Validation of Evacuation Assessment Algorithm in Finding the Best Indoor Evacuation Model

Amir Haikal Abdul Halim, Khyrina Airin Fariza Abu Samah*
Faculty of Computer and Mathematical Sciences
Universiti Teknologi MARA Cawangan Melaka Kampus Jasin, Melaka, Malaysia

***Abstract*—This paper proposed an indoor evacuation assessment algorithm. Indoor evacuation wayfinding to the nearest exit becomes more difficult due to the intricacy of the inside layout and the involvement of numerous people. Thus, evacuation models were developed by researchers to assist evacuees in safely exiting a building. Unfortunately, building owners are unsure which evacuation model is best for their high-rise buildings. Therefore, we proposed an assessment algorithm to help the owners assess the best evacuation model. This research uses floor plan levels 13 and 14 of Yayasan Melaka's, an office building, to simulate the evacuation. Ten simulation studies for each level are created. The proposed assessment algorithm focuses on three Microscopic evacuation models; agent-based, cellular automata, and social force. Hence, three simulation software were used to represent the mentioned evacuation model: Pathfinder, PedGo, and AnyLogic. K-Mean is then used to cluster the simulation time results. Elbow, Silhouette and V-measure techniques were applied to produce accurate results of the K-Mean. We compiled and analyzed the results from ten simulation studies for each level. The validation was done by comparing the final results. It shows that 70% of the lowest time taken is from Pathfinder, 30% from PedGo, and 0% from AnyLogic. Based on the result, it is proven that the proposed assessment algorithm can provide the best indoor evacuation model followed the attributes set for the building.**

Keywords*—*Assessment algorithm; evacuation model; indoor evacuation; k-mean; validation

I. Introduction

Evacuation is the organized, regulated, and supervised retreat, dispersal, or withdrawal of individuals from places of risk or hazard and their reception and treatment in secure environments [1]. Despite the limited space available in urban regions, the population of large and medium-sized cities worldwide continues to grow. As a result of the requirement to deal with this development, high-rise buildings have popped up fastly [2]. Thus, fires in high-rise buildings have become more prevalent in recent decades as high-rise structures significantly affect the skylines of major cities [3]. Therefore, proper emergency evacuation in any high-rise structure is critical.

According to the Fire & Rescue Service Department and the Occupational, Health and Safety Environment, the evacuation method by occupants in one building should be able to escape the building 3 minutes after the emergency alarm goes off. Building evacuation must be evaluated for time optimization to avoid human casualties [4]. Evacuees with a misperception of the building environment may display significant rounding or even be trapped, resulting in a significantly longer evacuation time. According to Ventura [1], people usually take a path of self-estimated speedy escape depending on their current condition. In addition, panic and stomping can lead to several people departing in an emergency. The architecture of escape routes from structures, human psychology and behaviour, and various social and behavioural patterns can significantly influence evacuation performance, resulting in a trapped situation [5]. For instance, a case in Gujarat, India, sacrificed 20 students in a fire because no safety equipment was installed in the building, and there were no escape routes [6]. Another example of disaster is the World Trade Centre (WTC) Twin Towers terrorist attack on September 11, 2001, where 3000 innocent people died [7]. Thus, a high-rise building must have an evacuation strategy to allow evacuees to evacuate the building safely.

Jiang et al. [8] stated there are three types of evacuation models which is microscopic, macroscopic, and mesoscopic. Individuals' geographical and chronological activities are frequently defined by microscopic models [9]. The continuum model, often known as the macroscopic model, integrates variables and monitors characteristics [10]. Finally, mesoscopic models, which focus on groups but offer more specific information about each pedestrian, considered the individuals but not individuals' interactions. The goal is to keep some control over the individual while moving the group as a whole and avoiding local interactions [11]. As a result, mesoscopic is not taken into account in this study. Shi et al. [12] claimed that microscopic and macroscopic models are often used in evacuation evaluations to illustrate pedestrian traffic. Macroscopic models, which reflect overall population movement, do not typically characterize individuals.

On the other hand, microscopic models focus on the smallest of individuals' details. Microscopic models have been employed extensively in recent years [13] in various crowd simulation studies to understand better crowd behaviour in emergency scenarios [14]. For microscopic models, researchers have mostly employed these three models: Agent-based model (ABM), cellular automata (CA), and social force model (SFM) [15]. Thus, the microscopic model is the best among the three types of evacuation models for the indoor evacuation model.

Therefore, this research proposes an intelligent indoor evacuation assessment algorithm for critical incidents. The assessment algorithm can help select the best evacuation model for the chosen building. The best model selection is crucial since it depends on the environment and the building's needs. It also includes the evacuees' ability to evacuate safely and quickly. This paper's organization begins with a brief

*Corresponding Author.

introduction in Section 1. Section 2 explains the related work and is followed by the research methodology in Section 3. Section 4 elaborates on the results and discussion on optimal *k* number, v-measure score, intracluster distance, and chosen lowest time taken results. Finally, Section 5 concludes the study and briefly mentions future enhancement.

II. Related Work and Techniques

This section describes the related works in clustering algorithms and techniques related to the study.

A. Related Work

The related works involved in this research include the K-Mean algorithm and finding the optimal *k* number. In general, the K-mean approach is dependent on the value of *k*, which must always be provided before any clustering analysis can be performed. Clustering with various *k* values will provide diverse outcomes [16]. The algorithm in clustering can be a feature, as an example in Fig. 1. Training examples are shown as dots and cluster centroids as crosses, (a) original dataset, (b) random initial cluster centroids, and (c-f) illustration of running two iterations of K-Means.

The closest cluster centroid is allocated to each training sample in each loop. It is demonstrated by “painting” the training samples with the same colour as the cluster centroid to which they have been allocated. Then, for each cluster, the mean of the points assigned to it is shifted from the centroid to the mean of the points assigned to it.

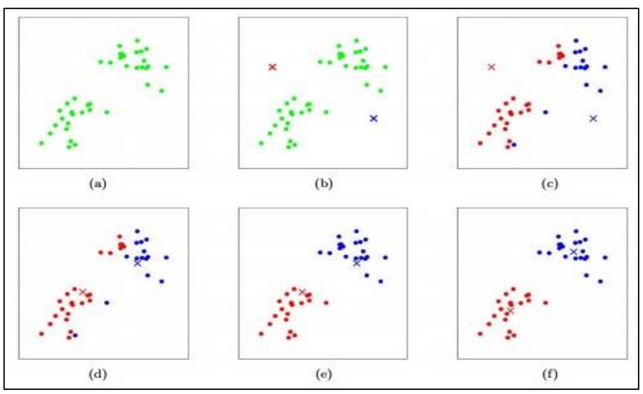

Fig. 1. Clustering example of K-Mean.

The process typically finishes when the centroids stabilize, or the points cease migrating to other groups. However, this depends on the type of grouped data, and the objective function used to quantify proximity. Because K-Mean might have difficulties with local optimum solutions, a proper initialization has proved to be an effective strategy to avoid being caught in the incorrect local optimal solutions [17]. Fig. 2 shows the K-Mean pseudocode [18]. The clustering aims to improve the objective feature (*f*) by measuring the range between entities and clusters (the most used measurement is the standard Euclidean Distance) as in (1) [19]:

$$f = \sum_{i=1}^{K} \sum_{j=1}^{N} \left\| x_j - C_i \right\|^2 j \in G_i \quad (1)$$

where K is the number of clusters, N is the number of objects, x_j is the coordinate of object j, C_i is the coordinate of the cluster *i* and G_i is the group of objects that belong to cluster *i*. The algorithm shifts the cluster in space to reduce the square distances within the cluster. The positions of all objects belonging to each cluster are recalculated by averaging. Calculation of the center uses as in (2):

$$C_i = \frac{1}{|G_i|} \sum_{j=1}^{N} X_j \; j \in G_i \quad (2)$$

where $|G_i|$ is the number of objects in the cluster *i*. The algorithm begins with a random set of the C_i cluster's initial *K* center points (*i* = 1, . . ., K), which are the present centroids.

Input: $\boldsymbol{K_y}$: the number of clusters $\boldsymbol{D_y}$: a data set containing n object
Output: A set of $\boldsymbol{K_y}$ clusters
Algorithm:
1. Input the data set and value of $\boldsymbol{K_y}$.
2. If $\boldsymbol{K_y}$= = 1 then Exit.
3. Else
4. Choose *k* objects from *D* randomly as the initial cluster centers.
5. For every data point in the cluster, *j* reissue and define every object into the cluster where the object matches, based on the object's mean value.
6. Update cluster means; after that, for each cluster, calculate the object's mean value.
7. Repeat from step 4 until no data point was assigned; otherwise, stop.

The satisfying criteria can be either number of iteration or the change of position of the centroid in consecutive iterations.

Fig. 2. Pseudocode of K-Mean.

Finding the best *k* number for the cluster is crucial because K-Mean requires a suitable initialization of the *k* number for clusters to avoid getting trapped at an incorrect local optimal solution. Running the algorithm numerous times and selecting the appropriate number of clusters based on a few validity criteria or automatically identifying them using practical ways or standards is a fundamental way to decide the number of clusters. The process may also change and tweak the cluster centers several times [20]. Several frameworks and techniques have been thoroughly investigated and developed in the past to provide cluster quality measures that indicate if a particular clustering is suitable. There are three ways to verify the clusters, which are called cluster validity index (CVI). These include external, internal, and relative validity indices [21].

More than one index should be used to obtain outstanding and accurate findings [22]. A few methods for determining the best *k* number have been considered for this study. Two commonly used approaches, the Elbow method and the Silhouette method, are investigated in this study to aid in the manual selection of the number of displayed clusters [23]. Internal validity indexes are used in both methods to assess the correctness of a clustering algorithm [24]. Another technique examined for this study is the V-measure, based on an external validity index. External validity indices such as V-measure are commonly used to determine the best clustering result for a dataset since they know the ‘real’ number of clusters in advance [25], particularly the number of clusters recommended by Elbow and Silhouette techniques for this study. Table I briefly describes the methods used to find the optimal *k* number for K-Mean.

TABLE I. METHODS TO FIND OPTIMAL *K* NUMBER

Methods	Description	CVI Type
Elbow	The consistency of the optimal number of clusters was visually checked by comparing the difference in each cluster's square error sum (SSE). The best figure is the most significant variation in elbow angle [25].	Internal
Silhouette	Uses a silhouette coefficient that combines separation and coherence. The larger the Silhouette coefficient, the better the cluster [24].	Internal
V-Measure Score	If items in clusters have independent labels, the V-measure is a handy tool for evaluating them. The degree of homogeneity of labels in clusters may be used to measure the quality of clustering objectively [20].	External

B. Related Techniques

The related technique used in this research is the indoor evacuation assessment algorithm based on our previous research [26][27]. Fig. 3 shows the detailed flow of the developed indoor evacuation assessment algorithm. The design and development are separated into six sections in general: 1) determine attributes, 2) run the simulation, 3) identify the best *k* number, 4) evaluate cluster performance, 5) compute intracluster distance, and 6) select the best evacuation model.

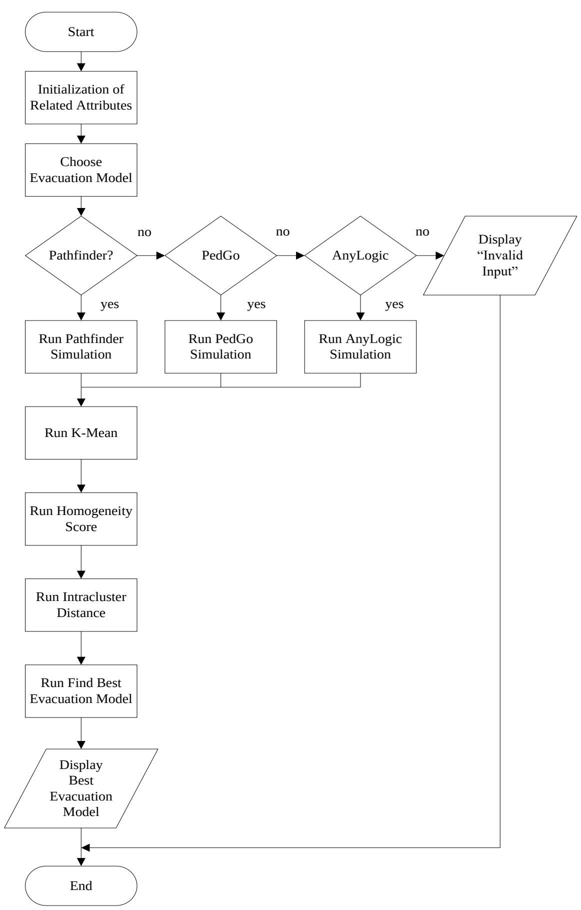

Fig. 3. Overview of Indoor Evacuation Assessment Algorithm.

The attributes involved consist of seven: 1) number of agents, 2) agents' behaviour, 3) room size, 4) number of doors, 5) number of staircases, 6) blockage status, and 7) number of exits. Once entering attribute values, they are used in the selected evacuation simulation software. Three simulation software programs calculate how long the agents will take to evacuate the building. The simulation software involved is Pathfinder, PedGo, and AnyLogic. The K-Mean clustering technique is used once the findings are generated. Several actions are conducted at this point in order to obtain correct findings. The processes involve determining the optimal *k* number, confirming it with the V-measure score, and determining the lowest intracluster distance between clusters to find the lowest time taken. Finally, the assessment algorithm presents the most effective evacuation model.

III. METHODS

This section divides the research methodology into two phases: 1) drawing and mapping floor plans; and 2) simulation studies.

A. Drawing and Mapping Floor Plans

The floor plan of the chosen building is drawn and mapped in the simulation software. The high-rise building used for this research is Yayasan Melaka's building. The chosen floors are levels 13 and 14, which level 14 being the highest level. Yayasan Melaka is a large office with several rooms and barriers that might make evacuation difficult. This construction is a high-rise skyscraper with two access paths on each floor. Staircases are said to be an escape route. Elevators and windows are not permitted to be utilized as exits since elevators are outlawed, and the building's height renders window escape difficult.

The simulation software used to produce time taken results is Pathfinder, PedGo, and AnyLogic. The simulation software represents the evacuation model chosen, ABM, CA, and SFM, respectively. The drawing and mapping of the floor plan are based on the simulation studies created. A few ground rules were observed during the mapping process because each simulation software's functional capabilities vary; such criteria are observed. Two rules are: 1) for each simulation, the paths are set in stone and 2) the agents are positioned in the same room for each simulation software.

As a result, particular simulations require manually mapping the agents' path from the beginning point to the endpoint so that they can travel during the experiment. Fair simulations are ensured by placing agents in the same rooms for each simulation software. The procedures required to map the layouts in each simulation program differ from one another when it comes to mapping.

B. Simulation Studies

The assessment algorithm aims to find the most suitable evacuation model for the given structure. The evacuation simulations were used to apply simulation findings for the research purposes for the assessment process. These simulation studies are implemented in Pathfinder, PedGo, and AnyLogic simulation software. For each level 13 and level 14, ten simulation studies highlight the seven simulation attributes. Level 13 simulation studies are shown in Table II, while level 14 simulation studies are shown in Table III.

TABLE II. SIMULATIONS STUDIES FOR LEVEL 13

Simulation Study	Number of agents	Agents' behaviour	Room size, ft^2	Number of doors	Number of staircases	Blockage condition	Number of exits
SS13-1	50	Group	1.5E	13	26	Yes	2
SS13-2	50	Scattered	1.5E	13	26	Yes	2
SS13-3	100	Group	1.5E	16	26	Yes	1
SS13-4	100	Scattered	1.5E	16	26	Yes	1
SS13-5	150	Group	1.5E	21	26	No	2
SS13-6	150	Scattered	1.5E	21	26	No	2
SS13-7	200	Group	1.5E	20	26	No	1
SS13-8	200	Scattered	1.5E	20	26	No	1
SS13-9	250	Group	1.5E	22	26	Yes	2
SS13-10	250	Scattered	1.5E	22	26	Yes	2

TABLE III. SIMULATIONS STUDIES FOR LEVEL 14

Simulation Study	Number of agents	Agents' behaviour	Room size, ft^2	Number of doors	Number of staircases	Blockage condition	Number of exits
SS14-1	50	Group	1.5E	13	28	Yes	2
SS14-2	50	Scattered	1.5E	13	28	Yes	2
SS14-3	100	Group	1.5E	14	28	Yes	1
SS14-4	100	Scattered	1.5E	14	28	Yes	1
SS14-5	150	Group	1.5E	20	28	No	2
SS14-6	150	Scattered	1.5E	20	28	No	2
SS14-7	200	Group	1.5E	21	28	No	1
SS14-8	200	Scattered	1.5E	21	28	No	1
SS14-9	250	Group	1.5E	22	28	Yes	2
SS14-10	250	Scattered	1.5E	22	28	Yes	2

The values are chosen depending on the building's appropriateness. The number of agents begins at 50 and rises by 50 in each iteration until the total number of agents reaches 250. A group or scattered behaviour distinguishes the agent. The room size is based on the original layout set and is set at 1.5E ft^2. The number of doors is determined by the total number of doors utilized by the agents, and the number of staircases can either be two or four, depending on the structure. This research uses the time taken for agents to escape using stairs of 0.44m/s for the mean overall movement speed [28], and the length of the stairs is 7384mm from up to down [29]. The requirement for a blockage is assessed, and the number of exits is set to one or two.

IV. RESULT AND DISCUSSION

A. Optimal k number Results

When using K-Mean clustering algorithms, determining the appropriate k number is crucial. The best k number for K-Mean is found using the Elbow and Silhouette approaches. The Elbow and Silhouette method findings and the Silhouette analysis are included in the results. The graph depicts the outcomes of finding the best k number. The elbow point in the graph for the Elbow technique reveals that the point is the ideal k number for determining the optimal k number based on the graphs. The optimum k for the Silhouette technique is the point with the highest silhouette score. The result of visualization graphs depends on the simulation study; thus, we only show the result for SS13-1 since inserting all the results will take too many pages. Fig. 4 depicts the Elbow method's result where the elbow point can be seen as either 3 or 4. 4 is chosen to be the elbow point. Fig. 5 shows the Silhouette method's result where the highest silhouette score shown is 2. Silhouette analysis in Fig. 6 shows the silhouette plot of the clusters and the visualization of the clustered data. The dotted red line in the silhouette plot of the clusters shows the optimal silhouette coefficient value. Table IV shows the k number results suggested by both Elbow and Silhouette methods for level 13, and Table V shows the k number suggested by both Elbow and Silhouette methods for level 14.

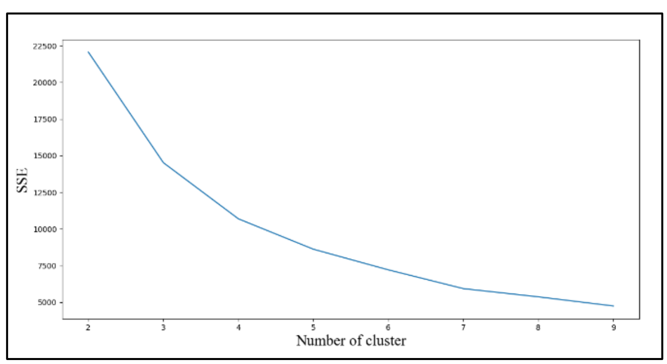

Fig. 4. Elbow method result for SS13-1

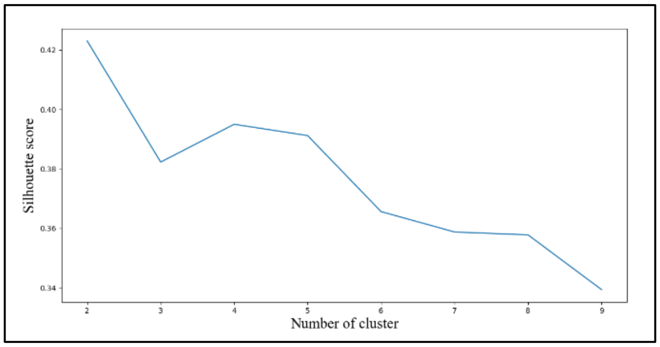

Fig. 5. Silhouette Method Result for SS13-1.

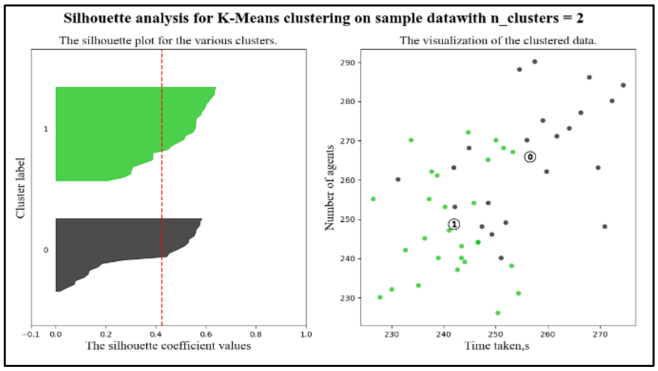

Fig. 6. Silhouette Analysis for SS13-1.

B. V-measure Score Results

The V-measure score is then used to validate the suggested optimal k number. It will compare the Elbow and Silhouette methods outcomes. If one of the scores is higher than the other, the Elbow or Silhouette approach with the highest score is picked. Table VI shows the V-measure score results based on the k number results suggested by Elbow and Silhouette methods for level 13. Table VII shows the V-measure score results based on the k number results suggested by Elbow and Silhouette methods for level 14. The chosen k number is also shown in the tables.

TABLE IV. SUGGESTED OPTIMAL K NUMBERS FOR LEVEL 13

Simulation study	**Elbow method**	**Silhouette method**
SS13-1	4	2
SS13-2	5	2
SS13-3	4	2
SS13-4	3	2
SS13-5	3	2
SS13-6	3	2
SS13-7	3	2
SS13-8	3	2
SS13-9	3	3
SS13-10	4	3

TABLE V. SUGGESTED OPTIMAL K NUMBERS FOR LEVEL 14

Simulation study	**Elbow method**	**Silhouette method**
SS14-1	-	2
SS14-2	4	4
SS14-3	5	2
SS14-4	3	2
SS14-5	3	2
SS14-6	4	2
SS14-7	4	2
SS14-8	-	2
SS14-9	4	2
SS14-10	4	2

TABLE VI. V-MEASURE SCORE RESULTS FOR LEVEL 13

Simulation study	**Elbow method**	**Silhouette method**	**Elbow's V-measure Score**	**Silhouette's V-measure score**	**Chosen *k* number**
SS13-1	4	2	0.5221779373241466	0.2983631321334766	4
SS13-2	5	2	0.5714202764885019	0.2983631321334766	5
SS13-3	4	2	0.4491895619366153	0.2615824154232080	4
SS13-4	3	2	0.3824680569409242	0.2616480412956257	3
SS13-5	3	2	0.3578833679207950	0.2430208702257761	3
SS13-6	3	2	0.3583568830279575	0.2359561227375162	3
SS13-7	3	2	0.3429001741769688	0.2312453476439503	3
SS13-8	3	2	0.3417016541809229	0.2312453476439503	3
SS13-9	3	3	0.3192609377271065	0.3192609377271065	3
SS13-10	4	3	0.3961601706307684	0.3265114737514012	4

TABLE VII. V-MEASURE SCORE RESULTS FOR LEVEL 14

Simulation study	Elbow method	Silhouette method	Elbow's V-measure Score	Silhouette's V-measure score	Chosen *k* number
SS14-1	-	2	-	0.3007347242825145	2
SS14-2	4	4	0.4868437889158798	0.4868437889158797	4
SS14-3	5	2	0.5136239262825523	0.2615824154232080	5
SS14-4	3	2	0.3847749621887950	0.2600032659164130	3
SS14-5	3	2	0.3573284764772723	0.2430208702257760	3
SS14-6	4	2	0.4318826415735761	0.2430482521519111	4
SS14-7	4	2	0.4062920631507129	0.2275753301350341	4
SS14-8	-	2	-	0.2311419664100973	2
SS14-9	4	2	0.3964760790239892	0.2215198295727177	4
SS14-10	4	2	0.3953084843355343	0.2228414459888911	4

C. Intracluster Distance Results

The result of time taken from each simulation research is incorporated in K-Mean using the Elbow and Silhouette techniques to discover the optimal k number and the V-measure score to decide which optimal k number is superior when both approaches are compared. The intracluster distance may then be computed for each cluster in each simulated experiment. The intracluster distance is calculated using Rapidminer. Table VIII shows each simulation study's lowest intracluster distance results for level 13, and Table IX shows each simulation study's lowest intracluster distance results for level 14. The chosen cluster is also shown in the tables.

TABLE VIII. INTRACLUSTER DISTANCE RESULTS FOR LEVEL 13

Simulation Study	Lowest Intracluster Distance	Chosen Cluster
SS13-1	-251.299	3
SS13-2	-181.858	3
SS13-3	-1726.339	3
SS13-4	-1847.029	0
SS13-5	-1265.699	0
SS13-6	-1399.664	0
SS13-7	-3823.050	0
SS13-8	-3723.412	1
SS13-9	-5497.067	2
SS13-10	-4800.702	1

D. Chosen Lowest Time Taken Results

The intracluster distance aids in determining which cluster is ideal for finding the quickest evacuation time. The evacuation model implemented in the chosen building is determined by the lowest time chosen from the three simulation software findings based on each simulation study by level. The simulation software's time-based findings are incorporated into the assessment algorithm, which is then examined and contrasted. For level 13, Table X provides the lowest time taken findings from the selected clusters based on each simulation study and its accompanying simulation software. For level 14, Table XI provides the shortest time taken findings from the selected clusters based on each simulation study and its accompanying simulation software.

TABLE IX. INTRACLUSTER DISTANCE RESULTS FOR LEVEL 14

Simulation Study	Lowest Intracluster Distance	Chosen Cluster
SS14-1	-809.222	0
SS14-2	-323.855	0
SS14-3	-1081.111	3
SS14-4	-1944.537	0
SS14-5	-4780.017	1
SS14-6	-3604.302	2
SS14-7	-1878.660	0
SS14-8	-2626.092	1
SS14-9	-10050.669	2
SS14-10	-10286.633	1

TABLE X. LIST OF LOWEST TIME TAKEN FOR LEVEL 13

Simulation Study	Number of agents	Agents' behaviour	Room size, ft^2	Number of doors	Number of staircases	Blockage Condition	Number of exits	Lowest Time Taken, *s*	Evacuation Simulation
SS13-1	50	Group	1.5E	13	26	Yes	2	241.96	Pathfinder
SS13-2	50	Scattered	1.5E	13	26	Yes	2	243.63	Pathfinder
SS13-3	100	Group	1.5E	16	26	Yes	1	231.63	Pathfinder
SS13-4	100	Scattered	1.5E	16	26	Yes	1	231.13	PedGo
SS13-5	150	Group	1.5E	21	26	No	2	228.26	Pathfinder
SS13-6	150	Scattered	1.5E	21	26	No	2	227.13	PedGo
SS13-7	200	Group	1.5E	19	26	No	1	241.26	Pathfinder
SS13-8	200	Scattered	1.5E	19	26	No	1	235.68	Pathfinder
SS13-9	250	Group	1.5E	21	26	Yes	2	225.56	Pathfinder
SS13-10	250	Scattered	1.5E	21	26	Yes	2	250.13	PedGo

TABLE XI. LIST OF LOWEST TIME TAKEN FOR LEVEL 14

Simulation Study	Number of agents	Agents' behaviour	Room size, ft^2	Number of doors	Number of staircases	Blockage Condition	Number of exits	Lowest Time Taken, *s*	Evacuation Simulation
SS14-1	50	Group	1.5E	13	28	Yes	2	245.92	Pathfinder
SS14-2	50	Scattered	1.5E	13	28	Yes	2	244.12	Pathfinder
SS14-3	100	Group	1.5E	14	28	Yes	1	300.92	PedGo
SS14-4	100	Scattered	1.5E	14	28	Yes	1	256.82	Pathfinder
SS14-5	150	Group	1.5E	20	28	No	2	242.55	Pathfinder
SS14-6	150	Scattered	1.5E	20	28	No	2	242.52	Pathfinder
SS14-7	200	Group	1.5E	21	28	No	1	247.92	PedGo
SS14-8	200	Scattered	1.5E	21	28	No	1	237.95	Pathfinder
SS14-9	250	Group	1.5E	22	28	Yes	2	244.07	Pathfinder
SS14-10	250	Scattered	1.5E	22	28	Yes	2	272.92	PedGo

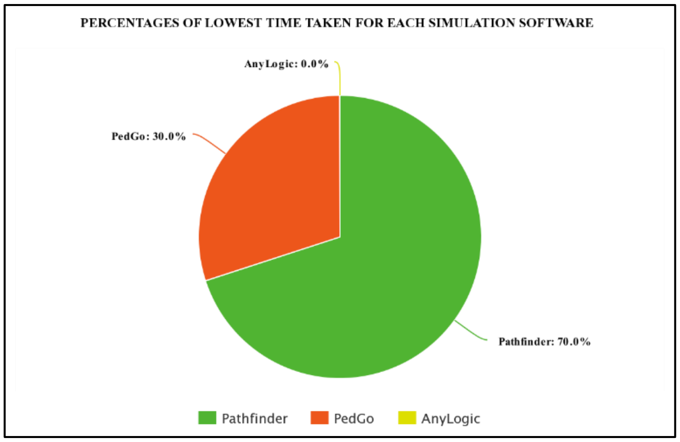

Fig. 7. Piechart of Lowest Time Taken for each Simulation.

As a reminder, the building's architecture determines the appropriateness of existing evacuation models. Different types of evacuation models are suitable for different high-rise structures. Based on the distributed result for each level, Fig. 7 depicts a piechart of the percentages of the lowest time taken for each simulation software. Pathfinder accounts for 70% of the lowest time taken, PedGo for 30%, and AnyLogic for 0%. As a result, it can be determined that ABM is the optimal evacuation model for Yayasan Melaka's building.

V. CONCLUSION

Many developed evacuation models now focus on investigating various evacuation behaviours and times. As a result, the characteristics of the models differ, making it difficult for users to choose a suitable evacuation model. Thus, we presented the indoor evacuation algorithm for high-rise buildings and assessed the proposed solution. Methods and specific attributes for each simulation software were identified, and we managed to compare and analyze the results. It helps to prove how well the assessment algorithm can assess the evacuation model. The result of the lowest time taken has been validated to determine the best evacuation model. Since this study uses a single case study for the simulation and assessment, thus, for future recommendations, the developed assessment algorithm is advised to be evaluated using various high-rise buildings and expand the research by examining the complete building plan. It is fascinating to compare and contrast because each layout, structure, construction, and fire-resistant capability has its degree of difficulty.

ACKNOWLEDGMENT

The research was funded by Universiti Teknologi MARA Cawangan Melaka under the TEJA Grant 2022 (GDT 2022/1-19).

REFERENCES

[1] G. M. Ventura, "Patient evacuation resource classification system (PERCS) for residential healthcare facilities: Patient classification system translatable to healthcare evacuation protocols, system modeling, and transportation resources," The George Washington University, 2017.

[2] N. Ding, T. Chen, Y. Zhu, and Y. Lu, "State-of-the-art high-rise building emergency evacuation behavior," Physica A: Statistical Mechanics and its Applications, vol. 561, 2021.

[3] N. Ding, T. Chen, and H. Zhang, "Simulation of high-rise building evacuation considering fatigue factor based on cellular automata: A case study in China," Building Simulation, vol. 10, no. 3, pp. 407–418, 2017.

[4] H. Sharbini, R. Sallehuddin, and H. Haron, "Crowd evacuation simulation model with soft computing optimization techniques: A systematic literature review," Journal of Management Analytics, vol. 8, no. 3, pp. 443–485, 2021.

[5] Y. Chen, C. Wang, H. Li, J. B. H. Yap, R. Tang, and B. Xu, "Cellular automaton model for social forces interaction in building evacuation for sustainable society," Sustainable Cities and Society, vol. 53, 2020.

[6] Z. Siddiqui, "Indian police file case against three over coaching centre fire, death toll rises to 20," 2019.

[7] L. Zhai, "The comparison of total and phased evacuation strategies for a high-rise office building," 2019.

[8] Y. Jiang, B. Chen, X. Li, and Z. Ding, "Dynamic navigation field in the social force model for pedestrian evacuation," Applied Mathematical Modelling, vol. 80, pp. 815–826, 2020.

[9] P. Kontou, I. G. Georgoulas, G. A. Trunfio, and G. C. Sirakoulis, "Cellular automata modelling of the movement of people with disabilities during building evacuation," 2018 26th Euromicro International Conference on Parallel, Distributed and Network-based Processing (PDP), pp. 550–557, 2018.

[10] N. A. A. Bakar, K. Adam, M. A. Majid, and M. Allegra, "A simulation model for crowd evacuation of fire emergency scenario," 2017 8th International Conference on Information Technology (ICIT), pp. 361–368, 2017.

[11] F. Martinez-Gil, M. Lozano, I. García-Fernández, and F. Fernández, "Modeling, evaluation, and scale on artificial pedestrians: A literature review," ACM Computing Surveys, vol. 50, no. 5, 2017.

[12] M. Shi, E. W. M. Lee, and Y. Ma, “A novel grid-based mesoscopic model for evacuation dynamics,” Physica A: Statistical Mechanics and its Applications, vol. 497, pp. 198–210, 2018.

[13] Y. Li, M. Chen, X. Zheng, Z. Dou, and Y. Cheng, “Relationship between behavior aggressiveness and pedestrian dynamics using behavior-based cellular automata model,” Applied Mathematics and Computation, vol. 371, 2020.

[14] I. Sakour and H. Hu, “Robot-assisted crowd evacuation under emergency situations: A survey,” Robotics, vol. 6, no. 2, 2017.

[15] L. Fayez, “Modeling family behaviours in crowd simulation,” Qatar University, 2017.

[16] M. Ahmed, R. Seraj, and S. M. S. Islam, “The k-means algorithm: A comprehensive survey and performance evaluation,” Electronics (Switzerland), vol. 9, no. 8, pp. 1–12, 2020.

[17] Nurhayati, N. S. Sinatrya, L. K. Wardhani, and Busman, “Analysis of k-means and k-medoids’s performance using big data technology,” 2018 6th International Conference on Cyber and IT Service Management, CITSM 2018, pp. 1–5, 2019.

[18] P. Arora, Deepali, and S. Varshney, “Analysis of k-means and k-medoids algorithm for big data,” Physics Procedia, vol. 78, pp. 507–512, 2016.

[19] A. B. S. Serapião, G. S. Corrêa, F. B. Gonçalves, and V. O. Carvalho, “Combining k-means and k-harmonic with fish school search algorithm for data clustering task on graphics processing units,” Applied Soft Computing Journal, vol. 41, pp. 290–304, 2016.

[20] A. Pugazhenthi and L. S. Kumar, “Selection of optimal number of clusters and centroids for k-means and fuzzy c-means clustering: A review,” 2020 International Conference on Computing, Communication and Security (ICCCS), pp. 5–8, 2020.

[21] V. B. B. Anguiano, “Integration and visualization of sparse-grid based clustering methods in the SG++ datamining pipeline,” Technical University of Munich, 2019.

[22] O. Arbelaitz, I. Gurrutxaga, J. Muguerza, J. M. Pérez, and I. Perona, “An extensive comparative study of cluster validity indices,” Pattern Recognition, vol. 46, no. 1, pp. 243–256, 2013.

[23] J. Guo, “Developing a visualization tool for unsupervised machine learning techniques on *Omics data,” University of Washington, 2018.

[24] D. M. Saputra, D. Saputra, and L. D. Oswari, “Effect of distance metrics in determining K-Value in KMeans clustering using elbow and silhouette method,” SICONIAN 2019 Sriwijaya International Conference on Information Technology and Its Applications, vol. 172, pp. 341–346, 2020.

[25] A. Wani and R. Riyaz, “A new cluster validity index using maximum cluster spread based compactness measure,” International Journal of Intelligent Computing and Cybernetics, vol. 9, no. 2, pp. 179–204, 2016.

[26] A. H. A. Halim, K. A. F. A. Samah, Z. Ibrahim, and R. Hamzah, “Conceptual framework for intelligent indoor evacuation model assessment algorithm using integrated assessment model,” International Journal of Advanced Trends in Computer Science and Engineering, vol. 9, no. 1.4, pp. 289–294, 2020.

[27] A. H. A. Halim, K. A. F. A. Samah, M. N. H. H. Jono, and L. S. Riza, “A Review on Indoor Evacuation Model and Clustering Techniques in Developing Evacuation Assessment Algorithm,” vol. 7, no. 2, pp. 608–619, 2022.

[28] E. D. Kuligowski et al., “Movement on Stairs During Building Evacuations,” National Institute of Standards and Technology Technical Note, no. January, pp. 1–213, 2015.

[29] H. Hyun-seung, C. Jun-ho, and H. Won-hwa, “Calculating and verifying the staircase-length for evacuation analysis,” Pedestrian and Evacuation Dynamics, 2011.