Simulation Study of Parameter Estimation Two-Level GSTARX-GLS Model

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Abstract *– GSTAR is a special form of the VAR model and is one of the commonly used models for modeling and forecasting time series data and location. At GSTAR modeling, estimation method used is OLS, the method is considered to have a weakness, which will result in an inefficient estimator. Thus, one appropriate method is GLS. In this study, conducted modeling GSTARX two levels by adding a predictor of calendar variation model. Parameter estimation of the first level models made of predictors with a linear regression model, while the second level models using error models which is done on first level with GSTAR model. Calendar variation model discussed is the impact of Ramadhan effect. Results of the simulation study showed that GSTAR-GLS models produces a more efficient estimator than GSTAR-OLS, seen from the obtained standard error smaller.*

Index Terms *– Calendar Variations, Efficient, GLS, GSTARX, Ramadhan, Two Levels.*

INTRODUCTION

Study on GSTAR parameter estimation is still limited to using OLS method [1]. Parameter estimation using the OLS residuals are correlated between equation will result in inefficient estimators. One appropriate method to estimate the parameters correlated with residual inter equation is GLS, which is commonly used in the model Seemingly Unrelated Regression (SUR) [2]. Parameter estimation GSTARX-GLS models obtained by minimi-zing the sum of square generalized sum of square $\varepsilon'\Omega^{-1}\varepsilon$, where $\varepsilon = (Y - X\beta)$, so that the equation

$$\varepsilon'\Omega^{-1}\varepsilon = (Y = X\beta)'\Omega^{-1}(Y - X\beta) \quad (1)$$

then do decrease $\varepsilon'\Omega^{-1}\varepsilon$ to the βparameters, so that would be obtained estimator

$$\hat{\beta} = (X'\Omega^{-1}X)^{-1}X'\Omega^{-1}Y \quad (2)$$

Two-levels GSTARX(1_1) model of simulation study written in the form

- Model for first level

$$Y^*_{i,t} = \beta_0 + f\left(D_{g,t}, D_{g,t-1}\right) + u_{i,t} \quad (3)$$

Where

$f\left(D_{g,t}, D_{g,t-1}\right) = \sum_g \alpha_g D_{g,t} + \sum_g \gamma_g D_{g,t-1}$, $D_{g,t-1}$ and $D_{g,t-1}$ repre-sents dummy variable for the during month Eid and one month before Eid, g indicate the number of days prior to the date of Eid.

- Model for second level

$$\begin{bmatrix} u_1(t) \\ u_2(t) \\ u_3(t) \end{bmatrix} = \begin{bmatrix} \phi_{10} & 0 & 0 \\ 0 & \phi_{20} & 0 \\ 0 & 0 & \phi_{30} \end{bmatrix} \begin{bmatrix} u_1(t-1) \\ u_2(t-2) \\ u_3(t-3) \end{bmatrix} + \begin{bmatrix} \phi_{11} & 0 & 0 \\ 0 & \phi_{21} & 0 \\ 0 & 0 & \phi_{31} \end{bmatrix}$$

$$\begin{bmatrix} 0 & w_{12} & w_{13} \\ w_{21} & 0 & w_{23} \\ w_{31} & w_{32} & 0 \end{bmatrix} \begin{bmatrix} u_1(t-1) \\ u_2(t-2) \\ u_3(t-3) \end{bmatrix} + \begin{bmatrix} e_1(t) \\ e_2(t) \\ e_3(t) \end{bmatrix} \quad (4)$$

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METHOD

Stages of simulation study carried out in two-level GSTARX model are as follows:

Step 1: Determining the dummy variable for the period of calendar variations (see Table 1).

Table 1. Eid celebration for the period 1990 to 2010.

Year	Date	Year	Date	Year	Date
1990	27-28 Apr.	1998	30 - 31 Jan.	2005	3 - 4 Nov.
1991	16 - 17 Apr.	1999	19 - 20 Jan.	2006	23 - 24 Oct.
1992	4 - 5 Apr.	2000	8 - 9 Jan.	2007	12 - 13 Oct.
1993	25 - 26 Mar.		28 - 29 Dec.	2008	1 - 2 Oct.
1994	14 - 15 Mar.	2001	17 - 18 Dec.	2009	21 - 22 Sept.
1995	3 - 4 Mar.	2002	6 - 7 Dec.	2010	10-11 Sept.
1996	21 - 22 Feb.	2003	25 - 26 Nov.		
1997	9 - 10 Feb.	2004	14 - 15 Nov.		

Step 2: Determine coefficient parameters of the vector AR(1) model

$$\Phi_1 = \begin{bmatrix} 0{,}30 & 0{,}10 & 0{,}10 \\ 0{,}15 & 0{,}20 & 0{,}15 \\ 0{,}20 & 0{,}20 & 0{,}25 \end{bmatrix} \quad (5)$$

Step 3: Generate residual at three locations multivariate normal distribution with a mean of zero and variance covariance matrix Ω.

Step 4: Determining two simulation scenarios, i.e. (1) residual is not correlated in three locations and (2) residuals are correlated in three locations.

Step 5: Perform parameter estimation model for first level with OLS method by the equation

$$Y^*_{i,t} = \beta_0 + f\left(D_{g,t}, D_{g,t-1}\right) + u_{i,t}$$

where i = 1,2,3.

Step 6: Perform parameter estimation model for second level with OLS and GLS method by the equation

$$u(t) =$$

$$\mathbf{u}(t) = \mathbf{\Phi}_{i0}\mathbf{u}(t-1) + \mathbf{\Phi}_{i1}\mathbf{W}^{(1)}\mathbf{u}(t-1) + \mathbf{e}(t).$$

Step 7: Calculate the efficiency (%) of GLS method.

RESULT AND ANALISYS

Training and validating network for predicting hardness of ceramics had been accomplished. In training part, the network give NRMSE value of 0, which mean the minimum value of NRMSE. Simultaneously, network show best performance of coefficient ratio when it had raised 1. Moreover, at the validation part, the network also gives excellent performance when NRMSE value is 0.077 and R value is 0.94.

Figure 2 show the comparison of simulation results and target data. Those figure shows that the simulation data have same pattern to experimental data as target. They show that network can be used to predict the hardness properties of ceramics.

Prediction of flexural strength of ceramics also has been done when network has NRMSE 0 for training and 0.094 for validation. Also, performances in R value explain that network has R value 1 for training and 0.981 for validation. Thus, from these values, network can be confirmed that can be used to predict flexural strength of ceramics. Simulation of prediction network which is compared to experimental data as target can be shown on Figure 3.

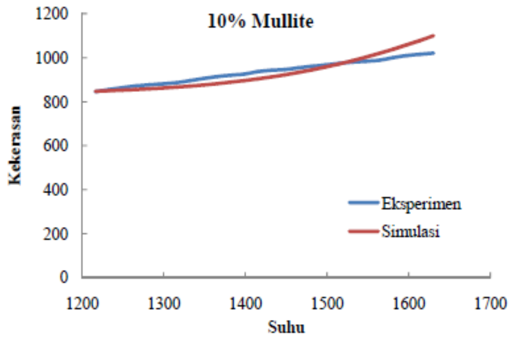

Figure 2. Comparison of simulation and target value for hardness prediction of ceramics

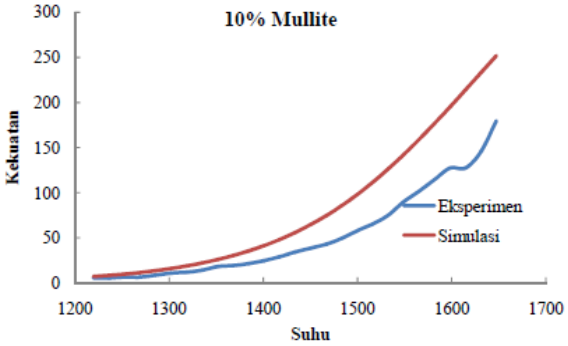

Figure 3. Comparison of simulation and target value for flexural strength prediction of ceramics

CONCLUSION

Neural network has been built to predict flexural strength and hardness of ceramics. Performance in training and validation prove that NN can predict both of these mechanical properties. NRMSE values are closed to 0 and R values are closed to 1.

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