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Public transport bunching: A critical review with focus on methods and findings for implications for policy and future research

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Abstract

Bunching affects both public transport users and operators adversely. It increases waiting time at stops and onboard, reduces travel speed and comfort, costs more, and substantially deteriorates service reliability. This paper reviews the definition of bunching, underlying causes, modeling, and control strategies. Terminology is to classify demand and supply-related bunching determinants based on spatio-temporal and static and dynamic variability, which is overlooked in the existing literature. Furthermore, seven potential control strategies are examined within a systematic classification of control methods for qualitative assessment purposes. In this assessment, various passenger and operator attributes are utilized to examine the performance of each method based on findings from a comprehensive survey of the relevant articles in the state-of-the-art. Headway and schedule-based holdings, speed control, stop skipping & boarding limit, and short turning strategies are grouped within operator-oriented-method (OOM). Real-time demand control, as the only passenger-oriented method (POM), has also shown promising results in reducing bunching incidents and service reliability improvement. The lack of a practical classification of control methodologies and not capturing spatio-temporal variation of contributing factors led to an imbalance in the number of studies explored each method. OOM such as holdings are well researched, but demand-related control strategies are overlooked. Exploring dynamic demand control and hybrid micro behavioral management paramount research for the future. This review can assist policymakers in adopting the most appropriate strategy.

1. Introduction

1.1. Bunching definition

Bunching is one of the key contributors to Public Transport Reliability (PTR) deterioration (Rashidi et al. 2017). It is a complex problem to be solved analytically, which received particular attention as a service deteriorator (Daganzo 2009; Turnquist 1980). Bunching can make the schedule useless, spreading network-wide with minor disruptions and a positive feedback loop to service disturbance (Xuan et al. 2011; Daganzo and Pilachowski 2011). As a result of service bunching, travel time increases, and system instability indicators deteriorate, including headway variability and schedule deviation. Also, in bunching conditions, passengers and operators encounter extra costs such as excessive waiting time and in-vehicle time, degraded travel experience in crowded vehicles with fewer passenger seats, a surge in operating costs, and inefficient resource allocations for operators. Bus bunching reduces the popularity of public transport, reflected in the number of users who have already switched/are likely to switch in the future. The bunching phenomenon is defined as two or more public transport vehicles that serve the same line in pairs or very close to each other as a result of deviation from originally published headways or schedules. Earlier studies suggest a stationary threshold, (Feng and Figliozzi 2011) considered three minutes of headway between two consecutive buses to identify bunching. Any headways below the given value are considered bunched. More recent works propose a dynamic threshold based on the type of service and temporal variability (Gong et al. 2020). Bunching is strongly associated with high frequency and high demand services. Controlling bunching incidents as a common contributor to PTR planning and operation can explain reliability improvement. It is therefore crucial to understand bunching, its occurrence, underlying causes, consequences under no control conditions, modeling and prediction in research, and policy studies implications in practice.

1.2. The effect of bunching on sustainability

Bunching as a PTR variable can indirectly promote transport sustainability by increasing PT popularity. The transport sector accounts for 26% of global CO_2 emissions (Chapman 2007), mostly from private vehicles. Research revealed that in the short term, the policy to change travel behavior is more important than technological solutions for transport sustainability (Anable and Boardman 2005). For instance, modal shift onto sustainable transport alternatives such as PT can help stabilize the transport sector's carbon emissions (Chapman 2007). Reliability has been reported to be an essential feature in passengers' perception of PT services compared to other elements such as frequency, type of vehicle, and driver behavior (Balcombe et al. 2004). Additionally, instability in public transport operations challenges PT operators to deliver credible services (Ceder 2007). A slight decrease in service reliability caused by bunching may translate into a reduction in popularity and number of users, substantially burdening the cost-revenue of the service. In line with transport sustainability indicators summarized in Litman's paper, it is crucial to improve service reliability by controlling bunching occurrences (Litman 2021).

1.3. Literature review

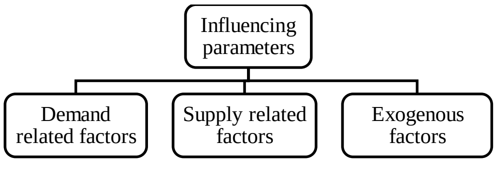
PT bunching has received well attention in transport literature since the early nineteen sixties, and it has been considered a potential factor in PT service quality. Since then, extensive research has studied bunching formation, causes and consequences, and controlling strategies. (Newell and Pott 1964) modeled bus bunching for the first time, and(Osuna and Newell 1972) investigated an optimal strategy to reduce the average waiting time per passenger. (Nagatani 2001) simulated bunching under different conditions to understand bunching behavior, and (Hammerle et al. 2005) used AVL and APC data to study bunching. Numerous researchers focused on control strategies, stochastic holding control model (Hickman 2001), headway-based holding method (Daganzo 2009), and many others studied holding methods further. (Daganzo and Pilachowski 2011; Sun and Hickman 2005) suggested speed control and stop skipping, respectively. (Delgado et al. 2012) examined hybrid model combining boarding limit and holding. (Currie and Shalaby 2008; Shalaby et al. 2002) analyzed signal priority for the streetcar (tram). Few others applied the potential of new technologies and automated data from Automatic Passenger Count (APC), Automatic Fare Collection (AFC), and Automatic Vehicle Location (AVL) to relieve vehicle platoon in real-time. (Ma et al. 2021) developed a real-time predictive control strategy (Berrebi et al. 2018) evaluated holding method with and without real-time predictions, and (Moreira-Matias et al. 2016)'s online model predicts and controls bunching before it happens. More recently, some researchers studied the impact of passenger choice on controlling bus bunching (Wang et al. 2021; Drabicki et al. 2021; Drabicki et al. 2022). This scheme studies the implication of passenger's Willingness-To-Wait (WTW) for the next arrival on travel experience improvement and bunching.

Despite various studies, a critical review to conduct a comprehensive analysis exploring the overview of the bunching phenomenon, an in-depth examination of the causes, and the performance of control methods in achieving defined objectives are missing in the literature. In the absence of a critical review focusing on methodology per the given set of objectives, some promising methods are being overlooked. Also, the absence of proper terminology in classifying the contributing factors leads to an imbalance in the number that studied specific factors in-depth while some others. Systematic classification of control strategies for performance evaluation and benchmarking within similar groups were absent. This review paper aims to classify the proposed methodologies and causes in the literature to identify the overlooked potential research directions. It proposes a benchmark for similar strategies to evaluate their outputs with methods having similar features and objectives. Lastly, it assists the direction for policymakers to implement the methodology that suits the specific objectives and groups, as explained in Table 1 in section 4. In section 2, the contributing factors that cause and amplify bunching scenarios are reviewed, and section 3 summarizes the bunching modeling approaches. A practical framework analyzing bunching control methods has presented in section 4, which is followed by conclusions and recommendations in section 5.

2. Contributing factors: An inclusive classification

Understanding the cause of a problem will help to choose the right solution. In bunching studies, it is essential to understand what contributes to bunching. Based on the type of occurrence, they are defined as systematic (Endogenous) and non-systematic recurrent (Exogenous) problems, which are addressed through operational planning (OP) and operational control, respectively (Moreira-Matias et al. 2016). The endogenous causes in the system have a positive feedback loop which substantially progresses to bunching. It is classified into demand and supply classes based on the source of influence (Gong et al. 2020). The lack of a comprehensive classification leads to an imbalance in the number of studies dealing with each category; some are sufficiently surveyed, while some others are disregarded. Also, because of the diversity of influencing parameters in bunching, the enclosure of all the inducing factors in modeling is computationally infeasible. Therefore, an explicit understanding of parameters may help to address this gap. In this study, a systematic classification of bunching contributors based on spatio-temporal variability and user heterogeneity is presented. It is anticipated that the classification helps to understand the specificity of the causes to formulate the exact problem and solution than testing in a trial-and-error manner. This classification contains three main categories: 1. Demand-related, 2. Supply-related, and 3. Exogenous factors as shown in Figure 2.

Figure 2: Classification of bunching contributive factors based on the reviewed articles



2.1. Demand related variables

Demand variables are one of the primary sources of bunching and reliability problems, divided into three types: first, demand variability in different spaces: high and low traffic segments and type of land use. Second, demand variability at different times, i.e., weekdays, weekend, peak, off-peak, and intra-peak. Third, heterogeneity of users such as seniors, adults, and youth. Bunching identification only solves part of the question but understanding the associated attributes can help to answer the following question fully. Are bus bunching attributes the same for different route segments during different times of the day? (Feng and Figliozzi 2011). (Chioni et al. 2020) found that number of traffic lanes at the stop level is negatively associated with bunching in less congested areas, in contrast to the positive correlation in heavy traffic segments. The bunching rate increases with an increase in the distance from a subway stop in the outer part of the city. (Iliopoulou et al. 2020) analyzed the factors that affected bunching duration and severity and discovered that temporal factors, such as weekends and afternoon peaks, affect bunching duration. (Degeler et al. 2020) Examining bunching probability patterns for workdays and weekends, and (Gong et al. 2020) showed that bunching behavior differs during peak and off-peak.

Therefore, it is inefficient to utilize the same control method for different places and times of the day and days of the week. Based on the variability of bunching duration, pattern, and behaviour, it is more likely to cost higher if the bunching solution for peak or densely populated areas applies to less concentrated or off-peak and vice versa. Unfortunately, there is a limited number of studies exploring spatio-temporal variability of bunching and its determinants; further research is required to understand it fully. Different types of users have specific dwell times and behaviour. An elderly passenger may prefer to wait for a less crowded bus with seats and safer boarding in a less crowded situation. Based on passenger trip purpose and trip length, the perception of ignoring onboard comfort for short trips and trips in the morning is higher than the counterparts. Therefore, it is critical to consider variability in time, space, and among users in bunching problem modelling and solution adoption.

2.2. Supply related variables

Bunching is closely associated with high demand and high-frequency services. Thus, accounting supply-related factors are critical. It can help to understand where and when bus bunching will happen (Gong et al. 2020). Demand side influencing factors dynamic variation in space and time affect bunching, whereas static, physical, and design factors also tend to stimulate bunching as supply-related parameters. For example, without any change to the original architectures improper network design, irregular fleet design, and type of vehicles can cause bunching. Also, using double-deck buses, different types of fare payment may influence bunching incidents.

Therefore, a detailed analysis based on the static and dynamic nature of the supply contributing factors is required. It will help to adapt the relevant control strategy that may effectively mitigate bunching. Not appropriately using static and dynamic components may also mislead the models in bunching prediction and correction. The static parameters triggering bunching are the service route design, network layout and alignment, type (interchange, stop), number of routes and overlays, spacing between stops, inappropriate number of stops, proximity with the signalized intersection, the fleet size and type, the payment method, dwelling time, and curbside parking conditions. The dynamic components that change in time and space are service frequency and headway, schedule, dispatching discrepancy, dynamic interaction between departing and arriving vehicles, speed variability, and driver's behavior. Knowing the contributing factors' type and nature simplifies the method's usage that can relieve the problem. For example, as described by (Daganzo and Pilachowski 2011), only adjusting the cruising speed in some cases can help prevent bus bunching without additional measures to reduce cost.

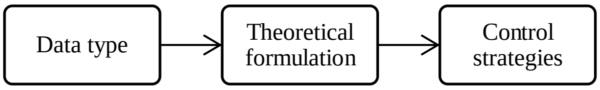
2.3. Exogenous factors

Exogenous disruptions also play a role in degrading the quality of PT service. It may cause variability in travel time, leading the vehicle to arrive early or late at the upstream stop or affect the dwell time for late arrival with more passengers accumulating downstream. Traffic accidents and jams can affect running time in the mixed-use right-of-way and left/right turning traffic (Moosavi et al. 2020). Because of the complex nature of the surrounding circumstances and uncertainty in when and where the disruption happens, it is more difficult to predict and react to exogenous service reliability deteriorators (Moreira-Matias et al. 2016). Signal timing, adverse weather, and vehicle breakdown are some other potential exogenous disruptions that cause bunching.

3. Bunching modelling

There are three core components in bunching problem modeling and analysis in public transport: the input (data type and source), mathematical & statistical formulation, and control method, as illustrated in Figure 3.

Figure 3: Core components in bunching studies for articles reviewed



3.1. Data type

The development of information and communication technologies (ICT), portable GPS, 4G, 5Gs, GTFS, and automated data in transport enabled researchers to study bunching problems at a mega-scale. In the last decade, AFC, AVL, and APC data have been the most common datasets used in bunching research. It generally lays into two groups based on its collection, storage, and availability: offline (historical) and real-time (streaming) data. A significant number of studies developed bunching models on top of offline datasets. Whereas, with the power of real-time data in recent years, more researchers are deviated to work on real-time data provision for better accuracy, prediction, and prevention. For instance, (Jiang et al. 2019) modeled the number of waiting for passengers at stops based on bus speed and historical data from the smart card. (Yu et al. 2016) used smart card data to detect bus bunching via predicted headway pattern at stop level. (Rashidi et al. 2017) utilized AVL bus data to estimate and model bunching. (Du and Dublanche 2018) conducted a series of studies from bunching identification to solution development using large-scale data from the smart card. (Moreira-Matias et al. 2012) mined AVL and historical data to find Bunching Black Spot (BBS); the sequence of bus stops where systematic bunching occurs. With advanced technology on the rise and digitalization of the physical world, automated and big data will play a critical role in transport planning and operation. Nonetheless, modeling based on data fusion from different sources and real-time demand data at scale is still in the early stages. It is expected that data integration from various sources such as fare cards, GPS, passenger count, and interconnected signalization will attract a significant number of studies for future research development. To date, (Wang and Sun 2020) suggested using real-time passenger demand information globally for all bus stops in machine learning for better performance. Previously,(Varga et al. 2018) identified the incorporation of real-time traffic signalization and public transit priority in their model as interesting future work. (Yu et al. 2016) also advised GPS location data integration with smart cards to generate more reliable results in bunching studies and dwell time estimation.

3.2. Theoretical formulation

In the theoretical formulation of bunching, various variables and numerous methodologies are used to model and predict bunching in real-time and offline. Different tools and techniques such as mathematical and statistical models, machine learning and deep learning models, and simulation are used to solve and optimize developed models. Because bunching could not be modeled directly, different bunching determinants are analyzed instead. These are headway, schedule, speed, arrival time, synchronization, and many more. (Hickman 2001) developed convex quadratic programming to optimize holding time. (Daganzo 2009; Daganzo and Pilachowski 2011) modeled headway as a bunching determinant using stochastic law of motion and (Xuan et al. 2011) extended and optimized Daganzo's model of control motion law. (Ibarra-Rojas and Rios-Solis 2012) modeled and solved bus synchronization timetabling problem to reduce bunching. (Xin et al. 2021) constructed different bus propagation models using Finite State Machine. (Wu et al. 2017) formulated dynamic passenger queue swapping behaviour, vehicle overtaking, and capacity constraint. (Hernández et al. 2015) developed optimization model considering bus interaction in a multiple lines network. (Andres and Nair 2017) used data-driven headway prediction to reduce headway deviation. (Sirmatel and Geroliminis 2018) considered a dynamic model including both continuous and binary states of the system and (Dai et al. 2019) built a headway-based model based cooperative game theory. (Li et al. 2019) defined bus motion with delay disturbance and passenger demand uncertainties as a state space model. (Yu et al. 2017) incorporated bus headways, travel time, and passenger demand as time series problems to estimate the probabilistic prediction of headway. (Fonzone et al. 2015) proposed passenger arrival decision and waiting time in a bus system with overtaking possibility. And (Cats et al. 2010b) conducted a Mesoscopic simulation model to reproduce bunching. As seen, headway as a primary explanatory variable for bunching has been widely studied in the literature. In addition, other variables are also studied, including schedule, bus synchronization, passenger demand uncertainty, arrival pattern, waiting time, bus motion propagation, delay disturbance, travel time, and so on.

3.3. Solution techniques & algorithms

Numerous techniques containing analytical, optimization, machine learning, deep learning, and simulation strategies are vastly used in the literature to find an optimal solution for bunching models. With the growing popularity of high-performance GPUs and superpower computations, reinforcement and deep learning is ramping up as the popular algorithms capable of capturing more complex scenarios and realistic representation of the public transit system. Because it is computationally expensive, there is a trade-off in choosing between cost and performance in the research and practice. Different researchers adopted different techniques based on the operator's need, size and complexity of the network, availability of the data, the severity of the bunching problem, and specificity of the objective. For simplicity and lack of supercomputers, simple hypothetical networks with strict assumptions were ubiquitous in the past, but with recent advancements in telecommunications and computational power, the direction is shifting to use more robust algorithms.

Some of the most commonly used techniques are listed below. Artificial Neural Networks, regression analysis, Probabilistic Reasoning, and Perceptron's learning for bunching prediction and control method deployment (Moreira-Matias et al. 2016). Support Vector Machines (SVM) and Bayes Networks (BN) in predicting bus travel speed based on real-time traffic information (Julio et al. 2016). Multi-agent deep reinforcement learning (MDRL) to capture the agent's (bus) interaction with the following/leading buses for achieving efficient global coordination in long-term bus operation (Wang and Sun 2020). The application of reinforcement learning (RL) in the tram (streetcar) bunching control automation (Ling and Shalaby 2005). Multi-agent reinforcement learning (MARL-H) in bunching mitigation (Chen et al. 2016; Gong et al. 2020). Bunching pattern extraction using unsupervised machine learning (Degeler et al. 2020). Usage of new multi-agent deep reinforcement learning (MDRL) framework to establish reliable holding policy accounting for the whole transit system instead of a single cause on which the previous MDRL models are mainly built (Comi et al. 2022). Q-learning algorithm deployment in optimizing holding time (He et al. 2022). Maintaining schedule adherence and headway regularity problems by using distributed deep reinforcement learning (DRL) (Shi et al. 2021). Formulation of route-level bus fleet control using asynchronous multi-agent reinforcement learning (ASMR) problem (Wang and Sun 2021). Detection of bunching at stop-level using several SVM algorithms (Yang et al. 2019). And (Yu et al. 2017) estimated bus headway and travel speed using Relevance Vector Machine (RVM) and a novel deep learning method, variational mode decomposition long short-term memory (VMD-LSTM), respectively.

These are some potential research works that benefited from the power of machine learning. Nevertheless, the implementation of deep learning and reinforcement learning techniques is at an early age, and there is still room to improve the model performance, prediction accuracy, and optimized computational time and cost using different methods, distributions, and solution algorithms. Research further in this area for future transit sector contributions. Likewise, the control strategy is crucial in bunching modelling and analysis. With the positive feedback loop among bunching determinants such as headway, number of passengers, and dwell time, it is unlikely the bunching to be solved without any control strategy application.

4. Control strategies: a practical framework analyzing control methods in bunching

Various control methods to reduce bunching are proposed in the literature under various solution themes, including technical, strategic, and policy. Based on input attributes, specific methods perform better for particular objectives. Wherein some methodologies are studied well, a few other control schemes with similar or even better performance in bunching reduction are understudied. Similarly, a potential benchmark to evaluate different practices is absent in the qualitative assessment of bunching control strategies. The performance of different approaches is benchmarked versus the no-control situation and bus holding method. It is an insignificant comparison because of the variability in input, objective, limitations, and set of assumptions present in each methodology. This section presents a practical framework to classify existing bunching control strategies based on how well the given objectives are executed. This will help to conduct a comprehensive qualitative assessment in developing a unique performance benchmark for different methods within the same class and unveils overlooked promising control strategies for the future research direction. Finally, it has policy implications helping policymakers target certain groups from user and operator or trade-offs. Passenger-oriented methods (POM) help passengers, operator-oriented methods (OOM) are more in favor of operators, and common methods (COM) trade-off to balance between two sides.

The contribution of each control scheme to different attributes of passengers and operators is qualitatively assessed and presented in Table 3. The left lists are existing control methods in the literature classified as demand and supply control management. Associated objectives to each method are on the top, classified as passenger or operator's attributes. The corresponding number of (+) or (–) demonstrate how good or bad the method performs in achieving that objective, respectively, based on the reported outcomes in the original articles. Scopus and web of science databases are used in this search, and no time range limit is applied. In this assessment, NA denotes not applicable, NR: not detected in this review or biased in the identification of the relevant articles by author, (+): acceptable results and covered slightly, (+ +): promising results and covered relatively, (+ + +): significant results and covered sufficiently in three or more original works. The rightest column classifies the control approach based on the target beneficial group: (POM), (OOM), and (COM). In this assessment, seven potential approaches in two groups of supply and demand control managements are evaluated by the given set of objectives.

Table 1: Authors synthesized qualitative assessment of control methodologies in bunching mitigation based on type of intervention and passenger/operator attributes

Beneficiary		**Passenger**				**Operator**				
Objective / **Control method**		Waiting time at stop (+)	Waiting time on-board	Trip experience & comfort	Volunteer/forced criterion index (+ & -)	Headway regularity	Schedule adherence/ recovery	Effective resource allocation	Travel time/speed improvement	**Class**
Headway-based holding	Supply Control Management	+ + +	– –	–	NA	+ + +	+	NR	–	**OOM**
Schedule-based holding	Supply Control Management	+ +	–	–	NA	+	+ + +	NR	–	**OOM**
Signal priority	Supply Control Management	+ +	+ +	+	NA	+ +	+	NR	+ +	**COM**
Speed control	Supply Control Management	+	+ +	+	NA	+ +	+ +	NR	+ + +	**OOM**
Short turning	Supply Control Management	+	+ +	NR	NA	+	+ +	NR	+	**OOM**
Stop skipping and boarding limit	Demand Control Management	+	+ + +	NR	– –	+ +	NR	+ +	+ + +	**OOM**
Real-time demand control	Demand Control Management	+	+ +	+ + +	+ + +	+ +	+	+ + +	NR	**POM**

In the fifth column, volunteer to forced criterion index, (+): means voluntarily choosing to wait for the next arriving vehicle without any external interference. (–): forcibly denied boarding through boarding limit or stop skipping policies. In essence, (+) is translated into a positive trip experience, and (–): a negative perception toward using PT services. Assumed double (+ +) rating for voluntarily willing to board the next vehicle comes from a reduced associated cost for both: crew scheduling and fleet scheduling costs through improving resource allocation evenly.

Summing the total number of (+) and (–) corresponding to user's attributes and subtracting from the total number of operator's features in Table 1, can be done to classify each method's orientation, if (+passenger > +operator) passenger-oriented (POM), else if (+passenger < +operator) operator-oriented (OOM), else (+passenger = +operator) common-method (COM). Because headway-based holding (HH) requires longer holding time, it increases in-vehicle time roughly twice as schedule-based holding (SH). It is doing better in headway regularity and less effective in schedule recovery than SH. Signal priority is expected to improve waiting time more than speed control as facing fewer delays at traversing intersections, and further research is required to understand better. Stop-skipping and boarding limit strategies are supposed to effectively reduce in-vehicle time while solely adding burden to waiting passengers who are left behind. Finally, despite the stop skipping methodology's excellent performance from the user, it is primarily designed for speed and headway maintenance and leaves waiting passengers behind; it is considered an OOM. In Table 1, some parameters, i.e., effective resource allocation, trip experience, and comforts, are assumed in this review. In essence, those are none/less observed parameters in majorities of the discussed strategies, and future studies are needed to quantify impacts. A few other parameters regarding short-turning, real-time demand control based on passenger choice behavior are unknown and assumed based on general findings from the literature survey.

4.1. Supply control management

4.1.1. Headway-based holding (HH)

(Koffman 1978) is amongst the earliest who tested holding the buses to control headway in a hypothetical single bus routes simulation. Since then, several researchers have investigated headway-based holding control to improve headway. Conventionally, a static headway threshold was defined to trigger bus holding at control points, and (Rossetti and Turitto 1998) extended it to a dynamic threshold. With the availability of real-time demand data (Abkowitz and Lepofsky 1990) implemented a headway-based control method in real-time. (Eberlein et al. 2001) formulated holding as deterministic quadratic programming, and (Fu and Yang 2002) optimized the number and location of control points based on forward and backward-looking headways-based holdings. (Puong and Wilson 2008) discussed train holding problem as a non-linear program. (Daganzo 2009) analyzed adaptive holding control based on real-time headway information. Later (Cats et al. 2010a) deployed HH to a large-scale BusMezzo simulation model.

Various researchers examined hybrid models integrating the holding method with other bunching strategies. (Delgado et al. 2012) integrated with boarding limit to improve operational speed. (Nesheli and Ceder 2014) combined with stop skipping and (Wu et al. 2017) tested holding considering vehicle overtaking and passenger boarding behavior. (Koehler et al. 2019) and (Seman et al. 2020) combined headway with priority control. Moreover, (Manasra and Toledo 2019) optimized holding and speed change control. The results have shown the hybrid model’s superiority in reducing waiting time over the holding method alone. It also improved operational speed, headway regularity, in-vehicle times, and schedule adherence. Several works have been devoted to optimizing the number and location of control stops and holding time. As is shown by (Cats et al. 2012) that holding and dispatching buses from a limited number of control stops was not effective in improving the bus’s regularity along the route. (Hickman 2001) pioneered in modeling optimal holding time stochastically (Dai et al. 2019; Berrebi et al. 2018; Cats et al. 2014) more recently explored the topic further.

4.1.2. Schedule-based holding (SH)

Despite promising results from the HH method in maintaining even headways and reducing waiting time, holding methods based on headways alone cannot help buses adhere to the published schedule (Xuan et al. 2011). Therefore, a dynamic holding control based on schedule deviation is proposed. (Li et al. 2019) integrated holding with operating speed control considering congestion delay and passenger demand uncertainties to improve headway regularity and schedule adherence. With the development of smartphone technologies and the availability of real-time transport-related information such as arrival and departure times and onboard crowding levels, it is expected that schedule-based services are getting more attention. On the contrary, research revealed that people do not plan their trips and arrive randomly at stops for services with short headways of 10-minute or less (Currie et al. 2012). 10-15 minutes were considered as a transition point from random to non/less random passengers arrival (Fan and Machemehl 2009; Fan and Machemehl 2002). Thereby, analyzing users’ arrival behavior at stops with the availability of real-time information through smartphones, considering trip purpose and type of users, will be a meaningful research question to explore in the future.

Various holding methods are studied sufficiently; hence, integrating the holding method with new strategies is still a profound research direction. Concluding based on the findings from the cited articles, headway-based holding is found to be more effective in reducing waiting time for passengers (Fabian and Sanchez-Martinez 2017), regularizing even headways (Daganzo 2009), but requires long holding times (Berrebi et al. 2018) and is less effective in schedule recovery (Wu et al. 2018). On the other hand, schedule-based holding is promising in schedule adherence and recovery, requiring less holding time but unable to regularize even headways. Both methods reduce operational speed (Xuan et al. 2011) and increase in-vehicle time for onboard passengers while holding the vehicles at control stops. Since waiting time is observed to have a higher perceived cost value than in-vehicle time, this drawback could be traded off or reduced by hybrid models by combining holding with other methods (Esfeh et al. 2021).

4.1.3. Signal priority & speed control

Signal priority control is mainly integrated with the holding method to overcome bunching. This method decreases user waiting time and delays (Chandrasekar et al. 2002; Delgado et al. 2015) and regulates headways (Chow and Li 2019). It is simple and applicable to real-time applications (Koehler et al. 2019) and can reduce bunching and onboard waiting time (Seman et al. 2020). Besides, speed control through cooperation between leading and following buses by adjusting their speed to keep evenly spaced headways (spring-effect) and faster travel time (Daganzo and Pilachowski 2011). It is further integrated with signal adjustment (Bie et al. 2020), and holding control (He 2015) yielded higher headway & schedule reliability and speed improvement with less slack added to the schedule.

Additionally, cruising speed alteration in a road segment is more practical and shortens waiting times at stops and onboard (He et al. 2019). (Deng et al. 2020) using real-time data revealed similar findings, which improved travel time and headway regularity. Short-turning strategy (ST) is specifically effective for longer routes with traffic congestion in some segments along the routes, which convert a few regular trips to short turning trips to minimize schedule deviation and waiting time (Tian et al. 2022; Tian 2021). ST is reported to be effective in schedule adherence and waiting time. Because ST is not sufficiently researched yet, its impact on other bunching determinants requires further research.

4.2. Demand control management

4.2.1. Stop skipping & boarding limit

Stop skipping (SS) as a form of service operation treatment appeared in (Eriksen 1972) paper for the first time and was tested in a hypothetical situation by (Koffman 1978). SS method is frequently used in combination with holding and speed control (Cortes et al. 2010; Moreira-Matias et al. 2016). It has been reported that SS can reduce total waiting time, in-vehicle time, and travel cost, maximize the number of transfers, reduce the number of buses in use, and increase bus lane capacity (Liu et al. 2013; Yu et al. 2013; Ceder et al. 2013; Feng et al. 2013; Cao and Ceder 2019; Levinson and Jacques 1998). Similarly, the combination of boarding limit and holding reduces bunching and excess waiting time, maintains even headways, and improves travel time and level of service (Delgado et al. 2012; Zhao et al. 2016). Nevertheless, both methodologies perform in favor of operators and only partially take passengers into account. Frustrated passengers waiting at the stop that arriving bus is going to skip will become more dejected about uncertainty in the next arrival. Because of the higher value of waiting time over in-vehicle time, the trade-off by this method should be explored further as it solely places the burden on waiting passengers. Researchers recently approached to more user-centric practice, so-called *bottom-up* decision-making architecture (Drabicki et al. 2021). In this tactic, planners leave the choice to passengers to board the current bus or wait for the next by informing them about the real-time arrival time of the next service and its crowding conditions.

4.2.2. Real-time demand control provision

A few works explored the association and impact of demand variability on reliability issues using real-time and offline demand information (Enayatollahi et al. 2019; Li et al. 2019; Ma et al. 2021; Fonzone et al. 2015; Estrada et al. 2021; Chen et al. 2012). However, the vast majority of the control strategies focus on controlling the service's supply side in tackling bunching problems, and demand control, especially in real-time, is very new in transport literature. The existing format mainly enforces the demand aspect, such as capacity constraints and stop-skipping measures. The popularity of user-centric approaches that account for passengers' choice behavior and willingness to board currently crowded or waiting for the arrival of the less crowded vehicle, is receiving attention in recent years (Drabicki et al. 2021; Wang et al. 2021; Wang et al. 2019; Drabicki et al. 2022). In this approach, researchers provide real-time information such as next arrival time, crowd level, the difference in fare, and other helpful information to facilitate choice scenarios to users for compensating a few more minutes waiting for the sake of seat availability, trip comfort, and easy boarding and alighting with respective short dwell time. This strategy has proved sophisticated in regulating headways, reducing bunching, improving trip quality, and allocating resources efficiently by evenly distributing passengers among vehicles. However, since a limited number of works studied this approach, further research is recommended to analyze its impact on other variables and test using real-time demand data. A hybrid model integrating dynamic demand control (DDC) and micro behavioral management (MBM) measures to improve service quality, and reliability is absent in the public transport state of the art. This paper identifies DDC & MBM as potential research directions for future works. It is expected that the mechanism of offering incentives to waiting for passengers through dynamic fare management on top of real-time information provision will significantly help to sustain service reliability.

5. Conclusion and recommendation

This review paper presents bunching definitions, an in-depth analysis of the underlying causes using novel terminology, bunching modeling and formulations, and a practical framework focusing on classifying the existing standard methodologies. Next, future research works and policy implications for transport operators and policymakers are explained.

5.1. Bunching causes and modeling

Firstly, several studies observed different bunching behavior considering spatio-temporal variability and user heterogeneity (Iliopoulou et al. 2020; Degeler et al. 2020; Gong et al. 2020). So, it is critical to consider time and space variability in associated factors with bunching in future research. On the one hand, using the same control method for peak and high concentrated road segments to off-peak and low concentrated zones is cost inefficient. On the other hand, trip comfort and boarding behavior are perceived to differ among users at different times of the day. Besides, bunching formation patterns are different spatially and temporally. Secondly, real-time bunching modeling based on the fusion of different data sources at scale is one of the hot topics in bunching analysis, yet in its early stages.

Further research is required to enhance the quality and accuracy of modeling prediction while reacting proactively to bunching incidents in real-time. Lastly, few original works explored the potential of deep learning and complex reinforcement learning in bunching studies. With technology development, super-powered GPUs, ICT, portable GPS devices, and availability of real-world demand data at a large-scale, exploiting deep learning potentials would be an exciting research objective.

5.2. Control methodologies in bunching analysis

With the availability of real-time transport-related information such as arrival and departure times and onboard crowd level, schedule-based services are expected to gain more popularity. At the same time, previous research findings revealed random arrival of passengers at stops for headways of ten minutes or less (Currie et al. 2012; Fan and Machemehl 2002; Fan and Machemehl 2009; Esfeh et al. 2021). Understanding users' arrival behavior and trip planning with the availability of real-time information through smartphones in the age of technology explosion will be a meaningful research question. With a few works available (Drabicki et al. 2022; Drabicki et al. 2021; Wang et al. 2019), the real-time information provision stimulates passenger behavior change in improving service reliability, and bunching mitigation has shown promising results. It helps headway regularity, reduces waiting time and bunching, and improves resource allocation and travel experience. A positive trip experience could be translated into attracting more passengers, which promotes PT. Thereby, studying the impact of real-time information provision on different attributes of service reliability such as bunching is paramount for future works.

Research findings indicate the potential of providing real-time information in invigorating passengers' behavior. In this review, a hybrid model integrating dynamic demand control (DDC) and micro behavioral management (MBM) measure to improve service quality and reliability is proposed for the first time. This paper identifies DDC & MBM as potential research directions for future transport enthusiasts. It is expected that offering incentives to waiting passengers through dynamic fare management on top of real-time information provision will have phenomenal results helping sustain service reliability and promote PT transit as a sustainable alternative. Lastly, the qualitative assessment in this paper can help in deciding which control strategies to use for policy implications in practice. It enables policymakers to choose the method/s which is explicit to users and operators or balance between two based on project need and scope.

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