A dynamic model of Indonesian National Health Insurance participation types

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Abstract. In this paper we will discuss the dynamic model of Indonesian National Health Insurance (JKN) participation number. In this model, we divide JKN participation types into three categories: PBPU, PBI and PPU. The dynamic model is built using ordinary differential equation (ODE) system from a multiple states model that describes the transition of JKN participation types from time to time. The parameters of the model are estimated from data that is refined by an exponential smoothing time series method. As a result, the estimated number of JKN participation for each type until 2045 is obtained.

1. Introduction
The National Health Insurance Program (JKN) was launched on 1st January 2014 by the Indonesian government to ensure equitable and comprehensive health services for all Indonesian people. Its a government effort to achieve universal health coverage (UHC) in 2019, which includes promotive, preventive, curative, and rehabilitative services organized by the Health Social Security Organizing Agency (BPJS Kesehatan).

BPJS Kesehatan was expanding its participation progressively by targeting all Indonesian people to become JKN participants in 2019. The number of participants makes the JKN program one of the most extensive health insurance programs in the world that are managed through the single payer institution approach. As of the end of 2018, based on the sample data of BPJS Kesehatan [1] the number of JKN participants reached 200,259,147 people or 75.8 percent of the total of Indonesian population in 2018, and all participants were registered at 22,024 First Level Health Facilities (FKTP) scattered throughout Indonesia.

In this paper, JKN participants are divided into several types based on the source of funding, that is independent, government, and employee. The independent participant is that everyone who works or make an effort on his own or also called the PBPU (Workers Not Recipients). Participants funded by the government are referred to as PBI (Contribution Assistance Recipients), namely those who are poor. The employee or PPU (Wage Recipient Workers) is everyone who works.

Furthermore, we will discuss a dynamic model for the type of participation number of JKN. The dynamic model has properties change to time, and the structure of the phenomenon has a causal nature. Okoducu [2] models the human population by developing demographic models into information-based models. In a dynamic population model, it is not defined constant but is defined as a function of time. The model built in this study uses an ordinary differential equations system from a multi-state model that describes the transfer of JKN participant from
time to time. The parameters of the model are estimated from data refined by an exponential smoothing time series method introduced by Holt [3] and Winter [4] with seasonal adjustments being made to the linear trend model. Two types of adjustments are suggested-additive and multiplicative.

2. Construction of the multiple states model

The model used for the transition of JKN participation is a dynamic model with closed modeling, where there is no inflow or outflow from/into the system. Participation in this model is the proportion of PBI, PPU, and PBPU participants to the total population of Indonesia at the time. The population of Indonesia is obtained from SUPAS BPS 2015 [5], which is the projection of the population of Indonesia in 2015-2045. Next, each state is described, with W as a proportion non-JKN participants, X as a proportion of PBI, Y as a proportion of PPU, and Z as a proportion of PBPU. The parameter $\mu_{ij}$ states the rate of transition from $i$ status to $j$ assuming that there is no transition of status from PPU and PBPU to PBI or from each PBI, PPU, and PBPU to Non-JKN and the sum of $W, X, Y$ and $Z$ is equal to one.

The above model has a system of differential equations as follows

$$\frac{dW(t)}{dt} = (-\mu_{WY} W(t) - \mu_{WX} W(t) - \mu_{WZ} W(t))$$

$$\frac{dX(t)}{dt} = (-\mu_{XY} X(t) - \mu_{XZ} X(t)) + \mu_{WX} W(t)$$

$$\frac{dY(t)}{dt} = \mu_{WY} W(t) + \mu_{XY} X(t)$$

$$\frac{dZ(t)}{dt} = \mu_{WZ} W(t) + \mu_{XZ} X(t).$$
where \(0 \leq X(t), Y(t), W(t), Z(t) \leq 1\). Solution of the equation above are as follows

\[
W(t) = \frac{-C_1e^{-t(\alpha X + \mu W X + \mu W Y + \mu W Z)}(\mu W X + \mu W Y + \mu W Z - \mu W X \mu W Z - \mu W Y \mu W X - \mu W Z \mu W Y - \mu W Z \mu W Y + (\mu W Z)^2)}{\mu W X \mu W Z + \mu W Y \mu W Z - \mu W X \mu W Z - \mu W Y \mu W Y - \mu W Z \mu W Y - \mu W Z \mu W Z + (\mu W Z)^2}
\]

\[
X(t) = \frac{C_1\mu W X e^{-t(\alpha X + \mu W X + \mu W Y) \mu W X + \mu W Y + \mu W Z - \mu W X \mu W Z - \mu W Y \mu W X - \mu W Z \mu W Y - \mu W Z \mu W Y + (\mu W Z)^2}}{\mu W X \mu W Z + \mu W Y \mu W Z - \mu W X \mu W Z - \mu W Y \mu W Y - \mu W Z \mu W Y - \mu W Z \mu W Z + (\mu W Z)^2} - \frac{C_4 e^{-t(\beta Y + \mu W X) \mu W X + \mu W Y + \mu W Z - \mu W X \mu W Z - \mu W Y \mu W X - \mu W Z \mu W Y - \mu W Z \mu W Y + (\mu W Z)^2}}{\mu W X \mu W Z + \mu W Y \mu W Z - \mu W X \mu W Z - \mu W Y \mu W Y - \mu W Z \mu W Y - \mu W Z \mu W Z + (\mu W Z)^2}
\]

\[
Y(t) = C_2 + \frac{C_4 \mu W Y e^{-t(\beta X + \mu W X) \mu W X + \mu W Y + \mu W Z - \mu W X \mu W Z - \mu W Y \mu W X - \mu W Z \mu W Y - \mu W Z \mu W Y + (\mu W Z)^2}}{\mu W X \mu W Z + \mu W Y \mu W Z - \mu W X \mu W Z - \mu W Y \mu W Y - \mu W Z \mu W Y - \mu W Z \mu W Z + (\mu W Z)^2}
\]

\[
Z(t) = C_3 + \frac{C_4 e^{-t(\gamma X + \mu W X) \mu W X + \mu W Y + \mu W Z - \mu W X \mu W Z - \mu W Y \mu W X - \mu W Z \mu W Y - \mu W Z \mu W Y + (\mu W Z)^2}}{\mu W X \mu W Z + \mu W Y \mu W Z - \mu W X \mu W Z - \mu W Y \mu W Y - \mu W Z \mu W Y - \mu W Z \mu W Z + (\mu W Z)^2}
\]

where \(\mu^{ij} \geq 0\) is parameter for state \(i\) to state \(j\).

### 3. Time Series Model

The data used [1] is a monthly time series. Before modeling, data will be decomposed into three main components, i.e. trend, seasonal, and irregular. When there is a trend in the data, it can be used the Holt-Winters exponential smoothing method with two parameters (also called double exponential smoothing). In Holt-Winters two parameters, the parameter \(\alpha\) is a parameter in smoothing the level or average of the data while the parameter \(\beta\) is a parameter for trend smoothing. With the exponential smoothing formula as follows:

\[S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + T_{t-1}) \quad , 0 < \alpha < 1 \quad (1)\]

\[T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1} \quad , 0 < \beta < 1 \quad (2)\]

If the data contains seasonal random components, can use the Holt-Winter smoothing method for three parameters, with \(\alpha\) for smoothing levels, \(\beta\) for smoothing trends, and \(\gamma\) for seasonal components. There are two models of Holt Winter, namely multiplicative models and additive models. In the multiplication model, it is assumed that the time series data can be represented by the model:

\[X_t = (\beta_1 + \beta_2 t)S_t + \varepsilon_t \quad (3)\]

With \(\beta_1\) as a fixed component of time series, \(\beta_2\) as a linear trend component, \(S_t\) as a seasonal index component, and \(\varepsilon_t\) as an Irregular or random error component. Whereas in the additive model, time series data is assumed to be represented by the model

\[X_t = \beta_1 + \beta_2 t + S_t + \varepsilon_t \quad (4)\]

If the seasonal length is \(L\) period, the seasonal index is defined so that the total value is \(L\) in the multiplicative model

\[
\sum_{1 \leq t \leq L} S_t = L
\]
and the total value is 0 in the additive model

$$\sum_{1 \leq t \leq L} S_t = 0.$$  

The component trend $\beta_2$ can be removed from the model if the data does not contain a trend. The smoothing equation with the Holt Winter multiplicative model is given by the following equation:

1. **Smoothing Level**

   $$I_t = \alpha \frac{X_t}{I_{t-L}} + (1 - \alpha)(I_{t-1} + T_{t-1}), \quad (5)$$

2. **Smoothing Trend**

   $$T_t = \beta (S_t + S_{t-1}) + (1 - \beta)T_{t-1}, \quad (6)$$

3. **Smoothing Seasonal**

   $$S_t = \gamma \frac{X_t}{S_t} + (1 - \gamma)I_{t-L}, \quad (7)$$

where,

$$S_L = \frac{X_1 + X_2 + ... + X_L}{L},\quad T_L = \frac{1}{L} \left( \frac{X_{L+1} - X_1}{L} + \frac{X_{L+2} - X_2}{L} + ... + \frac{X_{L+L} - X_L}{L} \right),$$

$$I_1 = \frac{X_1}{S_L}, I_2 = \frac{X_2}{S_L}, ..., I_L = \frac{X_L}{S_L}.$$

The smoothing equation with the additive model is as follows:

1. **Smoothing level**

   $$I_t = \alpha (X_t - I_{t-L}) + (1 - \alpha)(I_{t-1} + T_{t-1}), \quad (8)$$

2. **Smoothing trend**

   $$T_t = \beta (S_t + S_{t-1}) + (1 - \beta)T_{t-1}, \quad (9)$$

3. **Smoothing seasonal**

   $$S_t = \gamma (X_t - S_t) + (1 - \gamma)I_{t-L}. \quad (10)$$

**4. Discussion**

The data from [1] of each participant of PBI, PPU, and PBPU plotted as in Figure 2, 3, and 4. From the data, it can be seen that the data has a trend component. For more details, the data is decomposed to see the trend and season components with the additive model. The results of decompose with additives in each participation of PBI, PPU, and PBPU can be seen in Figure 5, 6, and 7. It saw that PBI, PPU, and PBPU data has a trend and is seasonal. Next, the data will be smoothed using triple Holt-Winter.
Figure 2. Plot of PBI.

Figure 3. Plot of PPU.

Figure 4. Plot of PBPU.

Figure 5. Decomposition of PBI.

Figure 6. Decomposition of PPU.

Figure 7. Decomposition of PBPU.

Table 1. SSE value of Additive and Multiplicative

| Participation type | Additive       | Multiplicative |
|--------------------|----------------|----------------|
| PBI                | $4.557528 \times 10^{13}$ | $4.587635 \times 10^{13}$ |
| PPU                | $5.346264 \times 10^{13}$ | $7.865527 \times 10^{13}$ |
| PBPU               | $3.909056 \times 10^{13}$ | $5.158724 \times 10^{13}$ |

From Table 1, it can be seen that the seasonal model of Holt-Winters additive has a smaller SSE value so that it is a better model for smoothing the data of PBI, PPU, and PBPU. After
the time series data are modeling with Holt-Winter, the data obtained are smooth on each participation type. The results of the data plot can be seen from Figure 8 to Figure 10.

Furthermore, parameter estimation is obtained from data resulting from Holt-Winter time series model. From the data, it can be determined the initial value for $t = 0$, so

$$W(0) = 0.513953,$$
$$X(0) = 0.363534,$$
$$Y(0) = 0.100315,$$
$$Z(0) = 0.022199.$$

With those initial values, we obtained the following parameters for the ODE system:

$$\mu^{WX} = 0.004679170789608,$$
$$\mu^{WY} = 0.005903001992840,$$
$$\mu^{WZ} = 0.00239310062461,$$
$$\mu^{XY} = 0.000000000000000,$$
$$\mu^{XZ} = 0.00000003107384,$$
and

\[ C_1 = -0.089763, \]
\[ C_2 = 0.336939, \]
\[ C_3 = 0.663061, \]
\[ C_4 = -0.551098. \]

Finally, we have data prediction for each type of JKN participation from 2015 to 2045 with dynamic models.

![Data prediction for each type of JKN participation from 2015 to 2045](image)

**Figure 11.** Data prediction for each type of JKN participation from 2015 to 2045

5. **Conclusion**

Based on the explanation in the study and discussion above, we use the Holt-Winters method to eliminate irregular effects from data. Furthermore, from data that has been refined, estimations are carried out with a dynamic model to obtain participant estimates for each type of participation. From here we get the number of Non-JKN decays or close to zero in 2045. Then PBI, PPU, and PBPU participants go up to the specific point. From this result, it can be estimated that JKN membership will reach almost the entire population of Indonesia in the year 2040-2045 with each type of participation will be suitable for a certain amount.

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