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# SMALL SIGNAL STABILITY ANALYSIS OF POWER GENERATION SYSTEM BASED ON TIME SERIES PATTERN USING FUZZY MODEL PREDICTIVE CONTROL

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**Abstract**

This paper proposes a Fuzzy Model Predictive Control (FMPC) model as a small signal stability control of a power generation system. Load fluctuations are one of the problems with small signal stability. But in reality, load fluctuations form a dynamic pattern of time series so that it can be predicted. DSARIMA time series models meet predictive criteria. Predicted results are used as load cluster models. Load clustering aims to optimize the operation of the generating system criteria. The FMPC method proposed in this study is the development of the Fuzzy Takagi-Sugeno model. Fuzzy T-S consists of a state estimator (Fuzzy State Estimator) approach to identify each load change and identify the optimal control model (FMPC) for each control input state. The development of Fuzzy T-S in fuzzy state estimators and FMPC functions as multiple soft-switching for each load condition. Through this method, FMPC is able to predict electrical power near real load conditions. FMPC has a performance that can guarantee all load conditions with better frequency and voltage stability than conventional optimal control methods.

Keywords: Clustering, FMPC, Model prediction, Small-signal stability, SMIB model.

## 1. Introduction

Dynamic stability of a power generation system or called small signal stability is still an interesting topic to date. The latest statement regarding the definition and classification of stability in the electric power system has been reformulated by CIGRE and IEEE [1]. In the latest development, the study of small signal stability dwells on renewable energy sources [2-4]. Renewable energy sources are cheap and environmentally friendly, but have an impact on uncertain operating conditions. The uncertainty of energy resources as well as integration with traditional energy sources has become trend stochastic studies of present [5-7].

However, the study of small signal stability not only dwells on the analysis of the generation system. Electric power fluctuations in the load center cause the generator system to become unstable. Electricity needs at any time form a time-series pattern and can be predicted [5, 8]. Prediction is an important in planning operation power plant system both short, medium and long term planning [9]. Time series based predictions are the right and accurate choice to date [10]. The time series prediction approach based on the double seasonal ARIMA model is the best choice from several recent studies [11-12]. Predictions are used as reference control parameters. So that the control will always be able to balance every difference in electrical power generated and fluctuations in the load center. Load cluster based Fuzzy Takagi-Sugeno algorithm approach is designed for the stability control model. This approach is able to respond quickly to any load changes and is able to guarantee all load conditions. The model proposed can be illustrated in Fig. 1:

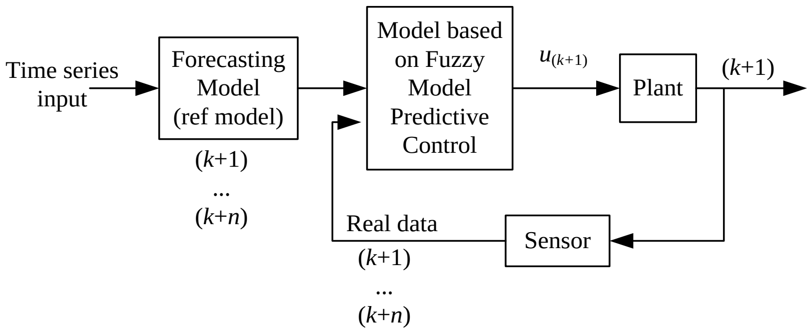



**Fig. 1. The proposed fuzzy model predictive control.**

The forecasting model in Figure 1 is the result of the prediction as the steps carried out in Appendix A Fig. A-1 as the time series input. The FMPC obtains the optimal initial reference before obtaining a real data measurement signal at the load center. DSARIMA's prediction model works as multiple soft-switching on Fuzzy devices. So the controller is able to adapt to the conditions of changes in electrical power. Prediction of step $1(k+1)$ is used as the initial reference data for cluster settings. Reference data will be compared with real data $(k+1)$ through error deviation. The controller decision is based on referencing the real data signal$(k+1)$ ... $(k+n)$ with two options: if there is an error between the prediction results and the real data measurement results, the controller algorithm will work based on the real data measurement signal information; if the error difference is zero then the controller works according to the tunning parameters in the previous cluster. The working pattern of the FMPC is shown in Appendix A Fig. A-2 as a step of electrical load control. Reference controllers are able to minimize the work area of the controller approaching the estimated measurement results so as to accelerate the controller's work response in maintaining the dynamic stability of the generating system at any time. FMPC in Fig. 1 represents a fuzzy state estimator feedback model to identify load parameters in each cluster and fuzzy control (FMPC) that identify the optimal gain control that corresponds to the load parameter identification model. The main idea of this study wanted an auto-control device and was applied online to achieve fast and accurate system stability.

## 2. Load Prediction Based Time Series Analysis

### 2.1. DSARIMA model

The Double Seasonal ARIMA method or commonly called DSARIMA is a development of the Box-Jenkins ARIMA method. The ARIMA model (*p*, *d*, *q*) is a combination of parameters AR (*p*) and MA (*q*) with a difference process *d* [13]. Predict procedure through five repetitive stages, in order:

i. Check data stationarity.
ii. Identify potential ARIMA models by looking at samples of autocorrelation and partial autocorrelation.
iii. Estimation of the ARIMA parameter with the least squares method.
iv. Check the adequacy of the model used by plotting normal, ACF and PACF probabilities on the residual model.
v. Predict results.

ARIMA model with a double seasonal pattern is written as ARIMA $(p, d, q)(P_1, D_1, Q_1)^{s_1}(P_2, D_2, Q_2)^{s_2}$, has a common form as [13]:

$$\phi_p(B)\,\Phi_{P_1}\left(B^{s_1}\right)\Phi_{P_2}\left(B^{s_2}\right)(1-B)^d\left(1-B^{s_1}\right)^{D_1}\left(1-B^{s_2}\right)^{D_2}\dot{Z}_t$$
$$=\theta_q(B)\,\Theta_{Q_1}\left(B^{s_1}\right)\Theta_{Q_2}\left(B^{s_2}\right)\alpha_t \qquad (1)$$

with

$s_1$ and $s_2$ is a different seasonal period

$$\phi_p(B)=1-\phi_1 B-\phi_2 B^2-\ldots-\phi_p B^p$$

$$\Phi_P\left(B^s\right)=1-\Phi_1 B^s-\Phi_2 B^{2s}-\ldots-\Phi_P B^{Ps}$$

$$\theta_q(B)=1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q$$

$$\Theta_Q\left(B^s\right)=1-\Theta_1 B^s-\Theta_2 B^{2s}-\ldots-\Theta_Q B^{Qs}$$

### 2.2. Parameter estimation

This study used the least squares method in estimating parameters [14]. The ARIMA model parameter was based on the time series observed along $Z_1, Z_2, \ldots, Z_n$. The quadratic method assumed that the best curve was that which had the least square error of the data set. The parameter values *p*, *d*, and *q* ARIMA models were determined through the stationary ACF and PACF graph plots.

## 2.3. Method of measuring data accuracy

Predicted results in this study used the Mean of Absolute Percentage Error Method. *MAPE* is defined as follows:

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{Z_i - \hat{Z}_i}{Z_i} \right|}{n} \times 100\% \quad (2)$$

## 3. Modeling And Dynamic Stability Of Electrical Power Plant Systems

Small signal stability of the electric power generation was analyzed through a model of a single-machine power generation system based on Park modeling. The model assuming resistor resistance was ignored, the condition of the system was considered balanced and the saturation of the core in the generator was ignored, and the load was considered static with the price of impendence considered constant. Model is a synchronous machine that refers to a single-machine with infinite bus that is introduced by De Mello and Concordia. And also has been developed by Hamdy A. M. Mousa and Y. N. Yu is a multi-machine model [15-17]. Until now a single engine generator model remains the focus and attention of researchers [18-19].

Small signal stability is detected after the first swing period when the response of a control instrument such as a governor, AVR, or complementary equipment has been taken into account. The process of engine dynamics can be either mechanical or electrical dynamics changes. Mechanical changes occur because of changes in the rotor angular velocity. The rotor angular velocity will swing around the synchronous angular velocity. While electrical changes due to changes in reaction to the anchor on the side of the exciter and the impact on the change in terminal voltage of the generator. The generator voltage will swing at the terminal voltage value. Stability will be achieved by returning the rotor angular velocity to the synchronous generator speed and convergent voltage to a certain value around its nominal value.

To obtain the dynamic characteristics of an electric power generation system, the state space equation approach is carried out as follows [20]:

$$\Delta \dot{x} = A \Delta x + B \Delta u \quad (3)$$

$$\Delta y = C \Delta x + D \Delta u \quad (4)$$

State vector generator system refers to a single engine generator system, which is defined as follows:

$$\Delta x = \left[ \Delta Y \quad \Delta T_m \quad \Delta \delta \quad \Delta \omega \quad \Delta E_q^{'} \quad \Delta v_F \right]^T \quad (5)$$

$$\Delta y = \left[ \Delta Y \quad \Delta T_m \quad \Delta P \quad \Delta \omega \quad \Delta v_t \quad \Delta v_F \right]^T \quad (6)$$

$$\Delta u = \left[ u_g \quad u_E \right]^T \quad (7)$$

## 4. Controllers For Power Generation

### 4.1 Optimal control

Referring to the state of space equation, optimal *K* feedback matrix with the equation is as follows [21]:

$$u(t) = -K\,x(t) \tag{8}$$

To determine the optimal control law $u(x,t)$ used a quadratic performance index called the Linear Quadratic Regulator. The optimal control law is applied in order to move the model from the initial state to the final state in such a way as to provide an optimal performance index.

The optimal LQR is determined by the minimum index of error deviation from the state variable and minimum energy from the input variable.

$$J = \int_{t_0}^{t_1} \left[ x^T(t) Q\,x(t) + u^T(t) R\,u(t) \right] dt \tag{9}$$

To solve Eq. (9), the following Lagrange multiplier method is used:

$$(x,\lambda,u,t) = \left[ x^T Q\,x + u^T R\,u \right] + \lambda^T \left[ A\,x + B\,u - x \right] \tag{10}$$

Optimal value is obtained by equating the partial derivatives equal to zero, is written:

$$p(t) = -p(t)A - A^T p(t) - Q + p(t)\,B\,R^{-1} B^T\, p(t) = 0 \tag{11}$$

called is Riccati differential equation. Solution to the Riccati equation is simplified to be a suboptimal case, namely $t_f = \infty$ and produces $x(t_f) = 0$, so the value of $p(t)$ is equal to zero, obtained:

$$p\,A + A^T\, p + Q - p\,B\,R^{-1} B^T\, p = 0 \tag{12}$$

The *p* matrix leads to a constant, therefore the completion of the matrix *p* is constant, then *K* value is also constant, equal to:

$$K = R^{-1} B^T\, p \tag{13}$$

With the *K* feedback equation, the state variable becomes:

$$\dot{x}(t) = (A - B\,K)\,x(t) \tag{14}$$

The roots of this characteristic equation can be determined by the following equation:

$$\left| s\,I - (A - B\,K) \right| = 0 \tag{15}$$

Thus, feedback LQR is used to adjust the speed deviation angle of the rotor at a synchronous speed and voltage generator converges to a certain value around the nominal value.

### 4.2 Fuzzy Model Predictive Control

The Fuzzy Takagi-Sugeno [22-23] model developed in this study aims to identify optimal state and *K* values for any changes in electrical power.

Identification of state variables due to changes in instantaneous load was developed through the fuzzy state feedback approach as a fuzzy state estimator for each cluster, rules:

$$R^i : IF\ x_1\ is\ F_1^i\ AND\ x_2\ is\ F_2^i \ldots AND\ x_n\ is\ F_n^i$$
$$THEN \begin{cases} \dot{x} = A_i\, x + B_i\, u \\ y = C\, x \end{cases} \quad i = 1,\ldots, L \tag{16}$$

Takagi-Sugeno method has been developed and modified into a state-feedback control rules. The local controller will be distributed to each rule into a global fuzzy state controller that covers all plant operating points [24]. Predictive approach in this research-based optimal control LQR for each identification state is the development of this method [25-26]. The equation can be rewritten into

$$R^i : IF\ x_1\ is\ F_1^i\ AND\ x_2\ is\ F_2^i \ldots AND\ x_n\ is\ F_n^i$$
$$THEN \begin{cases} \dot{x} = A_i\, x + B_i\, u \\ u_i = -K_i\, x \end{cases} \quad i = 1,\ldots, L \tag{17}$$

where $K_i$ is optimal LQR gain vector of state-space model of the *i*-th rule. Vector nominal gain for the model represented by:

$$K = \sum_{i=1}^{L} \mu_i\, K_i \tag{18}$$

FMPC concept refers to the model approach Fuzzy State Estimator for each load cluster. The identification result is fed in accordance with the optimal *K* value. *K* optimal for any identification of the reference control on the input side of the turbine $(u_g)$ and the excitation.and excition side $(u_E)$. For more details, it can be studied in the simulink model that has been proposed in this study which refers to Appendix B Fig. B-1. block diagram of FMPC.

## 5. Simulation and Analysis Results

This research consists of 7 stages, namely the analysis and simulation program stages in the following order:

*Step 1*

Every half hour load data obtained through Generation Unit PT. PLN Gresik Indonesia. Load data on January 1, 2009 to December 24, 2011 were used as forecasting. December 25 to 31 2011 was used as testing. Load prediction results had been carried out in previous studies with *MAPE* of 2.06% [27].

*Step 2*

Prediction results in the form of variations in the load of 336 data over the next week. Comparison of load cluster modeling has been done by previous researchers [28]. This research uses descriptive analysis approach presented in graphical form distribution. Interval range between a minimum value of prediction results, first quartile, median, third quartile, and maximum value is used as a cluster model for each load conditions in units of pu. Fig. 2 shows the distribution of predicted results based on the cluster area controller.

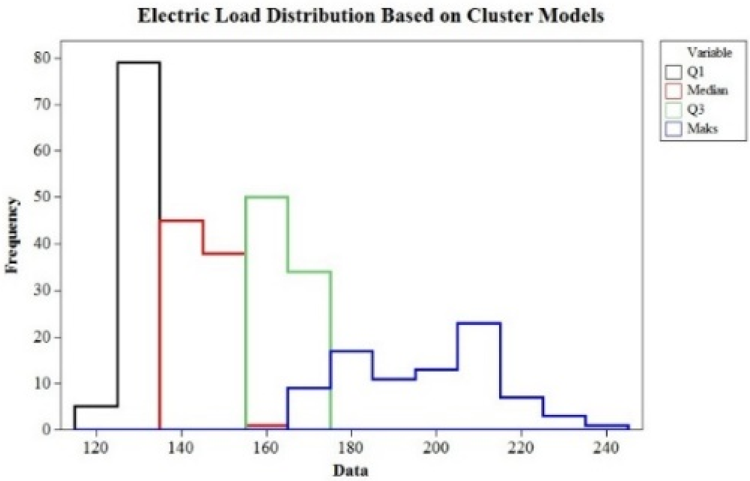



**Fig. 2. Distribution of data based on cluster patterns.**

Figure 2 shows the load pattern containing cluster conditions with a MAPE of 2.06 percent. This means that there is an increase and or decrease in margins of that size for each cluster. This pattern can be applied in a load cluster based fuzzy model in Fig. 3 as membership function of the fuzzy state estimator and FMPC.

*Step 3*

Before getting the optimal control parameter value from the available plant model. Identification is one of the important factors that will support the success in engineering a control system that is stable, robust and able to adapt well to all conditions. Identification of the plant model is done by order 3. The identification technique uses a prediction error estimate (PEM) approach [29]. The results of the plant identification are in the form of a state matrix. Table 1 is the result of identification of the 4 predefined clusters.

**Table 1. Results matrix identification of each cluster.**

| Cluster | Matrix *A* $(3 \times 3)$ | | | Matrix *B* $(3 \times 2)$ | | Matrix *C* $(3 \times 3)$ | | |
|---|---|---|---|---|---|---|---|---|
| 1 | 1.0006 | 0.4699 | -0.0567 | -1.1014 | -0.4644 | -0.0333 | -0.0208 | 0.0594 |
| | -0.0562 | 0.8521 | 0.0317 | 0.0906 | -0.8310 | -0.0179 | -0.1015 | -0.0531 |
| | -0.0208 | 0.1863 | 0.9662 | -0.5709 | -0.7381 | 0.2325 | 0.5239 | -0.4321 |
| 2 | 0.9499 | 0.6371 | -0.0459 | -0.6493 | -0.4438 | -0.0056 | 0.0043 | -0.0084 |
| | -0.0397 | 0.8488 | -0.0070 | 0.0823 | -0.9872 | -0.0246 | -0.1114 | 0.0185 |
| | 0.0234 | -0.3796 | 0.9921 | 0.4765 | 0.6902 | 0.1572 | 0.3463 | 0.2393 |
| 3 | 1.0513 | 0.5022 | 0.2361 | 0.1099 | -0.9611 | 0.0022 | 0.0125 | 0.0049 |
| | -0.0662 | 0.8710 | -0.0124 | -0.2356 | -0.6486 | -0.0735 | -0.1159 | -0.0107 |
| | 0.0251 | -0.1192 | 0.8908 | 0.5362 | 0.5751 | 0.0960 | 0.4697 | 0.2131 |
| 4 | 0.8189 | -1.1845 | -0.5249 | 0.1141 | 2.4466 | -0.0188 | -0.1593 | -0.1006 |
| | 0.0910 | 1.3565 | 0.2761 | -0.1583 | 0.7748 | 0.0151 | 0.0293 | -0.0686 |
| | -0.1205 | -0.4570 | 0.5857 | 0.2317 | -1.7243 | 0.0310 | -0.2124 | -0.1050 |

*Step 4*

The results of the identification of state for each cluster condition are the basis for determining optimal gain. The optimal LQR control refers to Eq. (13). The next step determines the optimal state of control vector in each cluster, as follows:

**Table 2. Results parameter optimal control of each cluster.**

| **Cluster** | **Matrix R** $(2 \times 2)$ | | **Matrix Q** $(3 \times 3)$ | | | **Matrix K$_{optimal}$** $(2 \times 3)$ | | |
|---|---|---|---|---|---|---|---|---|
| **1** | 1 | 0 | 0.0555 | 0.1243 | -0.1015 | 0.0887 | 0.1188 | -0.2005 |
| | 0 | 1 | 0.1243 | 0.2853 | -0.2223 | -0.0461 | -0.2176 | 0.0694 |
| | | | -0.1015 | -0.2223 | 0.1931 | | | |
| **2** | 1 | 0 | 0.0253 | 0.0572 | 0.0372 | 0.0458 | 0.0390 | 0.0835 |
| | 0 | 1 | 0.0572 | 0.1324 | 0.0808 | -0.0360 | -0.1838 | -0.0425 |
| | | | 0.0372 | 0.0808 | 0.0577 | | | |
| **3** | 1 | 0 | 0.0146 | 0.0536 | 0.0212 | -0.0046 | 0.0187 | 0.0179 |
| | 0 | 1 | 0.0536 | 0.2342 | 0.1014 | -0.0665 | -0.2969 | -0.1252 |
| | | | 0.0212 | 0.1014 | 0.0456 | | | |
| **4** | 1 | 0 | 0.0015 | -0.0031 | -0.0024 | -0.0066 | -0.0816 | -0.0398 |
| | 0 | 1 | -0.0031 | 0.0714 | 0.0363 | 0.0481 | 0.1954 | 0.0837 |
| | | | -0.0024 | 0.0363 | 0.0258 | | | |

*Step 5*

The proposed FMPC consists of: in step 3, the Fuzzy State estimator to identify the measured state parameters $(x_i)$ namely in the form of a state space matrix in Table 1 and in step 4, the Fuzzy Model Predictive Control based on optimal control as the control system $(U_i)$ namely in the form of the optimal LQR control matrix in Table 2.

*If (Pbeban is PbCluster1) and (X1 is X1) and (X2 is X2) and (X3 is X3) then (U1 is U1Cluster1)(U2 is U2Cluster1)*
*If (Pbeban is PbCluster2) and (X1 is X1) and (X2 is X2) and (X3 is X3) then (U1 is U1Cluster2)(U2 is U2Cluster2)*
*If (Pbeban is PbCluster3) and (X1 is X1) and (X2 is X2) and (X3 is X3) then (U1 is U1Cluster3)(U2 is U2Cluster3)*
*If (Pbeban is PbCluster4) and (X1 is X1) and (X2 is X2) and (X3 is X3) then (U1 is U1Cluster4)(U2 is U2Cluster4)*

The membership function in the rules of Fuzzy Inference System is determined based on the results of step 2 in units of pu with a *MAPE* of 2.06 percent. With intervals between clusters: cluster 1 between 0 - 0.125 - 0.25515; cluster 2 between 0.2397 - 0.375 - 0.5103; cluster 3 between 0.48455 - 0.625 - 0.76545; cluster 4 between 0.7294 - 0.875 - 1.

Representative of the membership function in the rules of Fuzzy Inference System is show in Fig. 3., as follows:

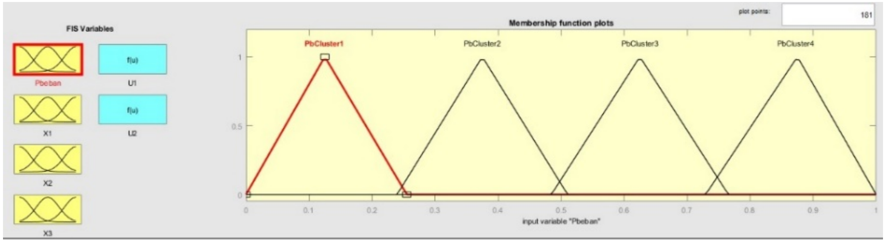



**Fig. 3. Membership function of the fuzzy state estimator and FMPC.**

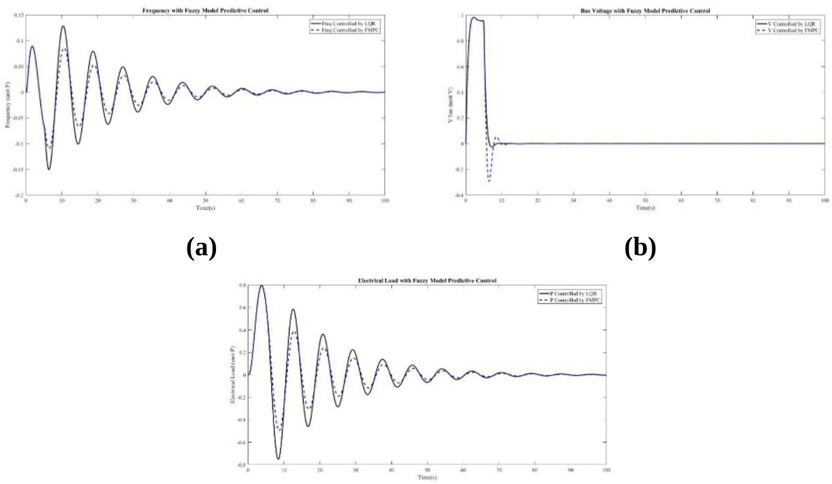
*Step 6*

Comparison *IAE* of each output for all cluster load changes expressed by Table 3.

**Table 3. Integral absolute error of each cluster**

| Electrical Load | IAE Output LQR | | | IAE Output FMPC | | |
|---|---|---|---|---|---|---|
| | **F** | **V** | **P** | **F** | **V** | **P** |
| **Cluster 1** | 2.168 | 4.878 | 12.11 | 1.577 | 5.139 | 9.081 |
| **Cluster 2** | 1.593 | 4.593 | 9.019 | 1.348 | 4.858 | 7.842 |
| **Cluster 3** | 1.033 | 4.443 | 5.807 | 0.9209 | 4.667 | 5.315 |
| **Cluster 4** | 1.29 | 3.615 | 7.018 | 1.252 | 3.819 | 6.773 |
| **Average** | 1.521 | 4.3823 | 8.511 | 1.2745 | 4.621 | 7.253 |

Table 3 shows the average value of the optimal control is better than FMPC. This indication is due to every change in load (burden) in manual tuning (offline). So that the optimal control response is better. It does not add weight to any errors in a system response. Simulations are carried out on each loading pattern (cluster 1$^{st}$ - cluster 4$^{th}$) using the optimal LQR controller and FMPC based on optimal LQR control. Simulation model using cluster 1 model as shown in Fig. 4.




**(a)** **(b)**

**(c)**

**Fig. 4. Load simulation output result in cluster 1:**
**(a) frequency, (b) bus voltage, (c) electrical load.**

## 6. Conclusions

The simulation results of this study indicate that changes in load cause variations in voltage and frequency in the generating system (SMIB). Improvements can be made using the optimal LQR control application. FMPC multiple soft-switching model based on optimal control is an implementative approach that is able to overcome variations in electrical power at the centre of the load FMPC is implemented as multiple soft-switching, so it is more implementative and simpler than conventional optimal control. With a *MAPE* of 2.06 percent the Fuzzy control model is able to handle shedding and load variants during generator system operations.

### Nomenclatures

| | |
|---|---|
| $A, B, C, D$ | State matrices |
| $B$ | Backward shift operator |
| $D_1, D_2, d$ | Order of differences |
| $d, p, q$ | Parameter AR, differencing, MA |
| $F_j^i$ | Fuzzy set for state variable |
| $J$ | Performance index |
| $K$ | Gain feedback |
| $L$ | Sum of all operating |
| $Q$ | Minimum deviation |
| $R$ | Minimum energy |
| $R^i$ | Rule relating to the operation of *i*-th |
| $s_1, s_2$ | Seasonal periods |
| $u_E, u_g$ | Control signal on the side of turbine and generator |
| $u, x, y$ | Control vector, input, and output |
| $Z_t$ | Real value in period *t* |
| $\dot{Z}_t$ | predict load electrical in period *t* |

***Greek Symbols***

| | |
|---|---|
| $\alpha_t$ | White noise |
| $\Delta$ | Small deviation or change in the state vector |
| $\Delta E_q^{'}$ | Generator transient voltage change, W/A |
| $\Delta P$ | Change value electrical power, J/s |
| $\Delta T_m$ | Mechanical torque rotation change, N.m |
| $\Delta v_F$ | Voltage change, W/A |
| $\Delta v_t$ | Terminal generator voltage change, W/A |
| $\Delta Y$ | Change in valve height, mm |
| $\Delta\delta$ | Rotor angle change, rad/s |
| $\Delta\omega$ | Rotor angular velocity value, rad/s |
| $\theta_q(B)$ | Regular moving average polynomials of orders *q* |
| $\Theta_{Q_1}(B^{s_1}), \Theta_{Q_2}(B^{s_2})$ | Moving average polynomials of orders |
| $\varphi_p(B)$ | Regular autoregressive polynomials of orders *p* |
| $\Phi_{P_1}(B^{s_1}), \Phi_{P_2}(B^{s_2})$ | Autoregressive polynomials of orders |

### Abbreviations

| | |
|---|---|
| IAE | Integral Absolute Error |
| MAPE | Mean Absolute Percentage Error |

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## *Appendix A*

## Representation of Design Charts

This research as a whole is represented by Figs. A-1 and A-2. The first stage or so-called time series analysis is represented by the first step to get predictive data. The second step is to determine the electrical load cluster pattern. At this stage researchers have done [28, 29]. Flowchart is shown in Fig. A-1. The second stage or called the power system control design stage with the input time series parameters of the results of the analysis of the first stage. This stage is represented in step 3 to identify the generator system parameters [30]. Step 4 adopts the optimal control model as control of the generating system [22]. Step 5 is to adopt a model approach based on fuzzy feedback Khaber et al. [25]. The second stage is shown in Fig. A-2 based on Fuzzy Model.

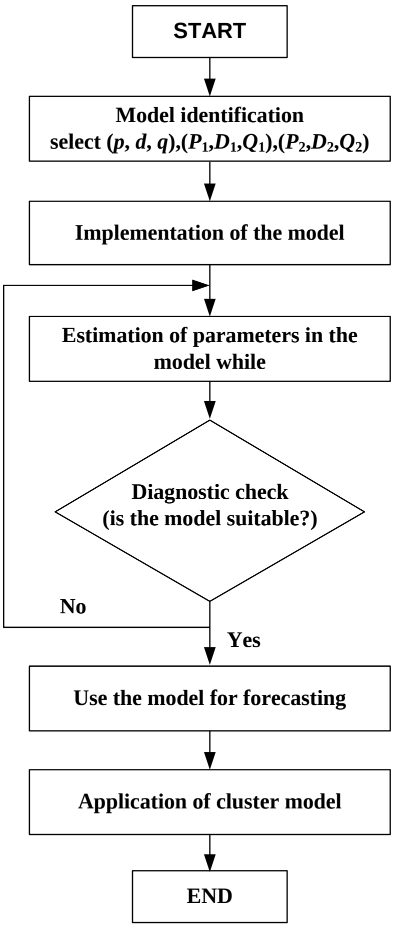



**Fig A-1. Step of time series.**

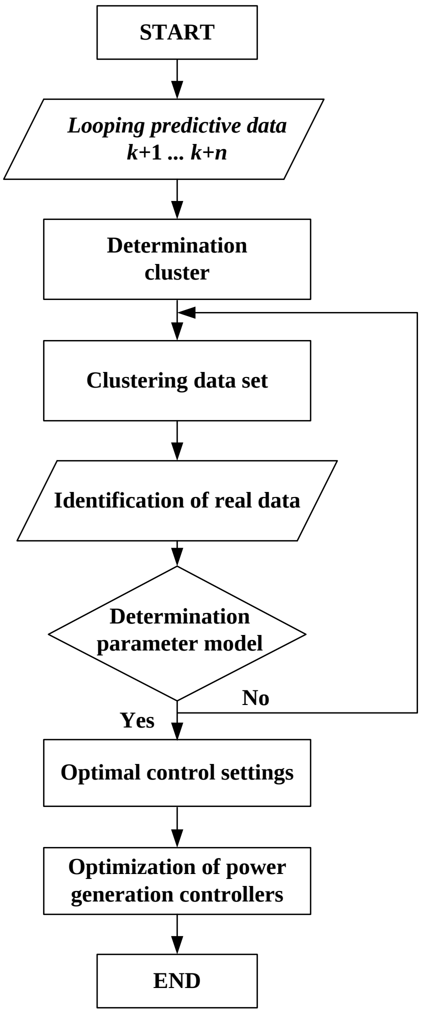



**Fig. A-2. Step of electrical load control.**

## *Appendix B*

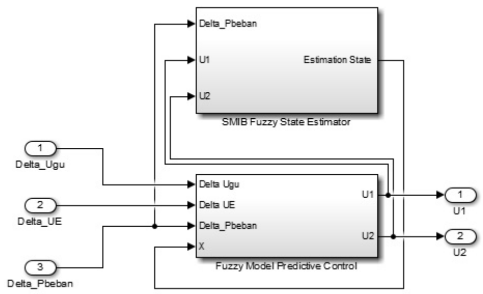
## Simulation Model

### B. 1. Introduction

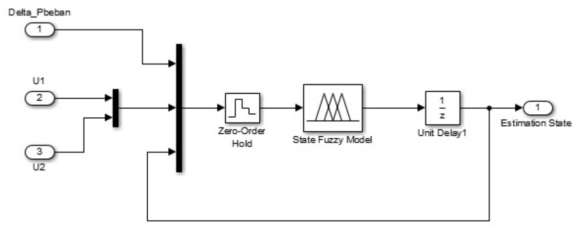
Design and simulation of FMPC control using the Simulink Matlab program. The simulation modeling stage consists of modeling a single machine infinite bus, approach model identification of the 3rd order, calculation of optimal LQR control, and FMPC modeling.

### B. 2. Programme Structure and Description of Subroutines

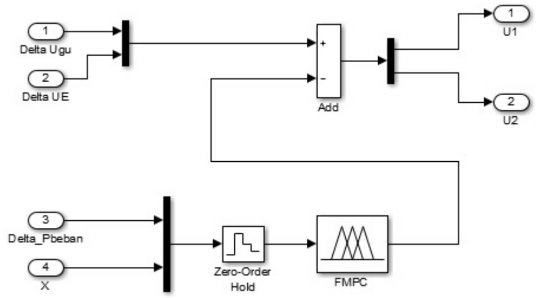
FMPC consists of the Fuzzy State Estimator model approach that is able to identify changes in load state and optimal control-based Fuzzy Model Predictive Control as shown in Figure B-1.




(a)




(b)




(c)

**Fig. B-1. Block diagram of FMPC, (a) FMPC proposed, (b) subsystem of Fuzzy State Estimator, (c) FMPC.**