Optimising the Introduction of Connected and Autonomous Vehicles in a Public Transport System using Macro-Level Mobility Simulations and Evolutionary Algorithms

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ABSTRACT

The past five years have seen a rapid development of plans and test pilots aimed at introducing connected and autonomous vehicles (CAVs) in public transport systems around the world. Using a real-world scenario from the Leeds Metropolitan Area as a case study, we demonstrate an effective way to combine macro-level mobility simulations based on open data (i.e., geographic information system information and transit timetables) with evolutionary optimisation techniques to discover realistic optimised integration routes for CAVs. The macro-level mobility simulations are used to assess the quality (i.e., fitness) of a potential CAV route by quantifying geographic accessibility improvements using an extended version of Dijkstra's algorithm on an abstract multi-modal transport network.

CCS CONCEPTS

• **Theory of computation** → **Random search heuristics**; • **Applied computing** → **Transportation**; • **Computing methodologies** → **Discrete space search**.

KEYWORDS

public transport, multi-modal transport, macro-level mobility simulations, reachability isochrones, evolutionary algorithms

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1 INTRODUCTION AND BACKGROUND

Recent technological developments regarding connected and autonomous vehicles (CAVs) offer transport authorities novel avenues for the improvement of existing public transport systems (PT) systems [6][5]. For example, impactful gains can be obtained via a niche CAV deployment on routes where PT provisioning can bring important social benefits to local communities [2], even if expected passenger volumes are too low to be economically viable.

More specifically, our real-life application scenario is to support the West Yorkshire Combined Authority (WYCA) with automatic optimised route discovery for a CAV-centred pilot project in the district of Adel and Wharfedale — Leeds Metropolitan Area, UK. This route must include Horseforth Train Station (a key PT multi-modal hub). The quality of the route is assessed by the improvement of average commuting time across the district when aiming to reach Leeds (Central) Station by 10:00 AM on a workday. The baseline to improve upon is 56 minutes and 19 seconds.

2 PROPOSED APPROACH

While employing classic spatial-temporal modelling [4] to construct an abstract transport network from Open Street Map (OSM) and General Transit Feed Specification (GTFS) data, our bespoke **macro-level mobility simulation** procedure for multi-modal PT systems achieves efficiency gains by:

- allowing for the independent modelling of the static (i.e., roads, pathways, existing PT routes) and transient (i.e., evaluated CAV route) parts of the PT network;
- opting for a reversible graph structure that facilitates the computation of both inbound and outbound accessibility (i.e., t_g – the commuting times to/from a fixed destination) using Dijkstra's shortest path algorithm [3] on a set of equally-spaced grid points $g \in G$.

We use a bitstring encoding to represent a given CAV route (i.e., a solution candidate). Each bitstring x is of length 120 — the total number of available PT stops in the district. After decoding the list of selected PT stops (i.e., $L = \{i : x_i = 1\}$) from x, the transient GTFS information of the CAV service associated with route x must be generated prior to running the macro-level mobility simulation and computing the fitness $f(x)$ using Equation 1.

$$f(x) = \left(\frac{1}{|G|} \sum_{g \in G} t_g(x) \right) * \left(1 + P \cdot \frac{max\{n(x) - 8, 0\}}{100} \right) \quad (1)$$

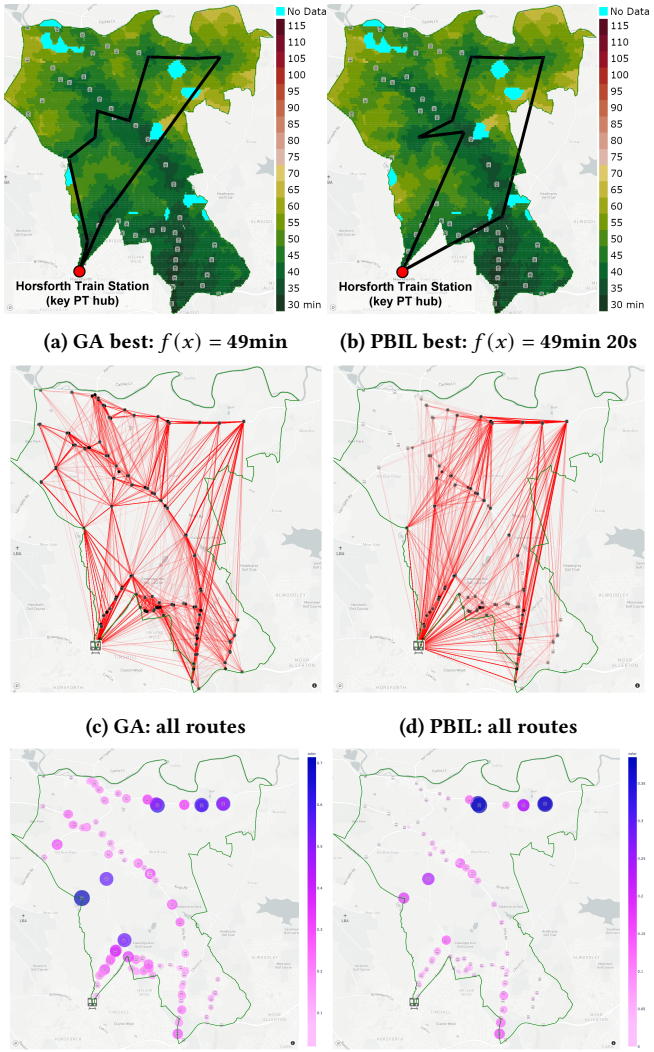
Based on feedback from WYCA domain experts, the CAV service is constructed under the following assumptions: bi-directional and circular routes starting from Horsforth Station, daily availability between 06:00 AM and 07:00 PM, minimal service frequency of one bus every 10 minutes across all stops, PT stop waiting time of 30 seconds, average CAV travel speed of 32 km/h, average walking speed of 5 km/h. A penalty factor of $P\%$ is used inside Equation 1 to model the WYCA suggestion that any CAV route x should ideally be serviceable using at most $n(x) = 8$ vehicles.

The optimisations were carried out using a standard **genetic algorithm** (GA) and a basic estimation of distribution approach – the **population-based incremental learning** (PBIL) algorithm [1] . The two solvers were chosen as they are well-suited to assessing the viability of nature-inspired optimisation on novel real-world problems given their wide-application record, lightweight implementation, and generally robust performance. For each solver we evaluated 36 parameter combinations using 10 independent runs and we experimented with biasing searches towards shorter routes by sampling the initial populations from the distribution $p_{start}(x) = \Pi_{i=1}^{120} p_{start}(x_i)$, with $0.1 \leq p_{start}(x_i = 1) \leq 0.5$.

3 RESULTS AND CONCLUSIONS

We performed an initial series of test runs with the penalty parameter P from Equation 1 set to 0% and the average number of CAVs – i.e., $\mu(n(x))$ – required by the end-of-the-run solutions / routes was 19.6 for the GA and 16.9 for PBIL. When increasing the penalty factor to 1% the average number of CAVs required to service the 360 end-of-the-run solutions shown in Figures 1c and 1d dropped to 11.47 in the case of the GA and 8 in the case of PBIL. For $P = 1\%$, average GA solution quality is 50 minutes and 58 seconds, while the average PBIL solution quality is 50 minutes and 31 seconds (i.e., $\approx 11\%$ improvement over the baseline).

More importantly, for both evolutionary solvers, the **best solutions** (illustrated in Figures 1a and 1b) require the usage of only 8 CAVs to deliver **improvements of $\approx$ 13%**. It is noteworthy that both the best GA route and the best PBIL route have an intuitively reasonable South-West $\leftrightarrow$ North-East orientation that aims to correct the poor North-East average commuting time of the baseline by using the CAV service to link the North-East with Horsforth Station along the shortest OSM path. The general ability of both solvers to identify key (North-East) PT stops that must be serviced by an optimal route is evidenced in Figures 1e and 1f by the frequency of stop selection among all 360 end-of-the-run solutions.



(a) GA best: $f(x) = 49$min (b) PBIL best: $f(x) = 49$min 20s

(c) GA: all routes (d) PBIL: all routes

(e) GA: stop frequencies (f) PBIL: stop frequencies

Figure 1: Information regarding all the 360 GA and PBIL end-of-the-run solutions when applying a penalty of $P = 1\%$.

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