Chapter 12
Dynamic Travel Time Estimation Techniques for Urban Freight Transportation Networks Using Historical and Real-Time Data

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ABSTRACT

Effective travel time prediction is of great importance for efficient real-time management of freight deliveries, especially in urban networks. This is due to the need for dynamic handling of unexpected events, which is an important factor for successful completion of a delivery schedule in a predefined time period. This chapter discusses the prediction results generated by two travel time estimation methods that use historical and real-time data respectively. The first method follows the k-nn model, which relies on the non-parametric regression method, whereas the second one relies on an interpolation scheme which is employed during the transmission of real-time traffic data in fixed intervals. The study focuses on exploring the interaction of factors that affect prediction accuracy by modelling both prediction methods. The data employed are provided by real-life scenarios of a freight carrier and the experiments follow a 2-level full factorial design approach.

INTRODUCTION

Distribution arguably accounts for a significant percentage of the total logistics execution cost (Ballou, 2004). Urban freight distribution in particular is more susceptible to unexpected costs and delays that arise *during* the execution of the delivery plans due to unforeseen adverse delivery conditions, such as vehicle breakdown, traffic delays, road works, customer depot overload, and so on (Rego and Roucairol, 1995; Savelsbergh and Sol, 1998; Psaraftis, 1995).

Techniques to minimize distribution costs typically focus on the creation of a near-optimal *a priori* distribution plan. Lately, freight carriers have adopted the use of automated vehicle routing systems in order to create such plans. However, the use of an initial distribution plan, although necessary, is by no means sufficient to address events that are likely to occur during delivery

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execution and may have adverse effects on delivery performance. In such cases, typical in an urban distribution setting, a priori solutions may no longer be relevant and the distribution plan needs to be adjusted in real-time as a function of the dynamic system state.

Latest technologies such as real-time fleet management systems, give the ability to freight carriers to monitor the execution of the daily delivery schedules and handle some of the aforementioned issues. However, in order to cope with unforeseen events and manage possible deviations from the initial plan, there is a need for accurate travel time prediction. Indeed, estimation of arrival is critical in urban freight distributions in order to predict in advance possible delays and time window violations in the remaining customers.

The ability to accurately predict future link travel times in transportation networks is a critical component for many intelligent transportation systems (ITS) applications, such as fleet management systems (FMS), in-vehicle route guidance systems (RGS) and advanced traffic management systems (ATMS). Travel time in an urban traffic environment is highly stochastic and time-dependant due to random fluctuations in travel demands, interruptions caused by traffic control devices, incidents, and weather conditions. It has been increasingly recognized that for many transportation applications, estimates of the mean and variance of travel times significantly affect the accuracy of prediction (Chien & Kuchipudi, 2003).

To this end, this chapter presents and evaluates two travel time estimation techniques for urban freight transportation networks using historical and real-time data. The first method follows the *k-nn* model, which relies on the non-parametric regression method, whereas the second one relies on an interpolation scheme which is employed during the transmission of real-time traffic data in fixed intervals. The study focuses on exploring the interaction of factors that affect prediction accuracy by modelling both prediction methods. The data employed are provided by real-life scenarios of a freight carrier and the experiments follow a 2-level full factorial design approach.

The chapter is organized as follows. Section 2 reviews current techniques and methods for travel time prediction and traffic forecasting models. Section 3 describes the characteristics of the two proposed methods whereas Section 4 presents the evaluation of both techniques. Section 5 discusses the experimental results and the chapter concludes with Section 6 where important ascertainments are outlined together with a future research agenda.

BACKGROUND

Travel time can be defined as the total time required for a vehicle to travel from one point to another over a specified route under prevailing conditions. Its calculation depends on vehicle speed, traffic flow and occupancy, which are highly sensitive to weather conditions and traffic incidents (Park et al., 1998). Nonetheless, daily, weekly and seasonal patterns can be still observed at large scale. For instance, daily patterns distinguish rush hour and late night traffic, weekly patterns distinguish weekday and weekend traffic, while seasonal patterns distinguish winter and summer traffic. It has been increasingly recognized (Smith and Demetsky, 1996; Park et al., 1998; Chien & Kuchipudi, 2003; Stathopoulos & Karlaftis 2003) that for many transportation applications, estimates of the mean and variance of travel times affect the accuracy of prediction significantly.

Travel time data can be obtained through various surveillance devices, such as loop detectors, microwave detectors, and radars, though it is not realistic to have the road network completely covered by detectors. With the development of mobile and positioning technologies, the data can be more reliably collected and transmitted. More importantly, these devices can be set up on vehicles with minimal hardware using non-sophisticated communication and installation. However, travel time estimation is not so straightforward because

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