

Flow reroute problem

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1 Thoughts on using CMS for rerouting control: problem dimensions

We begin by stating the various dimensions of the problem.

- Problem types (scenarios) we want to do control to relieve
 - recurring congestion
 - congestion due to pre-planned events and related demand
 - congestion due to incidents

Relieving congestion due to incidents requires an online model, and detection of incidents. For pre-planned events and recurring congestion, we need to use estimates (e.g. historical) of demands to do the forward simulation.

- Control objective
 - System optimal (SO) flows (unlikely without incentives)
 - User optimal (UE), Nash equilibrium

If we want to do control based solely on CMS, then if we simply display real time information (and only give true information), we will push the system towards a Nash equilibrium (UE). This can still be interesting if the uncontrolled state is worse than Nash. If we want to do better than Nash, then we need to think about what kind of information to display (while still being truthful).

- On-line Vs. off-line

We need historical estimates in all cases to be able to forward simulate the system. For on-line control we additionally need real time measurements.

- Compliance rate
 - Full compliance
 - Partial compliance

- Control mechanism
 - Phone app
 - Changeable message signs (CMS)

If we use a phone app, we will have better estimates (OD demands), and more refined control (control can be adapted to individuals). If we use CMS, the same message is displayed to everyone.

- Control response model
 - Explicit control of vehicles to a given route (Incentive for taking a new route. Most likely this will require a phone app)
 - Control via information (CMS)
 - Implicit control via prodding (CMS)

- Buffer model¹

¹See section 3 on the boundary FIFO problem for details

- One large buffer (most relaxed FIFO)
- Many cell-sized buffers with one large last buffer
- One cell sized buffer with a feeder queue
- Input data: Historical and Real-time
 - Aggregate flows across all links only (most likely)
 - Aggregate flows across all links plus OD for controllable flow (possible with phone based control)
 - Full OD data (pipe dream)

We will most likely need an estimate of the OD for the controllable flow for the problem to be meaningful.

- Route information encoding
 - Path-based
 - Split ratio based

Path-based information gives a cleaner formulation, but requires more storage, and more input data (OD estimates). Depending on the network structure, a path-based formulation may be OK (e.g. parallel network)

- controllable OD estimation via boundary flows (behavior model)
 - Online OD estimation via response to control
 - Offline OD estimation via some historical model

Estimate the OD demands for the controllable flow.

- Network types From most to least restrictive. The less restrictive, the more data we need.
 - Single destination for controllable flow with no off and on ramps
 - Single destination for controllable flow with either on or off ramps (can recover controllable flow)
 - Single destination for controllable flow with on and off ramps
 - Multiple destinations for controllable flow

In the single destination with no on-ramps or no off-ramps, it is sufficient to know the total flux demand and the split ratios. If we have both on-ramps and off-ramps, we additionally need an estimate of the OD demand for the controllable flow.

- Limitations of CMS control
 - Most probably a binary controller, but we might be able to increase the granularity of control via the strength of the wording.
 - No Lagrangian data as in the phone based control approach.

We may need to abstract the control for now, by assuming that we control a split ratio at a given junction, and solve for the optimal split ratio. Then we map the optimal control strategy to an actual message to display, but that is a separate problem.

2 Potential models with limited input data

Let there exist a particular origin-destination pair $o - d$ with a CMS near o . There are two paths that can be taken to go between o and d , and the CMS will post a message addressed to those traveling $o - d$ to take route 1 over 2, with some percentage of those drivers complying. For simplicity, we assume instead that our control is a split ratio β for the $o - d$ drivers at the point of the CMS.

In addition, there are an arbitrary number of additional sources and sinks, but the CMS only targets $o - d$. The additional sources and sinks may have viable paths through both o and d , complicating the determination of demand between $o - d$ specifically. The Eulerian flow is known over each link in the network, over all discrete time steps.

We cannot determine which flows belong to $o-d$ drivers versus all others from this problem setup due to the non-uniqueness of OD-estimation problem. But if we assume we know the path flows of just taking $o-d$, then source flows and split ratios may be determined for the other OD's. From this assumption of data (path flows for $o-d$, source flows and split ratios for all others), one can use the Piccoli class-based forward simulation framework as the flow model, where the classes are controllable $o-d$ flows and uncontrollable flows from all other OD pairs. This is illustrated in Figure 1.

One special case of this set of assumptions is rerouting drivers not attending a popular event, while those attending have no rerouting options.

One approach is to determine an upper and lower bound on the demands on routes 1 and 2 for $o-d$. Then we take a robust optimization approach to create an optimal split-ratio policy β^* for the worst case *actual* demand on $o-d$. It is unclear how robust optimization exactly fits within the adjoint framework, but there is previous work in this area.

Another approach seeks to *learn* the $o-d$ demands at the CMS location from a feedback-loop approach. After witnessing how the split ratio at the CMS changes due to some displayed split ratio, one can estimate the population of drivers that responded to the message from all drivers on the network.

Both of these approaches attempt to deal with the fact that we do not have enough information to do rerouting at the CMS and still guarantee that the original demand profiles would be satisfied. Any approach that seeks to do rerouting on Eulerian data would have to embrace such methods in some form.

3 Solving the FIFO problem at the boundary of the network

In the multi-class case of the discretized LWR models (as in Piccoli) the FIFO assumption is typically satisfied at the cell level. This is not full FIFO at the individual car level, but an accepted approximation of FIFO. In our buffer based boundary cell model, the FIFO assumption is further relaxed as the buffer can accumulate a large number of vehicles over time when the boundary is congested and the FIFO condition will only apply in this aggregate sense. To alleviate this problem, we need to keep track of the ratios of controllable and non-controllable vehicles that enter the boundary at a more granular level. The solution that would be equivalent to what happens within the network would be to have multiple buffers of the same size as a single cell and move flow forward through the buffers as the first buffer empties into the network. There need to be enough buffers to handle the maximum possible queue length at the boundary. A more precise way to follow the ratios would be to have a single buffer that is the same size as a cell and then keep an overflow queue for vehicles that can not enter the buffer. This queue will keep all the entering vehicles in order and feed them into the buffer as space opens up. The vehicle ratio at the buffer will be updated accordingly as new vehicles enter it. We require $\log_2(\text{max_queue_length})$ bits of storage at each boundary to store this information, but this should be a relatively small and manageable number. Modifications will be needed to have the derivative make sense in the adjoint formulation.

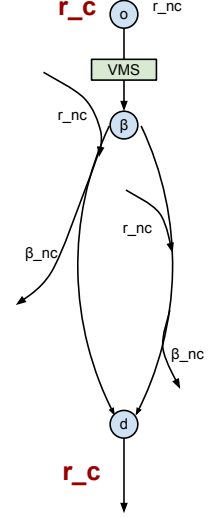


Figure 1: Diagram of network under consideration. r_c, r_{nc} are the flows in for controllable and non-controllable drivers. β_{nc} are the estimated split ratios for the non-controllable, which can be determined after estimating initial controllable flows on the left and right paths.