International Journal of Innovative Computing, Information and Control
Volume **17**, Number **3**, June **2021**

ICIC International ©2021 ISSN 1349-4198
pp. 1055–1065

IMPACT OF REMOVAL STRATEGIES OF STAY-AT-HOME ORDERS ON THE NUMBER OF COVID-19 INFECTORS AND PEOPLE LEAVING THEIR HOMES

Yuto Omae[1], Yohei Kakimoto[1], Jun Toyotani[1], Kazuyuki Hara[1]
Yasuhiro Gon[2] and Hirotaka Takahashi[3]

[1]College of Industrial Technology
Nihon University
1-2-1, Izumi, Narashino, Chiba 275-8575, Japan
oomae.yuuto@nihon-u.ac.jp

[2]Nihon University School of Medicine
30-1, Kami, Ooyaguchi, Itabashi, Tokyo 173-8610, Japan

[3]Research Center for Space Science
Advanced Research Laboratories
Tokyo City University
8-15-1, Todoroki, Setagaya, Tokyo 158-0082, Japan
hirotaka@tcu.ac.jp

Received January 2021; revised April 2021

Abstract. *As of November 2020, the COVID-19 pandemic continues to rage across the world. One of the measures that has been taken to curb the spread of the virus is blanket stay-at-home orders. Staying at home significantly limits close contact with others and can, thus, decrease the number of new cases. However, if people refrain from going out, this will cause significant economic damage. For this reason, some people think that these orders should be revoked after a short period of time, and people should get out more often. However, if blanket stay-at-home restrictions are lifted before a significant decrease is seen in the number of new cases, the number of infected people is likely to increase within a short period. This will, in turn, hasten the next round of blanket stay-at-home orders and lead to a further reduction in people who can leave their home. Against this backdrop, this study examines below phenomena, through a multi-agent simulation. The early removal strategies of stay-at-home orders for increasing the number of people leaving their homes have the effect of both increasing and decreasing the number of such people. Therefore, we consider the strategies do not lead to a sufficient increase in the overall number of people leaving their homes. To examine these phenomena, we conducted the simulations that consist of six scenarios with the different removal condition of stay-at-home orders. As a result, we could confirm that when more removal conditions of stay-at-home orders were eased, the tendencies of more number of infected people and death people were increasing with some exceptions. In contrast, there were almost no differences among the numbers of people leaving their home of these scenarios. Based on the results, we also examined the possibility of a strategy that covers both infected people and the number of people allowed to leave their homes.*
Keywords: COVID-19 infection, Blanket stay-at-home orders, Declared state of emergency, Multi-agent simulation

1. **Introduction.** The COVID-19 pandemic is spreading across the globe in November 2020. Particularly in Japan, the virus has infected 140,000 people in total and killed more than 2,000 people as of November 30, 2020 [1]. For this reason, Japan has imposed

DOI: 10.24507/ijicic.17.03.1055

a variety of measures. One such measure is the blanket stay-at-home order that was introduced after the country declared a state of emergency (imposed: April 7, 2020; lifted: May 25, 2020). This was a blanket call from the government for citizens to stay at home. The number of domestic confirmed cases reported in the week prior to the declared state of emergency was 300 per day, whereas the number reported the week right after was ~ 40 per day [2]. This allows us to conclude that blanket stay-at-home orders have had a significant effect on reducing the number of new cases.

However, stay-at-home orders imply that people do not go shopping, eat outside, and travel, thus causing major economic losses to the society as a whole. As the length of time of the blanket stay-at-home restrictions increases, society's demand for the removal of the restrictions is expected to increase. In such a case, we can speculate that the number of new cases will increase at a relatively faster pace. This means that the period wherein people are required to stay at home again will be earlier. Therefore, removing the blanket stay-at-home restrictions at an early stage may have the effectiveness of decreasing the number of people leaving their home – or increasing it.

It is difficult to assess whether this phenomenon could actually take place in modern society. In such a case, it is necessary to conduct simulations for verification. As previous researches, there are many cases developing virus infection simulators [3, 4, 5, 6]. By following these findings, the development of COVID-19 simulators that model infection transmission rates could be performed at a comparatively early stage. Examples include Hou et al. [7] for Wuhan, China, Prasse et al. [8] and Yang et al. [9] for Hubei, China, Chatterjee et al. [10] for India, Achterberg et al. [11] for Holland, and Liu et al. [12], for South Korea, Italy, and France. Moreover, Albahar et al. [13] conducted COVID-19 simulations with USA, Saudi Arabia and China using the ensemble machine learning. From these previous researches, it was clarified that the measures to isolate those infected with COVID-19 effectively reduce the number of infected people at the peak hours [7] and that city blockades can reduce the damage caused by infection by 90% [10]. In terms of assessing other benefits, Kurahashi [14] reported that working from home, staggered commuting self-isolation at home when running a fever, and other such measures were effective in reducing the number of new cases. Niwa et al. [15] reported that quarantining travelers at airports reduced the number of new cases by 90%. Certain studies also assessed the effectiveness of apps that notify users if they have been in contact with people infected with COVID-19 [16, 17, 18, 19, 20, 21]. Additionally, Yang et al. [22] and He et al. [23] have conducted COVID-19 infection transmission simulations. These results have enabled us to clarify the trends toward growth and suppression of the COVID-19 infection.

Thus far, these studies have focused on predicting the number of infected people and verifying the effectiveness of some measures on decreasing new infectors. Although these focuses are important, we consider increasing the number of people leaving their home is also important from the view point of economic activity. However, these previous studies did not evaluate the number of people leaving their home. Therefore, in this study, we take up stay-at-home orders which is one of measures and evaluate the effects on the number of infected people and people leaving their home. In particular, we use a multi-agent simulation (MAS) to verify whether the phenomenon occurs, in which "the strategy for early removal of blanket stay-at-home orders, for the purpose of increasing the number of people leaving the home is, when viewed from a long-term perspective, not effective in sufficiently increasing the number of people leaving the home". Following this, we present several strategies, including strategies for removing blanket stay-at-home orders after the number of new cases has sufficiently decreased, and we investigate the impact these strategies have on the number of new cases and the number of people going out.

Based on the results, we make some observations on the nature of the strategies proposed that help reduce the number of new cases while allowing a certain number of people to go out.

The construction of remaining sections is as follows. In Section 2, we briefly describe the simulation system used in this research. In Section 3, the objective, outline, the result and discussion of the experiment are explained, respectively. Section 4 is devoted to the summary and future work.

2. Simulator.

2.1. Daily flow. In this study, we estimate the transmission of COVID-19 infection using MAS. An overview is shown in Figure 1. The simulation is performed in plane spaces (minimum 0, maximum 1,000) with axes of x-y. These include four types of facilities: homes, companies, shops, and schools. Multiple facilities for each type are allowed. Home refers to the place of residence of the agent together with three other people: an office worker, a homemaker and a student. The agents, who set off from home, will, based on a probability, move to their destination facility at a predetermined time. The respective destinations are the company for the office worker, shops for the homemaker and school for the student. The agents that move along the shortest path, in terms of actual distance, can remain only for a certain amount of time that is determined by the above-stated probability. After that certain amount of time, they return home, taking the shortest path based on Euclidean distance. The above describes the processing flow for one day. This simulator uses one (1) step for every 10 minutes and moves to the next day once 24 hours (144 steps) have been completed. The simulation ends when it reaches the set time. The processes were proposed as previous research (In detail, see Section 2.2 in [20]).

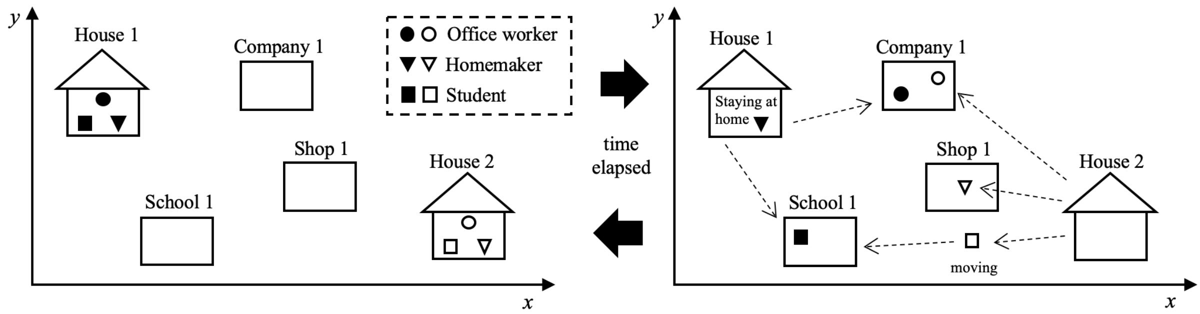

FIGURE 1. Constructed artificial society

2.2. Infection state transition. The MAS constructed in this study aims to simulate the virus infection transmission. For this reason, each agent has an infection state parameter. These are the five states – S, E, I, R, and D – as described below. The states were determined with reference to the SEIR (Susceptible, Exposed, Infectious, Recovered) model [22, 23] that simulates the COVID-19 infection transmission. "S: susceptible" is the state in which the agent has never been infected with the virus. As the agent is not immune, it has a likelihood of being infected. "E: exposed" is the state in which the agent is infected but is not yet symptomatic (latent period). "I: infectious" is the state in which the agent is infected and the symptoms have appeared (symptomatic period). "R: recovered" is the state in which the agent recovers after having been symptomatic. "D: death" is the state in which the agent did not recover and died.

The infection state transitions in the SEIR model are shown in Figure 2. The agent in the S state transforms to the E state, according to whether they have come into contact

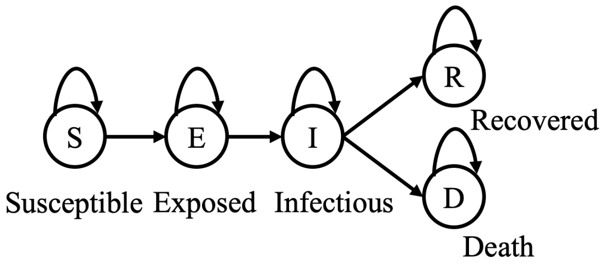

FIGURE 2. SEIR model

with an infected person. The definition of contact with an agent and infected person means that each other's Euclidean distance is under 1. It is possible to set whether infected people that can infect others are only those who are in the I state or whether those in the E state are also included. This means that it is possible to express infectiousness during the symptomatic state (I) and/or the latency state (E). An agent who has transformed from the S to the E state also transforms to the I state as time passes. Agents in the I state transform to the R or the D state as time passes. The question of whether patients transform to the R or the D state depends on the fatality rate of the cases. The numerical models of the state transitions mentioned here are described in Section 2.1 in [20].

2.3. **Small scale network.** As this simulator aims to estimate the virus infection transmission, the contact between agents has considerable weight. Despite considering a contact has been made when the Euclidean distance in the plane space is below a threshold (each other's Euclidean distance is under 1), this condition detaches the situation from reality. In this study, each facility (i.e., a company or a school) is managed as one coordinate, so all agents arriving at the facilities are in contact with one another from a Euclidean distance perspective. Therefore, even if there is one infected person among them, there is a risk that this person will infect all of the agents. However, in the real world, people work in company in separate departments, and in schools students take their lessons in their respective classrooms. Therefore, it is unlikely that everyone in the same facility would come into contact with each other in a day. However, in the case of long time simulation, we consider everyone would come into contact with each other in the same facility, indirectly.

To express this with MAS, it is necessary to assume that the agents gathered in one facility are divided into multiple subgroups and only those within each group are considered to come into contact with each other. For this reason, we have implemented the concept of a small scale network (SSN) on the simulator in our study. An image of this simulator is shown in Figure 3. This expresses the fact that there are 14 agents in this company; these are divided into 3 SSNs. Whereas all 14 are in the same coordinates in the plane space, only the agents in the same SSN come into contact with each other. Therefore, the risk of infection exists only when there are infected persons within the same SSN. When we incorporate the concept of SSNs within the simulator, it is necessary to have the maximum SSN size parameter. This describes the maximum number of agents that can exist within one network (in the example in Figure 3, this is five people). The agents are allocated to their respective SSN based on the order of arrival. Particularly, they are initially allocated to SSN1 and when the maximum size is reached, SSN2 is created, and this allocation processing is repeated. As the time at which each agent leaves home depends on probability, the order of their arrival to the facility is random. Therefore, the assigned SSN is random every day. The concept of judging whether contact has been established based on the allocated SSN is only introduced to the outside facility (company,

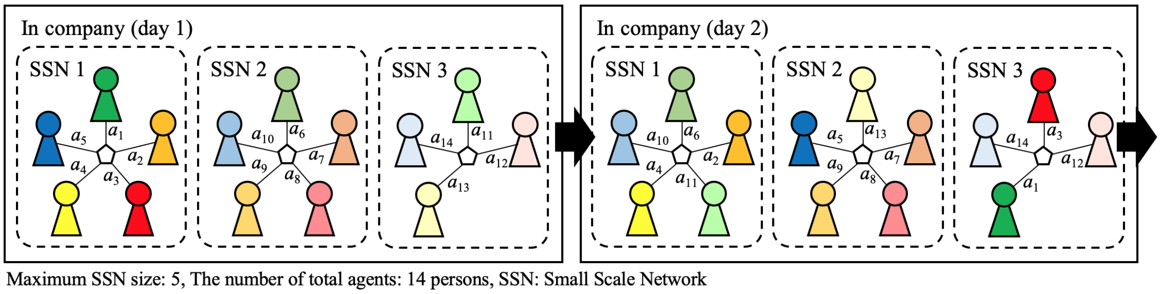

FIGURE 3. Small scale network

shop, or school). When agents are moving between the facility and their home, judging whether contact has been established is only based on Euclidean distance.

2.4. **Blanket stay-at-home orders.** Next, we would like to discuss the blanket stay-at-home orders for all agents. To express these, we need to prepare the three parameters of start conditions, removal conditions and restriction levels on going out. The standard for starting blanket stay-at-home orders is the number of symptomatic agents (number of agents in the I state) at the present time. Therefore, both the start and removal conditions are values that represent the agent in the I state. When the number of agents in the I state meets or exceeds the start condition, a blanket stay-at-home order is issued. Furthermore, when the number of agents in the I state falls below the removal condition, the blanket stay-at-home restriction is removed. In Section 2.1, we explained that agents go out every day. However, some agents do not go out, because all agents have the parameter of probability of leaving home, which is the probability of moving from their homes to their destination facilities (company, shop, or school). During the time that the blanket stay-at-home order is in place, the probability of leaving home of all agents decreases by the set of restriction levels on going out. For example, if the probability of leaving home is 100% and the restriction levels on going out is 90%, the probability of moving from their homes to their destination facilities during the blanket stay-at-home order is 10%. As it is difficult for all agents (including the I state) to leave their home, the probability the virus spreads in the companies, shops, and schools decreases, and it becomes easier to maintain the S state agent status. For this reason, by executing a stay-at-home order, it is possible to reduce the number of infections.

3. Experiment.

3.1. **Purpose and overview.** To effectively operate society during the protracted period of COVID-19 spread, it is necessary to not only reduce the total number of infections but also keep (or increase) the number of people leaving home. In this study, we investigate the impact of the strategy of blanket stay-at-home orders, which is one measure for suppressing the spread of COVID-19 infection on the total number of infections and number of people leaving their home. The strategy to be verified on this occasion is shown in Table 1. The stay-at-home order is issued when the number of agents in the I state meets or exceeds the number set in the start conditions, and the stay-at-home order is removed when the number falls below the number set in the removal conditions.

During the stay-at-home order, the rate of all agents going out is lowered according to the level of restrictions on going out. The start conditions, removal conditions and level of restrictions on going out are all important parameters, and on this occasion, the start conditions were fixed at 60 people and the level of restrictions on going out at 90%, with only the removal conditions variable. For strategy 0, the removal conditions

Table 1. Strategy for stay-at-home orders. Start conditions: when the number of people in the I state reaches a set number or above, a stay-at-home order is issued. Removal conditions: when the number of people in the I state is below a set number, the stay-at-home order is removed.

Strategy ID	Start cond. [people]	Removal cond. [people]	Level of restriction on going out [%]
Strategy 0	60	5	90
Strategy 1	60	10	90
Strategy 2	60	20	90
Strategy 3	60	30	90
Strategy 4	60	40	90
Strategy 5	60	50	90

were five people, and this means a return to normal life after the infection rate had sufficiently weakened following the issue of the stay-at-home order. As the number of strategies increases, the conditions for removal become more lenient. Strategy 0, in which the removal conditions are strict, focuses on the social demand to reduce the number of infections, whereas strategy 6, in which removal conditions are set to the largest value, stresses society's demand for people to quickly return to normal life. We simulated each strategy and analyzed the impact on the total number of infections and the number of people going out. When the simulation ends, the strategy with the lowest number of total infections and the highest number of people leaving the home is considered the desirable social operation strategy under the prolonged spread of COVID-19.

The other simulator conditions are shown in Table 2. The total simulation period was set to 365 days (1 calendar year). As there are 2,000 households and three agents per household (office worker, homemaker, student), the total number of agents in the entire space is 6,000 (the reason that the start conditions for the aforementioned blanket stay-at-home order were set to 60 people, so that it was a number comprising 1% of all agents).

Of these, five people were in I state, whereas the remaining 5,995 people were registered in S state. The destination facilities of the agents leaving the house were allocated as 10 each of companies, shops, and schools. The maximum SSN size was set to a value comprising an average of five networks per facility. There were 2,000 office workers, housewives/househusbands and students within the 10 companies, shops, and schools, respectively. Therefore, there were a maximum of 200 agents in each facility. Dividing this value by 5 gives us 40 agents, so the maximum SSN size is 40 people. Other items, such as EI state transition period (period for transitioning from E to I state), IRD state transition period (period from transitioning from I to R or D state), rate at which agent leaves the home, departure time, and stay time, were determined with reference to Omae et al. [20]. The infection probability (probability of moving from S to E state after coming into contact with a latent or symptomatic agent for 10 minutes) is not clear from the COVID-19 infection rate, so the value at which infection is high to some extent is searched for by trial and error, and 0.030% was adopted.

3.2. **Results and observations.** The time-series fluctuation in infections (latent cases and symptomatic cases) in relation to the executed simulation is shown in Figure 4. The six graphs show the results when adopting the six strategies defined in Table 1, respectively. In this investigation, the only variable parameter among those specifying the blanket stay-at-home order strategy is the removal condition. Although, for all of

TABLE 2. Simulation conditions

Parameters	Values
Simulation period	365 [days]
No. of households	2000 [households] (6000 [agents])
Initial number of symptomatic agents	5 [agents]
No. of facilities (company)	10 locations*
No. of facilities (shop)	10 locations*
No. of facilities (school)	10 locations*
Maximum SSN size	40 [agents]
Probability of leaving home (office workers)	99.0∼100.0 [%]
Probability of leaving home (homemaker)	50.0∼100.0 [%]
Probability of leaving home (students)	99.0∼100.0 [%]
Departure time (office workers)	8:30±1:30
Departure time (homemaker)	10:30±1:30
Departure time (students)	10:30±1:30
Stay time (office workers)	6:00∼8:00
Stay time (homemaker)	0:10∼0:30
Stay time (students)	5:00∼6:00
Infection probability in the case of having contact with infector	0.030 [%]
State in which infectors infect others	I state, E state
Fatality rate	10.0 [%]
Transition period from E to I	3, 5, 7 [days]
Transition period from I to R or D	8, 10, 12 [days]

*: coordinates are described in Appendix.

$a \sim b$: uniform random number from a to b.

$a \pm b$: mean a, standard deviation b normal random number.

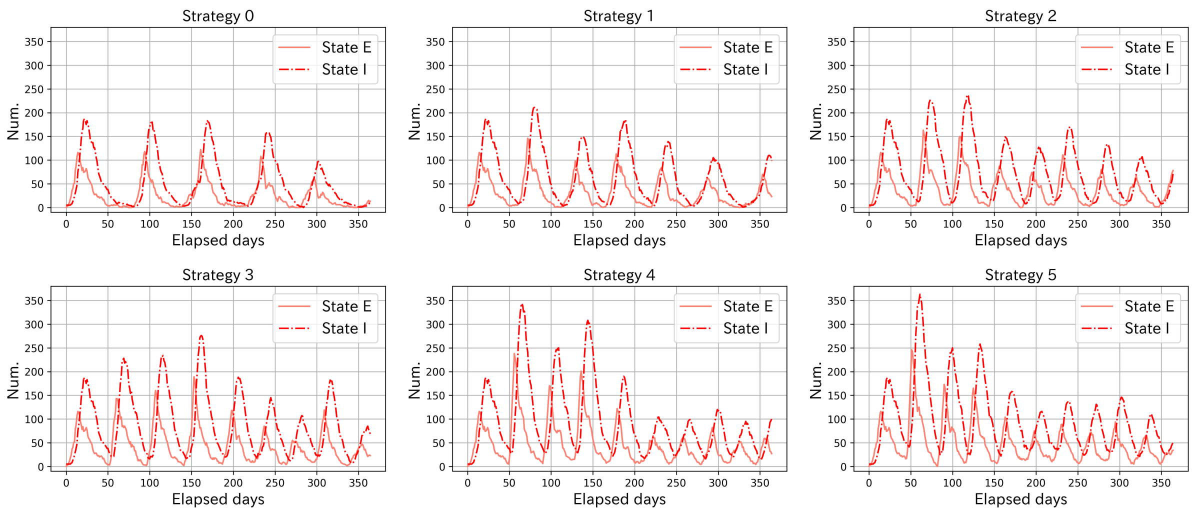

FIGURE 4. Time-series fluctuation in latent cases and symptomatic cases (E, I states) in relation to the strategy adopting a blanket stay-at-home order

the strategies, a stay-at-home order was issued when the number of symptomatic agents exceeded 60, it should be noted that as there are a large number of latent agents at that time, the number of symptomatic agents does not start to decrease the instant the stay-at-home order is issued, but rather the latent agents switch to becoming symptomatic agents, and only after a certain increase in the number of symptomatic agents does the number start to decrease.

Strategy 0 is a strategy for removing the order after the number of symptomatic agents has decreased sufficiently. With this strategy, the number of symptomatic agents peaks at 188 people, and this tends to be repeated in fixed cycles. As we move to strategies $1, 2, 3, 4, 5$, the blanket stay-at-home order removal conditions are relaxed. In accordance with this, we can see a trend toward the cycles becoming shorter in relation to the time-series fluctuation of infections. As the only measure introduced in this simulation to reduce infections is a blanket stay-at-home order, this means that stay-at-home orders are repeated in short cycles. We can confirm that the more number of days passed goes into the second half, the lower the number of peak symptomatic agents, but this just means that the number of patients in the S state that can be infected has decreased and that it has fallen into the state of herd immunity, which is something society as a whole should avoid. Moreover, we show the time-series fluctuation in states S and D in Figure 5. From Figure 5, we can understand that the number of state S is keeping high value and the number of state D is small in the case of strategy 0 comparied with other strategies.

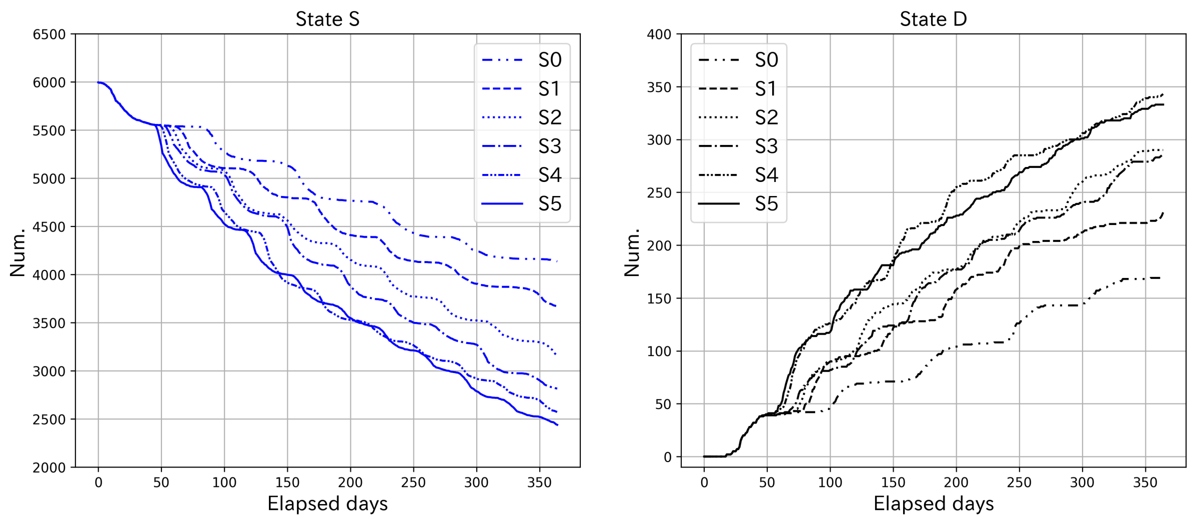

FIGURE 5. Time-series fluctuation in states S and D in relation to the strategy adopting a blanket stay-at-home order. Sn means strategy n.

To make quantifiable observations of these results, we derived several indicators, such as infection transmission and stay-at-home orders. These results are shown in Table 3. The total number of infections at the endpoint of the one-year simulation is the number of agents in the E, I, R, and D states. In the case of valuing small, it means that more agents (healthy people who have never been infected) are maintained in the S state. The maximum peak number of people is the maximum value in relation to the number of agents in the I state. The higher this value is, the higher the maximum number of symptomatic agents, which means that medical services may be overwhelmed. The peak number refers to the peak number of agents in the I state. The first-half cycle and second-half cycle are the first half and second half of 365 days, respectively, and this refers to the cyclical features calculated from the power spectrum in relation to the time-series fluctuations of agents in the I state. The larger the peak number or the shorter the cycle, the more

Table 3. The number of infections and number of people leaving the home in relation to the adopted strategy (total population: 6,000 people, total period: 365 days)

Strategy ID*	S0	S1	S2	S3	S4	S5
Total number of infections [people/year]	1864	2330	2849	3184	3428	3561
Maximum number at peak [people/day]	188	211	238	276	344	363
Peak number [unit]	5	7	8	9	10	10
First-half cycle [days]	60	60	45	45	45	36
Second-half cycle [days]	60	60	45	36	36	30
Total number of death people [people/year]	169	231	290	285	343	333
Average number of people leaving the home [people/day]	1917	2054	2000	1958	2055	2183
Stay-at-home order days [days]	255	246	250	253	246	236

*: Refer to Table 1 for strategy. Sn means strategy n.

times the medical services are likely to be overwhelmed, which means that stay-at-home orders will occur frequently. The average number of people leaving their home refers to the average number of people leaving their home per day in the one-year simulation. The number of stay-at-home days refers to the number of days covered by stay-at-home orders during the one-year simulation. The larger the average number of people leaving the house is, or the smaller the number of days covered by stay-at-home orders, the more active people are moving, so this means that economic problems are less likely to occur.

When looking at this, we can confirm that the more the removal conditions for blanket stay-at-home orders are eased, the tendencies of the more the total number of infections and death people, maximum peak number of people, and peak number increase, and the shorter the time-series fluctuation cycle for agents in the I state. However, there are also exceptions, e.g., the number of death people of S2 is higher than S3 and that of S4 is higher than S5. On the contrary, even if the removal conditions are eased, we can confirm that this does not greatly impact the average number of people leaving their home or the number of days covered by the stay-at-home order. As people can immediately leave their home when the removal conditions are eased, it can lead to an increased number of people leaving the home. However, even if the blanket stay-at-home order is released before the number of symptomatic agents has sufficiently decreased, it will have the effect of increasing the number of symptomatic agents immediately; thus, hastening the next stay-at-home order will lead to reduction in the number of people who can leave the home. As these conflict with each other, it is considered that the number of people leaving the house does not clearly increase even if the removal conditions are relaxed.

Normally, the motivation for removing blanket stay-at-home orders at an early stage comes from a desire to revitalize the movement of people and restart the economy. However, it has been confirmed that if a strategy is adopted such that a blanket stay-at-home order is removed before the number of symptomatic agents has fallen sufficiently, the number of infections will be increased. In such cases, not only will the potential for and frequency of the medical services being overwhelmed increase, but also this will also do not have a clear effect in terms of increasing the number of people leaving the house. From the above, we can see that when aiming for appropriate social operations during the time that COVID-19 is spreading, it is important from the perspectives of both number of infections and number of people leaving the home to adopt the strategy of not removing the blanket stay-at-home orders until the number of symptomatic agents has sufficiently decreased.

4. **Conclusion.** In this study, we used an MAS expressing infection transmission and analyzed the impact of the removal strategies for blanket stay-at-home orders on the number of infections and number of people leaving the home. We confirmed from the results that if blanket stay-at-home orders are removed at an early stage, not only the number of infections greatly will increase and the potential for medical services to be overwhelmed increase but also the speed of this cycle will be increased and the number of people leaving the home will not sufficiently increase. Particularly, if blanket stay-at-home orders are removed at an early stage based on the idea of restarting economic activity, society may be plunged into a major state of confusion. Therefore, if a blanket stay-at-home order is issued, it is important to remove blanket stay-at-home orders only after the number of infections has reduced sufficiently.

Moving forward, we plan to validate the effectiveness not only of blanket stay-at-home orders but also a variety of other measures, such as the COVID-19 contact check app COCOA, the avoidance of close contact with other people, and the expansion of medical resources, as well as conduct a more detailed study on the kind of strategy that can be effective in terms of both number of infections and number of people able to leave the home.

Acknowledgment. This work was supported in part by the Telecommunications Advancement Foundation (Y. Omae, No. 20203002) and JSPS Grant-in-Aid for Scientific Research (C) [J. Toyotani, 21K04535].

REFERENCES

[1] Ministry of Health, Labor and Welfare, *On the COVID-19 Outbreak in Japan*, https://www.mhlw.go.jp/stf/covid-19/kokunainohasseijoukyou.html, Accessed on 2020.12.02.
[2] Ministry of Health, Labor and Welfare, *The Number of New Infectors of COVID-19 (Open Data)*, https://www.mhlw.go.jp/content/pcr_positive_daily.csv, Accessed at 2020.11.30.
[3] F. Yang, Q. Yang, X. Liu and P. Wang, SIS evolutionary game model and multi-agent simulation of an infectious disease emergency, *Technology and Health Care*, vol.23, no.s2, pp.S603-S613, 2015.
[4] J. B. Dunham, An agent-based spatially explicit epidemiological model in MASON, *Journal of Artificial Societies and Social Simulation*, vol.9, no.1, 2005.
[5] H. Hirose, Pandemic simulations by MADE: A combination of multi-agent and differential equations, with novel influenza A (H1N1) case, *Information*, vol.16, no.7, pp.5365-5390, 2013.
[6] D. Chumachenko, V. Dobriak, M. Mazorchuk, I. Meniailov and K. Bazilevych, On agent-based approach to influenza and acute respiratory virus infection simulation, *The 14th International Conference on Advanced Trends in Radioelecrtronics, Telecommunications and Computer Engineering*, pp.192-195, 2018.
[7] C. Hou, J. Chen, Y. Zhou, L. Hua, J. Yuan, S. He and J. Zhang, The effectiveness of quarantine of Wuhan city against the Corona Virus Disease 2019 (COVID-19): A well-mixed SEIR model analysis, *Journal of Medical Virology*, vol.92, pp.841-848, 2020.
[8] B. Prasse, M. A. Achterberg, L. Ma and P. V. Mieghem, Network-inference-based prediction of the COVID-19 epidemic outbreak in the Chinese Province Hubei, *Applied Network Science*, vol.5, 2020.
[9] Q. Yang, C. Yi, A. Vajdi, L. W. Cohnstaedt, H. Wu, X. Guo and C. M. Scoglio, Short-term forecasts and long-term mitigation evaluations for the COVID-19 epidemic in Hubei Province, China, *Infectious Disease Modelling*, vol.5, pp.563-574, 2020.
[10] K. Chatterjee, K. Chatterjee, A. Kumar and S. Shankar, Healthcare impact of COVID-19 epidemic in India: A stochastic mathematical model, *Medical Journal Armed Forces India*, vol.76, no.2, pp.147-155, 2020.
[11] M. A. Achterberg, B. Prasse, L. Ma, S. Trajanovski, M. Kitsak and P. V. Mieghem, Comparing the accuracy of several network-based COVID-19 prediction algorithms, *International Journal of Forecasting*, 2020.
[12] Z. Liu, P. Magal and G. Webb, Predicting the number of reported and unreported cases for the COVID-19 epidemics in China, South Korea, Italy, France, Germany and United Kingdom, *Journal of Theoretical Biology*, DOI: 10.1101/2020.04.09.20058974, 2020.

[13] M. Albahar, A. Albahr, A. Alharbi, M. Thanoon and S. Karali, Forecasting the cumulative number of confirmed cases of COVID-19 in USA, Saudi Arabia, and China using ensemble model, *ICIC Express Letters, Part B: Applications*, vol.12, no.2, pp.143-151, 2021.

[14] S. Kurahashi, Estimating effectiveness of preventing measures for 2019 novel coronavirus diseases (COVID-19), *Transactions of the Japanese Society for Artificial Intelligence*, vol.35, no.3, 2020.

[15] M. Niwa, Y. Hara, S. Sengoku and K. Kodama, Effectiveness of social measures against COVID-19 outbreaks in Japanese several regions analyzed by system dynamic modeling, *SSRN*, DOI: 10.2139/ssrn.3653579, 2020.

[16] L. Ferretti et al., Quantifying SARS-CoV-2 transmission suggests epidemic control with digital contact tracing, *Science*, vol.368, no.6491, DOI: 10.1126/science.abb6936, 2020.

[17] R. Hinch, W. Probert, A. Nurtay, M. Kendall, C. Wymant, M. Hall and C. Fraser, *Effective Configurations of a Digital Contact Tracing App: A Report to NHSX*, https://045.medsci.ox.ac.uk/files/files/report-effective-app-configurations.pdf, Accessed on 2020.10.26.

[18] J. A. Kucharski et al., Effectiveness of isolation, testing, contact tracing, and physical distancing on reducing transmission of SARS-CoV-2 in different settings: A mathematical modeling study, *The Lancet Infectious Diseases*, vol.20, no.10, pp.1151-1160, 2020.

[19] J. Kurita, T. Sugawara and Y. Ohkusa, Effectiveness of COCOA, a COVID-19 contact notification application, in Japan, *medRxiv*, DOI: 10.1101/2020.07.11.20151597, 2020.

[20] Y. Omae, J. Toyotani, K. Hara, Y. Gon and H. Takahashi, Effectiveness of the COVID-19 contact-confirming application (COCOA) based on a multi agent simulation, *arXiv.org*, arXiv: 2008.13166, 2020.

[21] Y. Omae, J. Toyotani, K. Hara, Y. Gon and H. Takahashi, A calculation model for estimating effect of COVID-19 contact-confirming application (COCOA) on decreasing infectors, *arXiv.org*, arXiv: 2010.12067, 2020.

[22] Z. Yang et al., Modified SEIR and AI prediction of the epidemics trend of COVID-19 in China under public health interventions, *Journal of Thoracic Disease*, vol.12, no.3, pp.165-174, 2020.

[23] S. He, Y. Peng and K. Sun, SEIR modeling of the COVID-19 and its dynamics, *Nonlinear Dynamics*, pp.1-14, 2020.

Appendix. The (x, y) coordinates of companies, shops and schools in artificial society are $L_{\text{company}} = \{(x, y) = (100, 100n) | n = 0, \ldots, 9\}$, $L_{\text{shop}} = \{(x, y) = (500, 100n) | n = 0, \ldots, 9\}$ and $L_{\text{school}} = \{(x, y) = (900, 100n) | n = 0, \ldots, 9\}$, respectively.