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Freight activity chain generation using complex networks of connectivity

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Abstract

Freight vehicle movement can be captured using activity chains, which capture the freight related activities both spatially and temporally. This is an advancement over origin-destination matrices, since freight vehicles are studied at a disaggregate level. Digicore Fleet Management has provided GPS data of over 40,000 freight vehicles travelling in South Africa over a six month period, from which freight activity chains can be extracted. The first contribution of this paper is to generate synthetic freight activity chains using a complex network that captures the connectivity between firms where freight activities take place, and therefore also captures some aspect of the behaviour of the vehicles. The complex network is built with the activity chains of 60% randomly selected freight vehicles, called the training set. 10 synthetic populations are generated using this complex network, each representing a 10% sample of the total freight population in South Africa. As a second contribution, we use the observed activity chains of the remaining 40% of vehicles, called the test set, to compare to the synthesised activity chains. The results indicate that the complex network approach of generating synthetic populations correctly estimates the fraction of activity chains for different chain lengths. The chain start times of the synthetic populations are generally similar to that of the observed activity chains, except for some underestimation during the morning peak hours. Vehicle kilometres travelled are only slightly overestimated in the synthetic activity chains. This complex network approach to generating synthetic freight populations is novel, and the results indicate that the synthetic populations generated are an accurate representation of South Africa's freight population.

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Keywords: Synthetic population; Freight vehicles; Complex network

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1. Introduction

Freight vehicles perform activities that are critical to the health of the economy (Joubert & Axhausen, 2011). Fierce competition between suppliers and increasingly complex supply chains have forced companies to adapt their logistical requirements, resulting in complex freight movements: some companies choose consolidated shipments with other suppliers to decrease their transport costs; others may choose to ship smaller shipments more frequently; while some implement milk-runs and prevent empty truckloads on returning trips.

Customers want their products at a specific time and place, while companies wish to meet their requirements in the least-cost way. Therefore freight movements are derived from the demand for freight-related activities (such as pick-ups and deliveries), which is one of the important elements of activity-based theory (Bowman & Ben-Akiva, 2001). Other important elements are that activities are performed at different locations over time, and that the agents performing the activities usually return to a home base (depot) after completing the day's activities. Freight vehicles comply with these three elements; therefore we can model freight movements as activity-based models.

One way of capturing freight activities in detail, which is an advancement over origin-destination flows, is by using activity chains: it represents the sequence of all the activities that a freight vehicle performed, starting and ending with a depot-like activity, with pick-ups and deliveries along the way. Joubert and Axhausen (2011) extracted freight activity chains from raw GPS data provided by Digicore Fleet Management. The data reported on the activities of 41,712 freight vehicles travelling in South Africa over a six-month period. Each freight vehicle's movements can be described by multiple activity chains over the six-month period, each starting and ending with a depot stop: these were termed major activities, and were identified as any activity lasting longer than 5 hours. All activities that occur between the start and end major activities were assumed to be pick-ups and deliveries performed by the freight vehicle, and these were termed minor activities. All minor activities have a duration of less than 5 hours. For both major and minor activities, the coordinates and start and end times are recorded.

Commercial activities are often based on long-term contracts and agreements between firms, and the relationships between them are reinforced every time freight vehicles move between them. Therefore the commercial needs of firms induce travel, and the satisfaction of the needs can be captured as a complex network of freight movements. The same principle has been applied to individuals: Carrasco et al. (2008) and Arentze and Timmermans (2008) both use social networks to illustrate how social interactions induces the need for people to travel.

Joubert and Axhausen (2013) assumed that freight movements between firms indicated connectivity between them, and consequently built a complex network of connectivity from the freight activity chains. The complex network is a graph representation, $G(V,E)$, containing the facilities (where freight vehicles stop to perform activities) as a set of vertices, V, and the freight movements between facilities as a set of edges, E. Weights are associated with the edges, representing the frequency of freight movements, and therefore the connectivity, between firms. Using this complex network representation, we can determine which facilities are highly connected (these have many edges connected to them), and how strong these connections are (higher edge weights indicate more freight movements and stronger relationships). Since the edges are directed (in the direction of freight vehicle movement), the direction of connectivity can also be determined.

The contribution of this paper is twofold. Firstly, we will generate synthetic freight activity chains by sampling freight movements from this complex network of connectivity. Freight transportation modelling has lagged behind that of private vehicle modelling, and therefore we also see a lack of literature on the generation of synthetic freight populations, with a few exceptions, such as Farooq et al. (2013), Joubert and van Heerden (2013) and van Heerden and Joubert (2014). The purpose of generating synthetic populations are to capture the behaviour and demographics of a population for modelling purposes, without revealing any personal information. Although combinatorial optimisation is often used to generate synthetic populations of individuals, seminal work by Beckman et al. (1996), which introduced the iterative proportional fitting (IPF) procedure to generate synthetic populations of individuals and households, has since been used in numerous studies. These two techniques are employed using aggregate data, usually from a public use micro sample (PUMS) that is made available for research purposes. Each simulated agent then needs a travel plan assigned to it, for which travel diaries are often used. The demographics of respondents in the travel surveys are matched to the demographics of agents in the synthetic population, and travel plans are assigned to agents who have similar characteristics and live in the same area.

The second contribution is to compare the synthetic freight activity chains to the observed activity chains using the distributions of the number of activities per chain. To capture the variability involved in the generation of a