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Diagnosis of Irregularity Sources by Automatic Vehicle Location Data

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Abstract—In high frequency transit services, irregularity is unavoidable due to the stochastic context in which bus services are operated. As a result, the measurement of the regularity and the identification of possible irregularity sources provide an opportunity to maintain scheduled headways. As far as the authors know, the irregularity was typically investigated from data on scheduled and actual arrival (or departure) times at bus stops. However, information has been seldom inferred on arrival and departure headways between two consecutive bus stops. Since it is difficult to maintain the planned timetable with short headways, this paper proposes an offline framework to measure the regularity over all bus stops and time periods and disclose the most common irregularity sources from collected Automatic Vehicle Location (AVL) data. Easy-to-read control dashboards show the viability of this framework on a real bus route-direction with about 124,500 AVL data records. Therefore, transit managers would benefit from using this framework to make accurate regularity analysis and possible service revisions.

I. Introduction

While in low frequency transit systems, punctuality (*i.e.*, the adherence to timetable) is an appropriate time reliability facet [1]–[2], in high frequency transit systems, the regularity (*i.e.*, the adherence to headway) is a crucial time reliability factor for both users and transit operators [3]–[4]. Irregularity for users is associated with bunching phenomena or large gaps among buses, which result in a low appeal of the service for transit operators. Therefore, characterizing (or measuring) the regularity and observing irregularity causes are crucial steps to determine which are the related intervention areas (or irregularity sources) for addressing the irregularity. Sometimes a cause depends on more than one source, thus it is extremely desirable to understand the most relevant connections between observed causes and a complete list of systematic irregularity sources for any high-frequency route. This understanding is crucial and provides an opportunity to keep bus headways as planned.

On the one hand, the analysis of irregularity has captured the attention of academics and transit operators. Generally speaking, theoretical models have investigated the impact of passengers on headway regularity along the route (*e.g.*, [5]–[7]). However, transit operators do not eagerly adopt models, since practical and operational considerations arising in a specific case study cannot usually be taken into account (*e.g.*, rules negotiated with trade unions). On the other hand, measuring the regularity is technologically feasible by Automatic Vehicle Location (AVL) systems, which are commonly adopted by transit operators worldwide and can collect an abundance of disaggregated data on the delivered service [8]. As a result, transit managers can concentrate their efforts on areas where targets are not met. The studies on the irregularity by AVL concern two main research areas: the online (real-time) analysis and the offline (archived) analysis. In the first area, one aims to develop control strategies to mitigate irregularity phenomena due to bus bunching (*e.g.*, [9]–[13]). In the second area, one analyses AVL data to set bus schedule coverage and dispatching headways (*e.g.*, [14]–[16]), or understand which elements contribute to the observation of irregularity.

This paper aims to improve this understanding. Many studies have so far used AVL archived data to analyse the regularity by inferential (*e.g.*, [17]–[18]) or descriptive (*e.g.*, [19]–[27]) models and provide quantitative monitoring of service. In addition, regularity-driven operations could be used to adopt real-time control strategies [28].

This paper moves from an existing study on the analysis of time reliability [29] in order to investigate the regularity for high frequency routes. A new framework based on archived AVL data is proposed to pursue this objective. This framework is organized in two stages denoted by A and B, respectively. In stage A, one characterizes bus stops and time periods in which the regularity is not met. In stage B, one discovers the irregularity sources starting from the measurement and the causes observed in the specific route at hand. Although stage A uses algorithms successfully applied in [2], [21], [22] and [29]–[30] for the characterization of reliability, stage B advances the studies of [23] and [31], which focused on a limited subset of bus stops and time periods, and differs from [19]–[20], as it provides the analysis of bunching and large gaps together. Moreover, stage B removes the assumption of finding irregularity sources by the quantification of scheduled and actual times, because, if the actual service adheres to the scheduled time, it also adheres to the scheduled headway. This *modus operandi* may be troublesome in high-frequency routes in which buses run with short headways, and it is difficult to maintain the planned timetable, which is not very satisfying for passengers. Indeed, in this type of routes, passengers are assumed to arrive at bus stops independently from published timetables and actual vehicle arrivals. Moreover, passengers are usually supposed to board on the first vehicle (*i.e.*, no pass-ups) to minimize their waiting time, which is headway-dependent. As a result, it may be more effective to analyse the irregularity causes and sources by comparing arrival and departure headways between two consecutive bus stops. Moreover, easy-to-read control dashboards present the outcomes through tables and diagrams organized in time and space attributes.

Although a preliminary study was presented in [32], this framework differs in two crucial points. At a methodological level, it investigates for the first time the links among problems, causes and sources of irregularities. At an experimental level, this framework is tested with a huge amount of AVL data. Hence, this large experimentation provides detailed analysis and more solid understanding on causes and sources of irregularity.

This paper is organized as follows. Section 2 in-depth reviews previous studies on regularity diagnosis, which were neglected in [32]. Section 3 proposes a framework to analyze regularity and detect irregularity sources for any high frequency route. Unlike [32], Section 4 illustrates the experimentation of this framework on a more comprehensive real case study. Finally, Section 5 draws conclusions and offers research perspectives.

II. Prior Work

Regularity is a facet of time reliability. Therefore, according to [29], the analysis of regularity by archived AVL data can be organized as follows:

1) *Characterizing the regularity*, *i.e.*, including key data inputs, calculating additional attributes from inputs, describing service measures, setting bus-operator-dependent thresholds and generating performance reports.
2) *Identifying possible irregularity problem sources, i.e.*, detecting the intervention area for addressing the characterized irregularity problem.

A. Regularity Characterization

In this section, the steps on regularity characterization are briefly listed and related studies are mentioned.

- Data input is provided by collected data, which contain details on time and location. Data input may be mainly available through manual surveys or automated collection systems (*e.g.*, [17]–[38]).
- Output calculations are outcomes derived from a pair of data inputs. Typically, they may be headways between two consecutive bus arrivals (or departures) at the same bus stop (*e.g.*, [17]–[38]).
- Service measures are conducted by aggregated metrics to characterize the overall bus service, measure performances and evaluate the service. For example, possible service measures may include headway adherence (*e.g.*, [21], [22], [26], [35], [36]), service regularity [34], occurrence and distribution of bunching and other metrics (*e.g.*, [17]–[19], [23]–[25], [27]). Synthetic metrics can be expressed in terms of mean values and variance, coefficient of variation and the percentage of observation, because all of them are widely used, well-understood and clearly represented by quantification.
- Thresholds set the acceptability of output (*e.g.*, the calculation of a regular bus arrival at stop) and that of service measures, such as the LoS (*e.g.*, the percentage of regular buses [34]). Thresholds settings for regularity diagnosis can be found in (*e.g.*, [20], [34]).
- Performance reports are built by dashboards visualizing results and possible intermediate outcomes. They can be shown by tables or diagrams (*e.g.*, [19]–[22], [26]).

An accurate data collection process is generally recommended. In the case of manual collection, one has typically little input data and the inference of conclusions is quite problematic. In the case of AVL data collections, despite data abundance, additional processing is required to adjust data anomalies. They are missing data points, such as Technical Failure (TF) and Incorrect Operation in the Service (IOS), and Bus Overtaking (BO). A TF is a failed registration in AVL data, whereas a bus generates an IOS whenever it does not arrive at a bus stop. Conversely, BO is a swap of buses with respect to the original schedule. It is worth noting that TF is a matter of AVL architectures, regardless of the architecture type. Conversely, BO and IOS are more related to operations within the service. In any case, BO, TF and IOS always affect raw AVL data and they need to be recognized and adjusted before computing the measure, especially for high-frequency routes ([2], [21], [22], [29], [30] and [37]). To the best of our knowledge, data anomalies were totally or partially ignored in [17]–[20] and [23]–[26].

B. Identifying Possible Irregularity Sources

As far as the authors know, two types of approaches have been adopted for understanding irregularity sources from archived AVL data: inferential and descriptive statistics models. The first type aims to look for variables explaining irregularity phenomena [17]–[18]. The latter makes use of descriptive models to provide quantitative monitoring of service irregularities [19]–[26].

Inferential models are suitable for long-term analysis. However, they present some drawbacks. First, they did not report discussion and analysis on any AVL anomalies before calculating related measures (*e.g.*, headways between buses). Second, these models may use explaining variables, which might not be available in other case studies. Third, these studies did not perform disaggregated analyses at each bus stop and time period of a route. Even if previous models collected and analysed data at a trip level, they performed aggregated analyses clustering bus stops and time periods. However, a route may present criticalities in some parts and a more detailed analysis should be implemented to support bus operators.

Descriptive models present some drawbacks as well. First, [19] and [25] performed the analysis of bunching using time-space trajectory graphs, but this *modus operandi* is inappropriate for the identification of recurrent irregularity problems over a long time period when huge amounts of data are used. Second, [19] considered departure headway and analyzed bus bunching only. Moreover, [19] considered some possible causes, which are related to the previous and the following buses, and detected the causes through measures of late and early scheduled departure time, as in the case of low frequency routes. Third, even if [32] performed the concurrent analysis of arrival and departure headways, no studies investigated the links between causes and sources. This paper covers this gap. In addition, even if the framework of [29] can be used to detect irregularity sources, it adopted scheduled and actual arrival (or departure) times as input. However, when buses run with short headways (fewer than 10–12 minutes [2] and [29]–[30]), it is difficult to maintain the planned timetable, and a careful analysis of observed causes on poor headway adherence is required to understand the irregularity sources along a high-frequency route.

The separation between observed irregularity causes and irregularity sources for possible interventions has not been clearly investigated in the literature. For example, Cham [38] investigates only irregularity causes: schedule deviations at terminals, passengers loads, running times, environmental factors and operator behaviour. However, operator behaviour could be seen as an irregularity source of running times, when scheduled speeds are ignored. Additional causes may include inappropriate recovery time at the terminal, absenteeism and/or schedule disinterest of the operator, high and low passenger volumes at stop, vehicular or pedestrian traffic, weather, signalized junctions and work in progress, *etc.* Ceder [4] listed a number of problems associated with clear-cut intervention areas and, thus, they can be viewed as problem sources. He made the following list about: (i) uncertainties in the operating environment; (ii) lack of suitable data for efficient operations planning; (iii) improper service design; (iv) improper service monitoring and control; and (v) failures in executing designed schedules. This classification has been reorganized by [29] in the specific case of available rich data on operation planning (*e.g.*, AVL data) as follows: (i) Improper Service Design (ISD); (ii) Driver and/or Supervisor Failures (D&SF); (iii) Uncertainties in Passenger Volumes (UPV); and (iv) Uncontrollable External Factors (UEF). Although this list looks straightforward, it is well adopted and understood by transit managers. Moreover, sources could be linked to strategies classified according to their type and their applications. For example, some strategies are presented in [29].

To summarize, a gap exists on the identification of systematic irregularity sources. This paper is in the area of descriptive models and develops a method to identify and analyze spatial-temporal causes and derive related sources using archived AVL data.

III. Methodological Framework

This section illustrates the regularity control framework and it is organized as follows:

A. Characterizing the regularity;

B. Identifying (*i.e.*, detecting and evaluating) the magnitude of irregularity problem sources from observed irregularity causes by AVL data.

These stages interact with each other according to the scheme illustrated in Fig. 1. It shows how to switch from irregularity problem measures to problem causes, and to a complete list of problem sources. Problem measures show when and where irregularity problems occur. The most common causes are reported in the central column of Fig. 1 and are linked to the candidate problem sources reported in the right side of Fig. 1. It is worth noting that, even if additional connections may be reasonably considered, this paper focuses only on those, which can be inferred from a standard AVL data architecture.

Irregularity causes and their links to problem sources are described more precisely hereafter.

- Recovery times at terminals are planned for drivers as they are expected to begin the next run as scheduled. The primary role of recovery times is to adsorb possible

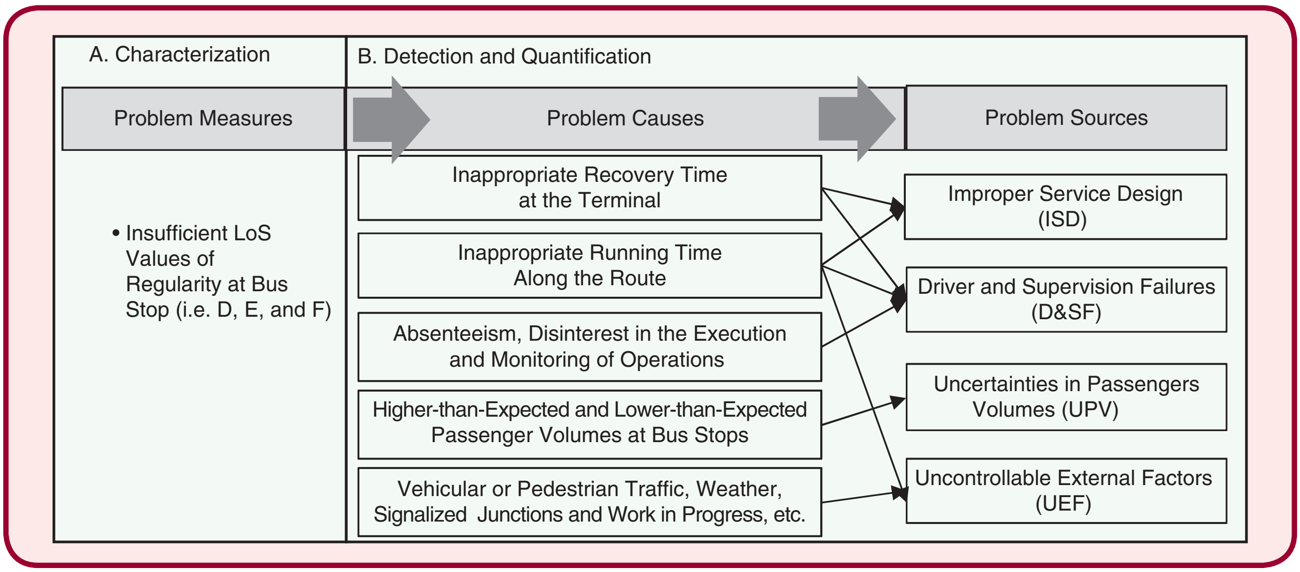

FIG 1 Measures, and links between causes and sources of irregularity.

irregularity (*i.e.*, a late arrival of a run at the terminal). Moreover, as a secondary role, recovery times are provided to afford a short break for drivers. However, scheduled recovery times may be different from actual ones. As a result, vehicles may start the new run with short or long headways, which may be originated by ISD or D&SF. UPV is not supposed to affect recovery times at terminals in high-frequency routes because more than one vehicle may be available at terminals, and passengers can choose the most suitable for them. Moreover, UEF is not supposed to be an irregularity source for the new run, since it already occurred in the previous one.

- Running times are planned to provide a safe, comfortable and efficient service for drivers, passengers and bus operators along the route. However, planned running times may be different from the observed ones because of ISD, UEF and D&SF. Although UPV does affect running time, this link is not considered in this analysis because we focus on sources between bus stops. Nevertheless, a specific problem cause is associated with UPV at bus stops.
- Correct service execution involves adherence to headway by efficient monitoring, and expected passenger volumes guarantee a satisfactory distribution of passengers among buses. However, if this is not the case, D&SF and/or UPV may occur.
- Vehicular or pedestrian traffic, weather, signalized junctions and work in progress may heavily interfere with the execution of the service. In this case, UEF is supposed to occur.

Fig. 1 shows that an irregularity source may be generated by several causes. Therefore, it is crucial to recognize the dominant source resulting in the observed cause. This recognition is performed in the framework by a proper analysis of the deviations from planned attributes, such as available recovery time, headway, time spent and planned speed. This analysis involves the current bus stop, the previous one and the leg between them. In this paper, a source is supposed to be dominant when its relative frequency is larger than 50% in a time period and bus stop.

The overall notation is summarized in the Appendix.

A. Characterizing Service Regularity

First, AVL data are collected from a database on the provided service concerning a high-frequency route. The main data provided by a standard AVL system are date, route, trip number, bus stop code and order, actual and scheduled transit times and, finally, the real time spent in a pre-defined area around each bus stop, or the dwell time, depending on the specific AVL architecture.

Second, since AVL data are not ready for use as they are, the framework performs proper handling on data anomalies to account for BO and distinguish among missing data points (*i.e.*, TF or IOS), according to [2], [21], [22] and [29]–[30].

Third, the actual and scheduled headways are computed as the difference between two consecutive bus arrival (or departure) times. The actual headways need different analyses, depending on the occurrence of TF and IOS. TF cannot be used to compute real headways due to the missing information on bus arrival (or departure) times occurring for real. Conversely, actual headways are computed in the case of IOS, because passengers suffer these headways for real.

Fourth, the regularity measure is obtained by the computation of the coefficient of variation of headway (C_{vh}). It is defined as the ratio between the standard deviation of the differences between actual and scheduled headway and the average of scheduled headway. The C_{vh} is calculated for all bus stops and time periods and is matched with a LoS in order to show which segments of the route do not attain a sufficient regularity level [35]–[36]. According to [21]–[22], this indicator is chosen as it is objective, penalizes longer waiting time (the input is 100% customer oriented), does not require particular applicability conditions and can be read as a probability of encountering an irregular service.

Fifth, if LoS values report a sufficient mark denoted by A, B or C, the regularity of the service can be considered as acceptable, and no further analysis is required. Conversely, if LoS values report an insufficient mark denoted by D, E or F, the service needs further investigation to understand the possible irregularity sources.

Sixth, AVL processed data are represented effectively using control dashboards organized in space and time attributes, in order to show which time periods and bus stops of the route contain most of the problems and deserve further analyses.

B. Detecting and Quantifying Irregularity Problems Sources

1) Analysis of Irregularity Sources at Terminals

Let A be the set of terminals and J be the set of runs. For each terminal $a \in A$, the departures of two consecutive runs $j \in J$ and $j-1 \in J$ are considered. Let:

- RDT_{aj} be the real departure time of run $j \in J$ at terminal $a \in A$;
- SDT_{aj} be the scheduled departure time of run $j \in J$ at terminal $a \in A$;

Next, for each terminal and run, the real and scheduled departure headways are computed as follows, respectively:

$$HDR_{a(j,j-1)} = RDT_{aj} - RDT_{a(j-1)} \quad (1)$$

$$HDS_{a(j,j-1)} = SDT_{aj} - SDT_{a(j-1)} \quad (2)$$

Since real and scheduled departure headways may be different, for each terminal and run, one may compute their difference as follows:

$$HD_{a(j,j-1)} = HDR_{a(j,j-1)} - HDS_{a(j,j-1)} \quad (3)$$

If $HD_{a(j,j-1)} \approx 0$, the real headway complies with the scheduled headway; if $HD_{a(j,j-1)} \neq 0$, the analysis of the recovery time at the terminal is performed. More precisely, if $HD_{a(j,j-1)} > 0$ buses run with a long gap in the execution of their service, whereas if $HD_{a(j,j-1)} < 0$ buses run with a short gap (bunching). Since long and short gaps represent irregularity problems, we then focus on their analysis. As real recovery times may be different from scheduled ones, it is important to derive the available recovery time. Let:

- SDT_{aj} be the scheduled departure time at terminal $a \in A$ for run $j \in J$;
- $RAT_{a(j-1)}$ be the real arrival time at terminal $a \in A$ for run $j–1 \in J$.

Next, for each terminal and run, the available recovery time is computed as:

$$ART_{aj} = SDT_{aj} - RAT_{a(j-1)} \tag{4}$$

The analysis of the headway deviation at the terminal and that of the available recovery time are crucial for detecting irregularity sources, because they may result in additional irregularity in the next run. Their combined analysis helps understand if irregularity mainly depends on ISD or D&SF. Nine different cases can be obtained, as shown in Table I, according to the sign of $HD_{a(j,j-1)}$ and ART_{aj}. Each entry in Table I shows the type of possible irregularity source or reports the string as "ok" when a good performance is obtained. For each entry in Table I, one can compute the related magnitude in terms of percentage values.

For each terminal and run, the notation ≈ 0 must be read as:

$$\alpha \leq HD_{a(j,j-1)} \leq \beta \tag{5}$$
$$\gamma \leq ART_{aj} \leq \delta \tag{6}$$

where α, β, γ, and δ are numerical thresholds set up by the bus operator and represent the minimum and maximum acceptable values of $HD_{a(j,j-1)}$ and ART_{aj} for each terminal $a \in A$ and run $j \in J$.

Table I shows that some critical combinations may occur.

- If $HD_{a(j,j-1)} < 0$ or $HD_{a(j,j-1)} > 0$ and $ART_{aj} < 0$, drivers do not have the available recovery time for the new run. As a result, the new runs fail to comply with the scheduled headway. The problem is ISD.
- If $HD_{a(j,j-1)} < 0$ or $HD_{a(j,j-1)} > 0$ and $ART_{aj} > 0$, drivers have sufficient recovery time to start the new run according to the scheduled headway, but they start bunched ($HD_{a(j,j-1)} < 0$) or overly spaced out ($HD_{a(j,j-1)} > 0$). Therefore, in this case, the problem depend on driver behaviour or the lack of public transport company supervision (D&SF).
- If $HD_{a(j,j-1)} \approx 0$ and $ART_{aj} \approx 0$ or $ART_{aj} < 0$, even if drivers do not have sufficient recovery times, according to their primary role, public transit operators assure the regularity between buses. Thus, drivers can begin his/her trip in order to maintain the planned headway. This represents a favourable condition in high frequency services, as passengers are more interested in buses adhering to headways rather than timetables. Conversely, if $ART_{aj} \approx 0$ and $HD_{a(j,j-1)} < 0$ or $HD_{a(j,j-1)} > 0$, irregularity problems occur. They may be a mix of ISD or D&SF. Besides, if one would better distinguish between ISD and D&SF, the following rules can be adopted. If 1) $\gamma < ART_{aj} < 0$ the problem source is ISD, whereas if 2) $0 < ART_{aj} < \delta$, D&SF is detected. Hence, the former collapses in the cases of $ART_{aj} < 0$, whereas the latter collapses in the cases where $ART_{aj} > 0$. Both cases are reported in Table 1.

Table I. Possible irregularity sources at the terminal.

	$HD_{a(j,j-1)}$		
ART_{aj}	< 0	≈ 0	> 0
< 0	ISD	ok	ISD
≈ 0	ISD or D&SF	ok	ISD or D&SF
> 0	D&SF	ok	D&SF

2) Analysis of Irregularity Sources En-Route

Let N be the set of all bus stops (including terminals) and J the set of runs. Consider a bus stop $n \in N \backslash A$ and a run $j \in J$, which can arrive (depart) bunched, regular or with a long gap with respect to the previous one. In order to understand the causes of irregularity, for each pair of consecutive bus stops $n-1 \in N \backslash A$ and $n \in N \backslash A$ and each pair of consecutive runs $j \in J$ and $j-1 \in J$, one computes the scheduled headway, the real headway and the headway deviation. Let:

- RAT_{nj} be the real arrival time of run $j \in J$ at bus stop $n \in N \backslash A$;
- SAT_{nj} be the scheduled arrival time of run $j \in J$ at bus stop $n \in N \backslash A$.

Next, for each bus stop and run the real and the scheduled arrival headways, as well as their deviations, are computed as follows, respectively:

$$HAR_{n(j,j-1)} = RAT_{nj} - RAT_{n(j-1)} \tag{7}$$
$$HAS_{n(j,j-1)} = SAT_{nj} - SAT_{n(j-1)} \tag{8}$$
$$HA_{n(j,j-1)} = HAR_{n(j,j-1)} - HAS_{n(j,j-1)} \tag{9}$$

Let:

- $RDT_{(n-1),j}$ be the real departure time of run $j \in J$ at bus stop $n-1 \in N \backslash A$;
- $SDT_{(n-1),j}$ be the scheduled departure time of run $j \in J$ at bus stop $n-1 \in N \backslash A$.

Next, for each bus stop and run, the real and the scheduled departure headways, as well as their deviations, are computed as follows, respectively:

$$HDR_{(n-1)(j,j-1)} = RDT_{(n-1),j} - RDT_{(n-1)(j-1)} \tag{10}$$

$$HDS_{(n-1)(j,j-1)} = SDT_{(n-1)j} - SDT_{(n-1)(j-1)} \quad (11)$$

$$HD_{(n-1)(j,j-1)} = HDR_{(n-1)(j,j-1)} - HDS_{(n-1)(j,j-1)} \quad (12)$$

As both bunching and large gaps in arrival (or in departure) for each pair of consecutive bus stops $n-1 \in N \backslash A$ and $n \in N \backslash A$ denote irregularity problems, in what follows, we focus on their analysis, which involves the selected bus stop $n \in N \backslash A$ and the previous $n-1 \in N \backslash A$. More in detail, one computes $HA_{n(j,j-1)}$ and $HD_{(n-1)(j,j-1)}$ according to eqns. (9) and (12), respectively, and analyzes their values. If $HA_{n(j,j-1)} \approx 0$, no further analysis is required as the regularity is assured (*i.e.*, regular headways are kept at the bus stop $n \in N \backslash A$). Therefore, six critical situations may occur for each pair $HA_{n(j,j-1)}$ and $HD_{(n-1)(j,j-1)}$ at bus stop $n-1 \in N \backslash A$ and $n \in N \backslash A$, where $HA_{n(j,j-1)}$ may be positive or negative and $HD_{(n-1)(j,j-1)}$ positive or negative or ≈ 0. A positive deviation means that the real headway is amplified with respect to the scheduled one that is the arriving (or departing) buses are increasing their headways. A negative deviation means that the real headway is lesser than the scheduled one, that is the arriving (or departing) buses are decreasing their headways.

For each bus stop and run, the notation ≈ 0 must be read as:

$$\varepsilon \le HA_{n\,(j,j-1)} \le \zeta \quad (13)$$

$$\eta \le HD_{(n-1),(j,j-1)} \le \theta \quad (14)$$

where ε, ζ, η, and θ are numerical thresholds set up by the bus operator, and represent the minimum and maximum acceptable $HA_{n(j,j-1)}$ and $HD_{(n-1)(j,j-1)}$ values for each pair of consecutive bus stops $n-1 \in N \backslash A$ and $n \in N \backslash A$.

Before analyzing these six critical situations, the proposed method computes the real and scheduled headways on time spent and determines the deviations at bus stop $n-1 \in N \backslash A$, in order to understand if the irregular departure may depend on passenger volumes as well. Although the dwell time can provide information on the volumes of boarding and alighting passengers, the time spent may be related to passenger volumes when less advanced transit operators do not automatically count passengers, or when AVL architectures are conceived to record the time spent in the proximity of bus stops instead of the dwell time. Let:

- $RTS_{(n-1)j}$ be the real time spent of run $j \in J$ at bus stop $n-1 \in N \backslash A$;
- $STS_{(n-1)j}$ be the scheduled time spent of run $j \in J$ at bus stop $n-1 \in N \backslash A$.

Next, for each bus stop and run, the real and the scheduled headways on the time spent, as well as their deviation, are computed as follows:

$$HTSR_{(n-1)(j,j-1)} = RTS_{(n-1)j} - RTS_{(n-1)(j-1)} \quad (15)$$

$$HTSS_{(n-1)(j,j-1)} = STS_{(n-1)j} - STS_{(n-1)(j-1)} \quad (16)$$

$$HTS_{(n-1)(j,j-1)} = HTSR_{(n-1)(j,j-1)} - HTSS_{(n-1)(j,j-1)} \quad (17)$$

It is worth noting that the deviation between real and scheduled time spent in eqn. (17) indicates that real passenger volumes may be different from the expected ones, in two consecutive runs. Hence, three cases may occur according to the sign of $HTS_{(n-1)(j,j-1)}$.

If $HTS_{(n-1)(j,j-1)} \approx 0$, passenger volumes does not affect the irregular departure. For each bus stop and run, the notation ≈ 0 must be read as follows:

$$\iota \le HTS_{(n-1)(j,j-1)} \le \kappa \quad (18)$$

where ι and κ are numerical thresholds set up by the bus operator, and represent the minimum and maximum acceptable values of $HTS_{(n-1)(j,j-1)}$.

Conversely, if $HTS_{(n-1)(j,j-1)} < 0$ or $HTS_{(n-1)(j,j-1)} < 0$, the irregular departure could depend on passengers, as the volume of boarding and alighting passengers in two consecutive runs is probably lower or greater than the expected one, respectively. Thus, UPV may occur.

As a result, in order to understand the possible irregularity sources along the route, one can jointly examine headway arrival deviations at bus stop $n \in N \backslash A$, headway departure deviations at bus stop $n-1 \in N \backslash A$ and headway time spent deviations at bus stop $n-1 \in N \backslash A$.

Table II shows the resulting 18 critical cases that may occur. The different cases can be clustered according to common characteristics related to the sign of all deviations and problem sources. The magnitude of clustered problems is expressed in terms of percentage values. The discussion of these cases is provided in what follows.

- If $HA_{n(j,j-1)} < 0$ (i.e., buses arrive bunched to bus stop $n \in N \backslash A$) and $HD_{(n-1)(j,j-1)} > 0$ (i.e., buses depart with gap from bus stop $n-1 \in N \backslash A$) or if $HA_{n(j,j-1)} < 0$ and $HD_{(n-1)(j,j-1)} \approx 0$ (i.e., buses depart regularly from bus stop $n-1 \in N \backslash A$), the problem sources is D&SF. Indeed, one may infer that $HTS_{(n-1)(j,j-1)}$ at bus stop $n-1 \in N \backslash A$ does not affect the regularity. Thus, the irregularity source depends on the operator's driving style that may be too sporty or the lack of supervision from coordinators.
- If $HA_{n(j,j-1)} < 0$ and $HD_{(n-1)(j,j-1)} < 0$ (*i.e.*, buses depart bunched from bus stop $n–1 \in N \backslash A$), the problem sources also depend on D&SF. Indeed, the irregularity is kept along the route between bus stops $n-1 \in N \backslash A$) and $n \in N \backslash A$. Thus, the scheduled travel time is usually suitable. Besides, there are three possible cases on the values of $HTS_{(n-1)(j,j-1)}$. If $HTS_{(n-1)(j,j-1)} > 0$, the difference between the real time spent of two adjacent buses is longer than the difference of the scheduled time spent, buses have been bunched; thus, the problem may also be related to D&SF. If $HTS_{(n-1)(j,j-1)} \approx 0$, passenger volumes does not affect the irregular departure, but the buses are bunched, and also, in this case, the problem may be due to D&SF. Conversely, if $HTS_{(n-1)(j,j-1)} < 0$, the difference between the real time spent of two adjacent buses is lower than the difference of the scheduled time spent, bus may depart whit a short gap. In this case, the irregularity source also depends on UPV, as few passengers

are supposed to be at bus stop $n-1 \in N \backslash A$. If one wants to understand which bus stays more than the other at bus stops $n-1 \in N \backslash A$, one must evaluate $HTSR_{(n-1)(j,j-1)}$ between two adjacent buses. If $HTSR_{(n-1)(j,j-1)} > 0$, the following bus stays longer than the previous one.

- If ***a)*** $HA_{n(j,j-1)} > 0$ (*i.e.*, buses arrive with a longer gap to bus stop $n \in N \backslash A$), and $HD_{(n-1)(j,j-1)} < 0$ (*i.e.*, buses depart bunched from bus stop $n-1 \in N \backslash A$) or if ***b)*** $HA_{n(j,j-1)} > 0$ and $HD_{(n-1)(j,j-1)} \approx 0$ (*i.e.*, buses depart regularly from bus stop $n-1 \in N \backslash A$) or ***c)*** if $HA_{n(j,j-1)} > 0$ and $HD_{(n-1)(j,j-1)} > 0$ (*i.e.*, buses depart with gap from bus stop $n-1 \in N \backslash A$), the problem sources depend on D&SF or ISD or UEF or UPV. More in detail, for cases ***a)*** and ***b)***, $HTS_{(n-1)(j,j-1)}$ at bus stop $n-1 \in N \backslash A$ does not affect the regularity. Indeed, even if departures are bunched (*i.e.*, $HD_{(n-1)(j,j-1)} < 0$) or regular (*i.e.*, $HD_{(n-1)(j,j-1)} \approx 0$), buses arrive at bus stop $n \in N \backslash A$ with a large gap. In both these cases, the irregularity source may be D&SF or ISD or UEF. Therefore, irregularity sources cannot be recognized by this analysis only; thus, a further refinement may be required. Conversely, in case ***c)***, $HTS_{(n-1)(j,j-1)}$ can affect the regularity when $HTS_{(n-1)(j,j-1)} > 0$. Indeed, the bus may depart with a longer gap. In this case, the irregularity source depends on UPV, as an unexpected number of passengers is supposed to be at bus stop $n-1 \in N \backslash A$. In the remaining cases, if $HTS_{(n-1)(j,j-1)} < 0$ or if $HTS_{(n-1),(j,j-1)} \approx 0$ buses keep the longer gap in the route. Therefore, the irregularity source is due to the driver's behavior or incorrect scheduled running time and/or scheduled time spent or uncontrollable external factors (*i.e.*, D&SF or ISD or UEF), as in cases ***a)*** and ***b)***.

When the irregularity source is identified as ambiguous (*i.e.*, it presents a combination of possible sources), an analysis of the speed between consecutive bus stops is recommended, as the speed can provide information about the running time. This analysis is compulsory when the irregularity sources en-route do not reveal a dominant source between ISD, D&SF and UPV, otherwise this analysis can be skipped without any loss of generality. This analysis for a fixed time period t considers the real speed along the leg between consecutive bus stops $n-1 \in N$ and $n \in N$. The analysis of the real and scheduled speed and the congestion speed helps distinguish between ISD, D&SF and UEF. This analysis is reported in [29] and [32].

IV. Experimentation in a Real Case

A. Case Study

The experiment was conducted on the major bus operator (*i.e.*, CTM) from Cagliari, a coastal Italian city with 0.4 M inhabitants. CTM manages 264 buses, serving around 35,500,000 passengers a year on 30 routes ([39]). For the sake of synthesis, the proposed method is tested on the northbound direction of a route about 9 km long, with 30 bus stops, which links the central area of the city with an external neighbourhood. The route has been chosen because of these characteristics, which are supposed to point out different problem sources. Its headway is 6 minutes from 7.00 to 19.59. The scheduled running times along the route and the average scheduled recovery times at the departure terminals are 33 minutes and 7 minutes on weekdays, respectively. Vehicles deployed on this route have the same typology from 7.00 to 19.59, a capacity of 105 passengers, a length of 12 m and low floor.

The overall route can be divided into four parts, depending on the different traffic conditions encountered. In Part 1 (from the terminal to bus stop 11), buses run along a contra-flow bus lane. Besides a minimal interference with authorized traffic due to the shared use of this lane with police patrols, taxis, *etc* are present. Moreover, buses conflict with the private traffic crossing the lane during the turn left movement. In Part 2 (from bus stop 12 to bus stop 21), buses move on a two-way street, in mixed traffic, and much interference occurs: a high number of pedestrians and double-parked vehicles may interfere with buses. As a result, buses may perceive several perturbations during their service. In Part 3 (from bus stop 22 to bus stop 24) buses move along a with-flow bus lane and the same interferences of Part 1 are detected.

Finally, in Part 4 (from bus stop 25 to the arrival terminal), buses move along larger streets in mixed traffic conditions, even if interferences with cars and bikes (running in a dedicated lane) is also possible. As a result, buses may perceive many perturbations in the operation of their service. Since parts 1 and 3 have dedicated lanes, one could expect limited ISD and UEF from the outcomes.

B. Experimental Setup and Results

Since 2007, all buses have been equipped with a specific AVL architecture, which mainly records actual and scheduled arrival times at every bus stop, measured in minutes

Table II. Possible irregularity sources along the route.

	$HA_{n(j,j-1)} < 0$			$HA_{n(j,j-1)} > 0$		
	$HTS_{(n-1),(j,j-1)}$			$HTS_{(n-1),(j,j-1)}$		
$HD_{(n-1),(j,j-1)}$	< 0	≈ 0	> 0	< 0	≈ 0	> 0
< 0	UPV	D&SF	D&SF	D&SF or ISD or UEF	D&SF or ISD or UEF	D&SF or ISD or UEF
≈ 0	D&SF	D&SF	D&SF	D&SF or ISD or UEF	D&SF or ISD or UEF	D&SF or ISD or UEF
> 0	D&SF	D&SF	D&SF	D&SF or ISD or UEF	D&SF or ISD or UEF	UPV

Northbound Direction

Part	Bus Stop	7.00 7.59	8.00 8.59	9.00 9.59	10.00 10.59	11.00 11.59	12.00 12.59	13.00 13.59	14.00 14.59	15.00 15.59	16.00 16.59	17.00 17.59	18.00 18.59	19.00 19.59
1	1	A	E	E	C	D	D	E	F	E	C	C	D	D
	2	B	B	C	B	C	C	C	nd	B	B	A	C	B
	3	A	B	C	C	C	C	C	D	C	B	B	C	C
	4	B	B	C	C	C	C	C	D	C	B	B	C	C
	5	n/a	n/a	n/a	n/a	C	C	C	E	n/a	n/a	B	C	D
	6	B	B	C	C	C	n/a	n/a	D	C	B	B	n/a	C
	7	C	B	D	C	C	D	D	D	C	B	C	C	C
	8	C	C	D	C	D	D	D	D	C	C	C	C	C
	9	n/a	n/a	n/a	n/a	D	D	D	E	n/a	n/a	C	D	D
	10	n/a	n/a	n/a	n/a	D	D	D	E	n/a	n/a	C	D	D
	11	C	C	D	D	D	D	D	D	D	C	C	D	C
2	12	C	C	D	D	D	D	D	E	D	C	D	D	D
	13	D	C	D	D	D	E	D	E	D	C	D	D	D
	14	C	D	E	D	D	E	D	E	D	C	D	D	D
	15	n/a	n/a	D	D	D	E	D	E	n/a	C	D	D	D
	16	C	D	E	D	D	E	D	E	D	C	D	D	D
	17	C	D	D	n/a	D	n/a	E	E	D	n/a	n/a	n/a	n/a
	18	n/a	n/a	D	E	E	E	D	E	n/a	C	D	D	D
	19	C	D	D	E	E	E	E	E	D	C	D	D	D
	20	C	n/a	D	n/a	D	n/a	n/a	E	D	n/a	D	D	D
	21	n/a	D	E	E	E	E	E	E	D	D	n/a	n/a	n/a
3	22	D	n/a	D	n/a	D	n/a	n/a	E	D	n/a	D	D	D
	23	D	n/a	D	n/a	E	n/a	n/a	E	E	n/a	E	D	D
	24	D	D	E	E	E	E	E	E	E	D	D	D	E
4	25	D	D	E	E	E	E	E	E	E	D	D	D	E
	26	n/a	E	E	E	E	E	E	E	E	D	E	D	E
	27	D	E	E	E	E	E	E	E	E	D	D	D	E
	28	D	n/a	E	E	E	E	n/a	E	E	n/a	E	D	E
	29	D	n/a	E	E	E	E	n/a	E	E	E	E	E	E
	30	D	E	E	E	E	E	E	E	E	D	D	E	E

FIG 2 The first control dashboard, which characterizes the regularity in all bus stops and time periods in terms of LoS. According to [25], the LoS ranges as follows. LoS F means that coefficient of variation of headway is larger than 0.75 (*i.e.*, most vehicles bunched). LoS E reports coefficient of variation of headway ranging from 0.53 to 0.74 (*i.e.,* frequent bunching). LoS D reports coefficient of variation of headway ranging from 0.40 to 0.52 (*i.e.,* irregular headways, with some bunching). LoS from A to C reports coefficient of variation of headway lower than 0.40 (*i.e.,* satisfactory regularity). The symbol n/a means data not available.

Table III. Terminal analysis at selected time periods.

	12.00 – 12.59		
Terminals	D&SF	ISD	OK
Departure	25%	7%	68%
Arrival	31%	19%	50%
	14.00 – 14.59		
Terminals	D&SF	ISD	OK
Departure	43%	15%	42%
Arrival	18%	33%	49%

and seconds ([40]). Around 100,000 AVL data records are available on a daily basis over the overall network. In addition, control room operators follow buses in real time at the dispatch center and inform drivers of online actions to improve the regularity. As a vehicle terminates its service, it moves back to the depot where data recorded during the daily shift are downloaded by a wireless connection. Daily AVL data are stored in a central database. The AVL data of this route direction are collected during weekdays in March 2016. In this analysis, AVL data were collected from 07.00 to 21.59, but we focus only on the interval from 7.00 to 19.59, when the management of the route is regularity-based.

The method in Section III was developed and implemented on MS Access and MS Excel running on a standard PC (Pentium 4, CPU 2.80 gHz, RAM 1.00 gb). At the end of stage A, we processed 124,500 AVL data, and the outcomes are represented in the control dashboard of Fig. 2, in which rows represent bus stops, and columns represent time periods. Each entry represents the LoS at that bus stop and at that time period, according to the values obtained by the C_{vh}, as described in Section III-A. Fig. 2 clearly shows that some problems are largely clustered in the last part of the route with special emphasis on specific time periods, even if the time periods from 12.00 to 12.59 and from 14.00 to 14.59 seem to be particularly critical.

In order to carry out the experimentation of stage B, the selection of the time period is required. As regularity discloses widespread criticalities in the previous time periods, they are selected and analysed. In stage B, the analysis at the departure terminal is reported in Table III. On the one hand, it shows that negligible problems occur from 12.00 to 12.59, because almost regular situations are analyzed in at least 50% of the terminals. On the other hand, D&SF is relevant at the departure terminal from 14.00 to 14.59 (see the shaded entry). Therefore, even if drivers have an adequate recovery time at terminal, they fail to start the next run according to the scheduled headway. Only 15% of trips cannot maintain planned headway due to the lack of available recovery time.

Overall, problems sources amount to approximately 58%.

Nevertheless, 42% of trips maintain headways as planned. At the arrival terminal, about 33% of problem sources depend on ISD. Therefore, one may expect that the relationship between D&SF at the departure terminal and ISD at the arrival terminal could depend on the absence of available recovery time at the arrival terminal, which could be corrected by drivers through a larger-than-scheduled speed. In the following route analysis, we will try to find a confirmation of this expectation.

Since the bus operator does not include time spent at stops in its schedule (it is used to consider this time at terminals only), the en-route analysis makes use of a derived scheduled time spent. It is computed multiplying the average number of passengers (data gathered from manual surveys) at each bus stop $n \in N$ by the average boarding time for passengers, which is supposed to be 2 s/pass. The boarding time for each passenger depends on the ticketing systems in use. As the bus operator uses an on-board *proof-of-payment* ticketing system [41] based on magnetic and contactless tickets, this value can be considered suitable. These values are not too dissimilar from those gathered in experimental studies

FIG 3 The second control dashboard represents the analysis of irregularity sources along the route without (a) and with (b) speed analysis from 12.00 to 12.59.

[42]–[43]. Moreover, the computation of averages of the real running time might be affected by exceptional values. This problem is addressed by removing extreme values using bus-operator-dependent thresholds. The en-route analysis is reported in Figs. 3 and 4 for the time periods 12.00–12.59 and 14.00–14.59, respectively, for each bus stop. The percentage of occurrence of regularity and irregularity sources is represented by different colours, as explained in the legend. According to this representation, peaks represent the most common occurrences where major attention must be paid. Moreover, these figures show the results of speed analysis, which allows dissolving the ambiguities arising from nested irregularity sources cases.

This analysis is performed in the case of a congestion speed of 10 km/h ([44]) to detect UEF. Moreover, a real speed ranging between 0.9 and 1.1 times the scheduled speed is set according to bus operator guidelines, in order to detect ISD or D&SF, respectively. Interestingly, these figures point out that different sources may be relevant. More precisely, despite the missing data points in the central part of the route, Fig. 3 shows that the decrease of regular situations is associated with the increase of D&SF and UPV. These sources become relevant in Part 4. These results are confirmed by the characteristics of the route.

Indeed, the dedicated priority lanes in parts 1 and 3 are unlikely to result in ISD and cannot lead to UEF.

Fig. 4 shows that, in the associated time period, there are few missing data clustered in the first part, which result in an easier-to-read trend on the different problem sources along the route. Moreover, results look different from those in Fig. 3 because irregularity problems already exist at the departure terminal, as shown in Table III. Along the route, even if there is not a dominant irregularity source at each bus stop and leg, the occurrences of problem sources amount at an average of about 60%. Moreover, as expected, problem sources increase mainly when buses leave Part 1 and enter Part 2. From Part 2 to the end, the speed analysis shows that the highest relative source is D&SF. Thus, even if buses run along a with flow bus lane in Part 3, they maintain larger-than-expected speeds also in Part 4. Therefore, irregularity problems may depend on the too “sporty” driving style, *i.e.*, buses run beyond the planned speed.

As expected before, the occurrence D&SF could be explained by the information on missing recovery times at the arrival terminal. Interestingly, in the overall route, the second highest percentage of irregularity is UPV, which does not come as a surprise, because low passenger volumes have been usually observed in separated manual counting procedures. As a result, drivers do not arrest at many

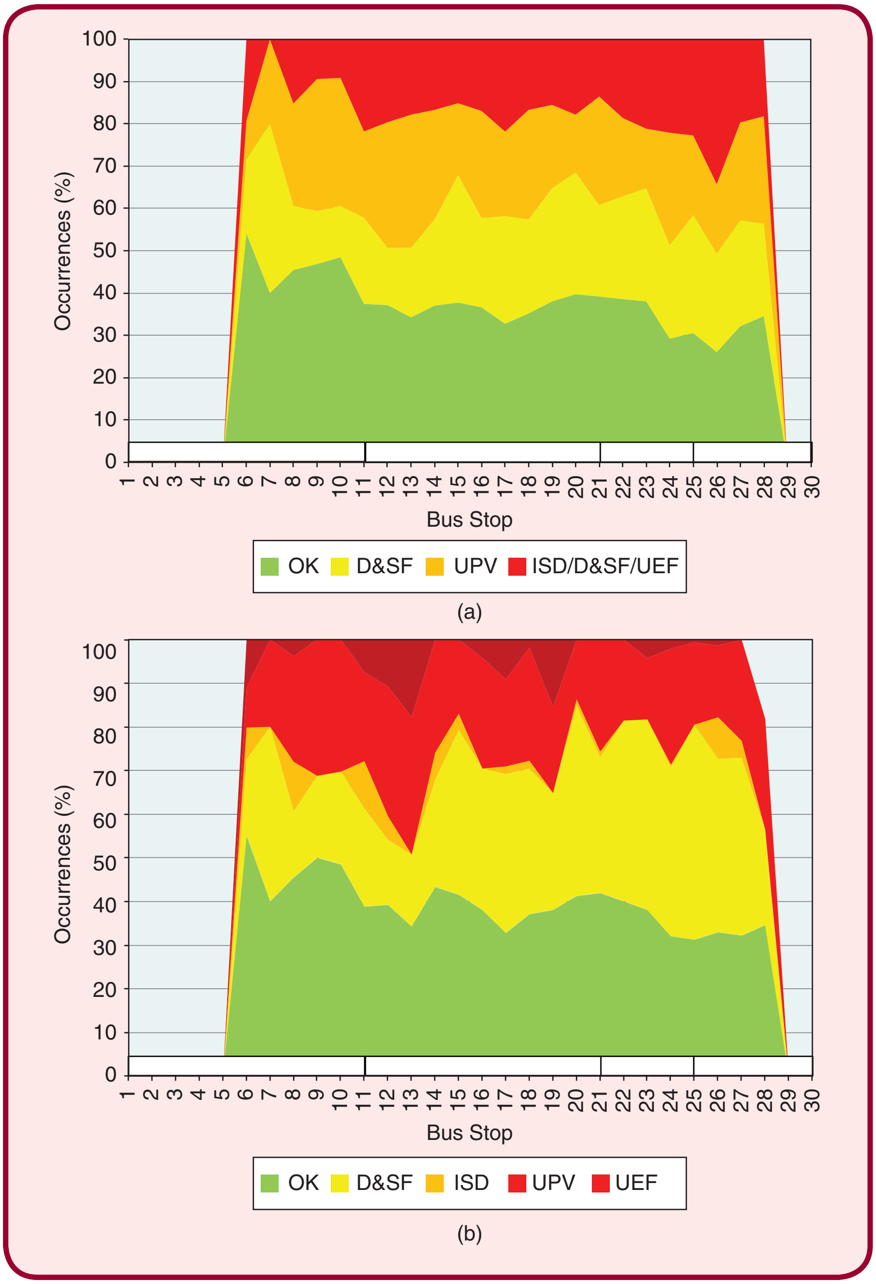

FIG 4 The second control dashboard represents the analysis of irregularity sources along the route without (a) and with (b) speed analysis from 14.00 to 14.59.

stops. When the average boarding time is set at a different value (*e.g.*, 4 s/pass), in both time periods, similar results have been obtained, even if they are not reported in this paper. Hence, the average boarding time seems to be irrelevant for the variability of outcomes in this experimentation.

Finally, these results show that different strategies need to be investigated in different time periods and, possibly, within each time period. For example, a viable strategy could be based on the checking of drivers' behaviour by AVL supervisors. However, it is important to evaluate how this strategy will impact the values of UPV, which cannot be disregarded in both time periods. Therefore, incorporating the dwell time into the schedule is expected to be beneficial for keeping the headway as planned. These strategies will be investigated in a future work.

C. Comparison of Results with other Cities

Some descriptive comparisons are reported among the results in this case study and those obtained in other worldwide cities. At the end of stage A of the method, our results

Table IV. Notational Glossary.

Symbol	Description	Units
N	Set of all bus stops (including terminals)	
$A \subseteq N$	Set of terminals	
J	Set of runs	
n	Bus stop index	
j	Run index	
RDT_{nj}	Real departure time at bus stop $n \in N$ for run $j \in J$	hh:mm:ss
RAT_{nj}	Real arrival time at bus stop $n \in N$ for run $j \in J$	hh:mm:ss
SAT_{nj}	Scheduled arrival time at bus stop $n \in N$ for run j	hh:mm:ss
SDT_{nj}	Scheduled departure time at bus stop $n \in N$ for run $j \in J$	hh:mm:ss
RTS_{nj}	Real time spent of run $j \in J$ at bus stop $n \in N \backslash A$	hh:mm:ss
STS_{nj}	Scheduled time spent of run $j \in J$ at bus stop $n \in N \backslash A$	hh:mm:ss
$HDR_{n(j,j-1)}$	Real departure headway at bus stop $n \in N$ between runs $j \in J$ and $j-1 \in J$	s
$HDS_{n(j,j-1)}$	Scheduled departure headway at bus stop $n \in N$ between runs $j \in J$ and $j-1 \in J$	s
$HD_{n(j,j-1)}$	Departure headway deviation at bus stop $n \in N$ between runs $j \in J$ and $j-1 \in J$	s
ART_{aj}	Available recovery time at terminal $a \in A$ for run $j \in J$	s
$HAR_{n(j,j-1)}$	Real arrival headway at bus stop $n \in N$ between runs $j \in J$ and $j-1 \in J$	s
$HAS_{n(j,j-1)}$	Scheduled arrival headway at bus stop n between runs $j \in J$ and $j-1 \in J$	s
$HA_{n(j,j-1)}$	Arrival headway deviation at bus stop $n \in N \backslash A$ between runs $j \in J$ and $j-1 \in J$	s
$HTSR_{n,(j,j-1)}$	Real time spent headway at bus stop $n \in N \backslash A$ between runs $j \in J$ and $j-1 \in J$	s
$HTSS_{n,(j,j-1)}$	Scheduled time spent headway at bus stop $n \in N \backslash A$ between runs $j \in J$ and $j-1 \in J$	s
$HTS_{n,(j,j-1)}$	Headway time spent deviation at bus stop $n \in N \backslash A$ between runs $j \in J$ and $j-1 \in J$	s
α	Minimum acceptable $HD_{n(j,j-1)}$ at the terminal, which is set –120s. in advance, according to bus operator guidelines	s
β	Maximum acceptable $HD_{n(j,j-1)}$ at the terminal, which is set + 120 s. of delay, according to bus operator guidelines	s
γ	Minimum acceptable available recovery time, which is set –60s.in advance, inspired from [38])	s
δ	Maximum acceptable available recovery time, which is set +60s.of delay, inspired from [38]	s
ε	Minimum acceptable $HA_{n(j,j-1)}$ along the route, which is set – 120s. in advance, according to bus operator guidelines	s
ζ	Maximum acceptable $HA_{n(j,j-1)}$ along the route, which is set + 120 s. of delay, according to bus operator guidelines	s
η	Minimum acceptable $HD_{n(j,j-1)}$ along the route, which is set – 60 s. in advance, according to bus operator guidelines	s
θ	Maximum acceptable $HD_{n(j,j-1)}$ along the route, which is set + 60 s of delay, according to bus operator guidelines	s
ι	Minimum acceptable $HTS_{n,(j,j-1)}$, which is set –4s, according to bus operator guidelines	s
κ	Maximum acceptable $HTS_{n,(j,j-1)}$, which is set + 4s, according to bus operator guidelines	s

pointed out that the hour of the day affects significantly the reliability, as described in the case of Rome [1]. Conversely, our results slightly differ from those provided by [34] who showed that in New York city the regularity seems to be better during the AM peak period rather than midday off peak. However, our results are different because a midday peak exist, unlike in [34]. In addition, our results show that the regularity worsens along the route, according to [45] in the Netherland, [28] in Stockholm and [33] in Beijing. Indeed, [28] showed that successive buses depart from the origin stop with uneven headways and the coefficient of variation of the headway worsens along the route. In [33], the increase of route length results in the reduction of reliability. Moreover, changing the distance between a bus stop and the origin terminal also caused bus service reliability to worsen.

At the end of Stage B of the method, our results are in accordance with [38] in Boston. She also noticed that the main cause of service unreliability was identified in poor headways adherence at the terminal, which propagates and creates further reliability problems along the route. These causes were inferred to be a combination of poor terminal supervision and operator behaviour. Along the route, operator behaviour and passenger loads are observed to affect reliability. Moreover, our results are in accordance with those of [18] in Portland and [46] in Malaysia, where the irregularity along the route is supposed to depend on passenger loads. Indeed, in our experimentation, we provided evidence the decrease of regular situations is also associated with the increase of UPV.

V. Conclusion

AVL data are widely used in transit networks for the real-time monitoring of buses. Less attention has been devoted to the use of archived data for the detailed understanding of irregularity, which is crucial for the quality and efficient operational planning of high frequency bus routes. AVL systems provide a much higher level of detail than human-collected data, but they also give rise to additional challenges, such as characterizing regularity and detecting possible irregularity sources.

This paper contributes to the research by developing an offline framework for any high frequency route to:

- point out where (bus stops) and when (time periods) the regularity is not met by the accurate processing of AVL data to reflect the service received by passengers;
- disclose who/which is responsible for the irregularity (*i.e.*, the irregularity sources), starting from what irregularity measures are (*i.e.*, the performance measures generated by AVL data) and why irregularity occurs (*i.e.*, the originating causes).

The new framework accurately uses an AVL system and results in significant time and energy savings in the investigation of large datasets. User-friendly control dashboards are constructed to show clear and synthetic outcomes from the analysis of irregularity.

The theoretical organization of the framework has been widely tested in an experimentation using 124,500 AVL real data records, to successfully provide a clear-cut list of relevant sources. The outcomes confirm the preliminary expectations based on the complaints of passengers and the opinions of drivers. Nevertheless, further developments are recommended. First, the experience of the bus operator will be used for further tuning of thresholds in the case of other bus routes. Second, the proposed framework will be integrated with automatic passenger counting and automatic fare collection system for the accurate analysis of passenger data without any assumption on the time spent. Third, a new step is to build a web platform incorporating this framework. Hence, bus operators are in the position of analyzing sources, and possibly select strategies to improve regularity. Nevertheless, the analysis of possible strategies may be also done by suitable traffic simulation software. Finally, an interesting research perspective is the real-time prediction of reliability measures. These research topics have great relevance for future Smart Cities.

Appendix

See Table IV.

About the Authors

Benedetto Barabino received the Ph.D. degree in transportation technology and economics from the University of Palermo, in 2007. From 2010 to 2016 he has been the Managing Director of Technomobility srl, a research society in the public transport industry. In 2017, he has been the Head of the Department of Studies and Researches of CTM in Cagliari. Since 2018, he has been Assistant Professor of Urban Transports at the University of Cagliari. His research interests include intelligent transportation systems, public transport planning, operations, and service quality.

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