Real-time control of traffic flows under disruptive events

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1 Introduction

Vehicular traffic volume in big cities, particularly the freight transportation part, is burdensome and is expected to be continuously growing in the near future. At the same time, the development of infrastructure and road safety measures do not always keep pace with the increase in the demand for transportation. This leads to congestion and, hence, to an increased risk of infrastructure failure, more hazardous road conditions, and many other risks. Beside being potentially dangerous, these phenomena usually cause network congestion when road sections have to be closed or their capacity has to be reduced. Although recent advancements in smart traffic systems have improved the efficiency of the network, a gap still remains in dealing with disruptive events, such as bridge failures, works in progress and many others. These disruptive events could have a tremendous impact on network efficiency and, hence, put a strain on the network resilience. Most of these events are due to the high levels of traffic that insists on specific road segments and reducing such traffic levels could lead to a significant decrease in the risk that such events occur. In fact, for such events, smart traffic management technologies could be used to enforce coordinated traffic assignment mechanisms. Traditionally, traffic assignment mechanisms are divided in two opposing concepts: the system-oriented coordinated assignment and the selfish one with sat-nav devices. According to Roughgarden & Tardos (2002), there are significant inefficiencies in terms of travel time induced by the selfish assignment. In contrast, the system-wide approach is "unstable" as it may be unfair and, hence, users tend to do not comply with the provided assignment. The first attempt to bridge the two perspectives is provided in Jahn *et al.* (2005), in Angelelli *et al.* (2021) and in Jalota *et al.* (2023). They all proposed a system-oriented coordination of the traffic flows using only paths that are convenient for drivers and assume a steady-state behavior. When dealing with sat-nav guidance, no knowledge about the augmented risk is provided and, hence, risk is known only when a disruptive event happens and congestion rapidly gets worse. A bold step in this direction is to detect incoming vehicles in real-time and to coordinate them in order to prevent such disruptive events to happen.

Contributions. The problem of controlling traffic flows in real-time under disruptive events is new in the literature. We show that, when the traffic level is high, the traditional approach leads to severe damages to infrastructures and to congestion phenomena while the real-time control of traffic flows allows to reduce the risk of such events while minimizing the impact of such control on the network congestion. We propose a traffic management system that collects, in each time period, information about the traffic network status and computes the best fair paths to assign to vehicles entering the network in order to reduce the risk of a disruptive event to occur. We cast the problem of assigning paths so as to optimize traffic flows under disruptive events into a

Mixed-Integer Linear Program (MILP) called *Time-dependent Risk-AvoidiNg System-optimum* model (TRANS). We show, on a real-world case, the potential benefits that can be achieved by using such algorithm as a tool to support decision-making in traffic control.

2 Methodology

We tackle the problem of a road network in which a number of road sections, called *monitored roads*, are subject to risks of different nature and, thus, require to be kept under control. Good practices in traffic planning should focus on avoiding as much as possible such situations, without worsening the congestion of the road network.

The real-time framework. The real-time traffic management system has three main actors: a central traffic coordinator, the vehicles entering the network through time, and the smart road network. The *central traffic coordinator* is the heart of the communication flows as it collects information from both the *smart road network* and the *incoming vehicles*, and uses them to communicate routing instructions to such vehicles. In each time period, once information from the smart road network has been retrieved, the central traffic coordinator evaluates if the traffic flow due to incoming vehicles will represent an excessive risk for the monitored roads, and decides if incoming vehicles have to be diverted on convenient alternative paths, selected among convenient and vehicle-compliant paths, or if they can continue to follow their original route. This is done by means of the TRANS optimization model. Whenever a diversion is required to mitigate a risk increase, the central traffic coordinator sends instructions to each incoming vehicle regarding the path to be followed.

The TRANS optimization model. The primary objective of the TRANS model is the minimization of the risk on the monitored roads and, secondly, the reduction of the impact that the rerouting process has on the congestion level of the roads of the network. Once vehicles have been routed to their optimized paths, knowledge about the future state of the network is updated accordingly and used in future optimizations. The risk for each monitored road is calculated through a *risk function* which uses as input a series of risk parameters and the traffic flow traversing the monitored road. In order to model the risk function on each monitored road, two thresholds on the amount of traffic traversing the road will be defined: the *risk-free threshold* and *the critical threshold*. As long as the traffic flow is below the risk-free threshold, the monitored road experiences an acceptable level of risk and no intervention is needed. However, as soon as the flow exceeds the risk-free threshold, the risk on the monitored road increases increases in a convex, more-than-linear manner. Moreover, the total flow of the vehicles traveling on a monitored road should not, under any circumstance, exceed the critical threshold, as the risk of disruptive events is considered extremely high. According to Ventura *et al.* (2024), when the risk is above the critical threshold, the most common solution is to close the entire road section. As a result, the whole traffic will be diverted, with undesired effects on congestion levels. The traffic congestion occurs when the current experienced travel time is much greater than the free-flow travel time. We measure congestion through the well-known *travel time index*, defined as the ratio between the experienced travel time and the free-flow travel time. More details on other congestion measures are provided in Falcocchio & Levinson (2015) and Morandi (2023).

In details, the TRANS model objective function minimizes the combination of the two hierarchical objectives. The primary objective measures the percentage of risk in excess to the risk-free threshold, averaged through the entire time horizon and among all monitored roads. The risk function is determined by the specific problem under investigation. In our experimental setup, it depends on the vehicle weights and is derived based on the risk assessment outlined in Ventura *et al.* (2024). The secondary objective measures the congestion level, through the travel time index, on the whole network through the time horizon. In our experimental setup,

		Avg. Risk			Max. Risk		
		Low	Medium	High	Low	Medium	High
γ (%)	0	0.29%	6.13%	27.11%	7.01%	111.37%	250.00%
	10	0.29%	6.13%	27.11%	7.01%	111.37%	250.00%
	20	0.00%	0.00%	0.00%	0.00%	0.00%	0.03%
	50	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	∞	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Figure 1 – *Percentage increase w.r.t risk-free threshold for increasing incoming vehicles levels*

		Avg. Congestion			Max. Congestion		
		Low	Medium	High	Low	Medium	High
γ(%)	0	102.99%	103.54%	105.90%	106.67%	115.01%	149.91%
	10	103.06%	103.66%	106.37%	111.03%	120.94%	175.95%
	20	103.03%	105.07%	115.80%	107.40%	142.54%	269.67%
	50	102.98%	103.71%	110.59%	106.13%	115.48%	190.45%
	∞	102.97%	103.57%	108.90%	106.06%	112.45%	176.64%

Figure 2 – *Travel time index for increasing incoming vehicles levels*

the objective function is a weighted average of the two objectives in which more importance is given to the risk minimization. The model also ensures that every vehicle is assigned to only one of the paths available and that flows on each arc are evaluated considering both previous optimizations and predictions/measurements of traffic flows of unmonitored vehicles and the flows generated by the actual assignment. Traffic assignment models are known to be effective only when unfairness among drivers is negligible. To this aim, we generate only paths that are almost fair for each driver, as proposed in Angelelli *et al.* (2021). The generation procedure is applied on a sub-network that contains arcs representing roads in which the transit of vehicle is allowed and provides that the generated paths are no slower than a certain percentage γ of their fastest path traversing some of the monitored roads. We recall that setting $\gamma = 0\%$ means allowing vehicles to travel only on their fastest paths.

3 Computational results

Dataset generation. As the problem at study is new to the literature, no benchmark instances are available and we generated a set of instances inspired by the real-world application driving this research, i.e. the road network surrounding the city of Brescia (Italy), where there are many bridges that are subject to dangerous mechanical stresses when severe traffic conditions occur. The structure of the road network, arc capacities, monitored arcs parameters and traffic flows have been gathered from the Italian Ministry for Infrastructure and according to real measurements provided in Ventura *et al.* (2024). Then, we generated instances for different monitored arcs deterioration levels and incoming traffic levels.

Results. Figure 1 shows the average and the maximum risk for increasing levels of incoming vehicles levels. When we allow for more alternative paths, i.e. γ is increased, the algorithm is able to reduce and remove the increase in risk w.r.t. to the threshold $R^{risk-free}$. When increasing levels of incoming vehicles are considered, the increase in risk rapidly grows. However, with a proper γ, it rapidly drops to negligible values. When a high level of vehicles enters the network, in some time slots the bridge reaches the critical threshold, i.e. 250% of the risk-free threshold, where partial or full arc closures are likely to happen.

Figure 2 shows the average and the maximum travel time index for an increasing incoming vehicles level. For $\gamma = 20\%$ we have a significant increase in the average and the maximum travel time index, getting even worse with increasing incoming vehicles' level. The phenomenon is explained by the fact that the model, with $\gamma = 20\%$, is able to reduce the risk to zero by

		Risk-free			Critical		
		Low	Medium	High	Low	Medium	High
γ(%)	0	3.41%	11.70%	12.80%	0.00%	0.24%	10.30%
	10	3.41%	11.70%	12.80%	0.00%	0.24%	10.30%
	20	0.00%	0.18%	0.34%	0.00%	0.00%	0.00%
	50	0.00%	0.08%	0.20%	0.00%	0.00%	0.00%
	∞	0.00%	0.04%	0.20%	0.00%	0.00%	0.00%

Figure 3 – *Time slots (%) in which thresholds are exceeded for increasing incoming vehicles levels*

detouring some of the incoming vehicles from the bridge on other surrounding roads and, hence, deteriorating their traffic condition. For greater values of γ, the model has already eliminated the risk and could aim at minimize the secondary objective, i.e. minimize the travel time index on arcs. This could be seen for each incoming vehicles level but it is particularly striking when high levels are observed.

Table 3 shows the percentages of the time slots in which both the risk-free and the critical threshold are exceeded for an increasing incoming vehicles level. The percentage of time slots in which the risk-free threshold is exceeded increases from around 3% to 13% of the time slots for $\gamma = 0\%$ and $\gamma = 10\%$. The same behavior can be observed for the time slots in which the critical threshold is exceeded. If we allow for a higher γ, then the percentage of risky time slots is negligible, even if a few time slots still remain where, even with $\gamma = \infty\%$, the risk-free threshold is exceeded. This happens because, even though the primary objective is the risk elimination, detouring all vehicles could lead to very high travel time indexes on surrounding roads that do not balance the advantage of having zero risk versus an extremely low risk. We highlight that, under a high level of incoming vehicles and using only fastest paths ($\gamma = 0\%$), it reaches, in 10% of the time slots, a dangerous situation in which the arcs should be closed or some recovery actions have to be performed.

4 Discussions

In this work, we studied a real-time traffic management system that is able to reduce and, if possible, eliminate the risk of disruptions due to infrastructure overloading while not burdening network congestion. We also showed empirically the benefits of using such framework on a real-world network using real vehicular data. Future developments may concern the introduction of a re-routing mechanisms applied also to already routed vehicles, fare mechanisms to enhance compliance, the possibility to delay the starting time of some vehicles and many others.

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