Available online at http://scik.org
Commun. Math. Biol. Neurosci. 2023, 2023:34
https://doi.org/10.28919/cmbn/7922
ISSN: 2052-2541

NETWORK CLUSTERING METHOD FOR PREVENTING THE SPREAD OF COVID-19 IN INDONESIAN SCHOOLS

MOKHAMMAD RIDWAN YUDHANEGARA*, KARUNIA EKA LESTARI

Mathematics Education Department, Universitas Singaperbangsa Karawang, Karawang 41361, Indonesia

Abstract: The COVID-19 pandemic has caused many problems, especially in education. The education issue will be difficult to overcome because Indonesia has a large population. A unique strategy is needed for each school to carry out learning to ensure the education process continues. Online learning has been implemented since the pandemic entered Indonesia. This paper proposes a new learning strategy for teachers and students through hybrid learning based on network clustering. The community network or community generated from network clustering provides information that the state of the environment is the large number of people who have COVID-19. If the sum of COVID-19 sufferers is too large, the students are advised to use online learning. The students are advised to apply offline learning when the sum of COVID-19 sufferers is insignificant. Based on the simulation, combining the hybrid learning model with the community network generated through network clustering effectively anticipates the next wave of the COVID-19 pandemic.

Keywords: community network; graph theory; multinomial distribution; hybrid learning.

2020 AMS Subject Classification: 92D30.

---

*Corresponding author
E-mail address: mridwan.yudhanegara@staff.unsika.ac.id
Received February 22, 2023

1. INTRODUCTION

Indonesia's population in August 2022 reached 275,361,267 people (www.bps.go.id). It is a formidable challenge for the Indonesian government to continue to anticipate the wave of the Coronavirus Desease (COVID-19) pandemic that may occur next time. Considering that Indonesia has an extensive area with a large population, if a pandemic occurs, it will decrease the quality of education. For this reason, unique learning strategies are needed to continue the educational process. In addition, research results show a relationship between learning strategies and student motivation [1]. A good learning strategy can increase student motivation.

Several studies report that learning with blended learning can overcome problems in education in schools. Ashraf et al. [2] reported that several studies on blended learning are very effective in overcoming educational problems, especially distance learning. Distance learning and face-to-face learning can be combined simultaneously through information and communication technology, namely, using software for online learning [3].

Blended learning is one of the most frequently used approaches to applying information and communication technology in education [4]. One of the effective blended learning models of learning for teachers and students is hybrid learning. *Hybrid learning* is a learning method that combines or combines online learning with face-to-face learning or offline learning [5].

Furthermore, students are arranged or set a schedule to enter the class and vice versa, learning from home online. Students continue to attend classes by using online learning methods. Then they will take turns with other students to have the same opportunity. Through this hybrid learning, it is hoped that it can overcome the limitations of distance learning or online learning. There are times when social interaction occurs when students come face to face with the teacher. For example, students meet teachers in class during the COVID-19 pandemic.

Online learning has been implemented since the pandemic entered Indonesia. It has caused many problems. The lack of social interaction between students and teachers leaves psychological problems. Stress is one of the effects caused by the learning system. So many parties want this online learning to end, especially with its dependence on devices to go online and the internet network. So, problems arise more quickly during learning than in face-to-face or offline learning. However, online and offline learning solutions can reduce stress for students.

The COVID-19 pandemic allows it to happen again. So, until now, there has yet to be a full face-to-face meeting in every region in Indonesia. In the end, the government implemented a limited offline learning policy. One of these policies is hybrid learning, combining online and offline learning.

Many papers report the benefits of the clustering method in research. The benefits of clustering include education [6] [7], item delivery [8], traffic density prediction [9], Etc. In this paper, the clustering method is used in education. The next problem is determining the group of students who do online learning and those who do offline learning. The solution offered in the study in this paper is to form a community. The community is an area of student groups in a network community. This community network is obtained from the results of network clustering. The network represents the map of the student's presence area. Through the school community network, it is easy to obtain information about the high or low conditions of people with COVID-19. The community also provides information on which students are in the area.

2. Materials and Methods

2.1 Network

Based on several references, a network is closely related to a graph, which is part of mathematics [10] [11], especially graph theory. Furthermore, the graph is defined in the definition below. The graph $\mathrm{G} = \mathrm{G}(\mathrm{V},\mathrm{E})$ is a set pair (V,E) with $\mathrm{V} = \{\mathrm{v}_1, \mathrm{v}_2, \cdots, \mathrm{v}_n\}$ called the set of vertices/nodes that are finite and non-empty, and $\mathrm{E} = \left\{e = \left(\mathrm{v}_i, \mathrm{v}_j\right): \mathrm{v}_i, \mathrm{v}_j \in \mathrm{V}, i \neq j\right\}$ is the set of pairs between two points called edges [12].

The graph is classified into connected graphs and unconnected graphs. This study focuses on connected graphs. A graph is connected if it only consists of one component [13]. This definition implies that a connected graph will have a path connecting a vertex to other vertices. Newman [10] defines a *network* as a connected graph. Furthermore, in this study, the network is represented as a simple graph, see Figure 4.

The focus of this study is related to problems in dynamic networks. Dynamic networks experience changes in structure and weight from time to time [14]. A network $G(g_e) = (\mathrm{V}, \mathrm{E})$ with edge weight g_e is called a weighted network if each edge is mapped to a positive real number and reaches the edge weight [13].

In this case, the network weight is the number of people with COVID-19 in the area that connects the nodes. The node is the location or address of the student's residence. The network's weight is dynamic because, along with the information, there are many people with COVID-19.

Network clustering in graph theory is a graph partition that divides a graph into more than one subgraph [15] [11]. This partition divides $\mathrm{G}(g_e)$ into p subsets of independent parts, and it is determined by considering the minimum number of side weights between subnets. Mathematically, to get p partition $(\mathrm{V}_1, \mathrm{V}_2, \dots, \mathrm{V}_p)$ from V that is

(1) $$\cup_{i=1}^{p} \mathrm{V}_i = \mathrm{V}, \text{where } \mathrm{V}_i \cap \mathrm{V}_\mathrm{j} = \emptyset, i \neq j,$$

such that it is obtained

(2) $$\min \sum_{v_i \in \mathrm{V}_p, v_j \in \mathrm{V}_q, p \neq q} g_e.$$

Generally, a network can be partitioned into more than one subnet consisting of several subgroups with group members having similar characteristics. The group is a network community, in the future, referred to as a community.

2.2 Research Design

There are many algorithms for obtaining the community [10], but in this study, the algorithm is focused on the spectral bisection method. Community search using the spectral bisection method is based on the eigenvalues and eigenvectors of the Laplace matrix of a network [16] [17]. *Spectral* *bisection* is a clustering method that divides the network into two communities. The resulting community formation is based on the Fiedler vector of the Laplace matrix, which corresponds to the nodes on the network [18]. In this study, network clustering uses spectral bisection recursively through Algorithm 1 [17].

ALGORITHM 1. Spectral bisection recursively:

1) Get the matrix Laplace $\mathbf{L}_{\mathrm{G}}$ of $\mathrm{G}(g_e)$.
2) Get the Fiedler vector $\boldsymbol{\varphi}_2$ from the second smallest eigenvalue λ_2.
3) Calculate the median $\mathrm{me}_{\boldsymbol{\varphi}_2}$.
4) Find the community members by selecting $\mathrm{V}_1 = \{\mathrm{v_i} \in \mathrm{V}: \boldsymbol{\varphi}_{2_i} < \mathrm{me}_{\boldsymbol{\varphi}_2}\}$ and $\mathrm{V}_2 = \{\mathrm{v_i} \in \mathrm{V}: \boldsymbol{\varphi}_{2_i} > \mathrm{me}_{\boldsymbol{\varphi}_2}\}$.
5) Get the matrix Laplace of subnet $\mathrm{G}'(g_e)$.
6) Determine the community members according stage 2, stage 3, and stage 4.

2.3 Analyzing of Data

For the data, we used 65 students for simulation. The network represents a map of student locations or addresses in this case. The purpose of making a network is to facilitate the process of grouping students into several communities. We can create a community of the network by using the network clustering method. In communities with a high frequency of COVID-19 sufferers, students are advised to take online learning. Students are advised to take offline learning for communities with a low frequency of COVID-19 sufferers.

Hybrid learning is applied when a network experiences edge weight fluctuation. If the sum of network weights is too large, it is advisable to use online learning. If the sum of network weights is not large, it is advisable to apply offline learning. Furthermore, the hybrid learning strategy is illustrated in Figure 1.

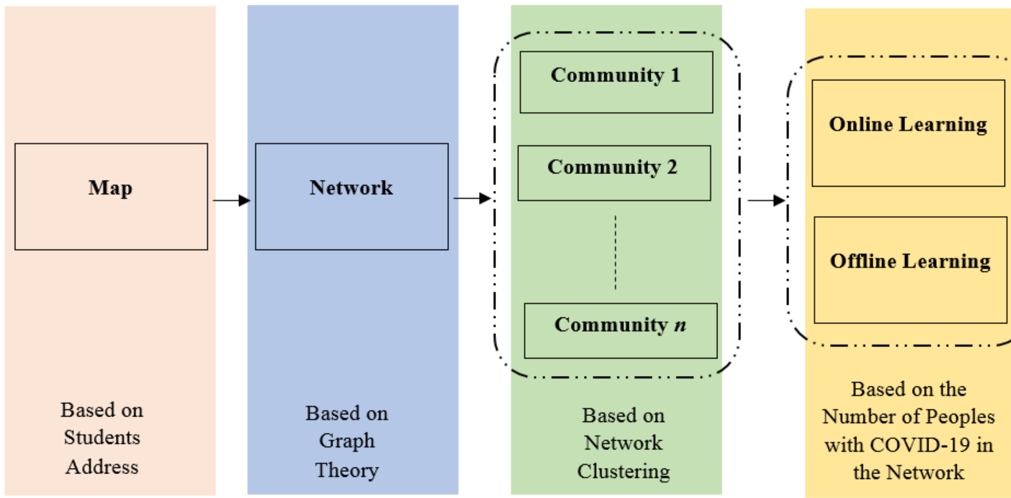

FIGURE 1. Hybrid learning strategy

2.4 Statstical Test

We use a multinomial distribution as a simulation. Because this distribution represents the number of events at a certain time. The test used is statistical which refers to Theorem 1 and Corollary 1 in Indratno et al. [9].

Theorem 1. *Let* $L_l(\boldsymbol{\theta}) = \prod_{t=1}^{l}\left(\frac{n!}{\prod_{i=1}^{m} x_{i,t}!}\prod_{i=1}^{m}\theta_i^{x_{i,t}}\right)$ *be a multinomial likelihood function, for* $n, m, l \gg 1,$ *then random variable* $log\, L_l(\boldsymbol{\theta})$ *has a normal distribution with mean* $\ddot{\mu} = \sum_{t=1}^{l}\sum_{i=1}^{m} x_{i,t}\, log\, \theta_i - \sum_{t=1}^{l}\sum_{i=1}^{m} log\, x_{i,t}! + \sum_{t=1}^{l} log\, n!,$ *and variance* $\ddot{\sigma}^2 = \frac{m}{(m-1)}\sum_{t=1}^{l}\sum_{i=1}^{m}\left(x_{i,t}\, log\, \theta_i - \frac{\sum_{i=1}^{m} x_{i,t}\, log\, \theta_i}{m}\right)^2 - \sum_{t=1}^{l}\sum_{i=1}^{m}\left(log\, x_{i,t}! - \frac{\sum_{i=1}^{m} log\, x_{i,t}!}{m}\right)^2.$

Corollary 1. *Let* $L_l(\boldsymbol{\theta}) = \prod_{t=1}^{l}\left(\frac{n!}{\prod_{i=1}^{m} x_{i,t}!}\prod_{i=1}^{m}\theta_i^{x_{i,t}}\right)$ *be a multinomial likelihood function, for* $n, m, l \gg 1,$ *then random variable* $\left(log\, L_l(\boldsymbol{\theta}) - \sum_{t=1}^{l} log\, n!\right)$ *has a normal distribution with mean* $\ddot{\ddot{\mu}} = \sum_{t=1}^{l}\sum_{i=1}^{m} x_{i,t}\, log\, \theta_i - \sum_{t=1}^{l}\sum_{i=1}^{m} log\, x_{i,t}!,$ *and variance* $\ddot{\ddot{\sigma}}^2 = \ddot{\sigma}^2.$

The multinomial goodness-of-fit test applies the following hypothesis test:
H_0: $\left(\log L_{l+1}(\boldsymbol{\theta}) - \sum_{t=1}^{l+1}\log n!\right)$ Follows a normal distribution with the mean $\ddot{\ddot{\mu}}$ and variance $\ddot{\ddot{\sigma}}^2$, The hypothesis test used is the Z statistical test with the formula

$$z_{statitical} = \frac{\left(\log L_{l+1}(\boldsymbol{\theta}) - \sum_{t=1}^{l+1}\log n!\right) - \ddot{\ddot{\mu}}}{\ddot{\ddot{\sigma}}}, \tag{3}$$

where $\log L_{l+1}(\boldsymbol{\theta}) - \sum_{t=1}^{l+1}\log n!$ is random variable under the assumption H_0 [9]. The decision-making criteria H_0 is not rejected when $-z_{\frac{\alpha}{2}} \leq z_{statitical} \leq z_{\frac{\alpha}{2}}$, H_0 is rejected if $z_{statitical} < -z_{\frac{\alpha}{2}}$ or $z_{\frac{\alpha}{2}} < z_{statitical}$.

The margin of error for the confidence interval $(1-\alpha)$ in statistics on Equation (3) can be determined through Theorem 2 [9]. This theorem provides a formula for the error tolerance limit for the population average at the confidence interval $(1-\alpha)$.

Theorem 2. *Let* $\left(\log L_{l+1}(\boldsymbol{\theta}) - \sum_{t=1}^{l+1}\log n!\right) \sim N(\ddot{\mu}_l, \ddot{\sigma}_l^2)$ *be a random variable, where* $\ddot{\mu}_l = \sum_{t=1}^{l}\sum_{i=1}^{m} x_{i,t}\log\theta_i - \sum_{t=1}^{l}\sum_{i=1}^{m}\log x_{i,t}!$ *and* $\ddot{\sigma}_l^2 = \frac{m}{(m-1)}\sum_{t=1}^{l}\sum_{i=1}^{m}\left(x_{i,t}\log\theta_i - \frac{\sum_{i=1}^{m} x_{i,t}\log\theta_i}{m}\right)^2 - \sum_{t=1}^{l}\sum_{i=1}^{m}\left(\log x_{i,t}! - \frac{\sum_{i=1}^{m}\log x_{i,t}!}{m}\right)^2$, *then margin of error* (ε) *for the confidence interval* $(1-\alpha)$ *is* $\varepsilon = z_{\left(1-\frac{\alpha}{2}\right)}\ddot{\sigma}_l$.

For testing data based on historical data are presented in Algorithm 2 [9].
ALGORITHM 2. Data testing:

1) Input $(\ddot{\mu}, \ddot{\sigma}^2)$
2) Find the estimated parameter $(\boldsymbol{\theta})$ of the predictive distribution (based on historical data).
3) Enter the new observed value under the assumption H_0.
4) Perform the Z statistical test at the significance level α. H_0 is not rejected, it means that $(l+1) \sim N(\ddot{\mu}, \ddot{\sigma}^2)$.
5) Update the parameters $(\boldsymbol{\theta})$ and $(\ddot{\mu}, \ddot{\sigma}^2)$ if H_0 is rejected.
6) Return to step 3.

3. RESULTS AND DISCUSSION

We have 65 students' locations mapped on the map; see Table 1 and Figure 4. Then, we take a map from google maps (https://www.google.com/maps/@-6.9159506,107.6513172,16z) based on the addresses or areas of all students; the results are shown in Figure 2 and Figure 3.

TABLE 1. Students' location in network

Locations	Students	Locations	Students
Node 0	Subject 1, Subject 2, Subject 3	Node 10	Subject 38, Subject 39, Subject 40
Node 1	Subject 4, Subject 5, Subject 6	Node 11	Subject 41, Subject 42, Subject 43
Node 2	Subject 7, Subject 8, Subject 9, Subject 10	Node 12	Subject 44, Subject 45, Subject 46
Node 3	Subject 11, Subject 12, Subject 13, Subject 14	Node 13	Subject 47, Subject 48, Subject 49
Node 4	Subject 15, Subject 16, Subject 17, Subject 18	Node 14	Subject 50, Subject 51, Subject 52
Node 5	Subject 19, Subject 20, Subject 21, Subject 22	Node 15	Subject 53, Subject 54, Subject 55
Node 6	Subject 23, Subject 24, Subject 25, Subject 26	Node 16	Subject 56, Subject 57, Subject 58
Node 7	Subject 27, Subject 28, Subject 29, Subject 30	Node 17	Subject 59, Subject 60, Subject 61
Node 8	Subject 31, Subject 32, Subject 33	Node 18	Subject 62, Subject 63
Node 9	Subject 34, Subject 35, Subject 36, Subject 37	Node 19	Subject 64, Subject 65

The map with satellite mode is presented in Figure 2.

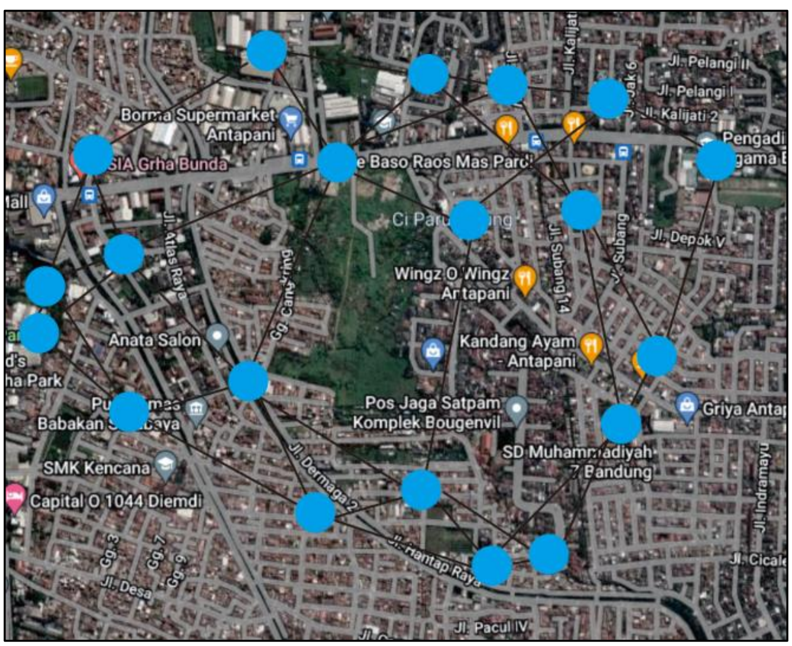

FIGURE 2. The map with satelite mode

The map with terrain mode is shown in Figure 3.

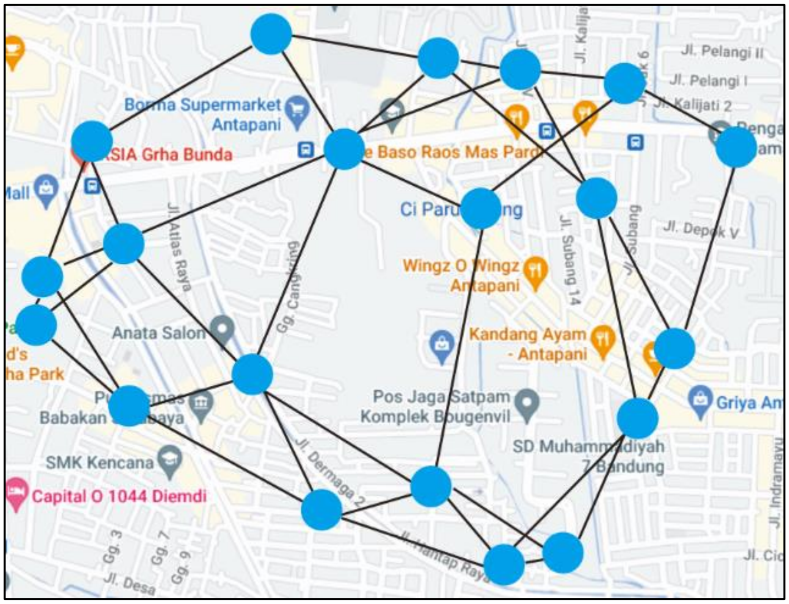

FIGURE 3. The map with terrain mode

The maps are already marked with nodes and edges. Based on the map, we get a network which is a connected graph; see Figure 4.

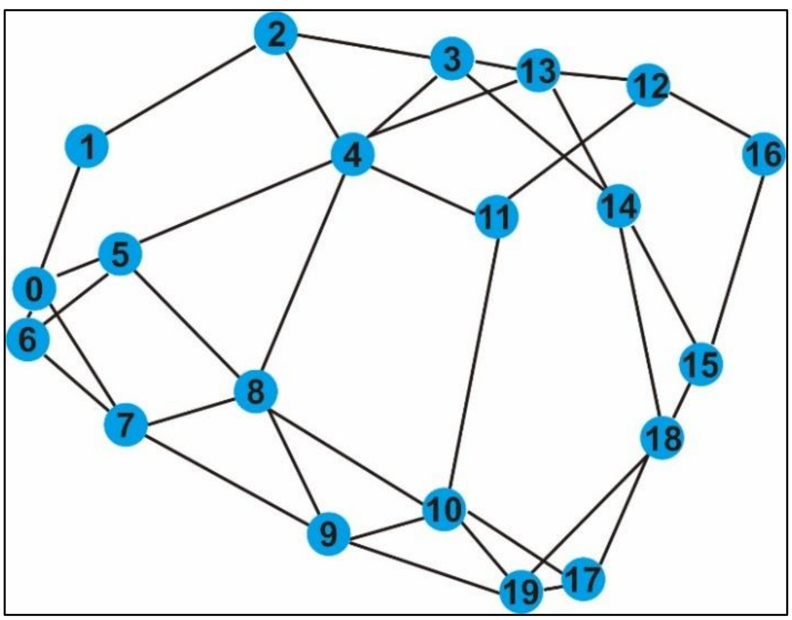

FIGURE 4. The network formed based on the map

Let $\mathbf{X}_t = \left[X_{1,t}\ X_{2,t} \ldots X_{m,t}\right]^T$ be a random vector representing the number of people with COVID-19 who are in each lane at time-t, where $X_{i,t}$ is a random variable that states the number of COVID-19 sufferers who are in the edge-i at time-t. Then, assuming $\mathbf{X}_t$ follows a multinomial distribution with the probability parameter θ. Furthermore, it is given the total of 2,500 events with 38 categories. In this case, a map is presented in a network, and categories are represented as edges connecting the nodes [16] [17]. The total number of events is the total number of people with COVID-19.

The data is generated 40 times under the assumption of a multinomial distribution with the probability mass function of $\mathbf{X}_t \sim \text{Mult}\,(\theta_1, \theta_2, \ldots, \theta_{38}, 2500)$. The function is

(4) $$p(\mathbf{x}; \boldsymbol{\theta}) = \frac{2500!}{\prod_{i=1}^{38} x_{i,t}!} \prod_{i=1}^{38} \theta_i^{x_{i,t}},$$

where $\sum_{i=1}^{38} \theta_i = 1$ and $\sum_{i=1}^{38} x_{i,t} = 2500$. The parameter $\boldsymbol{\theta}$ is generated randomly from the standard uniform distribution $\big(U(0,1)\big)$. For estimation parameter $(\boldsymbol{\theta})$ of historical data, it is obtained $Z_{statitical}$ in Table 2.

TABLE 2. Hypothesis testing, $\alpha = 0.05$ and $z_{critical} = 1.96$ or -1.96

$(\boldsymbol{\theta})$ and $(\ddot{\mu}, \ddot{\sigma}^2)$	Data Analysis	$z_{statitical}$	Decision of H_0	Clustering Strategy Changes	Parameter $(\ddot{\mu}_l, \ddot{\sigma}_l^2)$	Error (ε)	Daya/ Time
$D_{1\text{-}24}$	$D_{1\text{-}24}$ versus D_{25}	-0.15	not rejected	No	$D_{1\text{-}24}$	0.23	
$D_{1\text{-}24}$	$D_{1\text{-}24}$ versus D_{26}	-0.30	not rejected	No	$D_{1\text{-}25}$	0.22	
$D_{1\text{-}24}$	$D_{1\text{-}24}$ versus D_{36}	-2.00	rejected	Yes	$D_{1\text{-}35}$	0.31	Time 1
$D_{1\text{-}36}$	$D_{1\text{-}36}$ versus D_{37}	-0.01	not rejected, updating $(\boldsymbol{\theta})$ and $(\ddot{\mu}, \ddot{\sigma}^2)$	No	$D_{1\text{-}36}$	0.19	
$D_{1\text{-}36}$	$D_{1\text{-}36}$ versus D_{38}	-0.27	not rejected	No	$D_{1\text{-}37}$	0.21	
$D_{1\text{-}36}$	$D_{1\text{-}36}$ versus D_{39}	-2.01	rejected	Yes	$D_{1\text{-}35}$	0.32	Time 2
$D_{1\text{-}36}$	$D_{1\text{-}36}$ versus D_{39}	-0.02	not rejected, updating $(\boldsymbol{\theta})$ and $(\ddot{\mu}, \ddot{\sigma}^2)$	No	$D_{1\text{-}36}$	0.1940	
$D_{1\text{-}36}$	$D_{1\text{-}36}$ versus D_{40}	-2.42	rejected	Yes	$D_{1\text{-}38}$	0.30	Time 3

D_{25} = 25th data, $D_{1\text{-}24}$ = 1st to 24th data

We conduct simulations on the first day (time-1) to see the condition of the number of COVID-19 sufferers in all communities. The results are shown in Figure 5.

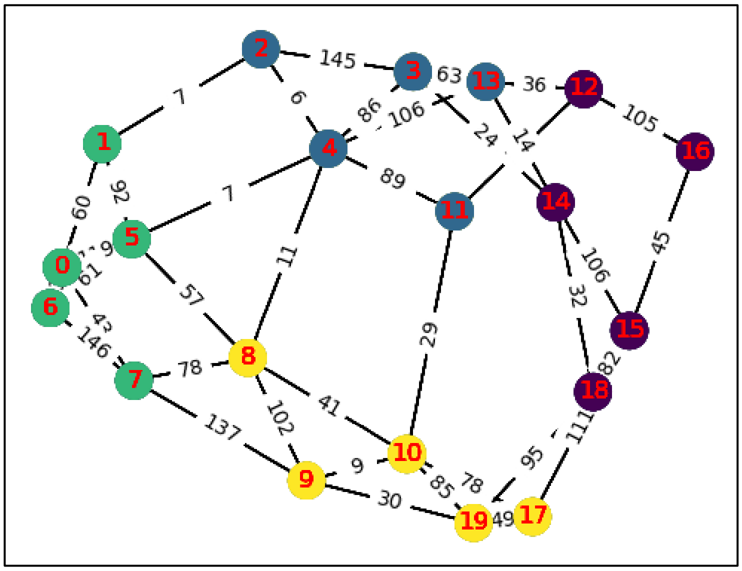

FIGURE 5. The network in the first simulation

The number of people suffering from COVID-19 in the green community is 499 people; in the grey community is 495 people; in the yellow community is 394 people, and in the purple community is 370 people. Students should apply online learning for the green and grey communities in this first simulation. Meanwhile, the yellow community and purple community conducted offline learning.

The simulation on the second day (time-2) is shown in Figure 6.

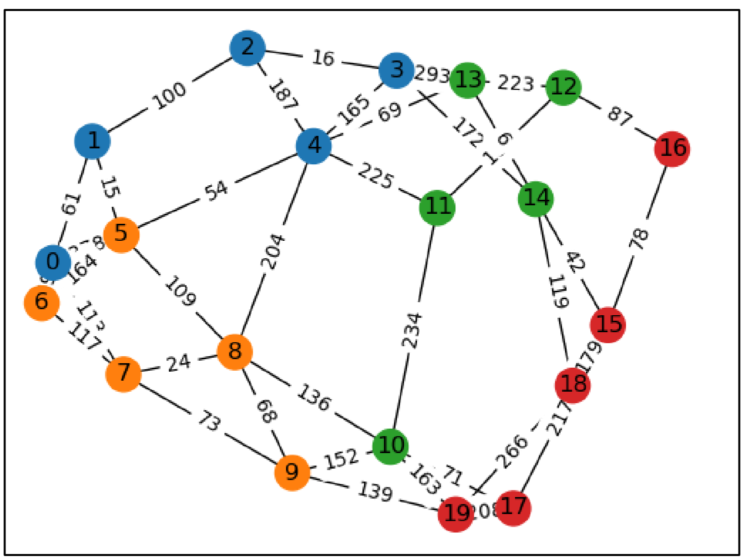

FIGURE 6. The network in the second simulation

The number of people suffering from COVID-19 in the red community is 948 people; in the green community, it is 799 people; in the orange community is 668 people; in the blue community is 529 people. In the second simulation, many communities have COVID-19. Therefore, all communities do online learning.

The simulation results on the third day (time-3) are shown in Figure 7. People who suffer from COVID-19 in the yellow community are 497 people, 476 people in the purple community, 460 people in the grey, and 371 in the green community.

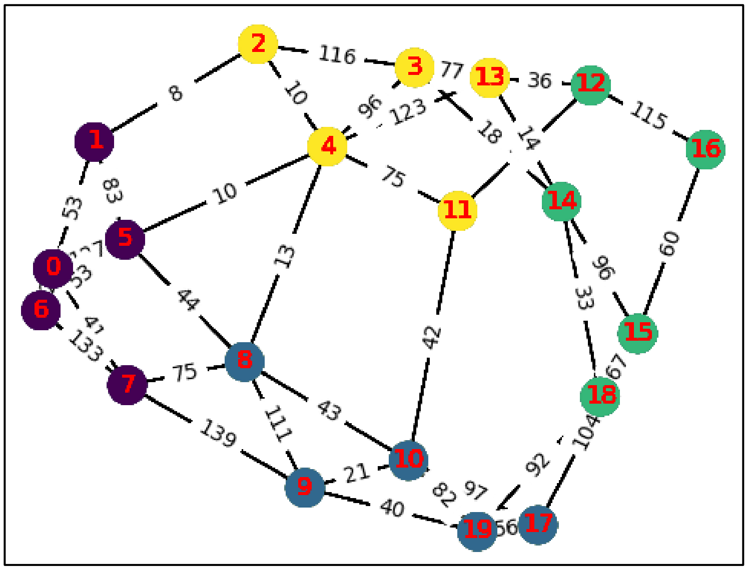

FIGURE 7. The network in the third simulation

Based on the simulation results on the third day, three communities have suffered from COVID-19. So, the yellow, purple, and grey communities should do online learning. The green community is doing offline learning.

4. CONCLUSION

The learning strategies produced in this study are aimed at schools or universities located in urban areas, especially in densely populated Indonesia. Combining the hybrid learning model with the community network generated through network clustering effectively anticipates the next wave of the COVID-19 pandemic.

Detecting communities with network clustering makes it easier for us to implement hybrid learning in education. The combination of a hybrid learning model with network clustering is one form of machine learning product. Machine learning is a science that many people are working on around the world [19]. Through machine learning, artificial intelligence products can be produced [19] [20].

For future research, it can combine this model for categorical data by adding a correspondence analysis [21]. Furthermore, the development of the model will be made in the form of a program to become an artificial intelligence product [20]. The learning strategy in this study assumes that roads connect all student locations. If a highway connecting these locations is broken or not functioning, this research study does not apply. This strategy can also be used if there are fluctuations in people with COVID-19 with a fixed total population.

ACKNOWLEDGMENT

The authors would like to thank LPPM Universitas Singaperbangsa Karawang for the research funding through HIPLA 2022 Scheme and assistance, i.e., Miss. Dini Gustiani, Mr. Hamdhani, and Mr. Ikhsan Baihaqi.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

REFERENCES

[1] H. Hariri, D. Hermanto, E. Yayah, et al. Motivation and Learning Strategies: Student Motivation Affects Student Learning Strategies, Eur. J. Educ. Res. 10 (2021), 39-49. https://doi.org/10.12973/eu-jer.10.1.39.

[2] M.A. Ashraf, M. Yang, Y. Zhang, et al. A systematic review of systematic reviews on blended learning: trends, gaps and future directions, Psychol. Res. Behav. Manage. 14 (2021), 1525–1541. https://doi.org/10.2147/prbm.s331741.

[3] M. Al Breiki, A. Al-Abri, The extended technology acceptance model (ETAM): Examining students' acceptance of online learning during COVID-19 pandemic, Int. J. Emerg. Technol. Learn. 17 (2022), 4-19. https://doi.org/10.3991/ijet.v17i20.29441.

[4] O. Dakhi, D. Irvan, Blended learning: a 21st century learning model at college, Int. J. Multi Sci. 1(2020), 50–65.

[5] Masson, A. MacNeill, C. Murphy, et al. The hybrid learning model – a framework for teaching and learning practice, Int. J. Emerg. Technol. Learn. 3(2008), 12–17.

[6] S. Trivedi, Z.A. Pardos, G.N. Sarkozy, et al. Spectral clustering in educational data mining, in: Proceedings of the 4th international conference on educational data mining, (2011), pp. 129–138.

[7] M.R. Yudhanegara, K.E. Lestari, Clustering for multi-dimensional data set: a case study on educational data, J. Phys.: Conf. Ser. 1280 (2019), 042025. https://doi.org/10.1088/1742-6596/1280/4/042025.

[8] M.R. Yudhanegara, S.W. Indratno, R.K.N. Sari, Clustering for item delivery using rule-k-means, J. Indones. Math. Soc. (2020), 185–191. https://doi.org/10.22342/jims.26.2.871.185-191.

[9] S.W. Indratno, K.N. Sari, M.R. Yudhanegara, Optimization in item delivery as risk management: multinomial case using the new method of statistical inference for online decision, Risks. 10 (2022), 122. https://doi.org/10.3390/risks10060122.

[10] M.E.J. Newman, Detecting community structure in networks, Eur. Phys. J. B - Condensed Matter. 38 (2004), 321–330. https://doi.org/10.1140/epjb/e2004-00124-y.

[11] M.E.J. Newman, M. Girvan, Finding and evaluating community structure in networks, Phys. Rev. E. 69 (2004), 026113. https://doi.org/10.1103/PhysRevE.69.026113.

[12] M.R. Yudhanegara, S.W. Indratno, R.R.K.N. Sari, Clustering for Items Distribution Network, J. Phys.: Conf. Ser. 1496 (2020), 012019. https://doi.org/10.1088/1742-6596/1496/1/012019.

[13] K. Ferland, Discrete mathematics: an introduction to proofs and combinatorics, Houghton Mifflin Company, 2009.

[14] A. Casteigts, P. Flocchini, E. Godard, et al. Brief announcement: waiting in dynamic networks, in: Proceedings of the 2012 ACM Symposium on Principles of Distributed Computing, ACM, Madeira Portugal, 2012: pp. 99–100. https://doi.org/10.1145/2332432.2332452.

[15] U. Elsner, Graph partitioning-a survey, Preprint SFB393/97-27, 1997.

[16] M.R. Yudhanegara, S.W. Indratno, RR.K.N. Sari, Dynamic items delivery network: prediction and clustering, Heliyon. 7 (2021), e06934. https://doi.org/10.1016/j.heliyon.2021.e06934.

[17] M.R. Yudhanegara, S.W. Indratno, K.N. Sari, Role of clustering method in items delivery optimization, J. Phys.: Conf. Ser. 2084 (2021), 012011. https://doi.org/10.1088/1742-6596/2084/1/012011.

[18] F. Chung, Spectral graph theory, American Mathematical Society, Providence, Rhode Island, 1996. https://doi.org/10.1090/cbms/092.

[19] K. Oqaidi, S. Aouhassi, K. Mansouri, Towards a students' dropout prediction model in higher education institutions using machine learning algorithms, Int. J. Emerg. Technol. Learn. 17 (2022), 103–117. https://doi.org/10.3991/ijet.v17i18.25567.

[20] X. Li, Path Planning for the fragmented learning of college students based on artificial intelligence, Int. J. Emerg. Technol. Learn. 17 (2022), 176–190. https://doi.org/10.3991/ijet.v17i19.34513.

[21] K.E. Lestari, U.S. Pasaribu, S.W. Indratno, et al. Generating roots of cubic polynomials by Cardano's approach on correspondence analysis, Heliyon. 6 (2020), e03998. https://doi.org/10.1016/j.heliyon.2020.e03998.