Investigating the effect of controller locations on centralised dynamic traffic control with equilibrium constraints

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Abstract

Traffic control policies aim at reducing the negative externalities that ever-growing demand is causing on transportation networks, such as congestion and pollutant emissions. To achieve these goals, policies coordinating and aligning the effects of several individual traffic controllers have received increasing attention in research and development in the past decades. Notwithstanding the considerable efforts, peak-hour congestion is still a global problematic, with commuters spending up to 100 hours per year in traffic jams in major cities like Los Angeles (INRIX's Global Traffic Scorecard, 2017).

In this work we try to assess whether the gap between desired and experienced performance in advanced control policies might indeed be tied to inefficient network design, rather than algorithmic prowess. Based upon our earlier work, we investigate whether a trend can be found between determining locations of controllers in a network following control theoretical insights, and try to confirm our earlier intuitions when dealing with dynamic traffic management, featuring accurate propagation and spillback dynamics. Results comparing the performance of optimal control based on 50 randomly chosen locations and a deterministically chosen set of controllers are shown, highlighting how indeed a strong link exists between controller locations and reachable performance in optimisation based control strategies.

Introduction & Literature review

Dynamic traffic management applications have witnessed a considerable rise of interest in the last decades, in reaction to the exponential rise in transportation demand worldwide. This has been accompanied by considerable efforts in research, both in developing transport models able to properly account for traffic flow and congestion dynamics (Daganzo, 1995; Geroliminis and Daganzo, 2008; Yperman, 2007) and in developing efficient control schemes (Haddad et al., 2013; Hegyi et al., 2005; Papageorgiou et al., 2003).

Considering the scale of application, control techniques and schemes developed in transport can be roughly subdivided in three categories:

- Local control policies, (Smith, 1979; Varaiya, 2013; Webster, 1958), which deal with optimising the performance of a single intersection based on locally sourced data and individual control actions;
- Coordinated control policies, (Hunt et al., 1981; Lowrie, 1990; Mauro and Taranto, 1990), where separate controllers are aligned in order to achieve some common goal, e.g. triggering green wave effects on arterial corridors, or creating a pricing cordon around a protected network area;
- Centralised control policies, (Li et al., 2015; Rinaldi et al., 2016; Van De Weg et al., 2016), which instead consider the effect of each individual controller on the whole network, seeking to achieve some global objective, such as minimal total travel time.

In recent years, thanks to technological advancements enabling faster, more powerful computation, model-based approaches have been introduced and applied successfully in all the above categories. Compared to their rule-based counterparts, model-based approaches exhibit the advantageous property of empowering predictive control schemes, due to their innate ability to assess the system- or network-wide impact of a given control action, including its consequences in the immediate future (e.g. the eventual build-up of queued vehicles at an intersection receiving extra red time). When considering the specific instance of model-based approaches, a further subcategorization can be carried out considering the underlying traffic model's granularity (microscopic vs mesoscopic vs macroscopic), the degree to which user behaviour is captured by the chosen model (departure time choice, route choice, …), the specific objective function being optimised (minimal total travel time, maximal throughput, minimal pollution, …), etc.

Model-based approaches often employ optimisation algorithms to generate control actions, determining the given objective function's sensitivity to changes in control and therefore identifying an appropriate action that directly results in a descent direction in the objective function's value. This represents a considerable theoretical advantage in comparison with rule-based heuristics, which instead react to current measurements through predefined actions, hence only exploring a limited set of points in the objective function's solution space.

However, especially when considering oversaturated networks, objective functions can exhibit severe non-convexity and discontinuities (Patriksson, 2004; Rinaldi et al., 2018), due to both i) congestion propagation and spillback dynamics and ii) the effect of increased travel times on user behaviour, e.g. route choice. This represents a major obstacle to optimisation algorithms: non-convexity implies that global minima might be far - if not unreachable - from the given initial guess.

Another key factor determining whether or not the globally minimal value for a given objective function is reachable, so far largely disregarded in literature, is whether or not the equipped control infrastructure is sufficient to trigger the desired behaviour. Depending on the amount, location and type of controllers installed on a network, specific configurations of the network's state (in terms of flows, buffered vehicles' locations and quantities, split fractions, chosen routes, …) might simply be impossible to trigger through control actions. In our previous study (Rinaldi, 2018) we have shown that placing controllers in order to achieve full controllability is a sufficient condition to ensure that the true global minimum of a given objective function (specifically, Total Cost) can be reached in the static assignment domain.

In this work we aim to extend these results to dynamic traffic management applications, through simulation based empirical experiments. Specifically, we minimize the Total Time Spent dynamic objective function, subject to full Dynamic Traffic Assignment, considering different locations of controllers in a network bearing an adequate degree of complexity. The preliminary results presented in this work showcase that, indeed, placing controllers according to our previously developed approach yields major advantages for dynamic traffic management applications, far outperforming the vast majority of randomly selected locations.

The rest of this short paper is structured as follows: in the next section we detail the full experimental setup employed in this work, and we quickly recap our controllability based methodology. We then present our preliminary results for the chosen network, showcasing different simulation results in terms of Total Time Spent and its evolution, as well as providing simulation snapshots showcasing how best-case and worst-case random locations exhibit profound differences in terms of resulting network conditions. Finally, some conclusions are drawn.

Methodology

This work's objective is that of assessing the extent to which locating controllers on a given transportation network affects the performance of model-based control strategies. The sole design variable under consideration is therefore the set of controllers, $M = \{m_1, ..., m_M\}$.

Given a transportation network described by a directed graph $D(N, L)$, with $N = N_o \cup N_d \cup N_t$ the set of nodes, where N_o is the subset of origin nodes, N_d the subset of destination origins and N_t the set of standard traversal nodes, and, finally, L the set of links, we consider two possible strategies to generate viable sets of controllers:

- a *random* strategy, through which a quantity M of (non-identical) controllers is extracted from the uniform distribution $U(\inf(N_t), \sup(N_t))$, that is, target control nodes are uniformly selected from the set of traversal nodes alone;
- a *controllability* strategy, based upon our earlier work, for which target control nodes are selected from the set of traversal nodes alone based on algebraic properties of the node adjacency matrix.

Specifically, for the latter approach node to node adjacency information is extracted from the graph D and compiled in an adjacency matrix $A \in \Re^{|N_t| \times |N_t|}$, and successively enriched by extracting additional indirect node-node relationships from the network's route set (we refer the interested reader to (Rinaldi, 2018) for further details on this subject). Following the work of (Yuan et al., 2013), by performing opportune algebraic operations on matrix A we extract the minimum set of nodes that must be controlled in order to ensure that the full set N_t is controllable.

For each obtained controller set, we simulate the effect of model-based dynamic traffic management by minimising the Total Time Spent metric on the network, subject to Dynamic User Equilibrium constraints:

$$\begin{aligned}
&\min_{\{g_1(k_1),...,g_M(k_1),g_1(k_2),...,g_M(k_{T_{tot}})\}} \sum_{l \in L} \sum_{k_s=1}^{k_{T\,tot}} T_s \cdot n_l(k_s, \{g_1(k_s), ..., g_M(k_s)\}) \\
&s.t. \begin{cases} n_l(k_s) = F(n_l(k_s - 1, k_s - 2, ...), \{g_1(k_s - 1), ..., g_M(k_s - 1)\}) \\ 0.05 \le g_m \le 1 \;\forall m \in M \\ F(\cdot) \; the \; Dynamic \; User \; Equilibrium \end{cases}
\end{aligned} \tag{1}$$

that is, for each simulation time step k_s (considering a time discretisation interval T_s) and for each controller $m \in M$ we seek to determine the corresponding control signal $g_m(k_s)$ that minimises the total number of vehicles n_l traversing each link $l \in L$, and hence total time spent in the system per each individual vehicle. Dynamic User Equilibrium is computed through a Dynamic Traffic Assignment model, featuring first order compliant vehicle propagation and dissipation based on the Link Transmission Model (Himpe et al., 2016), and turning fractions at nodes computed through the projected gradient approach of (Gentile, 2016). Although facing considerable computational hardships, we adopt a fully centralised approach (all control variables are minimised in a single shot optimisation) in order to exclude any bias possibly introduced by more advanced optimisation heuristics (Rinaldi et al., 2016).

Following our two controller set generation policies, we equip the network with individual node controllers in the form of mainstream meters, which reduce the given node's maximum outgoing flow per each outgoing link separately, as a function of the desired outflow ratios g_m multiplied by the links' individual capacities. A minimum service rate of 5% of capacity is guaranteed by the constraint set in (1).

We compare the results of solving problem (1) on 50 random controller set instances and our proposed one-shot controllability approach. All tests are performed considering the network shown in Figure 1.

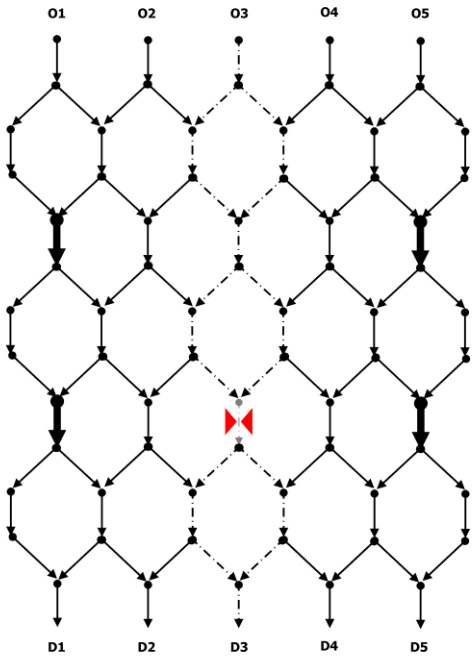


Figure 1: Test network

The network is composed of five OD pairs (O1-D1, O2-D2, O3-D3, O4-D4, O5-D5). All links have a capacity of 1800veh/h, except the four thicker links serving the two external OD couples, which have a capacity of 3600veh/h. Additionally, a bottleneck is active on the highlighted link for the central OD couple, whose capacity is reduced from 1600veh/h to 1500veh/h. Finally, as represented by the dotted lines, the links serving the central OD couple have a free flow speed of 80 km/h, whereas the speed is limited to 60 km/h for the rest of the network. These design choices trigger a specific property: when operating in undersaturated conditions, flows from all OD couples will try to traverse the central links of the network, since they provide faster travel times. However, as demand increases to peak conditions, the bottleneck will activate, triggering spillback and congestion in the central portion of the network, possibly spilling back to adjacent OD couples. A well-devised control solution should anticipate this behaviour, and correctly steer vehicles away from the central OD during peak hour.

We simulate a total of 10 hours of operations in this network, considering a time discretisation interval $T_s = 5\min$, with on-peak conditions starting from 1h and lasting until 4h.

OD demands in veh/h are shown in Table 1.

Table 1: OD demands for the simulated network (offpeak/**onpeak**)

	D1	D2	D3	D4	D5
O1	500/**1600**				
O2		500/**1600**			
O3			500/**1700**		
O4				500/**1600**	
O5					500/**1600**

To ensure consistency in results, all tests consider the same initial guess for the optimisation of (1): $g_m^0(k_s) = 0.5 \; \forall m, k_s$. All models and codes are implemented in MathWorks® MATLAB™, optimisation was performed natively through the *fmincon* function, configured to seek minima through the quasi-newton BFGS approach. The gradient of the Total Time Spent objective function was approximated numerically through a central differences scheme. While no strict time limits where set to the optimisation procedure, a computational limit of 100000 function evaluations was set. This limit was however not met by any of the performed simulations, who instead all converged to significant (albeit local) minima.

Results

In this section we showcase our simulation results. As mentioned earlier, we compare a total of 51 different controller sets placed on the network of Figure 1, 50 of which have been obtained by randomly selecting nodes from a uniform distribution. Figure 2 showcases how the Total Time Spent function evolves throughout the 10h simulation for all different simulations.

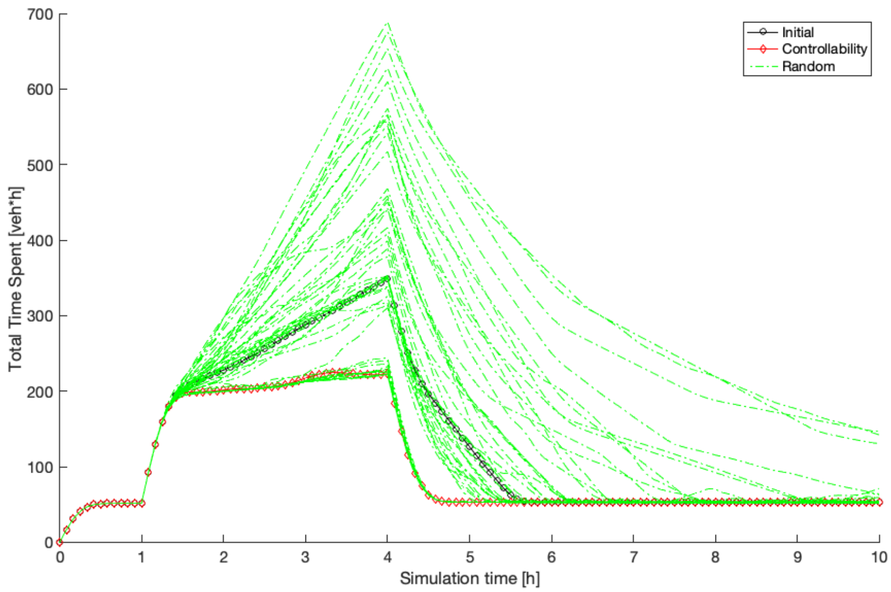
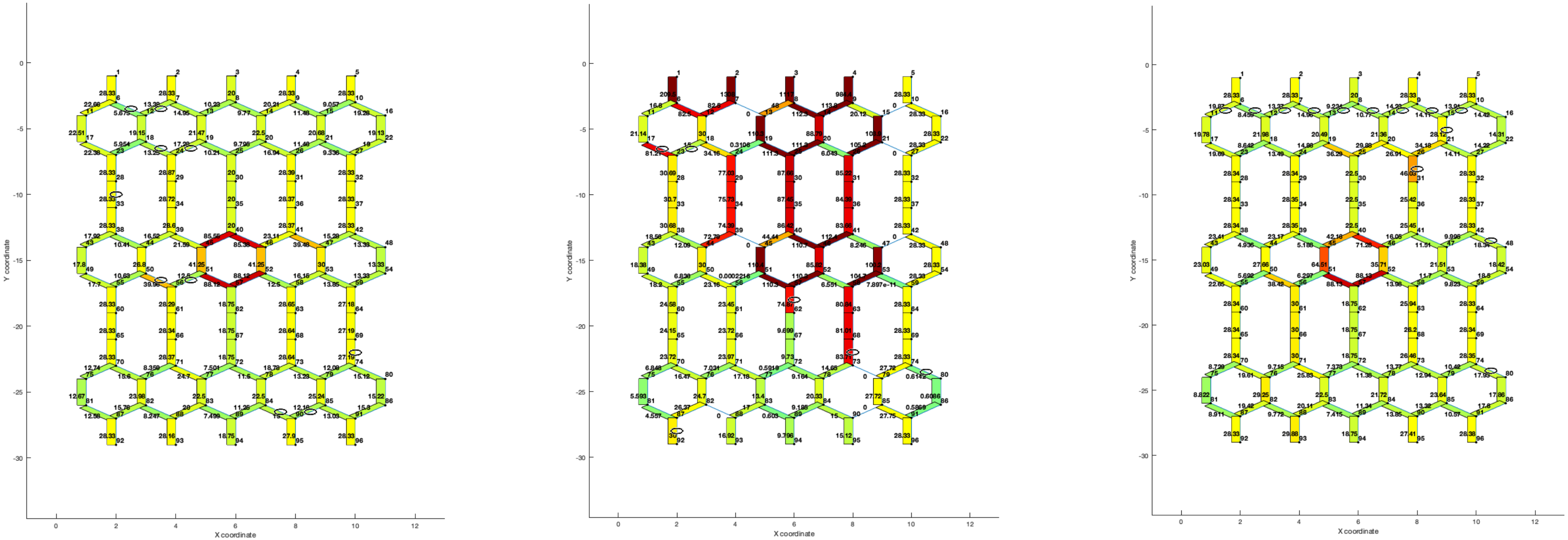


Figure 2: Total Time Spent evolution over simulation time.

The network is empty as the simulation is initialised, and vehicles gradually load it until reaching equilibrium conditions after roughly 30m. Peak demand begins entering the network at the 1h mark, and lasts until the 4h mark. As can clearly be seen by considering the green lines in Figure 2, randomly located controllers exhibit severe variability in performance, with the punctual value of Total Time

Spent at the height of peak hour (i.e. when simulation time is exactly 4h) ranging from 200 veh*h to almost 800 veh*h, a worst-case increase of about 400%. Selecting instead the controller locations according to our proposed controllability approach yields the black line, when considering the initial guess vector, and the red line post-optimisation. As can clearly be seen, these results are in line with the "lucky" guesses produced by the random approach.

To better highlight this effect, in Figure 3(a-c) we show snapshots of the simulations for, respectively, best-case random set, worst-case random set and controllability set, once again at the height of peak hour. Colours represent the vehicle density $\rho^l(k_s)[veh/km]$ at each link, expressed as percental value with respect to critical density ρ_c^l , ranging from green ($\rho^l(k_s) \ll \rho_c^l$) through red ($\rho^l(k_s) = \rho_c^l$) and further towards black ($\rho^l(k_s) = \rho_{jam}^l \gg \rho_c^l$). Controller locations for each control set are also highlighted by black ellipses, placed on the corresponding links.



(a) Best-Case Random Locations

(b) Worst-case Random Locations

(c) Controllability-based Locations

Figure 3: Snapshot of simulations at peak hour [4h] for different controller locations.

As can clearly be seen, the effects of misplaced locations on the performance of model-based control strategies can be profound: the controller set of Figure 3(b) cannot successfully steer the excess demand entering the network, failing to reduce congestion altogether. Furthermore, it can clearly be seen that a few controllers have been placed on entirely ineffective locations, see e.g. the bottom right controller, where flow is too low to be of any effect, or on the bottleneck itself, where no-control is by definition the only desirable action (unless second-order effects such as capacity drop are modelled).

Conclusions

The initial results presented in this short paper indeed appear to confirm the intuition built in the static assignment context, i.e. that selecting appropriate locations (and quantity) for controllers in transportation networks is key to the success of advanced control strategies.

Further empirical validation on networks with larger heterogeneity in both demand and supply characteristics is naturally required, although the computational burden of fully centralised optimisation subject to DUE will quickly become a major constraint. Decomposed control strategies will therefore be applied.

Another research direction worth exploring, whose results will possibly be presented at the symposium, is whether controller locations also play a major role for rule-based, local approaches, such as the Maxpressure policy (Varaiya, 2013).

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