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DOI
10.1109/ITSC57777.2023.10421983

Publication date
2023

Document Version
Final published version

Published in
Proceedings of the IEEE 26th International Conference on Intelligent Transportation Systems, ITSC 2023

2023 IEEE 26th International Conference on
Intelligent Transportation Systems (ITSC)
24-28 September 2023. Bilbao, Bizkaia, Spain

2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC) | 979-8-3503-9946-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ITSC57777.2023.10421983

Real-time Routing and Scheduling of On-demand Autonomous Customized Bus Systems

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Abstract— **The integration of autonomous vehicles and on-demand customized bus systems is expected to be beneficial for responding to real-time demands. This paper investigates the autonomous customized bus (ACB) system that leverages passenger demand prediction to enhance service quality and vehicle utilization. A novel ACB service design optimization model that determines vehicle movements and passenger-to-vehicle assignments is developed for the real-time routing and scheduling problem. Then, a rolling horizon approach, incorporating travel demand prediction, proactive dispatching and reactive adjustment, is proposed to address the studied problem. The performance of the introduced ACB system is evaluated using smartcard data from Beijing and the state-of-the-art machine learning algorithm. Results show that the proposed ACB system can effectively improve system performance and service level in terms of operating cost and passenger waiting time compared to reactive operations.**

I. Introduction

The demand-responsive customized bus (CB) has become an appealing alternative to traditional public transit (PT) services, due to its enhanced accessibility, flexibility and reliability [1]. This on-demand service has gained popularity and has been implemented in a number of large cities, such as Beijing and Shanghai [2].

Unlike traditional bus services, CBs offer the convenience of allowing passengers to pre-submit their travel requirements and reserve customized services through an online platform. Reserved demands are then aggregated for routing and scheduling purposes by the CB system. Examples of successful studies include [3], [4], wherein travel demands are assumed to be fixed and known beforehand [3]; the CB service design is treated as a vehicle routing problem with pickup and delivery [4]. A key operational challenge for CB systems, however, is how to respond to the real-time demands submitted during operation. To tackle this class of demand, researchers have exploited the real-time operational strategy, such as the dynamic dispatching strategy and demand insertion approach [5]. The work of Wu et al. [6] proposed four passenger handling approaches and addressed the real-time passengers via periodic re-optimization procedures. Nonetheless, when human-driven buses are used, these strategies face limitations due to driving behaviors and crew scheduling constraints, which significantly restrict the efficiency and flexibility of CBs.

The emerging autonomous vehicle (AV) technology has the potential to mitigate the above-mentioned issues by eliminating driver-related constraints and facilitating automated vehicle allocation, that can concretely enhance the performance of real-time operation of demand-responsive systems [7], [8]. Despite its significant potential, only limited studies have explored the use of AVs in CBs. Guo et al. [9] integrated the AVs into CB systems and put forward a two-phase optimization model to deal with reserved and real-time demands; then, they extended the autonomous customized bus (ACB) system by considering the modularity of AVs in dynamic scheduling [10], which improved the system performance in terms of capacity utilization.

Even with the successful deployment of AVs in CB systems, the existing studies primarily focus on reactive services. They aim to adapt the existing routes and schedules for fulfilling the uneven and uncertain demands in real time, which fosters the necessity of short-term travel demand forecast. The adoption of demand prediction can foresee the temporal and spatial fluctuations in real-time demands, and respond proactively to offer a better travel experience to passengers. Numerous efforts have been made in the field of shuttle buses and metro services [11], [12], where the smartcard data, including spatial and temporal attributes are utilized to estimate the high-value travel information with advanced machine learning or deep learning methods [13], [14]. However, there is a lack of work to accurately estimate and predict travel requests in CB systems.

To bridge this gap and enhance service level, this paper aims to achieve real-time operation of the ACB system to address both reserved and real-time demands by leveraging passenger demand prediction. Given the proven efficacy of the rolling horizon approach in managing real-time operation for on-demand mobility systems [15], this paper proposes a rolling horizon approach integrated with demand prediction. This method aims to deliver a combination of proactive and reactive service design, that utilizes predictive insights and maintains adaptability to tackle the real-time routing and scheduling of the ACB system. The contribution of this paper is threefold: First, we develop an ACB service design optimization model to capture the vehicle routes, schedules and passenger-to-vehicle (P2V) assignments, intending to minimize the operating costs and passengers' waiting costs. Second, we devise an rolling horizon approach that incorporates demand forecasting, plan adjustment and dynamic dispatching mechanisms, to adapt and update services. Third,

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we evaluate the effectiveness of the proposed approach through a city-scale experiment, where historical smartcard data and the state-of-art machine learning algorithm are exploited for demand prediction. The findings suggest that the proposed ACB system can effectively improve system performance and service level in contrast to non-prediction cases operation.

The remainder of this paper is organized as follows. Section II introduces the problem description and the mathematical formulation. Section III presents the rolling horizon approach with demand prediction. Section IV reports the computational results of the experiment. Finally, Section V gives the conclusions.

II. Problem description and formulation

This section presents a real-time routing and scheduling problem of the ACB system, which aims to serve all the reserved and real-time demands with minimal operating costs and passenger waiting time. Then, the problem formulation regarding the optimization problem is established.

A. Problem description

Let $G = (V, A)$ be a geographic graph representing the road network, where V is the set of vertices, including pick-up and drop-off vertices and depots, denoted by set $S = S^+ \cup S^-$ and O, respectively. A is the set of arcs between pairs of vertices. We discretize time into intervals of fixed length Δt. Considering a planning horizon $\mathcal{T}$ with T time steps at time t: $\mathcal{T} = [t+1, t+2, ..., t+T]$. For the sake of convenience and to maintain generality, we assume the planning horizon starts from step $t = t_0$.

In the proposed ACB system, the set of reserved demands submitted before operation is defined as P_{t_0}. The set of real-time travel demands aggregated at each time step t is denoted by P_t. These collected actual demands in t come from the real-time passengers who submit the travel requests in the last step $t-1$, and prefer to be picked up in step t. To harness the benefits of passenger forecasting, the ACB system can also obtain the predicted passengers who will submit requirements in t, and prefer to be picked up in the next step $t+1$. Under this assumption, let $\widehat{P}_{t_0}$ and $\widehat{P}_t$ denote the set of expected passengers obtained in step t_0 and t.

With the goal of enhancing system performance, the proposed ACB system aims to leverage foresight to offer proactive plans, while retaining the flexibility to adjust plans as real information becomes available. The ACB system first generates the initial plan for the reserved demands P_{t_0} and estimated demands $\widehat{P}_{t_0}$ at t_0. Then, the system dynamically updates the plan based on real-time P_t and expected passengers $\widehat{P}_t$ in each step. To leverage the future demand information into current decision-making, $\widehat{P}_t$ is used to proactively design services. To be specific, two dynamic dispatching approaches (i.e., activating an idle vehicle or dispatching en-route vehicles to detour and turn for serving) are applied to serve $\widehat{P}_t$. Considering the predictive accuracy of $\widehat{P}_t$, P_{t+1} collected in the step $t+1$ is utilized to adapt the service to better fulfill real demands. Thereby, a reactive adjustment procedure is implemented for accommodating real-time changes in each step: (i) if $p_t < p_{t+1} (p_t \in \widehat{P}_t, p_{t+1} \in P_{t+1})$, the system is triggered to assign unforeseen demands; (ii) if $\widehat{p}_t > p_{t+1}$, the extra services will be removed from the plan. Note that there is no rejection of assigned passengers due to the application of AVs. However, the passenger waiting time can occur when the vehicle arrival time at each pick-up vertex is greater than the latest pick-up time. Figure 1 gives the framework of the ACB system.

A homogeneous fleet of vehicles $K = \{1, 2, ..., |K|\}$ is available with the fixed capacity cap at time t_0. K_{It} and K_{Et} represent the idle vehicle set and en-route vehicle set in step t. Each vehicle is characterized by the vehicle state Veh_t, including location loc_{kt}, remaining capacity state q_{kt}, and idle vehicle set K_{It}. In each step t, the vehicle state is recognized based on a set of routes and schedules generated in step $t-1$:

$$loc_{kt} = \sum_{i \in V} \sum_{j \in V} j \cdot x_{ijkt-1}, k \in K_{Et}, t \in \mathcal{T} \tag{1}$$

$$q_{kt} = q_{kt-1} - \sum\nolimits_{p \in P_{t-1} \cup \widehat{P}_{t-1}} y_{pkt-1}, k \in K_{Et}, t \in \mathcal{T} \tag{2}$$

$$q_{kt} = cap, k \in K_{It}, t \in \mathcal{T} \tag{3}$$

$$K_{It} = (K_{It-1} \cup R_{t-1}) \backslash D_{t-1} \tag{4}$$

$$K_{Et} = K \backslash K_{It}, t \in \mathcal{T} \tag{5}$$

where R_{t-1} and D_{t-1} are the sets of vehicles that return to the depot and remain en route in step $t-1$, respectively. These two sets can be defined as follows:

$$R_t = \{k : z_{kt-1} = 1, z_{kt} = 0\}, t \in \mathcal{T} \tag{6}$$

$$D_t = \{k : z_{kt} = 1\}, t \in \mathcal{T} \tag{7}$$

Each passenger request p ($p \in P_t \cup \widehat{P}_t$) has a paired pick-up vertex i and drop-off vertex j, preferred pick-up time window $[e_{pi}, l_{pi}]$. The boarding time is assumed as t_b. The vehicle arrival time ξ_{ikt} at i should follow $[e_{pi}, l_{pi}]$, and the passenger waiting time w_{pt} at i is related to ξ_{ikt}:

$$\begin{gathered} \min_{p \in P_t \cup \widehat{P}_t} \{e_{pi}\} \leq \xi_{ikt} \leq \max_{p \in P_t \cup \widehat{P}_t} \{l_{pi}\}, \\ i \in S^+ \cap S_p, k \in K, t \in \mathcal{T} \end{gathered} \tag{8}$$

$$w_{pt} = \xi_{ikt} - e_{pi}, p \in P_t \cup \widehat{P}_t, k \in K, t \in \mathcal{T} \tag{9}$$

where S_p is the set of demand vertices of p.

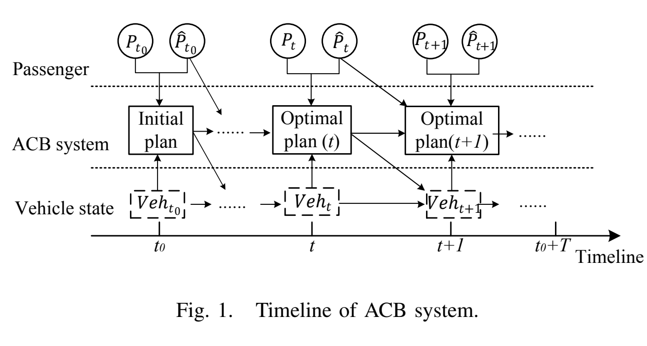

Fig. 1. Timeline of ACB system.

We make the following assumptions for the proposed problem: (1) reserved demands are known before the operation, expected demands at each step are predicted, and real demands are known at each step; (2) the travel distance and travel time of each arc are known; (3) at any time, in-vehicle passengers cannot exceed vehicle capacity.

B. Problem formulation

This section presents the optimization model that dynamically designs ACB services to reduce operating costs and passenger waiting time. At each step, the system takes the collected real demands, anticipated demands, and vehicle states as input, then solve an optimization problem to adjust and update the plan, including vehicle routes, schedules, and P2V assignment. Five decision variables are defined:

- $x_{ijkt} \in \{0,1\}$, routing variable, equals to 1 if the route segment (i,j) is traveled by vehicle k in step t.
- $y_{pkt} \in \{0,1\}$, P2V assignment variable, equals to 1 if the request p is assigned to vehicle k in step t .
- $\xi_{ikt} \geq 0$, represents the vehicle arrival time at vertex i in step t.
- $w_{pt} \geq 0$, denotes the passenger p waiting time at pick-up vertex in step t.
- $z_{kt} \in \{0,1\}$, vehicle utilization variable, equals to 1 if vehicle k is used in step t

For simplicity, the decision variables are grouped into the sets: $\mathcal{X} = \{x_{ijkt} | (i,j) \in A, k \in K, t \in \mathcal{T}\}$, $\mathcal{Y} = \{y_{pkt} | p \in P_t \cup \widehat{P}_t, k \in K, t \in \mathcal{T}\}$,$\div = \{\xi_{ikt} | i \in V, k \in K, t \in \mathcal{T}\}$, $\mathcal{W} = \{w_{pt} | p \in P_t \cup \widehat{P}_t, t \in \mathcal{T}\}$,$\mathcal{Z} = \{z_{kt} | k \in K, t \in \mathcal{T}\}$.

$$\begin{aligned} \min_{\mathcal{X},\mathcal{Y},\div,\mathcal{W},\mathcal{Z}} & \sum_{k \in K} \sum_{t \in \mathcal{T}} c_d z_{kt} + \sum_{(i,j) \in A} \sum_{k \in K} \sum_{t \in \mathcal{T}} c_{ij} x_{ijkt} \\ & + \sum_{p \in P_t \cup \widehat{P}_t} \sum_{t \in \mathcal{T}} c_w w_{pt} \end{aligned} \tag{10}$$

s.t. (1)-(9),

$$\sum_{k \in K} y_{pkt} = 1, p \in \widehat{P}_t, t \in \mathcal{T} \tag{11}$$

$$\sum_{i \in V} x_{ijkt} = \sum_{i \in V} x_{jikt}, j \in S, k \in K_{It}, t \in \mathcal{T} \tag{12}$$

$$\sum_{j \in S} x_{ijkt} = \sum_{j \in S} x_{jikt}, i \in O, k \in K_{It}, t \in \mathcal{T} \tag{13}$$

$$\begin{gathered} \sum_{j \in S} x_{ijkt} \geq y_{pkt}, \\ i \in S^+ \cap S_p, p \in \widehat{P}_t, k \in K_{It}, t \in \mathcal{T} \end{gathered} \tag{14}$$

$$\begin{gathered} \sum_{i \in S} x_{ijkt} \geq y_{pkt}, \\ j \in S^- \cap S_p, p \in \widehat{P}_t, k \in K_{It}, t \in \mathcal{T} \end{gathered} \tag{15}$$

$$\sum_{p \in \widehat{P}_t} y_{pkt} \leq q_{kt}, k \in K_{It}, t \in \mathcal{T} \tag{16}$$

$$\begin{gathered} \xi_{jkt} \geq \xi_{ikt} + M(x_{ijkt} - 1) + x_{ijkt}(t_{ij} + t_b), \\ (i,j) \in A, k \in K_{It}, t \in \mathcal{T} \end{gathered} \tag{17}$$

$$z_{kt} \geq x_{ijkt}, (i,j) \in A, k \in K, t \in \mathcal{T} \tag{18}$$

$$\begin{gathered} x_{ijkt} = \mathbf{\Phi}(q_{kt}, P_t, \widehat{P}_{t-1}), \\ (i,j) \in A, k \in K_{Et}, t \in \mathcal{T} \end{gathered} \tag{19}$$

$$\begin{gathered} x_{ijkt} = \mathbf{\Psi}(y_{pkt}, loc_{kt}, q_{kt}), \\ (i,j) \in A, p \in \widehat{P}_t, k \in K_{Et}, t \in \mathcal{T} \end{gathered} \tag{20}$$

The objective Eq. (10) aims to minimize the departure cost, vehicle traveled cost and passenger waiting cost, c_d is the per vehicle departure cost, c_{ij} is the travel cost per route segment, c_w is the waiting cost per min. Constraints (11) specify that any estimated request can be served by an idle or en-route vehicle. Constraints (12)-(17) formulate the operation for activating idle vehicles for anticipated demands. Specifically, constraints (12)-(13) are the routing constraints, enforcing the flow balance constraints. Constraints (14)-(15) are the space constraints. Constraints (16) is the vehicle capacity constraints. Constraints (17) ensure the time flexibility for visiting arcs, where t_{ij} is the travel time of arc (i,j), M is a large number. Constraints (18) indicate the vehicle utilization state. Constraints (19) model the plan adjustment for real demand P_t. Constraints (20) model the dispatching procedure if the anticipated demand is assigned to en-route vehicles. They will be discussed in Section III-C and III-D.

III. Rolling Horizon Approach

In this section, we propose the implementation of the rolling horizon approach and demand prediction in the real-time ACB routing and scheduling problem in Section II-A. The rolling horizon method is a highly flexible approach designed to handle optimization problems in dynamic environments, especially with unforeseen circumstances [16].

Algorithm 1 Rolling Horizon Approach with Prediction

Input: Planning horizon $\mathcal{T}$, time interval Δt, initial step $t = t_0$, reserved demands P_{t_0} and vehicle states Veh_{t_0}
1: $\widehat{P}_{t_0} \leftarrow$ demand prediction
2: $\mathcal{X}_{t_0}, \mathcal{Y}_{t_0}, \mathcal{W}_{t_0}, \div_{t_0}, \mathcal{Z}_{t_0} \leftarrow$ generate initial plan (see Section III-A)
3: $t = t_0 + 1$
4: **for** $t \leq t_0 + T$ **do**
5: $P_t \leftarrow$ real demand collection
6: $\widehat{P}_t \leftarrow$ demand prediction
7: $Veh_t \leftarrow$ vehicle state update.
8: $\mathcal{X}, \mathcal{Y}, \mathcal{W}, \div, \mathcal{Z} \leftarrow$ solve the problem in Section II-B
9: $t = t + 1$
Output: $\mathcal{X}, \mathcal{Y}, \mathcal{W}, \div, \mathcal{Z}$

The proposed approach is summarized in Algorithm 1: at initial time step t_0, we first identify the vehicle state Veh_{t_0} (including loc_{kt_0}, p_{kt_0}, K_{It_0}) to recognize the available vehicles, and collect the reserved demands P_{t_0} and anticipated demands $\widehat{P}_{t_0}$. Then, the initial plan is generated by solving a mixed-integer programming model (see Section III-A). After the defined time interval Δt, i.e., in the next time step t, the ACB system updates the vehicle state Veh_t with Eqs.(1)-(7), obtains real P_t and anticipated demands $\widehat{P}_t$, and acquires the optimal plan by solving the problem in Section II-B. This process is repeated during the entire planning horizon.

A. Initial plan generation

The initial plan generation focuses on the reserved and anticipated demands collected at step t_0, which aims to determine routes, schedules and P2V assignments for all idle vehicles. This static ACB routing and scheduling problem with fixed demands is formulated as a mixed integer program:

$$\min \sum_{k \in K_{It_0}} c_d z_{kt_0} + \sum_{(i,j)\in A} \sum_{k \in K_{It_0}} c_{ij} x_{ijkt_0} + \sum_{p \in P_{t_0} \cup \widehat{P}_{t_0}} c_w w_{pt_0} \tag{21}$$

s.t. (3), (8)-(9), (11)-(18),

$$loc_{kt_0} = v_o, o \in O, k \in K_{It_0} \tag{22}$$

$$\xi_{okt_0} = t_0, o \in O, k \in K_{It_0} \tag{23}$$

$$K_{It_0} = \{1, 2, ..., |K|\} \tag{24}$$

where $k \in K_{It}$ and $p \in \widehat{P}_t$ in constraints are modified to $k \in K_{It_0}$ and $p \in P_{t_0} \cup \widehat{P}_{t_0}$, $t \in \mathcal{T}$ is removed from all constraints. This problem can be solved by commercial solvers.

B. Travel demand prediction

The introduced approach relies on predicting travel demands at t. Let f be a predictive model trained with historical travel records, $\alpha(t)$ a diverse set of features relevant to the model available at the time window of prediction (including day type, OD, demand size, etc.). We denote $\mathcal{T}_f$ as the forecasting horizon, that is same as the planning horizon $\mathcal{T}$. The predicted demands in t of day d are related to the travel data from the corresponding time period in the past n days. The estimated demands can be predicted with the model $\widehat{P}_t = f(\alpha(t), P_{td-t_n})$, where $P_{td-t_n} = f(P_{td-1}, P_{td-2}, ..., P_{td-n})$. The process of demand prediction and predictive model are discussed in Section IV-B.

C. Plan adjustment

The plan adjustment in step t is proposed to deal with the inaccurate prediction obtained in $t-1$, as shown in Algorithm 2. This reactive component enables the adaptability of the pre-planned service to better cater to the differences between the predicted demands in $t-1$ and real requirements in t. There are two conditions:

(i) If $p_t > p_{t-1} (p_{t-1} \in \widehat{P}_{t-1}, p_t \in P_t)$, then the unexpected demands are served by assigning to en-route vehicles. This dispatching procedure is discussed in Section III-D.

(ii) If $p_t < p_{t-1}$, and $p_t = 0$, then the system removes the demand vertices of p from the route J_{kt-1} (J_{kt-1} is the planned vehicle route for serving p in $t-1$).

D. En-route vehicle dispatching

The allocation procedure used here shares some elements with the operational strategies 2 and 3 proposed in [10], that insert passengers to en-route vehicles. However, here we do not consider modular features, increasing the importance of exploiting predictions to maximize the use of vehicles' space. For the detailed dispatching and demand insertion algorithm the reader is referred to [10].

Algorithm 2 Plan Adjustment

```
adjustment procedure
    P_t, P̂_{t-1} ← obtain demands at t and t − 1
    for ∀p ∈ P_t
        if p_t > p_{t-1} then
            J_kt = Dispatch(J_{kt-1}, p_t − p_{t-1})
        else if p_t < p_{t-1} and p_t = 0 then
            J_kt = J_{kt-1} \ S_p
```

IV. Empirical Analysis

In this section, we present the results of our experimental analysis aiming at demonstrating the efficiency of the proposed approach on a large-scale urban network in Beijing.

A. Experimental Settings

We implement the proposed ACB system on a real urban road network of Beijing. To accurately capture the travel patterns of passengers, we employ the smartcard data (SCD) that contains 12 million travel records per day of conventional buses from November 2018 to February 2019, to estimate the travel requirements of customized services. The SCD contains the card IDs, line numbers, boarding and alighting time and stations, which can be used to identify and aggregate the OD demands, including the passengers' origins and destinations, and preferred pick-up time. All experiments are conducted with CPLEX 12.8 and MATLAB R2021a on a machine equipped with a 3.4 GHz CPU and 16 GB of RAM.

Data generation. Considering the CB services primarily appeal to commuters, we focus on commuting trips during peak morning hours (7:00-9:00AM), determined by the methodology presented in [17]. We consider trips made between major residential communities and working places, and use the trips taken between 3rd December 2018 and 18th January 2019 for training, and those between 21st and 25th January 2019 for testing. The dates have been selected to reduce the impact of external factors, such as COVID-19 and Chinese New Year. The map of the urban road network and the distribution of the 53 demand vertices is shown in the work of [9].

Parameters. We consider a homogeneous fleet of AVs for operation. The vehicle capacity cap is given as 40 people. The vehicle running cost per km of each route segment and departure cost per vehicle are ¥15 and ¥500, respectively. For each passenger, the waiting cost per min is ¥2. The planning horizon is set from 7:00 AM to 8:30 AM, and the time interval is set as 15 min.

B. Travel demand prediction

Data processing. The considered prediction problem can be tackled as a regression problem, which aims to estimate the passengers who will require the service between every possible OD within the defined time window. To maximize the prediction accuracy, it is crucial to leverage on the available data. We introduce and extend six uncorrelated prediction features, available in the considered dataset:

- Week Day. This feature is extended from the date, to refer to the working days of the week.
- Type. To indicate whether the day is Monday or Friday, that have specific patterns for commuters, or other working days.
- Period. This feature is derived from the boarding timestamps collected from the OD demand data. Five time categories have been identified, namely 7:00-7:30 AM, 7:30-7:45 AM,7:45-8:00 AM, 8:00-8:15 AM, 8:15-8:30 AM, where the first corresponds to the reserved demands, and the remaining are the forecast time intervals for future demands.
- OD. It is a combination of origin-destination vertices.
- Size. This feature represents the size of the passengers of each OD.
- Presence. It is a Boolean feature that implies the existence of the demand for a specific OD pair.

Predictive model generation and performance. To generate the regression predictor, we use the well-known Extreme Gradient Boosting (XGBoost) approach [18]. It is a powerful machine learning approach, that is a scalable, distributed Gradient-Boosted Decision Tree (GBDT) algorithm, that has been recently used for passengers' prediction in traditional public transport systems.

The trained XGBoost model performed well in the considered ACB scenario, with a MAE (Mean Absolute Error) of 1.23, and a RMSE (Root Mean Squared Error) of 1.75. In summary, it can provide meaningful predictions with limited error in terms of passengers number.

C. Impact of demand prediction

This section aims to validate the fruitfulness of using demand prediction in the proposed solution approach. Three types of approaches are considered here:

- ACB-Pure. The approach described in Algorithm 1 does not incorporate prediction. The system updates the service with real demands in each step without proactive design for the predicted demands.
- ACB-Oracle. The approach described in Algorithm 1 where the demand prediction leverages oracle, its performance provides the upper bound of the proposed approach.
- ACB-XGBoost. The approach described in Algorithm 1 exploits the XGBoost for prediction.

Table I and Figure 2 present the results generated by the different solution approaches. In both prediction cases, we can obverse that demand forecasting plays an important role in operational indicators, compared to the non-prediction case (ACB-Pure). Despite the fact that the exploitation of prediction can lead to higher vehicle traveled distance with an average increase of 4.6%, the savings in terms of operating cost, running vehicles and average waiting time are significant, at about 12.2%, 23.3% and 25.4%, respectively. There are two reasons: (i) demand prediction allows the proactive operation in response to the fluctuations of passengers, leading to highly efficient vehicle allocation and reduced passenger waiting time; (ii) the integration of rolling horizon manner and prediction enables service adjustments in each step to address the inaccurate prediction, which can better manage demand changes and avoid unnecessary or inefficient services. However, the vehicle allocation under the demand forecast may result in longer detours and turns.

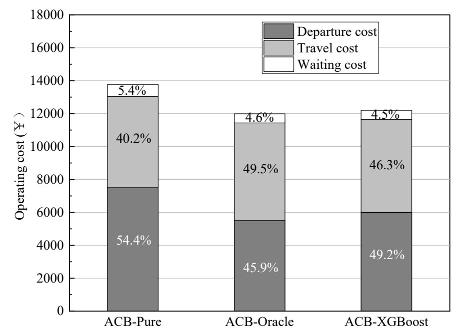

Fig. 2. Operating cost under ACB-Pure, ACB-Oracle and ACB-XGBoost.

TABLE I
IMPACT OF DEMAND PREDICTION.

	Distance/km		Vehicle/veh		Avg.W/min	
		Increase		Saving		Saving
ACB-Pure	369.0		15		1.23	
ACB-Oracle	395. 5	7.2%	11	26.7%	0.92	24.9%
ACB-XGBoost	376.7	2.1%	12	20%	0.91	25.8%

Overall, the computed results indicate that the proposed approach with demand prediction outperforms the non-prediction method; it is noted that their performances highly rely on the accuracy of predictions. As the computational time of each case is below 0.2 seconds, an analysis of the computational efficiency is omitted.

D. Performance of the rolling horizon approach

To assess whether the rolling horizon method is worth exploiting, this section compares the performance of the introduced approach with those of a practical reactive operation. The baseline reactive optimization approach used here aligns with the conventional way of CB operations:

- Reactive. The demand prediction and periodical operation are not applied: when a passenger arrives, the system is triggered to respond either by activating new vehicles or by assigning the passenger to en-route vehicles.

Table II and Figure 3 show the performance indicators of the reactive baseline compared to ACB-Pure and ACB-XGBoost. First, it is easy to notice that even ACB-Pure case can lead to savings regarding operating costs and running vehicles, with 9.9% and 21.2%, respectively. This remarkable result indicates that even if the predictions are not involved, it is better to rely on the periodical operation manner, to achieve better vehicle allocation. Unsurprisingly, the rolling horizon manner may lead to a rise in passenger waiting time. The reason for this is that it assigns real-time demands received in each step uniformly, resulting in a delay in responding to some passengers, rather than updating or replanning the service once a request occurs, as in the case of reactive operation. However, this disadvantage can be mitigated by leveraging the benefits of demand forecasting, with a slight rise in waiting time of 7.0%.

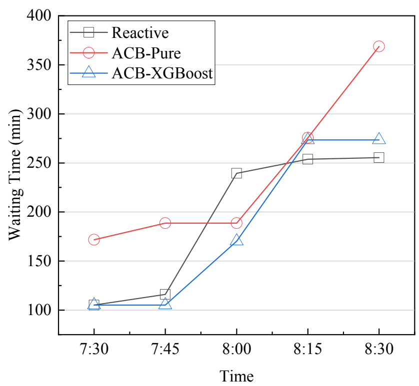

Fig. 3. Passenger total waiting time in each time step under Reactive, ACB-Pure and ACB-XGBoost

TABLE II

PERFORMANCE ON ROLLING HORIZON APPROACH IN TERMS OF OPERATING COST , TRAVELED DISTANCE AND OPERATED VEHICLES.

	Operating Cost/¥		Distance/km		Vehicle/veh	
		Saving		Increase		Saving
Reactive	15282.4		351.4		19	
ACB-Pure	13772.9	9.9%	369.0	5.0%	15	21.1%
ACB-XGBoost	12197.0	20.2%	376.7	7.0%	12	36.8%

V. CONCLUSION

To better exploit the benefits that can derive from autonomous customized bus systems, this paper presented an ACB system that effectively addresses fluctuations in reserved and real-time travel requests. We introduced a service design optimization model for real-time routing and scheduling problem, and put forward a rolling horizon approach that leverages travel demand prediction. An extensive experiment is conducted to assess and measure the impact of the proposed approach to the overall system performance, where the state-of-the-art machine learning method is applied for demand prediction. Our experimental analysis confirms that the hybrid of the proactive and reactive service design can significantly enhance service quality and operational efficiency: compared to the traditional reactive operation, the introduced ACB system can lead to significant savings across key operational indicators. Overall, the saving in operating cost is above 20%.

Future work will focus on extending the proposed approach to increase robustness to low-quality predictions or unforeseen circumstances.

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