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Integrated Demand Responsive transport in Low-Demand Areas: A case study of Canberra, Australia

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A R T I C L E I N F O

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A B S T R A C T

This paper evaluates Integrated-Demand Responsive Transport (I-DRT) as a solution to the challenges faced by traditional public transport (PT) systems in low-demand urban areas. The study investigates the implications of replacing local PT with I-DRT in low-demand urban areas. A multi-objective model, incorporating operational cost, environmental impact, passengers' travel time, and inequity is used to simulate the I-DRT performance. The analysis compares the performance of I-DRT and existing local bus lines in Belconnen, Canberra, Australia, based on number of utilised vehicles, operational cost, fuel consumption, average travel time, individual passenger travel time, delay, and inequity in delay distribution.

1. Introduction

Traditional public transport (PT) systems operate according to pre-scheduled timetables, travelling along fixed routes and stopping at predetermined locations. PT systems play a pivotal role in catering to the mobility needs of urban populations with high travel demand. However, these conventional systems often face limitations in effectively serving low-demand areas due to their inherent inflexibility and cost-inefficiency, where it may not be financially viable to provide a high-frequency service (Dytckov et al., 2022). As a result, PT systems have always faced challenges and have been the target of new ideas aimed at making them more efficient. One such solution is the implementation of Demand Responsive Transport (DRT) systems, which can play a crucial role in bridging the gaps of PT and providing a more efficient transport option in low-demand areas.

Two main research directions aim to utilise DRT as a solution to overcome the challenges of PT. The first direction focuses on investigating the impact of replacing regular PT in low-demand areas with DRT (Gökay et al., 2017a; Narayan et al., 2019; Oke et al., 2020). The second direction involves adopting DRT as an additional travel mode within the existing PT network. In the latter approach, DRT serves to facilitate the first/last leg of PT trips, acting as a feeder or connector service (Calabrò et al., 2020; Calabrò et al., 2022; Edwards & Watkins, 2013; Grahn et al., 2021; Lee & Savelsbergh, 2017). However, the integration of DRT systems into the existing PT network requires comprehensive coverage for all travel segments. This entails accommodating local trips from any origin to any destination throughout the service area and ensuring connectivity with the main PT network and adherence to its timetables. On the other hand, concerns have been raised regarding the performance of DRT systems. Despite extensive research analysing DRT performance, the primary focus has predominately revolved around operational costs and environmental impact, with considering a certain level of passenger service (Archetti et al., 2018; Dytckov et al., 2022; Gökay et al., 2017a; Martinez et al., 2015). However, the crucial aspect of how the replacement of PT with DRT influences passengers' experience has not received sufficient attention, where

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this factor can play a significant role in the overall success or failure of the system. In addition, although the performance of DRT systems has been examined through various angles such as operational costs and CO_2 emissions, previous studies have predominately focused on optimising their plans based on a single-form objective function (Calabrò et al., 2020; Calabrò et al., 2022; Dytckov et al., 2022; Edwards & Watkins, 2013; Lee & Savelsbergh, 2017) and the impact of different prioritisations within the objective function of the model has been largely neglected. It is important to consider and evaluate the effects of different priorities in the objective function to gain a more comprehensive insight into the trade-off between different factors that affect the performance of DRT systems.

In this study, we focus on a new version of DRT, the Integrated-DRT (I-DRT), which not only serves passengers as a feeder and connects residents of the servicing area to the rapid inter-regional PT network but also provides local services from any origin to any destination within the servicing area. We simulate I-DRT using a multi-objective Dial-a-Ride Problem, which includes operational cost, environmental impacts, passengers' travel time, and inequity as the objectives. Adopting a multi-objective function model with different prioritisations helps us to gain a deeper insight into the existing trade-off among objectives and the potential impacts of varying prioritisations on the performance of I-DRT. To evaluate the performance of the I-DRT, we conduct a systematic and extensive analysis by comparing the performance of I-DRT with fixed PT in a real-world setting. In our simulation, we replace the local bus lines of the Belconnen district in Canberra, Australia, with the I-DRT system. This analysis compares the performance of I-DRT and the existing local bus lines based on detailed measures with a focus on passengers' experience. We utilise indicators that include the number of vehicles, vehicle travel distance, operational cost, fuel consumption, passengers' average travel time, individual passenger travel time (comparing the travel time of each passenger in I-DRT and PT with the passenger's direct travel time), average delay, and inequity in delay distribution among passengers. The simulation results reveal that I-DRT has higher adaptability to demand changes, which results in lower operational costs and fuel consumption throughout the day. In addition, the I-DRT improves passengers' average travel time and leads to a more equitable distribution of excess travel times, enhancing the overall passengers' travel experience.

The remainder of the paper follows the following structure: Section 2 presents a concise literature review on DRT. Section 3 discusses the methodology and the adopted multi-objective function formulation for simulating I-DRT. Section 4 provides a description of the case study and details the process of data preparation. Section 5 presents the simulation results and evaluates the performance of I-DRT compared to the PT. Finally, Section 6 concludes the paper and presents the key findings.

2. Literature review

Since the 1970s, DRT systems have been at the centre of focus as flexible shared transport systems that cater to the demands of residents. These systems are designed to provide transport services that respond to passengers' personalised needs, carrying them from their specified origin to their desired destination at their desired time. The emphasis has been on personalising PT systems and making them flexible (Wang et al., 2023). Initially, DRT systems were mostly adopted for limited applications such as transporting elderly or disabled individuals (Davison et al., 2012) or providing services to specific destinations, such as airports (Reinhardt et al., 2013). Recently, with the widespread use of mobile internet technology, the concept of DRT has been broadened to go beyond its previous applications and referred to as flexible transport services, with the aim of providing personalised PT systems to a general group of passengers (Atasoy et al., 2015).

One proposal is based on running DRT systems in low-demand areas as an alternative to traditional PT services (Dytckov et al., 2022; Gökay et al., 2017b). The results of these research directions support the adoption of DRT as a replacement for PT in low-demand areas. It has been found that DRT systems are not only cost-efficient (Dytckov et al., 2022), but they also have the potential to increase ridesharing in such areas (Narayan et al., 2019), absorb demand from other modes of transport (Oke et al., 2020). Nevertheless, they may require a higher number of vehicles in some cases (Dytckov et al., 2022). While these DRT systems provide a Many-to-Many (M−to−M) transport service for passengers, they are not synchronised according to the time scheduling of mass PT networks.

Another approach is to adopt DRT as a feeder system to facilitate the first/last leg of PT travels (Calabrò et al., 2020; Calabrò et al., 2022; Edwards & Watkins, 2013; Grahn et al., 2021; Lee & Savelsbergh, 2017). Results of these studies have also demonstrated that DRT systems as feeders are more cost-effective and environmentally friendly when it comes to connecting passengers to mass rapid transit in low-demand areas. However, it is important to note that DRT systems as feeders are characterised as Many-to-One (M−to−1) or Many-to-Few (M−to−F) problems, where there are multiple origins/destinations with low demand and a single (or few) destination (s)/origin(s), as transport hubs. As a result, they are unable to provide transport services for passengers with local trip purposes. However, integrating DRT systems into existing PT networks requires the transport system to cater to all travel demands of the serviced area's residents, including local trips and connection trips.

On the other hand, several studies have extensively investigated numerous DRT systems worldwide, shedding light on the challenging nature of their sustainable development (Currie & Fournier, 2020; Davison et al., 2012). One of the primary reasons behind these challenges is that unsuccessful DRT projects are often designed without a thorough understanding of the market segments they aim to serve (Davison et al., 2012). There are series of studies that analysed DRT performance according to operational cost or environmental issues (Calabrò et al., 2020; Calabrò et al., 2022; Diana et al., 2007; Dytckov et al., 2022; Edwards & Watkins, 2013; Gökay et al., 2017a; Lee & Savelsbergh, 2017; Mortazavi et al., 2023b; Papanikolaou et al., 2017). The results indicate that in low-demand areas DRT systems offer notable cost efficiency and environmental friendliness compared to fixed PT. However, as demand increases, regular buses prove to be more cost-effective due to their ability to transport larger passenger volumes without requiring considerable changes in the number of vehicles (Dytckov et al., 2022; Mortazavi et al., 2023b). Despite the fact that the quality of service in flexible transport systems such as DRT can vary significantly, the aspect of passengers' experience within the context of DRT is not sufficiently investigated. One common approach in evaluating passengers' experience is to consider a certain level of service that is deemed equivalent to the level of service provided by the replaced PT system (Dytckov et al., 2022; Gökay et al., 2017a; Martinez et al., 2015; Narayan et al., 2019, 2020; Oke et al., 2020). While some studies used passengers' travel experience using aggregated indicators (Mortazavi et al., 2023b), adopting aggregated indicators has limitations in capturing passengers' precise and individual-based experiences. Consequently, they may not offer a complete and accurate picture of the actual experiences of passengers. Additionally, considering equitable distribution of facilities (travel time) among passengers can guarantee a consistent travel experience for all passengers. Neglecting this notion of balance of experiences may result in situations where a small group of passengers has a very negative experience, while aggregate indicators might suggest that, on average, the performance of DRT is satisfactory. Therefore, addressing the issue of equity in passengers' experiences is essential for obtaining a comprehensive understanding of DRT performance.

The literature indicates a lack of attention in assessing the performance of integrated DRT systems (I-DRT) that cater to both local and connection trips within the existing PT network. The primary objective of this study is to simulate an I-DRT system and address the challenges associated with its modelling. Furthermore, we aim to enhance our understanding of different prioritisations among the factors involved by developing a multi-objective function that encompasses operational cost, environmental impact, passengers' travel time, and inequity. Lastly, this study makes a significant contribution by conducting a comprehensive analysis of the performance of the modelled I-DRT system, with a specific focus on the passengers' experience. This analysis is conducted using disaggregated indicators to provide a thorough evaluation of the system's performance with respect to passenger experience.

3. Methodology

3.1. Problem description

We model the I-DRT system as a modified version of the standard Dial-a-Ride Problem (DARP) introduced (Cordeau & Laporte, 2003), considering operational features discussed in Section 3.3. DARP is a routing optimisation problem defined on a graph $G = (N, A)$, where N represents the set of all vertices, including pick-up points $(1, \cdots, n)$ and drop-off points $(n+1, \cdots, 2n)$, and A is the set of all connecting arcs. The number of requests is denoted by n, with each request having an origin node denoted by i and a destination node denoted by $n+i$. Additionally, each request is associated with a desired time window specified by the earliest visiting time (e_i) and the latest visiting time (l_i). In the context of modelling, we consider that a passenger may transfer to/from the mass PT network, and thus the values of e_i and l_i are determined accordingly as discussed in Section 3.3. Each vertex is associated with a load, which is set to 1 for pick-up points and -1 for drop-off points of each request and is denoted by q_i. Furthermore, the travel time for each passenger is constrained by the maximum ride time (L), and the duration of each vehicle tour should be less than the maximum tour duration (D) due to operational considerations such as drivers' rest and refuelling. Travelling along each arc (from i to j) incurs a travel distance denoted by C_{ij} and a travel time denoted by T_{ij}. In this study, the proposed linearly decreasing-deterministic annealing algorithm by Mortazavi et al. (2023) is adopted to solve the model. The mathematical problem formulation in this study is as follows:

$$Minf(s) = Min(\alpha \times f_1(s) + \beta \times f_2(s) + \gamma \times f_3(s) + \lambda \times f_4(s)) \tag{1}$$

Subject to:

$$\sum_{v \in V} \sum_{j \in N} X_{i,j}^{v} = 1 \forall i \in P \tag{2}$$

$$\sum_{j \in N} X_{i,j}^{v} - \sum_{j \in N} X_{i+n,j}^{v} = 0 \forall i \in P, v \in V \tag{3}$$

$$\sum_{j \in N} X_{j,i}^{v} - \sum_{j \in N} X_{i,j}^{v} = 0 \forall i \in P, v \in V \tag{4}$$

$$\sum_{j \in N} X_{0,j}^{v} = 1 \forall v \in V \tag{5}$$

$$\sum_{i \in N} X_{i,(2n+1)}^{v} = 1 \forall v \in V \tag{6}$$

$$A_j^v \geq \left(A_i^v + T_{i,j}\right) X_{i,j}^{v} \forall i,j \in N, v \in V \tag{7}$$

$$A_{i+n}^v \geq A_i^v \forall i \in P, v \in V \tag{8}$$

$$e_i \leq A_i^v \leq l_i \forall i \in N \tag{9}$$

$$A_{i+n}^v - A_i^v \leq L \forall i \in P, v \in V \tag{10}$$

$$A_{2n}^v - A_1^v \leq D \forall v \in V \tag{11}$$

$$Q_j^v \geq \left(Q_i^v + q_j\right) X_{i,j}^{v} \forall i,j \in N, v \in V \tag{12}$$

Table 1
list of utilised notations.

Variable	Definition
N	Set of all vertices
A	Set of all arcs
n	Number of requests
i	Passengers' indicator
e_i	Earliest visiting time of passenger i
l_i	Latest visiting time of passenger i
TW_i	Time window of passenger i
q_i	Number of passengers to be picked up at vertex i
Q_v	Capacity of vehicle v
Q_j^v	Occupancy rate of vehicle v at vertex i
L_i	Maximum ride time of passenger i
D	Maximum tour duration of each vehicle
C_{ij}	Travel distance from vertex i to vertex j
T_{ij}	Travel time from vertex i to vertex j
$f(s)$	Objective function
$f_1(s)$	Objective function component, related to operational cost
$f_2(s)$	Objective function component, related to fuel consumption
$f_3(s)$	Objective function component, related to passengers' travel time
$f_4(s)$	Objective function component, related to inequity
α	Objective function weight parameter, related to operational cost
β	Objective function weight parameter, related to fuel consumption
γ	Objective function weight parameter, related to passengers' travel time
λ	Objective function weight parameter, related to inequity
$X_{i,j}^v$	Binary variable, equal to 1 if arc from i to j is traversed by vehicle v, otherwise 0
A_i^v	Arrival time of vehicle v at vertex i
TD	Total travel distance
TD_{max}	Maximum possible travel distance
$C_{i,max}$	Travel distance of the longest link departing from vertex i
$Fuel_{con}$	Fuel consumption (litre per 100 Km)
$Fuel_{price}$	Price of fuel per litre
$N_{used_{veh}}$	Number of used vehicles
$N_{avail_{veh}}$	Total number of available vehicles
$shift_{hour}$	Shift duration of drivers
$Driver_{cost}$	Driver's payment per hour
ATT_i	Actual travel time of passenger i
DTT_i	Direct travel time of passenger i

$$\max(0, q_i) \leq Q_i^v \leq Q_v \forall i \in N, v \in V \tag{13}$$

$$X_{i,j}^v \in \{0, 1\} \forall i, j \in N, v \in V \tag{14}$$

In comparison to the standard DARP formulation, the adopted formulation in this study differs in two ways. Firstly, the objective function used in this study is a multi-objective function (equation (1)), as discussed in Section 3.2, whereas the common approach is to minimise travel costs as a single objective. Other constraints remain the same as in standard DARP. Equations (2) and (3) ensure that each request is visited only once and that its origin and destination are served by the same vehicle. In these equations $X_{i,j}^v$ is a binary variable (equation (14)), which is equal to 1 if the arc from i to j is traversed by vehicle v. Equation (4) ensures that vehicles depart from every visited vertex to ensure flow conservation. Equations (5) and (6) ensure that tour vehicles start from and end at the considered depot. Equation (7) ensures time consistency and is used for calculating arrival times. Equation (8) guarantees the destination is visited after the origin for each request. Equation (9) enforces the time window constraint. Equations (10) and (11) limit the on-board time of each passenger to the maximum ride time, and the operation time of each vehicle to the maximum tour duration, respectively. Equation (12) ensures the consistency of the load variable for each vehicle, while equation (13) checks the capacity constraint.

For linearising constraints in equations (7) and (12), two constants of $W_{i,j}^v \geq \min(Q_v, Q_v + q_i)$ and $M_{i,j}^v \geq \max(0, l_i + C_{ij} - e_j)$ are adopted to adjust these equations. The equations are transformed as follows:

$$A_j^v \geq \left(A_i^v + T_{i,j}\right) - M_{i,j}^v(1 - X_{i,j}^v) \forall i, j \in N, v \in V \tag{15}$$

$$Q_j^v \geq \left(Q_i^v + q_j\right) - W_{i,j}^v(1 - X_{i,j}^v) \forall i, j \in N, v \in V \tag{16}$$

The list of used notations in this article is summarised in Table 1

Table 2
Value of model's Fixed variables.

Variable	I-DRT (12-seater van)	Bus (48-seater bus)
$Fuel_{con}$	8.1 (litre/100 km)(12-seater)	28.1 (litre/100 km)(40-seater)
$fuel_{price}$	1.87 ($/litre)	1.87 ($/litre)
$Driver_{cost}$	35 ($/hour)	35 ($/hour)

3.2. Multi-objective function

In this study, we propose a multi-objective approach. While some of the previous studies have considered passenger costs or environmental impact as additional factors to operational cost in the objective function, they typically focused on optimising routes based on single form objective function. The proposed multi-objective approach in this study not only optimises routes based on various factors and their respective weights but also investigates the impact of different prioritisations (trade-offs between objectives) on DRT performance.

Our multi-objective function incorporates four key factors: operational cost, environmental impact, passengers' travel time, and inequity. Each factor is assigned a weight parameter, denoted by α, β, γ, and λ respectively (Equation (1)). These weight parameters reflect the relative importance of each factor in the objective function, ranging from 0 to 1. The sum of all weight parameters is equal to 1. To explore the trade-offs and different prioritisations among these factors, we optimise solutions using various weight combinations. In this study, we consider 35 different weight combinations. Each parameter ranges from 0 to 1 with increments of 0.25. We evaluate the solutions for all 35 wt combinations, and the results are presented in Section 5. This approach allows us to gain insights into the impact of different prioritisations on the simulated I-DRT performance and inform decision-making processes. Implemented different weight combinations represent different planning priorities. The operational plan is a solution for I-DRT which is determined based on these priorities, set by the modeller through the assigned weight values to the objective function parameters. These weights signify the varying degrees of importance attached to different facets of the objective, including operational cost, environmental impact, passengers' travel time, and inequity.

3.2.1. Operational cost

The operational cost is a critical factor that influences the success or failure of transport systems and is essential for the sustainability of DRT systems. Existing literature suggests that DRT may not always be financially sustainable and may fall short of developers' and planners' financial expectations (Currie & Fournier, 2020). Therefore, a case-by-case analysis is necessary to assess its viability. In our study, we have included operational cost as a factor in the objective function and a performance indicator to evaluate the I-DRT system compared to the local PT network. The operational cost model considered in this study encompasses both distance-based costs and drivers' costs, as shown in Equation (17).

$$f_1 = \frac{\left(TD \times Fuel_{con} \times Fuel_{price}\right) + \left(N_{used_{veh}} \times shift_{hour} \times Driver_{cost}\right)}{\left(TD_{Max} \times Fuel_{con} \times Fuel_{price}\right) + \left(N_{avail_{veh}} \times shift_{hour} \times Driver_{cost}\right)} \tag{17}$$

The first component of the numerator represents the distance-based cost. In this equation, TD represents the total travel distance in the optimal plan which is calculated using equation (18). TD_{max} is the maximum possible travel distance, calculated using equation (19), where $c_{i,max}$ represents the travel distance of the longest link departing from vertex i. $Fuel_{cons}$ refers to the fuel consumption per 100 km, and $Fuel_{price}$ represents the fuel price per litre. The second component in the numerator pertains to the drivers' expenses. $N_{used_{veh}}$ and $N_{avail_{veh}}$ denote the number of used (dispatched) vehicles and the total available vehicles, respectively. $Shift_{hour}$ represents the shift duration of drivers and $Driver_{cost}$ indicates the payment per hour for drivers.

To ensure fairness and comparability among different objectives with varying scales or units, all factors in the objective function have been normalised by dividing them by their maximum possible values.

$$TD = \sum_{v\in V}\sum_{i\in N}\sum_{j\in N} C_{i,j}X^{v}_{i,j} \tag{18}$$

$$TD_{max} = \sum_{i\in N} C_{i,max} \tag{19}$$

The parameters of the objective function consist of both the objective weights and operational features. The operational features, such as $Fuel_{con}$, $Fuel_{price}$, and $Driver_{cost}$, are fixed values and determined using the technical specifications provided by car manufacturers and the operational features of PT in Canberra (Australian Institute of Petroleum, 2022; Toyota, 2023; Transport Canberra, 2023a, 2023c). The specific values of these parameters can be found in Table 2.

3.2.2. Environmental impacts

The enhancement of PT services is typically regarded as an important element of policies aimed at achieving more efficient utilisation of energy resources and reducing emissions of pollutants. Significant investments have been made in developing and

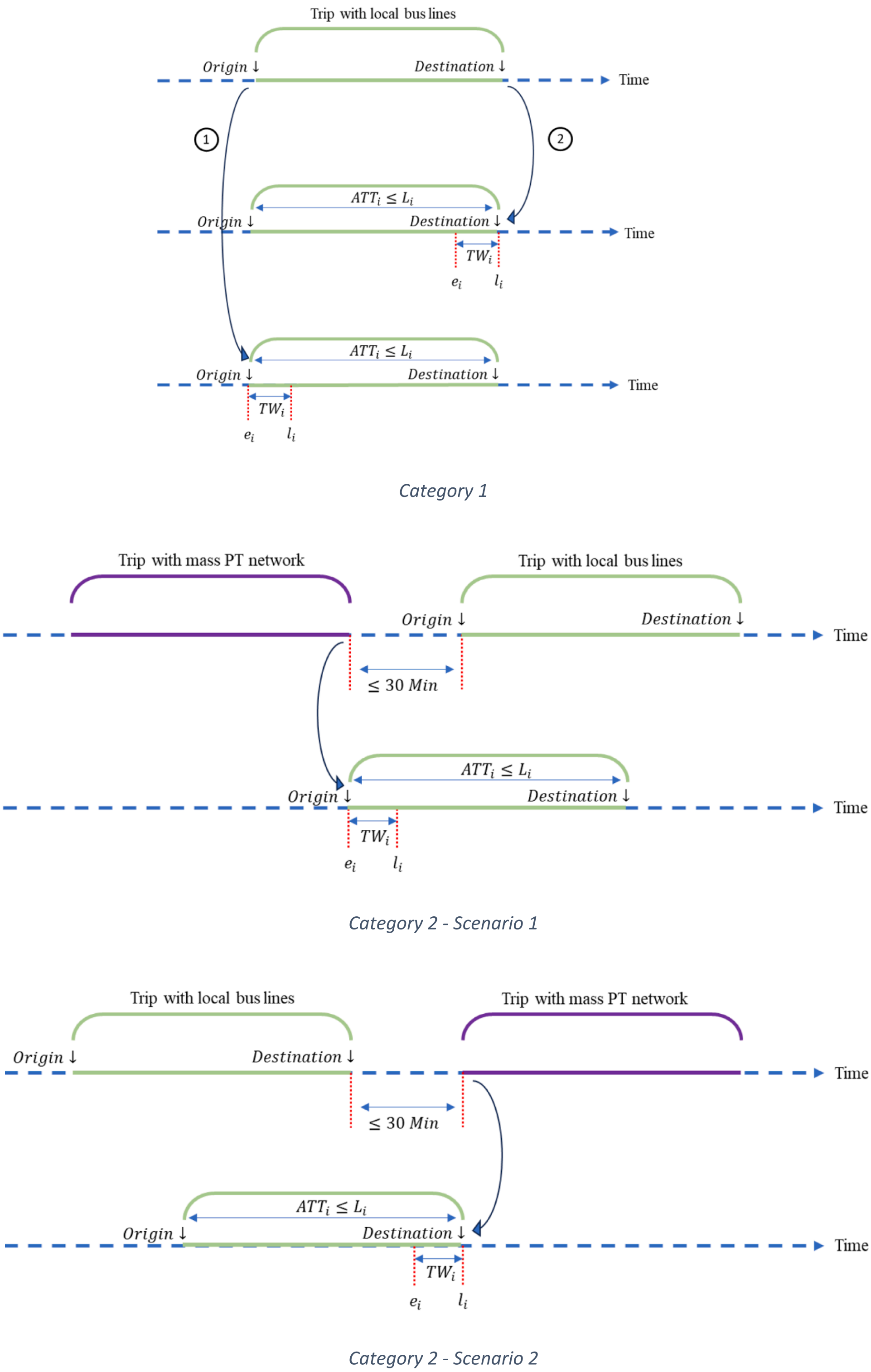


Fig. 1. Schematic diagrams representing how time window is determined for various travel arrangements.

implementing less polluting PT services as a priority (Diana et al., 2007). In line with this, we have included the environmental impacts of the I-DRT system in the objective function by using fuel consumption as a proxy, which is directly related to the CO_2 emission of system (Mickūnaitis et al., 2007). Equation (20) is used to calculate the required fuel for operating the system.

$$f_2 = \frac{(TD \times Fuel_{con})}{(TD_{Max} \times Fuel_{con})} \tag{20}$$

In this equation, the fuel consumed for operating the system based on the plan is normalised by dividing it by the maximum possible fuel consumption. This normalisation allows for comparability among objectives with different scales or units. The variables TD and TD_{max} represent the travel distance and the maximum possible travel distance, which are calculated using equations (18) and (19), respectively. While f_2, the adopted fuel consumption model in this study, strongly depends on the travel distance of the system, it differs from f_1, the adopted operational cost model, which encompasses both the travel distance of the system and the cost of recruiting drivers simultaneously. Therefore, considering these two objectives offers decision-makers the opportunity to prioritise I-DRT operational plan based on either environmental impacts or operational costs. The parameter $Fuel_{con}$ represents the fuel consumption rate per 100 km, and its value is determined based on the specifications provided in Table 2.

3.2.3. Passenger travel time

The quality of service provided by DRT systems can vary greatly depending on the operational plan implemented for passengers (Dytckov et al., 2022). This variability in service quality can directly influence passenger satisfaction, which plays a crucial role in the overall success or failure of the system. In order to address this aspect, the third objective considered in this study is minimising passengers' travel time, as described in equation (21).

$$f_3 = \frac{\sum_{v \in V} \sum_{i \in P} ATT_i}{\sum_{i \in P} L_i} \tag{21}$$

The total travel time of passengers in equation (18) is calculated by summing all passengers' actual travel time (ATT_i), which is equal to the time difference between the arrival time of the vehicle at the passengers' origins (A_i^v) and destinations (A_{i+n}^v). To ensure comparability among objectives with varying scales or units, the total travel time of passengers is normalised by dividing it over the total maximum possible on-board time (ride time) of passengers. The maximum ride time for each passenger, which is denoted by L_i, is considered equal to twice the direct travel time of the passenger in this study (Section 4.2).

3.2.4. Inequity

Inequity is an important aspect to consider in designing PT services, including DRT, for several reasons. Firstly, minimising inequity ensures fairness among passengers by aiming to provide equal treatment (travel time) for all individuals using the service. In addition, examining inequity, along with other indicators related to passengers' experience, such as total travel time, can provide more detailed insights into the potential disparities that passengers may face. By incorporating inequity as a factor in the DRT model, it is possible to strive for a more equitable distribution of resources and services among passengers. Therefore, we considered inequity as the fourth objective for I-DRT. This objective differs from the third objective. While the third objective function component focuses on minimising passengers' travel time, the fourth objective aims to reduce the disparity in passengers' excess travel times (regardless of their travel time) by minimising the standard deviation of the ratio between passengers' excess travel times and their direct travel time. This objective is formulated as shown in equation (22).

$$f_4 = Stdv((ATT_i - DTT_i)/DTT_i) \forall i \in N \tag{22}$$

In equation (19), ATT_i and DTT_i represent the actual travel time and direct travel time of passenger i, respectively.

3.3. Integration specifications

In this study, we conducted simulations of an I-DRT system that serves both local trips and connecting trips within a servicing area. For the purpose of local trips, the simulated I-DRT system should be capable of providing transport services from any origin to any destination within the area. However, to ensure consistency and fairness when comparing the performance of the I-DRT system with the existing PT, and due to the lack of access to specific origins and destinations of passengers, we considered the bus stops within the servicing area as the locations for starting or ending trips.

On the other hand, similar to feeder services, the I-DRT system is required to transport passengers who wish to transfer to the rapid inter-regional PT network based on their scheduled timings. To appropriately define drop-off time windows for these passengers, they are categorised into two groups, and the time windows of each category are determined according to their travel needs. These two categories are as follows:

1- Passengers who only use local bus lines. This category includes passengers who use local bus lines for local trips. For these passengers, either the departure or arrival time is randomly selected and used to set the earliest visiting time (e_i) or latest visiting time (l_i), respectively. Then, the time windows of passenger (TW_i) is considered according to the earliest and latest visiting time. The top part of Fig. 1 shows how the pick up or drop off times of a passenger is determined based on the passenger's observed travel time in the existing PT. For passengers in this category, the time window is either set for their pick up, approach 1, or for their drop off, approach 2. In approach 1, the observed boarding time is considered as the earliest visiting time and TW_i is applied to the origin, while in approach 2, the destination alighting time is considered as the latest visiting time and TW_i is applied to the destination.

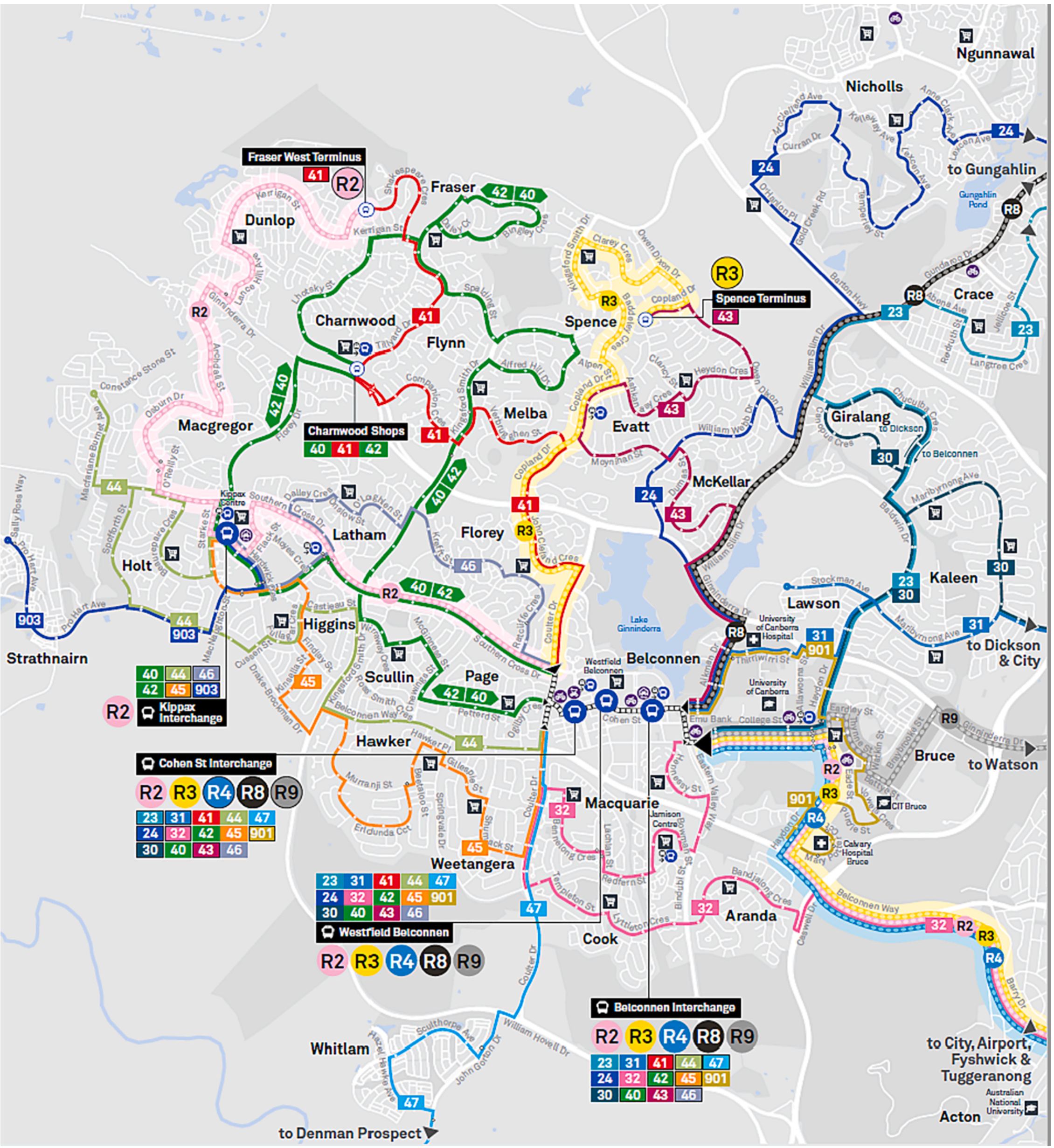


Fig. 2. Belconnen public transport network.

2- Passengers who use local bus lines and transfer from/to rapid inter-regional PT network. In this category, passengers use local bus lines to connect to the rapid inter-regional PT network. Passengers in this category are those for whom we have observed a transfer within 30 min after or prior to their trip with local bus lines. Depending on whether the transfer is before or after the ride with local bus lines, two scenarios are possible.

Scenario 1: If a passenger uses the rapid inter-regional PT network within 30 min prior to a trip with local bus lines, we consider it a transfer from the rapid inter-regional PT network to local bus lines. As shown in Fig. 1, Category 2 – Scenario 1, for these passengers, the earliest visiting time for their origin is assumed as their alighting from the rapid inter-regional PT network, and a time window of 30 min is set for their origin.

Scenario 2: If a passenger uses the rapid inter-regional PT network within 30 min (maximum headway for rapid line services over the weekend) after a trip with local bus lines, we consider it as a transfer from local bus lines to the rapid inter-regional PT network. As shown in Fig. 1, Category 2 – Scenario 2, for these passengers, the latest visiting time for their destination is set as their boarding time on the rapid inter-regional PT network. For these passengers, a time window of 30 min is applied to their destinations within the local PT network.

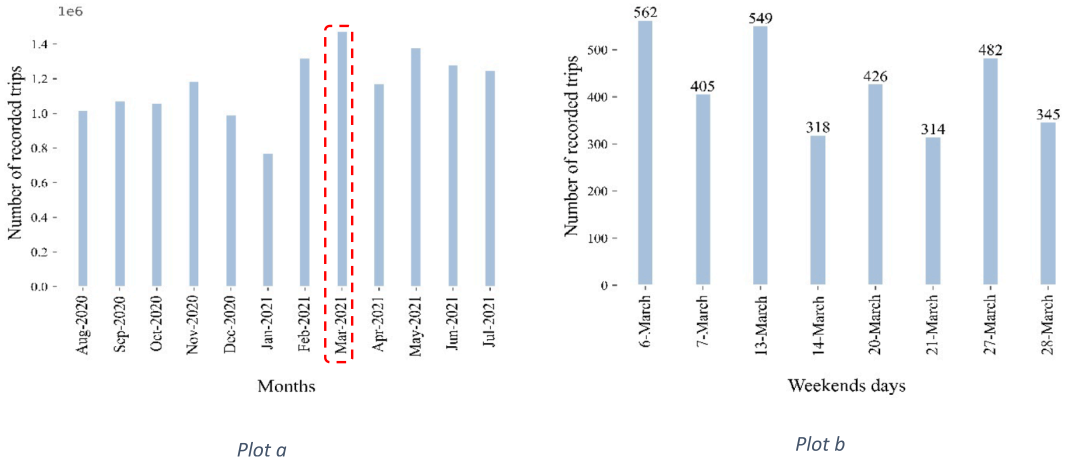


Fig. 3. Plot a: Number of total trips per each month (Canberra). Plot b: Number of local trips in the weekend (Belconnen).

Fig. 1 illustrates the adopted approaches used to assign passengers' arrival and departure times, aligning with the objective of the DRT system. The termed 'Integrated DRT' reflects its distinctive capability to accommodate local and connection trips within the existing PT network. This system's interaction with mass transit, such as the rapid bus line in our case study, ensures connectivity with the broader urban PT network. Differentiating from regular pick-up and drop-off points, connections to mass transit necessitate synchronisation with the frequency of mass transit vehicles to minimise transfer time. As depicted in Fig. 1, time windows associated with mass transit intersections are designed to ensure passengers don't miss their transfer service. In contrast, while feeder services (also known as first or last-mile services) for mass transit usually limit passenger flexibility by serving only specific locations, the modelled I-DRT services provide a high level of flexibility. Passengers can access these services for local trips from and to any local origin and destination, thereby enjoying a more adaptable local service.

4. Case study

The method introduced in section 3 is applied to the district of Belconnen in Canberra, Australia. Belconnen is located approximately 7 km northwest of the city centre. It is a diverse area that comprises residential, commercial, and recreational spaces. The district has a population of around 106,000 individuals and covers an area of approximately 77 square kilometres (Australian Bureau of Statistics, 2021).

The PT network in the district of Belconnen consists of various bus lines that provide local services or connect the district to the wider PT network of Canberra. There are five rapid bus lines (R2, R3, R4, R8, and R9) that provide fast connections to different parts of Canberra. In addition, there are five local bus lines (23, 24, 30, 31, and 32) that serve Belconnen and adjacent suburbs. Furthermore, there are eight local bus lines (40–47) that cater to specific neighbourhoods within Belconnen. Additionally, there are two school services (lines 901–903) to facilitate transport for students in the area (Transport Canberra, 2023b). Fig. 2 presents the map of PT network in the Belconnen district.

4.1. Passengers' request list

This study utilises real data obtained from the MyWay card dataset, which contains comprehensive information about PT travel records in Canberra. The dataset includes details such as trip origins, destinations, and departure/arrival times. The simulation is conducted for the busiest weekend day of the busiest month between August 2020 and July 2021. This is the period for which MyWay transactions are available to the research team. Fig. 3 presents the monthly distribution of recorded trips. According to this plot, the busiest month is March 2021 with almost 54,000 local trips by the local PT services within the Belconnen district (local bus lines: 40–47). Fig. 3 presents the distribution of trips over the weekends during March 2021. According to this plot, the 6th of March with 562 trips is the busiest weekend.

To ensure a fair comparison, the simulation utilises existing PT user data to represent the demand for the I-DRT system, while the list of requests is provided for the system to plan in advance, and it remains unchanged during operation. The passengers' boarding and disembarking bus stops are considered as their origins and destinations, respectively. However, this does not imply that the modelled I-DRT services are assigned to the same routes as the existing PT routes or that they lack flexibility. First, I-DRT services only visit bus stops requested by passengers, and the order of these visits can vary based on travel requests. Second, I-DRT services are not bound to predefined routes; they can choose different paths for transporting passengers, selecting the shortest path between each pair of visiting points in sequence. Third, the entire local PT system of a suburb is replaced by I-DRT services, which include various local buses. This means that the effects of a networked service are explored, and passengers from different bus routes may share the same I-DRT vehicle.

Next, each request in the DRT model is assigned a departure or arrival time based on the procedure described in Section 3.3. For

Table 3
Operational features of selected local bus lines, Belconnen, Canberra.

No. Line	Start Time	End Time	Operational time (Hr)	No. Vehicles Morning	No. Vehicles Evening	Headway (Min) Morning	Headway (Min) Evening	Number of loops	TD^{**} per loop	Total TD
40	6:00 am	1:00 am^{+*}	19	1	1	60	120	13	52	676
41	6:30 am	1:00 am^{+}	18.5	1	1	60	120	12	53	636
42	6:30 am	12:00 am^{+}	17.5	1	1	60	120	12	55	660
43	6:15 am	12:45 am^{+}	18.5	1	1	60	120	12	59	708
44	6:15 am	11:45 pm	17.5	2	1	60	120	12	60	720
45	6:10 am	11:40 pm	17.5	2	1	60	120	12	50	600
46	6:00 am	12:15 am^{+}	18.25	2	2	60	120	12	40	480
47	7:00 am	8:00 pm	13	1	1	60	120	10	50	500
Total			169.25	11	9					4980

* am^{+} shows the end time of the service is in the next day,
** TD denotes travel distance.

local passengers, their time window is either applied to their departure or arrival time, aligning with their actual boarding or disembarking time. Passengers with transfers have their earliest departure or latest arrival time determined by their transfer time to the rapid inter-regional PT network.

4.2. Operational features

The operational features of the selected local bus lines are outlined in Table 3. These details are based on the operational schedules of the selected lines as provided by Transport Canberra (2023d). The performance analysis of PT, provided in Section 5, is based on these operational features. As the table illustrates, there are variations in the operational plans between morning hours (prior to 12:00 pm) and evening hours, with the possibility of additional buses (and drivers) required for certain service times, which can affect the system performance in some regard, such as operational cost.

The operational features of the simulated I-DRT are set according to the operational specifications of the replaced local line to provide more convenient service to passengers. These operational features include the time window of requests, ride time of each passenger, tour duration, and capacity of DRT vehicles. The time window length in the simulated I-DRT system is set to 30 min, aiming to provide passengers with a better travel experience compared to the headway of the replaced local bus lines, which is 60 min during morning hours and 120 min during evening service time. According to the MyWay dataset, the actual travel time for passengers using existing PT services from the origin stop to the destination stop is, on average, twice the direct travel time for each passenger. Consequently, the maximum ride time is limited to double the direct travel time of each passenger ($L_i = 2 \times DTT_i$).

In addition, the maximum tour duration for each vehicle is set to 8 hr to allow for refuelling and avoid long driver shifts. Additionally, drivers are compensated for the entire duration of their shift, whether they are actively driving or on off-service status. Additionally, drivers must start/end their tour from/at the considered depot, which is set to the Belconnen interchange stop. Lastly, the number of available vehicles for the I-DRT system is determined to match the total provided capacity of the existing public transportation system. According to Transport Canberra (2023a), most buses in Canberra have a capacity of 48 seats. Assuming 12-seater vans are used in the I-DRT system, to achieve an equivalent capacity, approximately 44 vans are needed.

5. Performance analysis

This section summarises the performance analysis of the presented I-DRT system when applied to the described case study in Section 4. The performance analysis of the simulated I-DRT is divided into four sub-sections. Section 5.1 presents the examination of non-dominated solutions achieved for different objective function prioritisation. Section 5.2 presents the performance of I-DRT using various indicators and compares it with the existing local public transport network. Section 5.3 discusses the impact of changing demand on the system performance. Lastly, Section 5.4 offers a detailed analysis of the effects of replacing the local public transport network with I-DRT on passengers' travel experience.

5.1. Non-dominated solutions

The non-dominated solutions represent alternative trade-offs between the objectives (Dumedah et al., 2012; Dumedah et al., 2010). We initially examined the non-dominated solutions obtained from solving the mathematical formulation presented in Section 3. As discussed in Section 3.2, we consider 35 different combinations of parameters for the objective function of the model, resulting in 35

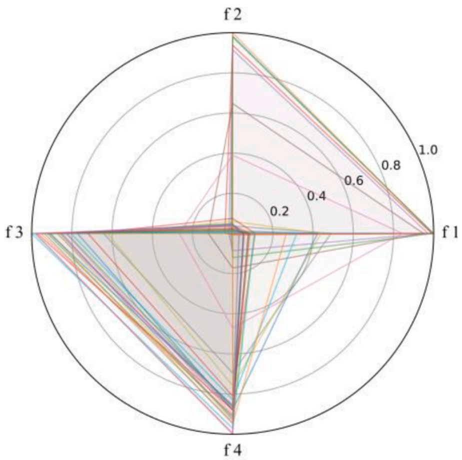


Fig. 4. Non-dominated solutions objective factors' values, where f_1, f_2, f_3, and f_4 are operational cost, environmental impact, passengers' travel time, and inequity objective function components, respectively..

distinct solutions. Across all combinations, the simulated conditions maintain consistent operational features, including the number of requests and their specifications such as pick-up and drop-off locations, along with desired travel times, which must be fulfilled. The only difference lies in the priority of the objectives, i.e., the relative importance of each objective over others. Fig. 4 presents the radar plot pertaining to the non-dominated solutions. This figure illustrates that out of 35 solutions, 27 are non-dominated (Table A 1 in the Appendix presents more details on the obtained solutions). While these solutions have distinct advantages over each other concerning specific objectives, they fall short in certain aspects i.e. they do not demonstrate absolute superiority over one another. The comprehensive results for all 35 wt combinations can be found in the Appendix. However, for ease of comparison and visualisation, the performance analyses are presented only for the worst, median, and best solutions based on the individual objective function components. The associated parameters' weight combination is presented as (α, β, γ, λ) where α, β, γ, and λ show the weights corresponding to objectives 1 to 4.

5.2. Performance analysis of I-DRT and PT

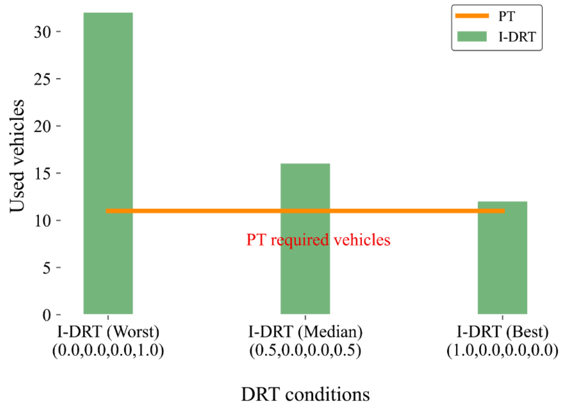
This section presents a performance analysis for the simulated I-DRT and a comparison with the existing PT network across various indicators. These indicators encompass the number of vehicles required, travel distance, operational cost, energy consumption, passengers' travel time, and standard deviation of additional travel time. Fig. 5 illustrates the comparison between I-DRT and PT across the six indicators. In general, I-DRT serves as a more sustainable alternative to local bus lines with respect to all indicators with the exception of the number of required vehicles (and drivers).

As depicted in Fig. 5 Plot a, the simulated I-DRT necessitates a higher number of vehicles. This finding aligns with existing literature (Dytckov et al., 2022; Mortazavi et al., 2023b). The number of vans can vary between 12 and 32, depending on the objective's prioritisation varying from minimising operational costs (weight combination of (1.0, 0.0, 0.0, 0.0)) to minimising inequity (weight combination of (0.0, 0.0, 0.0, 1.0)). However, it should be noted that the number of I-DRT vehicles are associated with 8 h tours, as every vehicle will only complete one tour during the day. This is while according to Table 3, in the PT system, 11 buses are operating from 6 am to 12 pm, and 9 of them continue their operation till almost midnight.

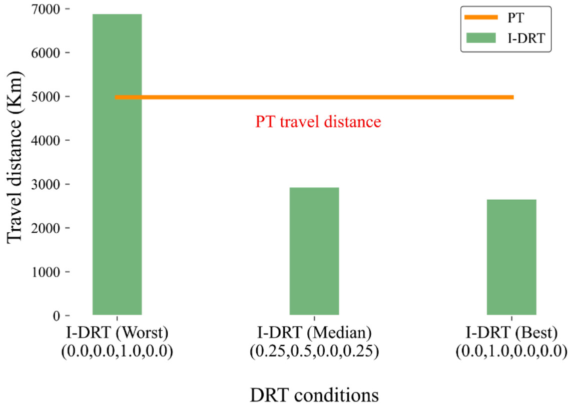
Fig. 5 Plot b compares the simulated I-DRT and PT in terms of travel distance. The results demonstrate that I-DRT has the potential to reduce travel distance by 46 percent (approximately 2,330 km) by preventing unnecessary travel when the focus is on minimising the system's environmental impact (weight combination of (0.0, 1.0, 0.0, 0.0)). However, the efficiency of I-DRT can be compromised when the focus shifts to minimising passengers' travel time (weight combination of (0.0, 0.0, 1.0, 0.0)). In this case, the simulated I-DRT requires travelling nearly 2,000 km more than the PT travel distance (equivalent to 38 percent).

The next comparison revolves around operational costs, including distance-based and drivers costs. As depicted in Fig. 5 Plot c, replacing the local bus network with the simulated I-DRT can result in a reduction of operational costs from $10,377 AU to $4,036 AU, equivalent to 61.1 percent savings, when the focus is on minimising operational costs (weight combination of (1.0, 0.0, 0.0, 0.0)). However, shifting the focus from minimising operational costs to minimising passengers' travel time (weight combination of (1.0, 0.0, 0.0, 0.0)) can lead to a loss in cost efficiency. In such cases, the operational cost of the I-DRT can increase to $10,621 AU, slightly surpassing the PT operational cost by 2 percent.

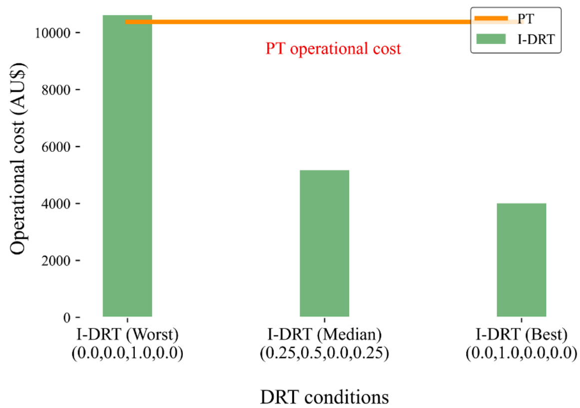
Three key factors contribute to the cost efficiency of the I-DRT system compared to traditional PT across the majority of examined weight combinations. Firstly, the technology employed in the adopted 12-seater vans for serving I-DRT passengers requires less fuel for the same travel distance. Secondly, based on Figure A1 plot b, I-DRT requires less travel distance across 28 wt combinations, contributing to its cost efficiency. The third and most significant factor is related to drivers' payments. Buses adhering to fixed, pre-scheduled operational plans necessitate drivers' services from early morning (6 am) to midnight (12 pm). Conversely, for each I-DRT



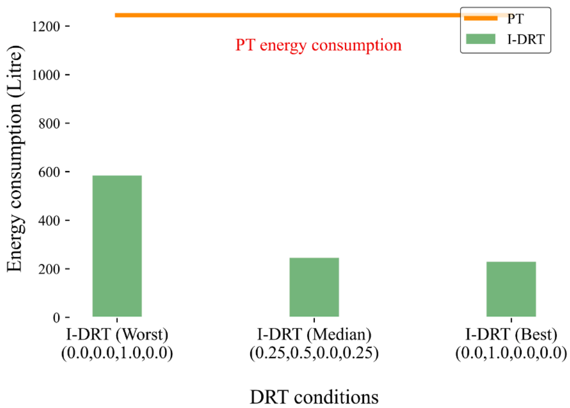
Plot a - The number of utilised vehicles



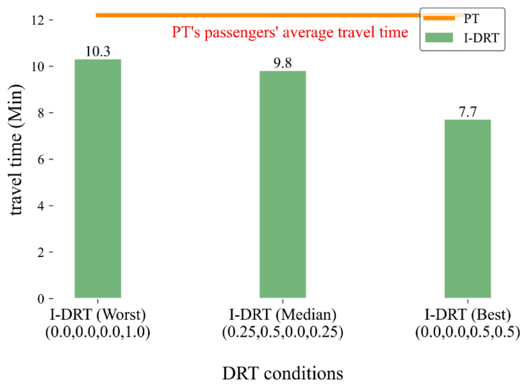
Plot b - Travel distance



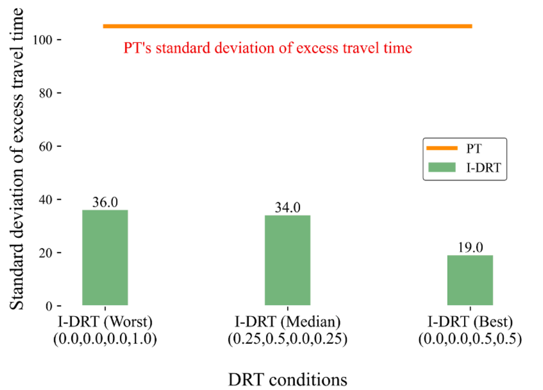
Plot c – Operational cost



Plot d – Energy consumption



Plot e – Passengers' average travel time

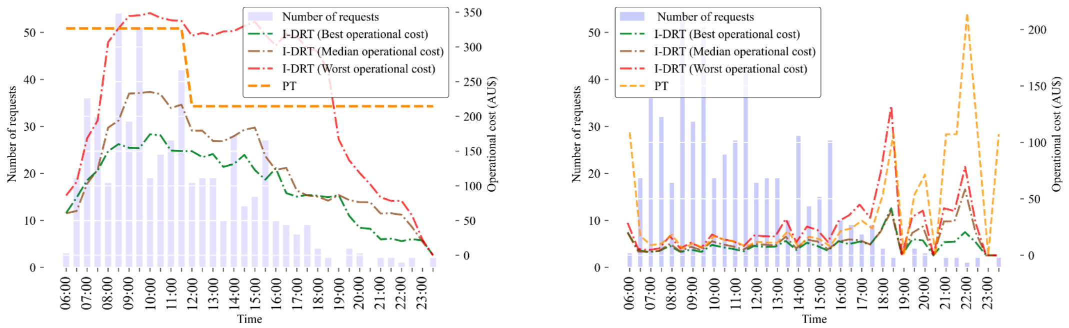


Plot f – Standard deviation of passengers' excess travel time

Fig. 5. Performance comparison between the existing local bus network (PT) and I-DRT (three weight combinations).

vehicle, drivers are paid for 8 hr. Consequently, in weight combinations requiring fewer than approximately 23 I-DRT vehicles, the system proves more cost-efficient than PT in terms of drivers' wages.

Fig. 5 Plot d examines energy consumption as an indicator of the systems' environmental impact. The results consistently



Plot a – Total operational cost per 30 minutes operation. *Plot b – Operational cost per each passenger.*

Fig. 6. Impact demand change on the operational cost over the examined day.

demonstrate the environmentally friendly nature of the simulated I-DRT across all weight combinations. Two factors contribute to this phenomenon. Firstly, the travel distance of the systems suggests that, in most cases, I-DRT requires a shorter distance to transport passengers across a variety of weight combinations. Secondly, as shown in Table 2, the 12-seater vans adopted for the I-DRT system exhibit greater efficiency in passenger transportation due to their size and technology compared to the buses used for the local bus lines. The results indicate that the energy consumption of the system can be reduced by 50 to 80 percent (equivalent to almost 600 and 960 L) when the model prioritisation is focused on minimising passengers' travel time and environmental impact, respectively. Furthermore, comparing the results presented in both Fig. 5 Plot c and Fig. 5 Plot d, it becomes evident that the same weight combination is chosen to illustrate the worst I-DRT condition in terms of operational cost and fuel consumption. Although the operational cost of I-DRT under this condition is slightly higher than that of the PT system, the fuel consumption for I-DRT remains less than half of that for the PT system. This comparison highlights the significant role of the number cost of recruited drivers on the operational cost of I-DRT.

In terms of passengers' travel time, the performance of I-DRT surpasses that of the replaced local bus network. Fig. 5 Plot e reveals that the average travel time for passengers using the local bus network is 12.2 min, whereas it decreases to 10.3 min (equivalent to a 15 percent reduction) in the worst-case scenario when the focus is on minimising operational costs and environmental impact (weight combination of (0.25, 0.75, 0.0, 0.0)). In the best-case scenario, when the focus is on minimising passengers' travel time (weight combination of (0.0, 0.0, 1.0, 0.0)), the average travel time is reduced to 7.7 min (equivalent to a 36 percent reduction).

In addition to the passengers' travel time reduction, I-DRT offers a more equitable distribution of delay among passengers. Fig. 5 Plot f presents the standard deviation of passengers' excess travel time. In this study, the excess travel time ratio for passenger i (ETT_i) is defined as the difference between the passenger's actual travel time and his/her direct travel time divided by the direct travel time ($ETT_i = (ATT_i - DTT_i)/DTT_i$). The standard deviation of passengers' excess travel time with the PT system is 105. However, I-DRT reduces this standard deviation to 36 and 19 (equivalent to 65 and 82 percent) in the worst case (prioritising operational costs) and best case (prioritising inequity among passengers). These results demonstrate that passengers experience a more equitable distribution of excess travel time ratio with I-DRT in comparison to the existing local bus network.

According to Fig. 5 (and Figure A1 in the Appendix), changing the weight combinations that reflect the objectives prioritisation can significantly affect I-DRT performance. The impact is more noticeable in indicators such as the required number of vehicles, travel distance and operational cost, as under specific weight schemes I-DRT will no longer outperform PT.

The required number of vehicles shows a higher variation among the weight schemes as shifting focus from minimising operational cost (weight combination of (1.0, 0.0., 0.0, 0.0)) to minimising inequity (weight combination of (0.0, 0.0, 0.0, 1.0)) will increase this indicator by 166 percent (equivalent to 20 vans). This is followed by operational cost, where shifting the focus from minimising operational costs (weight combination of (1.0, 0.0, 0.0, 0.0)) to minimising passengers' travel time (weight combination of (0.0, 0.0, 1.0, 0.0)) will increase the operational cost by 165 percent (equivalent to $6,592). Variation in travel distance is 160 percentage (equivalent to 4223 Km) and in energy consumption it is 155 percent (equivalent to 355 Litres). The worst standard deviation of passengers' excess travel time ratio is 90 percent (equivalent to 17) more than its best value obtained across different weight combinations. For passengers' travel time the difference is less significant as the highest average travel time is only 33 percent (equivalent to 2.6 min) higher than the best value.

The presented model facilitates informed policymaking by effectively capturing the trade-offs between objectives. It equips policymakers with an array of near-optimal solutions, each corresponding to distinct prioritisations. The analysis highlights that among the various indicators, operational cost exhibits the highest sensitivity, while passengers' travel time displays the least sensitivity to variations in weight combinations.

5.3. Impact of varying demand over the examined day

This section investigates the impacts of the varying passenger demand over the examined day on the performance of the two systems. Fig. 6 illustrates the changes in operational costs in response to demand variations. Fig. 6 Plot a compares the total operational

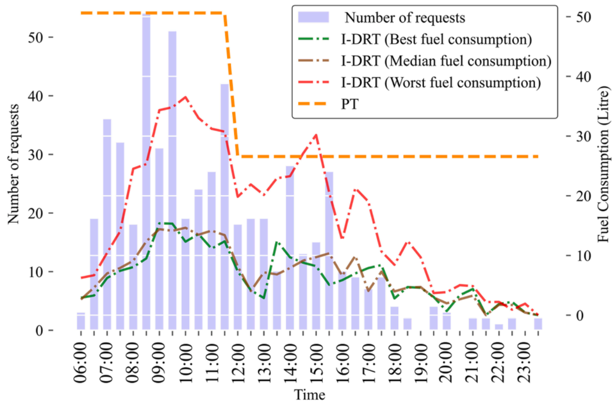


Fig. 7. Impact demand change on the fuel consumption of I-DRT and PT over the examined day.

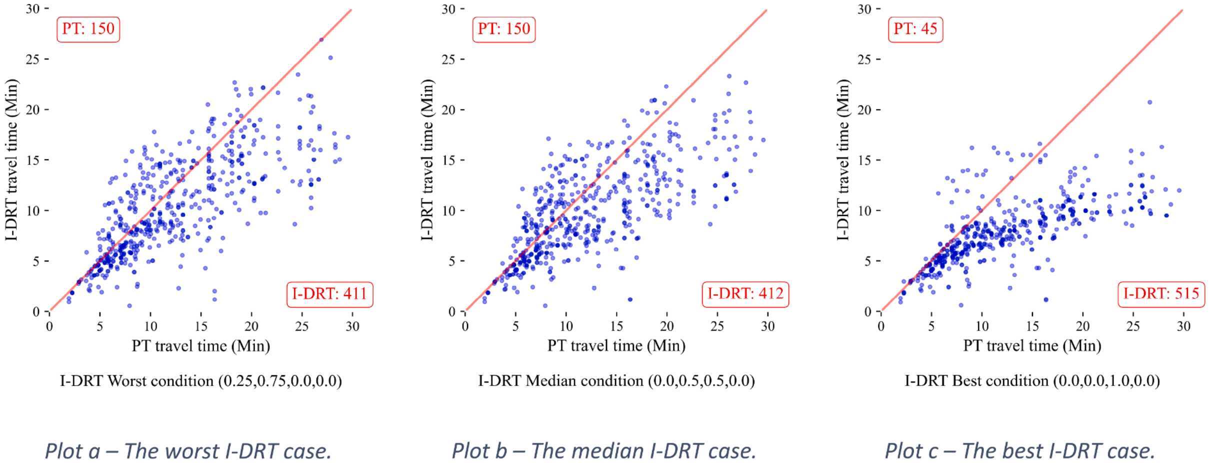


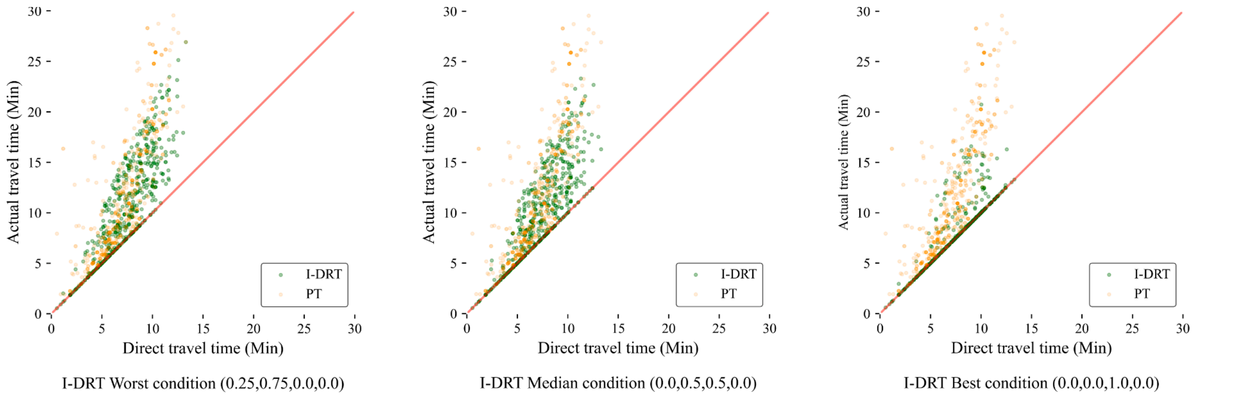
Fig. 8. Individual-based comparison of passengers' travel time between PT and I-DRT.

costs of I-DRT and PT over the examined day. For I-DRT, the performance of the system is presented for three weight combinations corresponding to the worst, median, and best cases, as depicted in Fig. 5 Plot c. The results demonstrate that the operational costs of I-DRT, in all three conditions, exhibit flexibility in response to demand changes. As the number of passengers decreases over time, the operational costs of I-DRT also decrease. However, there is only one reduction in the operational cost of the PT over the examined day, which occurs when the number of active services is reduced at 12:00 pm according to operational features of the local bus network (Section 4.2). The lack of flexibility in PT in response to demand changes is more evident during low demand periods. Fig. 6 Plot b reveals that while the operational costs per passenger in the morning hours are relatively close between I-DRT and PT, in the evening hours, the PT's operational cost per passenger sharply increases. The average operational cost for transporting each passenger using PT amounts to approximately 50 AU$ during the morning hours (6 am to 12 pm) and 40 AU$ during the afternoon hours (12 pm to 6 pm). This cost escalates to over 105 AU$ during the evening hours (6 pm to 12 am). In contrast, for the I-DRT system (best operational cost), the respective operational costs are 5 AU$, 10 AU$, and 24 AU$ during these time frames.

Fig. 7 shows the impact of demand changes on the fuel consumption of the systems. The results reveal that the PT system does not exhibit flexibility in response to demand changes. The fuel consumption of this system remains relatively steady, with the exception of one instance where the number of operating buses changes. In contrast, the fuel consumption of I-DRT shows a reduction corresponding to the decrease in demand. After 18:00, the fuel consumption for I-DRT drops to less than 10 L per hour, but PT continues to consume approximately 30 L every 30 min. These findings highlight the fuel efficiency and adaptability of the I-DRT system in response to varying demand levels.

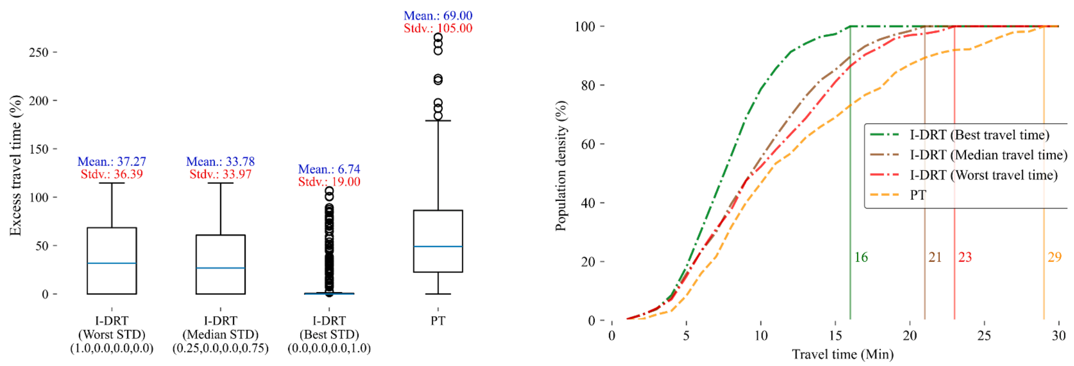
5.4. Passengers' travel experience

As discussed in Section 2, we do not set a constraint to limit passengers' quality of service, but we include this aspect as one of the objectives in the I-DRT model. This section presents a further and deeper analysis of passengers' travel experience with I-DRT. The first examination is an individual travel time comparison, where each passenger's travel time with the PT is compared to his/her travel time



Plot a – The worst I-DRT case. *Plot b – The median I-DRT case.* *Plot c – The best I-DRT case.*

Fig. 9. Individual-based comparison of passengers' actual travel time to respective direct travel time for PT and I-DRT.



Plot a *Plot b*

Fig. 10. Plot a: box plot of passengers' excess travel time for both I-DRT and PT. Plot b: proportion of passengers transported within specified travel time.

with the simulated I-DRT. Fig. 8 compares individuals' travel time between the PT and I-DRT, where Plots a to c are related to the worst, median, and best scenarios of I-DRT in terms of passengers' average travel time (Fig. 5 Plot e). The results show that in the worst case, out of the 561 passengers, 411 passengers (73 percent) have a shorter travel time with I-DRT, and 150 passengers experience a shorter travel time with PT. By prioritising passengers' travel time (moving from Plot a to Plot c), the number of passengers who experience shorter travel time with I-DRT increases to 515 (92 percent).

In the following examination, we compare passengers' travel times with both PT and I-DRT to their respective direct travel times. Fig. 9 presents the results of this comparison, considering three weight combinations related to the worst, median, and best average travel times for passengers in I-DRT. Ideally, the actual travel time of passengers would be equal to their direct travel time, resulting in all dots being located on the identity line. Our simulation shows while the nodes representing PT passengers are scattered sparsely above the identity line, the nodes representing I-DRT passengers are more densely clustered and closer to the identity line. Fig. 9 plots a to c illustrate that passengers in I-DRT are more likely to experience lower delays compared to PT. As we place a greater emphasis on minimising passengers' travel time (weight combination of (0.0, 0.0, 1.0, 0.0)), the gap between passengers' travel times and their direct travel time decreases. These findings demonstrate the effectiveness of I-DRT in reducing delays and providing a more efficient and convenient travel experience for passengers.

The final examination pertains to inequity in passengers' travel time. We examine inequity based on the standard deviation of excess travel time ratio and the cumulative distribution of travel time. The excess travel time ratio signifies the variance between the actual travel time of individual passengers and their corresponding direct travel time. To depict the diversity in passengers' excess travel time across different transport systems as an equity indicator, the standard deviation of excess travel time ratio is employed. In addition, the cumulative distribution of travel time illustrates the percentage of the population that might encounter extended travel times when utilising each of the transport systems investigated in this study. In both examinations, three weight combinations are considered. For excess travel time, the three weight combinations correspond to the worst, median, and best conditions according to

Table A1
Objective value for examined weight combinations.

Row	α	β	γ	λ	f_1 Operational cost	f_2 Fuel consumption	f_3 Passengers' Travel Time	f_4 Inequity	Dominated / Non-dominated
1	0	0	0	1	10597.48	578.59	4352.84	0.19	Non-dominated
2	0	0	0.25	0.75	10574.4	584.21	4346.5	0.191	Non-dominated
3	0	0	0.5	0.5	10597.06	576.95	4357.64	0.211	Non-dominated
4	0	0	0.75	0.25	10605.41	581.24	4356.16	0.204	Dominated
5	0	0	1	0	10611.75	584.48	4347.45	0.201	Dominated
6	0	0.25	0	0.75	10568.66	562.39	4401.67	0.191	Non-dominated
7	0	0.25	0.25	0.5	10586.89	554.27	4373.59	0.205	Non-dominated
8	0	0.25	0.5	0.25	10483.05	459.35	4518.15	0.22	Non-dominated
9	0	0.25	0.75	0	10155.83	367.72	4723.04	0.272	Non-dominated
10	0	0.5	0	0.5	9473.36	246.99	5335.91	0.317	Dominated
11	0	0.5	0.25	0.25	9198.22	242.44	5257.48	0.311	Non-dominated
12	0	0.5	0.5	0	8652.19	250.82	5229.34	0.322	Non-dominated
13	0	0.75	0	0.25	7423.05	231.82	5487.44	0.334	Non-dominated
14	0	0.75	0.25	0	8546.89	234.6	5441.45	0.343	Non-dominated
15	0	1	0	0	6841.37	229.3	5630.71	0.355	Non-dominated
16	0.25	0	0	0.75	4298.1	247.2	5516.68	0.341	Non-dominated
17	0.25	0	0.25	0.5	5172.4	257.19	5534.66	0.334	Dominated
18	0.25	0	0.5	0.25	5168.63	255.88	5367.87	0.331	Non-dominated
19	0.25	0	0.75	0	5217.64	262.08	5429.84	0.335	Dominated
20	0.25	0.25	0	0.5	4557.59	245.34	5583.36	0.34	Non-dominated
21	0.25	0.25	0.25	0.25	4873.1	243.42	5563.13	0.343	Non-dominated
22	0.25	0.25	0.5	0	4579.82	242.75	5524.24	0.347	Non-dominated
23	0.25	0.5	0	0.25	4560.58	233.23	5676.33	0.354	Non-dominated
24	0.25	0.5	0.25	0	5139.3	242.08	5582.46	0.352	Non-dominated
25	0.25	0.75	0	0	5132.01	231.62	5764.26	0.359	Non-dominated
26	0.5	0	0	0.5	4568.08	244.48	5637.54	0.339	Non-dominated
27	0.5	0	0.25	0.25	4641.88	261.26	5558.98	0.348	Dominated
28	0.5	0	0.5	0	4589.32	256.97	5573.6	0.351	Dominated
29	0.5	0.25	0	0.25	4150.21	234.8	5700.04	0.348	Non-dominated
30	0.5	0.25	0.25	0	4820.24	242.57	5557.52	0.349	Dominated
31	0.5	0.5	0	0	4832.62	236	5652.6	0.349	Non-dominated
32	0.75	0	0	0.25	4833.62	237.71	5725.32	0.343	Non-dominated
33	0.75	0	0.25	0	4558.79	242.71	5550.01	0.351	Non-dominated
34	0.75	0.25	0	0	4005.31	237.39	5739.47	0.364	Non-dominated
35	1	0	0	0	4017.77	244.07	5741.1	0.363	Non-dominated
				Ideal	4035.31	230.93	4346.5	0.19	
				Nadir	10621.75	587.48	5764.26	0.364	

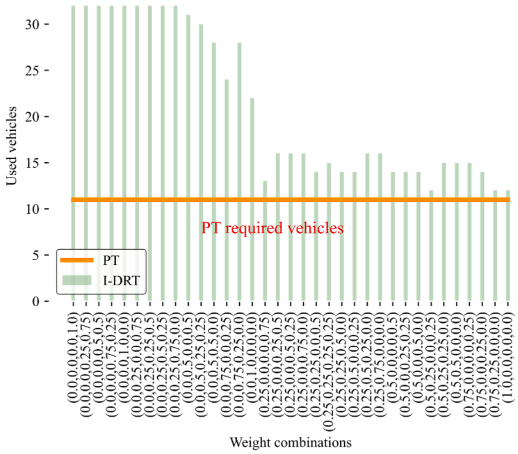
the inequity indicator as discussed in equation (22), and for cumulative distribution for travel time, the three combinations correspond to the worst, median and best conditions based on average travel time.

See Fig. 10 Plot a illustrates the range of passengers' excess travel time for both Integrated-DRTs (I-DRTs) and PT according to equation (22). The figure reveals that across all three presented scenarios for I-DRTs, passengers encounter a notably more similar excess travel time. Specifically, the standard deviations of excess travel time are 36, 34, and 19 for the worst, median, and best I-DRT conditions, respectively, as opposed to the corresponding value of 105 for PT. This shows the lower standard deviation in I-DRT, indicating a more equitable allocation of excess travel time among passengers. Fig. 10 Plot b illustrates the cumulative travel time distribution. According to this figure, the maximum travel times in the best, median and worst scenarios of I-DRT are 16, 21 and 23 minutes, respectively. However, in the case of PT, the maximum travel time is 28 min. For any given travel time, the portion of passengers experiencing higher travel times is higher in PT. For example, approximately 20 % of passengers experience a travel time higher than 20 min in PT, whereas this portion for I-DRT in the best, median, and worst scenarios are only 0 %, 1.6 %, and 2.5 %, respectively.

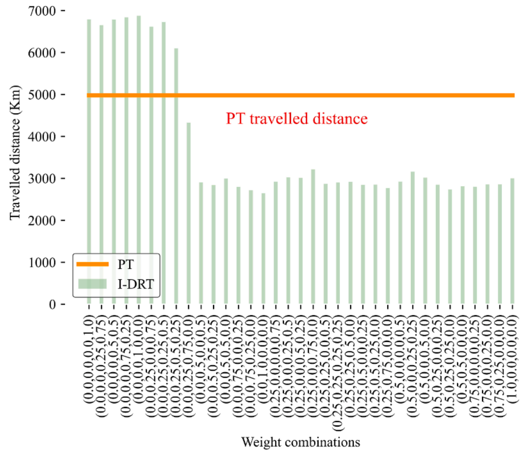
Therefore, it can be concluded that I-DRT is more effective in terms of passengers' travel time, not only successfully reducing the average travel time but also providing a more equitable travel experience by shortening the range of excess travel times.

6. Conclusion

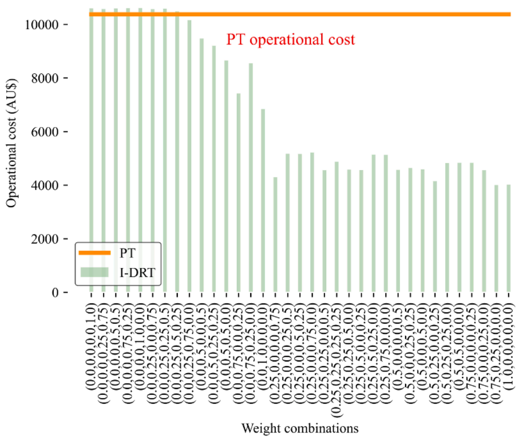
In this study, we introduced the Integrated-Demand Responsive Transport (I-DRT) system as a part of the existing urban Public Transport (PT) network. The aim is to replace local bus lines with I-DRT while keeping the system connected with the rapid mass PT lines in the servicing area. The performance of this system is simulated in the Belconnen district of Canberra during a weekend day, where eight local bus lines are replaced with the I-DRT system. The connection between I-DRT and five passing rapid bus lines within the district is considered in the modelling process. The adopted I-DRT in this study is modelled using a multi-objective function that considers operational cost, environmental impact, passengers' travel time, and inequity. A total of 35 different weight combinations are used to represent a variety of prioritisations in the model, allowing for an investigation of the trade-offs among the objective



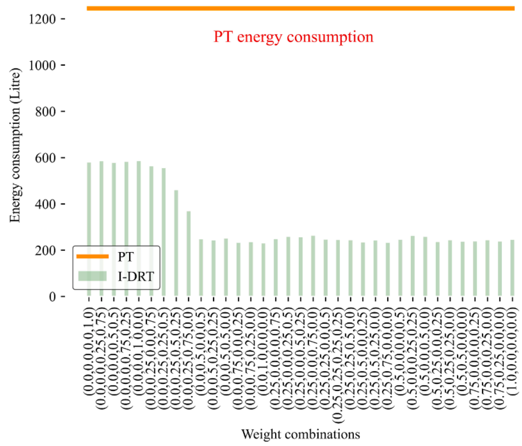
Plot a - The number of utilised vehicles



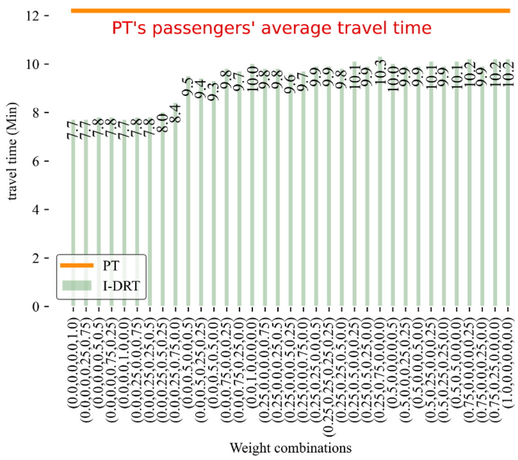
Plot b - Travel distance



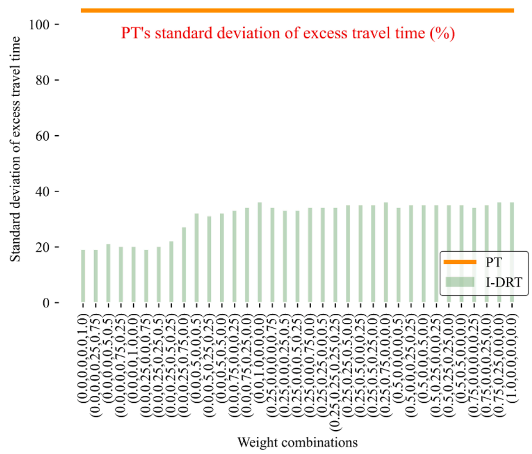
Plot c – Operational cost



Plot d – Energy consumption



Plot e – Passengers' average travel time



Plot f – Standard deviation of passengers' excess travel time

Fig. A1. Performance comparison between the existing local bus network (PT) and I-DRT (35 wt combinations).

factors. The performance of the simulated I-DRT is then compared against the replaced PT system using various indicators, with a specific focus on passengers' travel experience. The performance indicators used in this study include the number of vehicles, vehicle travel distance, operational cost, fuel consumption, passengers' average travel time, individual-based passenger travel time, average excess travel time, and inequity in the distribution of delays among passengers.

The results indicate that I-DRT requires a higher number of vehicles compared to PT, but it proves to be cost-effective in low-demand scenarios and offers an environmentally friendly alternative for passenger transportation. The I-DRT system may need between 11 and 32 vans to transport the same number of passengers that the existing PT serves with only 11 buses. However, I-DRT can still be efficient, leading to reductions of up to 45 percent travel distance (equivalent to 2,400 km), 50 percent operational costs (equivalent to \$6,360 AU), and 80 percent environmental impact (equivalent to 1,000 litres of fuel).

Another advantage of I-DRT is its adaptability to demand variations. PT operates based on a fixed operational plan and remains insensitive to demand reductions during evening hours. The simulation results demonstrate that while PT operational cost remains steady regardless of demand change, there is a remarkable 85 percent reduction in operational cost during off-peak hours as compared to its peak operational cost. Similarly, the fuel consumption of I-DRT exhibits adaptability in response to shifts in demand. Specifically, there is a significant 90 percent reduction in I-DRT's fuel consumption during off-peak hours as compared to its fuel consumption during peak hours. These findings highlight the flexibility and efficiency of I-DRT in dynamically responding to varying demands and optimising operational costs and fuel consumption throughout the day.

In addition, this study places emphasis on passengers' travel experience by considering two specific objective factors within the defined multi-objective model and utilising various indicators to evaluate the performance of the simulated I-DRT system. Overall, our findings demonstrate that the replacement of local bus lines with I-DRT not only improves the average travel time for passengers but also leads to a more equitable distribution of excess travel times. Specifically, the average travel time for passengers is reduced from 12.2 min with local bus lines to 7.7–10.3 min with I-DRT, representing a reduction of 15–36 percent depending on the model's prioritisation. Furthermore, passengers experience a more balanced distribution in terms of excess travel times. The standard deviation of passengers' excess travel times decreases from 105 for PT to 19–36 for I-DRT, indicating a more equitable and consistent travel experience for passengers.

The findings of this study contribute to a more comprehensive understanding of the potential impacts of integrating DRT into the existing public transport network. These findings further support the notion that adopting DRT systems as a replacement for PT in low-demand urban areas can enhance efficiency. It is important to note that the simulation conditions employed in this study are aligned with the existing state of the replaced PT. However, there is potential for future research to delve into how the replacement of PT with I-DRT could potentially influence passengers' travel patterns. This might encompass aspects like demand change, changes in passengers' origins and destinations, or alterations in passengers' travel times. Future research endeavours could explore the travel behaviour effects of this replacement and simulate more realistic scenarios.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix

Table A1 presents the components' values of objective function for each of the weight combinations examined in this study. The first four columns pertain to the weight parameters of the objective functions, while the subsequent four columns report the achieved values for each component of the objective functions. In this context, f_1 represents operational cost, f_2 represents fuel consumption, f_3 represents passengers' travel time, and f_4 represents inequity. The last column describes whether the solution obtained for its respective weight combination is dominated or nondominated.

Figure A1 compares the performance of simulated I-DRT in this study with the replaced PT across different indicators, while 35 different modelling prioritisations (weight combinations) are considered for I-DRT. These indicators encompass the number of vehicles required, travel distance, operational cost, energy consumption, passengers' travel time, and standard deviation of additional travel time.

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