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Improving the efficiency of repeated dynamic network loading through marginal simulation

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ABSTRACT

Currently, the applicability of macroscopic Dynamic Network Loading (DNL) models for large-scale problems such as network-wide traffic management, reliability and vulnerability studies, network design, traffic flow optimization and dynamic origin–destination (OD) estimation is computationally problematic. The main reason is that these applications require a large number of DNL runs to be performed. Marginal DNL simulation, introduced in this paper, exploits the fact that the successive simulations often exhibit a large overlap. Through marginal simulation, repeated DNL simulations can be performed much faster by approximating each simulation as a variation to a base scenario. Thus, repetition of identical calculations is largely avoided. The marginal DNL algorithm that is presented, the Marginal Computation (MaC) algorithm, is based on first order kinematic wave theory. Hence, it realistically captures congestion dynamics. MaC can simulate both demand and supply variations, making it useful for a wide range of DNL applications. Case studies on different types of networks are presented to illustrate its performance.

1. Introduction

Macroscopic Dynamic Network Loading (DNL) models are designed to represent traffic flow propagation in (large-scale) road networks. Given a set of input demand and supply parameters, they allow simulating performance measures like flows, densities, mean speeds and travel times. Any specification of the input corresponds to a single realization of a network loading. Often, the DNL model is used iteratively within a Dynamic Traffic Assignment (DTA) model, which also includes behavioral models (like user optimal route choice). In this paper, we focus on the DNL model and consider (route) choice only as an exogenous input.

Currently, a trade-off between realism and computational speed of the DNL model is often unavoidable for large-scale congested networks. Congestion dynamics are far more realistically captured by computationally intensive mesoscopic (Celikoglu and Dell'Orco, 2007) or macroscopic DNL simulation models such as models based on kinematic wave theory – for instance the Cell Transmission Model (CTM) (Daganzo, 1994; Lebacque, 1996), the Link Transmission Model (LTM) (Yperman et al., 2006) or METANET (Messmer and Papageorgiou, 1990) – than by faster models using for instance link exit or performance functions (as is shown in Nie and Zhang, 2005). Even so-called static models, which entirely disregard within-day traffic dynamics, are still often used in practice.

This paper presents marginal DNL simulation as a general methodology that retains realistic congestion dynamics while providing significant computation time savings in applications that require repeated DNL runs. In this introduction, we first

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give a brief overview of such applications. Next, we discuss a series of practical methods proposed in literature that aim at limiting the computation time in these applications. Finally, it is highlighted how marginal DNL simulation contributes to this state-of-the-art.

1.1. Applications with repeated DNL simulations

An obvious application with repeated DNL runs is DTA, where some choice model is equilibrated with the DNL in an iterative procedure (see e.g. Cascetta, 2001). A fortiori, in DTA with a probabilistic equilibrium (i.e. travellers' choices depend on the distribution of traffic states resulting from supply and/or demand perturbations), many DNL evaluations are required (Gao et al., 2010; Li et al., 2010). Furthermore, variability and vulnerability studies following a Monte-Carlo approach require a large set of perturbed samples (with varying demand and/or supply) to be simulated (e.g. Snelder et al., 2012; Van Lint et al., 2012). Also in optimization problems, iterative DNL (or DTA) simulations can be applied for numerically exploring the solution space. Example studies are origin–destination (OD) estimation (Frederix et al., 2011; Lu et al., 2013) – or more general calibration methods also including supply parameters (Balakrishna et al., 2007) – network design (e.g. Karoonsoontawong and Waller, 2006; Snelder, 2010) and optimization of traffic control measures, such as dynamic pricing, ramp metering, signal planning and route guidance (e.g. Kotsialos et al., 2002; De Palma and Lindsey, 2011; Gomes and Horowitz, 2006; Chung et al., 2012).

1.2. State-of-the-art approaches to save computation time

Several ways to reduce the computation time for repeated DNL have been reported in literature. A first way is to limit the number of simulation runs. For example, in optimization problems, imposing a maximum number of runs is often unavoidable. Obviously, this is undesirable, since reaching an optimum is not guaranteed. Also in travel time variability studies, a small set of samples is insufficient to estimate the probability distribution of travel times. Preferably, the necessary number of simulation runs should be reduced by smart sampling, i.e. focusing on those samples for which a large impact on the (network) performance or the objective function is expected (Tampère et al., 2009). Alternatively, vulnerability analyses may avoid large sampling sets by considering a two player game, in which one player – referred to in some studies as 'the evil entity' – aims at maximizing the damage by striking only the most vulnerable links (e.g. Bell and Cassir, 2002; Murray-Tuite and Mahmassani, 2004). Although smart sampling is advisable when tackling large-scale problems, additional computation time savings are often necessary.

A second option is to revert back to simpler, faster tools like (static) models with link exit or performance functions. For instance Noland et al. (1998) and Lo and Tung (2003) apply a model based on link performance functions to obtain the probabilistic distribution of travel times under stochastic link capacities. Chen et al. (2002) use a static assignment in their Monte-Carlo framework to assess reliability under correlated variations of link capacities. Snelder et al. (2007) do not consider congestion effects for their optimal redesign of the Dutch road network, and neither does Jenelius (2010) when assessing network vulnerability by imposing link closures. Although the application of simple, fast models can be justified for networks with relatively low traffic loads, proper modelling of congestion spillback is essential to obtain credible results on congested networks (Knoop et al., 2007).

A third strategy to reduce the computational burden is developing approximate methods so that repeated simulations are avoided. For example in real-time control applications, feedback approaches are often used instead of potentially more effective, but troublesome iterative procedures (e.g. Pavlis and Papageorgiou, 1999). Others use analytical approximations, e.g. Du and Nicholson (1997) and Bell et al. (1999), who study network reliability through analytical sensitivity analysis. Also Clark and Watling (2005) avoid Monte-Carlo sampling by analytically estimating the network travel time distribution under stochastic demand. Qian and Zhang (2011) – see also Shen et al. (2007) – approximate the travel cost sensitivity of link cumulative vehicle numbers to the addition of one unit of route flow. Similarly, Alibabai and Mahmassani (2012) develop an approximate methodology to quantify the sensitivity of route travel times to route flows, based on the assumption that route flow perturbations only cause flow changes at merges. Furthermore, Ukkusuri and Waller (2006) propose several approximation schemes to determine the solution to the probabilistic equilibrium problem through evaluation of one single-point demand pattern. Following the same philosophy, Ng and Waller (2009) transform a range of stochastic link capacities to one deterministic value to account for travel time variability due to supply variations. Some other work on vulnerability analysis avoids cumbersome simulations by developing heuristic quick scan methodologies (Scott et al., 2006; Tampère et al., 2007).

Furthermore, in dynamic gradient-based OD estimation (e.g. Cascetta and Postorino, 2001; Bierlaire and Crittin, 2004), the derivatives of the objective function – usually expressing the deviation between simulated link flows and detector counts – to the demand parameters is typically not determined numerically through repeated simulations (via finite differences). Rather, it is approximated by a so-called assignment matrix to speed up the optimization procedure. However, Frederix et al. (2011, 2013) explain the necessity of an improved gradient in dynamic OD estimation on congested networks.

Another emerging alternative to repeated simulation are stochastic DNL models (Sumalee et al., 2013; Osorio et al., 2011; Jabari and Liu, 2013). These produce probability distributions of network states under uncertain demand and supply.