

# Multi-Level Multi-Stage Agent-Based Simulation Model of Crowd Dynamics in last Floor of Al- Haram Al-Sharif

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## نموذج متعدد المستويات والمراحل قائم على الأفراد لمحاكاة حركة الحشود على سطح الحرم المكي الشريف

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### ملخص البحث (Abstract):

في هذا البحث قمنا بتطوير نموذج متعدد المستويات ومتعدد المراحل يقوم على محاكاة حركة الأفراد ويعمل على تطوير عمليات اتخاذ القرار أوتوماتيكياً خلال عمليات الإخلاء الجماعي في الحوادث الخطيرة. يتمثل النموذج المقترح في بنية متعددة المستويات لإدارة السلوك العام للحشود والسلوكيات الفردية باستخدام نهج النمذجة القائمة على الأفراد داخل البيئات المتغيرة ديناميكياً نتيجة الحرائق، والازدحام، إلخ. يُحاكي النموذج المكونات، والتغيرات السلوكية الفردية والظواهر في النظم المعقدة داخل الحشود الهائلة التي تتمثل في المصلين في المسجد الحرام. على وجه التحديد قمنا بتطبيق النموذج المقترح على إدارة الحشود المتمثلة في المصلين في الطابق العلوي للحرم المكي الشريف (سطح الحرم). سيقوم النموذج المقترح بتوليد مرشدين بين الحشود ديناميكياً وتمكن عملية التوليد هذه من توليد تلقائي للقرارات المثالية للأفراد المجاورين. ويشمل الإطار متعدد الاستخدامات المبادئ الأساسية للنمذجة التي تُطبق عادةً على حركة الحشود. ينقسم نموذج صنع القرار في محاكاة حركة الجمهور إلى ثلاثة مستويات: استراتيجية وتكتيكية وتشغيلية. يتم رسم الخطة وهدفها النهائي في المستوى الاستراتيجي. في هذا المستوى، لا يتم تقديم أي معلومات حول الظروف الحقيقية. في المستوى التكتيكي، تُنفذ جميع الأنشطة لتسهيل الخطة الموضوعية. يتناول هذا المستوى القرارات قصيرة الأجل مثل تجنب العقبات أو تغيير الخطط استناداً إلى معلومات جديدة. يتناول المستوى التشغيلي الإجراءات والأنشطة البدنية التي تم تطويرها على المستوى التكتيكي. الهدف من هذا البحث هو محاكاة السلوكيات والظواهر الحقيقية بدقة مما يسمح باتخاذ قرارات مطورة لتحسين عملية إدارة الحشود المعقدة في ظروف مختلفة. وكذلك أن نكون قادرين على محاكاة السلوكيات الذكية والتنظيم الذاتي للحصول على نتائج موثوقة. سوف تمكننا نتائج النموذج من تقييم الظروف التي قد تحدث داخل الشبكة، وتحسين فهمنا للافتراضات والتطورات المستقبلية التي يمكن أن يكون لها أثر كبير في إدارة الحشود

We develop a multi-level, multi-stage, agent-based framework that automates decision-making processes during crowd evacuations in dangerous scenarios. We model a hybrid architecture for managing crowd individual behaviors, and overall crowd behavior, using a heterogeneous agent-based modeling approach within dynamically changing environments due to external stimuli such as fires, congestions, etc. Our novel multi-component, agent-based modeling framework is applied to simulate the components, varying individual behaviors and phenomena of complex systems within massive crowds that represented among prayers in the last floor (the upper level) of Al- Haram Al-Sharif Mosque.

The proposed framework integrates a probabilistic model with a dynamic generating process of intelligent guide agents, which enables the automatic generation of decisions that are optimal for neighboring agents. The versatile agent-based framework we have developed encompasses the fundamental principles of modeling as commonly applied to crowd dynamics. Our crowd dynamics decision-making modeling is organized into three levels: strategic, tactical and operational. The formulation of a plan and its final objective are drawn at the strategic level. At this level, no information is provided about the real circumstances. At the tactical level, we compute and perform all activities to facilitate the formulated plan. This level addresses short-term decisions like avoiding obstacles or changing plans based on new information. The operational level addresses the physical actions and activities developed at the tactical level. We aim to accurately simulate the real crowd behaviors and phenomena, allowing for improved decisions taken to enhance the complex process of crowd management under various scenarios. Also, our goal is to be able to mimic intelligent, self-organizational behaviors and gain reliable results. The model results will enable us to evaluate the conditions that might occur within the network and improve our understanding of which assumptions and future developments could have the most impact in managing crowd.

### **Introduction**

Multi-agent systems are used to model and simulate complex systems, which range across various contexts and both biological and social systems. This simulation method is known as agent-based modeling (ABM) [1, 2]. The ABM approach which models complex systems is a form of optimization of individual solutions [3, 4]. The agents in the decentralized system have no direct information about their global position but do have information about their nearby neighbors and their environment locally. However, they can use this local knowledge to collectively construct a coordinate system [1-4].

Here we present a novel multi-component, agent-based modeling framework that simulates the components, behaviors and phenomena of complex systems [5, 6]. A decentralized multi-agent control strategy is proposed and investigated on an autonomous microgrid. In a crowd complex system [2, 4], agents adjust their behavior according to their current states, to other agents' states and to their environment. Thus, ABM is a suitable approach to use to study crowd behaviors. Our model [6] is a computational discrete-time simulation scheme. We outline our support system with finite-state machines and use a genetic algorithm to optimize the selections and decisions taken by crowd individuals. We build the model to explain and predict observed interactions among real agents [6].

### **Research aims**

We aim to accurately simulate the crowd behaviors and phenomena, thereby improving crowd management decisions. To ensure the effectiveness and robustness of our model in supporting crowd management decisions, we build a novel, multi-component, agent-based modeling framework. To this agent-based framework we introduce an adjustable approach for simulating human perception and decision-making in dangerous scenarios. The events that occur during a crowd evacuation are complex and have far-reaching implications for the safety of individuals [7]. Our framework will support crowd management decisions by elaborating what-if scenarios. Also, we aim to support event planners' and building designers' decisions. We use modeling and simulation as a means for developing a deep understanding of both complex systems and complex adaptive systems behavior. Because of the emergent phenomena of complex systems, ABM is an effective approach to address the question of how a system's behavior connects to the behaviors and

characteristics of its individual components. The main goal of this work is to create a model that is able to simulate varying individual behaviors within massive crowds that represented among prayers in the last floor (the upper level) of Al- Haram Al-Sharif in Makkah [8] (Fig. 1), during evacuation.

### **Research methodology**

In this proposed model we exploit the ABM approach and the non-homogeneous CA [9-18] to provide a multi-layered decision support system in cases of crowd evacuation. The work we propose here develops a new simulation method to understand the movement of large crowds during evacuations from buildings. Our work introduces a multi-levelled model where pedestrian dynamics are divided into three main levels of decision making [16, 18]: strategic, tactical, and operational. The planning for pre-trip of the route and the final destination is designed at the strategic level. At this level, no information is provided about the real circumstances [19]. At the tactical level, decisions for short term, like avoiding obstacles or change of route depending on the real situation, are addressed. Additional information about the crowd such as the flow of agents is available at this point [20]. The operative level represents the agents' movement that includes the connection with other pedestrians [21].

Our simulation model consists of multiple sub-models, as it is shown in the system overview in Fig. 2, starting with the model of how the agent selects its goal destination. Then, we model the act of avoiding obstacles as well as collision with neighbored agents. Also, our hybrid version of agent-based model includes simulating the leading and following behaviors of agents after dynamically upgrading certain agents to the intelligent level and enabling them to perform some sort of guidance behavior, as detailed below. Besides avoiding collisions with neighboring agents, the framework also includes a model of avoiding high density areas in order to reduce the overall travel time. Our work represents an approach for modeling and simulating complex and dynamic crowd systems, both at microscopic and macroscopic levels. The highest layer represents the macroscopic phenomena of the crowd that would be difficult to model in CA frames. This layer represents the connections between intelligent guide agents to enhance the decisions for the whole system as it will be described below. The base layer is composed of a high determination CA framework for every open space, which shows how the agents' neighborhood moves as well as the development of decision-making at the microscopic level of the system. Fig. 3 demonstrates the two-layered structure of the proposed system.

The environment component of this ABM model defines the elements of the physical space, such as a city, building, roads, etc. The simulation environment is presented as a lattice, which is a two-dimensional array of  $n \times n$  cells. We have designated specific types of cells in a lattice of a non-homogeneous cellular automaton. These are obstacle cells, which are unreachable, target cells, which represent exits in the evacuation scenarios, and the reachable cells, which are considered as the movement space. In this model, static floor field (SFF) [22] is used to indicate the distances to a destination for every agent in the environment. A target static floor field value is assigned to every cell to describe the distance to the earliest chosen target (exit).

The agents in our model are randomly assigned with objective and subjective parameters at the beginning of the simulation. The individuals' characteristics, or subject parameters, include awareness of the environment, education level, cooperativity, adaptability, flexibility, perception of potential risks, acceptance to follow orders, and ability to access global information about the environment. On the other hand, agents' objective characteristics include age, health status, propensity to panic, mobility, and communication capability.

### 1. Target-driven decision-making model

The optimal initial target decision is impacted by different factors that the agents perceive from the environment. In our model there are four important factors: the distance to a target, the width of the target (exit), the speed of the agent, and the density at the target. For each agent  $a$  we calculate the initial target decision ( $ITD$ ) function for each target. For  $j$  targets in the environment, the  $ITD$  function is calculated as follows:

$$ITD(a) = \min\left(\frac{d_j}{s_a} + \frac{td_j}{w_j}\right), \quad (2)$$

### 2. Transition decision-making model

At every time-stamp, the agent  $a$  will move to the neighbor empty cell with the highest transition probability,  $p_{ij}$  to move to an unoccupied neighbor cell  $(i, j)$  that is determined by the four factors: dynamic floor field, target floor field, obstacles floor field, and the density around the next target cell. In each time-stamp, the dynamic floor field  $D_{ij}$  decays with some probability and diffuses with some probability to one of its eight neighbor cells. In order to calculate the dynamic floor field, we first initialize all the cells to 0, i.e., at  $t = 0$ ,  $D_{ij}^0 = 0$  for all cells. Then we calculate the dynamic floor field ( $DFF$ ) according to decay and diffusion as follows:

$$D_{ij}^{t+1} = (1 - \alpha)(1 - \delta)D_{ij}^t + \frac{\alpha(1-\delta)}{4} (D_{i+1,j}^t + D_{i-1,j}^t + D_{i+1,j+1}^t + D_{i+1,j-1}^t + D_{i,j+1}^t + D_{i-1,j+1}^t + D_{i,j-1}^t + D_{i-1,j-1}^t), \quad (3)$$

In our model, we also consider that people usually avoid walking close to walls and obstacles. In our model, the repulsive obstacle potential is inversely proportional to the distance from the obstacles. Thus, the impact of the target static potential field is affected by the obstacles floor field ( $OFF$ ). The values for the cells occupied by obstacles is set to be the higher values of the cells in the environment. The obstacles' static potential field is calculated as follows:  $OFF(x,y) = \min(D_{max} d_{x,y})$ , (4)

For each agent  $a_i$  we calculate the transition probability to each empty cell  $(x, y)$  in its Moore neighborhood as follows:

$$P(x, y) = N \exp(-k_T TFF(x, y) + k_D DFF(x, y) + k_O OFF(x, y) + k_{den} Den(x, y) + k_I I), \quad (5)$$

### 3. Agent status upgrading model

The third stage in the ABM simulation is to classify different types of agents in the environment. The agent-based model here represents two sets of evacuees: the first set who is familiar with the building geometry, and the other one who is unfamiliar. In our proposed model, this is a major stage as we examine the agents' expected behaviors. This classification is done based on subjective and objective characteristics of the individual agents, as shown in Algorithm 1. Being an intelligent agent means that agent is relied upon during the decision-making processes by other agents. Particularly, unfamiliar agents apply only the operational level of crowd modeling by following or mimicking intelligent agents' movements, thus maintaining the collective pattern.

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**ALGORITHM 1:** Agents' Status Upgrade

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for each agent  $a$  in the simulation environment do
     $a.Objective-Parameter = \text{Random}[0,1];$ 
     $a.Subjective-Parameter = \text{Random}[0,1];$ 
end
Divide the environment space into equal regions;
for each environment region do
    if ( $Density > Density-T\ hreshold$ ) then
        if ( $a.Objective-P\ arameter < Objective-T\ hreshold$ ) and
        ( $a.Subjective-P\ arameter > Subjective-T\ hreshold$ ) then
             $a.Status = Intelligent;$ 
             $a.MooreNeighbors.Status = Follower;$ 
        end
    end
end
```

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#### 4. Evaluation of trustworthiness model

Trust between agents is defined as the agent's expectation about another's perspectives. In our model, we investigated a trust evaluation algorithm for agents in a multi-agent system based on the trustworthiness of related intelligent agents. We introduce here the trust concept as the agent's confidence in the ability of a related intelligent agent (information source) to deliver accurate information. Particularly, the probability that a following agent would approve of an intelligent agent's opinion on a specific target is dependent on the approval of the neighboring agents about the decision taken by the intelligent agent. Suppose an intelligent agent  $p$  provides knowledge, or decision  $q$  to agent  $a$ . Suppose  $n$  neighboring agents have contributed to the current decision  $q$ . In other words, agent  $a$  trusts intelligent agent  $p$  if trustworthiness probability value is greater than or equal to a predefined threshold. The trustworthiness probability about the decision  $q$  is calculated as follows:

$$P(q) = \xi \sum_{i=1}^N \sum_{j=1}^2 P(q|a_i^j)P(a_i^j), \quad (6)$$

#### Results and discussion

The ultimate aim is to test the capability of the presented model in improving the crowd behaviors during evacuation. Also, one of the main criteria for the performance evaluation of our crowd simulation model is the total travel time needed for the agents to reach their individual goals. We should ensure the shortest possible trip time for the agents to reach their destinations. Different attributes of the crowd have to be considered in the implementation of the model. This includes, but is not limited to, the individual characteristics of the agents, such as language, culture, age, and environment obstacles that could be caused by external events or the agents themselves.

Fig. 4 shows the variation of density to each target's static floor field (TFF). The blue radiance represents the higher force of attraction of the TFF value, while the yellow radiance illustrates avoiding areas that delay agents from reaching their exit.

The distribution of agents is random throughout the environment at the beginning of the simulation. When an agent reaches its target, he is considered evacuated from the environment, and removed from the simulation. The simulation

model was run with ten thousand agents (prayers) in two different cases. The first case represents our model where the tactical level is involved. In the second case we only implemented agent-based simulation without involving the tactical level. That means there is no existence of intelligent agents in the simulation, and no application of trustworthiness.

Our approach has yielded three main insights. The first finding illustrates the model's capability of improving the crowd flow pattern. Fig. 5 shows that agents' flow rate was higher in our proposed model (case 1) than the traditional ABM application (case 2). That indicates the ability of our model to improve the overall crowd flow during evacuation. We also found that the agents' average speed during the simulation was higher in the proposed model. Fig. 6 shows the estimation of the average speed of 400 agents during the simulation.

The second result is related to demonstrating the model's efficiency in promoting the crowd overall travel time during evacuation. Specifically, we observed that all agents in the environment have been evacuated in a short and reasonable time, while it took the agents a longer travel time to evacuate in the traditional ABM model, as shown in Fig. 6 that shows the total travel time for 200 agents in both cases. This result proves the benefit of relying on an intelligent agent to improve the evacuation overall travel time.

The results demonstrate the efficiency of our models in accurately simulating the events during crowd evacuations. Considerable changes of crowd dynamics have been detected during the simulations such as transitioning from a random to a coordinated motion and avoiding obstacles and high-density areas. We observed significant improvement of crowd flows during simulations compared to that observed with traditional applications of ABM. These observations could influence multiple aspects of how evacuations are planned. For example, design of where the exits are located in buildings, and how individuals are trained to behave during an evacuation. Taken together, our results show that the proposed multi-leveled multi-staged agent-based model outperforms the traditional ABM approach in improving the crowd dynamics during evacuation in a high-density simulation logic.

### **Summary and conclusion:**

Our proposed ABM model was able to improve crowd management solutions by considering the diversity of prayers and their characteristics involved. The aim of our model in such cases is to help Hajj and Umrah crowd management authorities build successful schemas by predicting the crowd's behaviors. Our model uses a finite state machine, in conjunction with an agent-based model, to determine how agents interact with each other locally in order to generate collision-free trajectories. The results of our model showed the ability to support the heterogeneity and high density observed among the massive number of prayers of Al- Haram Al-Sharif. That includes using small time steps in order to consider different pedestrian speeds and reduced mobility of some of them, e.g., elderlies. Our experimental results provide evidence that the hybrid, multi-layered approach can be successfully applied to efficiently simulate agent behaviors in intensive crowd environments. This research will provide promising solution to facilitate crowd management in case of increasing number of pilgrims based on 2030 vision; where the number of pilgrims will increase to approximately four and a half million in Hajj and thirty million in Umrah [23].

### **Recommendations:**

One of the essential applications of our model will be crowd management during the enormous annual gathering of the Hajj [24]. The Hajj involves over two million people from approximately 150 countries. The complex multi-agent system represented by their Hajj includes many agents, such as people with substantial variety of objective and

subjective characteristics, vehicles, communication systems, disaster and crowd management authority, etc. The Hajj crowd consists of a heterogeneous set of pilgrims with varying physical capacities and activities. Due to the special features of the Hajj, which include the massive number of people and approximately 30,000 vehicles contained in a limited space over a short period of time, crowd disasters such as stampedes and overcrowding are common [25, 26]. The crowd density during pilgrimages is extremely high. Many studies have been conducted attempting to improve crowd management during Hajj to avoid such disaster [24, 25, 27]. The model's implementation focus will include several real-world, expected scenarios during pilgrimage. These include evacuations under risky conditions, control of the crowd in case of panic, regimentering the massive number of pedestrians and vehicles quickly and in a safe manner, and improving the crowd management processes in the event of an increased number of pilgrims.

**Figures and Tables:**

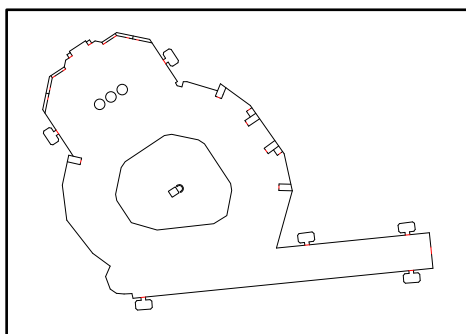


Figure 1

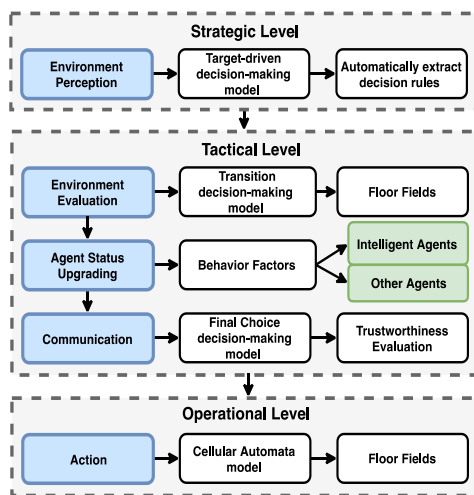


Figure 2

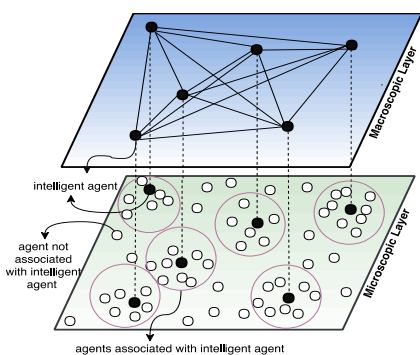


Figure 3

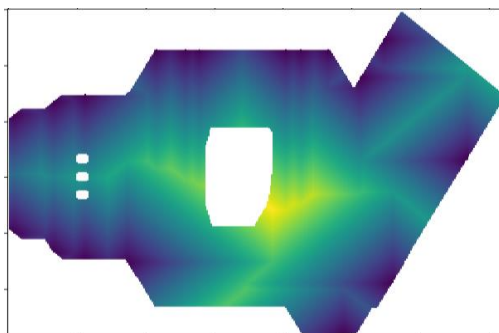


Figure 4

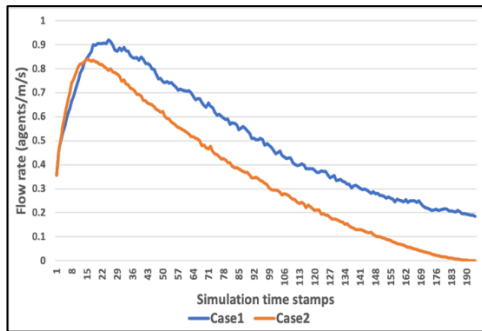


Figure 5

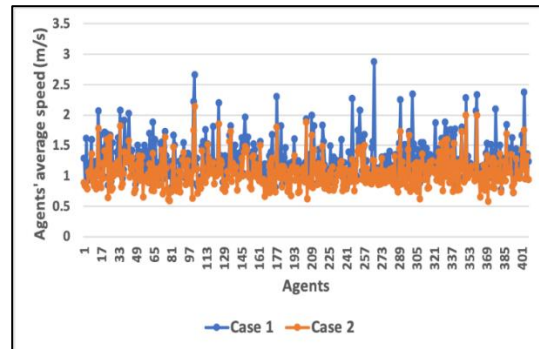


Figure 6

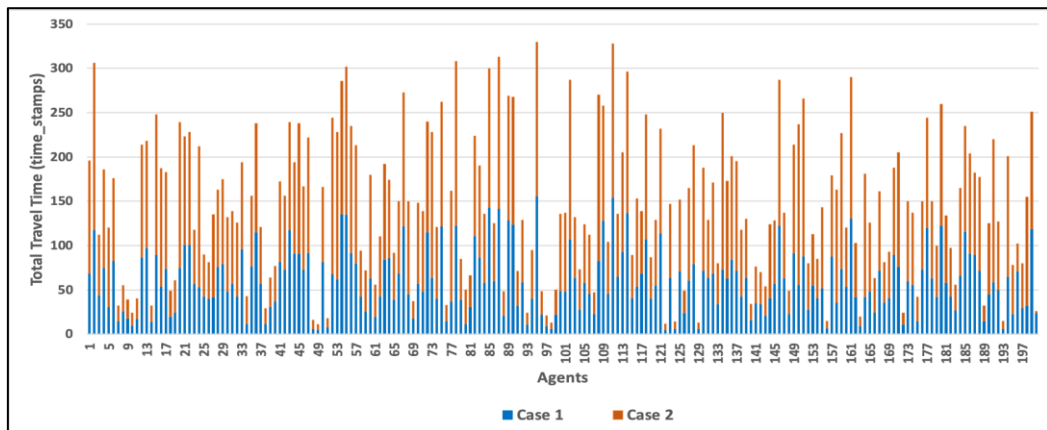


Figure 7

## References:

- [1] M. Niazi and A. Hussain, "Agent-based computing from multi-agent systems to agent-based models: a visual survey," *Scientometrics*, vol. 89, (2), pp. 479, 2011.
- [2] J. Waş and R. Lubaś, "Towards realistic and effective agent-based models of crowd dynamics," *Neurocomputing*, vol. 146, pp. 199-209, 2014.
- [3] N. Medina, A. Sanchez and Z. Vojinovic, "The potential of agent based models for testing city evacuation strategies under a flood event," *Procedia Engineering*, vol. 154, pp. 765-772, 2016.
- [4] B. Ni, Z. Li and X. Li, "Agent-based evacuation in passenger ships using a goal-driven decision-making model," *Polish Maritime Research*, vol. 24, (2), pp. 56-67, 2017.
- [5] R. Alqurashi, and T. Altman, "Multi-class agent-based model of crowd dynamics," in *Proceedings of the 2017 International Conference on Computational Science and Computational Intelligence*, pp. 1801-1802, 2017.
- [6] R. Alqurashi, and T. Altman, "Multi-level multi-stage agent-based decision support system for simulation of crowd dynamics," in *Proceedings of the 23rd International Conference on Engineering of Complex Computer Systems (ICECCS 2018)*, pp. 82-92, 2018.
- [7] O. Richardson, A. Jalba and A. Muntean, "The effect of environment knowledge in evacuation scenarios involving fire and smoke-a multiscale modelling and simulation approach," *arXiv Preprint arXiv:1709.07786*, 2017.
- [8] <https://www.gph.gov.sa/ar-sa/Pages/default.aspx>



- [9] J. Wąs *et al.*, "Agent-based approach and cellular automata-A promising perspective in crowd dynamics modeling," *Acta Physica Polonica B Proceedings Supplement*, vol. 9, pp. 133-144, 2015.
- [10] J. M. Czerniak *et al.*, "A Cellular automata-based simulation tool for real fire accident prevention," *Mathematical Problems in Engineering*, vol. 2018, 2018.
- [11] L. Crociani *et al.*, "Avoid or follow? Modelling route choice based on experimental empirical evidences," *arXiv Preprint arXiv:1610.07901*, 2016.
- [12] S. Sarmady, F. Haron and A. Z. Talib, "A cellular automata model for circular movements of pedestrians during Tawaf," *Simulation Modelling Practice and Theory*, vol. 19, (3), pp. 969-985, 2011.
- [13] K. Yamamoto and R. Nonomura, "Evacuation dynamics in room with multiple exits by real-coded cellular automata (RCA)," in *International Conference on Cellular Automata*, 2016.
- [14] R. Lubaś, J. Wąs and J. Porzycki, "Cellular Automata as the basis of effective and realistic agent-based models of crowd behavior," *The Journal of Supercomputing*, vol. 72, (6), pp. 2170-2196, 2016.
- [15] S. Bandini and G. Vizzari, "Heterogeneous dynamics through coupling cellular automata models," in *International Conference on Cellular Automata*, 2016.
- [16] L. Crociani *et al.*, "Cellular automaton based simulation of large pedestrian facilities-a case study on the staten island ferry terminals," *arXiv Preprint arXiv:1709.03297*, 2017.
- [17] D. Schaumann *et al.*, "A computational framework to simulate human spatial behavior in built environments," in *Proceedings of the Symposium on Simulation for Architecture & Urban Design*, 2016.
- [18] S. Bandini, A. Gorrini and G. Vizzari, "Towards an integrated approach to crowd analysis and crowd synthesis: A case study and first results," *Pattern Recognition Letters*, vol. 44, pp. 16-29, 2014.
- [19] L. Crociani *et al.*, "A CA-based model of dyads in pedestrian crowds: The case of counter flow," in *International Conference on Cellular Automata*, 2016.
- [20] L. Crociani *et al.*, "Adaptive tactical decisions in pedestrian simulation: A hybrid agent approach," in *Congress of the Italian Association for Artificial Intelligence*, 2015.
- [21] L. Crociani, G. Lämmel and G. Vizzari, "Multi-scale simulation for crowd management: A case study in an urban scenario," in *International Conference on Autonomous Agents and Multiagent Systems*, 2016.
- [22] L. Lu *et al.*, "A study of pedestrian group behaviors in crowd evacuation based on an extended floor field cellular automaton model," *Transportation Research Part C: Emerging Technologies*, vol. 81, pp. 317-329, 2017.
- [23] <https://vision2030.gov.sa/en/node/51>.
- [24] Y. A. Alaska *et al.*, "The impact of crowd control measures on the occurrence of stampedes during mass gatherings: the Hajj experience," *Travel Medicine and Infectious Disease*, vol. 15, pp. 67-70, 2017.
- [25] S. Jamil *et al.*, "Hybrid participatory sensing for analyzing group dynamics in the largest annual religious gathering," in *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 2015.
- [26] B. Basak and S. Gupta, "Developing an agent-based model for pilgrim evacuation using visual intelligence: A case study of Ratha Yatra at Puri," *Computers, Environment and Urban Systems*, vol. 64, pp. 118-131, 2017.
- [27] S. Gupta and B. Basak, "Alternate terminal location planning using accessibility analysis for improved pilgrim movement," *Anatolia*, vol. 28, (3), pp. 351-362, 2017.