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IMS project

Evacuation Simulation

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December 4, 2017

1 Introduction

Education buildings are common examples of commercial buildings that involve a meeting of a large number of people within a closed area. While designing such types of buildings, a common goal is to maximise the productivity of the available space, but it is essential to consider the safety aspects as well. One of such aspects is how efficiently can emergency evacuations be carried out due to the threat of fire. Whether a building layout is suitable for emergency evacuation is a difficult and rather ambiguous decision due to the fact that numerous factors must be taken into account, such as fire and smoke spreading, behaviour of every single individual as well as crowd dynamics and other random events. Modelling [ims-8] such situations can give an insight into the safety aspects of a building and identify its flaws.

This project addresses a question of how such evacuation processes can be modelled using cellular automata [ims-316]. Our work is mainly based on a research by Tissera et al. [14]; several modifications enhancing pedestrian behaviour are introduced, some of them inspired by the research by Yuan et al. [17]. We will use our approach to model evacuation processes inside two selected buildings, namely, D and E wings of a FIT BUT building [1]. Using these models [ims-7] we will simulate [ims-8] different fire scenarios and collect various statistics [ims-35] in order to evaluate key safety aspects of the systems [ims-7] under investigation.

Section 2 describes some basic concepts: a theory behind cellular automata, the laws of fire and smoke spreading, the principles of crowd dynamics and consequences of a smoke poisoning. In Section 3 we invoke these concepts and introduce an abstract model [ims-9] of a system. Section 4 briefly describes selected implementation features. Finally, in Section 5 we carry out the experiments and evaluate emergency suitability of selected buildings.

2 Preliminaries

2.1 Cellular Automata

Let us first briefly describe a mathematical apparatus in the core of our models, namely, cellular automata (CA) [16]. The CA are mathematical systems with discrete values in space, time and state. With respect to the structure a CA can be considered as a grid of locally interconnected cells that behave like finite automata. The input of each finite automaton (cell) is considered to be a state of the neighbouring cells. During each discrete step, a cell evaluates its input and produces an output, modifying its own state. Therefore, the state of the cell of a cellular automaton in a particular time step only depends on the states of its neighbouring cells and the state the cell had in the previous time step.

The spatial framework of the CA can be specified in any number of dimensions where cells may be of any regular shape. Similarly, the neighbourhood of the cell can be defined in various ways. Having established the structure of the automaton and the shape of the neighbourhood, one needs to define the set of states of a cell and the rules that dictate transitions between these states. In our case, we need to study the laws of fire/smoke propagation and people motion, which is the main interest of the following subsections.

2.2 Fire and Smoke Spreading

The phenomenon of fire and smoke spreading is extremely complex due to the involvement of numerous non-trivial chemical reactions and physical processes [18, 4]. Simulating such processes using means of CA usually involves two interconnected automata: one for fire spreading simulation and one for smoke spreading simulation [4]. The first one employs two factors: combustion materials that are placed in the two adjacent cells under investigation and information about airflow velocities. Capturing data to quantify the latter factor is not a trivial task and is usually performed by establishing a sensor network to measure these velocities real-time. Obviously, this is impossible for buildings that are being planned, so, again, simulations of the airflow are used, which is a non-trivial procedure on its own [19]. Therefore, this complex process is very often [14, 13] approximated by considering only flammability/combustibility of materials. The model is then reduced to a simple diffusion process where a probability of cell contamination at the current time is proportional to the contamination level of its neighbourhood.

The CA for smoke spreading simulation are quite similar to those developed for fire spreading with some adjustment of parameters [4]. The reason for this is that propagation speed of a smoke is typically much higher than the one related to fire and therefore the smoke automaton evolves much quicker than the fire automaton. Regarding this, our preliminary prototypes showed that for buildings of interest fire automaton remains almost stationary and, apart from generating toxic smoke, does not influence the model whatsoever. The reason for this lies in the fact that investigated buildings are relatively small (area of E wing is approximately 900 m^2), and evacuation proceeds too fast for the fire to spread; similar behaviour can be inspected in analogous experiments by [14]. An exception would be the case when large areas of a building instantaneously catch fire, although this requires a presence of a significant amount of flammable material (e.g. library) [13].

Does this imply that such buildings are safe? Not at all, one should not neglect the speed with which smoke propagates. This speed, again, largely depends on the spatial configuration of a building and generated airflows. For the exact same reasons as those mentioned before, smoke spreading is often approximated by a simple diffusion model where each contaminated cell also serves as a source of a smoke [14, 13]. Quantitatively, the propagation speed varies between $0.2-1.2$ m/s [9]. We will stick with the smaller values to account for relatively high ceilings in both E and D wings.

Also, note that in the initial phases of smoke spreading, the smoke tends to go up driven by the buoyant forces, which means that in the beginning no diffusion in horizontal direction occurs [4]. In our model, this delay is compensated by two factors: i) fire alarm is not triggered until the smoke reaches the ceiling and ii) it takes a significant amount of time for the individuals inside the building to realise a seriousness of a fire in order to initiate extraction.

2.3 Crowd dynamics

Crowd behaviour that arises from the behaviour of every single individual is arguably even more complex than the process of smoke spreading due to the fact that the former assumes numerous psychological factors as well [18, 17]. A model by Tissera et al. [14] completely ignores such factors and a behaviour of an individual is defined by his spatial distance: a person will proceed to the nearest exit no matter what. A model by Yuan et al. [17] considers occupant density in a sense that an individual might trade the nearest exit for the other one if the latter is less crowded and therefore a person has more chances for a safe extraction. Yuan's extended model also accounts for some characteristics of humans, such as unadventurous effect (a person will try to exit through the same route he entered), inertial effect (once a person moves towards a certain exit, he is less likely to change his direction) or group effect (group members will help one another in emergency). An improved model by Tissera et al. [13] manages to account for human factors by employing intelligent agents [11] where each agent possesses certain psychological, physiological and social characteristics that shape his behaviour inferred from (limited) perceived information.

In our work we will stick with the Yuan's basic approach (an individual chooses the nearest exit but might switch to the one that is less crowded) with one slight modification: an individual is also not ignorant of the danger of smoke poisoning and will prefer a clear path towards exit (choosing the cells without the smoke) and might even change his destination exit when the closest one is too toxic. This description might sound vague, but we will formally define such behaviour in the next section while introducing the abstract model.

2.4 Effects of Smoke Inhalation

Since we are not considering a spreading of fire inside a building and account only for smoke, we must be able to quantify its impact. Smoke inhalation injury, either by itself or in the presence of a burn, is now well-recognised [5] to result in severe lung-induced morbidity and mortality. Severeness of the intoxication depends on the components of the smoke, concentration and a temperature of combustion as well as the time of the exposure. For carbon monoxide (the most common smoke component) of heavy concentration ($\geq$ 10000 ppm), 15 minutes of exposure is estimated to be enough to incapacitate an adult (typically followed by a respiratory failure) [10, 7], 5 minutes is estimated to be a threshold when the smoke poisoning leads to long-term effects [5, 12, 7]. Impact can be even more severe if a person under exposure already possesses cardiovascular or respiratory conditions [5, 6].

It is hard to predict the nature of the smoke in our modelled buildings as well its concentration, so we will stick with the estimations of the heavy cases above and use a reference value of 5 minutes of smoke exposure to decide whether an extraction can be considered successful.

3 Model Description

Let us first describe a simplified version of a model to familiarise the reader with the basic rules; later we will introduce one advanced property that completes the model. We consider a finite two-dimensional grid of square cells with closed boundaries; each cell represents a 0.4×0.4 meters square, which is considered to be the space occupied by a person in a crowd with maximal density [2, 8]. We use *Moore Neighbourhood* [15], which is a common choice when one wants to allow a cell to act along all possible directions. A discrete time step represents 0.3 seconds of real time, which is estimated to be the time required for a pedestrian to move 0.4 meters (size of a cell side) [2].

3.1 Cell States

The set of all possible cell states Q is the following

$$Q = \{W, O, P, S, E, X, PS, OS, PX\}$$

where:

- W – Wall
- O – Obstacle
- P – Person
- S – Smoke
- E – Empty cell
- X – Exit

- PS – Person with Smoke
- OS – Obstacle with Smoke
- PX – Person at the Exit

A *Wall* cell represents an external or internal wall that cannot be occupied by a person or be penetrated by smoke; *Obstacle* cells (tables, vending machines etc.) also serve as a barrier for individuals, but do not stop the smoke spreading (OS exists as well). Other state names are self-explanatory.

There is one more cell state, PI (Person Initial position) which is used during the initialisation of the CA and is not involved in its evolution. For now we assume that a specific initial configuration is given and in the next section we will describe how such configuration is loaded into the program.

Each cell also carries one value, *sd* (*spatial distance*), that represents a distance (in cell hops) to the nearest exit.

3.2 Evolution Rules

1. Wall cell preserves its state throughout the whole simulation.

2. A cell with smoke (S, PS or OS) at time t will also have smoke at time $t+1$. If at time t a certain cell does not have a smoke (states E, P or O), but some of its adjacent cells have smoke, with a certain probability such cell will have smoke at time $t+1$ (E will become S, P will become PS, O will become OS). This probability is proportional to the number of cells with smoke in the neighbourhood; the exact value is computed using an expression $C_{SS} \cdot \frac{S}{T}$, where T is a total number of adjacent cells reachable by smoke (i.e. any cell but the wall), S is a number of adjacent cells affected by smoke and C_{SS} is smoke spreading coefficient. A smoke propagation speed of $0.2 - 1.2$m/s translates to $0.15 - 0.9$ cells per step; using assumptions stated in the previous section, we choose a value of normalising coefficient C_{SS} to be 0.2.

3. In one discrete step a person (states P and PS) can move to any cell in his neighbourhood provided that i) the target cell is unoccupied (states E, S and X) and ii) the distance to the exit *sd* of the target cell is less than or equal to the one that is being currently occupied. When a person reaches an exit ($X \rightarrow PX$), he remains there until the end of the discrete step (simulating the blocking of an exit) and is collected at the beginning of the next step, freeing it. Other aspects related to the people motion are described in the next subsection.

3.3 People Motion

In order to drive the movement of each individual we need to compute for each cell that can be occupied (neither walls nor obstacles) its spatial distance *sd* to the closest exit. We consider the cellular space as a graph, where each cell represents a node and all the edges connecting adjacent cells have weight one. Having multiple exits, a modified version of the Dijkstra's shortest path algorithm is applied where the edges are reversed and exits (destinations) are treated as sources (multiple source to single destination, MSSD) [3]. Each cell is then characterised by its distance to the nearest exit. Image 1 provides an illustration: exit distances are displayed in colours where warmer colours refer to smaller exit distances.

As was mentioned before, a person will try to move closer to the exit by selecting those adjacent cells that have an *sd* value less than the one that is being currently occupied. In case when there is more than one such cell, a cell is selected at random. To avoid collisions (when two or more individuals aim to occupy the same cell during transition) we perform update of person cells sequentially. The order of update is random and is different during every step in order to avoid any bias.

In case a person cannot move to the cell nearer to exit (because it is being occupied by another person), with certain probability he can move to the cell with the same spatial distance. This probability is denoted as C_{bp} (by-passing) and has a value of 0.25. This approach solves an issue addressed by Tissera et al. [14] when blocked individuals were standing still which often leads to unrealistic behaviour. This probabilistic shift can also simulate by-passing (on a local scope) of blockers ahead.

Finally, we have to answer a question how to enhance the abilities of individuals to evaluate current situation so that they are able to recognise bad routes and bad exits, either overcrowded or filled with smoke. This is achieved by introducing a notion of perceived distances.

3.4 Perceived Distances

In order to explain the idea behind perceived distances we will first modify our existing model and then justify these changes when the concept becomes more apparent. First, we change *sd* property of a cell to *pd*, which stands for *perceived distance*. Next, for MSSD path evaluation we use the following modifications:

- a distance from any cell to the cell that is occupied by an individual (state P) is C_{OP} (*occupied perception* factor)
- a distance from any cell to the cell that is filled with smoke (state S) is C_{SP} (*smoke perception* factor)
- a distance from any cell to the cell that is both occupied by an individual and filled with smoke (state PS) is $C_{OP} \cdot C_{SP}$
- all other edges have weight 1 (as before)

for $C_{OP} \geq 1, C_{SP} \geq 1$. A person then selects a cell which has a minimum value of *pd*.

In other words, when a target cell is occupied or filled with smoke, it is *perceived* as being further from the current one. Using these modifiers while solving MSSD problem allows for the heavily overcrowded (intoxicated) routes to magnify their *pd* property. Since the configuration of automaton is not stationary and the weights of the edges change dynamically, perceived distances must be recomputed in the beginning of each step. As a consequence of this, a person is now able (in each step) to evaluate the current situation, identify overcrowded or intoxicated areas and try to avoid them. Figure 2 illustrates the phenomenon. Please note that the presence of smoke or a person several steps ahead will not slow down an individual: the spatial distance between two adjacent cells is still 0.4 meters and it still takes 0.3 seconds to cover this distance. What changes is the *perception* (hence the name) of the surrounding area that drives a motion of an individual.

We still have to assign concrete values to parameters C_{OP} and C_{SP}. Note that for $C_{OP} = C_{SP} = 1$ the perceived distance is reduced to the spatial distance and individuals act solely upon information about nearest exits. Unfortunately, we failed to find any hard statistical data about a human perception of the crowds or the smoke that would suggest the choice of the parameters, neither could we derive them based upon real life experiments, for obvious reasons. Empirical value of 20.0 for C_{SP} was selected based on experiments with the model; such value leads to behaviour when a person is aware of the smoke poisoning but will not be blocked by the smoke

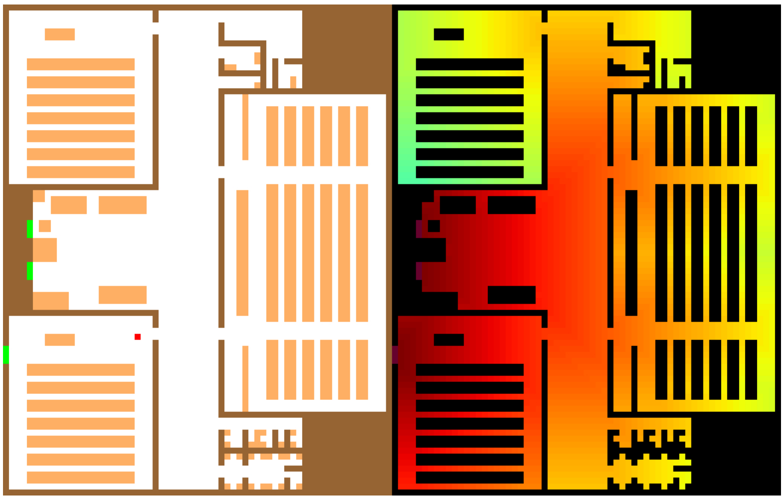

Figure 1: A model of a building (left) and a map of spatial exit distances (right). Shorter exit distances are displayed in warm colours. In this case a person in E104 room (red dot) will move towards the closest exit (green) via warmer cells.

screen if the nearest exit is close enough. The exact same argument applies to C_{OP} for which a value of 10.0 was chosen. Yuan's model [17] also quantifies this perception by means of a set of parameters.

4 Implementation

In this section we will briefly describe selected implementation features. Please note that the code is instrumented with Doxygen and the documentation is available using `make doxygen`. For information about program parameters, use `--help` option.

4.1 Input configuration (bitmap.*)

Description of a building is provided by means of a bitmap image (.bmp, 24-bit) where each pixel represents a cell. Such input can be created in any raster editor (e.g. MS Paint). We use the following colour scheme:

- Wall: brown (150, 100, 50)
- Exit: green (0, 255, 0)
- Empty: white (255, 255, 255)
- Smoke: grey (128, 128, 128)
- Obstacle: orange (255, 175, 100)
- Obstacle with Smoke: light grey (160, 160, 160)
- Person: red (255, 0, 0)
- Person with Smoke: light red (255, 100, 100)

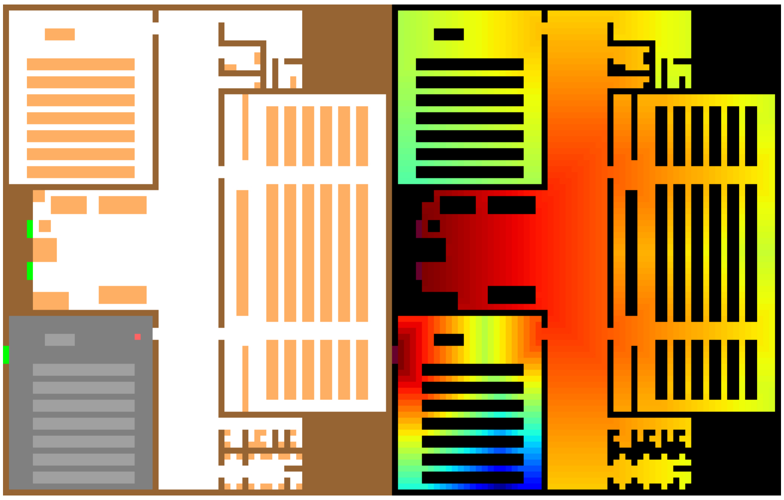

Figure 2: A model of a building (left) and a map of perceived exit distances (right). In this (artificially created) case an E104 room is heavily filled with smoke. A person (light red dot) standing next to the room exit will choose to leave the room and extract via central exits in order to avoid smoke intoxication.

- Person Initial position: light pink (255, 200, 200)

After loading a building description, initial positions of people are randomly distributed first along PI cells, then (if there are still individuals to distribute) along remaining unoccupied cells. Finally, smoke sources are randomly distributed as well.

4.2 Evolution of CA (evacuation.*)

Configuration of a CA is stored in one rectangular array. During a discrete step, we account only for cells capable of updating: first individuals (cells in states P or PS) and then smoke (cells in states S, PS or OS). All person cells are remembered to avoid propagating one person twice in one step; the same applies for smoke propagation.

4.3 Simulation controller (main.cpp)

Controller utilises modules mentioned above to construct the automaton, trigger evolution steps and collect statistics about the status of the CA. In case several runs of one automaton are required (to compute average results), we load the image description only once and then work with the copy of automaton; statistics are then aggregated after each run and in the end the average result is computed.

5 Case Studies

As was mentioned before, we focus on two existing buildings: D and E wings of a FIT VUT campus. In both cases we are interested if architectural plans are suitable for carrying out emergency evacuations. For each of the segments we created their bitmap analogues using the plans and by in-field inspection. Results are displayed in Figure 3.

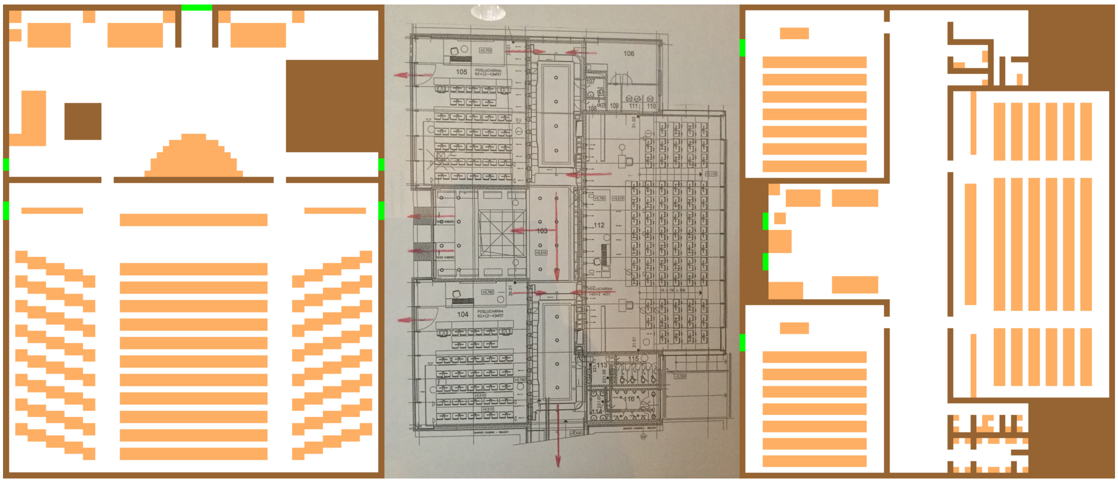

Figure 3: D wing model (left), E wing plan (middle) and its model (right).

For each object (wall, table, vending machine etc.) we estimate error in either of its dimensions to be ± 0.2 meters (half of the length of one cell side). Using PI cell states we specified primary positions for individuals (students) - students primarily occupy seats in lecture rooms, some may be in the halls - which simulates a common study session. For each of the wings we created five different scenarios that describe various building configurations, from normal state to the case where some of the exits or even room entrances are blocked/closed.

In each experiment we compute a total evacuation time (a time interval between alarm going off and an extraction of the last individual) and the time each individual was exposed to the smoke; in each experiment we report a maximum value. We are interested if this value will not exceed a threshold of 5 minutes. With the purpose of obtaining acceptable statistical data, the final results are obtained by averaging results of 1000 independent replications of each experiment.

5.1 Description of buildings

A ground floor of the D section consists of a lecture room D105 with capacity of 300 and a vestibule that is approximately half the size of the lecture room; there are two narrow entrances into the lecture room from the entrance hall; there are a total of five exits from the building: primary one on the east side, a pair of exits on the north/south side of the vestibule and a similar pair inside the lecture room. Note that a south vestibule exit leads to the corridor between D and A segments where an actual exit is located.

A ground floor of the E section consists of a lecture room E112 with capacity of 156, two smaller lecture rooms E104 & E105 of capacity 72 each, several toilets, a maintenance room and a corridor in between; there are two narrow entrances into the E112 and one entrance into E104 and E105 each; there are a total of four exits, each situated on the east side of the building: two from the hall in the middle and two from inside E104 and E105 lecture rooms. There is also a corridor linking E and C segments where another exit is situated, but it is too far away and requires blocking of all four E exits in order to be used; since it is not even considered in evacuation plans, C section was completely omitted.

5.2 Experiments

In all of the cases we consider a number of individuals to be 350 (full attendance + someone in the halls) and one random source of fire. For each wing we will consider several fire scenarios that mostly differ by an availability of selected exits, i.e. some exits or doors are made locked.

These cases are not as unrealistic as they seem, e.g. side exits from inside D105 are usually locked and are unlocked automatically when emergency occurs. In case a fire causes (or was caused by) a wiring fault, there is a probability that the doors might remain locked. Furthermore, these exits are always covered by external mechanical window blinds, which undoubtedly slows evacuation down. The exact same argument applies to exits from within E104 and E105 lecture rooms. Next, during our study we witnessed several cases when one of the entrances to D105 or E112 was locked for no apparent reason and a handyman had had to fix it. The last argument might sound strange, but the fact is, most of the students we interviewed did not even know that there are exits from E104 and E105 lecture rooms. During emergency, a group effect may take place and even those who know about the existence of these exits might panic and forget about them while following the majority that heads to the corridors.

Here is a list of five scenarios we will be considering for D wing:

- D1: a normal state
- D2: one exit in D105 and one side exit in the entrance hall are blocked
- D3: exits from inside D105 are blocked
- D4: all four side exits are blocked
- D5: all side exits are blocked, one of D105 entrances is blocked (worst-case scenario)

Results for each case reporting total evacuation time and a maximum smoke exposure time are displayed in Table 1. Full statistics and bitmaps for all experiments can be found in `experiments` folder.

Table 1: Results for D wing.

Case	D1	D2	D3	D4	D5	D5-3	D5-4
Evacuation time (seconds)	39.0	46.4	56.6	56.4	83.8	66.4	59.2
Maximum exposure (seconds)	1.9	4.5	7.4	9.2	21.8	12.5	10.5

Before evaluating building plans, let us first inspect the results to see if they make sense. In D1 all exits were functional and those sitting in D105 used two closest ones, which is what one would expect to happen. Those exits are not very far and an extraction time of forty seconds looks reasonable. In D2 one of side exits from inside the lecture room was blocked, the one outside was free, but it took quite longer to evacuate because of the narrow door in the way. In D3 the same happens on the other side, which again makes evacuation even longer. In D4 only main entrance is preserved, but evacuation time is roughly the same; the reason for this is that, in both D3 and D4 cases, large queues had been creating at the narrow exits from the lecture room, which is the main source of delay. In D5 one of this entrances is blocked and the effect here is even more apparent. This event is known as *bottleneck effect* and is illustrated in Figure 4.

Lecture room entrances seem to be a critical point; to confirm this, let's increase the door width and see what will be the impact. We use modifications of D5 case and vary door width from 2(D5) to 3 (D5-3) and 4 (D5-4). Results are displayed in the table 1. It is clear that

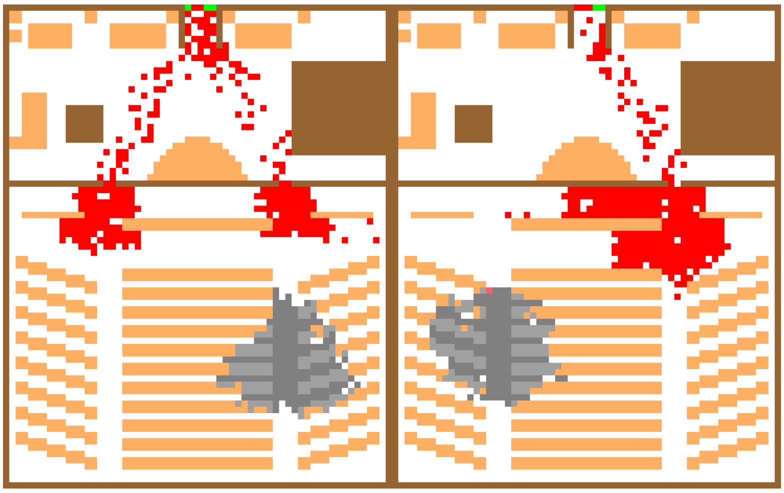

Figure 4: Evacuees accumulate at narrow exits from D105 lecture room. Figure illustrates possible situations in scenarios D4 (left) and D5 (right).

enlarging entrance(s) width will result in significantly more successful evacuations. Note that this should not necessarily mean that occupants must break down walls; a door to D105 room has a (re-)movable part that is usually held fixed and evacuees should not forget about it.

Let us now consider E wing. These are the scenarios:

- E1: a normal state
- E2: E105 exit is blocked
- E3: both E104 and E105 exits are blocked
- E4: both E104 and E105 exits are blocked, one of the main exits is blocked
- E5: both E104 and E105 exits are blocked, one of the main exits is blocked, one of E112 entrances is blocked (worst-case scenario)

The results are reported in Table 2. Again, as we gradually block the majority of exits, we inspect similar behaviour and results. One can notice that blocking both E104 and E105 exits (case E3) will hardly affect evacuation time compared to the case when only E105 exit is blocked (case E2) because in this case evacuees from E105 are a primary source of delay (they are most distanced from the central exit). It will, however, increase smoke exposure because blocking one of the exits will decrease amount of available extraction paths to the occupants from E104 and E112 rooms and will therefore decrease their chances to avoid smoke spots.

Table 2: Results for E wing.

Case	E1	E2	E3	E4	E5
Evacuation time (seconds)	34.8	42.5	42.4	55.9	74.9
Maximum exposure (seconds)	2.8	4.6	5.7	7.5	15.0

In the final experiment suite, we explore worst-case scenarios (D5 and E5) in more detail by varying a number of evacuees from 200 to 500 and then varying a number of fire sources from 1 to 3. The results are displayed separately for D (Table 3) and E (Table 4) wings. Again, we report a total evacuation time and a smoke exposure time, both in seconds.

Table 3: Results for D wing worst-case scenario.

Evacuees	200	300	400	500
Extraction time	54.4	74.0	93.5	113.2
Smoke exposure (1 source)	7.4	16.3	28.3	43.1
Smoke exposure (2 sources)	13.5	26.1	42.2	59.2
Smoke exposure (3 sources)	17.7	32.3	49.6	69.4

Table 4: Results for E wing worst-case scenario.

Evacuees	200	300	400	500
Extraction time	49.7	66.4	83.3	100.3
Smoke exposure (1 source)	5.6	10.9	18.7	29.9
Smoke exposure (2 sources)	8.7	18.9	31.6	46.2
Smoke exposure (3 sources)	12.6	25.2	41.3	57.8

It is clear that increasing a number of individuals will increase both evacuation time and smoke exposure; increasing number of smoke sources, however, will only increase the latter. Nonetheless, in all of our experiments smoke exposure rates and even total evacuation times are way below the threshold of five minutes, which indicates that even in the worst case no one should suffer substantial damage. Therefore, we declare both D and E wings to be suitable for emergency evacuations.

5.3 Model Validity

Assumptions about the system, description of the abstract model along with results of experiments were assessed by several students from the Faculty of Civil Engineering, BUT. Most of them expressed concerns about the smoke propagation sub-model, particularly for such non-trivial system as a D entrance hall, but agreed that the next best solution would be to install a sensor network to measure its characteristics and helped us with the choice of a C_{SS} (smoke spreading speed) factor (in [14] this speed was not normalized at all). They also questioned our assumptions about CO concentrations and stated that a value of 10000 ppm is very unlikely to be accumulated in such spatial rooms within such short times, but this only strengthens our conclusions about the safety of the buildings of interest.

6 Conclusion

In this project we considered a suitability of D and E wings of a FIT VUT campus for emergency evacuations due to the threat of fire. Inspired by research by Tissera et al. [14, 13] and Yuan et al. [17] and, exploiting concepts of fire and smoke spreading as well as crowd dynamics, we designed a model of these complex phenomena based on cellular automata. We then designed a diverse experiment suite representing different fire scenarios. Evaluating these cases we collected various statistics that allowed us to declare that both buildings of interest are indeed suitable for emergency evacuations.

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