

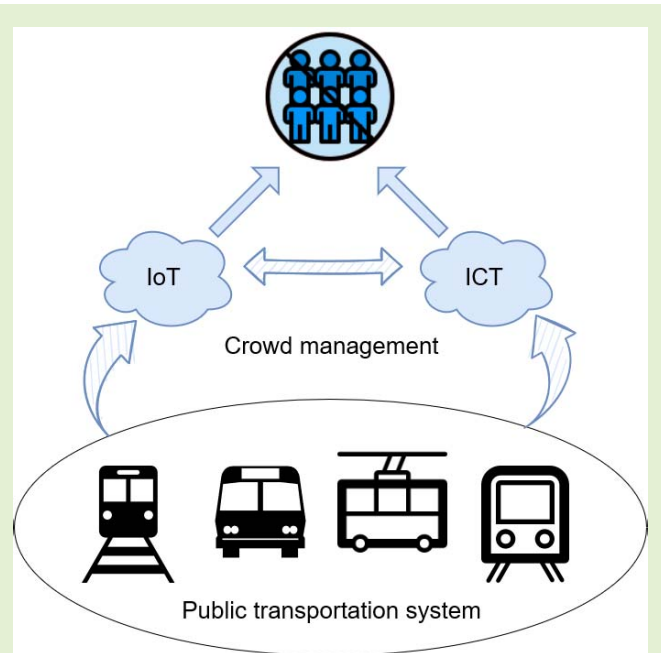
Sensing Technologies for Crowd Management, Adaptation, and Information Dissemination in Public Transportation Systems: A Review

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Abstract—Management of crowd information in public transportation (PT) systems is crucial, both to foster sustainable mobility, by increasing the user's comfort and satisfaction during normal operation, as well as to cope with emergency situations, such as pandemic crises, as recently experienced with coronavirus disease (COVID-19) limitations. This article presents a taxonomy and review of sensing technologies based on the Internet of Things (IoT) for real-time crowd analysis, which can be adopted in the different segments of the PT system (buses/trams/trains, railway/metro stations, and bus/tram stops). To discuss such technologies in a clear systematic perspective, we introduce a reference architecture for crowd management, which employs modern information and communication technologies (ICTs) in order to: 1) monitor and predict crowding events; 2) implement crowd-aware policies for real-time and adaptive operation control in intelligent transportation systems (ITSs); and 3) inform in real time the users of the crowding status of the PT system, by means of electronic displays installed inside vehicles or at bus/tram stops/stations and/or by mobile transport applications. It is envisioned that the innovative crowd management functionalities enabled by ICT/IoT sensing technologies can be incrementally implemented as an add-on to state-of-the-art ITS platforms, which are 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 to the passengers, such as online ticketing, vehicle access control and reservation in severely crowded situations, and evolved crowd-aware route planning.

Index Terms—Adaptive systems, communication systems, coronavirus disease (COVID-19), crowd management, intelligent transportation system (ITS), Internet of Things (IoT), public transportation (PT) systems, sensing technologies, smart cities, sustainable mobility.



Manuscript received 17 September 2022; revised 21 October 2022; accepted 14 November 2022. Date of publication 23 November 2022; date of current version 29 December 2022. The associate editor coordinating the review of this article and approving it for publication was Dr. Prosanta Gope. (Corresponding author: Francesco Verde.)

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Digital Object Identifier 10.1109/JSEN.2022.3223297

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 PT limitations in urban areas, a key role is expected to be played by intelligent transportation systems (ITSs) [2], which leverage information and communication technologies (ICTs) to enable the automated collection of transportation data, used to make transport safer, more efficient, more reliable, and more sustainable.

Two different classes of spatiotemporal data are available in state-of-the-art ITSs for PT: 1) vehicle data, such as location

and speed, which are obtained (usually in real time) by means of automated vehicle location (AVL) [3] systems, mainly based on satellite localization techniques and 2) passenger data, such as the number of passengers boarding a bus/train or entering a station, which can be obtained by means of automatic passenger counting (APC) [4] or automatic fare collection (AFC) systems [5]. Such data are commonly used as inputs for optimization and planning strategies for PT systems, which are surveyed in [6] at four different levels: strategic, tactical, operational, and real time. In particular, it is observed in [6] that lack of passenger arrival information, especially in real time, is a limiting factor for accurate studies. In many ITSs, indeed, real-time location data are available only for vehicles, which are used both to provide trip information to passengers and for medium-to-long-term management and monitoring of the service.

With the advent of Internet of Things (IoT) technologies, fine-grained and real-time passenger data collection is becoming a feasible task, especially in smart cities [7]. Indeed, the pervasive use of mobile and portable devices, equipped with different sensors, allows one to gather huge quantities of data in urban scenarios [8], [9], [10], [11], which can be used for different applications and tasks [12]. In particular, the fifth generation (5G) of cellular networks is potentially able to support massive IoT connections [13], where billions of smart devices are connected to the Internet and can be easily located and tracked; these features will be further extended by forthcoming sixth-generation (6G) networks [14].

Recently, some researchers have argued that the quality of service (QoS) perceived by PT users, as well as their travel satisfaction/quality of experience (QoE), is seriously affected by crowding [15], [16], [17]. To cope with this issue, it is required to acquire in real-time reliable and capillary information about the crowding status of PT rail or road vehicles (e.g., buses, trams, and trains) and the related access infrastructures (e.g., bus/tram stops and metro/railway stations). Indeed, it is stated in [18] that “the availability of real-time passenger demand data can significantly improve the performance of control models in the case of overcrowding.”

Motivated by the previous needs, new modeling, planning, and management strategies that collect real-time crowding data and use them to improve QoS/QoE in PT systems are appearing in the literature [17], [19], [20], [21], [22], and will be referred in the following as *crowd management* [23], [24]. Crowd management systems are composed [24] by *crowd analysis/monitoring* and *crowd control* components: the former includes a network of physical sensors aimed at detecting crowds and estimating their parameters, whereas the latter includes prediction, decision-making, and control strategies aimed at managing the crowd events. Crowd management should not be confused with *crowdsourcing/crowdsensing* [25]. In PT systems, crowdsourcing (also referred to as “sensing by the crowd” approach) is based on reporting activities by which passengers provide their suggestions and feedback, as well as announce problems to a PT company or, even, provide a resource or create a product, e.g., peer-to-peer services. Relying on crowdsourced data, PT companies work together with passengers to solve

a problem or jointly plan public transit by finding and developing solutions aligned with PT user preferences. Crowd management is instead based on the different principle of “sensing the crowd,” according to which environmental data collected through networks of IoT sensor devices and/or user terminals are shared with PT companies, which analyze such data for forecasting, choosing among several possible alternative options, as well as ensuring robust and safe operation of PT systems.

The problem of crowd management in PT systems has emerged dramatically during coronavirus disease (COVID-19) pandemic, which has first spurred our interest to this topic (see Section II for a discussion). During the acute outbreak phase, overcrowding of buses and trains needed to 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 smarter and more structural way since many experts predict that, in the future, recurrent waves of pandemic outbreaks could become the norm rather than the exception.

Although state-of-the-art AVL/APC/AFC systems collect a large amount of data about vehicles and passengers in ITS systems, often they are not suitable to perform real-time crowd monitoring and control. However, many ICT/IoT sensing technologies for crowd monitoring are already available or will be available soon in smart cities [7]. A recent special issue of this journal [26] reports the cutting-edge advances and ICT technologies pertaining to the seamless integration of sensors with the transportation infrastructure. The main focus of the contributions in [26] is on sensing technologies for *private* transportation systems, oriented to autonomous driving [27], [28], intelligent fault detection [29], [30], electric charging optimization [31], road condition monitoring [32], [33], precise fleet management [34], and speed detection and accident avoidance [35], [36]: in the same issue, less attention is dedicated to the integration of sensing technologies within PT systems. Moreover, sensing techniques for crowd monitoring are not specifically discussed.

A. Contribution

In this article, we argue that, although many sensing technologies for crowd monitoring are already available, the diffusion of crowd management techniques in modern PT systems is hindered by the lack of a structured framework and reference architecture. Motivated by this observation, we pursue three main goals in this article: 1) to present a survey and taxonomy of crowd monitoring technologies for PT systems based on ICT/IoT technologies; 2) to discuss their adoption into a reference architecture, aimed at integrating state-of-the-art ITSs (already available in many PT systems in urban areas) with the new crowd management functionalities; and 3) to highlight a series of challenges opened up by the proposed reference architecture that needs to be investigated, by also indicating what could be the best way to address them. Although some reviews regarding techniques for crowd

TABLE I
COMPARISON AMONG SURVEYS RELATED TO CROWD MANAGEMENT IN PT SYSTEMS

Ref.	Reference architecture	Considered aspects	Scenarios	Sensing technologies
[4]	No	Crowd analysis	Passenger counting inside PT vehicles	Infrared sensors, treadle mat sensors, and weigh-in-motion systems
[10]	Yes	Crowd analysis	PT systems are mentioned but no scenario is discussed in detail	Call detail records, origin-destination matrices, GPS, Bluetooth, WiFi, RFID, video, social networks, activity trackers, satellite, UAV, and census data
[16]	No	Crowd control	Inside buses and trains, inside stations	Physical sensing is not discussed
[21]	No	Crowd management	Inside buses	WiFi, GPS, and cellular system (3G)
[24]	Yes	Crowd management	Related to PT systems but no scenario is discussed in detail	CCTV systems, presence sensors, RFID, tracking mobile devices, and smartphones
[37]	No	Crowd analysis	Passenger counting Inside PT vehicles	Optical sensors, pressure sensors, computer vision, and WiFi
[38]	No	Crowd analysis and prediction	PT systems are mentioned but no scenario is discussed in detail	WiFi, cellular systems (4G/5G), social media, cameras, and taxi trajectories
[39]	Yes	Crowd prediction	Prediction of the urban flow (e.g. the traffic of crowds, vehicles, and bikes)	Physical sensing is not discussed
[40]	Yes	Crowd management	PT systems are mentioned but no scenario is discussed in detail	Physical sensing is not discussed
[41]	Yes	Crowd analysis	PT systems are mentioned but no scenario is discussed in detail	Physical sensing is not discussed
[42]	Yes	Crowd analysis	PT systems are mentioned but no scenario is discussed in detail	Physical sensing is not discussed
[43]	No	Crowd control	Bus and tram stops	Physical sensing is not discussed
This paper	Yes	Crowd management	Train and bus/tram vehicles, railway/metro stations, and bus stops	Infrared sensors, pressure/load sensors, optical and thermal cameras, LiDAR, acoustic/ultrasound sensors, RFID and NFC devices, Bluetooth, WiFi, and cellular systems (4G/5G)

monitoring inside PT vehicles exist (see [4], [37]), to the best of our knowledge, this is the first review addressing sensing technologies for crowd management in *all* the different segments of the PT systems. In this respect, [Table I](#) enlists all the related surveys in crowd management in PT systems, by comparing them with this review article at hand.

In our vision, the crowd management functionalities are built upon a distributed IoT subsystem, composed by a capillary network of heterogeneous active/passive sensors, aimed at monitoring passenger crowding inside buses, trams, and trains, at bus/tram stops, and in railway/metro stations. By means of a communication infrastructure, the acquired measures are transmitted in real time to a smart subsystem, which performs crowd control functionalities. Crowding information can also be reported (in aggregated or anonymized form, for privacy concerns) to PT users, by means of displays installed inside vehicles or at stations/bus stops, or through mobile transport apps (e.g., Moovit or proprietary operator applications).

In the proposed reference architecture, real-time knowledge of crowding data can be used by PT operators for fast or even *proactive* adaptation of some service features (e.g., vehicle holding, stop skipping, overtaking, limited boarding, speed changing, and short turning), 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 (O-D) flow analysis. The new crowd

management functionalities essentially achieve two scopes: 1) to improve the QoS/QoE of passengers, thereby fostering PT system usage and 2) to allow for safe PT usage during exceptional events like a pandemic outbreak, such as COVID-19.

B. Article's Organization

Section II highlights the adverse impact of COVID-19 pandemic outbreak on sustainable mobility and PT systems. In Section III, the main aspects of crowd management in PT systems are discussed. In Section IV, a crowd management reference architecture is proposed. A taxonomy and review of the sensing solutions for crowd management and their application in different PT scenarios is presented in Section V. Innovations and advantages provided by the adoption of the new crowd management functionalities are highlighted in Section VI. The main challenges and gaps related to the introduction of crowd monitoring management in ITS systems are discussed in Section VII. 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 the COVID-19 pandemic. A survey [44] carried out in China 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 transport (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., [45], [46]) have highlighted that the COVID-19 pandemic has seriously discouraged the use of PT systems.

To counteract the shift to private car usage during the COVID-19 pandemic, national governments have implemented different strategies. A widespread measure [47] has been to favor the use of individual sustainable mobility and micromobility means, such as bikes, electrical scooters, and segways, by deploying the related infrastructures (bike lanes) or empowering vehicle sharing services, which can shift to this transport mode a certain percentage of short- and medium-distance trips.

However, due 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 in such a scenario. During the acute phase of the outbreak, severe anti-COVID-19 measures were adopted [48] to minimize the contagion risk, such as back-door boarding, cashless operations, 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 [48], [49] to PT system operations, such as modifying timetables, frequencies, paths, and leveraging modal integration. Unlike other countries, the Land Transport Authority (LTA) of Singapore has made adjustments to train frequencies to reduce crowding on commuters' lines, increasing the peak-period frequency for trains from once every 5 min to once every 3 min [50]. Some of these measures, such as 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 and the increased operational costs [51].

Generally speaking, the COVID-19 pandemic has pushed toward 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 [52], 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 [53] and [54], 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 [49] from the perspective of the changes in demand patterns and limited capacity requirements associated with the COVID-19 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. Moreover, it is pointed out the importance to develop and deploy methods that are able to maintain the functionality of PT systems while minimizing the public health risks; it is suggested that some changes in service provision can be made at the tactical planning phase, by modifying timetables and/or service frequencies.

Some recent studies have explored the possibility to rely on ICT to organize and facilitate human mobility during the pandemic. Asad et al. [55] proposed 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, many ICT technologies, such as Wi-Fi, radio frequency identification (RFID), Bluetooth, and ultrawideband (UWB), are employed. Using a dataset of the London underground and overground network, different ML algorithms are compared in [55] 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 [56], a comprehensive review on human mobility research using big data is carried out: big data collected since 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. Rahman et al. [57], instead, pursued the objective of identifying data sources and ML approaches to properly estimate the impact of COVID-19 on human mobility reduction. In particular, the consequences of the pandemic on mobility patterns of urban populations are investigated in [57], by quantifying even the impact of mobility reduction on improving air quality in urban areas.

III. CROWD MANAGEMENT IN PT SYSTEMS

The main architecture of a crowd management system for PT applications is schematically shown in Fig. 1. A certain number of physical sensors S_1, S_2, \dots, S_n are used to collect all the relevant information regarding crowd events. After a suitable preprocessing of the collected information (e.g., dimensionality reduction, normalization, interpolation, denoising, and so forth), the output data are processed by the data fusion (DF) system. DF can conceptually be divided into three layers [58]: sensor fusion, feature-based DF, and decision fusion. Sensor fusion includes data classification, object refinement (e.g., spatiotemporal information alignment, correlation, clustering, grouping, state estimation, error elimination, and reduction), positioning, and recognition. The output of the sensor function layer has a consistent data structure. Data feature fusion helps to reduce the requirements of application services for system storage resources and computing performance, and it can provide additional complete and in-depth features. Decision-level fusion is aimed at detecting crowds and estimating their

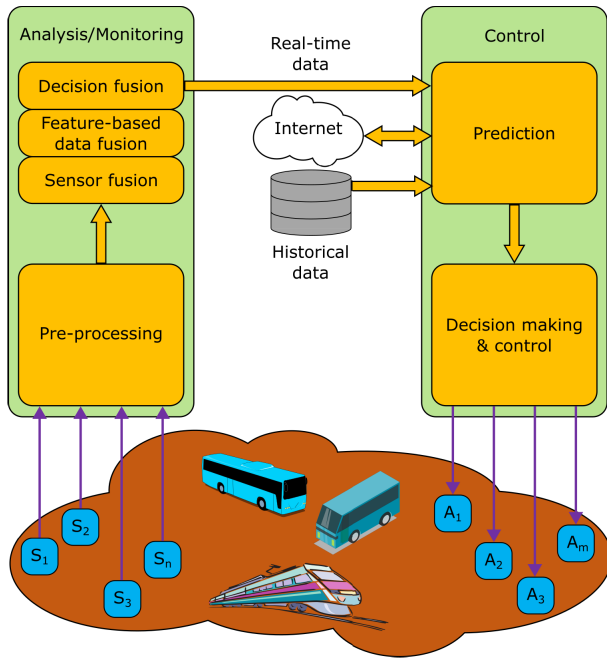


Fig. 1. Main architecture of the crowd analysis/monitoring and crowd control mechanisms.

parameters in real time. Prediction of crowd events and their manage is obtained by elaborating not only the output data of the decision-fusion layer but also other information arising from the Internet and historical databases. Control actions are finally implemented through a certain number of actuators A_1, A_2, \dots, A_m .

A general introduction to crowd management in transportation systems is provided in [24], where some limitations of state-of-the-art ITSs are highlighted, and the potentials of the new approach are discussed, together with a brief introduction to crowd analysis/monitoring techniques. In [16], different aspects of passenger crowding in PT systems are discussed, related to demand, supply, and operations, including effects on route and bus choice, as well as passengers' wellbeing. Table II subsumes some relevant works on crowd management discussed in the following, focusing in particular to those reporting numerical performance achievements in realistic scenarios.

The benefits of *real-time crowding information* (RTCI) dissemination on passenger travel choices have been discussed and assessed by simulations in [17], [59], and [60]. In particular, it is shown in [59] and [60] that providing RTCI at bus stops might help reduce the deleterious “bus bunching” effect [61]. In [17], a complete framework for RTCI modeling in PT systems is introduced, which incorporates RTCI in a dynamic path choice model: the new methodology is tested on a simplified model of the urban PT system of Kraków, Poland, showing that RTCI dissemination contributes to a more efficient distribution of passenger loads in the PT network, improving travel comfort and reducing waiting time by about 30%.

A field application of crowd management strategies to PT systems is considered in [19] and [21]. The proposed

solution, tested in the municipal bus infrastructure of Madrid, Spain, estimates the current number of passengers in a bus by exploiting the properties of the existing Wi-Fi connections (see Section V-H) and incorporates such information in a bus navigation system, which is capable of giving crowd-aware route recommendations. Well before the COVID-19 outbreak, the LTA in Singapore has been collecting AFC data [62] to help identify commuter hotspots, which enables them to better manage bus fleets and commuter demand, achieving remarkable service improvements, such as 92% reduction in the number of bus services with crowding issues and 3–7-min reduction in the average waiting time on popular bus services [63]. It is worth noting that recently, also Google started acquiring and disseminating crowding information to the users [64], [65], [66].

A. Crowd Prediction

Estimating and predicting (in space and/or time) some features of a human “crowd” in indoor and outdoor locations is an active research topic, with many applications, including surveillance and security, situation awareness, emergencies, and crowd management [38]. In transport applications, the feature of interest is the number of components of the crowd and/or its density.

Crowd prediction algorithms for transport applications can be classified based on the prediction horizon into *short-term* (less than 60 min) and *long-term* ones [69]. Moreover, they can be classified, based on the prediction methodology, into *model-based* methods or *data-driven* ones.

Model-based methods include time-series analysis, regression modeling, hidden Markov models [73], and Kalman filtering models [74]. Due to highly nonlinear and random nature of crowds, data-driven approaches have recently gained significant attention, including ML and deep-learning (DL) techniques. Several works consider ML-based approaches for crowd management (see, e.g., [39], [75]). Yuan et al. [40] provided a thorough survey on ML techniques for ITSs.

Although ML-based approaches can achieve good results in crowd flow prediction, several reasons pushed researchers to adopt DL-based methods, such as, above all, the ability to automatically extract relevant patterns from unstructured and heterogeneous data. Differently from ML ones, indeed, DL approaches do not require manually extracted or handcrafted features but can automatically extract the relevant features from the raw data collected by the sensors, process them, and make the subsequent decision. In [41], the reference structure of a crowd counting technique based on a convolutional neural network (CNN) is reported, whereas in [42], crowd counting techniques are classified, according to the network property, into basic, scale-aware models, context-aware models, and multitask models. In some cases, simulation tools to predict traffic flow, such as BusMezzo [76] or SUMO [77], have been considered as well.

Although crowd/traffic prediction and mobility forecasting are considered in several papers, mostly devoted to road congestion management in urban transportation, their application to PT systems is a relatively new topic: some recent studies are [67], [68], [70], [74], and [78]. In [70], a predictive model for

TABLE II
REPRESENTATIVE PERFORMANCES OF CROWD MANAGEMENT SOLUTIONS FOR PT SYSTEMS

Ref.	Scenarios	Approach	Validation	Performance achievements
[17, 59, 60]	PT network	RTCI dissemination	Simplified version of PT network of Kraków, Poland	More efficient distribution of passenger loads, reduction of the bus bunching effect, improvement of travel comfort and reduction of waiting time by about 30%
[22]	Bus network	RTCI dissemination and bus holding	Calibration of the model by a survey in Dalian City, China	Reduction of bus headway and single trip time by 20%, reduction of in-vehicle crowdedness by up to 25%
[67, 68]	Metro network	RTCI dissemination, real-time crowd estimation and prediction	Metro line in Stockholm, Sweden	Prediction accuracy improved from 70–80% to 80–95%
[62, 50, 63]	PT network	Management of bus fleet and commuter demand	LTA network in Singapore	Reduction of 92% in the number of bus services with crowding issues, reduction of 3- to 7-minute in the average waiting time on popular bus services
[69]	Metro line	Optimization of timetables to reduce platform over-crowding and passenger waiting time	Beijing metro data	Reduction of the PWT by 17.18% (off-peak hours) or 3.22% (peak hours), reduction of the number of passengers on platforms by 44.5% (off-peak hours) and 9.5% (peak hours)
[70]	Bus network	Predictive model for bus crowding based on ML	Bus system of Pittsburgh-area, USA	Prediction accuracy improved by 8x over baseline models
[71]	Metro line	Optimization of the passenger flows by installing unidirectional gates at the platforms	Metro line 4 in Santiago, Chile	Increase of the transport capacity by 5%, reduction of the travel time by 6.5%, positive passenger feedback
[72]	PT railway network	Joint optimization of train scheduling and passenger routes based on in-vehicle crowding	Urban railway network in Zürich, Switzerland	Reduction of the passenger in-vehicle travel time by 39%

PWT = Passenger Waiting Time, EWT = Extended Waiting Time

bus crowding is proposed and tested on an AVL/APC dataset taken from the Pittsburgh-area bus using ML techniques. In [67], a data-driven approach is considered to perform car-specific, metro, and train crowding prediction, aimed at providing accurate in-vehicle or station RTCI.

Real-time crowd estimation in [67] is based on load sensors (see Section V-B), which are used, together with historical data, to perform crowd prediction, whose accuracy is tested with data gathered on a metro line in Stockholm, Sweden. It is shown that real-time load data significantly improve the prediction accuracy (from between 70% and 90% to between 80% and 95%). In [68], a framework for personalized (i.e., user-specific) crowd prediction is proposed, which considers not only loading data but also other parameters that affect user comfort, such as seat availability, expected travel time standing, and excess perceived travel time (compared to uncrowded conditions). In [79], a system providing real-time short-term crowd predictions on trains and platforms is proposed, which uses both real-time AFC and O–D historical data.

B. Crowd Control

Crowd information can be incorporated in PT design, optimization, and control at different levels. Besides some approaches showing the benefits of RTCI dissemination to the passengers [17], [59], [60], [67], operator-based crowd control in PT systems is still at an early stage of development. Crowding data can be used at the strategic and tactical planning level in several fields, such as increased services, vehicle capacities, networks expansion, headway,

and timetable optimization (see, e.g., [71], [80] for solutions applied to the metro/subway scenario). In [81], a sequential heuristic method is introduced for rescheduling the timetables of demand-responsive public transport modes in near-real time. The approach was tested on data of Stockholm bus service, with reference to a figure of merit called excess waiting time (EWT). Due to the schedule changes, the operational performance of bus services demonstrated a remarkable service-wide EWT improvement (e.g., the service-wide EWT is reduced from 1.13 to 0.75 min for line 1).

In [69], a timetable optimization method aimed at reducing the passenger waiting time (PWT) in metro scenarios is proposed, employing a genetic algorithm (GA) integrated with the interior-point algorithm (IPA). The proposed method is tested by simulation on data of the Beijing Metro, showing that the PWT under the optimized timetable is reduced at best by 17.18% in off-peak hour and by 3.22% in peak hour in comparison with the standard timetable. Moreover, the method reduces the peak number of passengers on platforms by 44.5% during off-peak hours and by 9.5% during peak hours.

In many studies, the effects of crowding are represented by an additional in-vehicle travel time multiplier, so-called *crowding penalty* [16], which is typically estimated from historical data. A recent discussion of crowd-related studies in PT railway systems is provided in [72], which also proposes a control model for joint optimization of train scheduling and passenger routes considering in-vehicle crowding based on O–D data. Real-time crowd control techniques are less explored, mainly due to the lack of availability of fine-grained crowding data. Common measures to cope with service

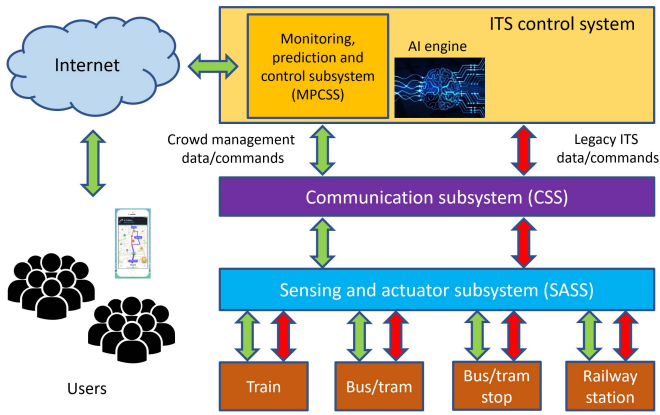


Fig. 2. Crowd management reference architecture for ITS.

irregularities in scheduled PT systems are vehicle holding, stop skipping, overtaking, limited boarding, speed changing, and short turning [43], [82]. All these strategies can further benefit from the availability of RTCI, both inside vehicles, and at the access infrastructure (e.g., bus/tram stops and railway/metro stations).

IV. REFERENCE ARCHITECTURE FOR CROWD MANAGEMENT

From the previous discussion, it is apparent that the integration of ICT/IoT sensing technologies into PT systems for crowd management is fragmentary and their potentials are not fully exploited to date. To bring together these technologies in a systematic and common scenario, we introduce a *crowd management reference architecture* for ITS, whose scope is to integrate/augment the ITS system already available in an urban PT system with the new crowd management functionalities, aimed at smart and proactive control and reduction of passenger crowding.

The key idea is to integrate heterogeneous 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 in practice, strong interdisciplinary design skills are needed, including transportation engineering, telecommunications, computer science, electronics, data analysis, and AI.

In our vision, the reference architecture encompasses (Fig. 2) three subsystems:

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

The architecture involves new data flows (marked as green arrows in Fig. 2) for crowd management, in addition to existing data exchanges (red arrows) commonly used in state-of-the-art ITS systems for PT services. The core and most innovative part of the system is the SASS, with particular reference to sensors for crowd monitoring. In Section V, we provide a taxonomy and discussion of the different sensing technologies that can be utilized to this aim. The actuator component mainly encompasses two crowd-related flows of information: 1) 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/tram stops as well as in railway/metro stations, and also inside vehicles; 2) toward the PT operators (drivers and staff), e.g., by means of evolved driver displays that communicate to the drivers' decisions regarding PT adjustments (e.g., holding, stop skipping, or even route changing) to be carried out in real time. It is worthwhile to note that, with the advent of *autonomous-vehicle PT systems* [83] (based on driverless buses or metro trains), the actuators can directly modify the vehicle behavior, without the need for human intervention.

As regards the CSS, its characteristics are strongly dependent on the communications infrastructure available in the urban area. In general, this subsystem 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 long-term evolution 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 crowd prediction, possibly employing AI and ML/DL techniques. Based on such predictions, modifications to the transport services can be implemented in real time (e.g., vehicle holding, stop skipping, overtaking, limited boarding, speed changing, and short turning) as well as at the strategical/tactical planning level (e.g., optimization of timetables and routes). The related control data are sent to service operators (drivers, supervisors, and so on), whereas service information, including RTCI, 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/tram 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.

V. SENSING TECHNOLOGIES FOR CROWD MANAGEMENT

From the transportation perspective, our taxonomy of sensing technologies for PT systems considers (see also Fig. 2) the following scenarios:

- 1) train and bus/tram vehicles (indoor scenarios);
- 2) railway/metro stations (indoor/outdoor scenarios);
- 3) bus/tram stops (mainly outdoor scenarios).

The sensing solutions to be adopted in these scenarios belong to the *crowd analysis/monitoring* [84] family. Detecting and estimating some features of a “crowd” in indoor and outdoor locations is an active research topic, with many applications, including surveillance and security, situational awareness, and emergencies (for a recent review, see [85] and references therein). In PT applications, the feature of interest is the number of components of the crowd (i.e., *crowd counting*) and/or its density (i.e., *crowd density estimation*); moreover, tracking of individuals in a crowd could be needed to build O–D matrices, useful for long-term planning. A review of

crowd analysis techniques for urban applications, including transportation systems, is provided in [10], where approaches based on different data sources, including information fusion techniques, are discussed and compared.

Sensing technologies for crowd analysis can be classified [86] as *visual-based* (VB) solutions, based on still or moving images/videos mainly acquired by optical, thermal, or laser cameras, or *nonvisual-based* (NVB) ones, which do not rely on images to estimate crowd parameters but resort to other physical quantities or features that can be related to crowd parameters, such as, e.g., those of radio signals, temperature, or sound.

To perform the crowd analysis, VB techniques resort to sophisticated image processing, pattern recognition, or computer-vision techniques [84], [87], [88]. Indeed, due to recent advances in AI, traditional camera sensors are becoming “smart” and can detect, recognize, and even identify persons. VB technologies perform *passive* sensing, relying on a network of dedicated sensors, without requiring active *cooperation/participation* of the users. However, VB data are subject to stringent protection regulations enforced by international data privacy laws, such as, e.g., general data protection regulation (GDPR) [89] in the European Union.

Among NVB technologies (see [90] for a recent review), sensing solutions based on mobile RF devices represent an interesting approach, due to the diffusion of smartphones and other portable/wearable devices, such as, e.g., pedometers, smart watches, or biometrical sensors. This approach to sensing is known as *mobile sensing* [91], *opportunistic sensing* [92], or *participatory sensing* [93]. Data collected by means of such *device-aided* NVB systems can be used not only to count people in a crowd but also to gather additional information about individuals (e.g., planned routes, O–D flows, and passengers using off-peak hours group ticket). However, a problem inherent to device-aided systems is that they usually require user cooperation/participation. Another important aspect of NVB systems is that they potentially collect sensitive data pertaining to individuals, such as, e.g., daily movements as well as home and work locations. To motivate participation, it is sometimes needed to introduce incentive or reward mechanisms, or apply radical modifications to the procedures to access the PT service, such as an authentication phase to use the service. Although this issue could enhance the aforementioned 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/privacy issues, RF-based *non-device aided* or *device-free* approaches can be pursued, which operate by analyzing the propagation channel variations of wireless signals induced by the people present in a given spatial area. In limited cases, NVB sensing techniques relying on physical properties different from those of RF signals (such as audio or ultrasound signals) can also be employed. From the user’s point of view, information collected through device-free solutions is less critical, as it may not affect users’ privacy.

The main sensing technologies for crowd management in PT systems are summarized in Table III and will be discussed in the forthcoming Subsections from V-A to V-H. Table III also provides a preliminary classification of sensing technologies based on their degree of privacy. We defer to Section VII for a more detailed discussion about privacy issues.

A. Infrared Sensors

Impulse-radio (IR) sensors are commonly used in traditional APC systems for counting the number of passengers boarding or alighting a vehicle (usually a bus or a tram). Commercially available solutions employ a couple of IR sensors (acting as a transmitter/receiver) forming a “light barrier” aimed at detecting the passage of people at the input–output gates of the vehicle. Alternatively, a single *pyroelectric* IR (PIR) sensor can be used, which detects the IR radiation emitted by the human body in the wavelength range 2–14 μm . To enhance reliability, the combined installation of IR/PIR sensors can also be conceived. Although IR sensors are very frequently used in PT systems, with counting accuracy generally well above 90% [94], their performances worsen when multiple people board through the same door simultaneously [95], [96]. Moreover, installation could be expensive since, typically, more than one barrier per door is needed to detect the passenger flow.

B. Pressure/Load Sensors

Another solution commonly employed in traditional APC systems counts the number of passengers boarding or alighting buses or trams by means of pressure-sensitive switches (“treadle mats”) placed on the vehicle steps, which are activated under the effect of the passenger weight. These solutions are simple, accurate (above 95%), and rugged, ensuring long operational life: installation of multiple treadle mats over different steps allows one to discriminate between infeed/outfeed motion [4]. An innovative pressure sensor is the Velostat/Linqstat one, which is a carbon-impregnated conductive polymeric foil that can be used as a low-power inexpensive pressure sensor. Such a sensor has been adopted in [97] to implement a system aimed at monitoring seat occupancy in a bus.

Another application of pressure/load sensors, placed on the ground or the suspensions, is in *weigh-in-motion* (WIM) systems, which estimate the number of passengers by the loading of the vehicle detected before and after the stops. Since most of the modern trains are equipped with electronic weighing sensors providing information to the braking system, a WIM solution exploiting such sensors has been proposed and implemented in the Copenhagen metro system [98]. In [99], two algorithms for passenger counting are proposed, which estimate the passenger load based on the pressure variations of vehicle air ride suspensions, which are commonly employed in almost all modern transit buses. WIM systems represent a convenient solution to measure crowdedness inside vehicles, even though it can be difficult to infer the actual number of passengers boarding or alighting [4].

TABLE III
TAXONOMY OF SENSING TECHNOLOGIES FOR CROWD MANAGEMENT IN PT SYSTEMS

	Technology	Frequency	Max range	Power consumpt. ^a	User cooper.	Accuracy	Processing complexity	Cost	Privacy issues	Scenario
Visual-based	Optical	Visible	100 m	Low	No	High	High	High	Critical	All
	Thermal	Infrared	500 m	Low	No	High	High	High	Moderate	Railway/metro station, bus/tram stop
	LiDAR	Ultraviolet, Visible, Near infrared	1 km	Medium	No	High	Medium-high	Medium	Moderate	Railway/metro station, bus/tram stop
	SAR	Ku/Ka band	10 m	Very high	No	High	High	High	Moderate	Bus/tram stop
Non-visual based	IR/PIR	Infrared	10 m	Very low	No	High	Low	Medium	Low	Bus/tram
	Pressure	Mechanical	Contact	Very low	No	High	Low	Medium	Low	Train and bus/tram
	Acoustic	0.01–100 kHz	20 m	Low	No	Low	Low	Low	Moderate	Train and bus/tram, railway/metro station
	IR-UWB	3.1–10.6 GHz	100 m	Low	No	High	Low	Medium	Low	Railway/metro station, bus/tram stop
	RSSI/CSI	Various	Variable	Very low	No	Medium	High	Low	Low	Railway/metro station, bus/tram stop
	RFID	13.56 MHz	10 cm	Very low	Yes	High	Low	Medium	Critical	Train and bus/tram, railway/metro station
	NFC	13.56 MHz	10 cm	Very low	Yes	High	Low	Medium	Critical	Train and bus/tram, railway/metro station
	Bluetooth	2.4 GHz	50 m	Very low	Yes	Medium	Low	Low	Critical	Railway/metro station, bus/tram stop
	WiFi	2.4/5 GHz	100 m	Medium	Yes	Low	Medium	Low	Critical	Railway/metro station, bus/tram stop
	LTE	800/1800/2600 MHz	10 km	High	Yes	Low	High	Medium	Moderate	Railway/metro station, bus/tram stop
5G	Sub-6 GHz	10 km	High	Yes	Low	Low	Medium	Moderate	Railway/metro station, bus/tram stop	
5G	MMW band	1 km	High	Yes	Medium	Low	Medium	Moderate	Railway/metro station, bus/tram stop	

^a Power consumption refers to a single sensor.

C. Optical Cameras

Optical cameras are widely used in private and public spaces for surveillance and security, such as in closed circuit television (CCTV) systems, and are routinely installed inside PT vehicles and stations to this aim. Since often they can support crowd monitoring functions with firmware/software upgrades, optical cameras are among the most versatile and used techniques for crowd analysis [87], [100]. Most works on crowd counting and detection based on optical cameras rely on computer-vision technologies [95], [101], [102], in which crowds are detected using specific features, e.g., facial recognition or motion tracking, extracted from images/videos. Moreover, the majority of recent works employ AI or ML/DL algorithms [103].

Camera-based solutions can be applied in all transportation scenarios, both indoor and outdoor ones. Video cameras mounted inside road or rail vehicles can be used to estimate the number of passengers and their flow (i.e., whether they are boarding or alighting) [95], [104], [105], [106]. An image-processing technique based on a modified Hough transform is proposed in [104], aimed at detecting the contour features of heads and estimating accordingly the number of passengers and their flow in a bus. Many recent approaches are based

on CNNs, such as the passenger counting system proposed in [107], which also exploits the spatiotemporal properties of video sequences acquired on a PT bus in China, or the solution proposed in [108], where crowd density inside a bus is detected and classified in five different levels (from very low to very high), to be displayed by LCD screens installed at the bus stops. A deeply recursive CNN-based solution is proposed in [109] and tested on a dataset of images taken at the bus rapid transit (BRT) in Beijing, China. A neural-network-based crowd density estimation algorithm is described in [110], targeted at underground station platforms, which has been experimentally tested on a sequence of CCTV images acquired at a metro station in Hong Kong. Finally, VB techniques for counting people at bus stops are proposed in [111] and [112], based on computer-vision techniques, which process measurements of foreground areas corrected by suitable perspective transformations.

In summary, crowd analysis based on optical sensors is versatile and powerful but has several limitations: camera sensors, indeed, are expensive, and each camera can only cover a small area, resulting in high deployment costs in complex and/or large environments. In some scenarios, optical camera-based systems do not allow to estimate the number of

people with sufficient accuracy, due to possible obstructions, clutter, and poor light/weather conditions. Moreover, crowd analysis techniques based on images require a high computing power. Finally, the management of optical camera-based systems might be cumbersome, due to privacy-related restrictions.

D. Thermal Cameras

Thermal cameras can detect people in low-light environments, complete darkness, or other challenging conditions, such as smoke-filled and dusty environments [113]. Thermal imaging cameras are currently used in some countries to prevent accidents and infrastructure damage in PT systems, detecting, for example, people walking on the tracks or fire events. This technology, however, can be employed also to monitor crowding situations both in indoor and outdoor scenarios.

Some people counters based on thermal cameras are proposed in [114], [115], and [116]. Different from optical cameras, people counters based on thermal cameras are less sensitive to the level of ambient lighting or background color contrasts, but their performance can be adversely affected by heat sources and weather conditions. In addition, real-time image processing can be computationally intensive. The high costs of instrumentation still limit the widespread use of thermography for crowd monitoring.

Recently, hybrid approaches, combining thermal and optical imaging sensors, and intelligent processing (based on DL and CNNs), have been implemented to improve the accuracy and real-time processing of camera-based systems [117], [118]. In [119], a people counting algorithm is developed, which uses low-resolution thermal images and employs small-size CNNs, being able to run on a limited-memory and low-power platform.

E. Light Detection and Ranging

Another option to detect and track persons is represented by light detection and ranging (LiDAR) sensors, especially in environments where there are several interacting people [120]. A LiDAR sensor is a distance-measuring system that works by illuminating the target with a laser beam and sensing the reflected laser light. There are different implementations of LiDAR sensors based on their coverage area and wavelengths.

Compared to traditional VB approaches, LiDAR is less sensitive to varying lighting conditions and requires, in general, lower data-processing times. Due to these features, LiDAR-based counting systems are suitable for all transportation scenarios, both indoor and outdoor.

A real-time 2-D LiDAR monitoring system for people counting is proposed in [121], which turns out to be useful in monitoring wide areas and dense groups of persons. The solution proposed in [122], instead, employs two LiDAR sensors set at different heights, aimed at detecting people's heads and knees, to improve the tracking performance. To increase the system accuracy, other solutions use 3-D LiDARs: in [123], for example, a technique for people counting is presented, which works well even if two or

three persons pass at the same time. However, an important limitation of 3-D LiDAR is represented by its computational cost, which can be even higher than optical camera-based solutions.

F. Acoustic/Ultrasound Sensors

Acoustic sensor-based approaches perform people counting by relying on audio signals transmitted by smartphones or produced by speaking people [90]. A crowd counting solution based on audio tones is presented in [124], leveraging the microphones and speaker phones available in most mobile phones. Effectiveness is proven through several experiments at bus stops or aboard, which show, however, that counting latency can significantly grow as the number of devices increases; as a consequence, this technique may be appropriate only for low-density scenarios.

Despite their simplicity, the applicability of purely acoustic-based solutions in crowd counting is largely limited by their high sensitivity to the environmental noise level. For this reason, hybrid solutions, employing not only acoustic sensors, have been proposed. In [125], for example, a multimodal sensor network is built, which exploits sound intensity in conjunction with additional information sources, such as carbon-dioxide level and RF link strength, in order to increase the estimation accuracy. Another hybrid solution is presented in [126], which proposes an opportunistic collaborative sensing system, based on acoustic and motion sensors integrated in smartphones.

A different option to count people is represented by acoustic-based solutions using ultrasound sensors, which perform well for indoor spaces and small crowds [90]. When the reverberation of the transmitted waves is received, the number of people can be estimated by exploiting information from the receive time or the signal decay. Based on this approach, an ultrasonic sensing technique for estimating the number of people is presented in [127], which exhibits satisfactory performance when the occupancy of the space does not reach its maximum.

G. Device-Free RF Sensing

Device-free crowd analysis based on RF signals is an emerging technique, which does not require installation of expensive cameras nor does it suffer from privacy-related concerns. It exploits the impact of the monitored crowd on RF communications to infer information regarding the size and/or density of the crowd, either using traditional radar methodologies (range and Doppler analysis) [128], [129], [130], mainly with IR-UWB signals [96], [131], or by analyzing features extracted by channel quality measurements, such as received signal strength indicator (RSSI) [132], [133], [134] or channel state information (CSI) [135], [136], [137].

People counting using RF signals can be used in dimly lit places and in smoky and dusty environments: hence, it represents an interesting solution for metro/subway stations and/or at bus/tram stops. In [96], a people counting algorithm using a couple of IR-UWB radar sensors is proposed, which

was tested in a subway platform in Seoul, South Korea, showing accuracy values higher than 90%. A solution to count the people in a queue, based on RSSI measurements carried out by Bluetooth low-energy (BLE)¹ devices, is described in [138]: the system is completely passive and estimates the number of persons in the queue by analyzing the mean and variance of the RSSI values between a BLE beacon and a receiver covering a certain area.

In general, RSSI-based approaches for crowd analysis exhibit good performances in small monitored environments, where the propagation channel variations are dominated by the attenuation caused by the people actually present in the environment. On the other hand, in a rich scattering environment, crowd analysis approaches based on CSI provide more reliable people counting but are considerably more complex. Belonging to this class, in [136] and [139], the received LTE and Wi-Fi downlink control signals are processed, respectively, to extract the changes of the propagation channel induced by the presence of different number of people: the related counting algorithms exhibit variable levels of accuracy in different scenarios.

Finally, more sophisticated microwave SAR tomography techniques [56], [140] can also be used, which provide specific RF images from which more detailed crowd information can be extracted, by using complex image classification algorithms (i.e., count, distribution, and mobility). Modeling issues induced by the intrinsic near-field scenario (e.g., typical for bus/tram stops) could be overcome using specialized algorithms [141].

In summary, excluding SAR-based techniques, device-free RF sensing is a moderate-complexity crowd analysis technique with low installation costs. Moreover, RF signals can penetrate obstacles to a certain extent and are not affected by weather/illumination. A moderate accuracy (around 80% for RSSI-based techniques, up to 90% and larger for CSI-based ones) can be expected in simple scenarios, but it is questionable whether this approach can be scalable to large crowds, especially in complex propagation scenarios [90]. Moreover, counting algorithms based on this approach usually require a site-specific training phase, which complicates practical installation and maintenance.

H. Device-Aided RF Sensing

In device-aided approaches for crowd analysis, users are expected to carry RF devices, which must be switched ON to enable people counting. Since modern smartphones are ubiquitous and, moreover, are equipped with several sensors and multiple RF interfaces, device-aided solutions are commonly used to gather different types of information for many different purposes and applications (see [90] for a recent review).

1) *RFID and NFC*: RFID-based solutions require that the passengers carry passive RFID tags, whose presence can be detected by a reader. Oberli et al. [142] proposed an APC system for bus vehicles employing commercial

EPC Gen2 tags, which are recognized by a reader located in correspondence of the bus gate. A similar short-range communication system is near-field communication (NFC) [143] technology, which is currently supported by many modern smartphones and tablets. When a device with NFC functionalities appears in the reader's working range, which can be placed at the station gates or at any other fixed access point, it "wakes up" and sends a signal containing encoded data. Finally, it should be observed that RFID and NFC technologies are used in traditional and emerging AFC systems for electronic ticketing, such as MIFARE contactless cards or mobile-based payment systems [144], which can also be employed for passenger counting. For these applications, privacy is characterized by the ability of unauthorized users to trace RFID and NFC devices using their responses to readers' interrogations. Since RFID and NFC devices are typically not tamper-resistant, an adversary can capture them and expose their secret parameters.

2) *Bluetooth*: Bluetooth is a consolidated short-range RF technology, supported by almost all smartphones on the market: crowd monitoring algorithms using Bluetooth have been proposed in several papers (see, e.g., [145] and references therein). An algorithm based on off-the-shelf Bluetooth hardware for counting bus passengers has been proposed in [146] and tested in the city of Funchal, Portugal. The system consists of a Bluetooth scanner mounted on the bus ceiling, which periodically scans for discoverable Bluetooth devices in its range and is aimed at discovering O-D relations by postprocessing data and correlating them with information related to bus location and tickets issued by fare machines.

Bluetooth can also represent an efficient solution for crowd counting at bus/tram stops. A crowd analysis solution based on BLE is proposed in [147], where a large population carries BLE proximity tags, acting as beacons, whose presence is sensed by smartphone carried by few volunteers. A reciprocal solution can be used at bus stops, where BLE beacons are installed at the bus stations and are detected by passenger smartphones in close proximity to the stops.²

Compared to Wi-Fi-based sensing (discussed later), Bluetooth devices are cheaper, less power-hungry, and are characterized by increased flexibility and simplified installation.

3) *Wi-Fi*: Many crowd analysis solutions exploit the characteristics of the IEEE 802.11 (Wi-Fi) protocol, which is widely used by passengers during their trips. The technique adopted in [19] and [21] estimates the current number of passengers in a bus by counting the number of *probe requests*, i.e., medium access control (MAC) addresses, sent by Wi-Fi-equipped devices in the vehicle. A similar approach is followed in [149], where a derandomization mechanism is introduced to counteract software randomization of MAC addresses, recently introduced in many operating systems.

One of the problems inherent to the use of Wi-Fi-based techniques for crowd counting inside vehicles is the ability to distinguish between people outside the vehicle and actual passengers. This issue was tackled in [19] and [21] by filtering

¹BLE is a low energy consumption version of Bluetooth standard, which assures better communication performances with limited power consumption.

²This solution relies on the same technology introduced by Google and Apple in the most recent versions of their smartphone operating systems and is used by many national contact-tracing apps (e.g., Immuni for Italy [148]).

the probes with a sliding window, aimed at removing MAC addresses that were not detected over a longer period of time. In addition, in [149], the received power is also used to discriminate devices that are likely to be outside the bus. The system in [19] and [21] was able to detect only around 20% of the passengers in a real setting since several users may have turned off the Wi-Fi interface. Underestimation of the number of passengers is a common problem for these techniques, which can be compensated by proper calibration of the procedure in each scenario of interest.

The main advantage of Wi-Fi-based techniques is that they allow to track passengers also when they alight the bus, allowing to estimate O–D flows. Wi-Fi-based counting can also be employed in metro/railway stations since access points are typically available in such scenarios.

4) *Cellular*: Similar to Wi-Fi, cellular signals, such as LTE and 5G ones, can be used for device-aided crowd counting, due to their ubiquitous availability and good penetration in indoor environments. Cellular signals could be available in areas where Wi-Fi coverage is not present, such as bus/tram stops, remote, and small railways/metro stations. A cellular-based crowd density estimation method is proposed in [150], which measures the signal strength emitted in uplink by the smartphones of the crowd components and classifies the crowd density in different levels using DL techniques, with an accuracy of 78% when three levels are considered.

In principle, the position of users in a cellular network can be obtained with satisfactory precision by combining knowledge of the serving base station, RSSI values, and triangulation principles [151], which can be at the basis for large-scale crowd analysis. However, this approach is difficult to be used in real time, whereas it is more suited for long-term travel demand estimation [152]. Real-time passenger counting using cellular data is rarely performed, due to several drawbacks: 1) it requires gathering data from different mobile operators; 2) it raises significant privacy concerns; 3) it does not allow one to precisely discriminate passengers from general public in open areas. A breakthrough could be the planned introduction in 5G systems of the millimeter-wave (MMW) band, which will require very small cells: from the viewpoint of crowd analysis, the placement of small cells allows one to more precisely monitor spatially limited areas, such as bus/tram stops.

I. Discussion

In this section, we provide a discussion regarding the applications of the abovementioned sensing techniques in the different transportation scenarios.³

1) *Trains/Buses/Trams*: Such vehicular scenarios are characterized by a well-delimited indoor space with a limited number of accesses (gates). Traditional APC systems [4], [37], [149] count the number of passengers inside vehicles on the basis of various onboard sensors, mainly IR or pressure-sensitive ones. The number of passengers can also be estimated by the number of validated/issued tickets, as in AFC systems,

which, however, requires user cooperation and can provide underestimated results in the case of diffuse fare evasion.

Although solutions based on sensors installed on the vehicles are simple, they require a large initial investment. Therefore, the diffusion of portable and mobile devices between passengers has pushed many researchers to study solutions based on RF techniques (both device-aided and device-free). Summarizing, as also indicated in Table III, even though more sophisticated VB/NVB sensing technologies may be used as well, their usage is not expected to lead to significant innovations in this scenario, compared to traditional solutions adopted in commercial APC systems.

2) *Railway/Metro Stations*: Many crowd monitoring options are available in this scenario since the access to the stations occurs through a limited number of gates. Moreover, CCTV surveillance systems are typically present inside stations and can be used for VB crowd analysis. The access to train platforms is usually governed by turnstiles where tickets/passes must necessarily be validated: thus, IR-based APC or AFC systems could be a reasonable option to count passengers in this scenario. However, this solution only counts people trying to access the platforms, disregarding other people which could walk inside the station for different purposes (e.g., for shopping or leisure). RF-based techniques could suffer from coverage problems, especially within metro/subway stations.

3) *Bus/Tram Stops*: This scenario is by far the most difficult to manage since bus/tram stops are usually located in outdoor spaces, not well delimited by fixed gates. In this case, both VB and NVB sensing technologies can be used, but it is imperative to adopt cost-effective, rugged, and low-power solutions, in order to reduce the maintenance cost. Moreover, solutions that do not require significant infrastructures are preferred since, in many cases, the stops are not equipped with shelters and are indicated by simple poles.

VI. MAIN INNOVATIONS AND ADVANTAGES

The crowd management functionalities of the new framework can provide several innovations and advantages that are not present in state-of-the-art ITSs.

A. Proactive Control of Station Access

In railway/metro applications, based on the knowledge of the number of passengers aboard the arriving trains and the prediction of those alighting at the station, it will be possible to predict the number of accesses to stations/platforms with a low error margin and in real time, so as to avoid crowding. This number can be communicated to 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 considering 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 operators, and teachers/students).

B. Vehicle Access Reservation

In bus/tram trips, a vehicle access reservation system can be implemented. A sensor at the bus/tram stop detects the user

³For a review and discussion of some industrial solutions employing some of these technologies for people counting in PT systems, see [90].

TABLE IV
MAIN ADVANTAGES RELATED TO ADOPTION OF CROWD MANAGEMENT IN PT SYSTEMS

Actor	Advantages
PT service operator (planner, 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, supervisors, staff)	Knowing in advance crowding situations at the stops or stations allows one to tackle in real-time critical situations (e.g., implementing holding or stop-skipping strategies, or following alternative routes)
PT users	Knowing crowding situations allows one to use alternative transportation modes or 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 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 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	An improved QoE of the PT system entails a reduction of private car usage and of pollution in urban areas, with benefits on energy consumption and climate change

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 vehicle (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.

C. Crowding Information Dissemination

Users receive real-time information related to available capacity (in terms of number of seats or in percentage) of the bus/trams/trains in arrival and/or crowding at the stops/stations, so as to avoid unnecessary waiting or crowding and possibly reschedule their trips. Such RTCI can be provided by means of displays installed in correspondence of the stops or at the entrance of the stations, or by messages/alerts issued by mobile transport apps.

D. Crowd-Based Route Planning

Users can plan their trips on the mobile transport app, by considering not only geographical information and traveling times (static data) but also traffic and crowding information about vehicles and stops/stations during the trip (dynamic data). The app may not necessarily suggest the shortest route, but the least crowded one, considering also crowding levels measured during the trip. Such a feature not only helps reduce crowds (and the consequent infection risk in the case of a pandemic) but also improves the passenger QoE, by distributing more efficiently the load on the transportation network.

E. Crowd-Aware Real-Time Control

Some of the typical functions of PT planning and operations can benefit from the availability of new crowd information.

At the strategic and tactical levels, average long-term crowding data can be used to plan the services. At the real time and operational level, critical situations (service disruptions and unusual crowding) or even random spatiotemporal demand variations can be tackled by implementing crowd-aware rescheduling solutions, such as holding, stop skipping, or similar ones, which can be communicated to the drivers and staff in real time, as well as to the passengers via displays and/or alerts.

The main advantages of the crowd management framework are summarized in [Table IV](#). Compared to static methods, like traditional survey-based compilation of O–D matrix flows, 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/DL 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 the other anti-COVID-19 solutions discussed in Section II, the new framework is not aimed at enforcing social distancing measures only. Its scope is wider since it tries to incorporate crowding information to adaptively optimize the overall performance of the PT system. As a by-product, it also allows 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 phases.

VII. MAIN CHALLENGES

In this section, in relation to the proposed reference architecture, we enlighten some of the main challenges to be addressed for the introduction of crowd management functionalities in existing or forthcoming ITS systems. The impact of such challenges on the subsystems of the introduced reference architecture is summarized in [Table V](#).

TABLE V

COLORTABLE SHOWING THE IMPACT OF THE MAIN CHALLENGES ON THE SUBSYSTEMS OF THE INTRODUCED REFERENCE ARCHITECTURE: THE INTENSITY OF THE COLOR VARIES FROM DARKER (MAPPING A HIGHER IMPACT) TO LIGHTER (MAPPING A LOWER IMPACT)

Challenge	SASS	CSS	MPCSS
Cooperative sensing			
Data fusion			
Security			
Privacy			
Communications			
Crowd control			

A. Cooperative Sensing

In NVB cooperative sensing approaches, a large number of users must be engaged to obtain significant amounts of data. Several works [153], [154] have proposed to introduce incentive mechanisms aimed at stimulating user motivation and encouraging participation. A common solution is to let participants earn credits in exchange of their data. However, such a strategy might present some privacy risks, by exposing sensitive data and linking them to users' identities. Several efforts have been made to propose privacy-preserving cooperative sensing approaches (based, e.g., on data anonymization, randomization, and aggregation). An interesting solution is discussed in [155], where a rewarding platform based on a voucher exchange system is proposed, which decouples mobile crowd-sensing instruments from participation incentives. Each voucher is produced as compensation for user's participation, and it is designed to be fully anonymous and not exclusive.

B. Security

As an ICT-based evolution of the state-of-the-art ITSs, the proposed reference architecture strictly relies on ICT infrastructures too, i.e., most of the functions accomplished by the MPCSS subsystem could be implemented using modern cloud technologies. Since every ICT infrastructure can be prone to well-known cyberattacks, security issues are particularly serious in all portions of our reference architecture, mainly due to the large volume of data exchanged among subsystems. A malicious user, for example, could launch a man-in-the-middle attack to the system, by intercepting and altering the content of the exchanged messages between crowd monitoring tools and vehicles, which could entail catastrophic effects in the decision-making phase, especially when self-driving vehicles are involved. Furthermore, denial-of-service attacks could be used to saturate the resources of the infrastructure to completely interrupt the decision-making process.

Security issues related to the IoT paradigm are well known in the literature, but there are some aspects peculiar to

ITSs [156]. In particular, one of the most limiting factors is represented by the scarce computational resources of many sensing devices used in ITSs, which may render the commonly used countermeasures (i.e., cryptography and authentication schemes) infeasible for providing secure communications. The proposed architecture, indeed, is based on a plethora of heterogeneous sensors and devices, which are required to be inexpensive, low energy, and, in some cases, have small form factor. However, energy-constrained sensors are resource-limited in terms of memory, computational capabilities, and communication range. Such constraints greatly limit the use of complex algorithms, useful even to guarantee security and privacy. Therefore, it becomes paramount to adopt energy-aware solutions to prolong the lifetime of the sensing subsystem. In this sense, a promising solution can be ambient backscattering [157], where small passive devices are able to transmit data by reflecting electromagnetic waves transmitted by existing RF transmitters.

C. Data Fusion

The availability of large amounts of data acquired by heterogeneous sensors can pose a challenging problem for crowd monitoring, prediction, and control tools. In the proposed architecture, indeed, the MPCSS subsystem must analyze in real time a large amount of multisource and multimodal data, which are characterized by different levels of resolution, accuracy, reliability, and redundancy. Various DF algorithms, aimed at associating, correlating, and combining information from multiple sensors, are commonly adopted to provide accurate and timely decision-making support. Among the commonly adopted approaches (i.e., statistical, probabilistic, and data-driven ones [58]), probabilistic-based methods seem to be more suitable in our scenario. In particular, Bayesian approaches, maximum likelihood methods, and Kalman filter-based DF techniques can be utilized for multisensor DF [158].

D. Privacy

Privacy is one of the major issues related to sensing technologies for crowd management. In what follows, VB and NVB techniques are discussed separately since they involve different privacy concerns that can be overcome by resorting to radically different technical solutions.

VB solutions must be designed to implement data protection principles, collectively referred to as *privacy-by-design*, set out in international data privacy laws. For crowd counting and crowd density estimation, identification is not necessary. Therefore, for such applications, *privacy-by-design* can be achieved by suitably choosing resolution and other modifiable factors of VB devices to ensure that no recognizable facial images are captured. In addition to *privacy-by-design*, some data privacy laws also mandate *privacy-by-default*. Under such an obligation, personal data collected through VB approaches must be used only for the specific purpose of crowd management. This means that the minimum required amount of personal data should be collected, their processing should be minimized, and their storage and accessibility

should be controlled. A viable approach to ensure privacy-by-default consists of turning VB feeds featuring individuals into numbers and heatmaps in such a manner that the data subject is not or no longer identifiable. Within the European Community, such countermeasures allow VB solutions to comply with the GDPR, which is one of the most restrictive legislations in the world in terms of safeguarding citizens' privacy.

Regarding NVB solutions, sensing solutions based on mobile RF devices pose important privacy issues, especially for device-aided crowd monitoring. Apart from the issues regarding participatory sensing, which have been discussed previously, many device-aided RF-based NVB techniques basically perform monitoring of over-the-air beacon signals sent by individuals' smartphones when they connect to a network or install an application. In this case, to extract relevant features for crowding information, processing of devices' IDs is required, e.g., MAC addresses in Wi-Fi networks. Most RFID tags emit unique identifiers when they respond to reader interrogation, even tags that protect data with cryptographic algorithm [159]. A similar problem arises for Bluetooth-enabled wireless devices [160], as well as for the NFC protocol that is based on the transfer of an ID for anticollision during the process of contactless reading of transponders [161]. Although cryptographic techniques can be used to transform ID data to preserve privacy, thereby complying with the GDPR, they are computationally intensive and require the generation and maintenance of multiple keys, which also leads to higher energy consumption. Alternatively, devices' IDs can be aggregated or perturbed in such a way that individual data privacy is preserved, but, at the same time, useful information for crowding management is not destroyed. In the case of Wi-Fi networks, a viable solution is represented by MAC address randomization [162], which is an available option in different operating systems, such as iOS, Android, and Windows. However, although it is compliant with the GDPR, some crowd counting methods are adversely affected by MAC address randomization.

A cutting-edge future research direction might be exploiting the mathematical concept of differential privacy [163], which addresses the challenging goal of learning nothing about an individual while learning useful information about a population. This is in accordance with existing data protection laws, including the GDPR. However, the feasibility of applying differential privacy approaches to crowd management remains an open topic of research. Device-free NVB solutions, both based on RF or other physical properties (such as audio or ultrasound signals), are less harmful to an individual's privacy since they do not require processing of devices' IDs and, thus, according to the GDPR, they do not collect personally identifiable information that could potentially be used to identify a particular person during people counting activities. This pushes toward emerging NVB techniques using reflected-power approaches [164], also referred to as passive NVB solutions, which reuse existing over-the-air signals to count people or estimate their flow, by viewing the signals as power carriers rather than information ones.

E. Communications

A constant stream of up-to-the-minute data can help PT system operators stay one step ahead of crowd situations. However, with limited budgets and compressed time frames, implementing a state-of-the-art CSS can present fundamental challenges. There are three basic challenges regarding ITSs based on acquisition and processing of large amounts of sensor data: bandwidth, latency, and heterogeneity of data and infrastructures.

A first critical issue is represented by the significant bandwidth demand to connect thousands of devices and support hundreds of real-time video feeds, along with data gathered from ubiquitous sensors. A potential approach to fulfill such a bandwidth demand is offered by the unlicensed band technology, which has attracted significant effort during the last decade. In particular, the new radio unlicensed (NR-U) technology appears to be particularly suited for ITS applications [165] since it considers multiple bands and other deployment scenarios, such as dual connectivity and standalone operation in unlicensed bands.

In addition to bandwidth, since some crowd management decisions are time-sensitive in nature, latency is another key performance indicator of the CSS. Cloud computing at the edge of the network [166], namely, close to railway/metro stations, bus stops, and ITS sensors, can provide a solution for satisfying latency and bandwidth constraints, thus avoiding unacceptable upload delays as well as energy consumption of IoT sensors. In those scenarios, when there is no edge server nearby that can offload the tasks, employing UAVs is a promising solution by serving as computing-communications edge server for resource-constrained IoT devices [167]. One can imagine a hybrid communication architecture for future ITSs where edge nodes locally process the time-critical raw sensed data, while non-time-sensitive data are transmitted to the cloud.

From a communication viewpoint, an ITS is a heterogeneous network, where a huge number of devices are connected to global networks using multiple technologies and platforms (i.e., cloud, edge, and wireless), with various intelligence levels. Traditionally, communication between different wireless technologies is achieved indirectly via gateways equipped with multiple radio interfaces, which will become a bottleneck when many heterogeneous IoT devices are deployed. Cross-technology communication (CTC) opens a new direction of direct communication among different wireless technologies when they operate in the same spectrum band [168]. These technologies are purely a software-based solution, requiring no hardware modification.

F. Crowd Control

A significant research effort is studying how to optimally employ (possible heterogeneous) crowding data to optimize (at the various levels) the PT system behavior. Suitable performance metrics must be defined, as well as optimization methodologies, especially when applied to large-scale complex PT networks involving thousands of vehicles and stations/stops. Indeed, in many papers, crowd control strategies

are localized, i.e., they are applied only to single lines or to a small portion of the network, whereas obviously crowd control must be applied holistically to the whole PT network. As an example, stop skipping can solve the problem of single-vehicle overcrowding but can negatively affect crowding at the stops or metro platforms. To perform complex system-wide optimization, it seems difficult to apply model-based approaches. Thus, the preferred choice should be resorting to techniques such as data mining, AI, or ML/DL, along the vision of *data-driven* PT systems [169]. An interesting issue is to assess the impact of inaccurate crowd monitoring/prediction measurements due to sensing on optimization strategies, in order to devise robust techniques. Another interesting development is how to incorporate crowding data in existing simulation tools for transportation planning, such as BusMezzo [76] or SUMO [77].

VIII. CONCLUSION AND DIRECTIONS FOR FUTURE WORK

A clean, smart, and resilient PT system is at the core of worldwide economies and is central to people's lives: this is why there have been an increased number of research articles that discuss the feasibility of integrating ICT/IoT sensing solutions in ITSs. In this article, we have reviewed the main ICT/IoT sensing technologies for crowd analysis, showing also how they can be adopted in a reference architecture aimed at introducing innovative crowd management functionalities in legacy ITS systems. The new 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. A series of challenges arises from the proposed reference architecture, such as incentive mechanisms for user cooperation, DF and processing of heterogeneous data, security, privacy, broadband and ultralow latency communications, and system-wide optimization of crowd control strategies.

Some features of the new framework are similar to those of a contact tracing system, which can be implemented more easily by resorting to 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 (such as 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 a PT system. However, the more appropriate crowd monitoring solution must be singled out case-by-case, in dependence on the scenario, the ICT infrastructure owned or leased by the PT operator, the socioeconomic context, and the cost–benefit ratio. The potentials of crowd management go beyond the scope of dealing with typical social distancing problems, by also allowing real-time optimization and adaptive management of PT systems.

Finally, the study of the open literature makes it clear that an in-depth performance analysis of the sensing techniques for PT systems reported in Table III has not yet been

carried out in each considered scenario. Therefore, the first interesting research development consists of performing a comparative statistical performance evaluation (numerical and/or experimental) of such sensing techniques for each outlined indoor/outdoor scenarios. An additional research issue is to carry out a performance analysis of the DF algorithms for associating, correlating, and combining information from different sensors, whose accuracy is crucial to provide effective actions.

ACKNOWLEDGMENT

The authors would like to thank the IEEE ComSoc/VTS Italian Chapter for supporting this work, by awarding the first prize to the SALUTARY (Safe and Reliable Public Transportation System) system concept within the call for ideas in response to COVID-19 outbreak in Italy.

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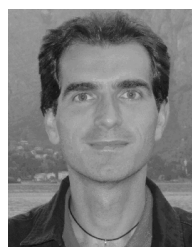
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