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***Abstract*—Accessibility is one of the key performance indicators in the evaluation of a multimodal transport system and, as a result, transport planning has become increasingly more oriented towards it. Demand Responsive Transport (DRT) services have been proposed as a measure for increasing accessibility of a Public Transit (PT) network by servicing users in inaccessible areas. Through multimodal planning and coordination, a DRT service can be integrated within the extended PT network and supply the network optimally. In the context of PT users headed toward airports, an integrated DRT service is proposed for those with extended first-mile connections. This service makes use of taxis to transport users to transit points of a dedicated train line supplying a major European airport. Ride-sharing is considered, while optimal order of service and transit points for modal change are determined. To capture the decentralized nature of matching taxis to users, a multi-agent-based algorithm based on Distributed Constraint Optimization Problems (DCOPs) is developed. Real-time information about routes and fixed schedules of the PT network are extracted via a dedicated routing Application Programming Interface (API). Experiments validate the applicability of the proposed solution by reporting a decrease in users' first-mile travel time that is approximately analogous to the modal share the service captures.**

***Index Terms*—Public Transit, Demand Responsive Transport, Distributed Constraint Optimization, First-mile Service**

I. Introduction

Strengthening mass transit is a strategic goal for many metropolitan cities around the globe. A resilient Public Transit (PT) network facilitates congestion mitigation, reduction of emissions, and can pave the way for a future of seamlessly integrated mobility. Achieving such future is contingent on improving accessibility in the transport systems. Accessibility has a direct impact on mode choice and the lack of it can lead to increased preference for less sustainable modes and under-utilization of the mass transit network.

Surface access to an airport is a specific type of urban trip where accessibility is significantly important. There have been few studies [1]–[4] researching surface access, but they mostly focus on factors impacting mode choice. Sustainability studies in aviation often overlook the impact of this type of travel compared to other issues. Nonetheless, access to and from the airport amounts to approximately 8% of the total emissions spent for a complete door-to-door trip [5]. Data from a report of the German Aerospace Center and the European Commission [6] show that utilization of PT for airport access can vary from 40% (Amsterdam Schiphol) to 20% (Barcelona International Airport El Prat). Further increasing the current surface access PT utilization rate can be facilitated by addressing accessibility issues, for example through multimodal coordination.

Coordination across modes can be realized through Demand Responsive Transport (DRT) systems. DRT services can target users that are inclined to use private transport due to low accessibility of their origin. In general, these are users that will not use PT. In this study, a DRT service is proposed for passengers with increased first-mile connections towards an airport. The service is complementary to the main mass transit network and makes use of fixed schedules of a dedicated train line to supply the airport. Candidate users are determined based on real-time traffic and PT information derived from a routing Application Programming Interface (API). Users are matched to taxis that support ride-sharing and optimal sequencing of pick-ups is determined, as well as transfer points for modal change.

The problem of matching users to taxis can inherently benefit from decentralization, as different taxis may have different criteria behind their decision-making and collaboration is not necessarily assumed. Regardless of collaboration across taxis, a system-wide assignment will benefit from scalability under a reduced, decentralized, and localized view of the system. To this avail, we apply a multi-agent perspective modeling the problem as a Distributed Constraint Optimization Problem (DCOP). Expected performance gains of introducing a first-mile-focused DRT service are evaluated through a case study for a major European airport. Overall, the effect of coordination across modes in the system-wide decrease of users' travel time is quantified. Additionally, the applicability of DCOP as a modeling framework is verified and the effect on the solution of different criteria in agents' decision making is assessed.

II. Literature Review

Even though the reported statistics vary from airport to airport, private vehicles (self-driving or drop-off) and taxis are a significant part of the modal share for ground access to airports. Travelers to and from airports tend to have a much higher willingness to pay compared to regular urban area trips [1], as there is usually less room for delays. To account for delays, travelers often use safety margins, i.e., an additional buffer time passengers allow in their planning to compensate for unexpected delays. As the trip time to the airport increases, the safety margin increases proportionally [2]. Generally, the out-of- and in-vehicle time of travel are also important factors in travel mode selection, as well as the overall saved time by mode choice and ease of use of the selected transport service. This highlights that multimodality might not be desirable for airport access, as it requires user coordination between modes which generally deteriorates the ease of use. In practice, trips to the airport that contain three or more modal changes are generally avoided [3]. However, airport travelers are in principle in favor of adopting new access modes, such as DRT, especially when they include transit or rail [4].

DRT services can greatly increase accessibility of a PT network. Demand-response transportation (DRT) is a service for low-population-density areas, using passenger cars, vans, or small buses dispatched in response to passenger requests [7]. The adoption of DRT in urban areas has been explored but not yet implemented [8]. Notwithstanding, the findings suggest that DRT services can have a significant impact in attracting many users compared to other taxi-focused services, especially under a Mobility-as-a-Sevice (MaaS) [9] ecosystem. Efforts have been made to explore integrated DRT services that target both first-mile and last-mile connections, as evidenced by previous studies [10], [11]. However, such efforts have not yet been made specifically for airport access. There is also interest in completely automating DRT services through the integration of autonomous vehicles and public transportation [12]. Resource allocation for DRT is crucial and is primarily addressed through the incorporation of ride-sharing techniques, as demonstrated in existing literature [13], [14].

When considering an inherently distributed system such as ride-sharing, different modeling choices on the level of centralization are available. In our context, we want taxis to be partially independent when selecting users, and to have access only to information that is relevant to them, as complete information about the system is often unnecessary for good-quality planning. Therefore, utilizing a distributed formalism such as DCOP can prove to be highly advantageous since it serves as a theoretical framework for multiple agents which must collaborate in making decisions regarding variable values in order to minimize the total cost of constraints or maximize the total utility values [15].

A DCOP consists of a set of agents, variables, domains, and constraints. A variable is controlled by a single agent, while constraints map the cost or utility of a specific variable selection and are by definition soft. Control is distributed, as agents can only assign values to variables they control, and have knowledge only of constraints that are mapped to their variables. However, variables may be constrained by variables owned by other agents by so-called inter-agent constraints that are satisfied through communication between agents. Some crucial DCOP assumptions are that (i) agents communicate only with their neighbors, (ii) each agent knows its variable and domain along with its neighbors, and (iii) each agent knows the cost function involving its own variables, not those of other agents. We refer readers to reference [16] for a thorough overview of the DCOP formalism. Given their broad applicability spectrum, DCOPs have been applied to many different fields such as disaster management and coordination [17], scheduling [18], vessel rotation planning [19], and traffic flow control [20] problems.

III. Problem Formulation

A. DCOP Formalism

The problem of matching taxis to users bares parallels with the Vehicle Routing Problem (VRP) [21], and more specifically the multi-depot VRP [22], both well-known NP-hard problems. In the proposed approach, taxis can be considered as "mobile" depots servicing users as efficiently as possible. In classic VRP formulations, the main goal of the planning is the minimization of the overall traveled distance. Our objective is different, as in this study the primary goal is to minimize the traveling time of users while guaranteeing timely access to target transit points. With *transit point*, we mean a specific location of the transport network when modal change occurs. In our context, this is a train station where taxi users are dropped off to shift mode and continue their journey to the airport.

We modeled the taxi-dispatching problem in a DCOP fashion as follows. Firstly, we consider that users originate from a set of total n origins $\mathcal{O} = \{o_1, o_2, .., o_n\}$. Multiple users may originate from a single origin to enable realistic planning for cases of users traveling together (e.g., families, etc.). Users have a desired arrival time at the airport, but the selection of the best transit point is decided exclusively by the planner. With regards to agents, we consider a finite number of m taxi agents defined as set $\mathcal{T} = \{t_1, t_2, t_3.., t_m\}$. Taxis have a standard maximum capacity c_t and an origin o_t, indexed by $t \in \mathcal{T}$. The cost of a complete trip via taxi, shared or not, is considered known and includes waiting time for pick-up. Finally, a PT agent is defined, representing assignment via mass transit as an alternative to taxis. Users originating from $o \in \mathcal{O}$ who cannot be serviced by the DRT service are assumed to use PT to reach a transit point with a first-mile cost for origin o equal to FM_o. In addition, agents are also characterized by the following features that define user and trips compatibility:

1) view ($\mathcal{V}_t$): the set of user origins visible to the taxi agent ($\mathcal{V}_t \subseteq \mathcal{O}$). This is defined by assigning to each agent a certain radius of service measured from its origin. For the PT agent, we set the radius to ∞, hence $V_{PT} = \mathcal{O}$ as all users are visible;
2) first-mile bound: the minimum time FM_o that a user would experience if using PT to qualify for inclusion in the DRT service for a specific agent. For the PT agent, the bound is set to zero;
3) lead-time: the amount of time in advance that an agent becomes aware of users requesting a trip, before the departure of the earliest scheduled dedicated service compatible with the user preferred arrival time. For the PT agent, lead-time is set to ∞;
4) local view ($\mathcal{LV}_t$): the set of users $\mathcal{LV}_t \subseteq \mathcal{V}_t$ satisfying all the aforementioned criteria for agent t.

We now formalize the DCOP as a tuple $< \mathcal{A}, \mathcal{X}, \mathcal{D}, \mathcal{C} >$, where

1) $\mathcal{A} = \{PT, a_1, a_2, ..., a_m\}$ is the set of agents;
2) $\mathcal{X} = \{x_{a,j} \ \forall a \in \mathcal{A}, j \in \mathcal{LV}_a\}$ are variables owned by an agent a and relate to an origin j in their local view;
3) $\mathcal{D} = \{d_{a,j} = \left[d^L_{a,j}, d^U_{a,j}\right] \ \forall a \in \mathcal{A}, j \in \mathcal{LV}_a\}$ is a set of finite domains for the variables such that $x_{a,j}$ takes values in $d_{a,j}$, with $d^L_{a,j}$ and $d^U_{a,j}$ being, respectively, the lower and upper bound. In this problem, all variables take binary values, hence all domains equal to $d_{a,j} = \{0, 1\}$;
4) $\mathcal{C} = \{c_1, ..., c_z\}$ is a set of z soft constraints, where each constraint maps to utility functions $c_z : \mathcal{D} \to \mathbb{R}_{\geq 0}$ that define the cost for a specific choice of variables.

The following DCOP constraints must be satisfied:

1) each origin o must be assigned to exactly one taxi or the PT agent. This is always an inter-agent constraint for taxi agents, as any variable relating to a user origin that they own is also visible to the PT agent. Hence, the PT agent is a neighboring agent to all taxis that can see at least a single origin. Communication might be needed between more taxi agents to determine assignments. This is a hard constraint that maps to an infinite cost if violated
$$\sum_{a \in \mathcal{A}_o} x_{a,o} = 1 \ \forall o \in \mathcal{O}$$
where $\mathcal{A}_o$ is the subset of agents that see origin o;
2) for each agent a, a combination of user origins within its local view has an associated cost, which relates to total travel time of users assigned to that agent, including waiting times for drop-off and pick-up. In practice, not all combinations are available and feasible, but only an agent-specific set $\mathcal{Z}_a$ of the N_b best that are returned through pre-processing via centralized planner. Hence, for a valid selection of users we have
$$\text{evaluate}(x_{a,1}, ..., x_{a,n}) = c_{a,z} \ \forall a \in \mathcal{A} \setminus \{PT\}, \ z \in \mathcal{Z}_a$$
where $x_{a,i}$ is unitary if user i is considered in the evaluated combination z for agent a consistently with the previous definition of set $\mathcal{X}$;
3) for scaling issues, the evaluate constraint is omitted for the PT agent due to the potential number of combinations. Instead, a more direct approach is followed
$$x_{PT,o} = 1 \implies c_{PT,1} = FM_o \ \forall o \in \mathcal{O}$$
$$x_{PT,o} = 0 \implies c_{PT,1} = 0 \ \forall o \in \mathcal{O}$$
where parameter c can only take a single user combination (hence $z = 1$ is the only possible second index in $c_{PT,z}$).

Minimization of cost c for each agent a by selecting optimal combinations z is the ultimate goal of the DCOP.

B. Centralized Planner

To compute the evaluate constraint, a centralized planner creates combinations of users and determines the optimal pick-up order, transit point selection, and the total cost for each individual taxi. The cost is the aggregated travel time of all users part of the trip. To facilitate modal change, all arrival times to a transit point should be earlier than the scheduled train departure, considering a pre-defined transfer buffer. Routing information is derived from a designated Application Programming Interface (API) [23], providing historical and real-time information for both PT schedules and routes. A travel timetable is constructed from the API for the Origin-Destination (O-D) matrix containing the agent origin locations, origins of users in the local view of the agent, and all possible transit points. The cost of each combination for all agent is determined via a Mixed Integer Linear Programming (MILP) model that maximizes occupancy of a taxi agent while minimizing travel costs. A pool of the N_b best solutions is sought, as selecting just the best agent-specific solution does not necessarily yield system-wide optimality. In Table I, the sets, parameters, and decision variables of the MILP are provided.

TABLE I: Sets, parameters, and decision variables of the centralized planner.

Sets	
$\overline{\mathcal{O}}$	Set of origins, indexed by i
Parameters	
$T_{i,j}$	Travel time cost from $i \in \overline{\mathcal{O}}$ to $j \in \overline{\mathcal{O}}$
G_i	Latest time to drop-off users at transit point $i \in \overline{\mathcal{O}}$. Greater than zero only for $i \in \mathcal{O}_{TP}$
N_i	Number of persons in $i \in \overline{\mathcal{O}}$. Greater than zero only for $i \in \mathcal{V}_t$
P_i	Processing time of node $i \in \overline{\mathcal{O}}$
max_p	Maximum allowed pick-ups
rwd	Reward of selecting a trip
Cap	Agent capacity
Decision Variables	
$z_{i,j}$	Binary variable, equal to 1 if a trip originating from i towards j is active
t_i	Continuous variable, defining arrival time at node i

Inheriting notation from Sec. III-A, we define the set of origins that can be visited by taxi $t \in \mathcal{T}$ as $\overline{\mathcal{O}} = o_t \cup \mathcal{V}_t \cup \mathcal{O}_{TP}$, where $\mathcal{O}_{TP}$ is the set of transit point origins. A feasible routing for taxi t starts in o_t, visits a subset of users $\mathcal{V}_t$, and ends in one element of $\mathcal{O}_{TP}$. We solve the MILP specific to taxi $t \in \mathcal{T}$ as follows

$$\max \sum_{i \in \overline{\mathcal{O}}} \sum_{j \in \overline{\mathcal{O}}} rwd \cdot N_i \cdot z_{i,j} - T_{i,j} \cdot z_{i,j} \tag{1}$$

s.t.

$$\sum_{j \in \mathcal{V}_t} z_{o_t,j} = 1 \tag{2}$$

$$\sum_{j \in \mathcal{V}_t \cup \mathcal{O}_{TP}} z_{j,o_t} = 0 \tag{3}$$

$$\sum_{i \in \mathcal{V}_t} \sum_{j \in \mathcal{O}_{TP}} z_{i,j} = 1 \tag{4}$$

$$\sum_{i \in \mathcal{O}_{TP}} \sum_{j \in \overline{\mathcal{O}}} z_{i,j} = 0 \tag{5}$$

$$t_j \geq t_i + P_i + T_{i,j} - (1 - z_{i,j})M \quad \forall i \in \overline{\mathcal{O}}, j \in \overline{\mathcal{O}} \tag{6}$$

$$t_i \leq \sum_{j \in \mathcal{V}_t} z_{j,i} \cdot G_i \quad \forall i \in \mathcal{O}_{TP} \tag{7}$$

$$\sum_{i \in o_t \cup \mathcal{V}_t \setminus \{j\}} z_{i,j} = \sum_{i \in \mathcal{V}_t \cup \mathcal{O}_{TP} \setminus \{j\}} z_{j,i} \quad \forall j \in \mathcal{V}_t \tag{8}$$

$$\sum_{j \in o_t \cup \mathcal{V}_t \setminus \{i\}} z_{j,i} \leq 1 \quad \forall i \in \mathcal{V}_t \tag{9}$$

$$\sum_{j \in \mathcal{V}_t} z_{o_t,j} + \sum_{i \in \mathcal{V}_t} \sum_{j \in \mathcal{V}_t \setminus \{i\}} z_{j,i} \leq max_p \tag{10}$$

$$\sum_{j \in \mathcal{V}_t} N_j \cdot z_{o_t,j} + \sum_{i \in \mathcal{V}_t} \sum_{j \in \mathcal{V}_t \setminus \{i\}} N_j \cdot z_{i,j} \leq Cap \tag{11}$$

$$z_{i,j} \in \{0,1\} \quad \forall i \in \overline{\mathcal{O}}, j \in \overline{\mathcal{O}} \tag{12}$$

$$t_i \in \mathbb{R}_{\geq 0} \quad \forall i \in \overline{\mathcal{O}} \tag{13}$$

The objective function 1 is defined as the weighted number of users part of the assignment minus the expected travel time for servicing such users. A preference is given to solutions that increase taxi ridership through the rwd parameter, but cost minimization is also included to guarantee optimal sequencing of users and transit point selection for drop-off. In general, a rwd greater than the lead-time of the agent will always prioritize occupancy maximization. Constraints 2-3 restrict the routing to ensure that exactly one trip will originate from the taxi start location and that there will never be a trip towards it. Similarly, constraints 4-5 ensure that the routing ends in a transit point and prevent trips from originating from a transit point. In constraint set 6, time precedence constraints are imposed. P_i is greater than zero only for $i \in \mathcal{V}_t$ and represents boarding time. Without loss of generality, we set t_{o_t} equal to the earliest time a taxi can perform a trip and P_{o_t} equal to zero. M is a big-M that can be set equal to $\max_{i \in \mathcal{O}_{TP}} G_i$. Constraint set 7 enforces that the visited transit point $i \in \mathcal{O}_{TP}$ is accessed no later than the time upper bound G_i (related to train departure). Constraint 8 is a flow conservation constraint for all user nodes, while constraint 9 enforces that a taxi can visit a user either from its starting location o_t or from a previously visited user. In constraints 10-11 we respectively ensure that the selected trips to users are fewer than the pre-defined number of allowed pick-ups and impose that the capacity constraint of a taxi is not violated. A number of maximum three pick-ups was considered realistic. Finally, in constraint sets 12-13 the domain of the decision variables is defined.

IV. Case Study & Results

A. Trip Generation

A case study is presented that focuses on Milano Malpensa Airport (MXP). MXP currently features a PT share for ground access to the airport, mainly through rail and various shuttle services, that is compatible with other European airports. Notwithstanding, MXP targets to increase such percentage by 2035 to reduce road congestion and increase environmental sustainability. Approximately 50% of the airport's traffic is generated from the Milano metropolitan area. A dedicated train line (Malpensa Express) and various shuttle services (Malpensa Bus, Malpensa Shuttle) are the main PT providers servicing the airport.

To simulate demand towards MXP, historical data were utilized based on recorded outbound passengers for the month of June 2022. 50% of recorded demand was considered, consistently with the average percentage stemming from Milano. We divided a day into 48, 30-minute time periods and users were assigned to expected clusters of arrival to the airport. We used a normal distribution with a mean of four clusters (2 h) before the flight departure cluster and a variance of two clusters. Modal choices were assigned randomly based on reported modal splits for ground access to the airport.

To determine origins of passengers, demographic characteristics of Milano were used. The city is clustered into 88 districts with unique social and cultural identity [24], also called Nuclei di Identità Locale (NILs). Given this zonal structure, population records [25] were used to determine the likelihood of a user group to originate from a specific district. In Fig. 1, the generated spatial distribution of origins, for a specific arrival cluster of users, is presented.

After determining all trip characteristics, groups were split into modes based on historical data for ground access to MXP. An estimated 17% of arrivals are considered to use the dedicated train line. Access to the train line was assumed to occur via other PT modes (e.g., metro, tram, or bus). For this subset of users the travel time spent on the first-mile, the optimal mode of transport, and the optimal transit point were computed via the designated API, based on their desired arrival cluster at the airport.

B. Experiments

In total, 24 instances were generated for three distinct clusters of arrivals M, N, and A, standing respectively for Morning, Noon, and Afternoon peaks. Instances were based

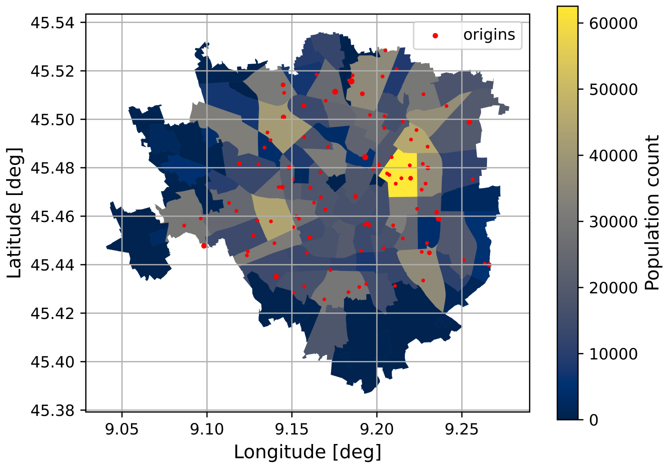

Fig. 1: Generated origins for PT arrivals in the [8:00-8:30] interval and demographic characteristics for the 88 NILs

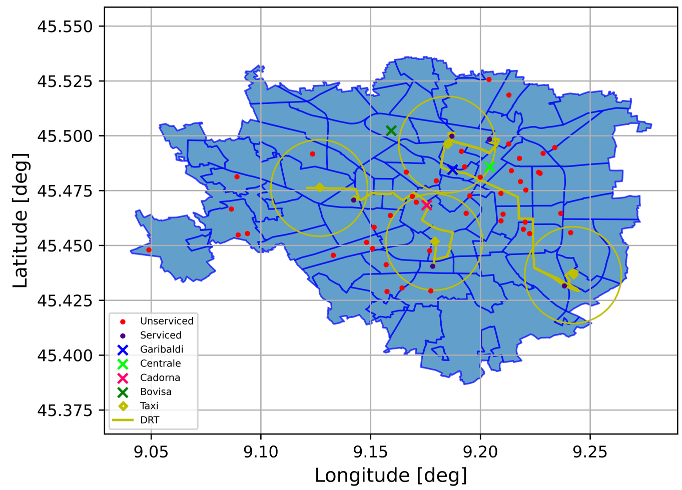

Fig. 2: Taxi assignment for Instance 2_30_4_A

on global agent-imposed criteria, to test the performance of the DRT service. For all instances, we experimented with two different radii for the agents' view (2 and 4 km). The starting locations of the taxis were generated based on NIL demographic characteristics and taxi cab stands, acquired through OpenStreetMaps [26]. The first-mile bound was set to either 30 or 40 minutes. It is noted that the average first-mile is approximately 30 minutes. Finally, a 30-minute lead-time was imposed and either 4 or 8 taxis were made available. The peak day of the first week of June 2022 was selected to simulate airport arrivals. Cluster M [8:30-9:00] relates to the peak of passengers by train (131 passengers) for that day, Cluster N [12:30-13:00] is close to the daily average per time period (63 passengers), while Cluster A [15:30-16:00] defines the afternoon peak (91 passengers). We unequivocally define an instance by listing, in sequence, the radius view, the first-mile bound, the number of taxis available, and the reference cluster. For example, instance 2_30_4_A relates to a view of 2 km, a first-mile bound of 30 minutes, and 4 available taxis for the time period [15:30-16:00]. In Fig. 2, the agent interaction with the environment for the described instance is shown as well as the optimal assignment after model execution.

The numerical results were obtained using a personal laptop running Windows with a 4-core Intel i7-1185G7 and 16 GB of RAM. Frodo 2.18.1 [27] was used to model the DCOP and solve it with the DPOP [28] algorithm. Solution time across all instances was below 15 seconds. The centralized planner was implemented in Python and solved with Gurobi [29]. A maximum pool of ten N_b best solutions per agent was used for constraint generation. Generating constraints for all agents with the centralized planner was more time-consuming, but it never exceeded 8 minutes for a single instance. Parallelization of this process would cut the running time to less than two minutes. In Table II, a summary of the reported results by the generated instances is presented.

Overall, the application of the DRT service reduces the total first-mile travel time experienced by all users, almost proportionally to the modal share. With modal share, we define the percentile ratio between serviced users by the DRT system and all users in the cluster. This reported reduction is significant, but expected since users that are most likely to be serviced are usually the most affected. The pick-up cost of the taxi, i.e., the traveling time between o_t and the first serviced user, increases with the view radius, but still remains approximately around 10 minutes, consistently with current ride-hailing practices. Increasing the taxi view can lead to a further travel time reduction up to 11% (instances 2_30_8_A and 4_30_8_A), but can even lead to no decrease (instances 2_30_4_N and 4_30_8_N). Increasing the first-mile bound is generally detrimental to system optimality, leading to an increase in travel time between 2 and 12%. However, it can lead to a more equitable assignment that truly targets the most affected users.

TABLE II: Cumulative Table of generated Instances

Instance	Travel Time (min)	Reduction	Sol. Time (s)	Taxis	Modal Share	Avg. Pickup Cost
2_30_4_M	3,919	7.9%	4	4	10.7%	5
2_30_4_N	1,745	9.5%	1	4	13.6%	8
2_30_4_A	2,511	8.6%	1	3	12.2%	4
2_30_8_M	3,720	12.6%	9	7	19.1%	5
2_30_8_N	1,661	13.8%	2	5	20.3%	6
2_30_8_A	2,285	16.9%	4	6	22.2%	4
2_40_4_M	4,079	4.1%	1	3	4.6%	6
2_40_4_N	1,900	1.5%	<1	1	1.7%	9
2_40_4_A	2,714	1.2%	<1	1	1.1%	5
2_40_8_M	4,047	4.9%	1	4	5.3%	6
2_40_8_N	1,877	2.6%	<1	2	3.4%	6
2_40_8_A	2,515	8.5%	<1	3	8.9%	6
4_30_4_M	3,813	10.4%	5	4	13.7%	8
4_30_4_N	1,646	14.6%	2	4	23.7%	9
4_30_4_A	2,511	8.6%	2	3	13.3%	4
4_30_8_M	3,554	16.5%	11	7	22.1%	8
4_30_8_N	1,448	24.9%	4	7	39.0%	9
4_30_8_A	2,187	20.4%	4	6	26.7%	8
4_40_4_M	3,926	7.7%	1	4	9.2%	8
4_40_4_N	1,726	10.5%	1	4	13.6%	11
4_40_4_A	2,689	2.1%	<1	2	2.2%	16
4_40_8_M	3,722	12.5%	2	7	15.3%	8
4_40_8_N	1,678	13.0%	1	6	15.3%	11
4_40_8_A	2,491	9.4%	<1	3	8.9%	9

V. Conclusions

The present study focuses on developing a new mobility service to support ground access to the airport. A Demand Responsive Transport (DRT) service was conceptualized that makes use of taxi-dispatching and ride-sharing to target users with long first-mile trips to a set of transit points. These transit points represent stations served by a dedicated train line connecting users to their final destination, i.e., the airport. Distributed constraint optimization was utilized in modeling the proposed service. Experiments show that utilization of the DRT service can lead to a decrease of the system's travel time that is roughly proportional to the increase of the modal share. On average, a 10% reduction of the users' travel time was reported across instances, with an average utilization of only 4 taxis.

Although the study focused on airport-bound trips, the service can be extended to include last-mile connections from the airport. An iterative procedure can be used to optimize pickups and deliveries simultaneously and improve taxi allocation. Allocation strategies for taxi positioning based on demand can also be considered. Additionally, the fully cooperative nature of the service can be removed, allowing for different decision-making criteria per agent when selecting users. This would enable the service to be integrated into the competitive environment of existing taxi and ride-sharing services.

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