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Repeated anticipatory network traffic control using iterative optimization accounting for model bias correction

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A B S T R A C T

Anticipatory signal control in traffic networks adapts the signal timings with the aim of controlling the resulting (equilibrium) flows and route choice patterns in the network. This study investigates a method to support control decisions for successful applications in real traffic systems that operate repeatedly, for instance from day to day, month to month, etc. The route choice response to signal control is usually predicted through models; however this leads to suboptimality because of unavoidable prediction errors between model and reality. This paper proposes an iterative optimizing control method to drive the traffic network towards the real optimal performance by observing modeling errors and correcting for them. Theoretical analysis of this Iterative Optimizing Control with Model Bias Correction (IOCMBC) on matching properties between the modeled optimal solution and the real optimum is presented, and the advantages over conventional iterative schemes are demonstrated. A local convergence analysis is also elaborated to investigate conditions required for a convergent scheme. The main innovation is the calculation of the sensitivity (Jacobian) information of the real route choice behavior with respect to signal control variables. To avoid performing additional perturbations, we introduce a measurement-based implementation method for estimating the operational Jacobian that is associated with the reality. Numerical tests confirm the effectiveness of the proposed IOCMBC method in tackling modeling errors, as well as the influence of the optimization step size on the reality-tracking convergence.

1. Introduction

Traffic control and management strategies offer great opportunities to improve traffic operations. Incorporating travelers' response is crucial to design appropriate strategies in controlled networks. To this end, *anticipatory traffic control* was proposed (Taale, 2008): the controller anticipates route choice response by the travelers to the control signals, aiming for the resulting flows to achieve system-wide objectives e.g. optimal network travel times. It can be considered as a special instance of the network design problem (Wie, 2007), where the design variables are limited to signal control and traffic management settings. Anticipatory control is commonly formulated as a bi-level or global optimization problem, with a user equilibrium model as a lower level constraint (Yang and Bell, 1998; Cascetta et al., 2006; Cantarella et al., 2012; Han et al., 2015). In game-theoretical terms, anticipatory control recognizes control optimization as a leader's role in the interaction

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between route choice (traffic assignment) and control, leading to a Stackelberg solution. In contrast, a mutually consistent calculation, which is known as Iterative Optimization and Assignment (IOA) procedure results in a less efficient Nash-Cournot solution (Yang and Bell, 1998; Meneguzzer, 2012) because the controller now follows routing decisions of the travelers rather than exploiting the fact that he can act first and while doing so, predict their reactions to force them towards more desirable states.

A main bottleneck for application of anticipatory control however is the presence of error and bias in the model used to anticipate the route choice response. In general, the real route choice can never be precisely described and it is usually approximated by traffic assignment models. Russo and Vitetta (2011) have suggested that as a priori errors in the traffic assignment models influence the network design decisions, these errors should be addressed in the network planning procedures. The presence of model bias (due to e.g. structural model mismatch, inaccurate parameters, and other unexpected disturbances) could result in suboptimal anticipatory traffic control, like for instance unpredicted delay, traffic congestion and spillback.

In order to achieve the optimal anticipatory control despite model bias, one option is to take advantage of the fact that traffic patterns repeat from day to day, allowing the controller to learn from earlier attempts to implement better control. For instance, he may observe the difference in the flow pattern predicted by his model and measured traffic flows in reality. In Yang et al. (2004), a repeated control policy for network tolling is proposed following such a trial-and-error structure. Whereas their approach is heuristic, in this paper, a more systematic iterative learning algorithm is considered, where flow observations are used to improve the model used by the controller to anticipate the travelers' route choice response while optimize his actions.

Although this repeated anticipatory network control approach acts over iterations from one epoch to another and considers measurement feedback to enhance control, it is important to distinguish it from day-to-day modeling on the one hand, and from reactive feedback (network) control on the other hand. The next sections frame repeated anticipatory control among these two approaches, after which we state the specific contributions to this type of control that this paper adds to previous work on the topic.

1.1. A daily signal setting context

In repeated anticipatory network control, the controller observes traffic flows during one epoch, to learn how to implement better control in the next epoch. This bears resemblance to day-to-day dynamic traffic modeling, also called dynamic process modeling (Bie and Lo, 2010; Smith, 2010; Cantarella et al., 2012; Kumar and Peeta, 2015). But there are significant differences. Dynamic process models consider day-to-day learning by travelers, by the controller or by both. They observe traffic on previous days to determine their behavior on the next day. Travelers update their perception of travel cost and adjust route choice based on this perception. Likewise, controllers update their perception of traffic patterns and select the best matching control variables hoping to achieve system optimal reactions.

By doing so, the controller in day-to-day models follows the dynamics of *previous* decisions of the travelers, while at the same time influencing their future decisions. Such daily signal adjustment procedures are characterized by an IOA procedure in which controllers are simply observing and reacting on the users' response, hence leading to the Nash-Cournot solution when the daily process converges. The fundamental difference with repeated anticipatory control is that there the controller looks *forward* to *anticipates* travelers' decisions rather than following them. The controller looks back at the travelers' behavior, but with the aim of learning how to adjust his predictive model about them, not to adjust to their previous actions. He uses this adjusted predictive model to solve a model-based control optimization (Kotsialos et al., 2002); this should lead to the Stackelberg solution associated with the real traffic system.

The assumptions on travelers' learning in repeated anticipatory network control are also different. Rather than reacting to the controllers and other travelers' actions on the *previous* day(s), we assume travelers to react to their *current* behavior. As a consequence, the repetition considered in repeated anticipatory control is to be interpreted in a longer period than single days, which is why we prefer the terminology 'epochs'. The epoch should be long enough for the travelers to experience the control settings and the responses of other travelers to it, in order to let the system settle in consistent and stable behavior. This in turn allows the controller to learn the outcome of his actions. We discuss this assumption and the idea of repeated epochs critically in Section 6.1 of this paper.

1.2. A feedback control context

The previous explanation also allows contrasting the feedback type in repeated anticipatory control to more traditional feedback control mechanisms. Such feedback mechanisms have been extensively investigated to compensate for model uncertainty in within-day time-domain traffic controls. In most of the existing studies the uncertainty is in the within-day traffic propagations. Some heuristic feedback laws have been typically applied for freeway traffic control, such as ALINEA (Papageorgiou et al., 1991). Moreover, some studies have developed simple, decentralized control laws for feedback route guidance (Pavlis and Papageorgiou, 1999). In view of dealing with model uncertainty, methods have been introduced to adjust traffic propagation modeling also in a rolling-horizon scheme, such as model predictive control (Hegyi et al., 2005; Dinopoulou et al., 2006; Aboudolas et al., 2009; Lin et al., 2010; Hajiahmadi et al., 2015). Taking into account route choice effect, a model predictive approach has been proposed for optimal dynamic route guidance (Hajiahmadi et al., 2013) and