A digital transformation approach to scaffold tourism crowding management: pre-factum, on-factum, and post-factum

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***Abstract*—Tourism would probably not be economically sustainable without some localized crowding phenomena. Whatever the carrying capacity of the points of interest, their tourism managers should plan, monitor, and analyze visitors' crowding data to either prevent or mitigate the well-known effects of tourism overcrowding, such as degrading the tourists' experience, impacting negatively the environment and the local population, be it humans or wildlife.**

The proposed digital transformation approach comprises three smart tourism tools (STTs) to scaffold crowding management issues, especially those related to overcrowding, i.e. when the carrying capacity of points of interest is exceeded. We report on the development and validation experiments of these STTs in the scope of the European Union RESETTING project.

The pre-factum STT aims at supporting simulation-based participatory discussions among tourism destination stakeholders. Proactive planning based on simulated scenarios allows the identification of potential tourism overcrowding situations and experimenting with possible mitigation actions.

The on-factum STT enables local monitoring of tourism crowding, by using several Wi-Fi activity sensors. The ability to obtain near real-time data, allows short-term decision-making, such as reinforcing or freeing up human and technical resources assigned to managing tourist crowding on the ground.

The post-factum STT is a geo-temporal 3D visualization platform to explore historical crowding data, visualize patterns, and understand and forecast trends. The main objectives of this STT are fostering cumulative learning from experience and forecasting the recurrence of troublesome crowding situations, allowing us to plan for mitigation actions.

***Index Terms*—Digital transformation, Tourism overcrowding, Smart tourism toolkit, Carrying capacity, Agent-based modeling and simulation, Crowding sensor, Wi-Fi detection, Geo-temporal 3D visualization**

I. Introduction

The tourism sector has been growing steadily. If the pre-pandemic trend is achieved from 2023 onward, it will reach 3 billion arrivals by 2027, according to the World Bank development indicators. As a consequence, the impact of tourist activities in popular destinations has risen significantly over the years, often fostered by the proliferation of cheaper local accommodation [1]. That increase led to the exceeding of the carrying capacity in those destinations, a phenomenon called *tourism overcrowding*, or simply *overtourism*.

Overtourism degrades visitors' quality of experience, reducing their feeling of safety, making it difficult to move around, enjoy the attractions, and use basic services, such as transportation and catering, due to long wait times, while reducing the authenticity from the perspective of tourists [2]. It also deteriorates the lives of residents, due to an increase in urban noise, less effective urban cleaning, higher prices for basic goods and services (as businesses seek to capitalize on the increased demand), displacement caused by local accommodation, and cultural clashes when visitors fail to respect local customs, traditions, and privacy, sometimes leading to the former expressing negatively against the latter [3]. Last, but not least, the environmental sustainability, structures, and cultural heritage of overcrowded destinations are also jeopardized, leading to a loss of authenticity [4]. These combined effects can, in the long term, make tourism in popular destinations unsustainable [5].

This paper describes the ongoing work on the development of smart tourism tools (STTs) for planning, monitoring, and analyzing collected crowding data, in the scope of the RESETTING[1] project, funded by the European COSME Programme.

These STTs aim to scaffold the work of destination managers to identify areas of concern and implement measures to mitigate the negative impacts of tourism while promoting smarter tourism practices. This can help ensure that tourism benefits both visitors and residents while preserving the natural and cultural resources that make destinations appealing.

Overtourism mitigation actions, such as promoting the visitation to less occupied but equally attractive areas, can be applied in recreational, cultural, or religious spots, both in indoor scenarios like palaces, museums, monasteries, or cathedrals, or in outdoor ones such as public parks, camping parks, open-air concerts, fireworks, or video mapping shows. Besides assuring

[1]RESETTING is an acronym for "Relaunching European smart and SustainablE Tourism models Through digitalization and INnovative technoloGies"

a better visiting experience, these actions are also necessary for security reasons (e.g., to prevent works exhibited in a museum from deteriorating or even being vandalized by exceeding room capacity), health reasons (e.g., preventing infection in pandemic scenarios by not exceeding the maximum people density specified by health authorities), or even for resource management (e.g. to reduce the intervention of security and cleaning teams).

Regarding planning, we will address an extreme scenario: mass public events require planning for the allocation of resources such as paramedics, policing, urban cleaning, and related equipment. We developed an STT for simulation scaffolding aimed at decision-makers responsible for deciding when to allocate or de-allocate the aforementioned resources.

Planning does not preclude the need for just-in-time actions regarding actual crowding, which calls for the ability to monitor this phenomenon in near-real time. We developed an STT to monitor tourism crowding based on mobile devices' wireless activity. Our sensors count the number of surrounding mobile devices, by detecting trace elements of wireless technologies, mitigating the effect of MAC address randomization, without infringing privacy rights.

Finally, destinations that do not study their history are doomed to repeat the same mistakes indefinitely. Tourism crowding is a phenomenon that can be well characterized in time and space. To replay and analyze collected tourism crowding data, detect patterns and trends, and predict its evolution, we developed a geo-temporal visualization STT that takes into account the carrying capacity of the destination sites when calculating crowding density.

The three STTs described in this paper were developed using the Design Science Research (DSR) methodology [6], and we refer to the case studies in which they were used. We also describe how we assessed their effectiveness and utility, i.e., how we conducted the DSR validation phase.

This paper is organized as follows: sections II, III and IV present three STTs to support managing the tourism crowding phenomenon before (pre-factum), during (on-factum) and after (post-factum) its occurrence, along with describing how they were validated; then, on section V, we draw some conclusions and finally, on section VI, we outline future work.

II. Pre-factum - simulating tourism crowding

Tourism destination authorities often organize events (e.g. music, fireworks, video mapping) in open urban public spaces, attracting many visitors. Although these events are usually peaceful, they require the presence of 1st line medical support and security teams and, ultimately, urban cleaning teams. In this context, a simulation model can be an effective planning tool for the various decision-makers involved to explore the complex system of maneuvers of the event in a participatory way, by testing various resource allocation scenarios without the need for empirical observation.

Emergency evacuations have received a great deal of attention in the literature on modeling and simulation [7]. However, very few studies have been conducted focused on modeling the egress on normal (non-urgent) events [8, 9] like the ones described in the previous paragraph. These events are usually attended by social groups (families, friends, colleagues) [10] who, when walking together, generate interactions that can affect the efficiency of the exit from the event. Another phenomenon affecting the egress flow, that we have not found modeled in the literature, is the inertia of visitors to leave the public space where the event took place, due to socialization within the groups and/or the presence of sales, usually street vendors, of food and drinks. We used open data (OpenStreetMap) and the GAMA simulation platform [11] to fill this gap, by developing an agent-based model (ABM) to support decision-makers in the planning of these events.

This ABM aims to understand how different built environments, crowd densities, exit choice scenarios, and group behaviors affect event visitors' exit patterns and space utilization. The pedestrians leaving the event were modeled as autonomous agents who interact with each other and with the environment to go to the exit gates, taking into account the greater or lesser social retention. The simulations generate data files for the analysis of the results. The main result variable obtained in the simulations is the number of visitors remaining in each simulation cycle, from which the output pattern graphs are obtained.

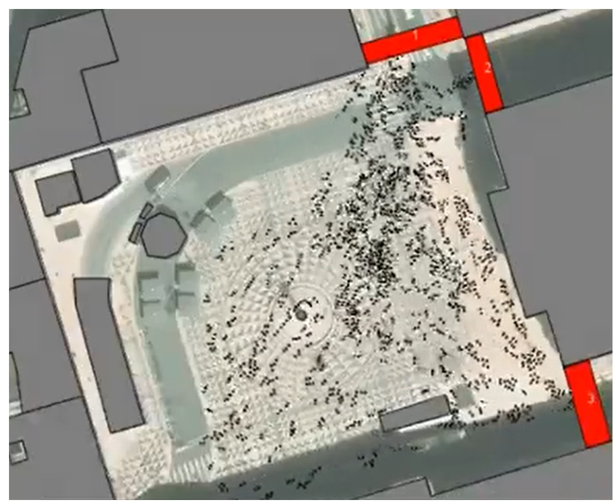

Fig. 1: Snapshot of simulation using the GAMA platform

As shown in Figure 1, the environment of the model is composed of the buildings or other obstacles that define the open space, the permanent or semi-permanent physical structures that can act as obstacles within the open space, and the exit geometries, which are modeled as the red polygons at the interface with the streets that border the open space polygon. Each exit is assigned an attractiveness percentage that totals 100%. These percentages are used for weighted random selection of exits by the groups. This makes it possible to test scenarios in which people choose different exits with different percentages, revealing possible bottlenecks due to exit preference.

The active agents that represent the system entities in the model are (i) the agents that represent visitors leaving the public open space, and (ii) the agents that represent the groups. The former moves toward the chosen output using an implementation of the extended Social Force Model (SFM) for group behavior presented by [10] and based on the model presented by [12]. For each simulation cycle, each visiting agent evaluates the repulsive social forces that other similar agents and the obstacles exert on him and the attractive forces that represent the cohesion of the group to which he belongs. Group agents store references of their members to improve efficiency in calculating group cohesion.

When an event is over, before heading to the selected exits, the visiting agents remain still until their group's social retention time has passed, to mimic a socialization period. The retention time is randomly assigned to the groups with a specific distribution for the type of event, ranging between 0 and the maximum expected social retention time (i.e. the expected time for the last group to decide to leave the space). This value shall be obtained based on observation and study of the type and location of the event taking place.

The simulations of a real event were compared with the number of mobile phones over time in that same event, to perform macroscopic calibration. The chosen case study was the Monumental Tour event, combining electronic music, heritage, and digital art (video-mapping) that took place in the City Hall square in downtown Lisbon, under the sponsorship of UNESCO, as shown in Figure 1. Overall, the model showed a good fit with the mobile phone data and a relatively low variability due to stochasticity (we ran the simulation 1000 times), showing the plausibility of the model. A video of this pilot study can be seen on the RESETTING YouTube channel.

The validation and collection of suggestions for improvement of the model were evaluated separately and consecutively with three focus groups: one with Architects, another with Geography and Tourism experts, and the last one with Ergonomics and Behavioural Psychology researchers. We improved the model after each focus group meeting until participants found no notable flaws in the model. A performance analysis was also developed to assess the feasibility of using this model for participatory planning among decision-makers.

III. ON-FACTUM - MONITORING TOURISM CROWDING

To implement short-term overtourism mitigation actions, crowding information should be made available in near real-time. Several approaches can be used for crowd detection, such as image capturing, sound capturing, social networks, mobile operator data, and wireless spectrum analysis. The latter can be performed using passive or active sniffing methods, characterized by exploring protocol characteristics and small information breaches, such as on Wi-Fi or Bluetooth protocols, extensively used in mobile devices.

It has long been observed [13] that the number of detected mobile devices is highly correlated to the real number of people present in an area. The best option regarding cost, precision, and the near-real-time availability of data required for managing tourism crowding effectively, while complying with privacy rights, is then the one based on sensing wireless communication traces in roaming devices, since the vast majority of tourists carry a mobile phone to take pictures and record videos during their visits [14, 15].

Earlier approaches relied on counting the number of unique MAC (Media Access Control) addresses in messages emitted by mobile devices. However, due to user privacy concerns, most mobile devices nowadays use MAC address randomization, i.e., the same device exposes different MAC addresses over time, making it more challenging to accurately count the number of devices, thus leading to inaccurate crowd counting.

We developed the crowding sensor in Figure 2 that performs real-time detection of trace elements generated by mobile devices from different wireless technologies, namely Wi-Fi and Bluetooth, while addressing the MAC address randomization issue through edge computing to determine the number of mobile devices in the sensors' vicinity. Therefore, only the number of devices detected is sent to the cloud server, allowing upload with LoRaWAN (Long Range Wide Area Network) in the absence of local Wi-Fi coverage, while granting user privacy since no personal information is sent to the server.

Fig. 2: A Wi-Fi sensor at a museum and its inside view

MAC address randomization performed by mobile device manufacturers, due to user privacy concerns, has made the identification of a mobile device a much more difficult task and, consequently, more difficult to accurately perform device counting. Therefore, an algorithm was developed for the detection of mobile devices through Wi-Fi, tackling the MAC address randomization issue using a fingerprinting technique.

This STT uses a variety of open-source software technologies, installed in off-the-shelf hardware (a Raspberry Pi board) available at affordable costs. For the operating system of our sensors, we have opted for a Kali Linux distribution. For the local database, a SQLite database was chosen for storing all gathered data, which requires low memory usage, a convenient feature for edge computing.

For performing Wi-Fi detection, the required hardware is a Wi-Fi card that supports monitor mode, which allows the board to capture all network traffic in its proximity. We have chosen the Alfa Network AWU036AC board for our sensor, which provides high performance at a low cost, having two antennas for dual-band detection (2.4 GHz and 5 GHz) without interfering with Bluetooth devices. As for the sniffing software, we have chosen the Aircrack-ng tool, an open-source software with several different applications for detecting devices.

For receiving all messages, our cloud server uses the Mosquitto MQTT, a lightweight message broker that implements the MQTT protocol. For the data ingestion of all measurements sent by sensors, a database is necessary. This database has to be lightweight, capable of querying data rapidly from timestamps, and also capable of providing support for data visualization platforms to observe the results in real time. That is why we chose InfluxDB, a time-series database focused on IoT applications.

To validate this STT, sensors have been placed at several indoor and outdoor spots across the university campus, such as areas with a large pedestrian flow, internal and external passages between buildings, and places for prolonged stays, such as a large study hall and the university library. Crowding information collected since September 2022, allowed us to identify crowding patterns and tendencies, such as time breaks between classes, lunch periods, and highly populated events. The counting accuracy was addressed in other contexts in a more controlled environment, as described in [16, 17], where the detections from sensors were compared with the real number of people, obtained through direct observation during a public event, to assess the effectiveness of the solution.

Furthermore, it was also possible to create notification policies, where alerts can be triggered if predetermined crowding thresholds are exceeded, by using several contact points such as e-mail, Telegram, Google Chat, Microsoft Teams, Slack, or PaperDuty, enabling users to make just-in-time decisions facing overtourism situations. These alerts can be easily configurable by using the Grafana tool, also used for 2D spatiotemporal visualization of crowding information.

Demos for configuring the edge nodes and the cloud server can be found at the RESETTING YouTube channel.

IV. Post-factum - analyzing tourism crowding

We are developing a geo-temporal visualization platform to explore historical or near-real-time crowding data, visualize patterns, understand trends, predict future crowding situations, and support short- and medium-term decision making. For example, tourists can be recommended alternative routes and less crowded but equally interesting attractions, or the times when the most popular sites should be avoided.

The frontend of the platform contains three GUI components, as shown in figure 3: a sliding timeline (top), a 3D map with columns (all background), and a time evolution graph (bottom left). The visualized data represent the selected crowding metric(s) and are referenced geographically and temporally.

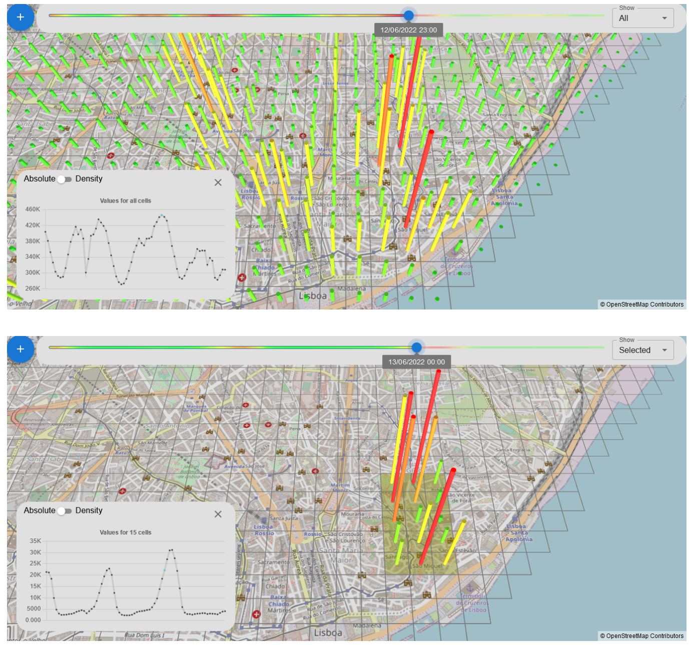

Fig. 3: Crowding visualization in Lisbon using the developed platform (all city on top, and only selected cells on bottom)

The main visualization is based on a 3D cartographic map, operating on open data (OpenStreetMap), which can be dragged and rotated, as well as varying the observation point and changing the scale (zoom). Cylinders are superimposed on the data capture locations, whose height and color are inferred by mapping the user-selected metrics. For example, the height can correspond to the number of roaming devices (tourists), and the color can represent the density of the same metric, using the carrying capacity of the corresponding zone as the denominator. The latter is calculated as in [18], with the algorithm described in [19].

The 3D map shows spatial data for a single moment in time. However, by varying this instant in the sliding timeline, a cinematic view is created. The graphic background of this slider is a color gradient that encodes the sum of the values for the entire map, or just for a selected region of interest (see Figure 3). Hovering over the slider timeline button shows a label with the date and time of the moment being displayed on the map.

Finally, in the graph of time evolution, which also allows dragging and scaling, the lines represent the instantaneous integral value of each of the selected metrics for the entire map or selected region of interest. In the case of two metrics, this graph will display two ordinate axes (to the left and right of the graph) each one with the corresponding scale. The horizontal time axis is not shown to clear the screen, but the date and time of each point can also be seen on a label above the cursor.

Technically, the platform is a cloud-hosted web application. To allow public access through the Internet, while maintaining data confidentiality, a control mechanism has been implemented that only allows access to authorized users, with encrypted keys stored in a database.

The *frontend* is developed with React, a JavaScript library for building user interfaces, compatible with a wide range of modern web browsers (e.g. Google Chrome, Mozilla Firefox, Apple Safari, Microsoft Edge). The *backend*, built with Flask, a web framework written in Python, includes a series of modules called *connectors*. Each connector implements an endpoint type: (i) loading historical data, (ii) loading real-time data, or (iii) retrieving a list of specified locations in GeoJSON format. This architecture allows connecting the platform to new data sources without modifying the source code. Connectors have been implemented for different open data sources: InfluxDB (time series database), Apache Kafka (event streaming platform), and OpenDataSoft (data integration platform).

Based on the previous connectors, three integrations were built with different data sources: one from a mobile network operator in Lisbon, another one from a network of motion sensors in Melbourne, and another in our university campus using the previously described Wi-Fi sensors. A video demonstrating these three case studies on using the platform can be seen in RESETTING YouTube channel.

Due to space limitation, we will mention only the case study of Lisbon, where data from Vodafone's mobile network provided by the Lisbon Urban Data Laboratory (LxDataLab) are used. It includes metrics such as the number of detected devices or only roaming ones (typically owned by tourists), in each 200x200m cell of the shown grid, every 5 minutes. The data come from triangulating the count of devices detected by each antenna of the cellular network. On the two snapshots of this use case, represented in Figure 3, regarding the 2022 Popular Saints festivities in Lisbon, we could expect the maximum number of devices detected in Lisbon to occur during the extended weekend, between 10 and 13 June. However, we can see from the line graph that the peak occurs on the 9th, indicating that many people return to their dormitory cities or travel during the extended weekend. By selecting the option to map the color of the cylinders to the density of devices taking into account the load capacity, it is possible to have a more immediate perception of the clumping spots. Moving on to the analysis of the event itself, we see in the graph of temporal evolution a local maximum on the night of June 12 to 13. By dragging the slider to moments of this time interval, we see that the areas with the most crowding are, as expected, Liberty Avenue where popular marches take place, and the historical Alfama district where many dancing festivities do occur. If we want to know when these specific areas were most crowded, we can select them by drawing polygons on the map. By doing so, we can see on the graph that the peak in this zone occurred around midnight (lower part of Figure 3).

To evaluate the usability of the platform, a standardized individual three-step experience was designed:

(i) to attend a demo on the available functionalities;
(ii) using the platform to answer a question about crowding at Rock in Rio Lisboa 2022 musical festival;
(iii) to complete the NASA Task Load Index (NASA-TLX) questionnaire [20] to assess the mental workload that the subject assigns to the performance of the referenced task.

Thirty-four volunteers with different levels of technological literacy participated in this experiment. The mean score for NASA-TLX, was 33.45 on a scale of 0 to 100, corresponding to a platform of low to medium difficulty, according to [21].

We also analyzed the platform's performance. The visualization of the data in the frontend is almost instantaneous, and the constraint in processing is at the level of data collection and processing in the backend, where the processing time increases in a non-linear way with the amount of data involved.

V. Conclusions

Overtourism degrades the visitor experience, the quality of life of local people, and the environment. Managing it means being able to anticipate critical situations, identify areas of concern in near real-time, and take action to mitigate its negative effects by promoting better practices to ensure that tourism benefits both tourists and locals while preserving natural and heritage resources. This paper reports on the development and validation of three STTs to frame a digital transformation of tourism crowd management.

The pre-factum STT for tourism crowding management aims at supporting participatory discussions among tourism destination stakeholders. Such proactive planning is based on simulated scenarios, allowing the identification of potential tourism overcrowding situations and experimenting with possible mitigation actions. To operationalize this approach, we developed an agent-based model upon the GAMA simulation platform, supporting the Social Force Model extended with group behavior features, such as the social retention phenomenon, and illustrated it with a sensible scenario, a mass tourism event in a public space in Lisbon. The model was validated and improved through a series of focus groups with experts, and calibrated with mobile phone data collected during the event, showing a good fit with real-life data.

For monitoring overtourism on-factum (i.e. in real-time) we developed an STT based on a set of sensors, built with off-the-shelf hardware available at affordable costs, that perform real-time detection of trace elements of mobile devices' wireless activity, mitigating MAC address randomization. Detected crowding values are put together in a cloud server either via Wi-Fi or LoRaWAN, depending on local availability. The crowding information can then be analyzed by destination managers to understand the crowding levels in areas where each sensor is placed in a clear and simple perspective, either by dashboards for temporal or spatial visualization of crowding information or using the raw data for custom-made integration. In addition, notification policies can be created when overtourism situations occur, providing the ability to implement just-in-time mitigation actions required by the nature of these often sudden and unpredictable circumstances.

The post-factum STT is a geo-temporal 3D visualization platform to explore historical crowding data, visualize patterns, and understand and forecast trends. The main objectives of this STT are to foster cumulative learning from experience and forecast the recurrence of troublesome crowding situations, allowing us to plan mitigation actions. Its backend architecture allows connecting the platform to new data sources without modifying the source code. We have demonstrated its feasibility by integrating three rather different data sources.

Ongoing work aims to provide detailed insights into how these STTs can be adapted to different environments, thus ensuring broader applicability. For example, our STTs can deal with other smart city scenarios beyond those that deal specifically with their visitors, as recognized in [22, 23].

VI. Future work

Regarding simulation, its duration increases quadratically with the number of agents, making it infeasible beyond a certain threshold for real-time decision-maker participation. We plan to improve algorithm efficiency and use ABM tools accelerated by graphics processing units (GPUs) to allow prompt visualization even in heavily crowded simulation scenarios. To improve the realism of the model, we also plan to collect empirical data from non-urgent crowd exit conditions, to calibrate the model parameters and detect additional macroscopic and microscopic behaviors of the agents. Other demographic variables, such as the age distribution that conditions the speed of pedestrians, will be included in future model versions.

A second version of the sensors is being designed, where the biggest challenge is unifying Wi-Fi and Bluetooth-based detections to avoid double counting. The hardware will be improved by using more powerful boards, new antennas with higher gains for greater detection ranges, directional antennas to perform detection in specific areas, custom heat sinks for the processing units to achieve the best possible performance, and new custom housings for the sensors.

We are currently developing a forecasting component for the visualization platform using machine learning techniques. We are also gathering evidence from tourism management stakeholders on how the platform can help them understand, predict, and plan actions to mitigate tourist crowding.

For more comprehensive details on the technical development and operational aspects of the STTs, please refer to [16, 17, 19] and to the RESETTING@Iscte site.

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