Balancing Fairness and Efficiency in Transport Network Design through Reinforcement Learning

Extended Abstract

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ABSTRACT
Designing well-functioning and fair transport networks is not a trivial task, given the large space of solutions and constraints one must satisfy. Moreover, different spatial segregation sources can render some transportation network interventions unfair to specific groups. It is thereby crucial to optimize the transportation system while mitigating the disproportional benefits it can lead to. In this paper, we explore the trade-off between efficiency and fairness in the Transport Network Design Problem (TNDP), via the use of Deep Reinforcement Learning (Deep RL). We formulate different fairness definitions as reward functions — inspired by Equal Sharing of Benefits, Narrowing the Gap, and Rawl’s justice theory. We apply our method to Amsterdam (The Netherlands) and Xi’An (China) and show that vanilla Deep RL can lead to biased outcomes. By considering different fair rewards, however, we can shed light on possible compromises between fairness and efficiency in the TNDP.

KEYWORDS
Transport Network Design; Deep Reinforcement Learning; AI for Social Good; Fairness; Equity

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1 INTRODUCTION
Public transportation planning driven by economic principles of efficiency has exacerbated urban inequalities [12]. It is, therefore, crucial to look beyond optimizing the efficiency of public transport networks and to consider potential disparities they can lead to.

The Transport Network Design Problem (TNDP) is an NP-hard optimization problem, where the goal is to design a new line that maximizes the total citizens’ travel demand satisfied. TNDP has traditionally been addressed through integer optimization and heuristic algorithms [1, 7, 11, 13, 15]. These methods, however, require a long list of constraints to be formalized and imposed [18]. This suggested new prominent methods prone to be applied in real-world settings [14, 19]. Previous models ignore inequality issues, and as we show in this paper, can even worsen them.

To address disparities in the TNDP, we look into transport planning research, measuring inequalities along different dimensions [4, 6, 16]. We formulate the RL optimization problem of fairness and efficiency in transport network design and formalize fairness-based reward functions, evaluating their result along an efficiency-fairness trade-off. We apply this methodology in two real city environments: Xi’an in China [18], and Amsterdam in The Netherlands. We show that different reward functions can be used to navigate the trade-offs between efficiency and fairness and to provide a new toolkit for decision-makers to test how different fairness-efficiency requirements can map onto different transportation lines.

2 FAIRNESS VS EFFICIENCY IN THE TNDP
We model a city as a two-dimensional grid environment $H_{n \times m}$. A transport line is a spatial graph $G(N, E)$, connecting a set of cells in the grid. The goal is to create lines that optimize the total captured travel demand, expressed as a function $U_{od}$ of the estimated Origin-Destination (OD) matrix [8, 10]. To model TNDP as a Markov Decision Process (MDP), we adopt the formulation in [18]. An agent generates a transport line by taking sequential actions, i.e. select cells to be stops in the new line. At every time step $t$, the agent selects a cell $h \in H_{n \times m}$ to place a station on. At the end of the episode, the sequence of selected cells is the generated transport graph $G(N, E)$. The total selected locations are constrained by a budget $B$, a station number limit $T$, and direction-based constraints, so as to avoid unfeasible line shapes; for simplicity, we omit these constraints from the following discussion (see [18] for details). Formally, the MDP $(S,A,P,R)$ stands as:

- $S$: the state; sequence of previously selected grid cells to include a transportation line stop.
- $A$: the action; selected cell at each time-step to add a stop.
- $P : S \times A \times S \to \{0, 1\}$: state transition function.
- $R : S \times A \to \mathbb{R}$: the reward.

To consider fairness, we define a set $A$, representing different groups, based on the house-price index (proxy for an area’s development). Each cell $h$ is associated with a group $a \in A$. We adjust systems, formulating the TNDP as a Deep Reinforcement Learning (Deep RL) problem can inspire new solutions that enable non-myopic long-term decisions, as noted in recent work [5, 17].

Deep RL can effectively explore the search space in a variety of TNDP environments by optimizing a reward function, without requiring a long list of constraints to be formalized and imposed [18].
the objective function based on different notions of fairness [2]. We use $U(G)$ and $U_a(G)$ to denote the fraction of demand covered by the new transportation graph $G$, over all groups and for a specific group $a$, respectively.

**Variance Regularization**. This reward aims to achieve the Narrowing the Gap notion, by regularizing the variance of the groups’ satisfied travel demand with a hyperparameter $\lambda$:

$$r = \sum_a U_a(G) - \lambda \text{var}(U(G)).$$

(1)

**Rawls**. Reward based on Rawl’s theory of justice that aims at maximizing the benefits received by the least privileged group [2]:

$$r = U_{a_0}(G),$$

(2)

where $a_0$ is the group with least utility before adding the new line.

**Generalized Gini Index (GGI)**. This reward is used to achieve Equal Sharing of benefits. It is a weighted sum of the groups’ utility, where the lowest weight is assigned to the group with the highest utility. The weights are assigned via a hyperparameter.

$$\text{GGI}_w = \sum_{a \in A} w_d \sigma(U_a(G)).$$

(3)

$\sigma$ is a permutation that sorts the utilities in descending order and weights $w_d$ are non-increasing weights, $w_1 > w_2 > ... > w_{|A|}$.

We use a recently proposed Deep RL method to explore the trade-off described above and modify the reward function of the agent to achieve outcomes with different degrees of fairness [3, 18]. At each time step of the episode, the agent receives the current state as input and selects the next action based on a parametrized policy network $\pi(a|s, \theta)$. Action selection is stochastic during training and greedy during testing [3, 18]. The agent is trained via a policy gradient advantage actor-critic framework (A2C) [9]. Details on the architecture can be found in our supplementary code 1 and documentation, and in previous papers [3, 18].

### 3 EXPERIMENTS

We ran a vanilla Deep RL method (baseline) and our proposed modifications in two real-world case study cities: Xi’an and Amsterdam, evaluating them on total satisfied Origin-Destination (OD) % and the Gini index of satisfied OD % between groups — ranging from 0 (perfect equality) to 0.8 (maximum inequality — 0.8 due to there being five values, one for each group).

**Max Efficiency Baseline**. It maximizes the total efficiency of the line, without considering the benefits of different groups: $r = U(G)$.

**Accessibility Index Baseline**. The distance-decayed Wei et al. reward that aims to connect low and high-priced areas: $r = \sum_j D_j e^{-\beta t_{ij}}$, $i \neq j$, where $D_j$ is the house-price index of $j$, $t_{ij}$ is the distance between $i, j$ and $\beta$ is a tunable parameter.

In Figure 1, we show the generated transport lines, along with their performance on efficiency and fairness. We observe that utilitarianism can lead to disparities: the method assuming baseline reward (red circle) tends to achieve the best results on overall efficiency, but that comes at the expense of fairness. Disparities are mitigated by the proposed reward functions, which outperform the baselines in their respective fairness goals, providing a holistic view of the trade-off in the TNDP. In conclusion, our experiments show that due to segregation, different cities are characterized by different efficiency-fairness trade-offs, suggesting that policy-makers should consider multiple fairness criteria when applying these algorithms.

1 https://github.com/sias-uva/fair-transport-network-design

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**Figure 1**: Results in Amsterdam and Xi’an. In the left column, we show the average generated lines for each city. In the middle, we present the fairness-efficiency trade-off(s). In the right column, we show the distribution of the satisfied demand between the five groups for selected models. Here we use house prices as a proxy for placing individuals in different wealth bins.
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REFERENCES