

Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 78 (2024) 327-334



25th Euro Working Group on Transportation Meeting (EWGT 2023)

An integrated bus transit service for demand-responsive urban public transport

Mario Marinellia,*, Mariano Gallob

^aPolytechnic University of Bari, Via Orabona 4, 70125 Bari, Italy ^bUniversity of Sannio, Piazza Roma 21, 82100 Benevento, Italy

Abstract

Recent mobility reports have highlighted the need of integrating Information and Communication Technologies (ICT) as an essential element in the development of intermodal and on-demand services to enhance transport flexibility. In this context, this paper investigates the improvements that could be obtained by integrating Dial-a-Ride into a bus transit service. We model the problem as a dynamic Dial-a-Ride problem with both fixed and dynamic requests. We extend an integer linear programming (ILP) model for its application to the dynamic case. To reduce computational effort, the problem is decomposed at the single vehicle level, where each best route is computed using an exact solver and new dynamic requests are assigned using a greedy insertion heuristic. We have developed the optimization model as a GIS-based tool and applied it to a realistic case of a bus transit service in the city of Benevento (Italy). The results show the benefits that could be obtained with the proposed integrated service when also compared to fixed routes and micro-mobility.

© 2024 The Authors. Published by ELSEVIER B.V.

This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 25th Euro Working Group on Transportation Meeting (EWGT 2023)

Keywords: dial-a-ride; public transport; demand-responsive; integrated services; dynamic routing.

1. Introduction

The Covid-19 pandemic severely tested the resilience of public transport systems, i.e., their ability to recover from disruptive events, and highlighted their weaknesses. These events have generally caused high variations in both demand and supply, making service management difficult. Consequently, the rise of new flexible mobility services,

^{*} Corresponding author. Tel.: +39-080-5963374; fax: +39-080-5963414. *E-mail address*: mario.marinelli@poliba.it

such as shared mobility and micro-mobility, has been the "natural" solution to face stricter time responsiveness requirements and high demand elasticity.

In Italy, the exogenous factors (e.g., vehicle capacity limits) amplified the endogenous causes of the public transport crisis, since operators focused on reducing operating costs rather than attracting new customers and offering new services (ISFORT, 2022). Thus, transport supply was not based on changes in mobility demand, but on the ability of operators to plan services while minimising costs. As a result, public transport, especially in urban areas, showed low resilience and, according to the last Italian Mobility Report, its share (7.6% in the first half of 2022) is still lower than the pre-Covid situation (10.8% in 2019), as reported in Table 1. However, in parallel to this slow recovery of public transport, active mobility modes are facing a reduction in favour of private transport after an initial increase in 2020, due to a higher preference for walking and the rise of micro-mobility services. The latter shows a share (68.7% in the first half of 2022) higher than the pre-Covid situation (65.1% in 2019). There are several ways to improve the current situation of public transport: planning and operational tools more adapted to the territorial context; transport services that are more demand-driven than supply-driven; full integration of public transport with other modes (shared mobility, micro-mobility, ride-hailing) towards the development of the Mobility-as-a-Service paradigm. This requires the integration of Information and Communication Technology (ICT) into public transport necessary to increase its attractiveness and accessibility, also including the flexibility of Dial-a-Ride (DAR) services.

In this paper, we investigate the possibility of extending a common fixed-route bus transit service towards integration with a minibus fleet providing a DAR service.

Transport mode \ Year	2019	2020	2021	07/2022
Active mobility (walking, bike, micro-mobility)	24.1	32.8	26.8	23.7
Private transport (car, motorcycle)	65.1	61.8	66.7	68.7
Public transport	10.8	5.4	6.5	7.6

Table 1. Modal split share in Italy from 2019 to 2022

The paper is organized as follows. A brief literature review is given in Section 2, underlining the original contribution of this paper. Section 3 describes the problem and its mathematical formulation. The solution approach is introduced in Section 4, while the application to a realistic case study and the results are reported in Section 5. Finally, concluding remarks are given in Section 6.

2. Related works and contribution

Several forms of hybrid or semi-flexible mobility solutions were identified in the literature. Errico et al. (2021) introduced a semi-flexible system by combining DAR characteristics in a conventional transit system and proposed a decomposition approach for application to a single-line service. A hybrid transit design strategy was proposed by Chen and Nie (2017) who introduced a demand-adaptive service in parallel with a fixed-route transit system. Similarly, Ng and Mahmassani (2022) introduced semi-on-demand routes in transit services using autonomous minibuses and proposed a mathematical formulation with parallel routes for demand coverage. Pinto et al. (2020) proposed a bi-level programming model to design transit networks together with shared autonomous mobility services. A review of relevant studies in the area of shared autonomous vehicles for on-demand mobility can be found in Narayanan et al. (2020). Recently, an agent-based simulation framework was proposed by Fidanoglu et al. (2023) for solving the dynamic problem of shared autonomous vehicles integrated within the public transport. An optimization model for the design of customized bus services was proposed by Tong et al. (2017), using a solution approach based on the Lagrangian and space-time decomposition methods. Zhang et al. (2018) proposed a decision support system for selecting the best alternative between on-demand public bus and Park & Ride services for a linear corridor by a public transport operator. A transit service based on a dynamic switching between fixed-route and flexible-route options with idle-vehicle relocation was proposed by Sayarshad and Gao (2020).

This work extends the study by Marinelli and Gallo (2021) with the following contributions: i) a minibus Dial-a-Ride service integrated within an existing urban bus transport system is proposed; ii) the extension of an integer linear

programming (ILP) model to the dynamic DARP is presented; iii) instances are derived from the road network of the city of Benevento considering main urban bus lines integrated with a variable number of minibuses for the DAR service; iv) a GIS-based tool has been developed using the PyQGIS environment and Google OR-Tools as the optimization problem solver.

3. Problem formulation

The integration of a flexible service, such as Dial-a-Ride (DAR), into a fixed route bus service was modelled as an optimization problem solved by a hybrid approach. The model aims to analyse a demand-responsive service, exploiting the potential of each of them and considering the existing bus transit network. In particular, a DAR service using minibuses integrated with the urban bus transit system was modelled considering the availability of a mobile application for users to make requests and provide real-time information on service availability.

The Dial-a-Ride Problem (DARP) can generally be modelled as a Vehicle Routing Problem with Simultaneous Pickup/Delivery and Time Windows (VRPSPDTW), subject to constraints on routes, vehicle type, duration, etc. The considered problem is defined over a directed graph of the road network G = (N, A), where nodes in the set $N = P \cup A$ $D \cup \{0, 2n+1\}$ represent road intersections or pickup/drop-off points, and arcs in the set A represent road segments. The set N consists of a subset of pickup nodes $P = \{1, ..., n\}$ and a subset of drop-off nodes $D = \{n + 1, ..., 2n\}$. We assumed the existence of different depots, i.e., bus terminals or pickup/drop-off nodes, which could vary over time according to the current location of the vehicle, so nodes $\{0, 2n + 1\}$ represent the source and destination depots, respectively. A single request is represented by a pair (i, n+i) of pickup/drop-off nodes which can be selected from a subset of nodes that could be served by both buses and minibuses. A heterogeneous fleet of vehicles (buses and minibuses), belonging to the set K, serves both users at fixed stops and dynamic requests according to its residual capacity Q_k and maximum route duration T_k . A maximum ride time L_i^k for users is also considered and time windows $[e_i, l_i]$ are defined to ensure an acceptable waiting time. Each decision variable x_{ij}^k is 1 if vehicle k travels on arc $(i,j) \in A$. Thus, the objective function aims at minimizing the total routing and travelling costs including waiting times. We also considered a travel cost α to take into account the total travel time in the objective function, defined as the difference between the arrival time B_{2n+1}^k at the destination depot and the departure time B_0^k from the source depot. We added the latter to include the waiting time cumulated by each vehicle k on its route. The problem was first formulated as an integer linear program (MILP) for the static case and adapted to the dynamic problem by introducing a set of constraints related to the current position of the vehicles.

The proposed MILP formulation of the problem at a given time τ , with notations reported in Table 2, is as follows:

$$\min \sum_{k \in K_{\tau}} \sum_{i \in N_{\tau}} \sum_{j \in N_{\tau}} c_{ij}^{k} x_{ij}^{k} + \alpha \sum_{k \in K_{\tau}} \left(B_{2n_{\tau}+1}^{k} - B_{0,\tau}^{k} \right)$$
(1)

subject to

$$\sum_{k \in K_{\tau}} \sum_{i \in N_{\tau}} x_{ij}^{k} = 1, \quad \forall i \in P_{\tau}$$

$$\tag{2}$$

$$\sum_{i \in N_{\tau}} x_{ij}^{k} - \sum_{i \in N_{\tau}} x_{n_{\tau}+i,j}^{k} = 0, \quad \forall i \in P_{\tau}, k \in K_{\tau}$$
(3)

$$\sum_{i \in \mathbb{N}} x_{0j}^k = 1, \quad \forall k \in K_\tau \tag{4}$$

$$\sum_{i \in N_{\tau}} x_{ji}^{k} - \sum_{i \in N_{\tau}} x_{ij}^{k} = 0, \quad \forall i \in P_{\tau} \cup D_{\tau}, k \in K_{\tau}$$

$$\tag{5}$$

$$\sum_{i \in N_{\tau}} x_{i,2n_{\tau}+1}^{k} = 1, \ \forall \ k \in K_{\tau}$$
 (6)

$$B_i^k \ge B_i^k + d_i + t_{ii} - M_{ii}^k (1 - x_{ii}^k), \quad \forall i \in N_\tau, j \in N_\tau, k \in K_\tau$$
 (7)

$$Q_i^k \ge Q_i^k + q_i - W_{ii}^k (1 - \chi_{ii}^k), \quad \forall i \in N_{\tau,i} j \in N_{\tau,i} k \in K_{\tau}$$
(8)

$$L_{i}^{k} = B_{n_{\tau}+i}^{k} - (B_{i}^{k} + d_{i}), \quad \forall i \in P_{\tau}, k \in K_{\tau}$$
(9)

$$B_{2n_{\tau}+1}^{k} - B_{0}^{k} \le T_{k}, \quad \forall k \in K_{\tau}$$
 (10)

$$e_i \le B_i^k \le l_i, \quad \forall i \in N_{\tau}, k \in K_{\tau} \tag{11}$$

$$t_{i,n_{\tau}+i} \le L_i^k \le L, \quad \forall i \in P_{\tau}, k \in K_{\tau} \tag{12}$$

$$\max\{0, q_i\} \le Q_i^k \le \min\{Q_k, Q_k + q_i\}, \forall i \in N_\tau, k \in K_\tau$$

$$\tag{13}$$

$$x_{ij}^k \in \{0,1\}, \quad \forall i \in N_\tau, j \in N_\tau, k \in K_\tau$$
 (14)

$$B_i^k, L_i^k, Q_i^k \in \mathbb{Z}^+, \quad \forall i \in N_\tau, k \in K_\tau \tag{15}$$

The objective function (1) aims at minimizing the sum of the total routing cost and the total vehicle travel cost, which includes waiting time. Constraints (2) and (3) ensure that each request is served only once by a single vehicle. Constraints (4), (5) and (6) guarantee that the route starts at the source depot and ends at the destination depot. Constraints (7) and (8) ensure the consistency of time and load variables. The latter constraints are linearized using constants M_{ij}^k and M_{ij}^k defined as follows (Marinelli and Gallo, 2021):

$$M_{ii}^{k} = l_i + d_i + t_{ii}, \quad \forall i \in N_{\tau}, j \in N_{\tau}, k \in K_{\tau}$$
 (16)

$$W_{ii}^{k} = \max\{Q_{k}\}, \quad \forall i \in N_{\tau}, j \in N_{\tau}, k \in K_{\tau}$$

$$\tag{17}$$

The travel time of each user is given by equalities (9) and bounded by constraints (12). The latter constraints also guarantee the precedence of node i w.r.t. node n+i for all requests $i \in P_{\tau}$. Constraints (10) ensure that the total travel time of each vehicle is less than or equal to its maximum T_k . Time windows and vehicle capacity are defined and limited by constraints (11) and (13), respectively. Finally, constraints (14) and (15) define the nature of the decision variables.

Table 2. Model notations

Sets	
A	Set of arcs
$N_{ au}$	Set of all nodes including depos $\{0, 2n+1\}$ at time τ
P_{τ}, D_{τ}	Sets of pickup and delivery nodes at time τ
K_{τ}	Set of vehicles at time $ au$
Parameters	
n_{τ}	Number of requests at time τ
e_i , l_i	Earliest and latest time of service start at node i
q_i	Load quantity at node i
d_i	Service duration at node <i>i</i>
Q_k	Capacity of vehicle k
c_{ij}^k	Routing cost on arc $(i,j) \in A$
α	Travel time unit cost
Variables	
T_k	Maximum duration time of vehicle k route
B_i^k	Time at which vehicle k arrives at node i
Q_i^k	Load of vehicle k after its service at node i
L_i^k	Ride time of each user $i \in P_{\tau}$
x_{ij}^k	Decision variables, 1 if vehicle k travels on arc $(i, j) \in A$

4. Dynamic model and solution approach

The static Dial-a-Ride model is quite far from a flexible service paradigm and could only be used if all requests are known in advance and new requests cannot be accommodated during the running time. Therefore, due to the dynamic nature of a realistic Dial-a-Ride model, we included in the model the possibility of assigning new requests to available vehicles in the fleet, which consists of buses and minibuses. Accordingly, we assumed that the arrival time of new requests is unknown, beyond an initial routing plan regarding the fixed bus stops and a possible starting requests pool for both buses and minibuses. Thus, we considered a stochastic arrival time τ uniformly distributed and the possibility of accommodating new requests during the service time and within a 15-minute time window at the pickup node. We also assumed that the maximum user ride time for new requests must be lower than half of the direct walking distance and, finally, that buses have a fixed routing plan that must be respected during the service time.

In this work, the proposed solution method decomposes the problem at a single vehicle level which is solved using an exact solver within a computation time limit T_{comp} . To reduce problem dimensions, the proposed algorithm extracts partial routes according to the current position of vehicles coming from an assumed GPS tracking system (e.g., Automated Vehicle Location), thus a new origin is determined. Moreover, a greedy insertion heuristic is applied to assign upcoming requests to the available vehicles.

In particular, the algorithm, adapted from Marinelli and Gallo (2021), is articulated as follows:

- **Initialization**: If some requests already exist before departure, initial routes are computed by solving the static problem (1)-(17) using an exact method.
- Step 0: Consider a new request arriving at time τ and introduce it into the running vehicles.
- **Step 1**: For each running vehicle, partial routes are extracted from the next node to be served (new depot at origin) at time τ.
- Step 2: The optimization problem (1)-(17), including this request, is solved for each single running vehicle by an exact solver, within a time limit T_{comp} , adding the following constraints:

$$B_0^k = B_{i,\tau}^k, \quad \forall \ k \in K_{\tau} \tag{18}$$

where $B_{i,\tau}^k$ is the time at which each node *i* must be served by vehicle *k* at time τ . If a feasible solution is found, the increase in the objective function is evaluated.

- Step 3: If a feasible solution exists for more than one running vehicle, a greedy insertion heuristic is applied to assign a new request, i.e., the new request is assigned to the vehicle with associated the minimum increase in the objective function.
- **Step 4**: If a feasible solution is not found until T_{comp} or does not exist, a new vehicle is introduced to serve the new requests.
- Step 5: Repeat from Step 0 until $\tau < \tau_{max}$.

The algorithm is triggered for each incoming request (Step 0) until the end of the service time and, consequently, the origin depot is updated according to the last node visited by each vehicle to reduce the problem dimension. Moreover, the introduction of a computation time limit T_{comp} for the exact solver guarantees the time responsiveness of the proposed solution approach.

5. Application and results

In this paper, the urban bus transport of the city of Benevento was considered as a case study to test the proposed model and solution approach. We constructed the graph of the road network in Quantum GIS (QGIS) software, as shown in Figure 1, and developed the proposed model in PyQGIS, a Python-based environment within QGIS, as a GIS-based tool. We used the CP-SAT solver from Google OR Tools as it provides an open-source framework for optimisation problems which supports multithreading. The tool was applied to one of the main bus routes, integrating a fleet of 6-seater minibuses for the DAR service. We considered an end-to-end bus line consisting of 27 stops served by two vehicles: the first one (line 1A, from Stazione FS to Pacevecchia) has 18 stops with an average travel time of 28 minutes for a distance of 9.5 km; the second one (line 1R, from Stazione FS to Pacevecchia) has 18 stops with an average travel time of 23 minutes over a distance of 7.2 km. At the main terminal (Stazione FS) a recovery time of 7 minutes is also considered. In the application, we generated new random requests with a walking distance of at least

1 km between the origin and destination nodes, assuming that they can be carried by both buses and minibuses. We created 8 real scale instances considering two types of minibus routes, i.e. circular routes (scenarios "C") and end-to-end routes (scenarios "E"), possibly both using the existing bus stops (scenarios "CS" and "ES"), a fleet of minibuses from 2 to 4 vehicles and a number of new requests from 20 to 40.

First, we tuned the computation time limit for the exact solver, and it resulted in a good trade-off between solution quality and responsiveness for $T_{comp} = 10$ s for a basic scenario with 23 static requests (see Figure 2). The optimisation model was applied to each scenario and the results were collected over 5 runs related to a 1-hour service simulation. The average results of the optimisation model were compared with the active mobility modes (walking, cycling, escooter) to highlight the potential of the integrated service. In particular, we assumed the following average speeds for the comparison: 1 m/s for walking; 3.8 m/s for cycling (Bigazzi, 2017); 4.4 m/s for e-scooters (BIT Mobility, 2022). Table 2 shows the best results obtained for scenario CS-2-20 (i.e. minibus circular routes sharing the existing stops with 2 vehicles and 20 requests). We can observe that the existing bus service has limited flexibility, serving on average less than four dynamic requests as they are close to the fixed routes; the minibuses, on the other hand, can serve on average up to 7 requests. For this scenario, we obtained the best results for all quantities considered: average waiting time of 332 seconds; average ride time reduction compared to e-scooters of 10%, with a maximum of 32.8% for minibuses; total vehicle kilometres of 83.6. Figure 3 shows the aggregated results of all considered scenarios and it can be observed that the best results are associated with circular minibus routes, which consequently represent the best route design for this type of service. We reported an example of routes obtained for minibuses at two different times ($\tau = 6$ s, $\tau = 1196$ s) in Figure 4.

Vehicle	Avg. accepted requests	Avg. waiting time [s]	Avg. travelled distance [m]	% ride time reduction (walk)	% ride time reduction (bike)	% ride time reduction (scooter)
Bus Line 1A	3.6	245.9	18664.1	76.2%	9.4%	-4.9%
Bus Line 1R	2.6	155.6	17791.6	73.5%	-0.7%	-16.6%
Minibus FS	5.6	496.1	23929.3	84.1%	39.8%	30.2%
Minibus Pacevecchia	7.4	436.2	23268.8	84.7%	41.9%	32.8%

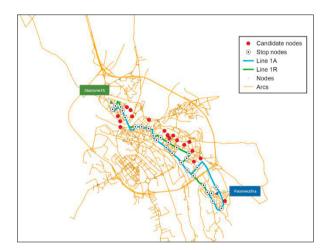


Fig. 1. Road network of the city of Benevento with considered bus lines.

6. Conclusions

This paper investigates the potential of an integrated service to improve an existing bus transport system by incorporating the flexibility of a service such as Dial-a-Ride (DAR). We presented an approach for planning and managing flexible mobility systems based on a combination of an exact and a heuristic method. The problem was first

formulated as an Integer Linear Programming (ILP) model and then adapted to the dynamic case with new constraints that take into account upcoming requests and the corresponding position of vehicles. A hybrid solution approach was introduced based on a single vehicle problem decomposition, a greedy insertion approach for assigning new requests to available vehicles, where each vehicle route is computed using an exact solver within a given computation time. We applied the proposed model to assess the impact of integration on an urban bus transport system through a real scale case study located in the city of Benevento. The case study refers to a bus line consisting of 27 stops served by two buses. We also assumed a DAR service operated by a fleet of 6-seater minibuses. The model was implemented in PyQGIS and 8 scenarios were developed taking into account different combinations of route types, sharing of existing bus stops, number of minibuses and number of upcoming requests within a service time of 1 hour.

The obtained results showed how the proposed optimisation approach can achieve high quality solutions within a computation time suitable for responsive applications. A comparison with ride times achievable by active modes (walking, cycling, e-scooter) was performed to better highlight the benefits of service integration. We found that the best solutions are related to circular routes of minibuses, which in the best case can reduce travel time by up to 33%. Thus, the integration of such a flexible service could have a positive impact on the attractiveness of public transport and the developed tool could be useful for operators in managing hybrid flexible services. As a further development, a combination of the proposed method with improvement heuristics and/or clustering techniques will be investigated.

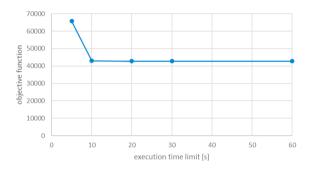


Fig. 2. Objective function values obtained for different exact solver time limits (scenario with 23 requests).

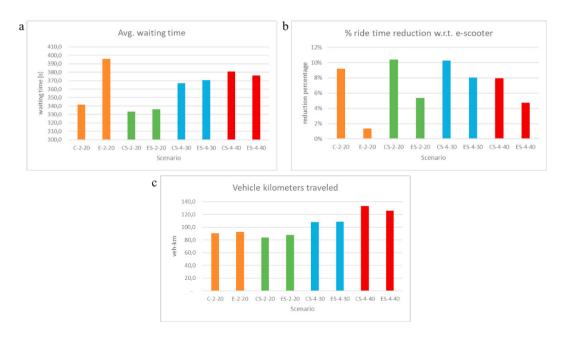


Fig. 3. Aggregated results of all scenarios in terms of (a) waiting time, (b) ride time reduction w.r.t. e-scooter, (c) vehicle kilometres travelled.

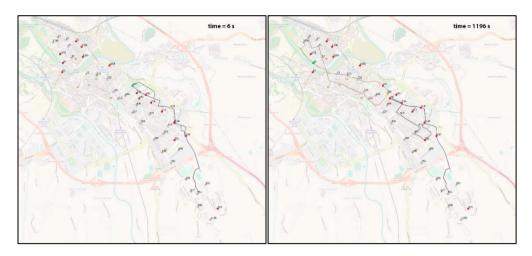


Fig. 4. Example of minibus routes obtained for scenario C-2-20 at two different simulation times.

Acknowledgements

This study was partially funded by the research project F-Mobility (CUP B32C18000210007), co-financed by the European Union, the Italian State and the Campania Region, under the POR Campania FESR 2014–2020, Priority Axis 1 "Research and Innovation".

References

Bigazzi, A.Y., 2017. Determination of active travel speed for minimum air pollution inhalation. International Journal of Sustainable Transportation

BIT Mobility, 2022. Available at: https://bitmobility.it/ (accessed online on 03/04/2023)

Chen, P. W., Nie, Y. M., 2017. Analysis of an Idealized System of Demand Adaptive Paired-Line Hybrid Transit. Transportation Research Part B: Methodological 102, 38–54.

Errico, F., Crainic, T.G., Malucelli, F., Nonato, M., 2021. The Single-Line Design Problem for Demand-Adaptive Transit Systems: A Modeling Framework and Decomposition Approach for the Stationary-Demand Case. Transportation Science 55.6, 1300–1321.

Fidanoglu, A., Gokasar, I., Deveci, M., 2023. Integrating shared autonomous vehicles in Last-Mile public transportation. Sustainable Energy Technologies and Assessments 57, 103214.

ISFORT (High Institute for Transport Education and Research), 2022. 19th Italian Mobility Report. Available at https://www.isfort.it/2022/12/02/19-rapporto-sulla-mobilita-degli-italiani/(accessed online on 07/02/2023)

Marinelli, M., Gallo, M., 2021. A Time-Responsive Approach for Sustainable and Flexible Mobility Services. In Proceedings of the 21th IEEE International Conference on Environment and Electrical Engineering (IEEE EEEIC 2021), 965-970.

Narayanan, S., Chaniotakis, E., Antoniou, C., 2020. Shared Autonomous Vehicle Services: A Comprehensive Review. Transportation Research Part C: Emerging Technologies 111, 255–293.

Ng, M.T.M., Mahmassani, H.S., 2022. Autonomous Minibus Service With Semi-on-Demand Routes in Grid Networks. Transportation Research Record 2677.1, 178-200.

Pinto, H.K.R.F., Hyland, M.F., Mahmassani, H.S., Verbas, I.O., 2020. Joint Design of Multimodal Transit Networks and Shared Autonomous Mobility Fleets. Transportation Research Part C: Emerging Technologies 113, 2–20.

Sayarshad, H.R., Gao, H.O., 2020. Optimizing Dynamic Switching Between Fixed and Flexible Transit Services With an Idle-Vehicle Relocation Strategy and Reductions in Emissions. Transportation Research Part A: Policy and Practice 135, 198–214.

Tong, L.C., Zhou, L., Liu, J., Zhou, X., 2017. Customized Bus Service Design for Jointly Optimizing Passenger-to-Vehicle Assignment and Vehicle Routing. Transportation Research Part C: Emerging Technologies 85, 451–475.

Zhang, J., Wang, D.Z.W., Meng, M., 2018. Which Service is Better on a Linear Travel Corridor: Park & Ride or On-Demand Public Bus? Transportation Research Part A: Policy and Practice 118, 803–818.