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An agent-based evaluation of transit network design

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Abstract

This article presents the design and evaluation of transit networks using a route expansion heuristic and agent-based travel demand simulation. The route expansion mechanism is a type of constructive heuristic algorithm that derives new transit routes by inserting neighbouring nodes into existing routes with the aim of improving the demand coverage. The resulting networks are evaluated with an agent-based travel demand simulation model. The use of agent-based modelling is a departure from the existing route expansion literature and indeed the broader transit network design discipline in which the four step model has been extensively used. The procedure is tested on a bus rapid transit network in the City of Cape Town in South Africa.

Keywords: transit network design; agent-based simulation; network evaluation; route expansion; node insertion; constructive algorithms

1. Introduction

Public transportation fosters socio-economic development by facilitating the effective mobility of people, and the exchange of goods, services and information. However, issues like congestion and pollution can reduce its attractiveness. Therefore, improvements that result in decreased travel time and good levels of service among other benefits, can potentially boost the utilisation of public transit networks. In this work, a method of designing public transit networks to increase the network demand coverage is proposed. It involves creating new routes by expanding existing ones. The method is a heuristic technique based on constructive algorithms. Generally, this class of algorithms create shortest paths from the routes of an existing network then expand them by inserting nearby nodes. It commences at a terminal node, and expands the route by incrementally inserting adjacent nodes into the route, while, checking that the newly created routes meet certain feasibility conditions. Agent based travel demand modelling is used to evaluate the resulting network solutions. The technique is a disaggregated model which is based on the microsimulation of

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people's activities patterns. Additionally, these models are able to describe the stochastic behaviour of stakeholders, more accurately than conventional trip based models like 4-step model. In the transit network design solution framework travel demand models are the primary means of measuring the performance of a transit network [2]. To this end, they are used as a sub routine, to evaluate how different stakeholders respond to proposed network solutions. Therefore, the goal of this work is to develop feasible transit networks through the combination of a constructive route creation algorithm and agent-based modelling (ABM). The technique is then applied to the case of a bus rapid transit (BRT) network in Cape Town, South Africa. The paper is structured as follows. A brief review of literature is done in section 2 to discuss concepts such as route insertion techniques and agent-based travel demand models which are helpful to understand the proposed work. In section 3, the modelling technique used is detailed. Section 4 discusses the results of the work and their implications while a conclusion is drawn in section 5.

2. Literature review

2.1. Constructive algorithms

Constructive algorithms are a group of algorithms that are used to create transit networks while minding constraints on demand coverage and travel time [5]. New routes are created by expanding skeleton routes (shortest path) between origin and destination nodes. The expansion is achieved by inserting single nodes that are adjacent to the route [1], or a pair of adjacent nodes [7]. [6] identifies the two previously mentioned works as examples of *general-purpose* constructive algorithms. The authors' work, detailed the results of applying their constructive algorithms specifically to grid networks. In addition, the work recognises that the network configuration can affect the performance of the newly created solution. This is, because, the technique essentially alters the layout of a transit network. Therefore, it is possible that after an expansion procedure, the performance of a route might be degraded.

2.2. Agent based modelling

Agent based travel demand models consider the interconnectivity between people's activities and trips that connect those activities. They are guided by behavioural theories which describe people's desire to take part in different activities in the face of logical constraints on factors like time and mobility considerations [3]. Over time, transportation planning problems have become more complex, requiring more advanced planning tools and techniques. For instance, it is no longer sufficient to predict traffic volumes for the construction of a road lane, but there is also the need to manage the demand for the infrastructure after it has been provided. The latter requires a microscopic understanding of people's activities, travel behaviour and interaction with other agents on the stated infrastructure. Furthermore agent based models can show how individuals move from one activity location to another during the day (or modelling time frame). For instance, in the model, where one trip ends, ultimately becomes the origin for the next trip. Hence, agent based models are seen as better representations of interactions that occur on transit networks, since they can more accurately describe these interactions.

2.3. Data and model assumptions

An automated fare collection (AFC) data set for a bus rapid transit system is used as the main data source for travel demand in this work. The system employs smart card technology in the collection and storage of the trip data for passengers that use the system. This allows for the automated collection of passenger network utilisation information, such as, boarding and alighting times and locations, trip date and duration within the system. In the data, a complete trip or satisfied demand may be represented in two specifications; boarding–alighting (B–A) or boarding–connection–alighting (B–C–A). This representation aligns with how demand coverage is defined in this work; demand that is satisfied with zero or 1 transfers (Section 3). In agent based travel demand models, the demand is generated from people's activities at different locations based on land use purposes such as work, shopping, recreation and education. Networks stops and stations are considered as activity locations following the availability of AFC data, and the inability to access information concerning other activities or activity locations. Consequently, activities refer to network transactions such as passenger boarding, alighting and transfers. The limitation of this approach is that the model only reflects the interactions that are internal to the transit network without recourse to external factors that can influence what happens on it. However, in the context of this paper, this is plausible because the scope of application is to a bus rapid transit network, which, has dedicated alignment that often operates with little or no interactions with the broader transportation system. The paper draws some lessons from the work of [6]. Its main innovative features being, firstly, that an agent-based simulation model is used to evaluate the network solutions rather than a conventional traffic assignment. Since the route expansion heuristic will be integrated with the agent-based model, the objective function score will be obtained from an analysis of the simulation result. Secondly, nodes to be inserted are not only those that are adjacent to or one link away from the route. Rather, a sub-routine which returns the set of nodes that are connected to the route at a specified radius is used. The nodes are ordered in an ascending order relative to their distance from the route, hence, the first node in the set is the adjacent node while the last node is the farthest from the route but within the allowed radius. This gives the network designer some flexibility to define and control an acceptable radius from which they would like to cover additional demand in the case that the immediate next link does not meet feasibility criteria for distance or available demand.

3. Model

In graph theory, a graph $\boldsymbol{G} = (\boldsymbol{N}, \boldsymbol{E})$ is a multi-connection of a finite set of nodes $n \in \boldsymbol{N}$ and edges $e \in \boldsymbol{E}$ that connect each pair of nodes. In this work the transit network is represented as a directed weighted graph comprising n nodes and e edges. Nodes represent stops and stations on the transit network, acting as points of travel demand productions and attractions (sources and sinks in graph theory). The links, denoted by e_{ij} and weighted by its length, represent road infrastructure connecting nodes i and j, where $i, j \in \boldsymbol{N}$. A route r on the network is a sequence of adjacent nodes connected by links where: $\{r \mid r \in [1 \ldots R]\}$. The route is either a shortest path between two nodes or one created by inserting adjacent nodes at a specified offset distance from the route. Travel demand is obtained by simulating users demand on the network with the agent based model. The travel demand on specific routes is represented by d_r. Lastly, the objective functions used to measure the feasibility of each created network route is as follows:

$$Z_1 = \sum_{j=1}^{R} (t_t + t_w) \tag{1}$$

$$Z_2 = \sum_{j=1}^{R} (\alpha v_t + \beta v_d) \tag{2}$$

where (1) represents the user perspective as the total travel time $t_r(hr)$ as a sum of the in-vehicle time t_t and waiting time t_w on all routes. On the other hand, the operator cost is represented in (2) by a simplified formulation of the total operational cost in monetary unit, comprising of vehicle operating hours $v_t(hr)$ and mileage $v_d(km)$. α and β are monetary conversion factors for v_t and v_d respectively. In (3) and (4), each route must meet a minimum length and demand coverage requirement to be considered as being feasible. Demand coverage in transportation planing is discussed in terms of the volume of demand satisfied with or without transfers. Only trips satisfied with a maximum of 1 transfer is considered, as passengers find trips less attractive with an increase in the number of transfers and would even change their mode of travel [9]. D_{min} is the minimum allowable demand coverage, while, D_{tot} is the total network demand. d_r is route demand coverage or demand that satisfied with 0 or 1 transfers. The constraint represents the minimum allowable demand coverage that allows a route to be considered viable for operations in the model. L_{min} is the minimum allowable route length, while L_{max} is the maximum. This indicates the upper and lower bounds on route length beyond which the transit service cannot operate. In the model, if the length of a route falls outside this bounds, the route will be discarded.

$$D_{min} \leqslant d_r \leqslant D_{tot} \tag{3}$$

$$L_{min} \leqslant l_r \leqslant L_{max} \tag{4}$$

3.1. Network creation

The network is created in two stages involving the generation of skeleton (shortest path) routes, then expanding the generated skeletons with a node insertion mechanism. An existing transit network may also be used as the initial network. Alternately, the route generation step may involve creating shortest-paths from the O-D pairs of the existing network. This is done using a k-shortest path algorithm [11], which enables the network designer generate a preferred number of alternative shortest-paths. This means that for each O-D pair, multiple alternative may be generated and checked, to see which one best satisfies the feasibility conditions for length and demand coverage is selected.

For each node in the current shortest path, a list of adjacent nodes falling within a specified radius is obtained. If a node has multiple adjacent nodes, the one with highest demand is given priority. The adjacent node is then inserted between consecutive node pairs of the skeleton route. If a new route is formed, the algorithm ensures that its length and demand coverage meet the minimum allowed value. A comparison is then made between the newly created route and shortest path, and the worst performing option is discarded. If multiple routes are obtained for an adjacent node, the best in terms of satisfied travel demand is saved as the feasible route. This prevents having multiple routes per O-D pair. Subsequently, the adjacent node that has just been processed is removed from the set of adjacent nodes. Lastly, after inserting all available adjacent nodes for a given O-D pair, it is removed from the list of O-D pairs. The next pair of nodes is then selected and the process starts over.

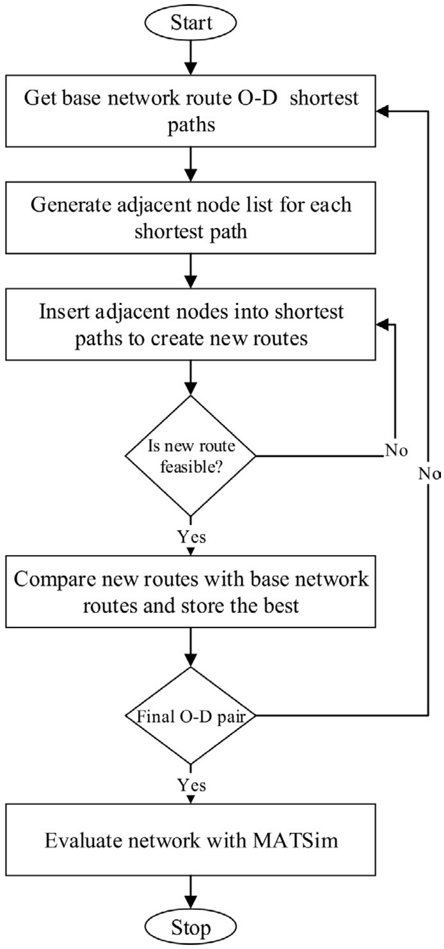


Fig. 1: Flowchart showing the model's processes.

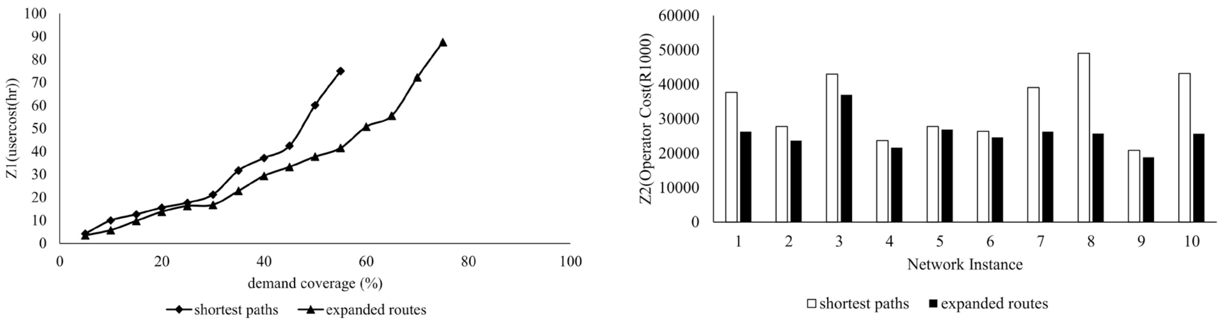
3.2. Network evaluation

This stage of the proposed solution model replaces the conventional traffic assignment models used in the previous researches such as the all or nothing assignment used in Mauttone and Urquhart [7]. The required inputs include the networks generated with the node insertion algorithm; a schedule of transit operations; transit vehicle fleet; a synthetic population of agents and their 24-hour activity schedules, created from the AFC data with the aid of a heuristic; and a configuration file comprising various parameter settings. The evaluation is done with an agent-based model known as the Multi Agent Transport Simulation (MATSim) [4] that simulates users' initial demand and subsequently optimises it in three steps namely *execution* or mobility simulation; *scoring* and *replanning*. Execution involves simulating the agent's plans in an efficient queue-based simulation. Two factors affect the travel behaviour of agents: the start time of their activities, and the spaces they invariably occupy within the network on the way to their respective activity locations. The latter affects the execution of other agent's plans, in that a possible formation of congestion could delay the travel time of agents that would have used the route. The overall effect of the actions of individual agents on a network at a given time, defines the prevailing network condition at that time. After execution, the agents' plans are scored by evaluating a utility function that represents their activity and trip. The function describes the agent's perception of various dimensions of time such as waiting time, travel time and time spent on an activity. It may be considered an objective function in optimisation terms, or a utility function in econometric terms. After the scoring is completed, the agent database is updated. Subsequently, a small percentage of (10% in this paper) of agents are allowed to *replan* their activities. Such modifications include changing the start time of another activity to compensate for time lost in congestion, or re-routing between activities. The objective of replanning is to enable the agents to modify their plans based on existing traffic conditions.

All the components of the model proposed in this paper were developed in the Java programming language. In computational terms, MATSim utilises a co-evolutionary algorithm. Experimentation has showed that the simulation converges after 100 iterations. As a way of minimising the error or uncertainty of the simulation model, multiple runs per simulation is done and the mean values obtained from the experiments are used. To achieve this, the models were run in parallel on a high performance computer with 22 Nodes and 1184 cores. For our computation 1 node with 64 dedicated cores was utilised per run. Tests were conducted to measure the performance of the algorithm. The tests are discussed in the next section.

4. Results

To test the algorithm, different testing scenarios are used to observe the performance of the proposed solution and how realistic the results are. In the first test, a comparison is made between networks comprising only skeleton routes (shortest paths) with no route improvement and networks that were derived from expanding the skeletons. This test measures the performance of the algorithm in terms of the user objective (total travel time) that is obtained from the function (1). This is achieved by recording observations of the objective function score at given intervals of demand coverage as route insertion proceeds (figure 2a). The result of this test shows that routes created with the model outperforms their corresponding skeleton network; at the same level of demand coverage the user costs are visibly lower. This implies that passengers would find these routes more attractive in comparison to the initial shortest paths owning to the reduction in travel time they would enjoy on the routes. The second test focuses on the operator perspective (figure 2b). In this test case, the operational cost are also lower for networks populated with the expanded routes. That is, operators would find them more attractive since they will incur lower cost while servicing the same passenger demand on the routes. That means that the expanded routes approach suggested in this paper



(a) Shortest path routes vs expanded route relative to users' objective. The same demand coverage can be achieved at a lower user cost with the expanded routes.

(b) Shortest path routes vs expanded route relative to operators' objective. Here we observed that the expanded routes are typically less expensive for the operator.

Fig. 2: Results of testing the algorithm against the two objective functions separately

provides better solutions to both the users' and operators' objectives when compared to the shortest path, skeleton routes. In terms of application, as indicated in section 1, the algorithm is applied on the *MyCiTi* BRT in Cape Town South Africa. The network has a radial configuration, with routes extending from the Central Business District to the suburbs. Present conditions on the network reveal that the network is largely underutilised [10, 8]. To this end, the network design method discussed in this work could have advantages in terms of improving the network utilisation levels for the service. The designed network is then compared to the existing network relative to different network performance indicators. The results are presented in Table 1. The results indicate that the expanded route show a higher level of network demand and utilisation, when compared to the skeleton network. There is also a considerable reduction in total travel time, which might be indicative of the fact that there are more direct trips satisfied my the expanded network. Finally, a decrease in the operational costs of the expanded network can also be observed. This test, reinforces the results in previous tests, and shows that the model developed in this paper can design effective public transit networks.

Table 1: Aggregate transit network performance indicators for the identified scenarios

Indicators	Existing network	Expanded network	Difference
Demand coverage (pax)	45195	51677	+
Utilisation (%)	69.23	79.16	+
Vehicle distance (km)	49997.74	43181.58	-
Vehicle time (hr)	1430.10	1314.20	-
Op Cost ('000)	17662.68	15041.42	-

5. Conclusion

In this paper, we introduced a method of designing transit networks that integrates a route insertion heuristic technique with agent-based simulation modelling. In applying the technique, demand coverage is used as the main feasibility criteria for selecting network routes, hence, each solution must achieve a minimum threshold in terms of satisfied demand. The agent-based transportation model MATSim is used as a replacement for the conventional traffic assignment model used in previous research. This new modelling approach is used to simulate user behaviour on the network's solution and to evaluate the performance of the resulting transit networks. Constructive algorithms under which the route insertion falls have been used in different ways including to design transit networks or to generate initial feasible transit route sets for optimisation algorithms. The results obtained shows that the resulting networks show improvements on the existing test case. This gives credence to the solution technique. To this end, this modelling approach can be considered as tools for the future in the pursuit of developing networks that would respond to the ever changing dynamics in the urban transit network context. Future research endeavours on this subject include on going research involving the integration of agent-based modelling and meta-heuristic algorithms for the optimisation of transit networks.

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