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# THE IMPLEMENTATION OF FINITE-STATES CONTINUOUS TIME MARKOV CHAIN ON DAILY CASES OF COVID-19 IN BANDUNG

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## ABSTRACT

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*Continuous-Time Markov Chain;*
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*Markov chain is a stochastic process to describe a phenomenon in the future based on a previous state. In practice, Markov chains are distinguished by time into two, namely discrete-time Markov chain and continuous-time Markov Chain. This research will discuss the continuous-time Markov chain with finite-state. COVID-19 phenomena can describe and predict using the continuous-time Markov chain. Authors use the data daily cases of COVID-19 in Greater Bandung, including Bandung City, Bandung District, West Bandung District, Cimahi City and Sumedang District. Used data came from simulated data of daily cases of COVID-19 in Greater Bandung from August, 2020 until November 14, 2021 that recorded through the website COVID-19 of West Java. In terms of describing and predicted the COVID-19 phenomenon in Greater Bandung for long-term probability, authors use stationary distribution and limit distribution. COVID-19 phenomenon is described into two states: state 0 (lower than average of data) and state 1 (higher than average of data). The result of continuous-time Markov chain with finite-state shows that the probability of the daily cases of COVID-19 for five locations in Greater Bandung is state 0 have a larger probability than state 1. It means that COVID-19 in Greater Bandung over thlong termrm will decrease*



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# 1. INTRODUCTION

Since its first appearance on December 2019 in Wuhan, China, the Covid-19 pandemic has spread and developed into several virus variants that have become endemic in various countries in less than a year. The latest one is the AY.4.2 variant which has spread to 42 countries. Reports say that the AY.4.2 variant has entered Malaysia which is detected after the arrival of several students from the UK [1]. Referring to Indonesia, the first confirmed cases of COVID-19 appeared on March 2nd, 2020 [2].

In case of confirmed cases, another report stated that active cases of COVID-19 in the world up to this date have reached 19,824,086 cases on November 20th, 2021 [3]. In case of West Java region, total of confirmed active cases on November 24th, 2021, was 707.403 cases [4].

The COVID-19 phenomenon presents a challenge for researchers to study and analyze the long-term situation. Researchers have introduced many methods and methods to predict COVID-19. One method that has developed a lot is the Markov chain method. Markov chain is a method used to predict the probability of future events based on past events [5]. Markov chain is divided into two concerning time: discrete-time Markov chain and continuous-time Markov chain. The application of discrete-time Markov chains is used to predict discrete-time phenomena, including forecasting non-food expenditures for the people of Tulang Bawang Regency [6], indicating rain events in Bandung City [7], forecasting the increase in COVID-19 patients in Indonesia [8], forecasting the number of graduates and the graduation predicate of FMIPA UNTAN students [9], calculation of life insurance premiums for heart patients in West Kalimantan [10] and the application of the hidden Markov model in predicting rice prices [11]. On the other hand, the application of continuous-time Markov chains is widely applied in simulations of the Epidemic Model, including the search for a stationary distribution in three compartments [12]–[14], the application of the Autoregressive Distributed Lag (AGL) model to describe disease progression [15], a model SIR epidemic represented by finite Markov jump [16], [17], evolutionary model of the number of COVID-19 sick individuals with four conditions [18], and deterministic and stochastic models in the SEIR model [19], [20].

The research gap is that there is no continuous time Markov chain forecasting using finite states and stationary distribution calculations. Stationary distribution is needed to see the COVID-19 phenomenon in the future in the long term. Related to the confirmed active case of COVID-19, we can define several state spaces to observe the movement between states that can occur cyclically. After determining all states, we used finite-states continuous-time Markov chain based on the predetermined state to analyze transitions between states, distribution limits, and stationary distributions, which will be explained further in this paper.

Based on the background above, we focused on how we predict confirmed COVID-19 cases in five different regions in Greater Bandung, West Java using finite-states continuous-time Markov chain, especially with distribution limits and stationary distribution. The objective is to estimate confirmed active cases in the future, which can help to make decisions based on the estimation we have obtained.

# 2. RESEARCH METHODS

In this research, there is a theoretical basis, namely the continuous-time Markov chain and the research steps, which are explained as follows:

## 2.1 Continuous-Time Markov Chain

We started our discussion with the following statements [21]: The continuous-time Markov chain $X(t), t \geq 0$ is defined by the jump chain and the set of holding-time parameters $\lambda_i$. The jump chain consists of a countable set of states $S \subset \{0,1,2,\cdots\}$ along with transition probability $p_{ij}$. Assumed 3 conditions:

1. $p_{ii} = 0$ for all states $i \in S$,
2. If $X(t) = i$, the time until the state changes form exponential $EXP(\lambda_i)$ distribution,
3. If $X(t) = i$, the next state will be $j$ with probability index $p_{ij}$. [21]

Therefore, we have the following definition [22]: $X(t), t \geq 0$ is continuous-time stochastic process with states space $i = 0,1,2,\cdots$, unless otherwise specified. If $P\{X(t) = x | X(t_1) = x_1, X(t_2) = x_2, \cdots, X(t_n) = x_n\} = P\{X(t) = x | X(t_n) = x_n\}$, then for all $0 < t_1 < t_2 < \cdots < t_n < t$, this process is called a *continuous-time Markov chain*. For any $s, t \geq 0$, we obtain $P\{X(t+s) = j | X(s) = i\} = P_{ij}(t)$ and that is transition probability where we assume that $P_{ij}(t)$ is independent of time (*stationary or homogeneous*).

Let us have states space is $1,2,3,\cdots,m$. With the definition above, we can obtain transition probability matrix $P(t)$ that is

$$P(t) = \begin{bmatrix} p_{11}(t) & p_{12}(t) & \cdots & p_{1m}(t) \\ p_{21}(t) & p_{22}(t) & \cdots & p_{2m}(t) \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1}(t) & p_{m2}(t) & \cdots & p_{mm}(t) \end{bmatrix} \quad (1)$$

where $P(t)$ have to satisfy the properties below **[21]**:

1. $P(0) = I$
2. $\sum_{j \in S} p_{ij}(t) = 1, \forall t \geq 0$
3. $\forall s, t \geq 0, P(s+t) = P(s)P(t)$.

In this part, we consider that the stationary transition probability $P_{ij}(t) = P\{X(t) = j | X(0) = i\}$ for continuous-time Markov chain $X(t), t \geq 0$ with finite states space $i = 0,1,2,\cdots,N$.We can see that $P_{ij}(t)$ have to satisfy the properties below **[22]**:

1. $P_{ij}(t) \geq 0$
2. $\sum_{j=0}^{N} P_{ij}(t) = 1\,; i,j = 0,1,2,\cdots,N$
3. $P_{ij}(t+s) = \sum_{k=0}^{N} P_{ik}(t) P_{kj}(s)\,; i,j = 0,1,2,\cdots,N$
4. $\lim_{t \to 0} P_{ij}(t) = \begin{cases} 1, i = j \\ 0, i \neq j \end{cases}$

Property 3 above can be written into matrix form $P(t+s) = P(t)P(s)$ where $P(0) = I$ and $P(t) = \left[P_{ij}(t)\right]_{i,j=0}^{N}$ **[22]**.

Now we assume time interval $h > 0$ and $\lim_{h \to 0} \frac{P_{ij}(h)}{h} = a_{ij}\,;\ i \neq j$. We also have the law of total probability: $P_{ii}(h) + \sum_{j=0}^{N} P_{ij}(h) = 1\,; i \neq j$. Hence, we define $a_i = \lim_{h \to 0} \frac{1 - P_{ii}(h)}{h} = \sum_{j=0}^{N} a_{ij}$ . *Infinitesimal generator* **A** represented as below **[22]**:

$$\mathbf{A} = \begin{bmatrix} -a_0 & a_{01} & \cdots & a_{0N} \\ a_{10} & -a_1 & \cdots & a_{0N} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N0} & a_{N1} & \cdots & -a_N \end{bmatrix} \quad (2)$$

with the entries are:

$$a_{ij} = \begin{cases} -\lambda_i\ ; & i = j \\ \lambda_i p_{ij}\ ; & i \neq j \end{cases} \quad (3)$$

Furthermore, we have to determine that Markov chain is *ergodic*. Since we have the interarrival times are *independent and distributed exponentially*, this problem was solved by following **Theorem [22]**: for finite-state Markov chain whose transitions are described by the infinitesimal generator **A**, when the process is in state $i$ $(i = 0,1,2,\cdots,N)$, the interarrival time to the next transition is independent and distributed exponentially with parameter $a_i$, where the probability of moving to the next stage $j$ $(j \neq i)$ is $a_{ij}/a_i$.

With this theorem, we can assume all states connected and communicate with each other resulting in Markov chain satisfied *irreducible* and *positive recurrent* properties that obtained from finite-state form. Markov chain also satisfied the *aperiodic* property. Hence, finite-state continuous-time Markov chain can be called as *ergodic*.

Related to the previous part, we have the following **Theorem [22]**: If all states communicate with each other for a finite-state Markov chain, there exist the limiting probabilities

$$\lim_{t \to \infty} P_{ij}(t) = P_j > 0 \quad (j = 0,1,2,\ldots,N) \quad (4)$$

which are independent of the initial state $i$. Let $\tilde{\pi} = [\tilde{\pi}_0 \quad \tilde{\pi}_1 \quad \cdots \quad \tilde{\pi}_N]$ be the stationary distribution vector of the Markov chain. Then $\tilde{\pi}$ is a unique and positive solution to

$$\tilde{\pi}\mathbf{A} = 0 \tag{5}$$

$$\sum_{j=0}^{N} \tilde{\pi}_j = 1\,. \tag{6}$$

### 2.2 Research Steps

In this paper, we used data on the number of confirmed positive cases for COVID-19 in Greater Bandung at five locations in order that are Bandung City, Bandung Regency, West Bandung Regency, Cimahi City, and Sumedang Regency from August 2, 2020, to November 14, 2021. This data was obtained on the Pikobar official website, which can be accessed at http://pikobar.jabarprov.go.id/. The work stage will be described as follows:

1. Collect and input research data. The data was obtained by downloading a file from Pikobar's official website, which was integrated in one file for 26 districts and cities in CSV format. We filter the data with Excel software to collect data in Bandung City, Bandung Regency, West Bandung Regency, Cimahi City, and Sumedang Regency only, which will become the research data. All collected data will be inputted into RStudio software in CSV format.
2. Determining states. The inputted data in RStudio will be classified using an *if-else* statement. The data was classified based on the mean of data, i.e., let $x_n$ be the $n$-th data entry and $\bar{x}$ be mean of the same data. If $x_n < \bar{x}$, $x_n$ is referred to as state 0 and if $x_n \geq \bar{x}$ is referred to as state 1. In this paper, we limit the state $N = 2$.
3. Calculating the transition probability matrix for the *jump chain*.
4. Represent interstate transition with a transition diagram. We use RStudio to depict the transition diagram from one state to another.
5. Determine parameters $\lambda_i = \lambda_0, \lambda_1$ with exponential distribution fitting in Matlab software.
6. Calculate the infinitesimal generator matrix $\mathbf{A}$ with $a_{ij}$ entries with the corresponding equation.
7. State the Markov chain is ergodic by the corresponding theorem.
8. Calculate distribution limiting and stationary distribution with the corresponding equation.

## 3. RESULTS AND DISCUSSION

### 3.1. Statistics Descriptive and Plot Data

Statistics descriptive of the data calculated using R Studio software which shown in **Table 1**.

**Table 1. Statistics Descriptive**

| Location | Bandung City | Bandung District | West Bandung District | Sumedang District | Cimahi City |
|---|---|---|---|---|---|
| **Min** | 0 | 0 | 0 | 0 | 0 |
| **1st Qu.** | 10 | 1 | 0 | 0 | 0 |
| **Median** | 48.5 | 14 | 2 | 0 | 3 |
| **Mean** | 78.43 | 61.88 | 17.86 | 8.311 | 21.73 |
| **3rd Qu.** | 88 | 78 | 13.75 | 4 | 21 |
| **Max** | 828 | 798 | 559 | 247 | 507 |

The data plot of the daily cases of COVID-19 in Greater Bandung at five locations is shown in **Figure 1**. and the data plot for each location is shown in **Figure 2**. Based on the plots data, COVID-19 phenomena shown for five locations in Greater Bandung have the same trend.

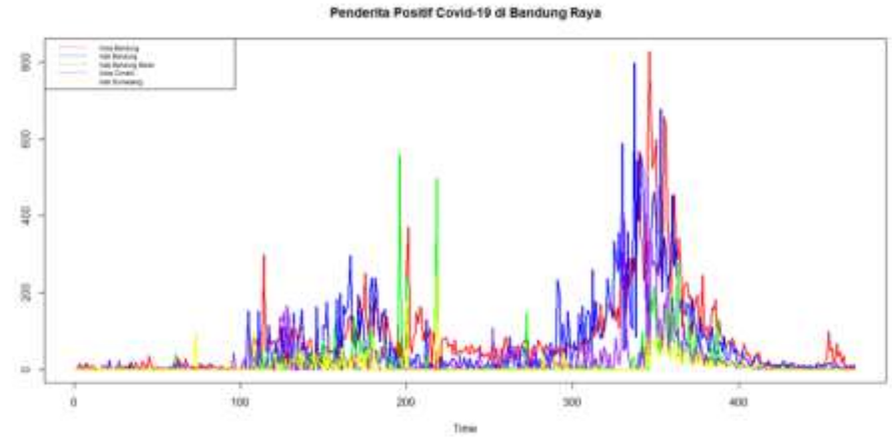


**Figure 1. Plot Data of The Daily Cases of COVID-19 in Greater Bandung**

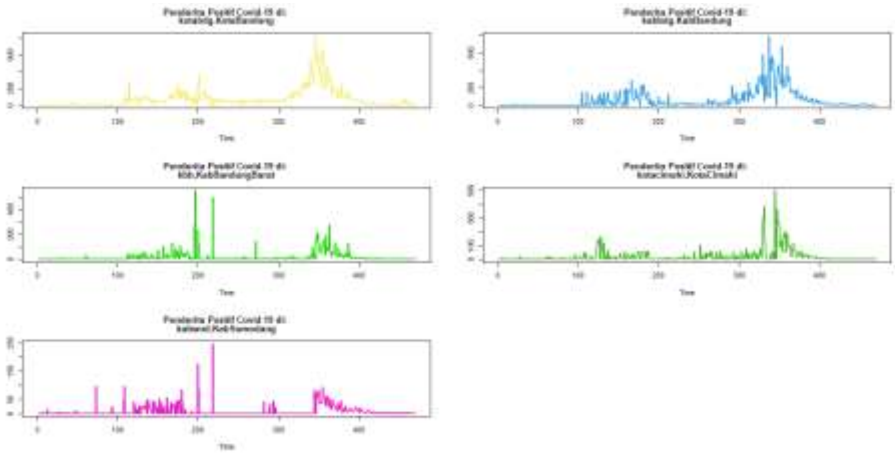

**Figure 2. Plot Data of The Daily Cases of COVID-19 for Each location**

## 3.2. Transition Probability Matrix for Jump Chain

Data on the daily cases of COVID-19 in Greater Bandung for each location is defined and classified following **Equation (1)**, by using RStudio software to calculate the transition probability matrix ($\mathbf{P}$). **Table 2** shows the result of transition probability matrix for five locations in Greater Bandung.

**Table 2. The Transition Probability Matrix for Five Locations**

| Location | The Transition Probability Matrix ($\mathbf{P}$) |
|---|---|
| **Bandung City** | $\begin{bmatrix} 0.909 & 0.091 \\ 0.214 & 0.786 \end{bmatrix}$ |
| **Bandung District** | $\begin{bmatrix} 0.896 & 0.104 \\ 0.261 & 0.739 \end{bmatrix}$ |
| **West Bandung District** | $\begin{bmatrix} 0.896 & 0.104 \\ 0.369 & 0.631 \end{bmatrix}$ |
| **Cimahi City** | $\begin{bmatrix} 0.847 & 0.153 \\ 0.470 & 0.530 \end{bmatrix}$ |
| **Sumedang District** | $\begin{bmatrix} 0.882 & 0.118 \\ 0.413 & 0.587 \end{bmatrix}$ |

To show the transition for each state, we can use the diagram transition. **Figure 3** shows the diagram transition in five locations by using RStudio.

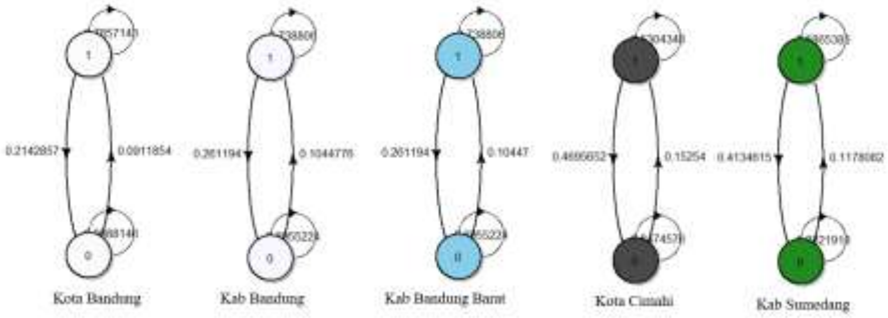


**Figure 3. Diagram Transition for Each location**

### 3.3. Calculate The Parameters for $\lambda_0, \lambda_1$

In the continuous-time Markov chain, there are parameters such as the time interval $t$ that occurs in a state. In this research, the time-lapse parameter of positive cases in state 0 denoted by $\boldsymbol{\lambda_0}$ and state 1 denoted by $\boldsymbol{\lambda_1}$. Furthermore, these parameters are calculated using Matlab software with an exponential distribution approach for each location. The result is shown in **Table 3** as follows:

**Table 3. The Parameter for $\lambda_0, \lambda_1$ for Each location in Greater Bandung**

| Variabel | $\lambda_0$ | $\lambda_1$ |
|---|---|---|
| **Bandung City** | 10.645 | 4.667 |
| **Bandung District** | 9.333 | 3.829 |
| **West Bandung District** | 9.410 | 2.710 |
| **Cimahi City** | 6.454 | 2.150 |
| **Sumedang District** | 8.318 | 2.418 |

### 3.4. Calculate The Infinitesimal Generator Matrix

By following **Equation (2)** and **Equation (3)**, we can calculate the infinitesimal matrix for each location as follows:

$$\mathbf{P} = \begin{bmatrix} 0.909 & 0.091 \\ 0.214 & 0.786 \end{bmatrix} \text{ obtained,}$$

$$a_{00} = -\lambda_0, a_{11} = -\lambda_1$$

$$a_{01} = \lambda_0 p_{01} = 0.091\lambda_0 \text{ , } a_{10} = \lambda_1 p_{10} = 0.214\lambda_1$$

So, the infinitesimal generator matrix **A** for Bandung city as follows:

$$\mathbf{A} = \begin{bmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{bmatrix} = \begin{bmatrix} -\lambda_0 & 0.091\lambda_0 \\ 0.214\lambda_1 & -\lambda_1 \end{bmatrix}$$

We use the same way for other locations. Next, we substitute the values of $\lambda_0$ and $\lambda_1$ for each location in **Table 3**. In simple terms, the results of the calculation for the infinitesimal generator matrix in five locations are shown in **Table 4**.

**Table 4. The Infinitesimal Generator Matrix for Five Locations**

| Location | The Infinitesimal Generator Matrix (A) |
|---|---|
| **Bandung City** | $\begin{bmatrix} -\lambda_0 & 0.091\lambda_0 \\ 0.214\lambda_1 & -\lambda_1 \end{bmatrix} = \begin{bmatrix} -10.645 & 0.968 \\ 0.998 & -4.667 \end{bmatrix}$ |
| **Bandung District** | $\begin{bmatrix} -\lambda_0 & 0.104\lambda_0 \\ 0.261\lambda_1 & -\lambda_1 \end{bmatrix} = \begin{bmatrix} -9.333 & 0.970 \\ 0.999 & -3.829 \end{bmatrix}$ |
| **West Bandung District** | $\begin{bmatrix} -\lambda_0 & 0.104\lambda_0 \\ 0.369\lambda_1 & -\lambda_1 \end{bmatrix} = \begin{bmatrix} -9.410 & 0.978 \\ 0.999 & -2.170 \end{bmatrix}$ |
| **Cimahi City** | $\begin{bmatrix} -\lambda_0 & 0.153\lambda_0 \\ 0.470\lambda_1 & -\lambda_1 \end{bmatrix} = \begin{bmatrix} -6.454 & 0.987 \\ 1.010 & -2.150 \end{bmatrix}$ |
| **Sumedang District** | $\begin{bmatrix} -\lambda_0 & 0.118\lambda_0 \\ 0.413\lambda_1 & -\lambda_1 \end{bmatrix} = \begin{bmatrix} -8.318 & 0.981 \\ 0.998 & -2.418 \end{bmatrix}$ |

### 3.5. Calculate The Stationary Distributions

Continuous-time Markov chain has been proven to be an ergodic Markov chain based on Theorem. So we can calculate long-term probability using stationary distribution. To calculate the stationary distribution for each location, it's necessary to find a solution of $\tilde{\pi} = [\tilde{\pi}_0\ \tilde{\pi}_1]$ in **Table 5** as follows:

**Table 5. Stationary Distribution for Five Locations**

| Location | Equations | Stationary Distribution |
|---|---|---|
| **Bandung City** | $\tilde{\pi}_0 = 0.909\tilde{\pi}_0 + 0.214\tilde{\pi}_1$ | $\tilde{\pi}_0 = 0.701$ |
| | $\tilde{\pi}_1 = 0.091\tilde{\pi}_0 + 0.786\tilde{\pi}_1$ | $\tilde{\pi}_1 = 0.299$ |
| | $\tilde{\pi}_0 + \tilde{\pi}_1 = 1$ | |
| **Bandung District** | $\tilde{\pi}_0 = 0.896\tilde{\pi}_0 + 0.261\tilde{\pi}_1$ | $\tilde{\pi}_0 = 0.715$ |
| | $\tilde{\pi}_1 = 0.104\tilde{\pi}_0 + 0.739\tilde{\pi}_1$ | $\tilde{\pi}_1 = 0.285$ |
| | $\tilde{\pi}_0 + \tilde{\pi}_1 = 1$ | |
| **West Bandung District** | $\tilde{\pi}_0 = 0.896\tilde{\pi}_0 + 0.369\tilde{\pi}_1$ | $\tilde{\pi}_0 = 0.780$ |
| | $\tilde{\pi}_1 = 0.104\tilde{\pi}_0 + 0.631\tilde{\pi}_1$ | $\tilde{\pi}_1 = 0.220$ |
| | $\tilde{\pi}_0 + \tilde{\pi}_1 = 1$ | |
| **Cimahi City** | $\tilde{\pi}_0 = 0.847\tilde{\pi}_0 + 0.470\tilde{\pi}_1$ | $\tilde{\pi}_0 = 0.754$ |
| | $\tilde{\pi}_1 = 0.153\tilde{\pi}_0 + 0.530\tilde{\pi}_1$ | $\tilde{\pi}_1 = 0.246$ |
| | $\tilde{\pi}_0 + \tilde{\pi}_1 = 1$ | |
| **Sumedang District** | $\tilde{\pi}_0 = 0.882\tilde{\pi}_0 + 0.413\tilde{\pi}_1$ | $\tilde{\pi}_0 = 0.778$ |
| | $\tilde{\pi}_1 = 0.118\tilde{\pi}_0 + 0.587\tilde{\pi}_1$ | $\tilde{\pi}_1 = 0.222$ |
| | $\tilde{\pi}_0 + \tilde{\pi}_1 = 1$ | |

### 3.6. Calculate The Limit Distributions

After obtaining the stationary distribution, we can calculate the limit distribution for each state using the following equation:

$$\pi_j = \frac{\frac{\tilde{\pi}_j}{\lambda_j}}{\sum_{k \in S} \frac{\tilde{\pi}_k}{\lambda_k}} \qquad S = 0,1,\dots,N$$

In this research, we use state 0 and state 1. So, the limit distributions calculate using this equation:

$$\pi_0 = \frac{\frac{\tilde{\pi}_0}{\lambda_0}}{\frac{\tilde{\pi}_0}{\lambda_0} + \frac{\tilde{\pi}_1}{\lambda_1}}, \pi_1 = \frac{\frac{\tilde{\pi}_1}{\lambda_1}}{\frac{\tilde{\pi}_0}{\lambda_0} + \frac{\tilde{\pi}_1}{\lambda_1}}$$

The calculation of the limit distribution for each location shown in **Table 6** as follow:

**Table 6. Stationary Distribution for Five Locations**

| Location | $\pi_0$ | $\pi_1$ | Limit Distribution ($\pi$) |
|---|---|---|---|
| Bandung City | $\pi_0 = \frac{\frac{0.701}{10.645}}{\frac{0.701}{10.465}+\frac{0.299}{4.667}}$ | $\pi_1 = \frac{\frac{0.299}{4.667}}{\frac{0.701}{10.465}+\frac{0.299}{4.667}}$ | $\pi = [0.508 \quad 0.492]$ |
| Bandung District | $\pi_0 = \frac{\frac{0.715}{9.333}}{\frac{0.715}{9.333}+\frac{0.285}{3.829}}$ | $\pi_1 = \frac{\frac{0.285}{3.829}}{\frac{0.715}{9.333}+\frac{0.285}{3.829}}$ | $\pi = [0.507 \quad 0.493]$ |
| West Bandung District | $\pi_0 = \frac{\frac{0.780}{9.410}}{\frac{0.780}{9.410}+\frac{0.220}{2.710}}$ | $\pi_1 = \frac{\frac{0.220}{2.710}}{\frac{0.780}{9.410}+\frac{0.220}{2.710}}$ | $\pi = [0.505 \quad 0.495]$ |
| Cimahi City | $\pi_0 = \frac{\frac{0.754}{6.454}}{\frac{0.754}{6.454}+\frac{0.246}{2.150}}$ | $\pi_1 = \frac{\frac{0.246}{2.150}}{\frac{0.754}{6.454}+\frac{0.246}{2.150}}$ | $\pi = [0.506 \quad 0.494]$ |
| Sumedang District | $\pi_0 = \frac{\frac{0.778}{8.318}}{\frac{0.778}{8.318}+\frac{0.222}{2.418}}$ | $\pi_1 = \frac{\frac{0.222}{2.418}}{\frac{0.778}{8.318}+\frac{0.222}{2.418}}$ | $\pi = [0.509 \quad 0.491]$ |

## 4. CONCLUSIONS

Based on the calculation for predicting the long-term probability of the daily cases of COVID-19 in Greater Bandung using stationary distribution and limit distribution with finite-state continuous-time Markov chain method, we know that the probability of state 0 is larger than state 1. It means that people who are confirmed positive for COVID-19 in Greater Bandung will be decreased than the average data for five locations such as Bandung City, Bandung District, West Bandung District, Cimahi City, and Sumedang District.

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