On the Role of Multi-Objective Optimization to the Transit Network Design Problem

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ABSTRACT
Ongoing traffic changes, including those triggered by the COVID-19 pandemic, reveal the necessity to adapt our public transport systems to the ever-changing users’ needs. This work shows that single and multi objective stances can be synergistically combined to better answer the transit network design problem (TNDP). Single objective formulations are dynamically inferred from the rating of networks in the approximated (multi-objective) Pareto Front, where a regression approach is used to infer the optimal weights of transfer needs, times, distances, coverage, and costs. As a guiding case study, the solution is applied to the multimodal public transport network in the city of Lisbon, Portugal. The system takes individual trip data given by smartcard validations at CARRIS buses and METRO subway stations and uses them to estimate the origin-destination demand in the city. Then, Genetic Algorithms are used, considering both single and multi objective approaches, to redesign the bus network that better fits the observed traffic demand. The proposed TNDP optimization proved to improve results, with reductions in objective functions of up to 28.3%. The system managed to extensively reduce the number of routes, and all passenger related objectives, including travel time and transfers per trip, significantly improve. Grounded on automated fare collection data, the system can incrementally redesign the bus network to dynamically handle ongoing changes to the city traffic.

1 INTRODUCTION

Mobility is a central aspect in modern societies, allowing people to take part in a multitude of activities that are the identity of our days. Worldwide Public Transport Systems are placing efforts to meet emerging changes to urban traffic demand pushed by the ongoing COVID-19 pandemic, increasing population at urban centers, changing road infrastructures, among others. An efficient public transport network is, in this context, further essential to meet individuals’ needs, promoting a sustainable urban mobility along its environmental, social and economical axes. In particular, this work addresses the Transit Network Design Problem (TNDP), where an efficient (multimodal) traffic network is one guaranteeing: i) comprehensive demand coverage, ii) low transfer rates and walking needs, iii) low travel times, iv) low waiting times, v) controlled operator costs, vi) low environmental footprint, and vii) safety guidelines such as maximum occupancy and recommended individual distances.

State-of-the-art TNDP approaches, when faced with multiple objectives, generally resort to one of two major options. First, an enumeration of solutions at the Pareto front using a Multi Objective optimization stance, providing decision makers with multiple solutions [6, 7, 13]. Despite their relevance, non-dominated solutions generally fail at providing an optimal compromise between all objectives, and existing works generally place strict assumptions on the variability of passenger demand. Second, complementary approaches pursue a Single Objective Optimization process by placing an weighted sum of all the target objectives [3, 10, 11, 14, 23]. In this context, weights are generally placed in accordance with the perceived importance of each objective, and further normalized according to their ranges of values. However, objective relevance is further dependent on additional confounding factors, including the extent of possible improvements per objective, turning this classic specification highly subjective.

This work proposes explores why and how single and multi objective optimization approaches can be synergistically combined to address the enumerated challenges associated with the TNDP problem. In this work, weights are dynamically inferred from ratings placed on non-dominated network solutions uniformly sampled along the Pareto front approximation. The network ratings are thus used to replace subjective perceptions on the objectives’ relevance, providing decision makers with better options to perform operational, tactic and strategic reforms in transport systems.

An end-to-end methodology for the TNDP task from raw automated fare collection (AFC) data gathered from multimodal public transport systems is further proposed, comprising principles for network processing, origin-destination matrix estimation, route generation, and efficient evaluation. Genetic Algorithms, considered within both single and multi objective approaches, are outlined to redesign the transport network. Grounded on AFC data, the optimized network can be dynamically revised in the presence of more recent validations to handle ongoing changes to the city traffic.

As a guiding case study, the proposed tool is applied to the Lisbon’s public transport network in Portugal. The system takes individual trip data given by smartcard validations at CARRIS buses and trams, and METRO subway stations. The combined multiple-and single optimization stance yields significant improvements in the design of the CARRIS bus network, with reductions in objective functions up to 28.3%. The gathered results show the possibility of using available fleet more efficiently to better serve passenger demand, moderately reducing transfer needs and travel times, while reducing the environmental impact of the network.

The manuscript is structured as follows. Section 2 provides essential background on optimization tasks. Section 3 surveys state-of-the-art contributions to the TNDP task. Section 4 describes the proposed end-to-end TNDP methodology. Section 5 discusses the results gathered from its application Lisbon’s network. Finally, major concluding remarks are drawn.
2 BACKGROUND

Finding the best elements, $x^*$, from a set of alternatives, $X$, according to a set of criteria, $F = \{f_1, f_2, ..., f_m\}$, is the essence of optimization. $x = \{x_1, x_2, ..., x_n\}$ is a set of what is called design or decision variables. $f_i : X \mapsto Y$, $(i = 1, 2, ..., m)$, with $Y \subseteq \mathbb{R}$, are the criteria or objective functions. These problems can have constraints that limit the values that the design variables can take. We can formalize optimization problems as follows:

$$\begin{align*}
\text{minimize} & \quad f_i(x), \quad (i = 1, 2, ..., m) \\
\text{subject to} & \quad h_j(x) = 0, \quad (j = 1, 2, ..., o) \\
& \quad g_k(x) \leq 0, \quad (k = 1, 2, ..., p) .
\end{align*}$$

In Single Objective Problems ($m=1$), it is easier to distinguish the quality of solutions. The lower the value of that objective, the better the solution. However, when we have more than one objective, such distinction becomes harder to make. For example, if we have two solutions for a bi-objective problem, $x^1$ and $x^2$, with $f_1(x^1) < f_1(x^2)$ and $f_2(x^1) > f_2(x^2)$, we may not be able to identify the best solution without subsequent inspection. In this context, a multi objective problem can be converted into a single objective one by creating a new objective function, generally defined as:

$$f'(x) = \sum_{i=1}^{m} w_i f_i(x) .$$

This formulation, however, limits the variety of solutions we can find since it does not reveal to the user where are the compromises between objectives. Pareto optimality becomes a relevant definition when dealing with multi objective problems as it provides us with a definition of optimality that considers multiple objectives. A solution is Pareto optimal if we cannot improve one objective without damaging the quality of the remaining objectives. A Pareto optimal solution compromises the different objectives in an optimal way. Different Pareto optimal solutions represent different balances between the objectives. The set of all Pareto optimal solutions is called the Pareto frontier. Pareto optimality is tightly coupled to the definition of domination. A solution $x^1$ dominates another solution $x^2$, in which case, we write $x^1 \prec x^2$ if, and only if:

$$\forall i \in \{0, ..., m\} : f_i(x^1) \leq f_i(x^2) \land$$

$$\exists j \in \{0, ..., m\} : f_j(x^1) < f_j(x^2) .$$

Now we can define the Pareto frontier, $X^*$, as the set of points that are not dominated by any other solution. In other words:

$$x^* \in X^* \iff \not\exists x \in X : x \prec x^* .$$

While Single Objective approaches try to find the best solution according to a single criteria, Multi Objective approaches approximate the Pareto front to identify compromises between objectives and assess their quality.

Genetic Algorithms (GA) are population-based optimization algorithms with well-established success towards both Single and Multi Objective ends. GA mimic nature’s evolutionary process. Solutions are individuals in a population represented as a string of symbols that encode a solution for the problem we are trying to solve. Individuals reproduce and mutate to give place to new individuals. Reproducing means combining the genetic code of two individuals to make new solutions that are based on their parents and mutation means randomly changing the genetic code of an individual to introduce variety and try to escape local minimums. As a result, the quality of populations is expected to increase along iterations. The Classic Genetic Algorithm was one of the first to use these principles in single objective optimization by John H. Holland in 1976 [18]. The Non-dominated Sorting Genetic Algorithm II is a multi objective optimization algorithm proposed by Deb et al. [9]. These are the algorithms extended in the present work.

3 RELATED WORK

Newell [16] points out the non-convex properties of the Transit Network Design Problem (TNDP), showing for instance that changing bus frequency (operation costs) may not impact user costs. Baaj and Mahamassi [2] further highlights the hard combinatorial nature of the problem caused by its discrete nature. In contrast with bus frequencies, lightly depicted as numeric decision variables in problem formulations, representation of network routes is more challenging. This makes Mixed Integer formulations, like the one proposed by Wan and Hong [21], rather ineffective to solve TNDP. In Wan and Hong’s formulation, the presence of each node in each route is modeled as a binary variable. This makes it so that a small network with 10 nodes and 19 links, ends up having 363 binary decision variables, 30 integer decision variables and 303 continuous decision variables when solving TNDP. In this context, metaheuristic approaches are necessary. While some works try to change the configuration of routes in a bus network. Others try to optimize both the route configuration and their respective working frequencies simultaneously, the so referred Transit Network Design and Frequencies Setting Problem (TNDFSP). A significant number of works have taken different approaches to solve these problems.

Most works reduce the problem to a single objective formulation (Eq.2) and then solve the single objective variant [11], reducing the variety of solutions found by these works. Yu et al. [23] used Ant Colony Optimization to TNDP, maximizing passenger flow and minimizing transfers. In their model, OD pairs work as the nest and the food source for several sub-colonies and the pheromone trail is based on passenger density. They tested their work on an existing network in the city of Dalian (3,200 links and 2,300 nodes with 89 lines), showing the possibility to reduce the number of lines to 61 without compromising satisfied demand. Pattnaik et al. [17] used GA to solve TNDFSP, minimizing traveling times and operating time of buses, given feasibility constraints. Their approach worked in two phases, first a Candidate Route Set Generation Algorithm (CRGA) followed by the GA identification of optimal routes and frequencies based on Fixed and Variable String Length codifications of routes. Bielli et al. [3] used GA to solve TNDFSP using considerably different modeling principles. Bielli et al. use a fixed length representation in which each chromosome is a network and each gene represents a pre-generated line with a frequency and an on/off switch that indicates whether the route is active in the network. This means that every pre-generated route will exist in every network but with different frequencies and it can be active or not. Their formulation places a weighted sum of efficacy, efficiency and quality of service metrics. The work shows significant improvements Parma city, Italy. Chien et al. [8] also used GA in the context of TNDFSP but with a different goal: optimizing feeder bus...
routes. Feeder routes bring people from (to) several points to (from) a central hub. Their objective function also minimizes user costs (access, waiting and in-vehicle costs) and operator costs (round trip time of the buses and the headway). They tested their approach in small networks and found that, when the parameters are properly tuned, the GA can find the optimal route. Fan and Machemehl [10] also used GA to solve TNDFSP. Their objective function considers, user costs, operator costs and unsatisfied total demand costs, with the relative importance easily parameterized. Similarly to Pattanaik et al., their approach uses Dijkstra’s algorithm and Yen’s k-shortest paths algorithm to generate routes between OD pairs. The authors show the role of GA methods against alternative population-based methods. Jia et al. [14] tackles TNDP for the bus network in Xi’an, a city in Northwest China, showing the role of Complex Network theory to improve sustainability and robustness without directly modeling demand.

In contrast, a scarcer number of TNDP approaches place multi-objective optimization stances in order to find non-dominated solutions of potential interest, providing stakeholders with multiple options. Jha et al. [13] approximated the TNDP Pareto front combining average passenger time and operating costs using Intelligent Water Drops (IWD) algorithm, a novel and tailored evolutionary optimization technique. Chen et al. [6] proposed a stochastic framing for multi-objective optimization for designing transportation networks under demand uncertainty. Arbex et al. [1] introduced an Alternating Objective Genetic Algorithm (AOGA) to boost efficiency, in which the objectives are cyclically alternated along the generations. Wang et al. [22] formulates the TNDP as a multi-level task described by the skeleton network, arterial network, and feeder network, proposing an hybrid heuristic approach. Despite the relevance of multi-optimization stances to assess alternative solutions, existing works generally focus on road developments and reforms [4], including street constructions, lane additions, allocations and reorientations [15]. Zhang et al. [24] seek non-dominated solutions for railway alignment considering costs and environmental impacts; Inti et al. pursued [12] non-dominated road developments balancing environmental, economic and constructability factors; and Sohn [19] identified road diet network solutions maximizing utility for cyclists with minimum impact on motorists.

Despite the relevance of the surveyed principles, Single Objective stances depend on the subjective and difficult task of weighting conflicting objectives; while Multi Objective stances generally fail at providing an adequate compromise between all objectives. In addition, most works focus on single transport modes and place strict demand assumptions, not assessing the impact of origin-destination demand variability, possibly given by all raw passenger trips in a (multimodal) transport system.

4 SOLUTION AND PROBLEM FORMULATION

This section introduces an end-to-end methodology to answer the targeted transit network design problem (TNDP), covering the essential aspects pertaining to: the inference of traffic demand from smart card validation; the consolidation of the road network with the public transport networks from different operators; the definition of evolutionary operators and principles for the effective generation of routes; the assignment of origin-destination needs to transportation means; and the formulation of the targeted multi and single objective approaches. An overview of the developed solution can be seen in Figure 1.

4.1 Preprocessing

To run an optimization process on a bus network that operates on top of a road network, we first have to have the available bus stops as nodes on a the road network. That way, we can then define a bus route as a sequence of stops and assume that the buses travel between the stops through the optimal time path. The road network was retrieved from the Open Street Map (OSM) database through the OSMnx python package which gives us the network as a NetworkX graph. The stop locations were taken from the CARRIS General Transit Feed Specification (GTFS). Since the stops and networks are built on inaccurate GPS readings, fixing the stops on the network is a complex task. For that end, we used the work of Vuurstaek et al. [20].

There are stops that exist in close proximity to others and whose only purpose is to provide people with multiple boarding points so that stops do not become overcrowded. These usually serve different routes, but from an optimization point of view, they are equivalent because they provide entry and alight points in the same general areas. Because we have routes that are generated randomly, we want to have all these stops clustered under the same stop so we do not generate redundant routes. To that end, two stops, \( u \) and \( v \) are clustered into one if the edge \( (u, v) \) exists in the road network and has a cost of less than 100m and if \( \text{deg}_\text{in}(v) = 1 \). We force the edge \( (u, v) \) to exist because, if a road node exists between the two stops, then that means that a route can go from \( u \) to one other stop, \( w \), without necessarily going through \( v \), making it so that, if stops \( u \) and \( v \) are clustered under the location of \( v \), that route would be way longer than it should as it would go from \( v \) to \( w \). We force \( \text{deg}_\text{in}(v) = 1 \) because if there is a route that goes from a third stop \( w \) to \( v \) and we cluster \( v \) and \( u \) under the location of \( u \) then that route would have to go from \( w \) to \( u \), potentially making it much longer than what it is, in fact, is. The 100m requirement is completely adjustable and it is there only so we do not cluster stops on different ends of the same avenue. If stops \( u \) and \( v \) can be joined and stop \( v \) can be joined with a third stop \( w \), then all the stops can be joined under the same cluster. We started with 2193 stops and managed to reduce this number to 1786 using this criteria to join stops.

The origin-destination estimation is also an essential step since buses require smartcard validation only upon entering. In this work, the estimators of Cerqueira et al. [5] were applied to produce OD matrices which then serve as input to our optimization processes.

4.2 Relevant networks and interactions

In this work, we use several different graphs to represent everything we need from the domain. It is then important to understand the different types of graphs, what is their purpose, and how they interact.

The road network, \( G_r \), has edges representing road segments and nodes representing road junctions, road ends or bus stops.

The bus network, \( G_b \), is the only one with several instances. This is the object of optimization and, as such, a genetic algorithm population is filled with networks of this type, i.e. at each time step
\( t \), we will have a population \( P_t = \{ G_1^t, G_2^t, ..., G_n^t \} \). These networks are built from a set of routes. A route is just a sequence of stops. All the tram routes are included in the bus networks but they are never interfered with during the optimization process. The edges in this network are identified by an origin stop, a destiny stop and a route making the connection.

The metro network, \( G_m \), also has edges identified by an origin station, a destiny station and a line color connecting the two. We want to assess what the use of the whole transportation network would be like with the bus network under evaluation, so the metro network must be present. It will not be changed and it is a singleton network. The metro trains are assumed to travel at \( 60 \text{Km/h} \).

Finally, the walking network, \( G_w \), connects the bus network with the metro network and close bus stops. It is assumed that people are willing to walk up to \( 300 \text{m} \) to transfer. The nodes are bus stops or metro stations and the edges represent possible walks between them. The walks are assumed to be a straight line from the origin to the destiny. People are assumed to walk at \( 5 \text{Km/h} \). This network is never changed.

During optimization, we integrate the bus network, under evaluation, with the walking and metro networks, creating a complete multimodal network, \( G_c \), in which trips that involve walking, bus and metro can be planned.

### 4.3 Network evaluation

In order to assess transfer needs, travel times, waiting times and all the other objectives we are striving to improve, we need to know how the public would use the transportation network under evaluation. In this work, passengers are grouped according to their origin-destination (OD) pair. To reduce computational complexity, OD units are not individual bus stops or metro stations, instead Lisbon is divided into a \( 30 \times 30 \) grid and the squares are the OD units.

Everyone moving between the same pair of squares is assumed to do so through the same trip. The trips are a result of a computation of time optimal paths in the complete network, \( G_c \), between all OD pairs. When a bus network is able to connect an origin and a destination, it does so through a trip, which is a path in the complete network, \( G_c \). For further analysis of the trips, we can divide the trip into stages. There are three different kinds of stages, a bus stage, a walking stage and a metro stage. Practically speaking, a bus stage is a path, along a single route, in the bus network, a metro stage is a path, along a single line, in the metro network and a walking stage is a single edge path that connects two bus stages or a metro stage and a bus stage. This distinction is important because, every time there is a stage change, we apply a transfer penalty and the path cost increases. This penalty intends to simulate user’s preference for trips with less transfers if that doesn’t incur a big increase in the overall trip time.

Now, we establish important notation for sequent formulations:

- \( W^O \) - the origin set of geographies;
- \( W^D \) - the destiny set of geographies;
- \( W \) - set of all origin-destination pairs;
- \( q(s, t) \) - amount of passengers traveling between \( s \) and \( t \);
- \( R \) - set of all routes in a bus network;
- \( T \) - set of all trips between all OD pairs,
  \( T = \{ T(s, t) \mid s \in W^O, t \in W^D \} \);
- \( T(s, t) \) - trip from \( s \) to \( t \), a sequence of stages,
  \( T(s, t) = (T^0(s, t), ..., T^n(s, t)) \), where \( n \in N^+ \);
- \( T_k(s, t) \) - the \( k \)th stage on the trip from \( s \) to \( t \). It is defined as sequence of triplets of the form \((u, v, r)\) where \( u \) and \( v \) are adjacent stops or stations and \( r \) is the route/line connecting them or a special marker indicating that the path from \( u \) to \( v \) was made by foot;
- \( T_{bus}(s, t) \) - bus stages in the trip from \( s \) to \( t \);
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4.4 Problem formulation and modeling

Now we can define some quality metrics regarding a bus network. The total length, $TL$, of a bus network is computed as:

$$ TL(G_b) = \sum_{r \in R} l_r. \tag{5} $$

The Unsatisfied Demand, $UD$, of a bus network is defined as:

$$ UD(G_b) = 1 - \frac{\sum_{(s,t) \in W} q(s,t) \times CO(G_b, s, t)}{\sum_{(s,t) \in W} q(s,t)}. \tag{6} $$

where $CO(G_b, s, t)$, the cover function, is one if the bus network $G_b$ provides, along with the rest of the transportation network, a connection between the origin $s$ and destiny $t$ within a number of transfers bellow the maximum allowed and zero otherwise.

In vehicle time (IVT) is computed as follows:

$$ IVT(G_b) = \sum_{(s,t) \in W} t_{inv}(s,t) \cdot q(s,t). \tag{7} $$

The Average Number of Transfers per passenger, $ANT$, is computed as follows:

$$ ANT(G_b) = \frac{\sum_{(s,t) \in W} (|T(s,t)|-|T_{walk}(s,t)|-1)q(s,t)}{\sum_{(s,t) \in W} q(s,t)}. \tag{8} $$

4.5 Single objective formulations

After we assess the quality of the solutions that are given by the multi objective formulations, we can have a sense of what we are looking for in a network. After we know that, we can try to get as close as possible to a global optimum that represents the compromise we are looking for in a network. To this end, we will be rating networks generated by NSGA-II. The rating will then serve as reference for a linear regression that will allow us to infer the weights for a weighted single objective formulation (Equation 2) that stand for what we are looking for. We are trying to estimate:

$$ w = (w_0, w_1, w_2, \ldots, w_m)^T, \tag{10} $$

so that we can have a finely tuned objective function, aligned with the perceived needs:

$$ f(G_b) = w_0 + \sum_{i=1}^{m} w_i f_i(G_b). \tag{11} $$

To this end, the find the best weight vector $w$ such that a given error function, $E(w)$, is minimized. The error functions measure the difference between the target and estimated values,

$$ y(x) = w^T \cdot x. \tag{12} $$

Minimizing the error is also an optimization problem, but in this case, $\nabla E(w) = 0$ is solvable when considering a squared error function, with optimal weights given by:

$$ w = (X^T \cdot X)^{-1} \cdot X^T \cdot t, \tag{13} $$

where $X$ is the design matrix. Assuming that we have $n$ bus networks from the NSGA-II algorithm, we have, for our particular TNDP problem:

$$ X = \begin{bmatrix} 1 & TL(G_b^{(1)}) & UD(G_b^{(1)}) & IVT(G_b^{(1)}) & ANT(G_b^{(1)}) \\ 1 & TL(G_b^{(2)}) & UD(G_b^{(2)}) & IVT(G_b^{(2)}) & ANT(G_b^{(2)}) \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & TL(G_b^{(n)}) & UD(G_b^{(n)}) & IVT(G_b^{(n)}) & ANT(G_b^{(n)}) \end{bmatrix}, \tag{14} $$

and

$$ t = \left( max - r(G_b^{(1)}) \right), \max - r(G_b^{(2)}) \ldots, \max - r(G_b^{(n)}) \right)^T, \tag{15} $$

where $r(G_b^{(i)})$ is the average rating given to the $i$th network and $\max$ is the maximum rating a network can be given. The target for each network is $\max$ minus its rating because we want the objective function to be minimized and so, the better the rating, the lower the objective function value should be.
5 RESULTS

In this work, we work with traffic data from October 2019. The CARRIS bus network deployed at that time can be seen in Figure 2. The network has 309 routes and 2,193 stops. Each route has, on average, 26.2 stops and each station, on average serves 3.7 routes. For the month of October 2019, we have 6.2 million smartcard validations at the bus entrances, spanning 4 days. These validations, as well as validations on the Metro network, are used as the input for the work of Cerqueira et al. [5] for inferring the OD demand.

The results presented in this section were obtained with genetic algorithm experiments run during 300 iterations, with a population size of 200, a mutation probability of 0.1 and, when applicable, a crossover probability of 0.8. These parameters were decided by doing sensibility analysis on a smaller data sample.

The networks that we discuss in this section were obtained with the NSGA-II algorithm. The maximum allowable number of routes is 400 and the minimum is 200. A sample of 9 networks was chosen for a careful examination and their objective function values can be seen side by side in Figure 3. These were subjected to a rating for a single objective optimization process. The networks are identified by their order in the crowd distance sorting. The number of routes in each network can be seen in Table 1.

The big majority of the networks has a number of routes very close to the minimum allowable number of routes. The network with the maximum number of routes is composed of 256 routes. We were expecting a more diverse set of networks when it comes to the number of routes, however the number of routes is not an objective, instead we opted to use the total length of the network as a measure of route efficiency so the diversity lies in the average length of the routes and not in the number of routes. The average route length varies from 9.5Km to 13.3Km and presents a bimodal distribution with peaks around the 10.5Km and 12.5Km marks.

All the networks present a total length bellow the original network but no network is capable of satisfying demand better. In terms of in-vehicle time and average transfers, there are networks in the Pareto Front capable of more direct and shorter trips but there are also networks that demand longer trips and a higher transfer rate.

Four experts were asked to rate the networks selected from 1 to 10. The average ratings for each network are depicted in Table 2.

After the linear regression we get the following weights:

Table 3: Objective function weights after Linear Regression.

We ran a Classic GA with the weights in Table 3. We ran the Classic GA again, but with the individual objectives summed and not in the number of routes. The average route length varies from 9.5Km to 13.3Km and presents a bimodal distribution with peaks around the 10.5Km and 12.5Km marks.

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We ran a Classic GA with the weights in Table 3. We ran the Classic GA again, but with the individual objectives summed and not in the number of routes. The average route length varies from 9.5Km to 13.3Km and presents a bimodal distribution with peaks around the 10.5Km and 12.5Km marks.

All the networks present a total length bellow the original network but no network is capable of satisfying demand better. In terms of in-vehicle time and average transfers, there are networks in the Pareto Front capable of more direct and shorter trips but there are also networks that demand longer trips and a higher transfer rate.

Four experts were asked to rate the networks selected from 1 to 10. The average ratings for each network are depicted in Table 2.

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The average weighted objective function value over the algorithm iterations can be seen in Figure 4 for both experiments ran. According to the criteria we set when rating the networks, when we use the weighted objective function, a Single Objective GA is able to produce networks that are better than the best network we got from the Multi Objective Optimization after about 60 iterations. When we use a uniform weight distribution with normalized objectives we can reach a level of quality superior to the Multi Objective Optimization, yet only after about 200 iterations.

In Figure 5 we can see the individual objectives of the networks obtained through Single Objective Optimization side by side with the ones selected from the Multi Objective Optimization and the original CARRIS network. Both networks obtained with Single Objective Optimization have 200 routes. The highest rated network was network 0 and, as we can see, the network obtained with the weights from the linear regression trumps that network in every objective. The network obtained with uniform weights and normalized objectives does not achieve the same success in the number of transfers but it manages to have smaller total length than the network obtained with a weighted function.

The best network obtained through optimization has 200 routes, 109 less than the original network which translates in a difference of around 1300Km that no longer have to be traveled by the buses. In Figure 6 we can see the differences in travel times imposed by the new network. Most of the passengers has their traveling time unaffected (differences of up to 2.5 are not considered) but the majority of trips in which there are significant changes were positively affected. The network also enabled more direct trips as seen in Figure 7. No passenger had their trips increased in more than one stage and the passengers that had stages cut off their trips are more than double of the ones that have to transfer one additional time now, some even cut two transfers off their trips. In these histograms, the central bar is omitted because the total amount of passengers is 566K, which would make the differences between the smaller bars imperceptible. For the big majority of passengers, travel times and transfers remained the same. This is due to the big majority of traffic happening in the center of Lisbon in which most trips are already direct with the existing network. The new network is not able to satisfy as many trips as the original network but the difference is marginal. In general, the new network is able to provide a similar service to the one provided in the original network, but does so in a much more efficient way, using less routes.

6 CONCLUSION

In this work, we propose an end-to-end system to redesign a (multimodal) transport network using OD demand inferred from smart-card validations. The target system synergistically integrates the potentialities of multiple and single objective optimization approaches to address the core difficulty associated with the formulation of weighting schema. The TNCP problem is modeled as an evolutionary problem, where solutions in the Pareto front are firstly identified with a multi objective algorithm. A comparative rating of solutions drawn from the Pareto front is used to produce the weighting
schema for single objective formulations through a (linear) regression model. In the context of our work, the targeted objectives are the unsatisfied demand, in-vehicle time, transfer needs, and the total length of the network as a proxy for the operator’s costs and environmental footprint. We further consider safety capacity concerns and walking distances in transfers as parameterizable constraints.

Overall, the application of the proposed system over the Lisbon’s public transport network showed moderate improvements in passenger-related objectives while massive improvements in operator-related objectives. According to the placed criteria, the best network in the Pareto Front approximation reduces the original network objective function in 23.1% and the network built through single objective optimization provides a 44.0% reduction relative to the original network. This last reduction translates to a 34.6% reduction in total network length (from 309 routes 200), a 5.1% reduction in average transfers, a slight reduction of in-vehicle time and an increase of unsatisfied demand from 0.7% to 1.3%. The transition from Multi Objective to Single Objective optimization proved effective. With a Single Objective optimization considering the weights inferred through our rating process being able to produce better networks than the best one in the Pareto Front after 60 iterations, while a Single Objective optimization considering a uniform weighted sum of all objectives normalized achieved the same only after 200 iterations.

This work shifts the focus from the subjective and difficult task of weighting conflicting objectives towards the objective task of ranking networks in accordance with their ability to satisfy the placed objectives. In addition, the proposed system consistently combines state-of-the-art principles on network processing, origin-destination matrix inference, route generation, and evolutionary approaches to optimization. Grounded on automated fare collection data, the system can be used to dynamically adapt the transport network in the presence of more recent traffic data, being able to handle ongoing changes to the city traffic.

As lines of future work, we highlight the evaluation of the proposed methodology in other urban transport systems; a comprehensive assessment of the impact of placing objectives as bounded constraints in the problem formulation; and the establishment of principles to assist with the necessary incremental network reforms to guarantee the successful translation of the redesigned networks.

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