second, $(X_{1i}, X_{2i}, \dots, X_{ki}, Y_i), i = 1, \dots, n$ are independently and identically distributed (i.i.d) random variables. Third, large outliers are unlikely. Fourth, no perfect multicollinearity. All of these assumptions should be tested on the model. If the results found that there are one or more violation then the model cannot be utilize as an estimator. This condition called as a classical assumption violation which is divided into three indicators; multicollinearity, heteroscedasticity, and autocorrelation. There are several testing can be applied in order to check multicollinearity, heteroscedasticity, and autocorrelation. Correlation test is utilized in order to test the presence of multicollinearity and White heteroscedasticity used to check heteroscedasticity. In addition, Durbin-Watson (DW) test (Farebrother, 1980) or serial correlation LM test (Bruesch Godfrey Method) determines the presence of autocorrelation in the model. The calculated DW statistics, of which measuring serial correlation of the residual, will be compared with lower bound and upper bound of DW table to determine the presence of serial correlation. Lastly, if the sample size is small (less than 30 number of observation/data) we should apply the normality test in order to check whether the error term is closely normal distributed by using the Jarque-Berra (JB test). Other econometric models are Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Conditional Heteroscedasticity (ARCH)/Generalized Autoregressive Conditional Heteroscedasticity (GARCH) will also be applied in the research. We will provide the detail explanation on the following part.

Forecasting Using Econometric Model

In this section, we consider forecasts made using an autoregression, a regression model that relates a time series variable to its past values. If we want to predict the future of a time series, a good place to start is in the immediate past. Autoregressive Integrated Moving Average (ARIMA) model is utilized only to forecast the dependent variable in the short run. This also called the Box-Jenkins (ARIMA) Methodology (Hanke and Wichern, 2005). Gujarati (2004) stated that if a time series is stationary (even in the first different), then we can construct the model in several alternatives.

Hanke and Wichern (2005) confirmed that models for nonstationary series are called autoregressive integrated moving average models and denoted by ARIMA *(p, d, q)*. Here *p* indicates the order of the autoregressive part, *d* indicates the amount of differencing, and *q* indicates the order of the moving average part. Consequently, from this point on, the ARIMA *(p, d, q)* notation is used to indicate models for both stationary *(d=0)* and nonstationary *(d>0)* time series.

Enders (2004) stated that conditionally heteroscedastic models (ARCH or GARCH) allow the conditional variance of a series to depend on the past realizations of the error process. A large realization of the current period's disturbance increases the conditional variance in subsequent periods. For a stable process, the conditional variance will eventually decay to the long-run (unconditional) variance. Therefore, ARCH and GARCH models can capture periods of turbulence and tranquility.

Min *et al* (2010) worked with econometric method to develop statistical model of residential energy end use characteristic for the United States. The authors utilized Ordinary Least Square (OLS) method with predictor variables such as energy price, residential characteristics, housing unit characteristics, geographical characteristics, appliance ownership and use pattern, and heating/cooling degree days. Dependent variables of the four regressions were natural log values of per-residential energy use for heating, water heating, appliance, and cooling.

Aydinalp *et al* (2003) developed a model of residential energy consumption at the national level. Three methods were used to model residential energy consumption at the national level: the engineering method (EM), the conditional demand analysis (CDA) method, and the neural network (NN) method. The EM involves developing a housing database representative of the national housing stock and estimating the energy consumption of the dwellings in the database using a building energy simulation program. CDA is a regression-based method in which the regression attributes consumption to end-uses on the basis of the total residential energy consumption. The NN method models the residential energy consumption as a neural network, which is an information-processing model inspired by the way the densely interconnected, parallel structure of the brain processes information.

Furthermore, some papers were utilized an econometric model in estimating and forecasting electricity consumption. Resosudarmo and Tanujaya (2002) examined several forecasts of energy demand conducted by the University of Indonesia, Directorate General of Electricity and Energy Development, and the Natural Resources Management Project. The result confirmed that energy policies planned by the Department of Energy focused on the supply side of energy. For the demand side one could suggest that Indonesia should also implement strategies that provide consumers to diversify the types of energy use and to increase their efficiency in using energy. A similar study in predicting electricity demand conducted by Utama *et al* (2010). The finding proved that in Indonesia, the error for 2000-

2008 predictions compare to the actual demand which is accounted 8% in average. Bianco *et al* (2009) found that consumption response to GDP and GDP per capita change is relevant. In the future, an increase in the total electricity consumption driven by both domestic and non-domestic consumptions, should be expected in Italy with an average rate equal to about 2% per year. Dilaver and Hunt (2010) utilized a structural time series model in predicting the electricity consumption. The paper found that Turkish residential electricity consumption is predicted will be somewhere between 48 and 80 TWh by 2020 compared to 40 TWh in 2008. While sudy of Hutson and Joutz (2013) utilized a combined structural dynamics-based approach in modelling and forecasting the US electricity consumption.

Meanwhile, some papers found to be focused on the determinant of electricity consumption. This topic would be highly related to the forecasting method in providing comprehensive analysis. McNeil and Letschert (2005) elaborated the appliance ownership and household income in contributing the electricity demand in developing countries. Bhattacharya and Tahsina (2008) also focused on macroeconomic challenges for the growth of energy sector in Bangladesh, as a comprehensive analysis. Papler and Bojnec (2010) estimated the determinants of electricity consumption in Slovenia. The paper found that the growth of electricity use by industry and business enterprises is largely driven by the real growth of incomes in the region. The real incomes have played also important role in demands by households, but significant role has played the price of electrical energy for households. A similar research reported by Safdari *et al* (2012) which is examined the effect of subsidies on the demand side of energy sector, productivity of industries and employment situation over 1998-2009. The findings showed that decreasing energy subsidies leads to down demand for energy. It finally causes to increase productivity of industry sector and employment rate. Tanoto and Praptiningsih (2013) elaborated the factor decomposition analysis of Indonesia's household electricity consumption during 2000-2010 through the additive-LMDI approach. The result confirmed that the intensity effect was still contributed toward a positive household's electricity growth given the efficiency improvement was failed to decrease the total change during the study period.

RESEARCH OBJECTIVES

Regarding to the proposed research topic, there are no findings made publicly available under this topic for the case of Indonesia in modelling the electricity consumption particularly, to the researcher best knowledge. Hence, as this research observes residential electricity consumption trend in Indonesia, the study tries to obtain several findings on it as follows: forecasting on annual residential electricity energy consumption based on appropriate econometric model.

Findings to be obtained from this research can be served as part of useful references, at least for the preliminary consideration to develop power sector policy in Indonesia for the next long term period after 2010, in conjunction to the economic growth projection as well as other important indicators. The residential sector is selected as the case study to deconstruct macro indicators contribution towards its electricity demand growth. For instance, the appropriate-well tested econometric model for the study period of 1990 – 2010 would provide the decison maker and government insight on how the selected macro indicators give their influence in developing residential electricity consumption pattern.

Due to limitations of available data, we agree that to construct an appropriate model within considerably short time frame is the most challenging part, as the model is ussualy well developed using long time frame, such as 30 – 40 years. Therefore, not all proposed variables may be suited to be used in developing appropriate short-term model. Rather, the resulting econometric model would be likely containing well-tested variables that lineary matched with the circumstances during the study period. Forecasting on annual residential electricity consumption would also give additional advantage as utility may have better prediction to serve residential power demand.

RESEARCH METHODOLOGY

Table 1. Research Stages for Econometric Model and Forecasting Development

Research stages	Measurable Indicator
Problem identification	Increasing electricity consumption in residential sector can be presented; List of possible macro indicator thought to affect it.
Problem definition and research scope	Mathematical model under Econometric method. Indicative study time frame of 1990– 2010 to analyze residential electricity consumption in Indonesia
Research objective	Econometric model using Multiple Linear Regression model, Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Conditional Heteroscedasticity (ARCH)/Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model
Literature review	Articles and textbooks or discussess econometric analysis for energy sector
Data gathering	Availability of several macro indicators as they were appeared initially in earlier stage and have throughly been evaluated, for 1990-2010.
Analysis and Result	Establishment of a Multiple-Linear Regression Model, Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Conditional Heteroscedasticity (ARCH)/Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model using Eviews. Appropriate parameter testing result includes R, R square, T, F, DW testing, Correlation test, White heteroscedasticity test, serial correlation LM test (Bruesch Godfrey Method), and normality test (Jarque-Berra-JB test), stationarity (unit root test-ADF test).

RESULTS AND ANALYSIS

In this chapter, results regarding to residential electricity consumption growth are presented in terms of appropriate annual electricity consumption model and corresponding forecasting model based on econometric method. Under econometric method, the study period is taken into account 1990–2010. The increasing historical total residential annual electricity consumption growth in Indonesia up to 2010, which is the focus of this research, is presented below. The data source taken from Statistic PLN (State-Owned Electricity Company) in 2011. The data set includes Total Residential Electricity Consumption (in million watt hour), Gross Domestic Product (in million rupiah) and Private Consumption Expenditure (in million rupiah).

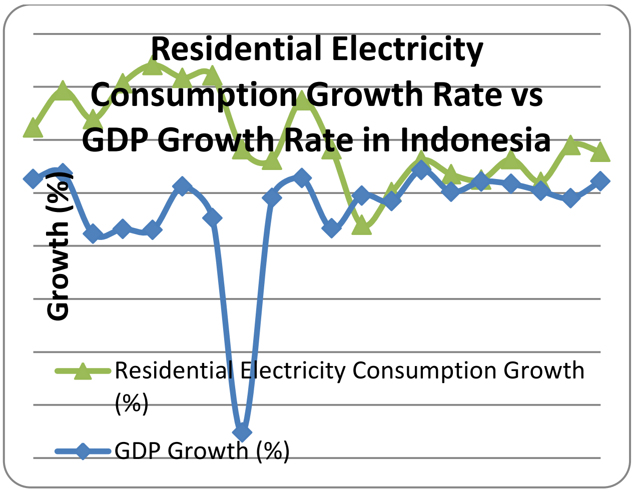
Figure 2. below presents total residential electricity consumption growth rate versus GDP growth in Indonesia. The graph shows that increasing electricity consumption growth rate in Indonesia is developed in the similar way with that shown by GDP growth rate.

Table 2. The historical residential annual electricity consumption in Indonesia

Year	Total Residential Electricity Consumption (MWh)	GDP (Million Rupiah)	Private Consumption Expenditure (Million Rupiah)
1990	8.785.293	195.597.200	106.312.300
1991	9.766.337	227.450.200	125.035.800
1992	11.199.029	259.884.500	135.880.300
1993	12.537.109	302.017.800	158.342.700
1994	14.460.106	382.219.700	221.119.300
1995	16.927.060	454.514.100	279.876.400
1996	19.610.853	532.568.000	325.585.300
1997	22.764.024	627.695.400	387.170.700
1998	24.835.703	955.753.500	647.823.600
1999	26.853.883	1.099.731.600	813.183.300
2000	30.538.269	1.389.769.900	856.798.300
2001	33.318.312	1.646.322.000	1.039.655.000
2002	33.978.744	1.821.833.400	1.231.964.500
2003	35.697.122	2.013.674.600	1.372.078.000
2004	38.579.255	2.295.826.200	1.532.888.300
2005	41.181.839	2.774.281.100	1.785.596.400
2006	43.748.580	3.393.216.800	1.668.718.895
2007	47.321.668	3.950.893.200	1.916.235.454
2008	50.182.040	4.948.688.397	2.234.595.269
2009	54.944.089	5.603.871.170	2.520.631.070
2010	59.823.487	5.501.126.146	2.863.609.098

Source: Statistic PLN, 2011

The annual percentage of electricity consumption growth rate is increased several-fold to the GDP growth rate in the respective year, except for some years. During the economic crisis period, i.e. 1997 – 1998, slower growth rate shown by residential electricity consumption is less compared to that shown by GDP. In addition, subsequent figure shows the increasing electricity consumption for total residential and sub-residential sector during 1990 – 2010. The residential sub-sector, which comprise of 3 group were classified started on 1998. However, for the purpose of decomposition analysis, the data taken into account started from 1990, which mean require data of 1989 in order to be involved in the calculation. Hence, residential sub-sector electricity consumption shown in the graph is started on 1989. As seen on Fig. 3, the total residential electricity consumption is primarily contributed by the R1 group, in which the biggest share of residential customer. Here, the main factors to influence electricity consumption in each residential group may not be the same as the consumption growth in fact are different one another.



Source: Statistic PLN, 2011

Figure 2. Residential Electricity Consumption Growth Rate (1991 – 2010)

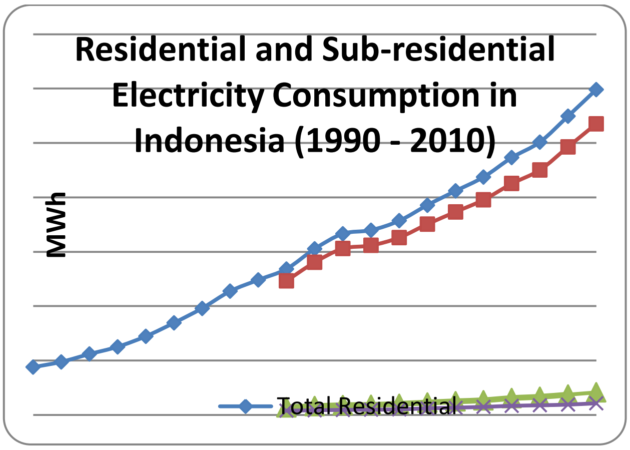


Figure 3. Total Residential and Residential sub-sector Electricity Consumption
Source: Statistic PLN, 2011

As residential electricity consumption pattern is observed in two part, i.e. through econometric and decomposition analysis, the total residential electricity consumption model along with its forecasting model are analyze using econometric approach whereas factors to influence for both total residential. The discussion described belows.

FORECASTING MODEL

Arima model

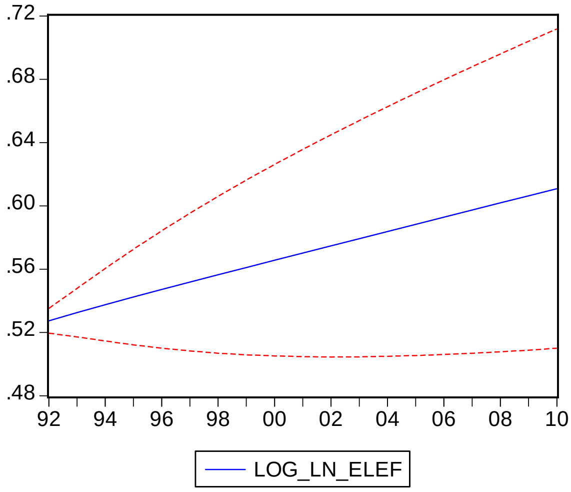
The research used the Box-Jenkins method in order to forecast each variable in the model by itself. In forecasting, first we assumed that all variables could be forecasted by other variables not just by the variable itself. The second assumption was the current value of each variable could be affected by the past value of the variable. These two assumptions are known as the autoregressive distributed lag model (ADL model). Nevertheless, the paper had a limitation of data observation, which is stated earlier. Therefore, we could not utilize the autoregressive distributed lag model in order to estimate and forecast the total energy consumption. However, we continued to forecast by using the simple Box-Jenkins method that is autoregressive (AR) model, moving average (MA) model, and the integrated and combination of AR and MA model, namely ARIMA model. First, we constructed the autoregressive (AR) model and moving average (MA) model. In order to construct the model, we had to check the stationarity of each variable by using the unit root test. We applied the Augmented-Dickey Fuller Test to test the stationarity of each variable. The result found that all variables, total energy consumption, electrification ratio, GDP, inflation, population, private consumption, and BI rate are stationary at first difference with trend and intercept (95% level of confidence). These results indicated that we could continue to forecast using the autoregressive dan moving average model. After we checked the stationarity, then we determined the lag of autoregressive (AR) model by using the correlogram test. Table 3 showed that the best model in forecasting each variable is choosen from many alternatives models. For example, we found that there are two best alternatives model for inflation. There are ARIMA (1,1,0) and ARIMA (0,1,1).

ARIMA Models
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004515	0.002923	1.544372	0.1409
AR(1)	0.697124	0.180636	3.859282	0.0013

R-squared	0.466985	Mean dependent var	0.005119
Adjusted R-squared	0.435632	S.D. dependent var	0.005057
S.E. of regression	0.003799	Akaike info criterion	-8.208954
Sum squared resid	0.000245	Schwarz criterion	-8.109539
Log likelihood	79.98506	F-statistic	14.89406
Durbin-Watson stat	1.982750	Prob(F-statistic)	0.001258
Inverted AR Roots	.70		

D(LOG_LN_ELECTRIFICATION_R) = 0.004514879351 + [AR(1)=0.6971241405]



Forecast: LOG_LN_ELEF
Actual: LOG_LN_ELECTRIFICATION_R
Forecast sample: 1990 2010
Adjusted sample: 1992 2010
Included observations: 19

Root Mean Squared Error	0.022516
Mean Absolute Error	0.020116
Mean Abs. Percent Error	3.396254
Theil Inequality Coefficient	0.019394
Bias Proportion	0.798176
Variance Proportion	0.000076
Covariance Proportion	0.201748

Dependent Variable: BI_RATE
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.394307	0.015873	24.84080	0.0000

R-squared	0.000000	Mean dependent var	0.394307
Adjusted R-squared	0.000000	S.D. dependent var	0.072741
			-
S.E. of regression	0.072741	Akaike info criterion	2.357380
			-
Sum squared resid	0.105825	Schwarz criterion	2.307641
Log likelihood	25.75249	Durbin-Watson stat	0.862596

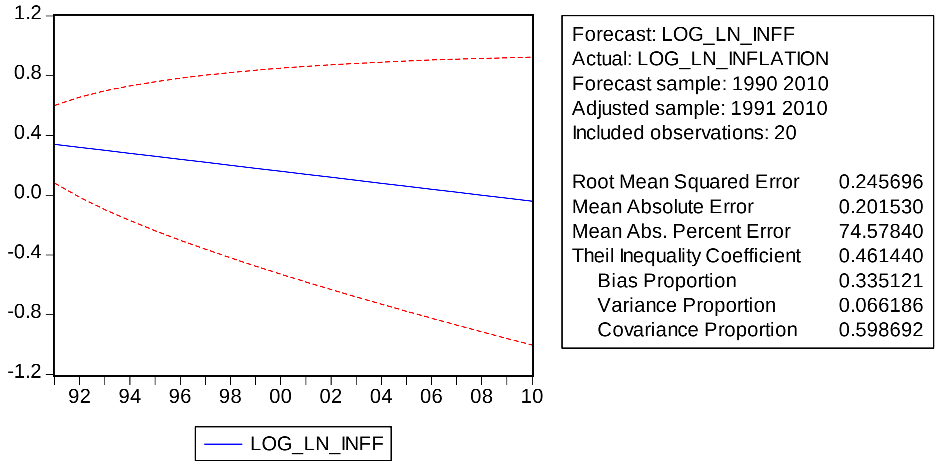
Dependent Variable: D(INFLATION)
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.020024	0.006320	-3.168237	0.0053
MA(1)	-1.820582	0.534403	-3.406760	0.0031

			-
R-squared	0.829282	Mean dependent var	0.003640
Adjusted R-squared	0.819797	S.D. dependent var	0.304896
			-
S.E. of regression	0.129429	Akaike info criterion	1.156728
			-
Sum squared resid	0.301534	Schwarz criterion	1.057155
Log likelihood	13.56728	F-statistic	87.43681

Durbin-Watson stat	2.861821	Prob(F-statistic)	0.000000

Inverted MA Roots	1.82
	Estimated MA process is noninvertible



D(LOG_LN_INFLATION) = -0.02002449863 + [MA(1)=-1.820582086,INITMA=1991]

Dependent Variable: ELECTRIFICATION_R
Method: Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.583230	0.007145	81.63172	0.0000

R-squared	0.000000	Mean dependent var	0.583230
Adjusted R-squared	0.000000	S.D. dependent var	0.032741
S.E. of regression	0.032741	Akaike info criterion	-3.953935
Sum squared resid	0.021439	Schwarz criterion	-3.904195
Log likelihood	42.51631	Durbin-Watson stat	0.046332

Arch/Garch model

Dependent Variable: ELECTRIFICATION_R
Method: ML - ARCH
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.596791	0.001879	317.6721	0.0000

Variance Equation				
C	1.46E-05	8.82E-06	1.649636	0.0990
RESID(-1)^2	1.757682	0.923721	1.902828	0.0571
GARCH(-1)	-0.621546	0.149115	-4.168225	0.0000

R-squared	-0.180124	Mean dependent var	0.583230
Adjusted R-squared	-0.388381	S.D. dependent var	0.032741
S.E. of regression	0.038578	Akaike info criterion	-5.508915
Sum squared resid	0.025301	Schwarz criterion	-5.309958
Log likelihood	61.84361	Durbin-Watson stat	0.039260

Dependent Variable: TOTAL_ENERGY_CONS
Method: ML - ARCH
GARCH = C(9) + C(10)*RESID(-1)^2 + C(11)*GARCH(-1) + C(12)
BI_RATE + C(13) ELECTRIFICATION_R

	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.225702	1.053294	-0.214282	0.8303
BI_RATE	-0.006631	0.007345	-0.902698	0.3667
ELECTRIFICATION_R	0.152716	0.032096	4.758166	0.0000
GDP	0.168744	0.125529	1.344257	0.1789
INFLATION	0.001088	0.003850	0.282581	0.7775
POPULATION	0.687059	0.868757	0.790852	0.4290
PRIVATE_CONS	0.204834	0.124833	1.640869	0.1008
AR(1)	0.004999	0.862628	0.005795	0.9954
Variance Equation				
C	9.04E-08	4.74E-06	0.019057	0.9848
RESID(-1)^2	0.149957	1.174349	0.127693	0.8984
GARCH(-1)	0.599990	3.219071	0.186386	0.8521
BI_RATE	7.34E-07	5.20E-06	0.141237	0.8877
ELECTRIFICATION_R	-4.39E-07	6.89E-06	-0.063736	0.9492

R-squared	0.997814	Mean dependent var	1.233702
Adjusted R-squared	0.994068	S.D. dependent var	0.014000
S.E. of regression	0.001078	Akaike info criterion	-10.59006
Sum squared resid	8.14E-06	Schwarz criterion	-9.942829
Log likelihood	118.9006	F-statistic	266.3198
Durbin-Watson stat	2.061551	Prob(F-statistic)	0.000000

Inverted AR Roots	.00

Table 3. Summary of ARIMA Model

Variables	Model Results
BI rate	ARIMA (0,1,1) or IMA (1,1)
Electrification ratio	ARIMA (1,1,0) or ARI (1)
GDP	no available model
Inflation	ARIMA (0,1,1) or IMA (1,1)
Population	no available model
Private consumption	no available model
Total energy consumption	ARIMA (0,1,1) or IMA (1,1)

In order to determine which model is the best one, then we should apply the residual test with correlogram Q-statistic to test the autocorrelation. The result was not significant or in other words that there is no autocorrelation. Further, we continued to check the error term by using the Schwarz-Criterion. The smallest value is preferable. The result confirmed that ARIMA (0,1,1) is the best model in forecasting inflation. The similar interpretation is applicable to all variables. The detail results of estimation are provided in appendix.

Arch/Garch model

The research also utilized the ARCH/GARCH model in order to forecast each variable. The main assumption in forecasting through this model is ignoring the violation of homoscedasticity. In addition, if the data series found to have heteroscedasticity problem, then we can continue to forecast using the ARCH/GARCH model. According to one of our purposes that are, find the best model in forecasting, therefore we also applied this model into our estimation and forecasting. First, we had to check the volatility of each variable. This volatility called as the ARCH effect. We used the residual test namely ARCH LM test. If the result found that the variable significantly proved had a volatility or ARCH effect then we continued to estimate the variable using the ARCH model. Table 4 showed that electrification ratio, GDP, inflation, and total energy consumption had the ARCH effect and the best model in forecasting are ARCH (1) and GARCH (1) in terms of 10% level of confidence. These results also confirmed that each of variables could affect the variable itself. The detailed results provided in the appendix. The summary of the results given as follows:

Table 4. Summary of ARCH/GARCH Model

Variables	ARCH/GARCH Effect	Model Results
BI rate	No	-
Electrification ratio	Yes	ARCH (1) and GARCH (1), α = 0,1
GDP	Yes	ARCH (1) and GARCH (1), α = 0,1
Inflation	Yes	ARCH (1) and GARCH (1), α = 0,1

Population	No	-
Private consumption	No	-
Total energy consumption	Yes	ARCH (1) and GARCH (1), α = 0,1

CONCLUSION

In this research, econometric model and forecasting model for Indonesia's electricity consumption growth are constructed and analyzed. Several findings related to the modelling in forecasting the residential electricity consumption are as follows:

1. The best model through ARIMA model in forecasting BI rate was ARIMA (0,1,1) or IMA (1,1); electrification ratio was ARIMA (1,1,0) or ARI (1); inflation used ARIMA (0,1,1) or IMA (1,1) and total energy consumption utilized ARIMA (0,1,1) or IMA (1,1).
2. The best model through ARCH/GARCH model in forecasting electrification ratio used ARCH (1) and GARCH (1); GDP used ARCH (1) and GARCH (1); Inflation used ARCH (1) and GARCH (1); and total energy consumption used ARCH (1) and GARCH (1).

According to the result of forecasting, we recommend to utilize all those alternatives models in order to policymaking in energy planning. The forecasting result also showed important findings in terms of supply capacity that should be prepared by the government. Those macroeconomic indicators such as GDP and inflation are confirmed to have a long term effect on residential electricity consumption particularly. The result confirming previous studies of Bianco *et al* (2009); Bhattacharya and Tahsina (2008); and Papler and Bojnec (2010). These particular papers proved that macroeconomic variables had an effect and inter-linkages into the electricity consumption.

According to the result, therefore the paper recommend to utilize the proposed model in forecasting the electricity consumption which is relevant with macroeconomic variables. The government should be able to predict the demand side along with the supply side of electricity. As one of the important energy, electricity should be intensively preserved as the primary energy that affecting the aggregate economy such as consumption, production, and also investment in the long term relatively to the other energy. Furthermore, the government also encouraged to anticipate the risk that might be happen related to the energy policy in the future.

REFERENCES

Aydinalp, M. *et al.*, 2003. "Modelling of Residential Energy Consumption at The National Level". *International Journal of Energy Research*, Vol 27, Issue 4, 441-453.

Bhattacharya, D., and Tahsina, T., 2008. "Macroeconomic Challenges For The Growth of The Energy Sector in Bangladesh in The Context of Regional Integration". *Conference on Energy in the Bay of Bengal*, A new Energy Frontier: the Bay of Bengal Region, Institute of Southeast Asian Studies, Singapore, 61-89.

Bianco, V. *et al.*, 2009. "Electricity Consumption Forecasting in Italy Using Linear Regression Models". *Energy*, Vol. 34, 1413-1421.

Dilaver, Z., and Hunt, L.C., 2010. "Modelling and Forecasting Turkish Residential Electricity Demand". *Surrey Energy Economic Discussion Paper Series, SEEC*, 1-38.

Enders, W., 2004. *Applied Econometric Time Series*, Second Edition, John-Wiley & Sons, Inc.

Farebrother, R.W., 1980. “The Durbin-Watson Test for Serial Correlation When There Is No Intercept In The Regression”. *Econometrica*, Vol 48, No. 6.

Gujarati, D., 2004. *Basic Econometrics,* Fourth Edition. New York: The McGraw-Hill.

Hanke, J.E. and Wichern, D.W., 2007. *Business Forecasting*, Eighth Edition, Pearson-Prentice Hall.

Hutson, M.D., and Joutz, F.L., 2013. *Modelling and Forecasting US Electricity Consumption.*

Jorgensen, J.B., and Joutz, F.L., 2012. “Modelling and Forecasting Residential Electricity Consumption in The U.S. Mountain Region”. *Research Program and Forecasting Working Paper* No. 2012-003, 1-42.

McNeil, M.A., and Letschert, V.E., 2005. “Forecasting Electricity Demand in Developing Countries: A Study of Household Income and Appliance Ownership”. *European Council of An Energy Efficient Economy Summer Study Proceedings*.

Min, J., *et al*., 2010. “A High Resolution Statistical Model of Residential Energy End Use Characteristics for The United States”. *Journal of Industrial Ecology*. Vol 14, Issue 5, 791-807.

P.T. PLN (Persero), 2011. PLN Annual report, Jakarta.

Papler, D., and Bojnec, S., 2010. “Determinants of Electricity Consumption in Slovenia”. *Journal of Business and Economics*, 226-234.

Resosudarmo, B.P and Tanujaya, 2002. “Energy Demand in Indonesia: Past and Future Trend”. *The Indonesian Quarterly,* Vol. XXX. No.2, 158-174.

Safdari, M., *et al*., 2012. “The Effect of Energy Subsidy on Macroeconomic Variables of Iranian Industry Sector (By Employing Simultaneous Equations Technique)”. *International Journal of Business and Social Science*, Vol.3, No.3, 165-174.

Stock, J.H., and Watson, M.W., 2010. *Introduction to Econometrics*, Second Edition, Pearson-Prentice Hall.

Tanoto, Y., and Praptiningsih, M., 2013. “Factors Decomposition of Indonesia’s Household Electricity Consumption”. *Engineering Journal*, Vol. 17, Issue 2, 19-28.

Utama, N.A., *et al*., 2011. “2050 ASEAN Electricity Demand: Case Study in Indonesia and Cambodia”. *Zero-Carbon Energy Kyoto 2010 Proceedings*, 32-40.