Safe Egress Scenario Detection: From Baseline to Active Events

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Abstract

Crowd management in public walking spaces has been a topical research theme. In fact, in some spaces such as squares, stations, and commercial areas, there is a strategic need of addressing the uprising challenges to public safety, ensuring an effective crowd evacuation in emergency scenarios induced by various hazardous critical events, including malicious actions performed by individuals or groups. Already existing engineering tools can support the evaluation of the egressing scenario by means of simulations so that such tools can support emergency operators in finding the best strategy during a dynamic egress scenario.

However, egress within a space is influenced by many factors, such as the number of bystanders and their age, or the position of the initiating event. As a result, an infinite number of combinations may occur, thus is unfeasible to provide a scenario to support emergency operators, which must rely on a subset of simulations to be called when the egress event starts. Moreover, it is difficult to identify if an egress event has started since the movement of people is usually recorded via people counter sensors which are placed at egress exits.

In this paper, a novel approach to safe egress is discussed. Such an approach, starting from pre-calculated simulations, defines a baseline of the number of people crossing an exit in a normal scenario. Such baseline can be compared with the real sensor data to identify anomalies and thus detect egress start. In this paper, sensor data is replaced with egress simulations for comparison.

Keywords

risk analysis, safety, evacuation, sensors, emergency scenario

1. Introduction

The safety and security of people in open public spaces are key aspects that must be safeguarded [1]. On this topic, the management and modelling of evacuation processes are critical tasks to ensure safe and secure scenarios. In fact, evacuation behavior is an essential factor which must be considered in the design of public spaces [2]. Many authors have published on issues associated with modelling egress processes. More in detail, these issues are divided into two main groups, namely the evacuation of large areas and those inside buildings [1]. In the

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literature, there are publications focused on the evacuation of urban areas [3] [4] [5], metro stations [6], chemical plants [7] [8], buildings [9], and aircraft [10].

Moreover, the analysis and modeling of mass evacuation planning and related challenges are deeply discussed in several works. According to [1], problems can be divided into four categories: spreading of consequences of crisis events, modeling the behavior of evacuated persons, evacuation and transport planning, and approaches dealing with multiple problems.

In this framework, real-time information from various sources can significantly help predict evacuation demand and dynamics reliably [11]. In fact, collecting pertinent safety data is fundamental for the optimal management of dynamic scenarios for which having the flexibility to update evacuation plans and responding procedures is crucial [12].

In this regard, different sources can be used to provide data about or support the evacuation. The main features of data sources typically considered are instantaneity, rapidity, and spatial coverage [13]. For example, online social media is a major real-time data source used in different contexts to support emergency management [11]. Urban safety and security infrastructures based on sensors are also of interest for providing data [14]. Moreover, the effectiveness of evacuation drills is often hard to measure, and evidence-based approaches are required [15].

Evacuation models can be adopted to simulate and investigate evacuation strategies under different scenarios [16, 17]. During the years some reviews [18, 19] have shown that such models are mostly developed and used for the assessment of buildings spaces, especially under fire scenarios. In fact, the study of human behavior and related models are aimed at translating into practice research outcomes to minimize the risk to people egressing from hazardous contexts.

However, evacuation models, in their flexibility, can be adapted to other types of scenarios such as large-scale evacuations from open public spaces or evacuations in transportation contexts (e.g., railway stations, airports, etc.).

The role of simulation is crucial in reproducing complex egress scenarios in light of analyzing the system's performance in routine and extreme conditions. It is acknowledged that, during emergency egress, people are confronted with critical decisions, including wayfinding and exit choice. Ensuring the knowledge and use of the safest or fastest available evacuation paths is crucial [20]. Moreover, evidence shows that evacuees are prone to use main entrances rather than emergency exits [21], determining adverse effects that, ultimately, may lead to an ineffective and dangerous evacuation. In this light, evacuation optimization is key for effective, safe and smart egress [22]. In this way, alternative and optimal strategies in a decision-making environment can be identified, including the evaluation of the performance of egress routes and the overall dynamics. In this framework, different decision-making stages originate from the initiating event. Among these, a crucial role is given to risk identification and assessment, which is the basis of an appropriate response to any critical scenario [23]. A coupled successful warning message is critical to provide a safe, effective, and appropriate action across the decision-making stages. The message should have some qualities including specificity about the threat involved, repetitiveness, consistency, and credibility. Therefore, a proper way to effectively tackle large egress operations in open public spaces is to implement proper methodologies for dynamically assessing the risk level in the target area, before and during egress operations [24]. A proper risk assessment is crucial in any critical scenario to ensure an adequate resilient answer [25, 26, 27].

Transferring evacuation models to the practice can be tricky [28, 29], because of some unpredictable factors related to human behavior [17, 30, 30]. In fact, it is difficult to identify if

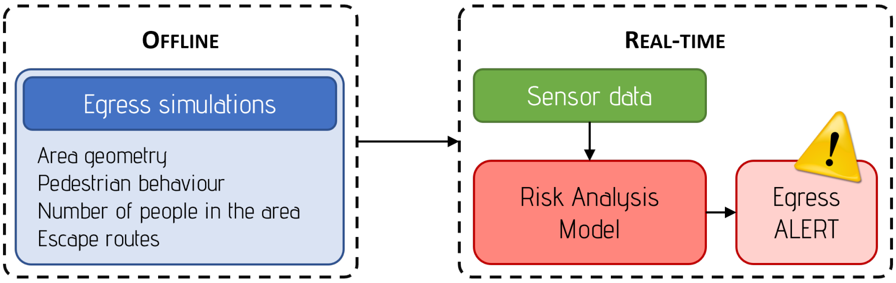

Figure 1: Methodology for risk evaluation in egress scenarios from public spaces.

an egress event has started: it is unfeasible to use cameras (due to the computational effort), thus, external sensors must be used [31]. In practice, people counters can be installed at the egress exit. In this way, the net number of people passing through an exit can be estimated. However, this type of data must be interpreted: a sudden spike in the number of people passing through an exit may not identify that an egress event has started (e.g., a large group of visitors has entered a square through a specific exit).

This paper aims to identify possible solutions in interpreting people's counter data to identify egress events. In particular, egress models are used to create baseline data that represent the normal flow of people within a square in a normal scenario; such baseline data can then be compared to people counter data to identify egress events. In our work, sensor data is substituted with egress simulations for better data evidence.

2. Methodology

This section introduces the methodology implemented for risk assessment of egress from public spaces.

The methodology consists of two main steps (Figure 1):

- An offline phase, in which some egress simulations are performed;
- A real-time phase, in which the egress simulations are compared to real-time sensor data to spot egress alerts.

The first step is related to the identification of a baseline. In other words, in order to spot egress alerts, it is necessary to establish how people behave within a square. Such information could be substituted by sensors' historical data, but it could be biased in the case of specific events (e.g., a seasonal market).

The second step is crucial to support emergency operators: if sensors capture some data which is very different from the baseline, something may be happening. However, sensor data may be influenced by a large group of people passing below a sensor. For this reason, multiple sensor samples must be considered to detect an alert.

2.1. Egress modelling

This section introduces the methodology for risk assessment of egress from public spaces.

Table 1
Maximum speed for different age profiles of occupants

Age profile	16-25	26-40	41-65	66-90
Maximum speed [m/s]	2.22-2.87	2.25-2.6	1.92-2.25	1.92-2.25

This work used Thunderhead Pathfinder® as the simulation engine to model the occupant movement to exits from the public space. More in detail, Pathfinder® provided support for importing the public space geometry, which is the preliminary step to set the simulation according to the proposed methodology. The imported geometry represented the walking space for the evacuation model. Relevant information includes the following:

- Extension of the public space
- Number, size, and availability of egress routes
- Presence of obstacles along the egress routes

The egress simulation included modeling occupants' movement to available exits in which each evacuee dynamically uses a combination of parameters to select the path to an exit. In other words, each occupant responds dynamically to changing queues during simulations without necessarily considering the closest exit or avoiding long queues. The approach included options where an occupant's movement conflicts with another due to geometry limitations or approaching an egress route. The analysis considered a flow-limiting condition while moving through a constrained egress route, and the contraction at a wide exit (i.e., the egress route) was analyzed.

We selected the occupant features according to the specific simulated scenarios; in this way, we allocated age profiles according to a statistic distribution for a general scenario [32]. The effective egress velocity resulted from a maximum velocity (also depending on the age profile) and the occupant density in the public space. Selected maximum velocities are given in Table 1.

We used the egress simulations to identify a limited number of reference scenarios on a specified geometry, classified according to an increasing criticality level. We ranked the criticality of a given scenario according to the following parameters:

- number of people that need to evacuate
- egress performance, including the time required for a safe egress operation, and the occurrence of situations of critical congestion
- availability of egress routes

In our approach, the reference scenarios can be compared to real-time data coming from sensors like people counters mounted in the target area. The recorded total number of occupants moving within the target area before an initiating event that requires egress can be used to rank the related scenario.

The impact of the availability of egress routes was analyzed in arranging the reference scenarios. As a base case scenario, all egress routes departing from the public space were considered available, letting people use them to evacuate without limitations except for hydraulic constraints. However, the present work was also focused on the rational analysis of the impact of egress routes' unavailability. The unavailability can be connected to physical obstacles and specific emergency management strategies. Selected egress routes can be designed as priority passages for rescue teams, especially in complex layouts, but this requires a detailed design. This work deals with the design of such scenarios, supported by numerical simulations.

The following parameters are linked to the complexity of a layout in terms of the availability of egress routes:

- overcrowding, with the maximum, allowed number of people in daily scenarios or during planned events, or the number of people instantaneously insisting on the public space served by the available egress routes
- availability of egress routes, this parameter depends on the actual number of egress routes and their width, but also on their position
- smart lighting, if available to support egress operations
- emergency plan

In planned events, the number of people also includes the staff working at the event. The instantaneous number of people in a public space can also be quantified with people counters.

As indicated, the availability of egress routes is also determined by geometric parameters. Ideally, an egress route should have a constant width to avoid localized overcrowding, but this feature requires assessment when dealing with real scenarios in open public spaces. It should also be noted that people involved in critical scenarios are characterized by different degrees of familiarity with egress routes and the general condition. It is the same situation in transit areas, including railway and subway stations and airports. These aspects modify the exit choice in an emergency evacuation because of the influence given by exit familiarity and neighbor behavior on the egress dynamics.

Smart lighting can affect the egress dynamics, especially the effectiveness of egress operations. The present work does not cover this topic. However, proper smart lighting can steer the flow of people toward the desirable exits while lowering the burden on selected escape routes used for emergency access.

The egress scenario was modeled with Thunderhead Pathfinder® v. 2021.3 on a realistic map imported as a DWG file. According to the considered scenario, the total number of people was set from 500 to 1000. The maximum velocity was set according to Table 1, and the age is evenly distributed. The egress dynamics were based on the action that causes an agent to take the fastest perceived route to a set of exits without any assistance. During the simulation are recorded the following parameters:

- the number of people flowing through an exit for a unit of time $[p/s]$
- the number of people flowing through an exit for a unit of time and for a unit of exit width $[p/(s \cdot m)]$

From the simulations, it is possible to define a baseline for a certain amount of people within a square. In other words, the baseline represents the mean number of people that flow through each exit on a normal day, without any emergency. Such baseline can be compared with real-time sensor data to identify possible egress alters.

2.2. Risk analysis

In a real-case scenario, it is important to identify egress events to help emergency operators and ensure people's safety. As a result, it is crucial to detect when the sensors encounter an anomaly, i.e., an unusual number of people crossing a certain exit.

A sensor usually provides an integer $n_i(t_j) \in \mathbb{Z}$ as the number of people that has passed through exit i in a timespan t_j. Such value can be a negative integer since it is the subtraction of the number of people that enter an area ($n_{in,i}$) and the number of people exiting the area ($n_{out,i}$):

$$n_i = n_{in,i} - n_{out,i} \tag{1}$$

In the baseline, the sum of all sensor data fluctuates around the null value, so that the number of people within the area is generally constant. Moreover, the sensor data is usually very close to the baseline data. In mathematical terms:

$$\left| \int_0^{t_j} \left(\sum_{i \in E} n_i(t) \right) \right| < e \tag{2}$$

$$\left| n_i(t_j) - n_{base,i} \right| < e \tag{3}$$

with E the set of exits, e an integer that handles the normal punctual fluctuation of the people's flow, and $n_{base,i}$ the baseline value for exit i.

This behavior is valid if a short timespan is considered: in fact, during the day an area may increase or decrease its occupancy based on the time and the services included within the area (e.g., an area full of restaurants may increase its occupancy during dinner hours and be nearly-empty during the morning). Nonetheless, the variation of occupancy is generally gradual during the day, without sudden large flows of people leaving the area.

Following this principle, an egress event can be detected. Two possible scenarios may occur:

1. there is a sudden reduction/increment of people within an area (Equation 2 is not satisfied)
2. at least one sensor detects an unexpected flow of people (Equation 3 is not satisfied)

It is worth noting that Scenario 1 is not possible without Scenario 2. In fact, as can be seen from Figure 2a, a sudden reduction/increment of people within an area may be possible only if there are large flows of people through the exits. Small flows of people cannot result in a large sudden reduction/increment of people within an area. Conversely, Scenario 2 is possible without Scenario 1. In fact, if there is a large flow of people entering an area while at the same time a large group of people is flowing out through another exit, the number of people within an area may not vary (Figure 2b). This is the case of egress routes: people flowing within a corridor usually do not stop in the corridor, but rather flow towards the exit.

The most important scenario to be detected to help emergency operators is the one depicted in Figure 2a, so the operator can identify the area where the egress started. In other words, both Scenarios 1 and 2 must be satisfied.

To do so, it is important to focus on the difference between the baseline and an egress event. For reference, Figure 3 must be considered, in which the data of a single exit for an area with 500 occupants is shown. Here, the baseline is represented by the red horizontal lines: the central

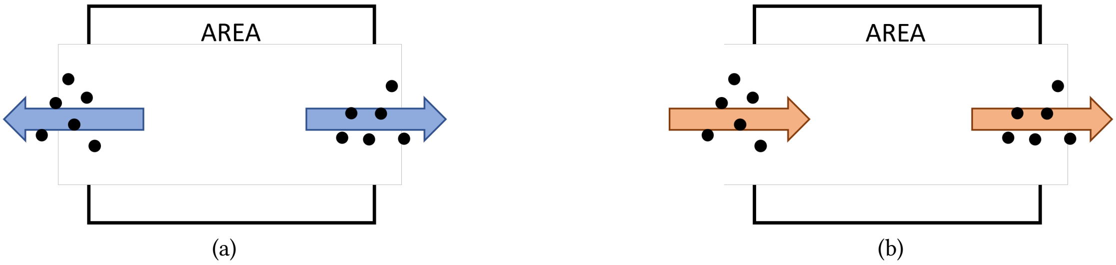

Figure 2: Egress scenarios: (a) the event occurs within the area, and the area suddenly reduce its occupants (both Equations 2 and 3 are not satisfied); (b) a big flow of people is moving from one area to another (only Equation 3 is not satisfied).

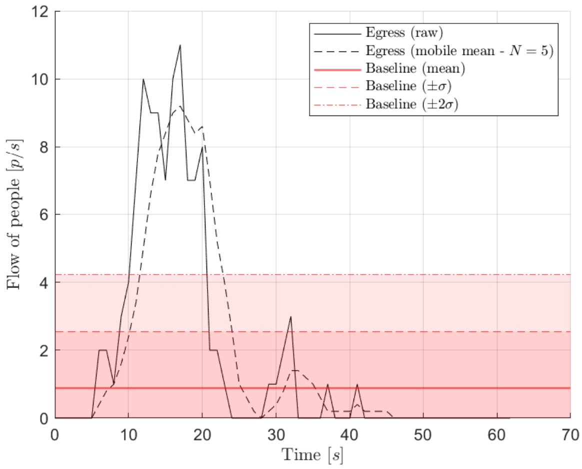

Figure 3: Flow of people moving through an exit. Baseline values in red, egress scenario in black ($N_p = 500$)

one is the baseline. In contrast, the red areas show the flow included between one standard deviation (darker red) and two standard deviations (lighter red).

The black lines represent the data coming from an egress simulation. It is clear that the number of people flowing through the exit is very high for a certain time period, exceeding two times the standard deviation. This behavior must clearly trigger an alarm. However, some false positives may occur if only the raw data is considered. In fact, even some baseline data may be outside of the range of the two times the standard deviation. In such a situation, emergency operators may be overwhelmed by the huge amount of false-positive alerts.

To overcome this issue, we propose to use a mobile mean to process the raw data. In this case, the value to be considered at every instant is the mean of the previous N samples, with N arbitrary. As a result, a false positive peak is mitigated by the previous $N-1$ samples, which, in return, may remove a false positive alert (because the processed data is placed within the two times standard deviation range. Such a behavior can be seen in Figure 3, where the processed data is the dashed black line, which presents lover peaks if compared with the raw data.

Such a reliable solution is characterized by some disadvantages:

- Since the processed data depends on previous samples, an egress event is detected with some delay, i.e., when the abnormal samples are significant with respect to previous data. As a result, it is important to choose N so that such delay is not too high for the emergency response times.
- A large N may completely hide an egress event. In fact, if a small number of people occupies an area, the egress may complete in a very low number of sensor samples. As a result, the processed data may present shallow peaks, all within the two times standard deviation range.

However, we are confident that the proposed method can be reliable in most cases, as shown in the following section.

3. Case study, results and discussion

To test the effectiveness of the method, it has been applied to the case of the open public space reported in Figure 4. It consists of a public square with a size of $98 \times 53m$ at the widest. Under normal circumstances, six egress routes are fully available, represented by public streets open to pedestrians and vehicles. These are indicated by arrows in Figure 4. Width and the eventual presence of obstacles characterize each egress route which, under specific conditions, can reach a saturated (i.e. the maximum) flow of people. This holds especially for the narrower egress gates and the increasing number of people in the open area that requires evacuation.In the case study, the narrowest egress route is Exit 02 (3.90 m), while the widest is Exit 03 (8.50 m, partially obstructed). However, considering the egress route less hindered by physical obstacles, Exit 05 is 7.30 m large and the widest. In the present case study, obstacles are represented by bike racks and vehicles usually parked alongside.

According to the proposed methodology, the egress of 1000 people under normal circumstances is modeled, as an example. Each exit is different from the others in terms of position and geometry, thus, the baseline varies [33]. In particular, it can be noted from the simulation results (Figure 5) that while the mean value is usually around the null value, the standard deviation in some cases is more relevant than in other cases. According to the results, a deviation from the baseline is detected at Exit 03 before other. In any case, a value of people flow larger than 2σ the mean baseline threshold is detected within 15 s from the onset of the evacuation scenario in all egress routes. It should be underlined that anomaly detection of people flow at Exit 02 (i.e. the lowest capacity exit) can be challenging.

In the present case study, at best, a crowd evacuating can be detected as early as 5 s from the onset. However, the performance strongly depends on the sample rate of counter-person sensors located at egress gates and data processing.

Following the proposed method, an egress simulation is used as a mock-up for sensor data. It was not possible to elaborate real sensor data due to the large number of actors that would have been required for such an experiment (1000 people). In the egress simulation, 1000 people are simulated to flow outside of the area (case of Figure 2a), and the baseline simulation with the same number of people is used for comparison.

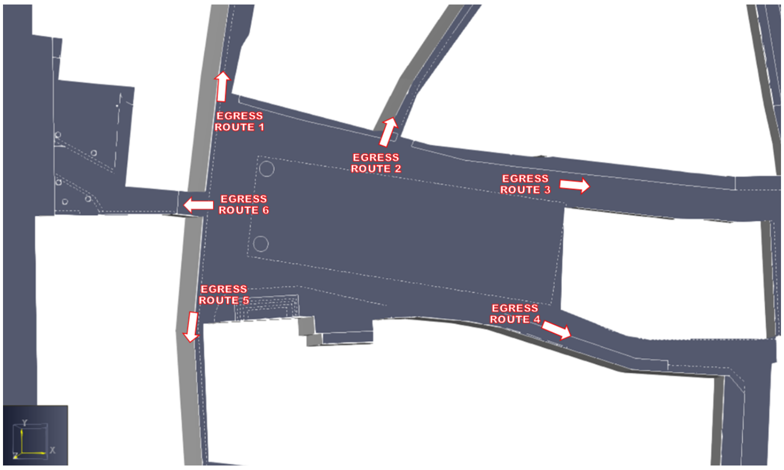

Figure 4: Open public space geometry and normally available egress routes (six).

From the results (Figure 5), it can be seen that by using the mobile mean method ($N = 5$) nearly all exits trigger an alert since the flow of people exceeds the two times standard deviation range. The only outlier is represented by Exit 04, in which the raw data exceeds the range, but the mobile mean obscures the peak, failing to go outside of the range.

Such behavior is expected for some types of exits (i.e., those less likely to be used). However, it has to be noted that it is important that at least one exit triggers the alarm for the emergency operators to be informed. Then, the operator may look at the raw data of all the area exits to have a better overlook of what is happening in the square (or use cameras, if installed).

4. Conclusions

In this paper, a novel approach to egress event detection is proposed. Baseline simulations provide the expected flow of people through the exits for a specific number of people in normal circumstances. Such baseline simulations can be compared with real sensor data to identify egress events. In fact, if at least a sensor detects a high flow of people, this could be an indicator that an egress event is happening.

However, the raw sensor data can be misleading since a single outlier sample may trigger unnecessary alarms. To avoid this problem, the mobile mean approach is used: the last N samples are averaged to remove outlier samples. Results show that such an approach, although conservative, is reliable in the case of an egress event.

Future work will focus on how to use a few simulations to estimate the behavior of different numbers of people within a square (i.e. to determine baseline values fast).

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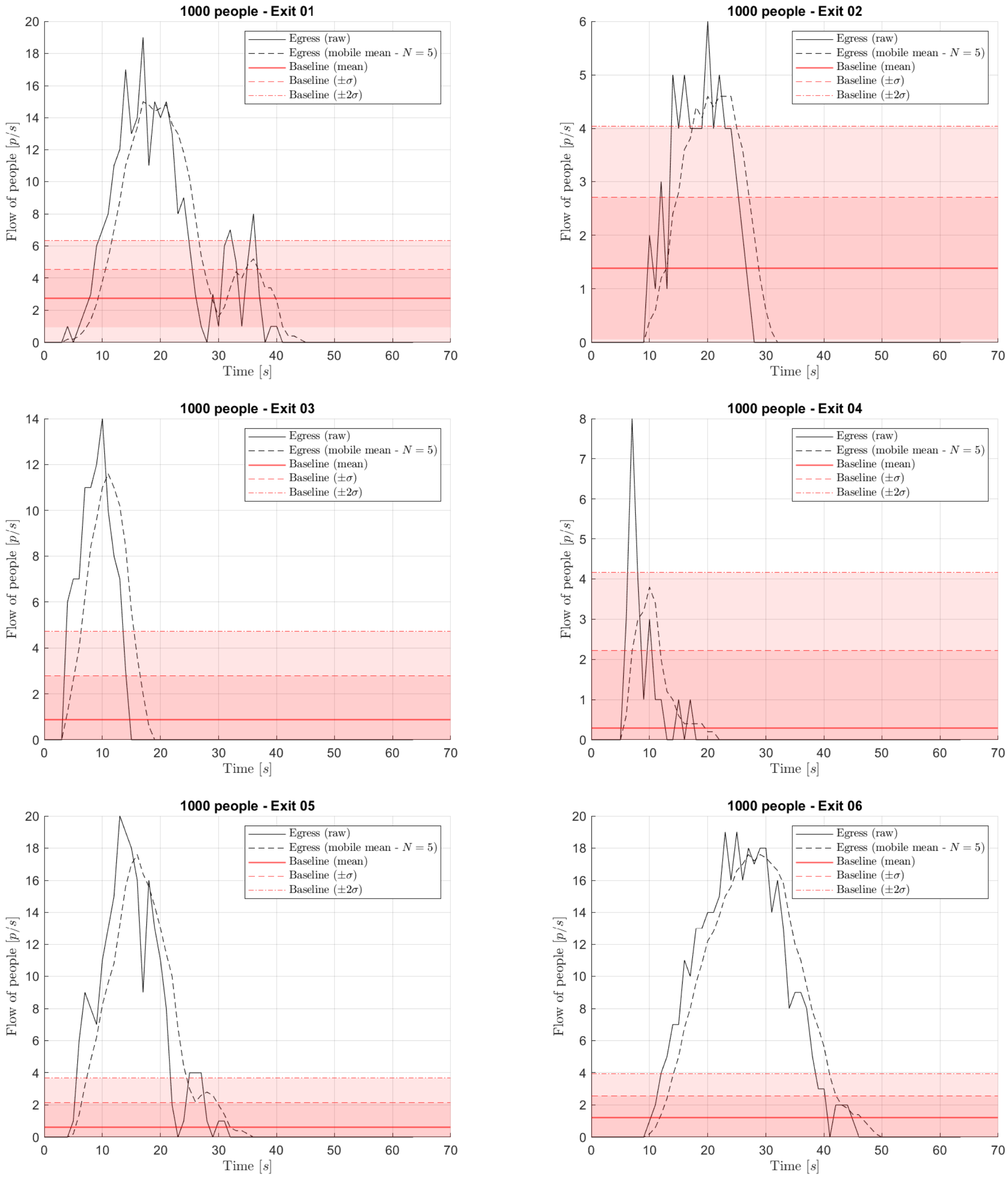

Figure 5: Case study results: in an egress scenario the anomaly is detected for nearly all exits.

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