Proceedings of the 2019 Winter Simulation Conference
N. Mustafee, K.-H.G. Bae, S. Lazarova-Molnar, M. Rabe, C. Szabo, P. Haas, and Y.-J. Son, eds.

STATIC ZONING DIVISION ELEVATOR TRAFFIC SIMULATION USING AGENT-BASED MODELING

Angelika C. Batosalem
Janelle Marie B. Gaba
Jan Bertel O. Ngo
Jonal Ray G. Ticug
Courtney Anne M. Ngo

College of Computer Studies
De La Salle University
2401 Taft Ave,
Malate, Manila, 1004, PHILIPPINES

ABSTRACT

Elevator traffic affects people who use elevators in high-rise buildings. This occurs due to elevators operating to cater passengers above its intended capacity. The next set of passengers still needs to wait approximately four minutes before they are serviced even if the elevators implement a static zoning division to reduce waiting time during peak hours. Hence, there is a need to optimize current systems. And to better understand how the system works along with its pitfalls, the environment will be simulated using agent-based modeling. The simulation will be modeled and fitted using data gathered from ID scans and CCTV footages. Through simulation, it would be possible to visualize the behavior inside the building and minimize elevator traffic. Removing the elevator service going down optimized the current system and reduced the round trip time of the elevators and waiting time of the passengers on high-rise buildings that use static zoning division.

1 INTRODUCTION

Infrastructure and technology have been progressing throughout the years and this has resulted to tall commercial, industrial, and residential buildings being built. With the advent of an era of a staggering range of new technologies to provide ease of mobility and transportation, elevators have become an essential component of all high-rise buildings (Kumar, Singh, and Singh, 2017). Elevators offer convenience and efficiency as it diminishes the trouble of using staircases. Although the process of an elevator system is simple, improving its configuration is where the difficulty and complexity come in. Considering the number of people who use the building each day, it is difficult to contain the elevator traffic, especially in peak hours. Intelligent elevator control systems are an essential part to obtain optimum performance in the development of high-rise buildings which involves lessened power consumption, floor traffic, and average waiting time of passengers (Rashid, Kasemi, Faruq, and Alam, 2011).

Different optimizations of elevator systems with heavy passenger traffic were done to optimize the system and lessen the total waiting time of the passengers. The same problem goes for the Br. Andrew Gonzalez Hall (AGH) in De La Salle University, Manila (DLSU). It is a 20-story building which houses four elevator cars for passenger use, and one elevator car exclusively for faculty and staff members. Passenger overcrowding on the building lobby has been one of the biggest issues in this university. The similar break times of students and professors results to the high volume of passenger traffic at the building. Different optimization techniques were implemented, such as introducing an interleaved zoning system as well as changing the static zoning division where certain elevators only cater to specific floors and changing these divisions termly. But recently, passenger crowd on the AGH has become stable which allowed the building to implement a static zoning division for the elevators. The configuration was introduced by the mechanical and electrical works office after given crowd statistics data from the information technology office. However, passengers still wait for an average of four minutes before they can board the elevator. This fits the criteria of an unacceptable system because it exceeds fifty seconds (Barney and Al-Sharif, 2016).

Agent-Based Modeling (ABM) is a simulation technique that has become increasingly popular in recent years. It utilizes decision making entities called agents that results in very realistic simulations. Different studies and developments regarding ABM have been done because of its ability to model actual scenarios. Applying ABM to simulate elevator systems gives a better understanding of how users interact with elevators, how they use them, and possibly how to improve it based on the generated actions and decisions by the agents. Previous studies like that of Jung (2017) made use of ABM instead of discrete event simulation to model and optimize high rise buildings. However, the modeled environment was fit to replicate an unfinished construction building where the behaviors of the agents are different from our target environment. With proper and realistic visualization, one will be able to understand and interpret the behavior of the passengers who use the elevators in the AGH. Based on the different applications of ABM in the reviewed literature, it is evident that there is no existing research that uses ABM on a completed building with a static zoning division system. The main objective of this research is to identify the properties of the agents to be considered in the elevator simulation and to use the results to provide recommendations to ease passenger traffic and optimize the current environment.

2 RELATED WORK

2.1 Modeling Techniques

According to Borshchev and Filippov (2004), there are three main core in simulation models, namely: System Dynamics (SD), Discrete Event Simulation (DES), and Agent-Based Modeling (ABM).

In SD, this involves a highly abstract method of modeling which ignores the fine details of a system and produces a general representation of a complex system. In DES, the system is being modeled as a process which breaks a continuous process into discrete parts to simplify analysis. ABM, on the other hand, is the most recent modeling method where agents and their interaction with other agents are visible in the simulation.

Equation-based modeling, similar to ABM, is used for simulating systems through models. Its models are based on different variables which are then used in an aggregate of equations. The aggregated equations are evaluated to generate output (Parunak, Savit, and Riolo, 1998). Rashid et al. (2011) used fuzzy logic, which contains different mathematical operations such as the AND, OR, and NOT logic gates. Sun and Cheng (2002) affirm that using equation-based models work best for systems that only has a single agent and can be generalized quickly. This is further evidenced in most of the papers (Crites and Barto, 1995; Charania and Depasquale, 2006; Rashid et al., 2011), where the system highlights the elevators as the main agents.

Simulations with passenger agents can produce more realistic results and can extrude patterns compared to equation-based models. Through simulations, Parunak et al. (1998) and Bonabeau (2002) agree that using ABM can extract more realistic results and generate better output for elevator systems. ABMs are suitable since it shows more depth when attention is also given to passenger behaviors that can cause some interaction. Passenger behavior may also influence results, therefore, changing how the algorithm or the configuration works. The analytical calculations only work for up-peak traffic wherein most of the people go up like in a typical office building in the morning. Agent-based models produce agents which are individual from one another and behaves according to the presence of other behaviors. For instance, a person may want to ride an elevator alone during a non-peak timeline. An equation-based model would probably just aggregate the result since averages are produced.

2.2 Agent-Based Modeling

According to Macal and North (2011), ABM is a simulation technique that uses individual, autonomous, interacting agents in modeling systems. Compared to other modeling techniques such as system dynamics and discrete event modeling, the agents in ABM can make the decision models more realistic and accurate. The behavior of the agent, referred to as decisions and actions, is determined by a function which takes the agents environment and interactions as parameters. In addition, agents are modular or self-contained. They have distinguishable attributes, behavior, and decision-making capability. Communication and information exchange are usually implemented as well to interact with other agents

Agent-based simulation has been applied to several traffic simulation such as that of Benhamza et al. (2014). They developed a multi-agent based traffic simulation by considering traffic flows. Their main goal was to provide a simulation of a real road scenario in order to forecast and avoid traffic congestion. The main agent is the autonomous driver who makes decisional activities on its environment. A set of behavioral rules were used to model the agent. This study showed that using agent-based microscopic traffic simulation gives more realistic results compared to traditional macroscopic simulation. The simulation's flexibility made it easier to tweak traffic scenarios by changing parameters. ABM should be used when dealing with agents whose decisions and behaviors can be clearly defined. These agents should have the ability to adapt and change behaviors based on interactions they have with other agents on the environment. Jung et al. (2017) conducted a study about an agent-based elevator system in high rise buildings. He opted to use ABM instead of DES. DES is used when studying the interactive effect of constrained resources and repetitive work process, but Jung did not opt for this because actions for DES agents are already predefined.

2.3 Performance Criteria

There are several factors that affect the performance of the agents in the simulation, because they can make decisions based on their statecharts and interactions they have inside the environment.

The main goal is to optimize the elevator configuration and to minimize the waiting time of the passengers. Barney and Al-Sharif (2016) discussed several factors that affect the performance of an elevator agent. Handling capacity pertains to the total number of passengers that the agent can transport in five minutes. Round trip time (RTT) is the time it takes for a single car trip from the time it opens at the main terminal until the door reopens and returns. The equation for round trip time must be evaluated to calculate the performance of an elevator system; this equation depends on three datasets concerning the building, the elevator system, and the passengers. Another performance criteria of an elevator agent is the waiting time of the passengers which the average time between the consecutive arrivals of the elevators to the ground floor. An excellent system has a waiting time of less than or equal to twenty seconds, a satisfactory system is between twenty-five to thirty seconds, while an unacceptable system is greater than or equal to fifty seconds.

2.4 Optimization Techniques

Destination-based control system, also known as call allocation, is a system where passengers want to get to their destination floor and the system responds with which specific elevator to ride (Sorsa, Hakonen, and Siikonen, 2006). By calculating the best elevator that will serve the passenger, the performance of the system will be optimized. With this strategy, it may be possible to minimize the requirement of having more elevators for any building. This optimization process will group together passengers going to the same destination floor. However, this might result in longer waiting time because the elevator that will be arriving might not be the one allocated in serving their desired floor. On the other hand, the elevators will make fewer stops which saves up the overall round trip time of an elevator. This means that they can move more people, and they have a greater handling capacity (Sorsa et al., 2006).

A paper written by Meng, Li, Lu, and Lu (2011) proposed an optimization model to help improve the traffic during the up-peak of an elevator system. Elevator groups in high rise commercial buildings usually have three transport schemes: random, odd even, and partitions. The random transport scheme allows all elevators to stop at any floor. Odd and even floor transport scheme assigns elevators to serve odd floors and other elevators to serve even floors. Partitions running transport scheme divides the set of floors into an upper and lower zone. These three schemes were compared in terms of optimized running time and energy consumption.

Another implementation was made by Walters (2015) known as the zone elevator allocation, here he separated floors to be served based on the total round trip time which is the number of floors to be served by each elevator. He divided three elevators to zones that the elevators need to serve based on the total distribution of time that one elevators gets from one floor to another and total number of serviced floor added together to service a passenger count per floor. He also considered the time it takes from one floor to another and the stop it makes per floor. This turned out to be more helpful in load managing.

An up-peak traffic period arises when the bulk of the passenger traffic is moving from the first floor up to the building (Pepyne and Cassandras, 1997). An optimal dispatching control for elevator systems was proposed by Cassandras and Pepyne (1997) targeting up-peak traffic. They implemented a scheduling technique where cars deliver passengers to their destination floor and return empty to the first floor to pick up the next set of passengers. Meaning, it does not pick up passengers going down. The priority here was given to the up-peak passengers. The completion of service generates a car arrival event indicating that at least one of the elevators is available for service.

2.5 Model Creation

Jung et al. (2017) conducted a study about an agent-based elevator system in high rise buildings. He noted that restricting floor range does not always improve performance outcomes because of other underlying factors. Jung et al. (2017) made use of four different types of agents:

- Floor Agent - collects the number of workers waiting on each floor
- Elevator Agent - pertains to individual elevators
- Elevator Group Control Agent - oversees a group of elevator agents
- Worker Agent - uses the elevators

In this study, Jung et al. (2017) made three different simulations and process model diagrams to visualize and understand how the proposed systems work. The first one has a whole-floor service where elevators can cater to all floors. This makes use of one queue and one elevator group connected to each floor. The second one implemented a zoning system with two zones. These zones are assigned to certain floors and function separately from one another. And lastly, a sky-lobby system with shuttle elevators where two processes are connected in a series, requiring passengers headed to destinations in the upper zone to transfer to shuttle elevators at the sky lobby. This has a more complex set of restrictions compared to the other two.

This paper by Jung et al. (2017) will be of high relevance to this study because a simulation of a similar scenario will be done. He was able to define and discuss the processes and roles that the agents play in the simulation.

3 THEORETICAL FRAMEWORK

Macal (2011) stressed that the modeling process of ABM should first consist of identifying agents, specifying their behaviors accurately and allowing agent interactions. Agents are the main elements for ABM. These agents are not necessarily people, and an agent can be anything of significance to the scenario that can be modeled and has its own specifications. Once this is done, one needs to have a theory of the identified agents' behavior that will serve as the basis for modeling. This will be done through observations of the current environment and system, thus validating the simulation model with observed data. He noted that it is best to use ABM when agents need to adapt and change their behaviors, learn and engage in dynamic interactions, and have a spatial component in their behaviors.

Model validation will be done where the accuracy of the model will be based on how it best fits the real-world data. A set of metrics is used for comparison and analysis. These metrics are key factors that would determine whether or not the simulation models represent the real-life system. In a book by Barney and Al-Sharif (2016), several performance measures were discussed: round-trip time, interval, and handling capacity. These measure the quantity of service or how many passengers an elevator system can transport on average during a specific period. Round trip time refers to the average time of an elevator to make a single round trip. Interval stands for the average time of successive elevator arrival at the ground floor serving the same set of subzone. Handling capacity denotes the number of passengers that can be accommodated in five minutes. As for the quality of service of the elevators, it can be measured through the average waiting time (AWT). This is the time from when a passenger makes the call until they have boarded the elevator, computed as

$$\mathrm{AWT} = \left(0.4 + \left(1.8 \times \frac{\mathrm{P}}{\mathrm{PC}} - 0.77\right) \times 2\right) \times I,$$
$$\text{where } \mathrm{I} = \text{interval; } \mathrm{PC} = \text{probably car capacity; } \mathrm{P} = \text{number of passengers carried} \qquad (1)$$

4 METHODOLOGY

In this step, CCTV footage of the lobby was taken in order to monitor and analyze the target environment. Afterwards, the gathered footage was processed where the passengers will be counted along with their waiting time. This information was used during modeling where the agents and states were defined. The agents and the environment was modeled using AnyLogic simulation software. The simulation was ran and the results were compared to ground truth data taken from the initial data collection. The configuration was tweaked until the simulation data accurately matched the ground truth, specifically the peak hours portion. This cycle repeats until the model fits the current environment.

4.1 Data Gathering

ID scans taken from the entrances and camera footages from the lobby of the AGH were the main sources of data. These ID scans were used to analyze and monitor the inflow of the passengers that enter AGH and use the elevators. This was fed to the model later on to determine the volume of passengers and their rate of arrival during certain periods of the day. Subsequently, the CCTV footage were used to compute the average waiting time and round trip time of these passengers. The floor plan of the building containing information about the classrooms and offices present in each floor was used to determine the probability of the destination of the passengers. Other assumptions made were based on previous studies and known information from the current environment modeled. It was assumed that all passengers are students who are capable to walk normally at a common speed defined by Sorsa, Siikonen, and Susi (2005) at 1.0 m/s, and would occupy the same amount of space in the elevator.

To properly eliminate the long queues that are present in the AGH, the researchers would need to understand the peak usage of the elevator such as the 15-minute break of classes where the passengers transferring classes normally occur. These time slots would include times such as 9:00 AM - 9:15 AM, 10:45 AM - 11:00 AM, 12:30 PM - 12:45 PM, 2:15 PM - 2:30 PM, and 4:00 PM - 4:15 PM. These class transfers are considered crucial because there are twenty floors in the AGH, and around half of these floors are classrooms where passengers take their lectures. Based on the floor plan, each floor consists of around ten classrooms.

4.2 Data Processing

In order to know the mean number of passenger who arrive at the AGH, ID scans taken from the information technology services starting January 7 until February 22 were processed. From the seven weeks of data, they were classified into one table per weekday for the entire schema in the MySQL database. After being segregated properly, graphs for each date representing the inflow of passengers were made. After cleaning the data, it was then grouped together to each day of the week. A graph was made to see if there were patterns present throughout the four days of the week, specifically Tuesday to Friday, which are the days that have regular classes (see Figure 1). The different days exhibited the same trend once consolidated. It is evident that the up peak times are consistently seen in the 15-minute interval of classes mentioned beforehand. The researchers divided the inflow of passenger traffic to a five minutes time frame starting from 7:00 AM to 6:00 PM. After being able to simulate the five minutes inflow for each day, these values were then averaged with the other seven weeks that had the same day of the week. These values will be used to produce the inflow of passengers for each day of the week in the AnyLogic Software.

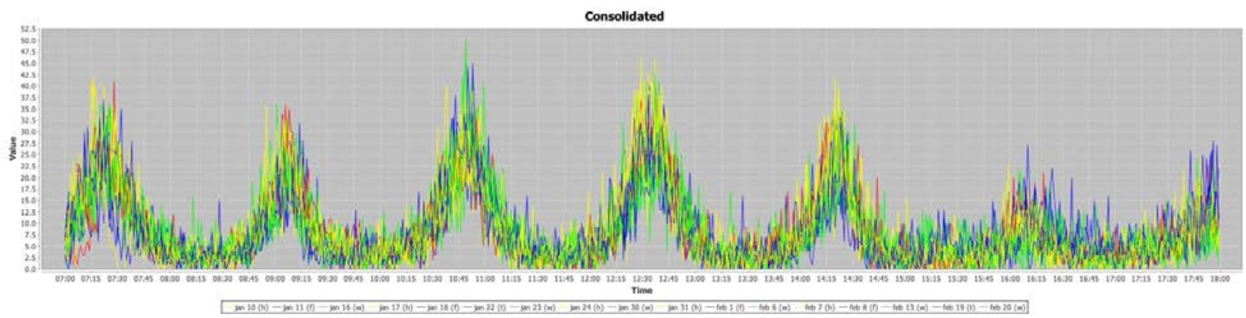

Figure 1: Distribution of passengers from Tuesday to Friday starting 7:00 AM to 6:00 PM.

In order to properly record the RTT for the elevators, a flood fill algorithm was implemented for four given points in the CCTV footage that was garnered. This algorithm helps in visiting each and every similarly colored pixel connected to the initial points to fill the entire area in order to determine the open and closing of the elevator doors. Once there is a change in these values, this would mean that the elevator door has opened, a screenshot would be taken. The screenshot is taken to address delays and skips in the CCTV footage taken from the security office. In this way, the researchers would have a copy of the exact timestamp of each interval. This process was done for all elevators, and it is currently assumed that one elevator will not open again until thirty seconds has passed. Timestamps found in the CCTV footages are visible to the naked eye, however they are too small to be trained using optical character recognition. So, they were manually encoded to a spreadsheet in order to compute for the RTT by subtracting the last arrival of the elevator to the current elevator at the ground floor of the AGH. The AWT per elevator was computed following the formula (1) of Barney and Al-Sharif (2016). The interval variable is based on the RTT values generated beforehand, the probable car capacity was set to twenty based on the elevator specifications, and the number of passengers carried were manually tabulated by the researchers based on the CCTV footage. RTT and AWT values for the simulation will be extracted, as the generated RTT and AWT values in the processing part will be the basis of validation of the model of the current environment. Moreover, it will be used later to compare the simulation of the current environment and the optimized one.

4.3 Model Creation

Models were made based on previous studies with modification on AnyLogic Professional 8.3.2. There are three views used in the simulation: 3D, 2D, and graphs. For 3D, a camera object in AnyLogic is placed to view certain angles of the simulation. The initial view is set to 3D, where the four elevators are present (see Figure 3). A zoomed out 3D version of the 20-story building can also be seen (see Figure 2).

Figure 2: The full 20 floors of the Br. Andrew Gonzalez Hall in 3D view.

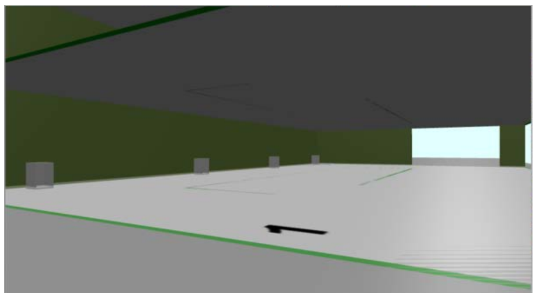

Figure 3: The 3D view showing the 4 elevators at the Ground floor represented by the grey elevator box.

The 2D view allows an overhead view of each floor where the flow and the line of passengers can be seen per elevator (see Figure 4). In this view, there is also a real time update of the flow of passengers in the statechart and flowchart present in the floor agent.

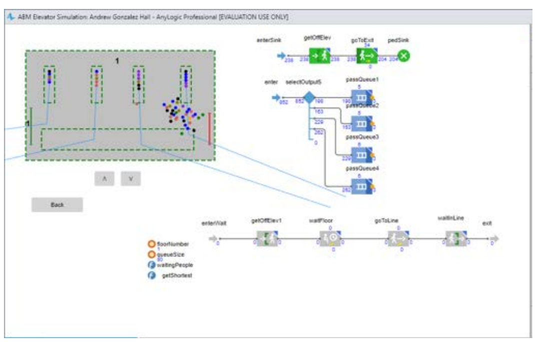

Figure 4: 2D View of the Ground Floor.

Figure 5: Graph View of the Simulation.

The graphs view shows a real time update of the values in the simulation being generated: average queue length per elevator, average waiting time, and average round trip time for each elevator. These values are essential for the model validation after running the simulation (see Figure 5).

The agents modeled were the floor agents, elevator agents, and passenger agents. Each agent can have its own presentation, flowchart, statechart, and variables. These agents interact with each other through the main class where the rate of the arrival of passengers based on the data gathering is found, as well as the array list containing all four elevator agents, the passenger agents, and the floor agents. Moreover, the specifications of the building is found here like the height of each floor and the number of floors. It is also where the floors served by each elevator is set. Because the AGH elevators caters to specific floors only, the researchers modeled the simulation accordingly. Where the first two elevators only cater to floors: 6, 9, 11, and 14, while the succeeding two elevators cater to floors: 7, 11, 14, and 17.

4.3.1 Floor Agent

There are three process flowcharts in the floor agent (see Figure 4). Although the floor is part of the environment, it holds its own variables and unique characteristics that is why it is considered as an agent. The process flowcharts handle the passengers entering the simulation, going to the queue, and exiting the simulation. The passengers are segregated into queues based on the passenger's destination. The capacity for each queue is set to eighty based on observations made in the current environment. After going to its initial destination, the next destination of the passenger will be generated. If the succeeding destination is on the ground floor, the passenger will go to the enterSink block where it will be removed from the simulation, else, it will go to the enter block again and repeat the process.

4.3.2 Elevator Agent

The behavior of the elevator agent is based on a statechart. It contains six states namely waiting, open, dropOff, pickUp, close, and moveTo. This represents the entire flow of the elevator from picking up passengers, dropping off passengers, waiting for the passengers hall call, as well as opening and closing of the elevator door after moving to a certain floor.

The elevator waits for a hall call. It will then move to the floor the call was made and it will only open on that specific floor. It then checks if passengers in the elevator would be getting off and drops them off accordingly. When all passengers have reached their destination, it can then either go to the closing state if there is no passenger left to serve or pick up new passengers who made a hall call in that certain floor. Finally it can go to the close state and return back to the waiting state to repeat the same cycle over and over (see Figure 6).

4.3.3 Passenger Agent

The statechart of the passenger agent contains five states, namely: moving, inline, waitElev, waitFloor, and exit.

The passenger starts at the moving state as it enters the building and falls in line to the assigned elevator based on its destination. When the elevator agent sends a message to the passenger agent in queue that signifies it has arrived, the passenger will now enter the waitElev state where the passenger agent is placed inside the elevator and a cabin call is made. The passenger will go to the waitFloor state which represents the time the students take their classes and stay on a certain floor. This entire process will repeat until the agent returns to the ground floor and leaves the simulation (see Figure 7).

Because AGH is used for academic purposes where classes of students are held which causes the mass volume of passenger traffic during the 15-minute interval of classes, the researchers implemented an endofClass event in the simulation. This event triggers when the students will leave their classes and call the elevator again for their next destination.

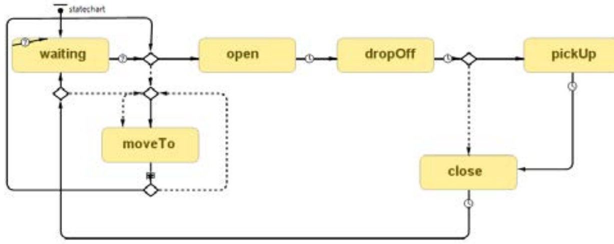

Figure 6: Elevator Agent Statechart.

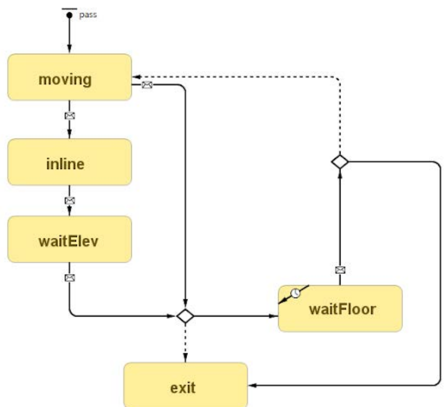

Figure 7: Passenger Agent Statechart.

4.3.4 Optimization Experiment

First, the researchers took into consideration different parameters that affected the performance of the elevator such as opening and closing of elevator doors, inflow of students, the current elevator configuration, rates at which they enter and exit the elevator, as well as the speed of the elevator travelling upward and downwards when modeling the system. Once the environment was accurately modeled, that is the only time the researchers started to implement optimization experiments to our system, such as no service going down. Conditions were added in the simulation so that when the passenger's direction is going down, its only option is to take the stairs to descend.

5 RESULTS AND ANALYSIS

Based on analysis and comparison, the researchers were able to simulate a model that was close to the actual environment of the AGH based on the RTT. It resulted to a similar pattern based on the plotting the researchers made with the Python notebook. The generated values from the simulation showed that it was able to model the up peak periods similar to the current environment. This is essential as this is the focus of the study and optimizing these said times. The checking was made by simulating the system thirty times which produced RTT results between two time frames. After the model fits the environment, the optimization technique of not allowing service going down was implemented and the simulation was rerun again for five times. The presented Figures below shows comparison of both the RTT and AWT values respectively. As a sample, elevators 1 and 3 ran on Tuesday is used because on the current environment, elevators 1 and 2 caters to different floors from elevators 3 and 4.

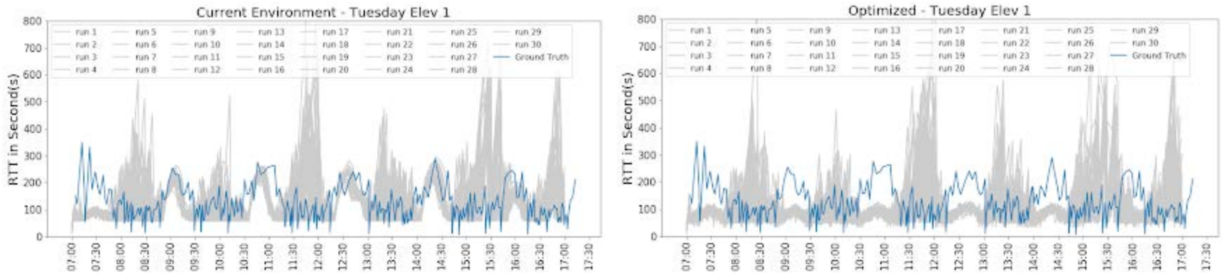

Figure 8: RTT for Tuesday Elevator 1: Current Environment (Left) Optimized (Right).

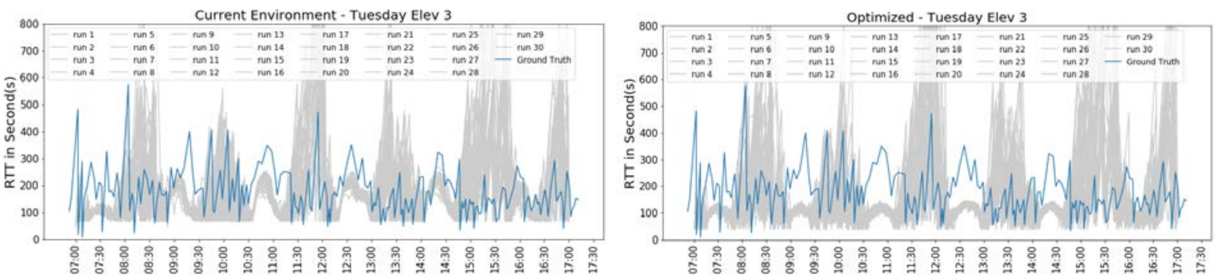

Figure 9: RTT for Tuesday Elevator 3: Current Environment (Left) Optimized (Right).

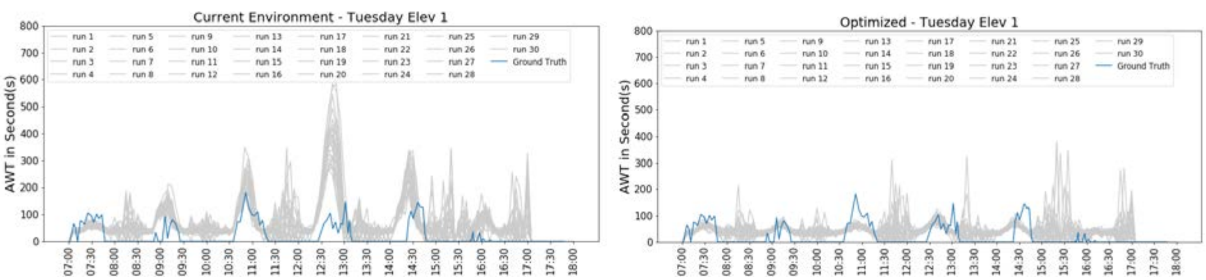

Figure 10: AWT for Tuesday Elevator 1: Current Environment (Left) Optimized (Right).

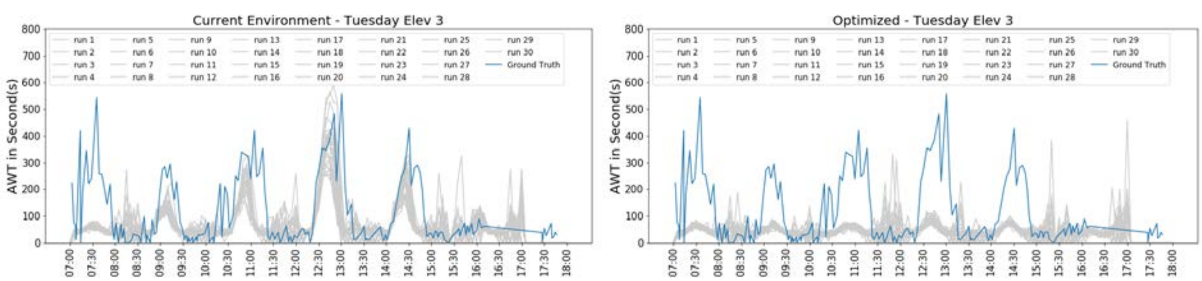

Figure 11: AWT for Tuesday Elevator 3: Current Environment (Left) Optimized (Right).

Implementing the optimization technique on the current environment showed great improvement in terms of the RTT of the elevators during the up peak times. On Figure 8, there is an evident decrease of RTT in the up peak periods in the optimized graph as compared to the current environment graph while the down peak periods remain the same. Similar results are seen on Figure 9, for the results of elevator 3. Because of the optimization, spikes in AWT diminished. The optimized result showed a steady and constant trend throughout the day with low values for AWT. Table 1 shows the average RTT of all the thirty runs made on both the current environment and the optimized one.

Table 1: Comparison of Experiments.

Round Trip Time	
Current	**Optimized**
2.30843 ± 0.03767	1.53990 ± 0.01858
Average Waiting Time	
1.92940 ± 0.16564	0.75916 ± 0.24882

6 CONCLUSION

The researchers can see that by tweaking the different parameters of the model created, it can either produce a more optimized RTT for the elevators or produce a RTT that takes more time to serve its passengers. Moreover, implementing optimization techniques lessened the AWT of the passengers and the RTT of the elevators. As seen in Figure 8-11, the waiting time of the passengers decreased as well as the round trip time of the elevators, which are the main goals of the study.

The researchers can try improving the model by considering the social behavior of the agents in the system such as getting on board the elevator then getting off when their friends are not able to ride the elevator as well. Another notable behavior based on observation, is the cluster formed by students during non-peak times, the students tend to form clusters instead of falling in line because there are not many people waiting for the elevator. The researchers can also try the system out on other high rise buildings if the current simulation and optimization technique would be helpful to them.

REFERENCES

Barney, G., and Al-Sharif, L. (2016). *Elevator Traffic Handbook: Theory and Practice* (2nd ed.). Routledge.

Bonabeau, E. (2002). *Agent-based Modeling: Methods and Techniques for Simulating Human Systems* (Vol. 99). National Acad Sciences.

Bruch, E., and Atwell, J. (2015). "Agent-based Models in Empirical Social Research". *Sociological Methods and Research*, 44(2), 186-221. (PMID: 25983351) doi:10.1177/0049124113506405

Cortés, P., Larrañeta, J., and Onieva, L. (2004). "Genetic Algorithm For Controllers in Elevator Groups: Analysis and Simulation During Lunchpeak Traffic". *Applied Soft Computing*. 4(2), 159 - 174. doi:10.1016/j.asoc.2003.11.002

Crites, R. H., and Barto, A. G. (1995). "Improving Elevator Performance Using Reinforcement Learning". *In Proceedings of the 8th International Conference on Neural Information Processing Systems* (pp. 1017-1023). Cambridge, MA,85 USA: MIT Press.

Jung, M., Park, M., Lee, H.-S., and Chi, S. (2017). "Agent-based Lift System Simulation Model for High-rise Building Construction Projects. *Journal of Computing in Civil Engineering*, 31.

Karima, Benhamza and Ellagoune, Salah and Seridi, Hamid and Akdag, Herman. (2019). *Agent-based Modeling for Traffic Simulation.*

Kumar, M., Singh, P., and Singh, S. (2017). "A Vlsi Implementation of Four-phase Lift Controller Using Verilog Hdl". IOP *Conference Series: Materials Science and Engineering*, 225(1), 012137.

Macal, C. M., and North, M. J. (2011). "Introductory Tutorial: Agent-based Modeling and Simulation". In *Proceedings of Winter Simulation Conference*, 2015, 1451-1464.

Meng, J., Li, Z., Lu, J., and Lu, X. (2011, Sept). "Optimization Model for Elevator System". In *2011 First International Workshop on Complexity and Data Mining* (p. 112-116). doi: 10.1109/IWCDM.2011.33

Parunak, V. D. H., Savit, R., and Riolo, R. L. (1998). "Agent-based Modeling vs. Equation-based Modeling: A Case Study and Users' Guide". In J. S. Sichman, R. Conte, and N. Gilbert (Eds.), *Multi-agent Systems and Agent-based Simulation* (pp. 10-25). Berlin, Heidelberg: Springer Berlin Heidelberg.

Pepyne, D. L., and Cassandras, C. G. (1997, Nov). "Optimal Dispatching Control for Elevator Systems During Uppeak Traffic". *IEEE Transactions on Control Systems Technology*, 5(6), 629-643. doi: 10.1109/87.641406

Rashid, M. M., Kasemi, B., Faruq, A., and Alam, A. Z. (2011). "Design of Fuzzy Based Controller for Modern Elevator Group With Floor Priority Constraints". In *2011 4th International Conference on Mechatronics (ICOM)* (p. 1-8). doi:10.1109/ICOM.2011.5937196

Siikonen, M.-L. (1993). "Elevator Traffic Simulation". *SIMULATION*, 61(4), 257–267. doi:10.1177/003754979306100409

Sorsa, J., Siikonen, M.-L., and Susi, T. (2005). "Passenger Behaviour In Elevator Simulation". *Elevatori*, 35 (5), 28-37.

Sorsa, J., Hakonen, H., and Siikonen, M.-L. (2006). "Elevator Selection with Destination Control System". *Elevator World*, 54 .

Sun, Y., and Cheng, L. (2002). *A Survey On Agent-based Modeling and Equation-based Modeling.* Department of Computer Science. Georgia State University. Atlanta.

Walters, A. (2015, March 18). *Everyday Algorithms: Elevator Allocation*. Retrieved June 24, 2019, from https://austingwalters.com/everyday-algorithms-elevator-allocation/

AUTHOR BIOGRAPHIES

COURTNEY ANNE NGO is an assistant professor from the College of Computer Studies at De La Salle University. She received her M.S. in detecting locomotion on mobile phones at DLSU. Her research interests are in agricultural technology, particularly in crop and species detection. Her email address is courtney.ngo@dlsu.edu.ph.

ANGELIKA BATOSALEM is an undergraduate student of De La Salle University - Manila. Taking up Bachelor of Science in Computer Science Major in Software Technology. Her email address is angelika_batosalem@dlsu.edu.ph.

JANELLE MARIE GABA is an undergraduate student of De La Salle University - Manila. Taking up Bachelor of Science in Computer Science Major in Software Technology. Her email address is janelle_gaba@dlsu.edu.ph.

JAN BERTEL NGO is an undergraduate student of De La Salle University - Manila. Taking up Bachelor of Science in Computer Science Major in Software Technology. His email address is jan_bertel_ngo@dlsu.edu.ph.

JONAL RAY TICUG is an undergraduate student of De La Salle University - Manila. Taking up Bachelor of Science in Computer Science Major in Software Technology. His email address is jonal_ticug@dlsu.edu.ph.