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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Evaluation and improvement the transportation system resilience against epidemic diseases: A system dynamics approach

Abstract

The influential role of health protocols in preventing the spread of the COVID-19 disease has led governments to seek effective methods for implementing these protocols in the society. Considering the importance of public transportation system in spread of viruses, this paper introduces and analyzes some methods of inspecting urban public transportation companies using system dynamics approach. First, the base model, which represents the status of a public transportation terminal, was created and validated using a system dynamics simulation approach. Then the impact of two penalty policies, including fixed penalty policy (FPP) and variable penalty policy (VPP) on the violations within the terminal was investigated. The simulation results show that the variable penalty policy significantly reduces the violations of passenger terminal drivers. Next, the extended model was developed which considered several terminals. Finally, by presenting two policies of fixed inspector assignment (FIA) and variable inspector assignment (VIA), the effect of four scenarios of combining inspection and penalties policies was investigated. The simulation results showed that combining the variable penalty and variable inspector assignment policies could significantly reduce terminal violations. Also, the implementation of this policy does not require an additional inspector. The results can help city managers to adopt appropriate inspection policies.

Keywords: Epidemics; Public transportation; Inspection; System dynamics; Policy making.

1. Introduction

Following the COVID-19 pandemic, irreparable damage has occurred to the world. Most industries, including tourism and welfare services, transportation services, and other urban services, have been affected by this disaster (Hobbs, 2020; Ntounis, Parker, Skinner, Steadman, &

Warnaby, 2022). According to reports, public transportation in some cities has decreased by 90% (Gkiotsalitis & Cats, 2021b). Governments seek disaster relief and improve resilience to the disease in a variety of ways. Urban resilience against epidemics has been studied in several studies (Blay-Palmer et al., 2021; Kaye-Kauderer, Feingold, Feder, Southwick, & Charney, 2021). Effective action in urban resilience is the provision of health protocols for various industries, and implementation of these protocols will prevent the spread of the disease in different areas (Giallonardo et al., 2020). One of the essential urban services that play a crucial role in preventing the outbreak of Covid-19 disease is the urban public transportation fleet (Gkiotsalitis & Cats, 2021b) Observing the maximum number of passengers in each vehicle, drivers and passengers using masks, disinfecting the vehicle after each trip, and spacing between passenger seats are among the rules in the form of health protocols, that transportation companies and public terminals are required to implement (Tirachini & Cats, 2020).

A critical issue after the approval of protocols is monitoring and review for their proper implementation. Experience has shown that organizations and companies fail to comply with the law without supervision and inspection (Nourinejad, Gandomi, & Roorda, 2020; Rass, Schauer, König, & Zhu, 2020). However, the limited resources to inspect and penalty violators is a challenge facing inspection organizations. Choosing the right inspection policy and strategy in many cases can effectively reduce the rate of violations (Rass et al., 2020; You, Li, Li, Cao, & Xu, 2020). As a result, one of the problems that researchers seek to solve is to review and determine better inspection policies in different situations using various approaches (Morales, Onieva, Pérez Mira, & Cortés, 2020; Tsebelis, 1990).

The interactions among inspectors, public transportation system staff and passengers are uncertain. This makes the determination of most suitable inspection policies complex. On the other hand, necessity of addressing inspection policies over time makes the problem at hand dynamic. The complexity of these problems has led some researchers to use the system dynamics approach in simulation (Nabi, El-adaway, & Dagli, 2020; Wang, Liu, Qin, & Zhang, 2020). It is essential to study the role of urban public transportation companies' inspections in coping with epidemic disasters. This study explicitly addresses government inspections of urban public transportation companies to implement one of the essential health protocols (number of vehicle passengers) using the systems dynamics approach. In this regard, the research questions considered in this study are:

A) What factors are effective in decreasing the number of violations of public transportation companies?

B) How to model these factors using the system dynamics approach?

C) How to compare the proposed inspection policies and which of them is more effective?

This study for the first time examines the relationship between government inspections, urban public transportation companies, and the number of violations committed in an epidemic disaster using a system dynamics approach and seeks to provide efficient and effective policies to inspect urban public transportation companies during an epidemic. In this regard, passenger entry rates to the terminal, the risk, and the behavior of transportation companies and drivers have been considered. Also, the impact of various inspection policies on the number of illegal passengers and the number of offending vehicles, in the long run, is examined for the first time.

The rest of this paper is organized as follows. In Section 2, a literature review is described. In the third section, the definition of the problem is given and the structure of the base model is explained. In section four, inspection policies are defined and modeled, and by using simulation, the results of each policy are presented. The fifth section provides an analysis and comparison between policies and presents managerial perspectives. Finally, the sixth section summarizes the content and conclusions and offers suggestions for future research.

2. Literature review

The present study examines the issue of inspection of public passenger transportation companies to observe the social distance in vehicles, which is one of the criteria in the health protocols, using the system dynamics approach. Thus, it is necessary to review the literature on "Public transportation system and epidemic disaster" and " System dynamics, transportation and inspection."

2.1 Public transportation system and epidemic disaster

With the onset of Covid-19 disease, many studies have examined the various dimensions of this catastrophe. Part of these researches can be found in the relationship between Covid-19 and public transportation system services. A group of researchers investigated the effects of COVID19 disaster on public transportation services. Using a questionnaire approach, (Mogaji, 2020) examined the impact of Covid-19 on Lagos public transportation services in Nigeria. His research shows that Covid-19 has a significant effect on public transportation services and has disrupted the people's economic, social, and religious activities due to its disruption. Downey, Fonzone, Fountas, and Semple (2022) investigated the impact of Covid on the future of public transport in Scotland using a questionnaire. According to the results, some factors significantly affected the use of public transportation, one of which is the perceived risk of COVID-19 infection. More than 60% of those who intended to use less public transportation considered the possibility of contracting Covid-19 from other passengers as an influential factor in this decision. (Jenelius & Cebecauer, 2020) studied the effects of covid on the daily use of public transportation in Sweden. Based on ticket sales data and passenger counts, they found a sharp drop in the use of public transport due to the spread of COVID-19 in the three largest Swedish cities. Bucsky (2020) studies confirm an 80% decrease in the use of public transportation during the outbreak of covid in Budapest, Hungary. Similar studies have examined the impact of this disaster on transportation in Colombia, Canada, China, Greece, India and other countries (Arellana, Márquez, & Cantillo, 2020; Cai, Cai, Xiong, Chen, & Yu, 2016; Tian, An, Chen, & Tian, 2021).

There have also been several studies on transportation system measures to prevent the spread of Covid-19. Dzisi and Dei (2020) examined the observance of social distancing and masks in Ghana's public transportation during the epidemic using observations. The results of 850 samples observed by the roadside observer indicated that social distancing was more observed than wearing a mask in public transportation. They also pointed out the spread of disease in public transport and suggested fines to enforce the rules. Shen et al. (2020) provided an overview of measures taken in China to manage public transportation in the field of Covid-19, from substance disinfection to information campaign. Referring to medical research on viruses remaining on the surfaces and transmission of microorganisms, Musselwhite, Avineri, and Susilo (2020) considered the cleaning and internal hygiene of public transportation vehicles to be among the most critical activities of the health protocol. Due to the social distancing provided by the World Health Organization, studies have addressed a reduction in the capacity of vehicles when transporting passengers. (Gkiotsalitis & Cats, 2021a) redesigned transportation services to reduce costs and reduce passenger capacity by presenting a quadratic mixed planning model. In continuation of the previous research, the present study also refers to reducing public transportation capacity during a disease outbreak.

2.2 System dynamics, transportation and inspection

System dynamics has been introduced as a new way to assess and control corporate performances (Forrester, 1997). The main idea in system dynamics is that every system consists of components interacting with each other. Feedback loops record interactions between system components and the overall pattern of system behavior over time (Zarghami, Gunawan, & Schultmann, 2018). The nonlinear relationships between the components of economic and social systems and their complexity have made it very difficult to analyze their behavior. System dynamics theory uses simulation to understand complex systems' dynamic behavior as they change over time. System dynamics is an efficient approach for analyzing systems in various fields such as management (Xiao et al., 2020), economics (Cosenz, Rodrigues, & Rosati, 2020), epidemic (Currie et al., 2020), etc.

Also, the dynamic system approach has been used by researchers in various fields and issues of transportation such as airports and airlines (Suryani, Chou, & Chen, 2012), road transportation (Gupta, Bandyopadhyay, & Singh, 2019), highway maintenance (Fallah-Fini, Rahmandad, Triantis, & de la Garza, 2010), urban transport system (Fontoura, Chaves, & Ribeiro, 2019), sustainable urban transportation (Sayyadi & Awasthi, 2020), and other cases. Specifically in the field of public transport, (Ercan, Onat, & Tatari, 2016) explored the impact of public use of public transport on CO_2 emissions and energy consumption , using a dynamic system approach. The specificity of the system dynamics approach allowed them to consider many variables in their model, such as labor force population, the number of individual trips, mode of transportation preferences, fuel/energy consumption, and CO_2 emission effects. Bajracharya (2016) studied the individuals' mode choice behavior in the context of a city and the issue of the propensity for public transportation versus personal vehicle. The proposed system dynamics model included transportation aspects like travel time, travel cost, and station accessibility.

(Ghosh, Bhattacherjee, & Ray, 1998) stated the first application of the system dynamics in the inspection process to control the hazards in the mines. First, they described hazard as an unsafe situation in a mine. Then using the system dynamics model, they identified systematic behavior in the mines and factors affecting safety against hazards and examined the effect of policy variables such as safety rules, inspection, and direct risk elimination. They concluded that management actions like inspections significantly improve the mining safety system. The application of system dynamics in mine safety was raised again by (Liu, Li, & Hassall, 2015). The focus of this study was specifically on the coal mines and inspection system. By presenting an evolutionary game on coal mines, they examined the interactions between the issue's stakeholders, including the State mines safety inspection agency, the local mines safety authority, and coal companies. Using simulation based on system dynamics approach, these researchers presented how to balance stakeholder decisions. After this study, other researchers used the evolutionary game theory approach and the system dynamics for mine safety and did similar work (Liu, Li, & Meng, 2019; Ma, Liu, Qiu, & Peng, 2020; Yu, Zhou, Cao, & Li, 2019; Zhao, Du, & Zhu, 2017). Duan, Li, Zhang, and Chang (2016) studied the environmental pollution control using evolutionary game theory and system dynamics. By examining two system dynamics models based on static and dynamic penalty policies, they discussed the interactions between government, industry, and the interests of society as a whole. In a dynamic penalty policy, the proportion of government inspections of industries increases as pollution in society increases. They showed that the implementation of hybrid policies has a more significant impact on improving the overall interests of society. In another study, (Cai et al., 2016) used evolutionary game theory and system dynamics to examine government legislation to address environmental pollution problems and inspect and monitor its implementation. These researchers, like other studies, defined the decision of companies to enforce or violate laws, eke the decision of inspection and non-inspection for the government, and concluded that the penalty coefficient has a significant impact on the legitimacy of companies. Azmi and Tokai (2017) estimated the number of used cars and electric vehicles in 2040 for Malaysia using the system dynamics approach. They examined the impact of different inspection strategies for collecting and replacing used vehicles, tax policies, and related laws through simulation. The results of their study showed that with the correct implementation of tax policies, inspection policies, and pollution standards regulations, the number of electric vehicles can increase by up to 70%. Zhu, Fan, Luo, Lin, and Zhang (2020) examined food waste management using the evolutionary game and the system dynamics approach. Referring to the conflict of interest between the government, restaurants, and garbage collection companies, they presented a system dynamics approach in which the government legislates and enforces inspections and penalties to prevent illegal behavior. Reviewing the results, they considered the existence of inspection and penalty plans necessary to reduce food waste and effective waste management.

3. Problem structure and formulation

3.1 Problem definition and assumptions

Due to the problem of epidemic diseases and the increasing number of patients, health protocols for the continuation of public transportation terminals activities have been defined as follows:

A) The driver and passengers must wear a mask.

B) Passengers at terminals and stations must observe the social distance.

C) Public transportation must be disinfected several times during the day.

D) In public transportation, social distance must be observed (the number of passengers must be determined within the criteria).

Although the first three clauses of these protocols do not cost much for drivers and passengers of public transport, not taking the passenger with an empty seat in a public vehicle will have a financial cost for drivers, which results in the driver's tendency to disobey and violate. Drivers of this type of equipment govern this law. Various reports indicate that many drivers of public passenger terminals do not comply with the law. However, if the policy of inspecting public passenger transportation is not appropriately implemented, the results of the enacted laws will be nothing but an outbreak of the disease.

This paper uses a simulation model for assessment and analysis of this problem. The assumptions considered in this simulation model are as follows:

1- The passenger's incoming rate to the terminal follows the Poisson distribution with a variable mean rate. This rate per specific hour of day is proportional to the volume of the public travel demand in the city in that hour. The hourly distribution of demand is the same on different days. In this study, the hourly demand information of public transportation trips in Isfahan (a city in the center of Iran) has been used to determine the average Poisson rate at different day hours. Daily travel demand for public transportation in Isfahan is shown in Figure 1.

2- The headway of vehicles (here bus) from the terminal is fixed. (Here 15 minutes)

3- Public transport vehicles all have the same specific passenger-carrying capacity. (25 passengers here)

4- The maximum number of passengers in each vehicle is specified according to health protocols. (15 passengers here)

5- The daily working hours of the terminal are specified. (Here from 8 am to 8 pm for 12 hours)

6- For the remaining passengers during the hours outside the working hours of the terminal, transportation services are not provided.

7- The average available inspection capacity is a certain amount. (Here 50 inspections per month, which is equivalent to 0.12 per hour)

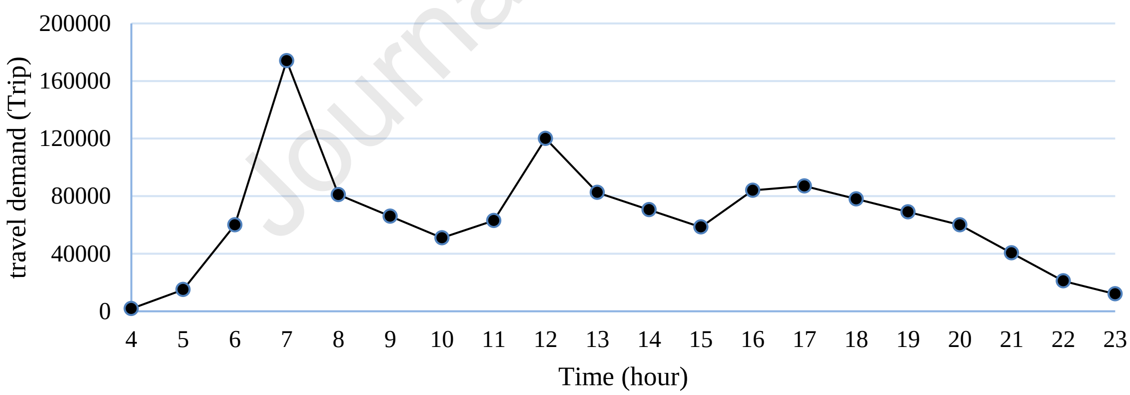


Figure 1 Daily public transportation travel demand for Isfahan city

Based on these assumptions, we now express the problem. During the daily working hours of the terminal, passengers enter the terminal randomly and are interested in getting on the bus as soon as possible and going to their destination. Every 15 minutes, a bus starts its trip from the terminal. During this time, one of the following four situations can occur. The first situation is when the number of passengers present in the terminal is less than 15. In this circumstance, the bus driver will pick up all the passengers and leave the station without additional passengers, and no passengers will be left behind. The second situation is when the number of passengers present at the terminal exceeds 15, but the driver decides to abide by the law. In this case, the driver will pick up 15 passengers and leave the terminal, and passengers who have not been able to board the bus will have to wait for the next bus. The third situation is when the number of passengers present at the terminal is between 15 and 25, and the driver decides to break the law. In this case, the driver will pick up all the passengers and leave the terminal, and there will be no passengers left for the next bus. Finally, the latest situation is when the number of passengers present at the terminal exceeds 25, and the driver decides to break the law. In this case, the driver will pick up 25 passengers and leave the terminal, and passengers who have not been able to board the bus will have to wait for the next bus.

With the initial definition of the problem and the assumptions associated with it, modeling is performed for situations that a passenger transportation terminal exists. This model is called the base model, and its purpose is to identify the behavioral pattern of the system and its main components.

3.2 Base model structure: current situation

In the modeling stage, the causal loop diagram is first presented to create the base model. In this diagram based on the definition of the problem and the dynamic hypotheses presented in the previous section, the problem variables and the causal relationships between them are defined. This model assumes that there is only one terminal. Drivers do not consider themselves bound by law enforcement. Then a flow diagram is drawn, and in the flow diagram state and rate variables are specified, and the relationships between the variables are shown more precisely than the causal loop diagram. The causal loop diagram can be seen in Diagram 1 and the related flow diagram in Diagram 2. Also, to better understand and develop the base model, the flow model's equations have been placed in Appendix A.

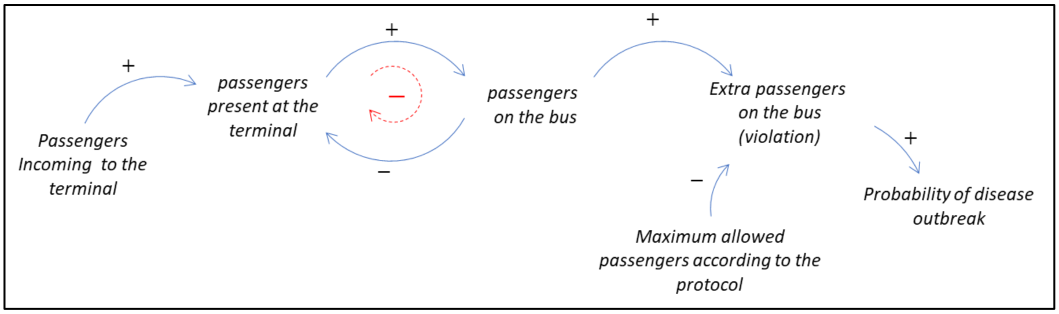
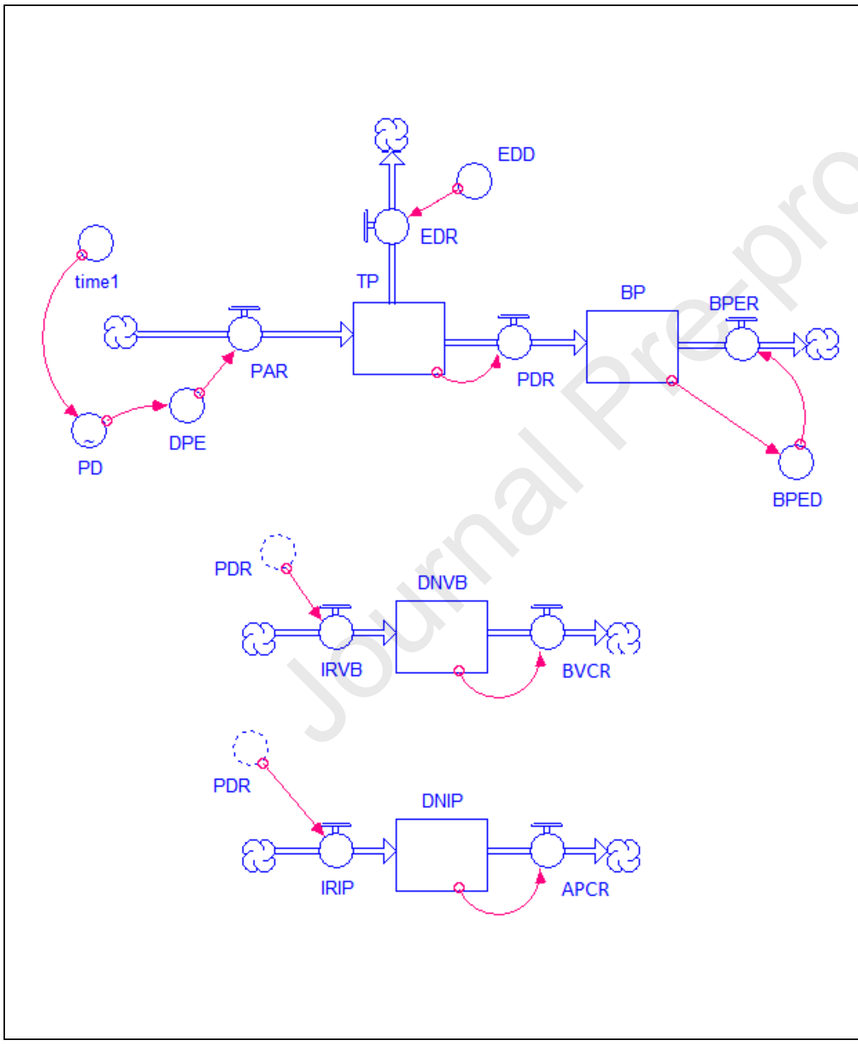


Diagram 1 Base Models' causal loop diagram



PD: Passengers travel demand	
DPE: Distribution of passenger entrance to the terminal	
PAR: Passenger arrival rate in terminal	
TP: Terminal passengers	
EDD: The end of day discharge distribution of terminal	
EDR: The end of day discharge rate	
PDR: Passenger departure rate from terminal	
BP: Bus passengers of terminal	
BPER: Terminal bus passengers' evacuating rate	
BPED: Terminal bus passengers' evacuating distribution	
IRVB: Increase rate of violating buses in Terminal	
DNVB: Daily number of terminals violating buses	
IRIP: Increase rate of illegal passengers in the terminal	
DNIP: Daily number of illegal passengers in the terminal	
BVCR: Bus violation counter reset	
APCR: Additional passengers counter reset	

Diagram 2 Base model's flow diagram

In this study, all the flow diagrams symbols used in each diagram are defined to the right of the diagram. It is necessary to explain the symbols used in the Diagram 2. In the description of the base models' flow diagram, it should first be said that the headway interval of buses is 15 minutes, and as a result, each working day includes 14 working hours, that means 57 buses a day exit from the terminal. The number of terminal passengers (TP) varies under the influence of two factors. Passenger arrival rate (PAR) to the terminal and passenger departure rate (PDR) by bus. Due to the assumption that at the end of the terminal working hours, the remaining passengers will not be served, these passengers will leave the terminal at the end of the working day without receiving services. End of day discharge rate (EDR) indicates the discharge flow of passengers at the end of the working day. Bus passengers (BP) is determined by the passenger entry rate (equivalent to the passenger departure rate by bus). Bus passengers exit rate (BPER) is the rate of unloading passengers at the destination. As mentioned, the number of authorized passengers on each bus according to health protocols is equal to 15 people. If the number of passengers on a bus exceeds this number, it will be added to the daily number of violating buses (DNVB), and the number of additional passengers on that bus will be added to the daily number of illegal passengers (DNIP). At the beginning of each day, in order to count the DNVB and DNIP, the values of these variables must be set to zero. Bus violation counter reset (BVCR) and additional passengers counter reset (APCR) are designed such that they take only at the beginning of each day, and their value at the beginning of the day is equal to the daily number of violating buses (DNVB) and the daily number of illegal passengers (DNIP), respectively. At other times of the day, the value of these variables is zero. Therefore, the bus violation counter reset (BVCR) resets the daily number of violating buses (DNVB) to zero at the beginning of the day, and the additional passengers counter reset (APCR) resets the daily number of illegal passengers (DNIP) to zero at the beginning of each day.

3.3 No-inspection policy (NIP): simulation results

The first policy that can be considered is the policy of no-inspection of terminal company (NIP). By implementing this policy, the Diagram 1 does not change. Due to the evaluation of (NIP) results, the simulation was performed for 25 days. Since the degree of risk of drivers is related to their previous information or status and fines, it is not correct to consider the model behavior in the early stages. Therefore, by testing the model and evaluating the results, it was determined that the model results have reached a stable state from the fifth day onwards and are valid after that. The first five days were set to eliminate the disturbances at the beginning of the simulation. Simulations were performed for two cases. In the first case passengers entering the terminal with a Poisson distribution with an average of 750 people per day, and in the second case passengers entering the terminal with a Poisson distribution with an average of 1500 people per day.

Apart from the passenger entry rate to the terminal, the rest of the simulation conditions are the same for the two simulated cases. In this way, it is possible to see the effect of changing the passenger entry rate component of the terminal on daily violations. Figure 2 shows the daily number of violating buses for two cases, and the daily number of illegal passengers in those cases between the fifth and twenty-fifth day.

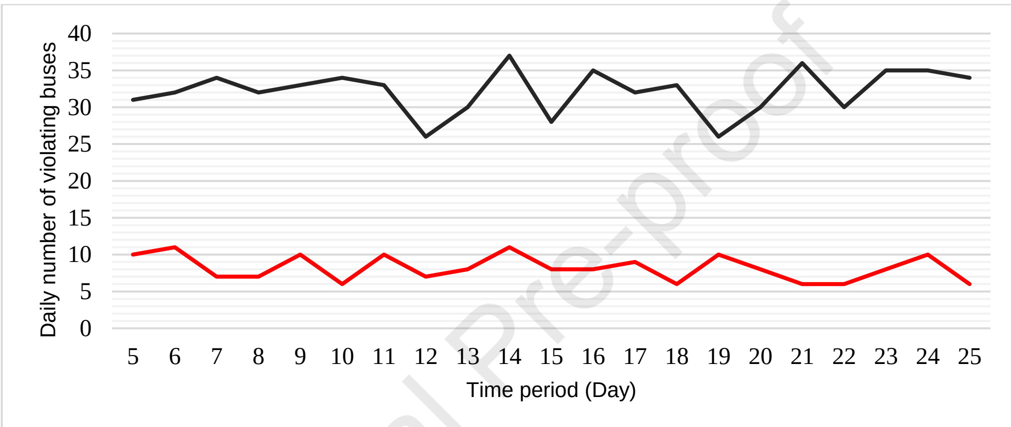


Figure 2 (a)

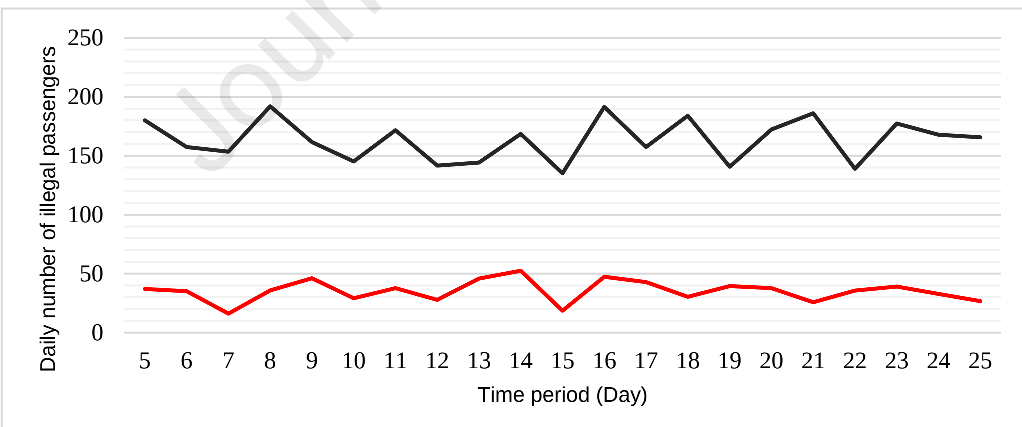


Figure 2 (b)

Figure 2 No-Inspection policy (NIP) results for two cases. The vertical axis in (a) represents the daily number of violating buses (DNVB) and in (b) represents the daily number of illegal passengers. The red line indicates the NIP results with an entry rate of 750 passengers per day to the terminal, and the black line shows the NIP results with an entry rate of 1500 passengers per day to the terminal.

As shown in Figure 2 the rate of passenger arrivals at the terminal has a significant impact on the number of daily violations at the terminals and the number of illegal passengers handled by the terminals. Increasing the number of passengers, the number of violations raises the possibility of infection and the number of patients. As a result, the need to adopt policies for the inspection of terminals is fully felt. In system dynamics models, negative feedback loops often make the system resistant to changes after policy adoption. Negative feedback loops may even lead to the aggravation of the problem in the system in the long run. As a result, by performing simulation after policy making, the results can be observed in the long term, and the resistance or change of abnormal behavior can be checked. After presenting each policy, this study examines the result of its implementation with long-term simulation. In the following, by proposing several inspection policies, the results of each simulation mode are reviewed.

4. Inspection and penalty policies and their effects

4.1 Fixed Penalty Policy (FPP)

In this type of inspection policy, the inspector enters the terminal at a random time of the day and inspects the bus that the passenger is riding at the moment, and he penalties the driver with fixed amount if he observes a violation, ends his inspection and leaves the terminal. The causal loop diagram of this inspection policy can be seen in Diagram 3.

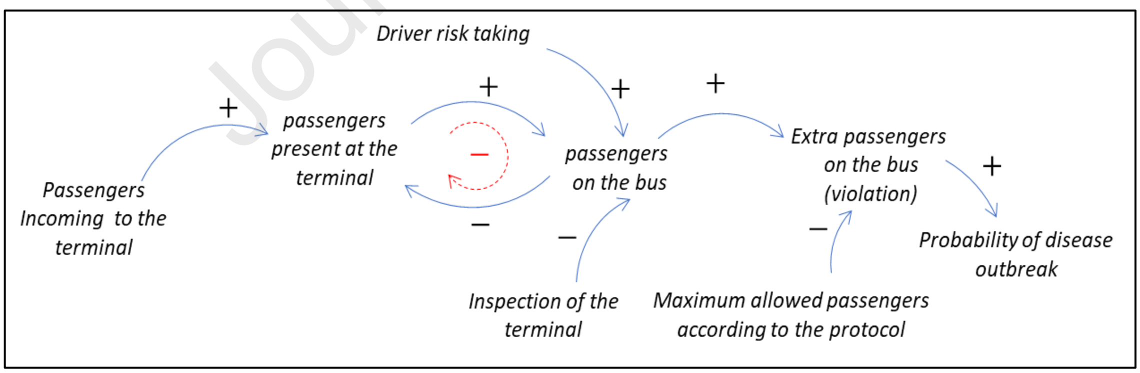
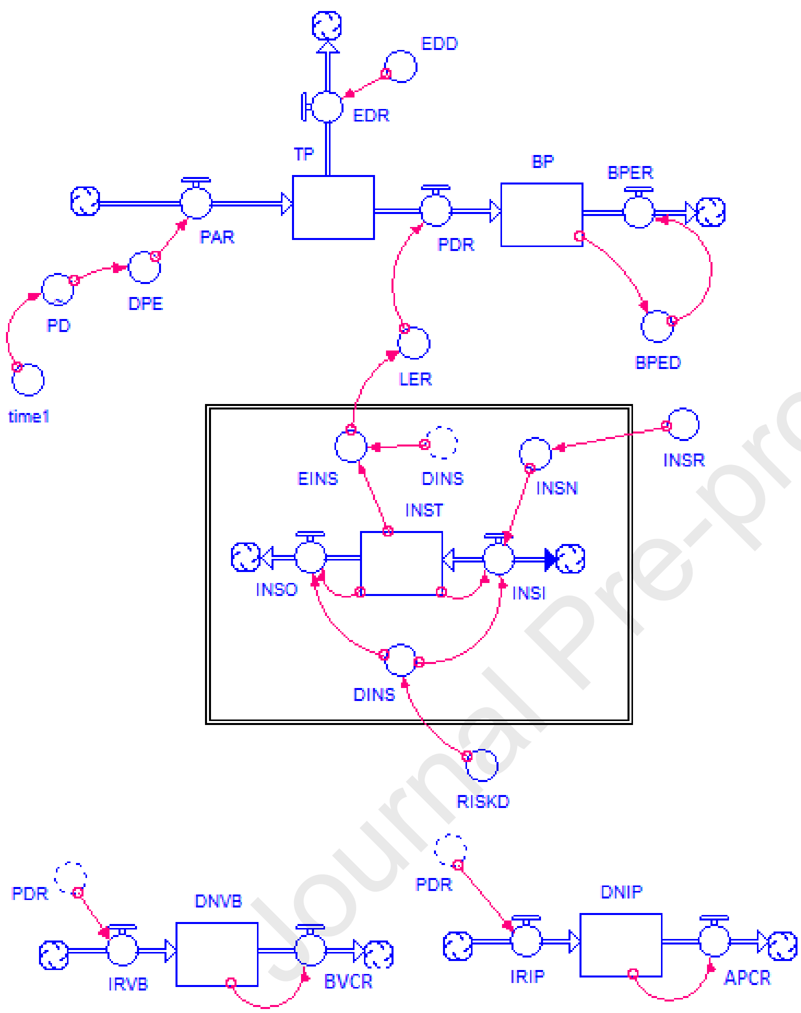


Diagram 3 Causal loop diagram of Fixed Penalty Policy (FPP)

As shown in Diagram 3, in addition to the passenger entry rate to the terminal, two other factors that affect the number of bus passengers are "terminal inspection rate" and "bus driver risk behavior". The inspection rate has a similar effect on compliance with the law on drivers. If the inspector is openly present at the terminal, the drivers inside the terminal will be affected by the inspector's presence and will decide to enforce the law. As a result, drivers' adherence to the law will increase as the terminal inspection rate increases.

Thus, the drivers' adherence to the law decreases over time after the most recent inspection, and drivers return to their previous process of not following the law. The rate of forgetfulness and declining regularity depends on the risk behavior of terminal drivers, which is expressed here by the term driver risk behavior. The higher the risk degree of the terminal drivers, the sooner the effect of the inspection disappears and the sooner the terminal drivers return to the violation process. Meanwhile, the value of penalties plays an essential role in the driver's risk behavior. The higher the penalty, the later the driver forgets and the more risk-averse he becomes. The effect of drivers' behavior on law enforcement has already been studied and confirmed in some studies (Ge et al., 2014; Sheikholeslami, Ayazi, & Moghadari, 2021).

Explanations of the impact of terminal inspection rates and risk-taking degree on compliance with the rule are given in Diagram 4. In this diagram, the subsystem enclosed in a square, shown as a dashed line, considers the two factors of inspection rate (INSR) and driver risk degree (RISKD) as input and the effect of these two factors on the regularity of the terminal drivers over time as output. It should be noted that the (RISKD) numerical value for drivers in the model is a number within the range of 0 and 1. For the highest risky drivers, RISKD is equal to 1, and for the lowest risky drivers, this variable is equal to 0.



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	DNVB: Daily number of terminals violating buses
	IRIP: Increase rate of illegal passengers in the terminal
	DNIP: Daily number of illegal passengers in the terminal
	BVCR: Bus violation counter reset
	APCR: Additional passengers counter reset
	LER: law enforcement rate of the terminal
	RISKD: Risk degree
	INSR: Inspection rate
	INSN: Inspection number
	INSI: Inspection input rate
	INSO: Inspection output rate
	EINS: Expectation of inspection
	DINS: Disremember of inspection

Diagram 4 Flow diagram of FPP

Figure 3 is drawn for two drivers with different risk degrees to understand the concept of risk-taking. The low enforcement rate can be interpreted as the probability of complying with the rules. In Figure 3, a value of 1 at a specific time means that the inspector is inspecting the terminal at that time, and the driver will not pick up any extra passengers for fear of being fined. It means that the driver's probability of adhering to the law equals 1. However, as time passes since the last inspection, the drivers gradually forget the inspector's presence and tend to pick up the extra passenger, and the low enforcement coefficient decreases. However, the driver's degree of risk-taking determines the reduced speed of adherence to the law (probability of complying with the rules) over time. The driver, who has a higher risk degree, returns to the pre-inspection procedure shortly after the inspection (red line), and the probability of his compliance with the rules decreases more quickly. On the other hand, the driver with a lower risk degree returns to the pre-inspection procedure a long time after the inspection (blue line).

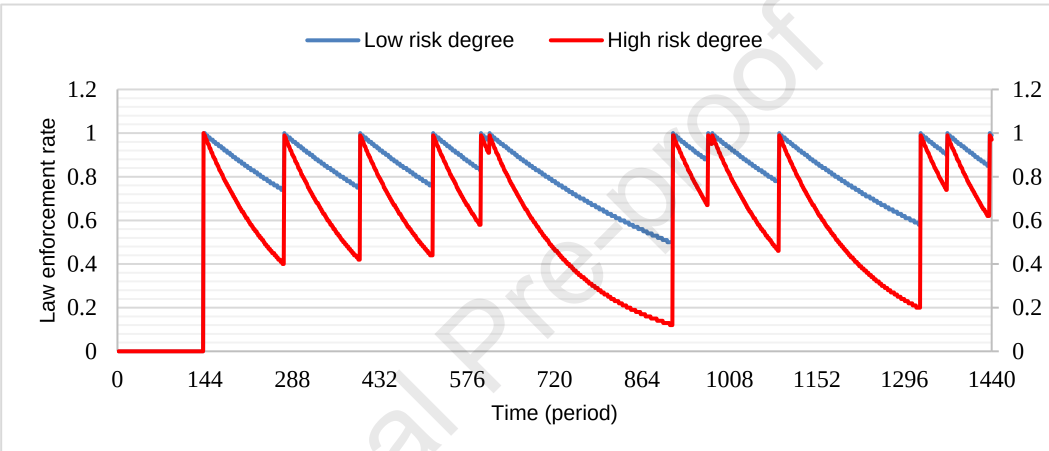


Figure 3 Comparison of the process of reducing law enforcement for two drivers with different risk degrees after the inspection. The red line indicates the behavior with high risk degree and the blue line indicates the behavior with low risk degree.

4.1.1 Results of fixed penalty policy (FPP)

In order to compare the effect of the FPP on the daily violations of terminal drivers, the simulation results of the FPP were examined and compared with no inspection policy (NIP). The simulation was performed to investigate the effects of implementing the FPP on drivers' performance. This simulation was operated for four months plus the first five days, i.e., 125 days. Terminals are considered with high-risk degree drivers' behavior in the simulation. The simulation results for 120 days for the number of daily violations and the number of daily illegal passengers can be seen in Figure 4.

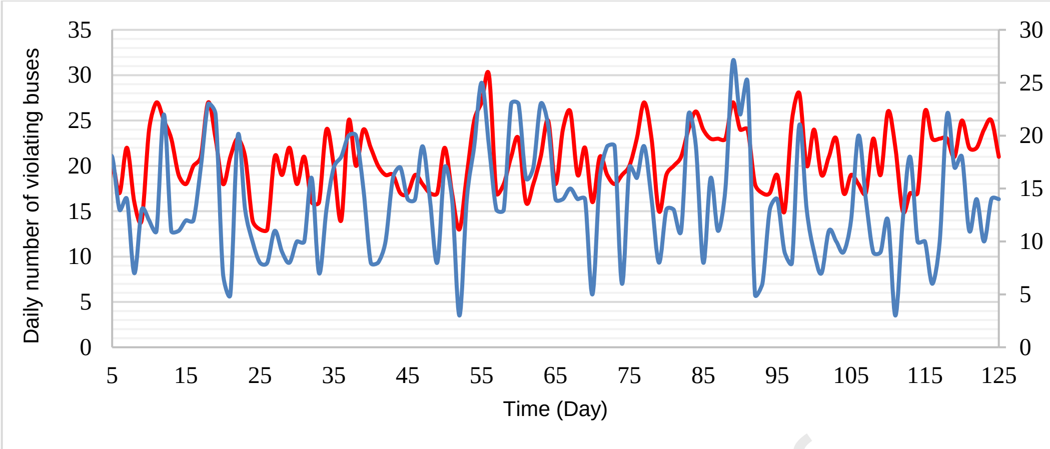


Figure 4 (a)

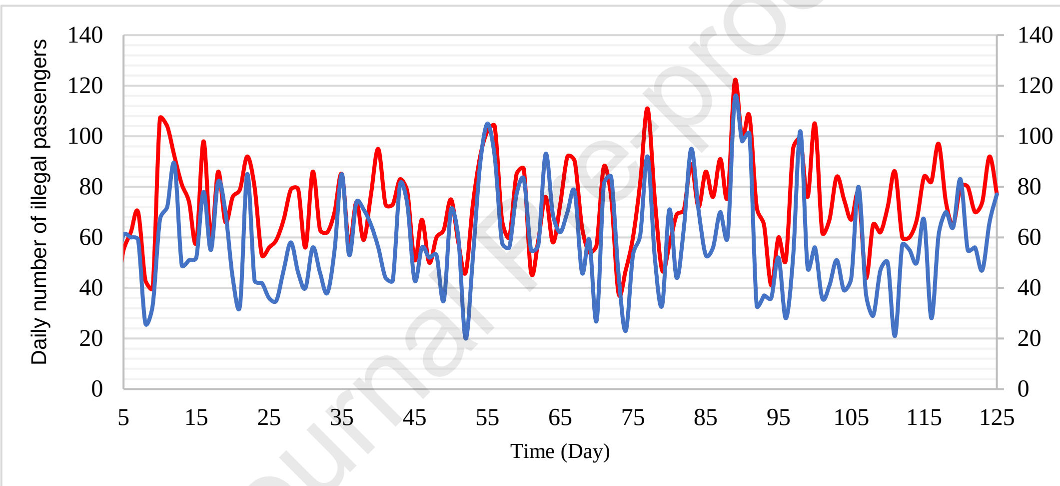


Figure 4 (b)

Figure 4 Comparison of fixed penalty policy (FPP) and no inspection policy (NIP) results. The vertical axis in (a) represents the daily number of violating buses (DNVB) and in (b) represents the daily number of illegal passengers. The red line indicates the NIP results, and the blue line shows the FPP results.

As can be seen in Figure 4, the FPP has significantly reduced the number of violations compared to the NIP. In order to show the effect of the influencing factors on the daily violations of the terminals during the implementation of the FPP, each time, only one influencing factor was considered different, and simulation was performed; finally, the simulation results are given below.

4.1.2 Inspection rate effect on the rate of violation by implementing FPP

A simulation was performed to investigate the effect of inspection rate on the violation rate in FPP. In this simulation, only the daily inspection rate was doubled. The rest of the conditions are the same for the two terminals, i.e., the passenger entry rate to each terminal has a Poisson distribution at a rate of 750 passengers per day and terminals are considered with high-risk degree drivers' behavior. The simulation results are shown in Figure 5.

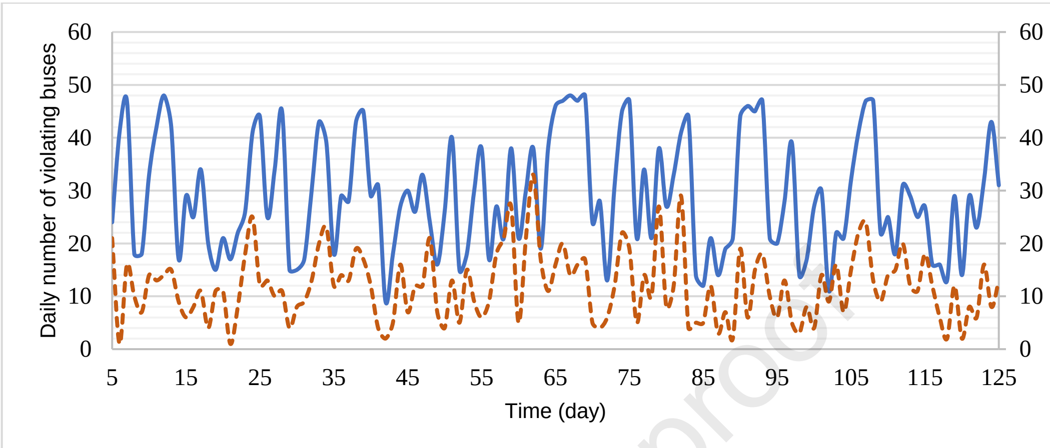


Figure 5 (a)

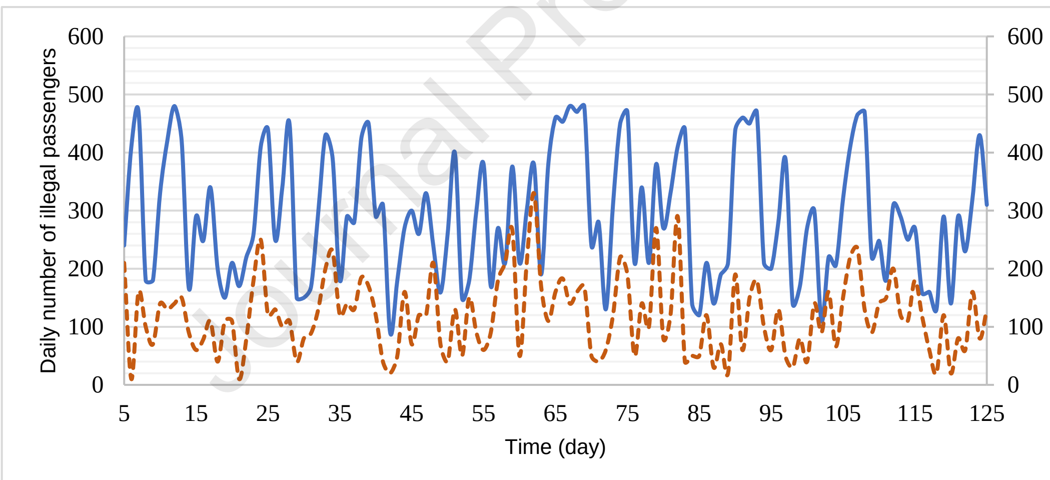


Figure 5 (b)

Figure 5 FPP results for two different inspection rates cases. The vertical axis in (a) represents the daily number of violating buses (DNVB) and in (b) represents the daily number of illegal passengers. The blue line indicates the results with 50 inspections per month, and the brown dashed line shows the results with 100 inspections per month.

As shown in the Figure 5, the different inspection rate from the terminal significantly affects the number of violations and the daily number of offending terminal passengers.

4.1.3 Terminal drivers' risk degree effect on the rate of violation by implementing FPP

To study terminal drivers' risk degree effect on the rate of violation, assume two terminals, the risk factor of terminal drivers is considered equal to 1 for one terminal and equal to 0.5 for the other. The rest of the conditions are the same for the two terminals, i.e., the passenger entry rate to each terminal has a Poisson distribution at a rate of 750 passengers per day and the total number of inspections is 50 inspections per month, which is equivalent to 0.12 per hour. A simulation was performed to investigate the effect of terminal drivers' risk degree on the violation rate in FPP. The simulation results are shown in Figure 6.

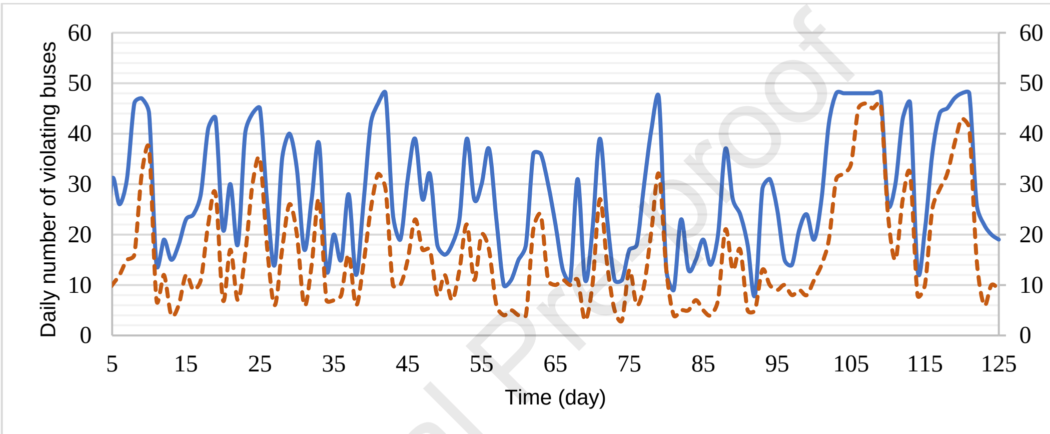


Figure 6 (a)

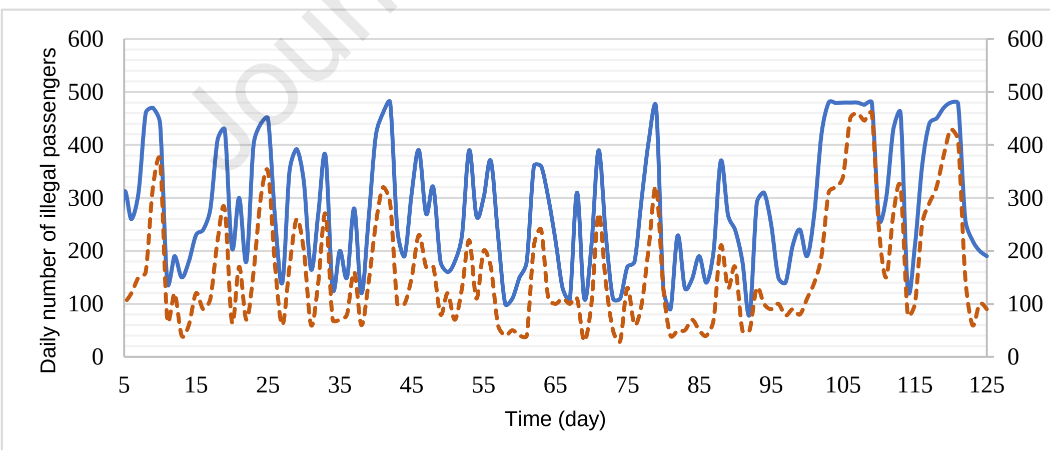


Figure 6 (b)

Figure 6 FPP results for two different drivers' risk behavior cases. The vertical axis in (a) represents the daily number of violating buses (DNVB) and in (b) represents the daily number of illegal passengers. The blue line indicates the results for drivers with risk degree equal to 1.0, and the brown dashed line shows the results for drivers with risk degree equal to 0.5.

As seen in the Figure 6, the degree of the terminal drivers’ risk significantly impacts the number of violations and the daily number of passengers in the terminal. As a result, if the inspection policy can affect the risk-taking of terminal drivers, the process of their violations will be significantly reduced.

Based on the sensitivity analysis above, generally it can be said that 1- Passenger entry rate to the terminal 2- The terminal drivers’ risk taking degree 3- Inspection rate of the terminal are three main components affecting the misconduct of terminal drivers and the resulting outbreak. Among these three components incoming passenger rate to the terminal is an exogenous variable. However, the inspection body can influence the inspection rate and the degree of risk of the terminals by presenting different policies. Then, policies for inspection and penalties of terminal drivers are presented and the results of the implementation of these policies are examined through simulations. In the continuation of the study, to review and analyze different inspection policies, terminals with high-risk degree drivers' behavior are considered.

4.2 Variable Penalty policy (VPP)

In this type of inspection and penalty policy, the inspector randomly visits the terminal over time, and during the inspection, first secretly observes the behavior of the terminal drivers for a while, and then determines the amount of penalty for the terminal according to the number of violations committed (the number of violating buses). As mentioned, amounts of penalties affect the risk degree of bus drivers. The more penalties are imposed on the offending driver, the lower the risk of terminal drivers. As shown in Figure 7, terminal drivers initially have a high risk degree (see the blue line). Rapid forgetfulness causes more violations of terminal drivers, and in proportion to the violations a higher penalty is applied to it and as a result, drivers' risk-taking is reduced and drivers' violations are reduced (see green line).

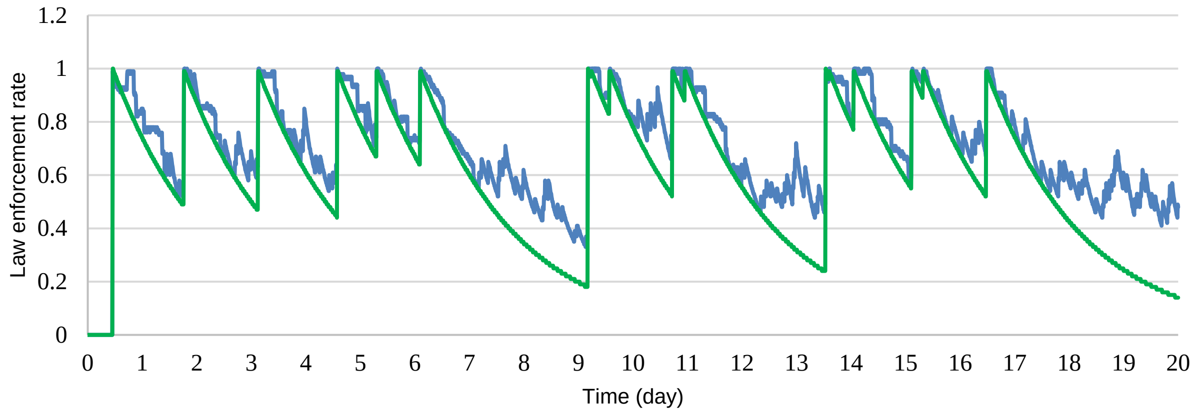


Figure 7 Comparison of terminal driver risk-taking with a fixed penalty (green) and a penalty commensurate with the violation (blue)

The causal diagram of the VPP is shown in Diagram 5 and the flow diagram of this policy is shown in Diagram 6.

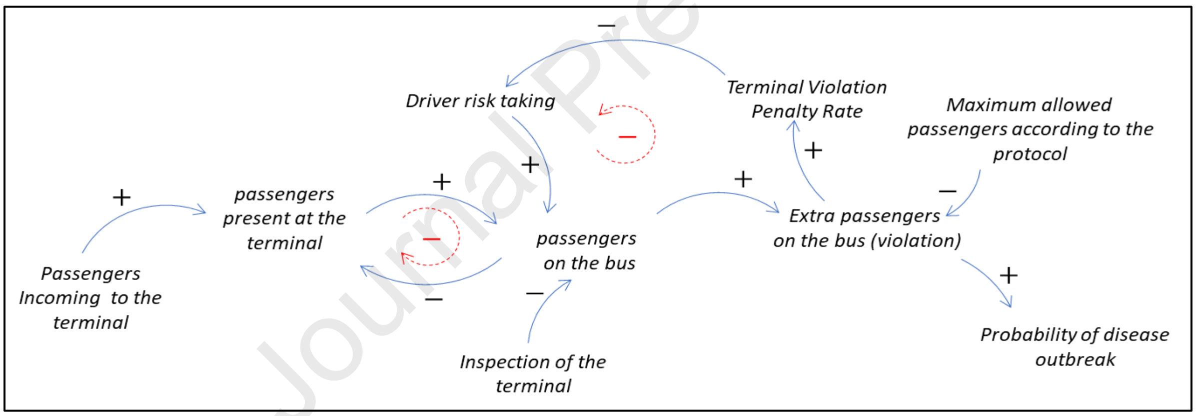
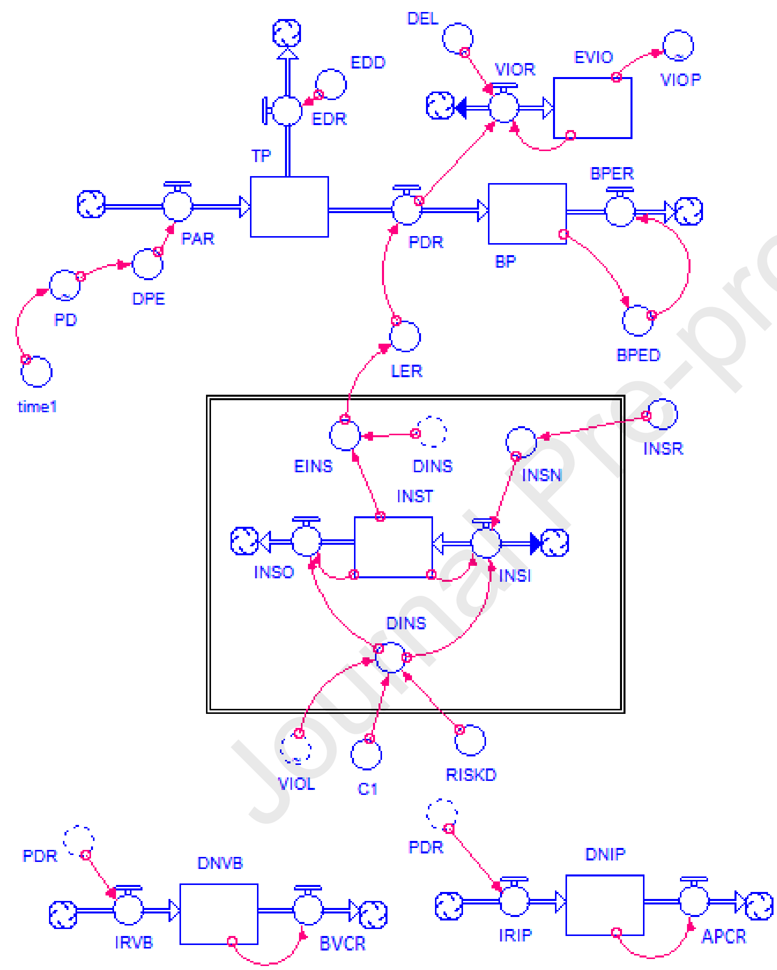


Diagram 5 Causal loop diagram of the VPP



PD: Passengers travel demand
DPE: Distribution of passenger entrance to the terminal
PAR: Passenger arrival rate in terminal
TP: Terminal passengers
EDD: The end of day discharge distribution of terminal
EDR: The end of day discharge rate
PDR: Passenger departure rate from terminal
BPED: Terminal bus passengers' evacuating distribution
IRVB: Increase rate of violating buses in Terminal
DNVB: Daily number of terminals violating buses
IRIP: Increase rate of illegal passengers in the terminal
DNIP: Daily number of illegal passengers in the terminal
BVCR: Bus violation counter reset
APCR: Additional passengers counter reset
LER: law enforcement rate of the terminal
RISKD: Risk degree
INSR: Inspection rate
INSN: Inspection number
INSI: Inspection input rate
INSO: Inspection output rate
EINS: Expectation of inspection
DINS: Disremember of inspection
VOIR: Violation rate
DEL: Delay
EVIO: Expected violation
VIOF: Violation penalty

Diagram 6 Flow diagram of VPP

Simulations were made to compare the results of the variable penalty policy (VPP) with fixed penalty policy (FPP). Simulations were performed by considering the conditions in VPP and FPP. The results of this simulation can be seen in Figure 8.

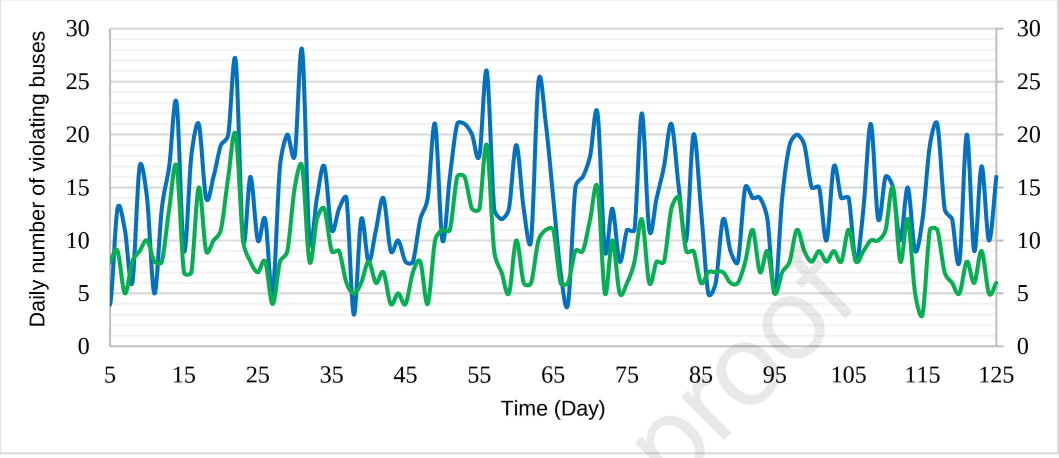


Figure 8 (a)

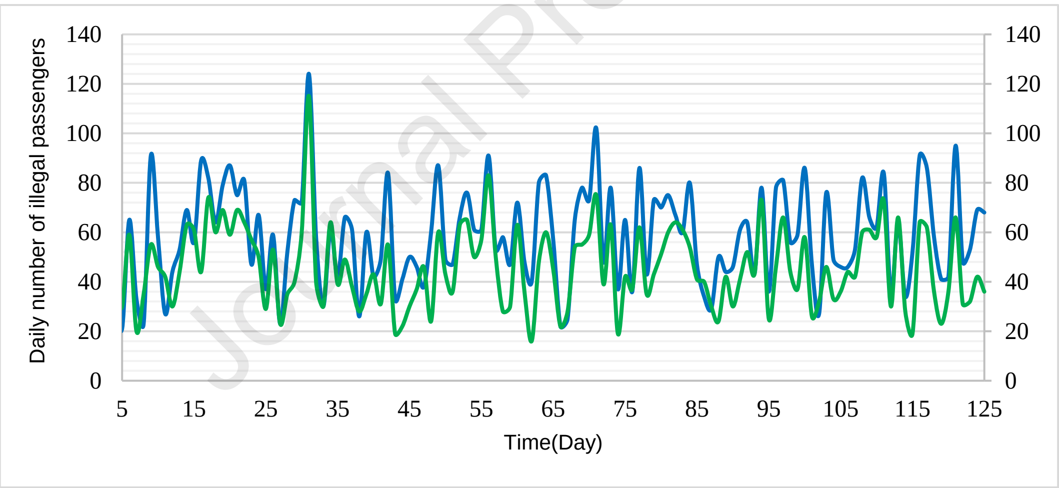


Figure 8 (b)

Figure 8 Comparison of variable penalty policy (VPP) and fixed penalty policy (FPP) results. The vertical axis in (a) represents the daily number of violating buses (DNVB) and in (b) represents the daily number of illegal passengers. The blue line indicates the FPP results, and the green line shows the VPP results.

As shown in Figure 8, the VPP has significantly reduced the number of violations compared to the apparent inspection. Considering the long-term results, it seems that choosing VPP over FPP for city managers will have better results in preventing the spread of the disease.

5. Model development with consideration of several public passenger terminals

In urban public transportation system, several public transportation terminals serve passengers daily in different parts of the city, and the inspection organization is in charge of inspecting these terminals. This section evaluates the effect of inspection policies on several public transportation terminals in a city. For simplicity, it is assumed that there are two public transportation terminals in the city and an inspection organization with a limited number of inspectors. It is assumed that there are two approaches to assigning inspectors to inspect terminals. In the first approach of assigning inspectors the terminals which called fixed inspector assignment (FIA), inspections are carried out randomly over time but at the same inspection rate. In the second approach of assigning inspectors to the terminal which called variable inspector assignment (VIA), inspections are carried out randomly over time but at variable inspection rates. The inspection rate of the two terminals in the VIA is determined based on information about the average violations of their drivers on the days of the previous week. Thus, the inspection rate for one terminal increases with relative increases of the average violations in that terminal compared to the other terminals. Diagram 7 is the cause-and-effect diagram for VIA in which the inspection penalty follows the VPP.

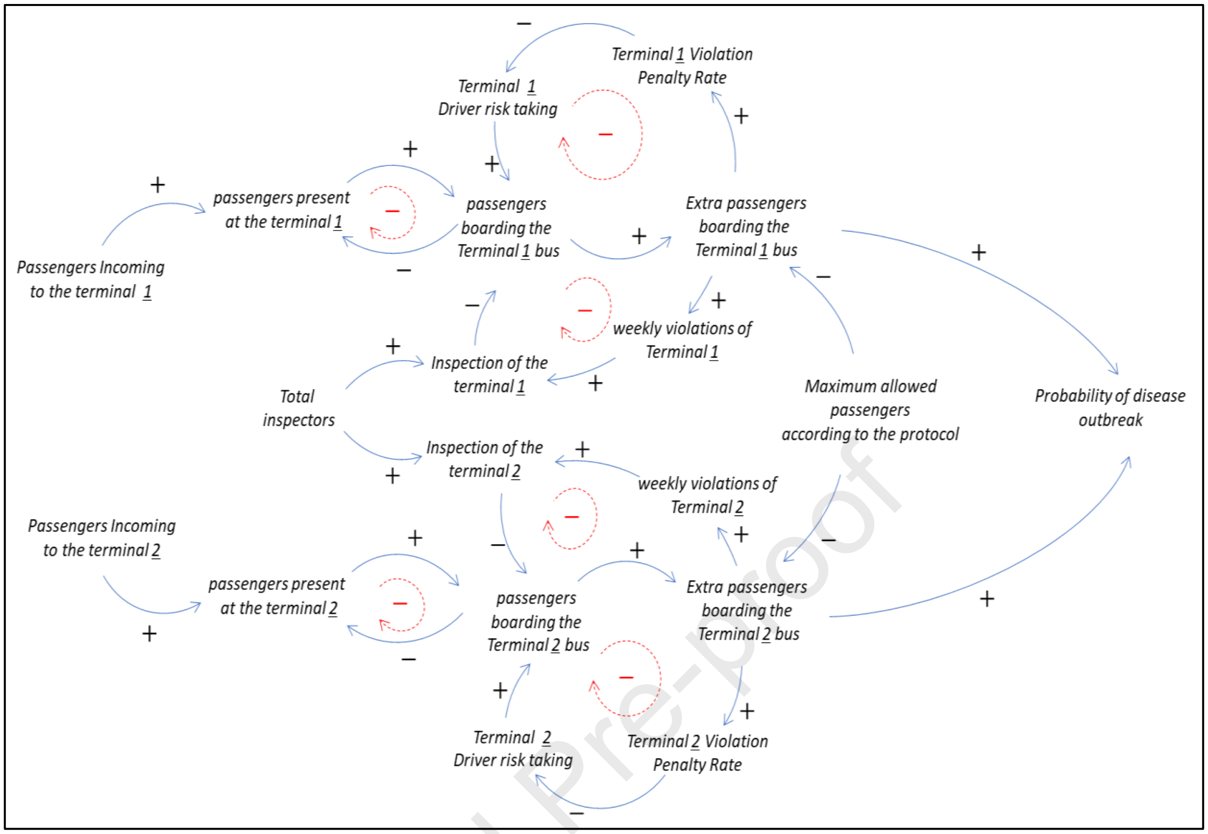


Diagram 7 Causal loop diagram of combination VIA and VPP

The model in Diagram 7 includes two public passenger terminals and an inspection organization with a fixed rate of inspection rate. The inspection rate of each terminal is based on the second approach of inspection allocation. Also, in this model, the inspection and penalty policy are based on the variable penalty policy (VPP). Figure 9 compares the number of daily bus violations and the number of illegal passengers, respectively, for fixed inspector assignment (FIA) and variable inspector assignment (VIA) scenarios.

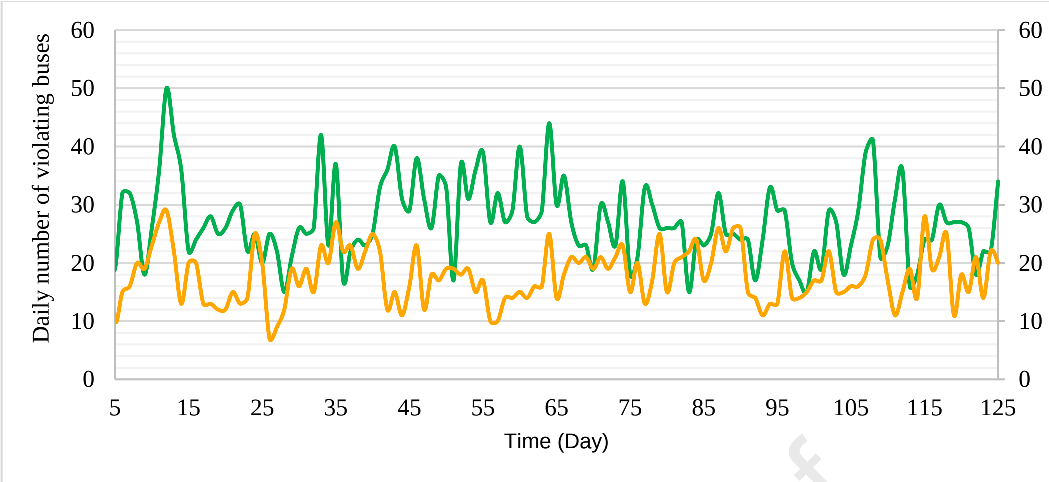


Figure 9 (a)

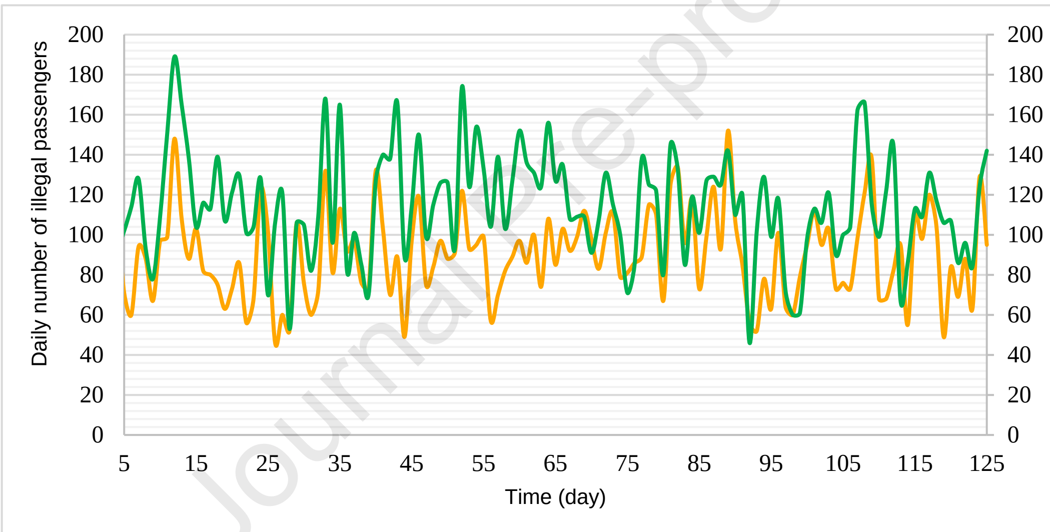


Figure 9 (b)

Figure 9 Comparison of variable inspector assignment (VIA) and fixed inspector assignment (FIA) results. The vertical axis in (a) represents the daily number of violating buses (DNVB) and in (b) represents the daily number of illegal passengers. The orange line indicates the VIA results, and the green line shows the FIA results.

As can be seen in these two figures, the VIA reduces violations and the number of illegal passengers compared to the first approach of assigning inspections and has achieved better results.

6. Comparison and analyzing the results of different inspection policies

In this section, different scenarios are considered under the conditions of the presence of two urban public transportation terminals and an inspection organization with a certain number of inspections. Scenarios are created by combining inspection policies and inspector assignment policies. Therefore, first, inspection policies and inspector assignment models are briefly reviewed:

• First inspection policy: the policy of non-inspection of terminal companies. (NIP)

• Second inspection policy: the inspection is explicit, and the penalty is the same and fixed. (FPP)

• Third inspection policy: the inspection is covert, and the penalty is commensurate with the registered violations. (VPP)

• First policy of inspector assignment: the inspection rate is divided equally between the two terminals. (FIA)

• Second policy of inspector assignment: the division of the inspection rate between the two terminals is based on the ratio of last week's violations of the two terminals. (VIA)

To compare and analyze the results of different scenarios, it was assumed that the passenger entry rate to each terminal has a Poisson distribution at a rate of 750 passengers per day and the total number of inspections is 50 inspections per month, which is equivalent to 0.12 per hour. The number of violations in each scenario is equal to the sum of the violations in the two terminals. The simulation is performed for 125 days and the results for the number of monthly violations and the total of four months are shown in Table 1.

Table 1 Comparison of the number of monthly violations in different scenarios for two terminals

	Scenario number	Inspection and penalty policy + Inspector Assignment policy	First month	Second month	Third month	Fourth month	Total
Total number of offending buses	Scenario 1	NIP	960	914	944	904	3690
	Scenario 2	FPP + FIA	724	680	726	686	2795
	Scenario 3	VPP + FIA	600	604	611	585	2381
	Scenario 4	VPP + VIA	506	512	496	483	1988
Total number of illegal passengers	Scenario 1	NIP	4156	4172	7289	4196	16815
	Scenario 2	FPP + FIA	3732	3596	3891	3793	15014
	Scenario 3	VPP + FIA	3279	3367	3330	3374	13351
	Scenario 4	VPP + VIA	2876	2887	2940	2840	11545

As can be seen, with the implementation of inspection policies, the number of violations has significantly decreased compared to the base model. Among the various scenarios, the number of violating buses in the fourth scenario (1988) has decreased by more than 47% compared to the first scenario (3690). Also, the investigation of violating buses in the fourth scenario compared to the second and third scenarios shows a reduction of 29% and 17%, respectively.

As the same way the investigation of illegal passengers in the fourth scenario compared to the first, second and third scenarios shows a reduction of 31%, 25% and 14%, respectively. Then, in order to better compare the violations of the basic scenario and other inspection scenarios, their diagrams were drawn during four months in fifteen-day cumulative periods, the results of which can be seen in Figure 10.

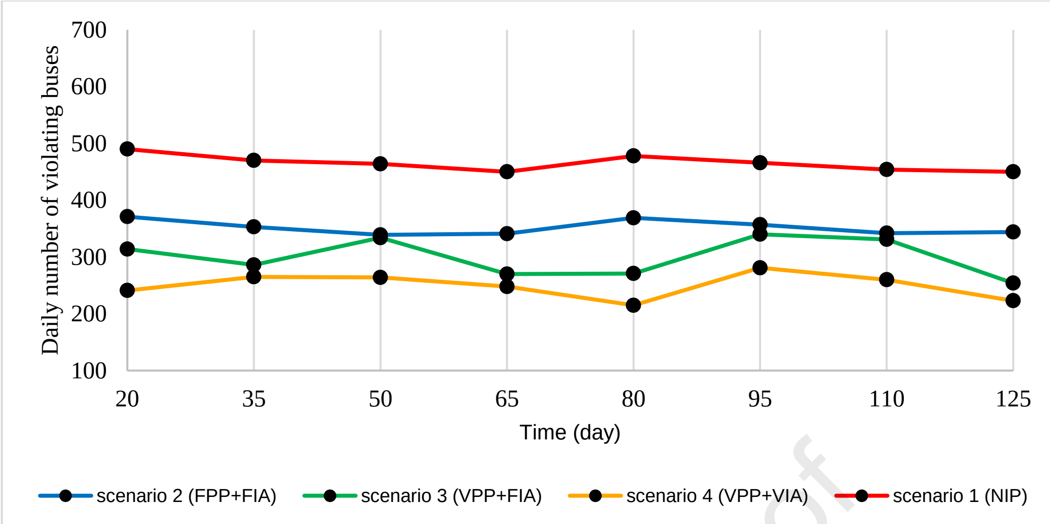


Figure 10 (a)

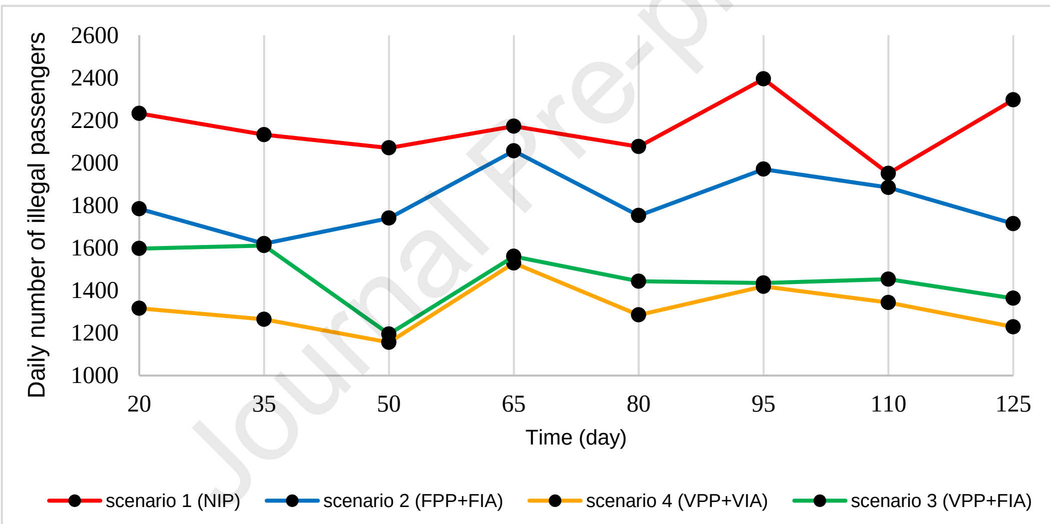


Figure 10 (b)

Figure 10 Comparison of different scenario results. The vertical axis in (a) represents the cumulative number of violating buses and in (b) represents the cumulative number of illegal passengers.

As can be seen in Figure 10, the fourth scenario, i.e., the combination of VIA and VPP, have the greatest impact on reducing violations and thus preventing the spread of disease. Given that the number of inspectors is the same in all three first to third inspection scenarios, the fourth scenario can be offered to managers and officials of public transportation inspection organizations as a suggested option.

7. Sensitivity analysis

The next critical issue is the sensitivity analysis of the model parameters. By performing sensitivity analysis, the robustness of the modeling can be examined. Sensitivity analysis can also provide various management tips and results to stakeholders. This section states the conditions that may change the model's parameters. Also, the results of the changes in the parameters are examined. in the simulations for each parameter, all conditions are considered in the same four scenarios.

A) Passenger arrival rate to the terminal: One of the possible scenarios that change the passenger entry rate to the terminal is the existence of days of the year, such as Christmas when the demand for daily trips of citizens increases. In this case, the modeling efficiency should be done, and the proposed scenarios should be examined. Therefore, simulation was performed by increasing the average passenger arrival rate from 10 passengers to 20 passengers in each period. Figure 11 shows changing the passenger entry rate to the terminal on the total number of violations for the four proposed scenarios. Based on what can be seen in Figure 11, increasing the passenger entry rate to the terminal increases the number of terminal violations. If not inspected (red line), this process will continue until all the buses violate and carry passengers to their total capacity. However, in all values of the passenger entry rate to the terminal, scenario four, namely the scenario of combining covert inspection policy and assigning variable inspector (VFP + VIA) to a reasonable extent, prevents the increase in the number of violations and maintains its superiority over other scenarios.

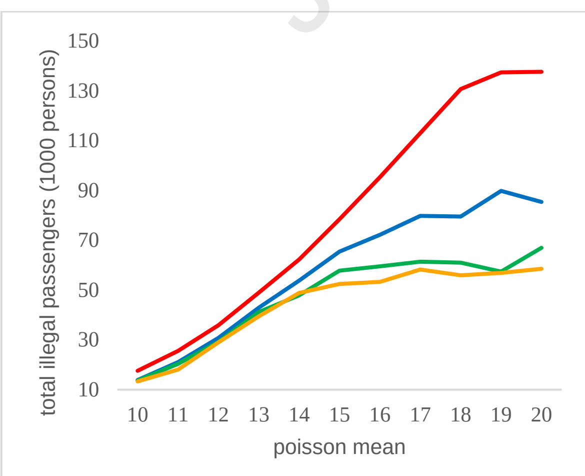


Figure 11 (a)

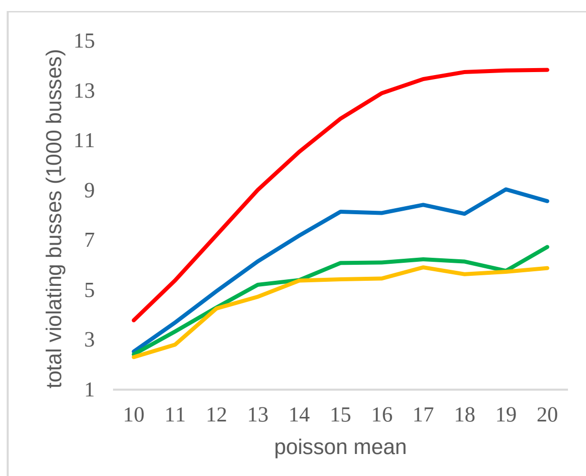


Figure 11 (b)

Figure 11 The passenger entry rate effect on the number of violations in different inspection scenarios

B) Inspection rate: The second issue of the analysis is the decision to increase the number of inspectors and increase the inspection rate. Most inspection agencies seek to examine the impact of increased inspection rates on violations. The number of inspections was considered 50 times a month in the previous sections. In this part, simulations were performed for the number of inspectors from 25 to 75. The simulation results can be seen in Figure 12. As shown in Figure 12, increasing the inspection rate reduces the number of violations in all inspected scenarios. Also, in all inspection rate values, the fourth scenario (VIP + VIA) compared to other inspection scenarios and fines could make the most of the increased inspection to reduce violations.

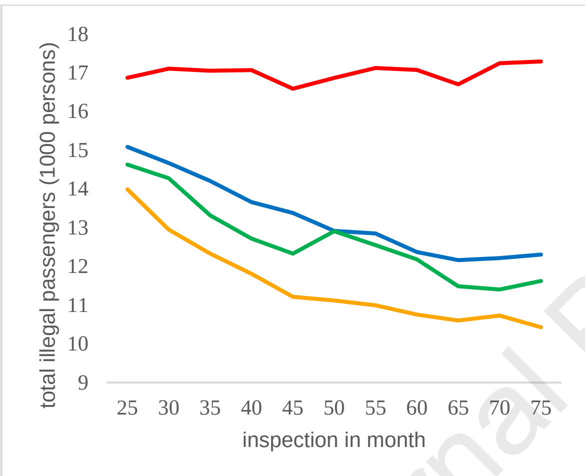


Figure 12 (a)

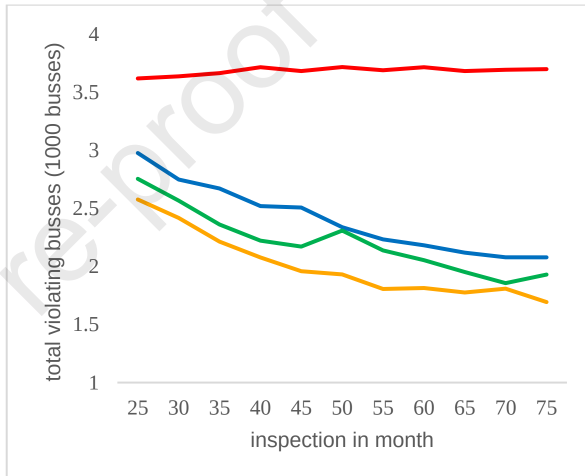


Figure 12 (b)

Figure 12 The inspection rate effect on the number of violations in different inspection scenarios

C) Drivers 'risk-taking rate: The third issue that transportation companies consider is the effect of terminal drivers' risk-taking characteristics on the rate of violations. To this end, simulations were performed with a risk-taking rate ranging from zero (completely risk-averse) to 1 (fully risk-averse). The simulation results can be seen in Figure 13. As can be seen, as the risk of drivers increases, the number of terminal violations in all scenarios increases. However, scenario four (VIP + VIA) was able to show its superiority over other scenarios in preventing the growth of violations in all values of the risk parameter.

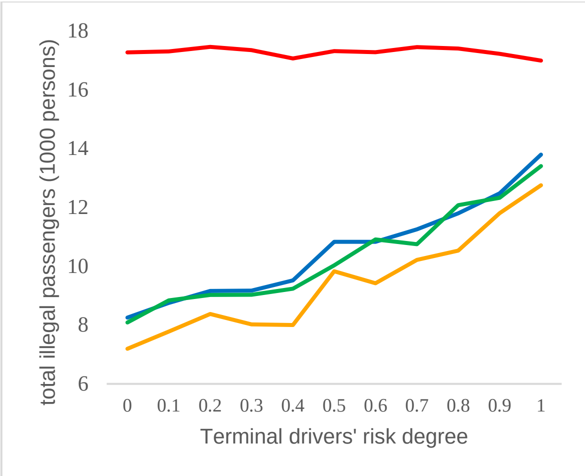


Figure 13 (a)

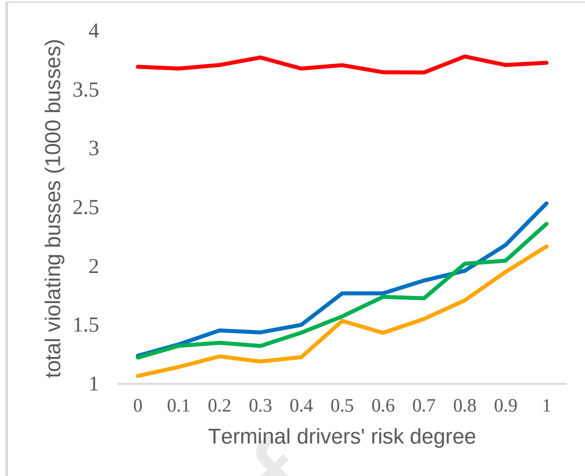


Figure 13 (b)

Figure 13 The terminal drivers' risk degree effect on the number of violations in different inspection scenarios

D) Schedule of buses: Finally, the fourth issue that is very important is the occurrence of accidents such as traffic jams in the city, weather conditions such as rain or ice, and the breakdown of buses in the middle of their route. The occurrence of these accidents affects the departure time of terminal buses. In proportion to the rate of accidents per day, the schedule of arrival and departure of buses in the terminal, which is quite regular and every 15 minutes, is delayed. Meaningfully, simulations were performed for the number of daily delays in the departure of terminal buses. The simulation results can be seen in Figure 14. As can be seen in Figure 14, the number of violations increases with the delay in the movement of terminal buses. In explaining this issue, it can be said that due to the accident and the delay in the bus movement, the population of passengers present at the terminal has increased, and conditions are provided for drivers to commit violations. The proposed policy to transport companies to avoid delays is to consider replacement buses in an accident. As shown in Figure 14, in this parameter, scenario four showed its superiority in reducing the violations compared to other scenarios.

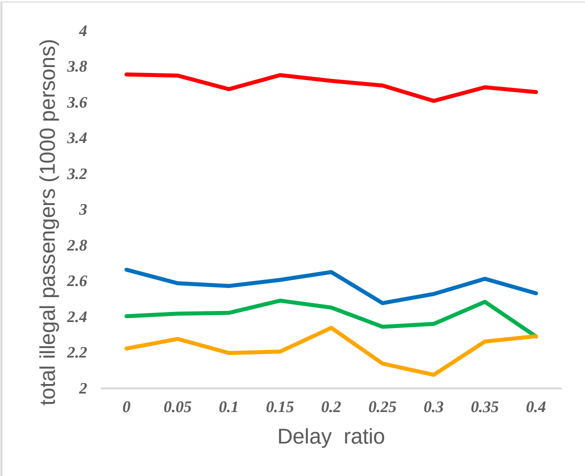


Figure 14 (a)

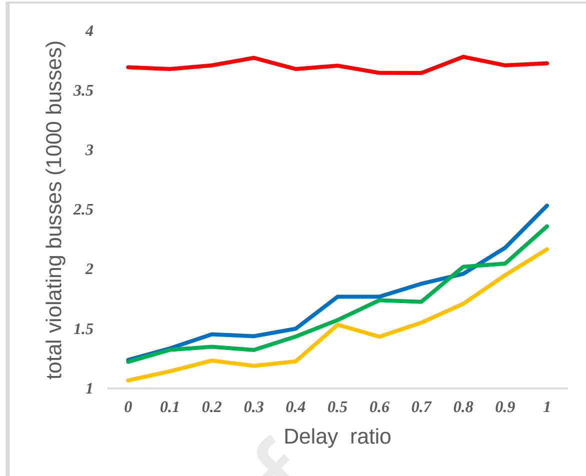


Figure 14 (b)

Figure 14 effect of delays in the movement of terminal buses on the number of violations in different inspection scenarios

According to the sensitivity analysis performed on the proposed model, it can be concluded that the results obtained are acceptable in most environmental conditions.

As the research questions mentioned in the introduction, this study sought to provide a dynamic systems model of the problem of disease outbreaks in transport companies and provide policies to improve resilience against epidemic disasters. Designing a comprehensible and expandable model based on systems theory can create a comprehensive understanding of the investigated problems and help design policies whose implementation will favor the system. Although the purpose of this study was not to present a complex model, the mathematical relationships among the model's components indicate the complexities in modeling. The sensitivity analysis can show these relationships' accuracy and the proposed model's validity.

8. Conclusions and suggestions for future studies

The influential role of health protocols in preventing the spread of the pandemic has led governments to seek their best implementation in society. Inspection is one of the policies that can be very effective in better implementation of these protocols. However, the limited resources available for inspections and the policy to enforce them, reduce the impact of inspections. Lack of social distance in public vehicles, which is the source of the movement of public transportation terminals, is one of the leading causes of epidemic diseases. This study examined and evaluated some of the inspection policies of urban public passenger terminals for the proper implementation of health protocols.

System complexity (such as interactions between inspectors, bus drivers, and passengers), nonlinear relationships between system components (e.g., the effect of penalties on drivers 'level of risk), problem dynamics (such as changes in drivers' risk behavior over time), and the randomness of some components (such as passenger arrival time at the terminal) caused this study to use the dynamic system approach to model the current state of the existing system (base model). By presenting the simulation results, the main factors of increasing violations in these terminals were introduced. These factors are the condition of the terminal congestion, the risk behavior of the terminal drivers, and the inspection rate that is done from the terminal. By introducing two types of policies, including fixed penalty policy (FPP) and variable penalty policy (VPP) and simulating them, it was shown that the VPP performs much better than the FPP. Then, the model extended by considering several passenger transportation terminals simultaneously, presenting two policies for inspector assigning to terminals, including fixed inspector assignment (FIA) and variable inspector assignment (VIA). The results indicate that the combining "VPP" and “VIA” has a good performance in the inspection.

Although in this research, an attempt was made to identify and consider most of the practical components to reduce violations in public transportation terminals, ideas can be proposed for future studies. The presented model can be expanded and complicated by analyzing the cost of adding an inspector or cultural advertising to reduce passenger arrivals and encourage legal terminals. Also, the process of recognizing drivers from the time and day of the inspectors' inspection can be added to the model by a negative feedback loop. Finally, competition between terminals is also another issue that can be addressed. Using methods such as game theory to examine terminal ticket pricing can benefit policy-making terminals competing with each other.

Appendix A: Equations of base model's flow diagram

```
BP(t) = BP(t - dt) + (PDR - BPER) * dt
INIT BP = 0
INFLOWS:
PDR = (PULSE((IF(TP>25) THEN (25) ELSE (TP)),2,3))
OUTFLOWS:
BPER = BPED
DNIP(t) = DNIP (t - dt) + (IRIP - APCR) * dt
INIT DNIP = 0
INFLOWS:
IRIP = IF((PDR-15)>0) THEN(PDR-15) ELSE (0)
OUTFLOWS:
APCR = PULSE(DNIP,167,168)
DNVB(t) = DNVB (t - dt) + (IRVB - BVCR) * dt
INIT DNVB = 0
INFLOWS:
IRVB = IF((PDR-15)>0) THEN (1) ELSE (0)
OUTFLOWS:
BVCR = PULSE(DNVB,167,168)
TP(t) = TP (t - dt) + (PAR - PDR - EDR) * dt
INIT TP = 0
INFLOWS:
PAR = DPE
OUTFLOWS:
PDR = (PULSE((IF(TP>25) THEN (25) ELSE (TP)),2,3))
EDR = EDD
BPED = PULSE(BP,5,3)
DPE = POISSON (10) *PD
EDD = PULSE (1000,167,168)
PD = GRAPH (time1)
time1 = (time MOD 168)
```

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Highlights

- The inspection issue of transportation companies in the Covid-19 era is studied.
- The systems dynamics approach is used for modeling and simulation.
- The effect of four inspection and penalties policies scenarios is investigated.
- Appropriate inspection and penalty policies can halve violations.
- The results can help city managers to adopt appropriate inspection policies.

November 18, 2022

Editorial Board
Transport policy
Elsevier Publication

Dear Editorial Board,

Please find attached our revised submission entitled, "**Evaluation and improvement the transportation system resilience against epidemic diseases: A system dynamics approach**" for publication consideration in the Transport policy. My co-authors and I have done our best to address all the comments made by respected reviewers. Specifically, we added a whole new section for sensitivity analysis. Moreover, we had the manuscript reviewed by a professional language editor.

In this work, we examine the relationship between government inspections, urban public transportation companies, and the number of violations committed in an epidemic disaster using a system dynamics approach and seeks to provide efficient and effective policies to inspect urban public transportation companies during an epidemic. In this regard, passenger entry rates to the terminal, the risk, and the behavior of transportation companies and drivers have been considered. This paper contributes to the literature by proposing two penalty policies, including fixed penalty policy (FPP) and variable penalty policy (VPP) and two inspector assignment policies, including fixed inspector assignment (FIA) and variable inspector assignment (VIA). Also, the effect of four scenarios of combining inspection and penalties policies is investigated. Our findings confirm that combining the variable penalty and variable inspector assignment policies could significantly reduce terminal violations. Also, the implementation of this policy does not require an additional inspector. The results can help city managers to adopt appropriate inspection policies.

To the best of our knowledge, we are the first to make the contributions listed above, and do believe that our work is a good fit for Transport policy. We certify that the submitted work is original, and that it is not under review at any other publication outlet. We have no conflict of interest to disclose.

We thank you for your attention and look forward to the review process.

Sincerely,

On behalf of the authors,

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