Forecasting the number of lecturers by multi-input intervention model for human resource university planning policy

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Abstract. Institut Teknologi Sepuluh Nopember (ITS) as one of the leading universities in Indonesia that is currently transforming into an internationally reputed research university, must have a plan for employee needs, in this case, lecturers who can meet the needs of the university in line with organizational change. Good Human Resource planning must be supported by complete data and information. One way to predict the needs of lecturers is to do time series modelling using data on the number of ITS lecturers in previous years. The time series modelling used is intervention modelling because the initial hypothesis of this study was the number of lecturers' needs had a significant change when ITS changed to BLU and PTNBH. Based on the background description above, the purpose of this study is to obtain an appropriate time series intervention model to predict the number of ITS lecturers based on the model that has been produced. Based on the results of data analysis, the best intervention model is ARIMA ([4, 5], 1, 0). It means that the number of lecturers in the t-month is influenced by the number of lecturers in the 4th, 5th, 6th months ago, and the forecasting results show that the number of lecturers will decrease every month, so it is necessary to add the number of lecturers regularly every year.

1. Introduction
Institut Teknologi Sepuluh Nopember (ITS) as one of the well-known tertiary university in Indonesia which is being transformed into an internationally reputed research university, must have a plan for employees that can meet employees need in accordance with organizational change. In accordance with ITS Rector Regulation number 2 of 2017, ITS employees consist of Government employees (PNS) and Non Government employees (Non-PNS), and in meeting the needs of PNS staff both lecturers and education staff, refers to formation in accordance with government regulations. While the ITS Chancellor's decision regulates the number of Non-PNS employee needs (lecturers and education staff) based on the size of the lecturer and student ratio and workload analysis.

Based on the above problems, this study constraint the research only to the lecturers data so the purpose of this study is to get the time series model of the number of lecturers and predict the total needs of lecturers at ITS in 2019.

The time series modeling used here is modeling with intervention analysis because the initial hypothesis of this study is the number of employee needs has a significant change when ITS changed to PTNBH.
2. Intervention Model

Time series data in practice are often found to be influenced by special events such as an intervention both external and internal that affects data patterns. In the intervention analysis, it is assumed that the intervention event occurred at the known \( T \) time from a time series (Box et al., 1994). The initial steps to obtain the estimated parameters of the intervention model based on the general form of the transfer function model are (Wei, 1990):

\[
Y_t = \frac{\omega_s(B)B^b}{\delta_{rj}(B)} I_t^r + \frac{\theta(B)}{\varphi(B)} a_t
\]  

(1)

The main objective of this analysis is to measure the magnitude and duration of intervention effects in a time series (Wei, 1990). Intervention model is a time series model that can be used to model and predict data containing shocks or interventions from both external and internal factors. There are two main functions used in the intervention model, namely the step and pulse function. Intervention events that occur from time \( T \) onwards over a long period of time are called step functions. Mathematically, this form of step function intervention is notated as:

\[
I_t = S_t = \begin{cases} 
0 & \text{if } t < T \\
1 & \text{if } t \geq T
\end{cases}
\]  

(2)

Whereas in the pulse function, the intervention event occurs only at time \( T \) and does not continue at a later time, for example the promotion of a 2 billion thunder by PT. Telkom Divre V (Suhartono and Wahyuni, 2002). Mathematically, this form of pulse function intervention is notated as follows:

\[
I_t = P_t = \begin{cases} 
0 & \text{if } t \neq T \\
1 & \text{if } t = T
\end{cases}
\]  

(3)

In identifying the order in the intervention model (\( b, r, \) and \( s \)), it can be done by looking at the residual plot. Residuals are obtained from the difference between observational data and forecast values using the noise model. Suppose the residual is denoted as \( Y_t^* \), then \( Y_t^* = Y_t - N_t = f(I_t) \).

The value of \( b \) is determined by looking at the effect of the intervention is taking place, the value of \( s \) indicate when a response motion weight began to decline, and \( r \) shows the pattern of the residuals.

2.1 Intervention Multi Input Model

The general form of the multi-input intervention model is (Wei, 1990):

\[
Y_t = \sum_{j=1}^{k} \frac{\omega_{s_j}(B)B^b}{\delta_{rj}(B)} I_{jt} + N_t
\]  

(4)

where \( Y_t \) is the response variable at time \( t \), \( I_{jt} \) is the \( j \)th intervention variable at time \( t \), a value of 1 or 0 which indicates the presence or absence of the effect of intervention at time \( t \), \( N_t \) is an error / noise that is the ARIMA model without the effect of intervention, and \( b \) is the delay the time at which the effect of the intervention began. Whereas \( \omega_s(B) \) and \( \delta_r(B) \) are defined as

\[
\omega_{sj}(B) = \omega_{0j} - \omega_{1j}B^1 - \omega_{2j}B^2 - \cdots - \omega_{sj}B^s \quad \text{and} \quad \delta_{rj}(B) = 1 - \delta_{1j}B^1 - \delta_{2j}B^2 - \cdots - \delta_{rj}B^r
\]  

(5)

2.1.1 The step function intervention model (\( b = 1, r = 1, s = 1 \)) followed by the pulse function (\( b = 1, r = 0, s = 1 \)) The multi input intervention model with the step function (\( b = 1, r = 1, s = 1 \)) and the pulse function (\( b = 1, r = 0, s = 1 \)) are as follows:

\[
Y_t = \frac{(\omega_{01} - \omega_{1j}B^1)}{1 - \delta_B} S_t + [(\omega_{02} - \omega_{1j}B^1)] P_t + N_t
\]  

(6)
Where $\delta$ is $0 < \delta < 1$, so the effect of the intervention is

$$Y_t^* = \frac{(\omega_{01} - \omega_{11}B)B^1}{1 - \delta B}S_t^* + [(\omega_{02} - \omega_{12}B)B^1]P_t^*$$

$= \omega_{01}S_{t-1} + (\omega_{01}\delta - \omega_{11})S_{t-2} + \delta(\omega_{01}\delta - \omega_{11})S_{t-3} + \cdots
+ \delta^{k-2}(\omega_{01}\delta - \omega_{11})S_{t-k} + \omega_{02}P_{t-1} - \omega_{12}P_{t-2}$

(7)

In model (7), the effect of the first intervention which is a step function occurs one period since the intervention event occurred with an effect of $\omega_{01}$. In the two periods after the intervention ($T_1 + 2$) the effect of the intervention is $\omega_{01} + (\omega_{01}\delta - \omega_{11})$, so that up to $T_1 + k$ will have an intervention effect of $\omega_{01} + \sum_{j=0}^{k-2}\delta^j(\omega_{01}\delta - \omega_{11})$ where $k = 2, 3, \ldots, n$ and $n = T_2 - T_1$, while in one period after the occurrence of the second intervention which is a pulse function ($T_2 + 1$) the effect is $\omega_{01} + \sum_{j=0}^{k-2}\delta^j(\omega_{01}\delta - \omega_{11}) + \omega_{02}$. In the two periods after the second intervention ($T_2 + 2$) the effect becomes $\omega_{01} + \sum_{j=0}^{k-2}\delta^j(\omega_{01}\delta - \omega_{11}) + \omega_{02} - \omega_{12}$. Then after three periods after the second intervention ($T_2 + 3$) the effect returns to $\omega_{01} + \sum_{j=0}^{k-2}\delta^j(\omega_{01}\delta - \omega_{11})$. Calculation of the intervention effect for this model is

$$Y_t^* = \begin{cases} 
0 & t \leq T \\
\omega_{01} + \sum_{j=0}^{k-2}\delta^j(\omega_{01}\delta - \omega_{11}) & t = T_1 + k, T_1 + k \leq T_2 \text{ and } t \geq T_2 + 3 \\
\omega_{01} + \sum_{j=0}^{k-2}\delta^j(\omega_{01}\delta - \omega_{11}) + \omega_{02} & t = T_2 - 1 \\
\omega_{01} + \sum_{j=0}^{k-2}\delta^j(\omega_{01}\delta - \omega_{11}) - \omega_{12} & t = T_2 - 2 
\end{cases}$$

(8)

With $k = 2, 3, \ldots$

2.1.2 The pulse function intervention model ($b = 1$, $r = 1$, $s = 1$) followed by the step function ($b = 1$, $r = 0$, $s = 1$) The multi input intervention model with the pulse function ($b = 1$, $r = 1$, $s = 1$) and the step function ($b = 1$, $r = 0$, $s = 1$) are as follows:

$$Y_t = \frac{(\omega_{01} - \omega_{11}B)B^1}{1 - \delta B}P_t + [(\omega_{02} - \omega_{12}B)B^1]S_t + N_t$$

(9)

Where $\delta$ is $0 < \delta < 1$, so the effect of the intervention is:

$$Y_t^* = \frac{(\omega_{01} - \omega_{11}B)B^1}{1 - \delta B}P_t + [(\omega_{02} - \omega_{12}B)B^1]S_t$$

$= \omega_{01}P_{t-1} + (\omega_{01}\delta - \omega_{11})P_{t-2} + \delta(\omega_{01}\delta - \omega_{11})P_{t-3} + \cdots + \omega_{02}S_{t-1} - \omega_{12}S_{t-2}$

(10)

In model (10), the effect of the first intervention which is a pulse function occurs one period since the occurrence of the intervention event with an effect of $\omega_{01}$. In the two periods after the intervention event ($T_1 + 2$) the effect of the intervention is $(\omega_{01}\delta - \omega_{11})$, so that up to $T_1 + k$ will have an intervention effect of $\delta^{k-2}(\omega_{01} - \omega_{11})$ and go to zero, where $k = 2, 3, \ldots, n$ and $n = T_2 - T_1$. While in one period after the occurrence of the second intervention event which is a step function ($T_2 + 1$) the effect is $\omega_{02}$. Since two periods after the second intervention ($T_2 + 2$) the effect becomes $(\omega_{02} - \omega_{12})$ and is constant at that value.

2.2 Intervention Multi Input Analysis Parameters Estimation

The initial steps to obtain the estimated parameters of the intervention model based on the general form of the transfer function model are (Wei, 1990):

1. Obtain the estimated parameters of the intervention model based on the general form of the transfer function model.
\[ Y_t = \frac{\omega_x(B)B^b}{\delta_r(B)} I_{t-b}^T + \frac{\theta(B)}{\phi(B)} a_t \] (11)

If there is a modification, equation (11) can also be written as follows:

\[ \delta_r(B)\varphi(B)Y_t = \varphi(B)\omega_x(B)I_{t-b}^T + \delta_r(B)\theta(B)a_t \] (12)

Or: \( c(B)Y_t = d(B)I_{t-b}^T + e(B)a_t \) (13)

With: \( C(B) = \delta_r(B)\varphi(B) = 1 - c_1B - c_2B^2 - \cdots - c_{p+r}B^{p+r} \)
\( d(B) = \omega_x(B)\varphi(B) = 1 - d_1B - d_2B^2 - \cdots - d_{p+s}B^{p+s} \)
\( e(B) = \delta_r(B)\theta(B) = 1 - e_1B - e_2B^2 - \cdots - e_{q+r}q \)

Then obtained:

\[ a_t = \frac{c(B)Y_t - d(B)I_{t-b}^T}{e(B)} \]

It is assumed that \( a_t \) is \( N(0, \sigma^2) \) and white noise, so that the conditional likelihood function is obtained:

\[ L(\delta, \omega, \varphi, \theta, \sigma_a^2|b, l, Y_0, a_0) = (2\pi\sigma_a^2)^{-n/2} \exp\left[ \frac{-1}{2\sigma_a^2} \sum_{i=1}^{n} a_i^2 \right] \] (14)

Furthermore, to obtain the parameter estimator can be done by minimizing the \( S \) function:

\[ S(\delta, \omega, \varphi, \theta|b) = \sum_{i=1}^{n} a_i^2 \] (15)

Suppose that \( t_0 = \text{max}\{p + r + 1. b + p + s + 1\} \) while the value of \( a_t \) is the residual as in equation (12).

3. Research Methodology

To achieve the research objectives, a secondary data collection step was conducted at the number of lecturers at ITS through the employment bureau at ITS and continued with data processing using statistical software. The research method will be explained in the following subsections.

3.1 Source of Data and Variable

Sources of data in this study were taken from the data records of the Employment Bureau ITS for 7 years (the data in the form of monthly data) starting in 2011 up to 2018. The variable used in this study is the number of lecturers at ITS which is the sum of the number of PNS and Non PNS Lecturers

3.2 Research Process

The Research Process follow these steps are:

1. Make a time series plot to see the pattern of intervention response and predict possible intervention variables
2. Form the ARIMA model from the data before the intervention (before ITS became BLU and PTNBH) using the Box-Jenkins method, which is preceded by the stationary check in the average and the variance for the initial data based on the time series plot that was made previously. Stationary checks in average can be done with the Augmented Dickey Fuller (ADF) test, while stationary checks in variance can be done through the Box-Cox Transformation Graph or Bartlett test.
3. Perform a process of differentiation (differencing) if it does not meet the stationary assumptions in the average and perform data transformation if it does not meet the stationary assumptions in the variance for the data prior to the intervention.
4. Identify all models that might have resulted from the ACF and PACF plots from the data prior to the intervention.
5. Estimating parameters of all possible ARIMA models from data prior to the intervention.
6. Test the significance of the parameters of the ARIMA model and choose a model with all the parameters produced is significant from the data before the intervention.

After getting the intervention model, the next step is to forecast the number of ITS lecturers with the steps below:

1. Check the residual assumptions of the formed ARIMA model. A good model is a forecasting model that meets the residual independence assumptions.
2. Evaluate the forecasting model that has been obtained by calculating the value of RMSE and AIC, and the best model is chosen based on the smallest RMSE and AIC values.
3. Forecasting data before the intervention occurs until the data after the intervention is fulfilled based on the model generated by the Box-Jenkins ARIMA method.
4. Calculating the residual response between the data after the intervention with the forecasting results from the data before the intervention.
5. Identify intervention response patterns and form intervention models through residual plots. ARIMA residual plot is used in determining the order b, s, and r.
6. Estimating the parameters of the intervention model using the least squares method.
7. Testing the significance of the intervention model parameters and selecting a model that produces all the significant parameters.
8. Check the residual assumptions of the intervention model that is formed. A good model is a forecasting model that meets the residual independence assumptions.
9. Selection of the best forecasting model by considering the smallest MSE values.
10. Perform forecasting using the best intervention models that have been formed.

4. Result and Discussion
Data on the number of lecturers from January 2011 to December 2018 is shown by the plot in Figure 1. The data series graph in Figure 1 shows that there is a repetition of data patterns at each particular time session, where when there is a decrease in the graph there are several interventions that make the chart pattern rise again. The data is then divided into two parts, namely in sample data and out sample data where in sample data consisting of data from January 2011 to December 2017 and out of sample data consisting of data from January to December 2018.

Checking stationary in variance is done by looking at the Box-Cox plot shown in Figure 2. Based on these images it is known that the lambda rounded value is 1.12. Because the value is more than one, it can be said that the data does not require transformation to stationary variance.

Then the stationary check in the mean is performed. Figures 3 show ACF and PACF in-sample data. ACF in Figure 3 shows a slow descending pattern. So it can be concluded that the data is not stationary in the mean. For this reason, regular differencing 1 is performed on the data.
Figure 1. Plot series data on number of lecturers

Figure 2. Box-Cox plot for checking stationary in variance

Figure 3. ACF and PACF plot

ACF and PACF after differencing 1 are shown in Figures 4. In Figure 4, ACF does not show a slowdown pattern anymore. This indicates the data has been stationary in the mean. The Time Series plot after the differencing process can be seen in Figure 5.
From the Time Series plot in Figure 5, there was a high increase in the number of lecturers in January 2013, May 2014, September 2014, November 2015 and September 2017. While in April 2014 and April 2015 there was a decrease in the number of lecturers. So the model is done by modelling the intervention with 7 intervention inputs namely:

a. January 2013 Step function of adding PNS and non PNS lecturers
b. April 2014 Pulse function reduction of non PNS lecturers
c. May 2014 step function addition of non PNS lecturers
d. September 2014 step function addition of PNS lecturers
e. April 2015 step function decrease in non PNS lecturers
f. November 2015 step function of adding PNS lecturers
g. September 2017 step function addition of non PNS lecturers

The change in the number of lecturers was allegedly due to a change in ITS organization from an ordinary state university to a public service university (BLU) since late 2012 and a change in ITS from a BLU to a legal entity university (PTNBH) since late 2014. This organizational change has many implications for university management both in the field of finance, and human resources, where ITS as a legal entity university has more freedom in its management.

Based on Figures 4 and 5 the proposed tentative model is an intervention model with ARIMA ([7], 1, 0). The parameter significance test results can be seen in Table 1.

| Parameter | Estimate | Error | T value | P value |
|-----------|----------|-------|---------|---------|
| $\phi_7$  | 0.23813  | 0.11673 | 2.04    | 0.0449  |
| $\omega_{10}$ | 66.09867 | 2.85306 | 23.17   | <.0001  |
| $\omega_{20}$ | -22.0987 | 2.85428 | -7.74   | <.0001  |
| $\omega_{30}$ | 23.57739 | 4.0451  | 5.83    | <.0001  |
| $\omega_{40}$ | 51      | 2.93247 | 17.39   | <.0001  |
| $\omega_{50}$ | -31     | 3.00988 | -10.3   | <.0001  |
| $\omega_{60}$ | 64      | 2.93247 | 21.82   | <.0001  |
| $\omega_{70}$ | 25.95251 | 2.96966 | 8.74    | <.0001  |

Based on Table 1, all parameters are significant with a confidence level of 95%. Then the model will be examined whether the residual meets the white noise assumption. White noise test is performed using Chi-Square Test Statistics with results as shown in Table 2.

| Lag | Chi-Square | DF | P value | -------------------------- | Autocorrelations-------------------------- |
|-----|------------|----|---------|---------------------------|------------------------------------------|
| 6   | 18.79      | 5  | 0.0021  | 0.17                      | 0.029                                    |
| 12  | 37.29      | 11 | 0.0001  | -0.061                    | 0.191                                    |
| 18  | 55.24      | 17 | <.0001  | 0.233                     | 0.21                                     |
| 24  | 72.97      | 23 | <.0001  | 0.149                     | 0.14                                     |

Table 2 shows that not all lags have a P value greater than 0.05, which means that the residuals are not yet white noise and in lags 4 and 5 the autocorrelation value is quite high, so the AR lag 4, and 5 parameters will be added to the model above. The results of the significance test parameters of the intervention model with ARIMA ([4, 5, 7], 1, 0) are shown in Table 3.

| Lag | Chi-Square | DF | P value | -------------------------- | Autocorrelations-------------------------- |
|-----|------------|----|---------|---------------------------|------------------------------------------|
| 4   | 18.79      | 5  | 0.0021  | 0.17                      | 0.029                                    |
| 5   | 37.29      | 11 | 0.0001  | -0.061                    | 0.191                                    |
| 7   | 55.24      | 17 | <.0001  | 0.233                     | 0.21                                     |
| 10  | 72.97      | 23 | <.0001  | 0.149                     | 0.14                                     |

Table 3 shows that the parameters are not significant, so these parameters are excluded from the model. The significance test results of the intervention model parameters with ARIMA ([4, 5], 1.0) are shown in Table 4.
Table 3. Estimation parameter of ARIMA ([4, 5, 7], 1, 0).

| Parameter | Estimate | Error  | T value | P value |
|-----------|----------|--------|---------|---------|
| $\phi_4$  | 0.27283  | 0.11661| 2.34    | 0.022   |
| $\phi_5$  | 0.29927  | 0.11236| 2.66    | 0.0095  |
| $\phi_7$  | 0.0937   | 0.11281| 0.83    | 0.4089  |
| $\omega_{10}$ | 66.63591 | 2.51594| 26.49   | <.0001  |
| $\omega_{20}$ | -22.0708 | 2.58802| -8.53   | <.0001  |
| $\omega_{30}$ | 26.22458 | 3.65486| 7.18    | <.0001  |
| $\omega_{40}$ | 53.52866 | 2.66995| 20.05   | <.0001  |
| $\omega_{50}$ | -29.6613 | 2.52405| -11.75  | <.0001  |
| $\omega_{60}$ | 66.5297  | 2.52452| 26.35   | <.0001  |
| $\omega_{70}$ | 25.64763 | 2.74081| 9.36    | <.0001  |

Table 4. Estimation parameter of ARIMA ([4, 5], 1.0).

| Parameter | Estimate | Error  | T value | P value |
|-----------|----------|--------|---------|---------|
| $\phi_4$  | 0.29949  | 0.11232| 2.67    | 0.0094  |
| $\phi_5$  | 0.31229  | 0.1111 | 2.81    | 0.0063  |
| $\omega_{10}$ | 67.21091 | 2.48279| 27.07   | <.0001  |
| $\omega_{20}$ | -22.2118 | 2.57059| -8.64   | <.0001  |
| $\omega_{30}$ | 26.142   | 3.6302 | 7.2     | <.0001  |
| $\omega_{40}$ | 53.6417  | 2.65485| 20.21   | <.0001  |
| $\omega_{50}$ | -29.6745 | 2.48673| -11.93  | <.0001  |
| $\omega_{60}$ | 66.66027 | 2.492  | 26.75   | <.0001  |
| $\omega_{70}$ | 25.64763 | 2.70163| 9.36    | <.0001  |

Table 4 shows that all parameters are significant. The white noise tests results are shown in Table 5 with all lags having a P value greater than 0.05, which means the residuals are already white noise. There are 2 intervention models that meet the significance of the parameters, namely the intervention model with ARIMA ([7], 1, 0) and ([4, 5], 1, 0), then the 2 models are used to model out-of-sample data. The best model is chosen based on the comparison of AIC values in in-sample data and RMSE values in out-of-sample data which can be seen in Table 6.

Table 5. White noise test for ARIMA ([4, 5], 1.0).

| Lag  | Chi-Square | DF | P value | Autocorrelations |
|------|------------|----|---------|------------------|
| 6    | 4.35       | 4  | 0.3613  | -0.029, 0.127, -0.095, -0.089, 0.102 |
| 12   | 11.58      | 10 | 0.3141  | -0.015, 0.073, 0.021, 0.112, 0.235, 0.013 |
| 18   | 17.21      | 16 | 0.3719  | 0.130, 0.086, -0.132, 0.039, 0.051, 0.092 |
| 24   | 23.86      | 22 | 0.3546  | 0.038, -0.001, 0.046, 0.075, -0.008, 0.216 |

Table 6. AIC and RMSE values for ARIMA ([7], 1, 0) and ARIMA ([4, 5], 1, 0).

| ARIMA       | Parameter significance | White Noise | AIC     | RMSE   |
|-------------|------------------------|-------------|---------|--------|
| ([7], 1, 0) | Yes                    | No          | 421.736 | 8.934  |
| ([4, 5], 1, 0)| Yes                  | Yes         | 408.854 | 6.689  |
The best multi input intervention model is a model with order $b=0$, $s=0$, and $r=0$ for explaining the impact of the first, second, ..., sixth step function intervention ($S_{1,t}$, $S_{2,t}$, ..., $S_{6,t}$), a model with order $b_2=0$, $s_2=0$, and $r_2=0$ for explaining the effect of the pulse function intervention ($P_t$) and ARIMA([4, 5],1,0) as the noise model. Hence, the best intervention model is written as

$$Y_t = 67.21091 S_{1,t}^{(25)} - 22.21177 P_t^{(40)} - 26.14200 S_{2,t}^{(41)}$$
$$+ 53.64147 S_{3,t}^{(45)} - 29.67454 S_{4,t}^{(52)} + 66.66027 S_{5,t}^{(59)}$$
$$+ 25.29949 S_{6,t}^{(81)} + \frac{1}{(1 - 0.29949 B^4 - 0.31229 B^5)(1-B)}a_t$$  \hspace{0.5cm} (16)

In addition to meeting the significance of the parameters and assumptions of white noise residuals, the model also has the smallest AIC value for in-sample data and the smallest RMSE in out-of-sample data.

Forecasting the number of lecturers in the $t$ period is influenced by the step function intervention in January 2013, May 2014, Sep 2014, Apr 2015, Nov 2015, and Sep 2017 and the pulse function intervention in April 2014. Besides forecasting is also influenced by the number of lecturers at 4, 5, and 6 months ago.

Figure 6. Forecast results on in-sample and out-sample data

Figure 6 show that the forecast data follows the actual data pattern. Next will be forecasting the number of lecturers using the intervention model with ARIMA ([4, 5, 7], 1, 0). Time series plot of actual and forecast data both in the in-sample, out-of-sample, and 2019 monthly data can be seen in Figure 7, and the forecast data shown at Table 7.

Figure 7. Forecast plot for out sample in 2019
Based on forecasting results show that the number of lecturers at ITS has a tendency to decrease each month due to the increasing number of retired lecturers, therefore it is necessary to increase the number of lecturers both PNS and non PNS lecturers each year which of course must be adjusted to the size of the student body owned by ITS. Changes in organizational management systems at ITS are proven to affect the number of lecturers at ITS and henceforth it is expected that the model produced in this study can explain how much influence organizational changes at ITS on changes in human resources in it.

Table 7. Forecast data for out sample 2019.

| Month     | Year | Forecast | Lower Bound | Upper Bound |
|-----------|------|----------|-------------|-------------|
| January   | 2019 | 987      | 980         | 994         |
| February  | 2019 | 988      | 979         | 998         |
| March     | 2019 | 980      | 968         | 992         |
| April     | 2019 | 975      | 961         | 989         |
| May       | 2019 | 977      | 960         | 993         |
| June      | 2019 | 978      | 958         | 998         |
| July      | 2019 | 975      | 952         | 998         |
| August    | 2019 | 971      | 946         | 996         |
| September | 2019 | 971      | 942         | 999         |
| October   | 2019 | 971      | 940         | 1003        |
| November  | 2019 | 970      | 936         | 1005        |
| December  | 2019 | 968      | 931         | 1005        |

5. Conclusion
The best Multi Input Intervention Model produced by this study is ARIMA ([4, 5] 1, 0), where forecasting the number of lecturers in the t-period is influenced by step function interventions in January 2013, May 2014, September 2014, April 2015, November 2015, and September 2017 and pulse function interventions in April 2014.

Besides forecasting is also influenced by the number of lecturers in the past 4, 5 and 6 months, so the number of lecturers at ITS has a tendency to decrease each month due to the increasing number of lecturers retired, therefore it is necessary to increase the number of lecturers both PNS and non PNS lecturers each year which of course must be adjusted to the size of the student body owned by ITS. Changes in organizational management systems at ITS are proven to affect the number of lecturers at ITS and henceforth it is expected that the model produced in this study can explain how much influence organizational changes at ITS on changes in human resources in it.

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7. References
[1] Box, G.E.P., Jenkins, G.M., and Reissel. G.C 1994 Time Series Analysis Forecasting and Control Englewood Cliffs: Prentice Hall.
[2] Enders, W., T. Sandler dan J. Cauley 1980 Assessing the impact of terrorist the warting policies An intervention time series approach Defence Peace Econ 2 1-18.
[3] Nuvitasari, E., Suhartono., and Wibowo, H.S 2009 Analysis of Multi Input Function Step and Pulse Interventions for Forecasting Tourist Visits to Indonesia Thesis Institut Teknologi Sepuluh November Surabaya.
[4] Republic of Indonesia Government Regulation Number 11 Year 2017 Concerning Management of Civil Servants.
[5] Rector Regulation Number 2 of 2017 concerning Personnel in the Institut Teknologi Sepuluh November
[6] Wei, W.W.S. 1990 Time Series Analysis Addison-Wesley California.
[7] Suhartono and Wahyuni, W 2002 Analysis of the Impact of Promotion and Price Increase on Fluctuations in Number of Customers and Credit Usage at PT. Telkom Divre V Forum Statistika dan Komputasi Special Edition of the National Statistics Seminar IPB Bogor