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Enabling and Emerging Sensing Technologies for Crowd Avoidance in Public Transportation: A Review

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Abstract— Avoidance of crowding situations in public transportation (PT) systems is crucial to foster sustainable mobility, by increasing the user's comfort and satisfaction during normal operation, as well as to manage emergency situations, such as pandemic crises as recently experienced with COVID-19 limitations. This paper presents a comprehensive review of several crowd detection techniques based on Internet of Things (IoT) technologies, which can be adopted to avoid crowding in various segments of the PT system (buses/trams/trains, railway/subway stations, and bus stops). To discuss such techniques in a clear systematic perspective, we introduce a reference framework called SALUTARY (Safe and Reliable Public Transportation System), which in our vision employs modern information and communication technologies (ICT) in order to: (i) monitor and predict crowding events; (ii) adapt in real-time PT system operations, i.e., by modifying service frequency, timetables, routes, and so on; (iii) inform the users of crowding events by electronic displays installed in correspondence of the bus stops/stations and/or by mobile transport applications. It is envisioned that the new anti-crowding functionalities can be incrementally implemented as an addition to the intelligent transportation system (ITS) platform, which is already in use by major PT companies operating in urban areas. Moreover, it is argued that in this new framework, additional services can be delivered, such as, e.g., on-line ticketing, vehicle access control and reservation in severely crowded situations, and evolved crowd-aware route planning.

Index Terms— COVID-19, crowd detection, intelligent transportation system (ITS), Internet of Things (IoT), public transportation (PT) system, sensing technologies, sustainable mobility, smart cities.

I. INTRODUCTION

SINCE 2002, the European Commission has promoted across Europe and beyond a campaign supporting the use of public transportation (PT) systems as a safe, efficient, affordable, and low-emission mobility solution for everyone [1]. To cope particularly with the growing emission and congestion problems in urban areas, a key role will be played by intelligent transportation systems (ITSs), which leverage information and communication technologies (ICT) to make transport safer, more efficient, and more sustainable. A recent special issue [2] reports the cutting-edge advances and ICT

technologies pertaining to the seamless integration of sensor technologies with the PT infrastructure.

One of the most powerful resource of ITSs is the collection of *vehicle data*, such as their location and speed, which are obtained (usually in real-time) by means of automated vehicle location (AVL) systems. Moreover, *passenger data*, such as the number of passengers boarding a bus/train or entering a station, can be obtained by means of automatic passenger count (APC) or automatic fare collection (AFC) systems. In [3], optimization and planning strategies for PT systems based on such data are surveyed, at four different levels: strategic, tactical, operational, and real-time. In particular, it is observed that the lack of passenger arrival information, especially in real-time, is a limiting factor for accurate studies.

In many state-of-the-art ITSs, real-time location data are available only for vehicles, and are used both to provide trip information to passengers and for medium-to-long term management and monitoring of the service. However, with the emergence of Internet of Things (IoT) technologies, fine-grained and real-time passenger data collection is becoming a feasible task. In particular, the fifth generation (5G) of cellular networks is potentially able to support massive IoT

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connections, where billions of smart devices can be connected to the Internet, and can be easily located and tracked.

Recently, some researchers have argued that the quality of service perceived by PT user as well as travel satisfaction are seriously affected by *crowding* [4]. To cope with this issue, it is required to acquire in real-time reliable and capillary information about the crowding of PT vehicles (e.g., bus, tram, and trains) and of the related access infrastructures (e.g., bus stops and railway stations). Indeed, in [5] it is stated that “the availability of real-time passenger demand data can significantly improve the performance of control models in case of overcrowding”. Hence, new planning and management strategies that collect real-time crowding data and use it to improve the quality of service in PT systems are appearing in the literature [6, 7, 8].

The problem of overcrowding in PT systems have emerged dramatically during coronavirus disease (COVID-19) pandemic, which first have spurred our interest to this topic. During the outbreak phase, overcrowding of buses and trains must be strictly avoided to protect people from contagion, which required emergency measures, such as, e.g., limiting to 50% the service capacity. These measures are generally not sustainable in the long-term, since they shift a significant portion of passengers to private transportation. Moreover, the problem of overcrowding in PT systems must be tackled in a more structural way, since many experts predict that in the future recurrent waves of pandemic outbreaks could become the norm rather than the exception.

Notwithstanding a large amount of data about vehicles and passengers are commonly available in modern ITS systems, they cannot often be used to achieve real-time crowd detection and prediction. However, many ICT/IoT technologies for crowd detection are already available. Thus, we argue that it is the lack of a structured common framework that can hinder the diffusion of anti-crowding techniques in modern PT systems. Motivated by the previous observations, this paper pursues two main goals: (i) to present a survey of crowd sensing technologies for PT systems based on ICT/IoT technologies; (ii) to discuss their adoption into a reference framework, which we have called *SALUTARY (Safe and Reliable Public Transportation System)*, aimed at integrating the legacy ITS (already available in many PT systems in urban areas) with the new anti-crowding functionalities.

More specifically, in our vision, such new functionalities are built upon a distributed IoT subsystem, composed by a network of capillary active/passive sensors, aimed at measuring passenger crowding in the different segments of the PT system (buses, trams, trains, bus stops, and railway/metro stations). The acquired measures are transmitted in real-time by a communication infrastructure to a control subsystem, which performs optimized and proactive management of the PT system. The crowding data can also be reported (in aggregated form, for privacy concerns) to the PT users, by means of *ad hoc* mobile applications (apps) or by integrating it in the existing mobile transport apps (e.g., Moovit or proprietary operator applications).

Real-time knowledge of crowding data can be used for fast or even *proactive* adaptation of PT operations (e.g., increasing

the service frequency, reallocating vehicles from one line to another, planning alternative routes), in order to cope with spatially and/or temporally localized crowding situations, which cannot be tackled by conventional (statistical) tools used in transportation system design, such as, e.g., origin-destination flows analysis. The new anti-crowding functionalities achieve two scopes: (i) to improve the user satisfaction, thereby fostering PT system usage; (ii) to allow for safe PT usage during exceptional events like a pandemic outbreak.

A. Paper organization

Section II highlights the adverse impact of COVID-19 pandemic outbreak on sustainable mobility and PT systems. The main ICT functionalities used to collect data in ITSs are summarized in Section III. In Section IV, relevant works on crowd analysis, detection, and prediction are discussed. An overview of the *SALUTARY* reference framework and its architecture is given in Section V. Various sensing solutions are reviewed in Section VI for different indoor and outdoor scenarios. Section VII is devoted to highlight innovations and advantages provided by the adoption of the new anti-crowding functionalities. Finally, conclusions are drawn in Section VIII.

II. SUSTAINABLE MOBILITY IN THE COVID-19 ERA

During the last years, the transport sector and mobility – in particular PT systems in urban areas – have been seriously affected by COVID-19 pandemic. A survey carried out in China [9] in 2020 estimated that, as a consequence of the outbreak, the use of private cars will be roughly doubled, increasing from 34% to 66%, whereas the use of public transports (buses/metros) will be more than halved, dropping down from 56% to 24%. Furthermore, due to the lack of trust in PT systems, more than 70% of the surveyed people not owning a car declared their intention to buy a new one, with negative consequences on the environment (landscape and air pollution) in urban areas. Other recent studies (see, e.g., [10]) have highlighted that COVID-19 pandemic has seriously discouraged the use of PT systems.

To counteract the shift to private car usage during COVID-19 pandemic, the governments have implemented different strategies. A common measure is to favor the use of individual sustainable mobility and micromobility means, such as bikes, electrical scooters, and segways, by deploying the related infrastructures (emergency bike lanes) or empowering vehicle sharing services, which can shift to this transport mode a certain percentage of short and medium-distance trips.

However, owing to the large number of passengers carried by PT systems in urban areas, it is of utmost importance to adopt measures aimed at safe and reliable PT usage. During the acute phase of the outbreak, severe anti-COVID-19 measures were adopted aimed at minimizing the contagion risk, such as back-door boarding, cashless operation, frequent sanitization of vehicles and stations, enforcing social distances, limiting the service capacity, and requiring the passengers to wear face masks. Other anti-COVID-19 measures were applied to PT system operations, such as modifying timetables, frequencies, paths, leveraging modal integration, and so on. Some

of these measures, like increasing PT service frequency or introducing extraordinary trips to compensate for the reduced vehicle capacity, are seen by PT companies as effective, but not sustainable in the long term, due to the limited number of drivers and vehicles [11].

In the second phase, with the completion of vaccination campaign, many countries have chosen to move into the final reopening by following a “cautious approach”, due to the diffusion of different coronavirus variants: in such a phase, while most restrictions are being lifted, some will be maintained. Indeed, with the reprise of school and university activities, and the progressive reduction of smart working, PT systems are coping with increasing volumes of passengers, leading to overcrowding situations. It should be mentioned that even checking the EU digital COVID-19 certificate, also referred to as the “green pass”, which is needed in some countries to access PT vehicles, can slow down the access flow to PT systems and, consequently, favor overcrowding at bus stops or railway stations gates.

Generally speaking, the COVID-19 pandemic pushed towards a critical rethinking of many economical, social, and cultural habits, not only those related to sustainable mobility. A plethora of innovative solutions have been proposed to cope with this new challenge, many of them employing ICT/IoT technologies. In [12], the use of new technologies, such as IoT, unmanned aerial vehicles (UAVs), artificial intelligence (AI), blockchain and 5G, has been considered for managing the impact of COVID-19 in health applications. In [13, 14] a review of technologies for social distancing has been provided, with emphasis on wireless technologies for positioning, including crowd detection and people density estimation.

As far as sustainable mobility is concerned, a review of the PT planning literature can be found in [15] from the perspective of the changes in demand patterns and limited capacity requirements associated with the pandemic crisis. It is evidenced that, besides reducing the service capacity to adhere to physical distancing measures, PT service providers worldwide have resorted to limiting service span in order to reduce operational costs as a consequence of the reduction in catchment area, by canceling certain services or closing some stations. The authors in [15] point out the importance to develop and deploy methods that are able to maintain the functionality of PT systems, while minimizing the public health risks. They suggest that some changes in service provision can be made at the tactical planning phase, by modifying timetables and/or service frequencies.

In [16], the Authors focus on the New York City’s bike sharing system, to gain insights on the socio-economic variables behind human mobility during the pandemic. In particular, they analyze the relationship between bike sharing and public transport, by enlightening that appropriate bike plans can reduce health risks in case of pandemic and avoid traffic congestion in cities.

Some recent studies have explored the possibility to rely on ICT to organize and facilitate human mobility during the pandemic. In [17], the Authors propose to use a machine-learning (ML) based approach to trace daily train travelers in different age cohorts of 16 – 59 years (i.e., the less vulnerable

age-group) and over 60 (i.e., the more vulnerable age-group) in order to recommend certain times and routes for safe traveling. In this work, WiFi, Radio-Frequency Identification (RFID), Bluetooth, and Ultra WideBand (UWB) technologies are employed. Using the dataset of the London underground and overground network, different ML algorithms are compared in [17] to properly classify different age group travelers, showing that the Support Vector Machine (SVM) approach performs better to predict the mobility of travelers and achieves high accuracy (more than 80%). In [18], a comprehensive review on human mobility research using big data is carried out. Big data collected thanks to the pervasive use of ICT/IoT can help, indeed, to discover the relationships between human mobility and resource use, thus entailing great opportunities for smart city development. In [19], instead, the Authors pursue the objective to identify data sources and ML approaches to properly estimate the impact of COVID-19 on human mobility reduction. In particular, [19] investigates the consequences of the pandemic on mobility patterns of urban populations, by quantifying even the impact of mobility reduction on improving air quality in urban areas.

III. VEHICLE AND PASSENGER DATA COLLECTION IN ITS

In a modern ITS, data about fleet vehicles are obtained by AVL systems, whereas passenger data are obtained by APC/AFC systems. AVL is a means for automatically determining and transmitting the geographic location of a vehicle. Satellite-based location, such as the global positioning system (GPS), and mobile communication systems represent the technological platform for AVL systems. They enable real-time passenger information, fleet management and operations, and PT priorities. The process of real-time on-board vehicle location can result in a large database, where the progress of the vehicle is stored typically on a second-by-second basis. These data could be used also to improve scheduling efficiency and for automatic performance monitoring.

In [20] an overview of AVL systems is provided, which focuses on real-time and non-real-time functions based on AVL data. Moreover, three main technologies to collect location and time data are recognized: (i) infrastructure-based sensors or fixed devices (certain cities are installing signpost sensor AVL systems); (ii) non infrastructure-based sensors or mobile devices (GPS); (iii) mixed sensors, also known as dead reckoning (by coupling GPS and inertial sensors). Cagliari’s AVL system is used as a case study in [21].

GPS-based AVL systems may perform poorly in urban areas where tall building structures and overhead freeways can block the GPS signal from one or more satellites. Since the accuracy of GPS depends on the geometry and the number of satellites in view, blockage of a satellite that the GPS receiver is currently using will directly result in a navigation position error. This type of signal blockage in a typical mid-sized city can cause the loss of position accuracy for long periods of time. The loss of the position of the vehicle in AVL makes the whole concept of tracking ineffective.

Dead Reckoning Navigation (DRN) [22] units are computers that evaluate changes in direction by measuring speed

and direction. DRN algorithms are initialized with a given position and continue to monitor speed and direction of the vehicle through various communication sensors. A DRN unit typically uses a speed sensor and a heading sensor to compute a position. The GPS unit is used to update the DRN when the GPS navigation solution is valid, whereas the DRN is used for navigation when the GPS signals are blocked, thus making possible to continuously track vehicles in urban areas.

Time reliability metrics at bus stop are proposed in [23]. Data on bus arrival/departure can be collected through AVL; passenger arrival data can be collected by surveys or direct observations. These data are hence processed to compute the percentage of passengers receiving regular or punctual service for regularity and punctuality evaluations, respectively.

A methodology to estimate passenger demand for PT services using cell phone data is presented in [24], by using Senegal as a case study. The Authors explore the use of cell phone data in order to dynamically infer about urban mobility patterns, so as to improve transportation planning (extension of existing routes, implementation of new routes, new mode services, scheduling change, etc.). In [25], a WiFi-based automatic bus passenger counting system is developed, which tracks passenger devices from the moment they board a vehicle until they alight. A system (hardware, firmware and software) assessing the factors affecting the comfort in public transportation system is proposed in [26]. In [27], data obtained through APC are used into an offline framework for addressing some challenges, such as bus frequencies determination, tackling anomalies, etc.

IV. CROWD ANALYSIS, DETECTION, AND PREDICTION

Estimating and predicting some features of a “crowd” in indoor and outdoor locations is an active research topic, with many applications, including surveillance and security, situation awareness, emergencies, and crowd management. In PT applications, the feature of interest is the number of components of the crowd and/or its density.

A. Crowd analysis and detection

A review of crowd analysis techniques for urban applications, including transportation systems, is provided in [28], where different data sources are compared and discussed, including information fusion approaches. When dedicated crowd detection infrastructures are not available, *crowdsourcing* or *participatory sensing*¹ applications have been developed to acquire such information [29, 30].

Some applications of crowd analysis to PT systems are discussed in [6, 8]. In [6], in particular, a low-cost hardware/software solution is described, which estimates the current number of passengers in a vehicle by counting the number of probe requests, i.e., medium access control (MAC) addresses, sent by WiFi-equipped (IEEE 802.11) devices in the vehicle. In [8], such a passenger counting technique is incorporated in a bus navigation system, which is capable of

giving crowd-aware route recommendations: such a system has been tested in the municipal bus infrastructure of Madrid, Spain.

One of the problem inherent to the use of techniques based on radio frequency (RF) for crowd sensing is the ability to distinguish between people outside the bus and actual passengers. This issue was tackled in [6, 8] by filtering the probes with a sliding window, aimed at removing MAC addresses that were not detected over a longer period of time. The system was able to detect only around 20% of the passengers, since several users may have turned off the WiFi interface. Moreover, the system is only tailored at crowd analysis in buses, and does not take into account other scenarios (trains, bus stops, and railway stations).

In [7], a crowdsensing-based PT information service is described, which exploits mobile or participatory sensing to enrich the static travel information without requiring deployment of a vehicle tracking infrastructure.

A solution to count the people in a queue, based on Bluetooth low-energy (BLE) devices, is described in [31]. The system is completely passive and estimates the number of persons in the queue by analyzing the mean and variance of the received signal strength indicator (RSSI) values between a BLE beacon and a receiver covering a certain area. In general, RSSI-based approaches for crowd analysis exhibit good performance only for small monitored environments, where the propagation channel variations are mainly dominated by the attenuation caused by the people actually present in the given environment. On the other hand, in a rich scattering environment, crowd analysis based on channel state information (CSI) provides a more reliable people counting. In this respect, the received WiFi and Long Term Evolution (LTE) downlink control signals are processed in [32] and [33], respectively, to extract the changes of the propagation channel induced by the presence of different number of people.

B. Crowd prediction

Crowd prediction algorithms for transport applications can be classified on the basis of the prediction horizon into *short-term* (less than 60 minutes) and *long-term* ones. They usually rely on three different types of information: (i) real-time load station data, (ii) real-time train load data, and (iii) historical data. The latter data aim to improve prediction by exploiting possible cyclic (daily, weekly, or seasonal) variations in passenger loads. Prediction approaches can be further classified, on the basis of the prediction methodology, into *model-based* methods or *data-driven* ones. Model-based methods include time-series analysis, regression modeling, and Kalman filtering models. In [34], e.g., a traffic flow prediction algorithm based on time-series modeling is employed, and many variants have been subsequently proposed to improve the prediction accuracy.

Due to the highly nonlinear and random nature of traffic flow, data-driven approaches have recently gained significant attention, including *k*-nearest neighbor (*k*-NN) methods and artificial neural networks techniques (see, e.g., [35, 36]). In some cases, traffic simulation tools to predict traffic flow have

¹The concept of crowdsourcing, mobile and participatory sensing is further discussed in Section VI.

Fig. 1. The SALUTARY reference framework.

been considered as well. Most of these techniques are mainly devoted to congestion management in urban transportation and can exploit information from a multitude of sensor sources, including inductive loops, radars, cameras, GPS, social media, etc. Passenger load prediction for PT systems, instead, is less common: recent studies are [37, 38, 39].

V. SALUTARY REFERENCE FRAMEWORK

From the reported literature, it is apparent that integration of ICT/IoT technologies into PT systems for crowd avoidance is fragmentary and their potentials are not fully exploited. To bring together all the aforementioned technologies in a systematic and common scenario, we introduce the SALUTARY reference framework, whose scope is to integrate/augment the ITS system already available in a PT urban system with innovative *anti-crowding* functionalities, aimed at smart and proactive control and reduction of passenger crowding.

The key idea is to integrate heterogenous sensing and communication technologies, in dependence on the operation scenario and the ICT infrastructure available in the urban area where the system must be implemented. To achieve such a goal, strong interdisciplinary design skills are needed, including transportation engineering, telecommunications, computer science, electronics, data analysis, artificial intelligence, and machine learning (ML).

In our vision, the SALUTARY reference framework encompasses (Fig. 1) three subsystems:

- 1) the *sensing and actuator subsystem* (SASS);
- 2) the *communication subsystem* (CSS);
- 3) the *monitoring, prediction and control subsystem* (MPCSS).

The framework involves new data flows (marked in blue in Fig. 1) compared to existing data exchanges (in violet) found in state-of-the-art ITS systems for PT services. The core and most innovative part of SALUTARY is the SASS, with particular reference to the IoT sensing technologies, whereas the actuator part mainly encompasses the flow of information toward the users, carried out by audio speakers, variable-message panels, or displays, which are typically already present in the PT system, or can be readily installed at the bus stops as well as in railway stations (and even inside the

vehicles). Due to its centrality in our review, we focus attention on such a subsystem in Section VI.

The characteristics of the CSS are strongly dependent on the communications infrastructure available in the urban area. In general, this might encompass public wireless networks (such as cellular networks) and/or private wired and/or wireless networks owned by the operator, such as e.g. Global System for Mobile Railway (GSM-R) or LTE for Railway (LTE-R). To cope with this heterogeneity, it is envisioned that, at the protocol level stack, the CSS can be readily interfaced with the other subsystems by means of standard or open interfaces and/or using simple adaptation layers.

The MPCSS performs data collection and real-time crowding prediction, possibly employing AI and ML techniques. Based on such predictions, modifications to the transport services can be implemented in real-time, the related control data are sent to service operators (drivers, supervisors, etc.), whereas service information is sent to the passengers by means of displays and/or mobile transport apps. This information could be notified by the same applications to all the users of the PT, so as to discourage the access to overcrowded stations and/or bus stops, and propose alternative travel solutions. The MPCSS can be strongly integrated (and typically colocated with) the ITS control system of the PT service operator.

VI. SENSING AND ACTUATOR SUBSYSTEM (SASS)

The transportation scenarios to be considered for the SASS are essentially of three types:

- 1) train and bus/tram vehicles (indoor scenario);
- 2) railway/metro station (indoor/outdoor scenario);
- 3) bus station (mainly outdoor scenario).

In general, the sensing solutions to be adopted belong to the *crowd detection* family introduced in Sec. IV-A. They can be further classified [40] as *visual-based* (VB) solutions, based on still or moving images acquired by optical, thermal, or laser cameras, or *non-visual based* (NVB) ones, which utilize techniques not based on optical sensors (mainly RF devices). The main characteristics of the available sensing solutions for the different scenarios are summarized in Table I and will be discussed in the forthcoming subsections.

The main advantage of VB technologies is that they do not require cooperation/participation of the users. Optical cameras are widely used in private and public spaces for surveillance and security. Thermal cameras can detect people in low-light environments, complete darkness, or other challenging conditions, such as smoke-filled and dusty environments. Another option to detect and track persons is represented by laser imaging detection and ranging (LIDAR) sensors, especially in environments where there are several interacting people.

Thanks to recent advances in AI, traditional optical, thermal and laser VB sensors are becoming “smart” and can detect, recognize, and even identify persons. However, these systems do not allow to estimate the number of present people with sufficient accuracy, due to possible obstructions, clutter, and poor light/weather conditions, and involve high deployment costs in complex environments. Moreover, they require electrical power supply and may incur in privacy problems.

Among NVB technologies, sensing systems based on mobile devices (also called *crowdsensing* or *mobile sensing* [41, 42]) represent an interesting solution, due to the diffusion of smartphones and other portable/wearable devices, such as pedometers, smart watches, or biometrical sensors. On one hand, compared to VB solutions, data collected by means of *device-aided* NVB systems can be used not only to count persons, but also to gather additional information (e.g., planned routes, passengers using off-peak hours group ticket, and so on). On the other hand, a problem inherent to device-aided systems is that they usually require the cooperation of the people who must agree to share their data (so called *participatory* or *collaborative sensing*).

To motivate participation, it is sometimes needed to introduce incentive or reward mechanisms, or introduce radical modifications in the procedures to access the PT service, such as an authentication phase to use the transportation service. Although this issue could raise significant privacy concerns, it could also be useful as a means to increase the overall safety of the PT systems during a pandemic outbreak, by reducing the risk that infected people can access the system.

When device-aided NVB techniques cannot be used for crowd characterization, due to, e.g., lack of user cooperation and/or security issues, RF *non-device aided* approaches can be pursued, by analyzing the propagation channel variations of wireless signals (e.g. WiFi or LTE), which are induced by the people present in a given spatial area. The impact of the monitored people on the RF signal can be assessed either using traditional radar methodologies (range and Doppler analysis) or by analyzing features extracted by channel quality measurements, such as RSSI and CSI.

A. Train and bus/tram

For vehicular scenarios, straightforward NVB solutions for passenger counting are passive infrared sensors (IR). In this case, a couple of IR emitter and receiver are mounted in correspondence of each gate of the vehicle. A passive IR (PIR) sensor can detect variations of the IR signal, depending on the temperature and the characteristics of the surface interrupting the beam. Many technologies are available to solve such a “crowd counting” problem in scenarios characterized by a well delimited space with a limited number of accesses.

In the transportation community, APC systems [43] for rail and road vehicles are widespread and mainly based on simple technologies, such as counting from the number of AFC or by using independent sensors, typically infrared (active) or pyroelectric (passive) sensors, or combinations thereof, aimed at detecting the passage of people at the gates. Other techniques can be based on load sensors placed on the ground or on the suspensions, or pressure-sensitive switches (“treadle mats”) placed on the steps, or weigh-in-motion (WIM) systems, which estimate the number of passengers by the ground loading of the vehicles detected before and after the stops. More sophisticated techniques can also be employed, such as camera-based systems or combined sensing (such as IR plus RF or IR plus ultrasound).

As indicated in Table I, even though more sophisticated NVB technologies may be used as well, their usage is not

expected to lead to significant innovations in this scenario, compared to the aforementioned simpler solutions and systems (i.e., PIR, APC, AFC, and WIM).

B. Railway/metro station

For this scenario, both VB and NVB technologies can be applied, as reported in Table I. Among the latter ones, Near Field Communication (NFC) represents a viable solution that does not need to deploy special hardware [44]. Nowadays, Android and iOS phones/tablets support this technology, by allowing mobile devices to act as a NFC reader/scanner. When a device with NFC functionality appears in the reader’s working range, which can be placed at the gates or at any other fixed access point, it “wakes up” and sends a signal containing encoded data. The reader receives and decodes such data, and sends them to a management entity.

Another interesting solution for such a scenario can be to install 802.11 (WiFi) access points in the stations, and the number of persons entering the stations can be estimated on the basis of the number of connections established by the user devices with the access points. In this case, the uplink signals transmitted by the user devices are sniffed to capture their network accesses and, thus, it can be categorized as a device-aided solution. In contrast, without requiring aid to the monitored devices, the number of users served by a WiFi access point can be estimated by sniffing the downlink control information transmitted by the access point and relying on the fact that, as expected, there is a strong correlation between the number of people in the considered area and the variations of some features (e.g., RSSI and CSI) of the signal received by a dedicated device designed as a people counter.

Similarly to WiFi networks, LTE signals can be used for device-aided and non-device aided crowd counting, thanks to their ubiquitous availability and good penetration in indoor environments. For instance, they could be available in areas where the WiFi coverage is not present, such as remote and small railways/metro stations.

C. Bus stop

This scenario is by far the most difficult to manage, since bus stops are usually located in outdoor space not well delimited by fixed gates. Also in this case, both VB and NVB systems can be used, but it is imperative to adopt cost-effective, rugged and low-power solutions, in order to reduce the maintenance cost, as well as solutions that do not require significant infrastructures, since in many cases the bus stops are not equipped with shelters and are indicated by simple poles. Bluetooth can represent an efficient solution: recently, a low-energy consumption version of the standard, called BLE, has been introduced, which assures better communication performances with a limited power consumption. *Bluetooth beacons*, i.e., small transmitting devices that transmit BLE signals to compatible devices, can be easily installed at the bus stations, since they can be battery-powered and are characterized by simpler flexibility and simplified installation compared to WiFi. This solution relies on the same technology introduced by Google and Apple in the most recent versions

TABLE I
COMPARISON OF AVAILABLE SENSING TECHNOLOGIES FOR THE SALUTARY FRAMEWORK.

	Technology	Frequency	Maximum range	Power consumption	User cooperation	Scenario
Visual-based	Optical	Visible	100 m	Low	No	Railway/metro station, bus stop
	Thermal	Infrared	500 m	Low	No	Railway/metro station, bus stop
	Laser	Ultraviolet, Visible, Near infrared	1 km	Low-high	No	Railway/metro station, bus stop
Non-visual based	NFC	13.56 MHz	10 cm	Very low	Yes	Train and bus/train, Railway/metro station
	PIR	Infrared	10 m	Very low	No	Train and bus/train
	BLE	2.4 GHz	100 m	Very low	Yes/No	Railway/metro station, bus stop
	WiFi	2.4/5 GHz	50 m	Low-high	Yes/No	Railway/metro station, bus stop
	LTE	800/1800/2600 MHz	10 km	High	Yes/No	Railway/metro station, bus stop
	5G	Sub-6 GHz	10 km	High	Yes/No	Railway/metro station, bus stop
	5G	MMW band	< 1 km	High	Yes/No	Railway/metro station, bus stop
	SAR	Ku/Ka band	< 10 m	Very high	No	Bus stop

of their smartphone operating systems, and is used by many national contact-tracing apps (e.g., Immuni for Italy [45]).

LTE and 5G signals can also be exploited for counting people in bus stop environments. In particular, the deployment of 5G wireless technology over the coming decade is expected to rely on the introduction of many small cells working in the millimeter-wave (MMW) band. From the viewpoint of crowd analysis, the placement of small cells allows one to more precisely monitor spatially limited areas, like bus stops, with and without the aid of user devices. In addition, at bus stops, microwave SAR tomography techniques [18, 46] could provide specific images from which more detailed crowd information can be extracted, by using complex image classification algorithms (i.e., count, distribution, mobility, etc.). Modeling issues induced by the intrinsic near-field scenario (e.g., typical for bus stops) could be overcome by using specialized algorithms [47].

VII. INNOVATIONS AND ADVANTAGES

The new anti-crowding functionalities of the SALUTARY framework can provide innovations and advantages that are not present in the legacy ITS:

Proactive control of station access: In railway/subway applications, on the basis of the knowledge of the number of passengers aboard the arriving trains and the prediction of those getting off at the station, it will be possible to program the number of station accesses with a low error margin and in real-time. This number can be displayed at the users (by displays at the station gates or by the mobile transport apps) and can be used by the security operators to filter passengers at the turnstiles. Priority policies can be envisioned, such as taking into account the time already spent in queue, or

the trip motivations (e.g., a priority could be assured to health workers, disabled or elder users, law enforcement, and teachers/students).

Vehicle access reservation: In bus/tram trips, a vehicle access reservation system can be implemented. A sensor at the bus stop detects the user presence and exchanges information with his/her device (i.e., the smartphone), so as to grant him/her the access to board the first arriving bus (a virtual queuing system) or putting him/her in an *overbooking list* (with priority) to allow him/her to board the next one. The application can generate an e-ticket with the access grant (e.g., a QR-code) that can be validated on board at the ticket machine.

Crowding information dissemination: Users receive information related to capacity (in terms of number of seats or in percentage) of the bus/trains in arrival and/or the crowding at the bus stops/stations by means of displays installed in correspondence of the bus stops or at the entrance of the stations, or by alerts issued by mobile transport apps, so as to avoid unnecessary waiting and crowding and possibly reschedule their movements.

Crowd-aware route planning: Users can plan their trips on the mobile transport app, by taking into account not only geographical information and traveling times (static data), but also traffic and crowding information about vehicles and bus stops/stations during the trip (dynamic data). The app may not necessarily suggest the shortest route, but the least crowded one, taking into account also crowding levels measured during the trip. Such a feature not only help reduce crowds (and the consequent infection risk in case of a pandemic), but also distribute more efficiently the load on the transportation

TABLE II
MAIN ADVANTAGES OF THE SALUTARY FRAMEWORK.

Actor	Advantages
PT service operator (manager)	Having real-time crowding data of the different segments of the PT system allows one to plan services more efficiently and to quickly readapt them to tackle critical situations, localized in space and time
PT operators (drivers, inspectors, etc.)	The possibility to know in advance crowding situations at the bus stops or stations allows one to tackle critical situations (planning for examples possible holding, stop-skipping, or alternative routes)
Users	Knowing crowding situations allows one to use alternative means or to make the trip in another hours, if not strictly necessary; by the reservation system, if available, the users can access vehicles without unnecessary crowding at the bus stops or stations
Police forces	Knowing in real-time and/or predicting possible crowds - potentially dangerous for public health and/or for public order - allows one a more timely and targeted intervention
Sanitary system	Smart reduction of crowding resulting from an agile management of the PT system allows one to reduce the diffusion of infection and prevent further outbreaks
General population	Reduction of private car usage, less pollution

network.

The main advantages of the SALUTARY framework are summarized in Table II. Compared to static methods, like traditional survey-based compilation of origin-destination matrix flows (see Section III), more efficient planning and real-time control of the operation of the PT system is allowed. The large amount of generated data can be used by AI and ML algorithms to better understand and plan a series of aspects generally associated with improvements of the quality of life in urban areas and smart cities.

Compared to other anti-COVID-19 solutions (see Section II), the SALUTARY framework is not aimed at enforcing social distancing measures only. Its scope is wider, since it tries to optimize the overall performance of the PT system. As a by-product, it also allow to partially recover the drawbacks and inefficiencies of PT systems due to the adoption of rigid social distancing measures during both pandemic and post-pandemic scenarios.

VIII. CONCLUSIONS

A clean, smart, and resilient PT system is at the core of worldwide economies and central to people's lives. This is why there has been an increased number of research articles that discuss the feasibility of integrating ICT/IoT solutions in ITSs. In this paper, we have reviewed such technologies for crowd sensing, showing also how they can be gathered into an innovative reference framework, called SALUTARY, which allows to improve the performance of legacy ITS systems. In particular, system-level considerations have been reported to corroborate the feasibility of integrating state-of-the-art wireless IoT technologies into the different segments of the PT infrastructure. The SALUTARY framework is based on some basic components and subsystems, which can be used as building blocks to implement an evolved ITS, capable of real-time monitoring and predicting crowd situations, as well as disseminating useful information to users at the bus stops/stations and/or through mobile transport apps.

Some features of the new framework are similar to those of a contact tracing system, which can be implemented more easily if based on user cooperation. In this sense, the crowd detection functionalities can be incorporated in a more complex system, which can implement, besides the typical mobile transport app functionalities (like Moovit), also the possibility to buy tickets and/or to reserve the access to the vehicles, in conditions of particular crowding. This could represent a decisive incentive to the use of the system. However, the more appropriate crowd sensing solution must be singled out case-by-case, in dependence on the ICT infrastructure owned or leased by the PT operator, of the socio-economic context, and the cost-benefits ratio. The potentials of the proposed framework go beyond the scope of dealing with typical social distancing problems, by potentially allowing real-time optimization and management of the PT system. However, in the future, the success in preventing the introduction and subsequent transmission of harmful viruses is strongly dependent on preventing disease transmission in the PT system used by workers, students, families, teachers, school staff, and all community members.

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