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The use of automated planning for the strategic management of transport systems in developing countries

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1. Introduction

This abridged paper provides an overview of an alternative way of approaching strategic transport planning utilizing pervasive crowd sourced data within an automated methodology citing the Rapidex model as an example. The presented model addresses road conditions due to the reason of data availability by TomTom and Google. Additional data is not as universally available yet. The approach specifically prioritizes speed over detail which meets the functional requirements in data-poor regions which need rapid high-level input to their preliminary planning. The paper begins with an exploration of the issue of 'data poverty' with an examination of the limitations it causes on affected regions as well as global implications because of environmental impact. Then, an overview is provided of the concept of 'automated transport planning' as a potential methodological solution to the noted issues which is somewhat analogous to the broader approach of automated planning in AI (Ghallab et al., 2004). Finally, future work and concluding remarks are provided to the reader.

2. Transport planning in 'data poor' regions

Cities within the developing world undergo urban development in a manner which is different to those in industrialised nations. Growth rates are more dramatic, the provision of informal infrastructure and services is more common, and institutions often lack the capacity to oversee and fund holistic planning solutions (Dimitriou, 2013). According to Verma and Ramanayya (2014) 'cities in developing countries are typically characterised by high density urban areas and poor public transport, as well as lack of proper roads, parking facilities, road user discipline, and control of land use, resulting in pollution, congestion, accidents, and a host of other transportation problems'.

The pollution concern is especially acute. Much of the pollution in cities in developing countries is caused to a large degree by traffic emissions. (Gupta et al., 2016). For example, in Delhi, the traffic – which has 'ground the city to a halt' - is partly responsible for the worst air quality in the world (Rajput, 2021). Pollution levels in cities in developed countries, however,

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are also partly caused by traffic. What makes the problem more severe in developing countries is that the pollution levels are generally higher than their developed country counterparts, yet the personal motorisation levels are far lower, and rising exponentially (Pucher et al, 2007). If this problem is not addressed, then the world faces a dramatic increase in greenhouse gases and a step-change depletion of energy sources (Siddique et al, 2011).

Effective transport planning to provide adequate road capacity and parking facilities and, where possible, to facilitate a modal shift away from personal modes of motorised transport, is key to facing this challenge. The more comprehensively planned and coordinated public transport services are, the greater the demand for their usage. Feeder services need to cleanly interface with long haul services through integrated timetables and ticketing, especially in areas where passenger densities and service levels are lower. Without excellent transport planning people struggle to access their daily needs, and societies cannot function efficiently, effectively, and sustainably (Addison, 2018). Moreover, high quality transport planning needs robust and comprehensive information around generative factors, trip origin and destinations, the split between the modes, and the routes that trips will take (SUTP, 2010). In short, effective transport planning needs high quality 'big' datasets and the associated models that offer the ability to forecast future conditions.

Yet the ability to collect good data, the capacity to derive insights from it using transport models and the skills to convert the findings to policy are not evenly spread in a global sense - the need to improve local statistical capacity in developing countries remains largely unsatisfied (Gunderman and Vance, 2021). Collecting data and developing forecasting tools is expensive and requires supporting institutional statistical capacity; most developing countries simply lack these capacities, and this situation looks set to continue for decades (Andersson et al., 2019). This situation is known as 'data poverty', a state which makes high quality modelling almost impossible (Dawwas, 2020).

As flagged, the urban transport planning model has four stages, a key part being the trip distribution component, which formulates an origin-destination trip matrix, showing how individual and aggregate journeys flow between pairs of zones. This is typically a highly data-intensive modelling exercise involving various socio-economic and demographic attributes of the population, the land use characteristics of an area, and detailed logging of the activities being undertaken. The lack of the necessary levels of data to compile this trip matrix, and in turn the route and mode taken to link the origin and destination means that cities in developing countries, due to data poverty, cannot typically benefit from a standard transport planning exercise (Lee, 2020).

3. Automated Transport Planning in overcoming data poverty

Conducting transport assessments and developing transport modelling tools requires surveying of the existing transport system and its operations. Historically, this involves using physical apparatus and/or human resources to measure vehicle properties (volumes, speeds etc), land use and capture demographic qualities of the study region. This is a time consuming and costly exercise that also has accuracy limitations associated with timing and sampling of the survey deployment (Tolouei et al., 2017). These issues are exacerbated in developing countries that are exposed to data poverty. In order to overcome these challenges, it is necessary to utilise low cost, simple and accessible data options. Smartphone technology has revolutionised the ability to track mobility patterns and the use of transport infrastructure leading to "crowd sourced traffic data".

Crowdsourced data options, such as Google and TomTom data, provide cost effective ways to procure large volumes of data (in some instances real-time data) for the purposes of transport analysis and management. However, research and development is currently being undertaken to collect and transform this data practically to serve data sources and models necessary for transport assessment (Nair et al., 2019; Dixit et al., 2020). This paper posits the overarching methodology of “Automated Transport Planning” which consolidates the recent developments in utilising crowd sourced data and presents a supplementary and cost-effective approach to deliver strategic transport guidance for practitioners.

The core principle underpinning the Automated Transport Planning framework is to utilise observed crowd sourced transport performance metrics to infer travel demand data, which inverts the traditional approach of defining or estimating demand to assess potential impacts across a network model. This leverages data that is easier to collect through crowd sourced options such as travel times and speeds, instead of collecting data related to trip generation and origin-destination mapping. Inferring travel demands that results in the measured network performance requires machine learning techniques and genetic algorithms that can be applied to the collected data in the context of the road network of the study region. Growth models and transformations of the existing derived demand can then be used to assess future conditions. The core methodological approach utilizes an Evolutionary Algorithm (EA) which has been developed over a long series of papers. Traffic equilibrium is employed within the EA fitness function to find a trip table that, when equilibrated on the inferred network, produces the observed data. Full methodological details are presented within the cited paper Waller et al (2001). This ATRF paper uses this same methodology but explores the noted specific case of data poor environments.

An example of growth models and transformations of the existing derived demand being used to assess future conditions is offered in Waller et al's (2021) Rapidex tool which estimated origin-destination matrices using crowd sourced data options. The tool allows the user to define network structure, travel zones and centroids using the open-sourced platform of OpenStreetMap. Travel time data from pervasive traffic data providers, such as TomTom and Google can be extracted, and a genetic-algorithm based metaheuristic technique is used to derive Origin-Destination matrices. These matrices can then be used as a source data for a network modelling process to estimate key metrics such as travel times, traffic volumes, and congestion levels for existing and future scenarios. This OD estimation technique can be seen as an advancement on past methods that rely on extensive and costly surveying of household travel behaviour thus providing a viable option for developing countries facing data poverty challenges (Duell et al., 2016; Aboudina et al., 2016; Zhang et al., 2018).

When rigorous validation is needed, the model and data must be validated on a case-by-case basis which will take on a bespoke aspect. There is no suggestion of the presented modelling approach should displace traditional planning (which will of course be more rigorous given the much longer time frames); the proposal is that it will act as a preliminary analysis, and in this instance a solid estimate when there is no data (and potentially unlikely to be any). In this instance the model was validated against traditional techniques using the Sydney Metropolitan Network (15,646 directional links, 8708 nodes and 178 zones). This testing revealed an 88% accuracy but requiring only 10% of the resources necessary to form the dataset and also execute the network modelling components. Thus, this tool is a steppingstone to realising automated transport planning. Within developing countries, the model has been tested in Delhi, India. The government authorities in Delhi planned to develop a large-scale simulation model for the entire city, which has an area of approximately 50,000 square kilometres and a population of more than 25 million. However, they did not have a readily available OD demand data as conducting household travel surveys in developing countries is either infrequent or non-existent. Rapidex was used as an alternative to the traditional approach with positive impacts. The tool allowed decision makers an evidence base rather than making complicated planning decisions based on perception-based surveys that are qualitative in nature. The key information can potentially improve the management of congestion leading to more sustainable city outcomes.

Such automated methodologies are also highly amenable to rapidly evolving crisis conditions due to the speed of the approaches. Currently, the techniques are being used to examine the emerging conflict in the Ukraine as an example. However, much remains to be done. It is difficult to sufficiently disentangle modality particularly for the critical domain of active transport. However, as each new crowd sourced data set emerges, a new option for synthesizing becomes available. Our approach is therefore to model what can be modelled globally now, continue to research bespoke solutions, and grow what can be done universally – i.e., for active transport - over time.

4. Conclusions and Future Work

This paper examines the impact of 'data poverty' along with the implications for affected regions. As a potential solution to these issues, the concept of 'automated transport planning' as a domain specialization of the broader AI approach of automated planning is introduced. This includes an examination of certain methodological developments which appear to match the functional needs of localized 'data poverty'.

However, it was also noted that future key research remains. Modal choice remains an active research topic with new techniques only in development now. Further, active transport requires new pervasive data streams to be identified. Finally, it remains a domain-wide issue in terms of integrating the many layers of transport modelling from the microscopic, to mesoscopic and macroscopic. Eventually, it would be ideal if transport models could provide mutually consistent views of activity. Regardless, this paper has noted one alternative approach that leverages pervasive crowd-sourced data which has been tailored for a specific niche of the complex transport landscape when local data is scarce, and conditions require rapid representation.

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