A Resilience-based Perimeter Control Strategy for Urban Roadway Systems with Internet of Vehicles

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Abstract

Besides the daily traffic congestion, external disruptions of the urban roadway systems, such as heavy rainfall, is one of the most important causes that can lead local congestion to large-scale cascading failure. This paper proposes a resilience-oriented perimeter control strategy under the framework of the Internet of Vehicles (IoV). A PI feedback controller is proposed that considers a time-dependent resilience index and tested in a two-region urban city with normal congestion and rainfall disruption scenarios using micro-simulation. The parameter of maximum inflow ratio ($u_{\max}$ in this paper) is tested. Results show that in this case study, when $u_{\max}$ is set to 0.52, 0.61 and 0.69, respectively, the system can treat daily congestion well, while in the case of severe rainfall disruption $u_{\max=0.52}$ deals with the heavy rainfall well. $u_{\max=0.61}$ demonstrates good mobility performance in both daily congestion and rainfall disruptions. The capacity of the number of flowing vehicles per second in a network is a crucial metric for the choice of $u_{\max}$ in this resilience-based perimeter controller. This study is a promising first step towards the development of urban resilience management strategies.

Keywords

Resilience; perimeter control; internet of vehicles.

1 Introduction

Global and rapid urbanization around the world aggravated the unbalance between supply and demand for our urban mobility. This unbalance becomes even more severe when dealing with external disruptions, such as heavy rainfall, which propagate congestion from local events to large-scale cascading failure. In recent years, "urban resilience" is a topic receiving attention, which aims at improving the city's absorption, adaption and recovery ability when dealing with emergencies. Resilience is an overall umbrella for the full life-cycle of system performance (Gritzalis *et al.* (2019)). Most of the studies on the urban roadway systems resilience are from the perspectives of assessment (Henry and Ramirez-Marquez (2012); Nogal and Honfi (2019)). A review on definition and measurement of system resilience can be found in (Hosseini *et al.* (2016)). The enhancement of urban resilience can be conducted by improving redundancy, structure reinforcement, and management (Zhang *et al.* (2019)), which are related to consideration of network topology, infrastructure, and operations, respectively. Nevertheless, the management of urban roadway systems resilience is more complex among the critical infrastructures of a city, which is caused by uncertainty due to the dynamic interactions among individuals, vehicles, the roadway system, and information.

Meanwhile, it is worth noting that Internet of Vehicles (IoV), is an indispensable component of future intelligent transport systems, similarly to Vehicle-to-Infrastructure (V2I), Infrastructure-to-Vehicle (I2V), and other radio frequency identification (RFID) technologies (Arena and Pau (2019)). Compared to traditional vehicles, each vehicle in IoV environment can be regarded as a data source (Joy *et al.* (2018)). That emerging technologies provide a new direction on state awareness and intelligent control, while the vehicles can also change their routes dynamically by the real-time updated travel times. Currently, studies on IoV cover a variety of aspects, such as vehicular cloud (Gerla *et al.* (2014)), cognitive intelligence (congestion awareness) (Paul *et al.* (2015)), and congestion avoidance (rerouting) (Yaqoob *et al.* (2019)). However, the studied control problems are of small scale, either from multiple intersections(Chen and Chang (2016)) or heterogeneous crowded vehicle levels (Wang *et al.* (2018)); few investigations have been done on large-scale traffic control utilizing the IoV environment.

Perimeter control (also known as gating) is a practical and frequently employed tool against over-saturation of significant or sensitive links or urban network areas (Keyvan-Ekbatani *et al.* (2012)), which regulates the transfer flows across boundaries to prevent congestion or stabilize flow in the protected network (PN)(Geroliminis *et al.* (2012)). Regarding its effectiveness in real-time and large-scale management, perimeter control could have similar performance in traffic resilience enhancement. Essentially, perimeter control is conducted with the use of macroscopic fundamental diagram (MFD), which is a widely observed relation between network-wide space-mean vehicles flow and density (Daganzo and Geroliminis (2008)). Among previous studies, solution approaches such as traditional feedback schemes (Keyvan-Ekbatani *et al.* (2012)), model predictive control (MPC), (Geroliminis *et al.* (2012)), piecewise affine approximations (Kouvelas *et al.* (2019)), multivariable feedback regulators (Aboudolas and Geroliminis (2013)), and Proportional-Integral (PI) perimeter controllers with data-driven online adaptive optimization (Kouvelas *et al.* (2017)), have been used for tackling this challenging control problem. The objectives of perimeter control can be either to maximize network throughput (Keyvan-Ekbatani *et al.* (2012)), maximize number of trips that reach their destination (Geroliminis *et al.* (2012)), minimize total time spent (TTS) (Sirmatel and Geroliminis (2017)), or desired accumulations (Haddad and Mirkin (2017)). Those objectives represent traditional traffic networks mobility indices. Finally, in the work of Yang *et al.* (2017), a multi-scale perimeter control in a connected-vehicle environment has been proposed, in which connected vehicles (CV) serve as the only data source.

In this paper, we proposed a resilience-oriented perimeter control methodology that utilizes the IoV concept. A microscopic simulation model is adopted, in which CV is not only acting as a data source for control purposes, but also have the ability to reroute according to real-time network information updates. The rest of this paper is organized as follows: Section 2 describes the main concept of the developed resilience-based perimeter control framework; Section 3 conducts a two-region case study for a large-scale city network in China; finally, Section 4 concludes the paper and some future research directions are presented.

2 Resilience-based perimeter control

In this novel idea, described here as resilience-based perimeter control, the average speed of the entire network is chosen as the Figure-of-Merit $F(\cdot)$, namely $F(t) = v^m(t)$, where m is the set of all flowing vehicles in the network. The open-source microscopic simulator SUMO and its Traffic Control Interface (TraCI) API are utilized as the process plant and traffic control centre, respectively (Wegener *et al.* (2008)). System resilience that corresponds to Figure-of-Merit $F(\cdot)$ can be expressed as a function of time (Henry and

Ramirez-Marquez (2012)), as follows

$$R_F(t_r|e_j) = \frac{F(t_r|e_j) - F(t_d|e_j)}{F(t_0) - F(t_d|e_j)} \tag{1}$$

where e_j represents a disruptive event (e.g. extreme weather), and t_r denotes any time between (t_d and t_f); here, t_0, t_e, t_d and t_f denote the initial time, beginning of disruption, time when $F(\cdot)$ reaches the minimum value, and recovery time, respectively.

The overall control objective is to maximize the integral of resilience loss (by utilizing gating control inputs), which can be expressed as

$$J = \max_u \left(\int_{t_d}^{t_f} R_F(t_r|e_j) \right) \tag{2}$$

This control objective has a result not to focus on mobility indices, but rather we are more concerned about the rapid system recovery to normal (uncongested) states.

In this paper, we consider a two-region problem, in which regions Θ_1 and Θ_2 represent the periphery and city center, respectively. Therefore, $u_{12} + u_{21} + u_y = 1$, where u_{ij} indicate gating rates from Θ_i to Θ_j, and u_y is the lost (yellow and all-red) time within a signal cycle, respectively. The resilience-based PI controller is expressed as

$$\Delta u(k) = K_\mathrm{P} \cdot e(k) + K_\mathrm{I} \cdot Ee \tag{3}$$

In Eq. (3), $e(k) = R_F(0) - R_F(k)$, where $R_F(0) = \theta$ is the system resilience when it operated at the set-point; $Ee = \int_0^T e(k)dk$ is the total resilience loss, and T is the control period; K_P term generates the corrective control action proportional to state error; K_I accelerates the movement of the process towards the set-point and eliminates the residual steady state error.

In the current case study, we modelled the case of morning peak, i.e. most of the vehicles traveller from outside areas (peripheral region) into the PN; therefore the control inputs u^*_{12} and u^*_{21} that are derived by a bang-bang controller can be described as follows

$$u^*_{ij}(k) = \begin{cases} u^*_{12} = u_{\max}, u^*_{21} = u_{\min}, & \forall R_F(\cdot) < \theta \\ u^*_{12} = u_{\min}, u^*_{21} = u_{\max}, & \forall R_F(\cdot) > \theta \end{cases} \tag{4}$$

Essentially, we minimize the number of vehicles entering the central region whenever the system's resilience $R_F(\cdot)$ is lower than θ. A smooth application of this bang-bang optimal control policy can be achieved by tuning of the parameter $u_{\max}$, and weights K_{P} and K_{I} of the PI regulator of Eq. 3 (Keyvan-Ekbatani *et al.* (2012)).

3 A Case study

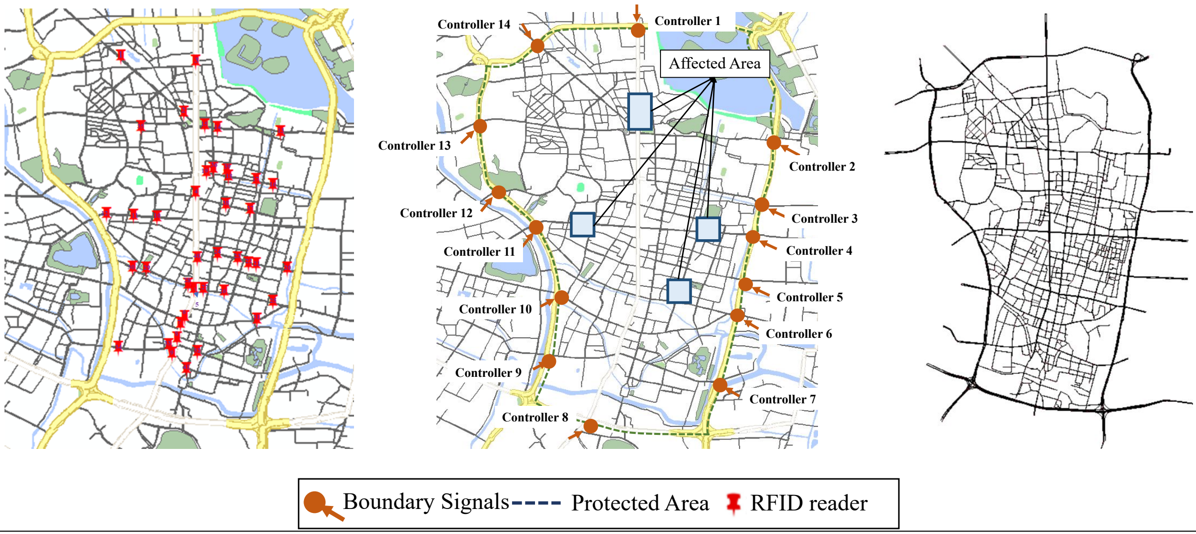
3.1 Simulation Setting

In this section, we describe the results from a case study that has been conducted for the urban network of central Nanjing city, in China, which is the second-largest city in southeast China. In Fig. 1, positions of RFID readers in the protected area (PN) (within the dotted line in Fig. 1(b)) are demonstrated (see also Zhu *et al.* (2020) for details on these data). This PN is the busiest area in Nanjing city, as it includes the business district, residence zones, and tourist attractions. The investigation period is 6:00am to 10:00am on a working day. In Fig. 1(b), 14 controlled intersections (gates) on the boundary and 4 rainfall affected areas are labelled. Noteworthy impacts on the main roads of the network occur due to the areas affected by the rainfall. Simulation model is shown in Fig. 1(c).

Traffic demand is a vital input of the simulator, and was calibrated with TraCI. Based on Adaptive Fine Tuning (AFT) algorithm (Kosmatopoulos and Kouvelas (2009); Kouvelas *et al.* (2011(b)), traffic demands were calibrated by minimizing the total error between RFID data and simulation flows (Zhu *et al.* (2020)). Rerouting of CV is implemented by vehicles choosing the new route via current minimum instantaneous travel time. This rerouting was performed every 30 minutes and for every vehicle in PN; note that more frequent rerouting would lead to computational issues but also other instabilities related to microsimulation equilibrium.

The control interval and cycle length for each boundary intersection are set equal, i.e. 90s. With the consideration of traffic flow stability and car accident risk, here, we only change the duration length of each phase but not their sequence. The minimum phase duration time is set to $5s$. The total green time of all phases that enter the PN is $g_n^{\mathrm{in}}(k) = u(k) \cdot C_n$, in which $C_n = \sum_j g_{n,j}(k) + L_n$ is the cycle length.

Figure 1: The case study of Nanjing city: (a) distribution of RFID readers; (b) PN and rainfall affected areas; (c) simulation model.



3.2 Controller performance: daily congestion

In this part, results of the resilience-based perimeter controller are demonstrated with daily congestion and rainfall disrupted scenarios. Traffic demand is assumed the same for both scenarios. From Fig. 2(a), the maximum number of flowing vehicles in PN is approximately 7800 vehicles under the daily congestion scenario. In the case of $u_{\max} = 0.69$, although the minimum velocity demonstrates almost the lowest value among the six different $u_{\max}$, the system recovers faster. Thus, this case we can be considered as the most resilient to the external disruption. When $u_{\max} = 0.61$, the mobility index, i.e. average speed, achieves the best performance among all simulated scenarios.

Some statistical results are concluded in Table 1. Here, since we only modelled some entry links of Θ_1, the resolution of average speed also concludes vehicles on these links. Therefore, this controller also considered local congestion issue on the boundary intersections. When $u_{max} = 0.52$, $u_{max} = 0.61$ and $u_{max} = 0.69$, the controlled urban roadway network can handle the daily congestion issue well.

Figure 2: Results of congested scenario:(a)running vehicles(veh/s); (b) average speed of the whole network (km/h)

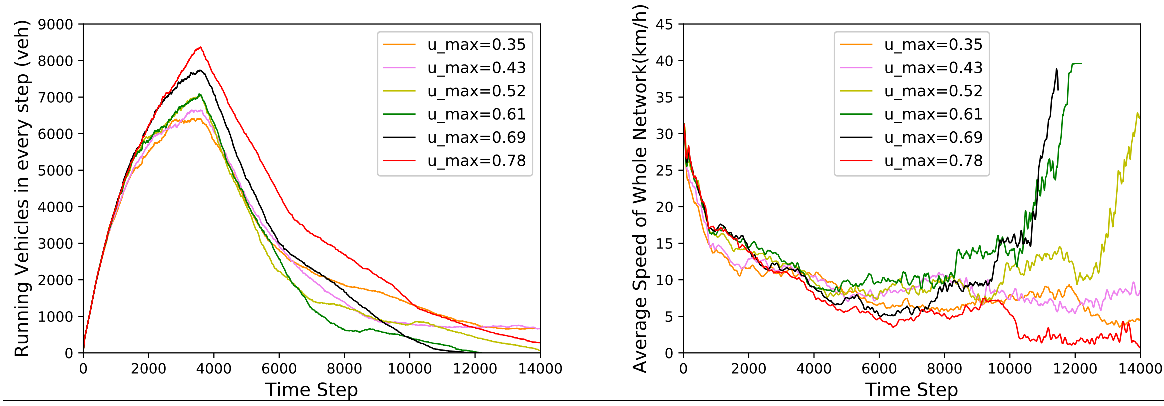


Table 1: Comparison between different $u_{\max}$ under daily congestion.

	Average Speed (km/h)	Timestep $<$ 10km/h	R_F ($t = 11000$)	R_F ($t = 12000$)
$u_{\max}$=0.35	8.53	10639	0.18	0.18
$u_{\max}$=0.43	9.71	10095	0.05	0.01
$u_{\max}$=0.52	13.76	5571	0.27	0.19
$u_{\max}$=0.61	15.01	3313	0.74	**1.00**
$u_{\max}$=0.69	12.41	5630	**0.92**	**1.00**
$u_{\max}$=0.78	6.92	11401	0.04	0.02

3.3 Performance of the controller: rainfall disruption

Besides the daily congestion scenario, we also considered a rainfall disruption case, in which the water-logging depth has a direct impact on the maximum speed of each link (Pregnolato *et al.* (2017)). A link that has high risk of waterlogging is marked in Fig. 1(b); we assume that with a slight disruption the maximum speed of these links will be gradually reduced to 14km/h, while for a severe rainfall their speed is reduced to 1km/h (almost loss of functionality), as shown in Fig. 3.

The simulation results under rainfall disruptions are shown in Fig. 4. Here, for the slight disruption, $u_{\max} = 0.52$ and $u_{\max} = 0.61$ have both the ability to recover quickly; but for the severe case, only $u_{\max} = 0.52$ demonstrates this ability. Although under the normal

Figure 3: Disruption curve of links with waterlogging risk.

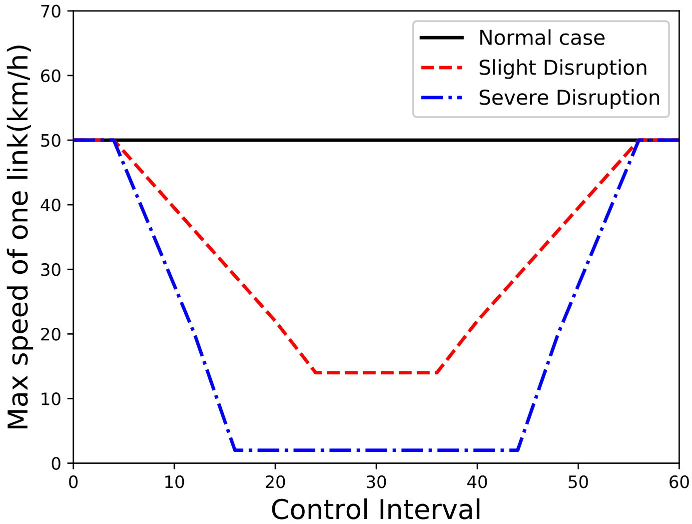
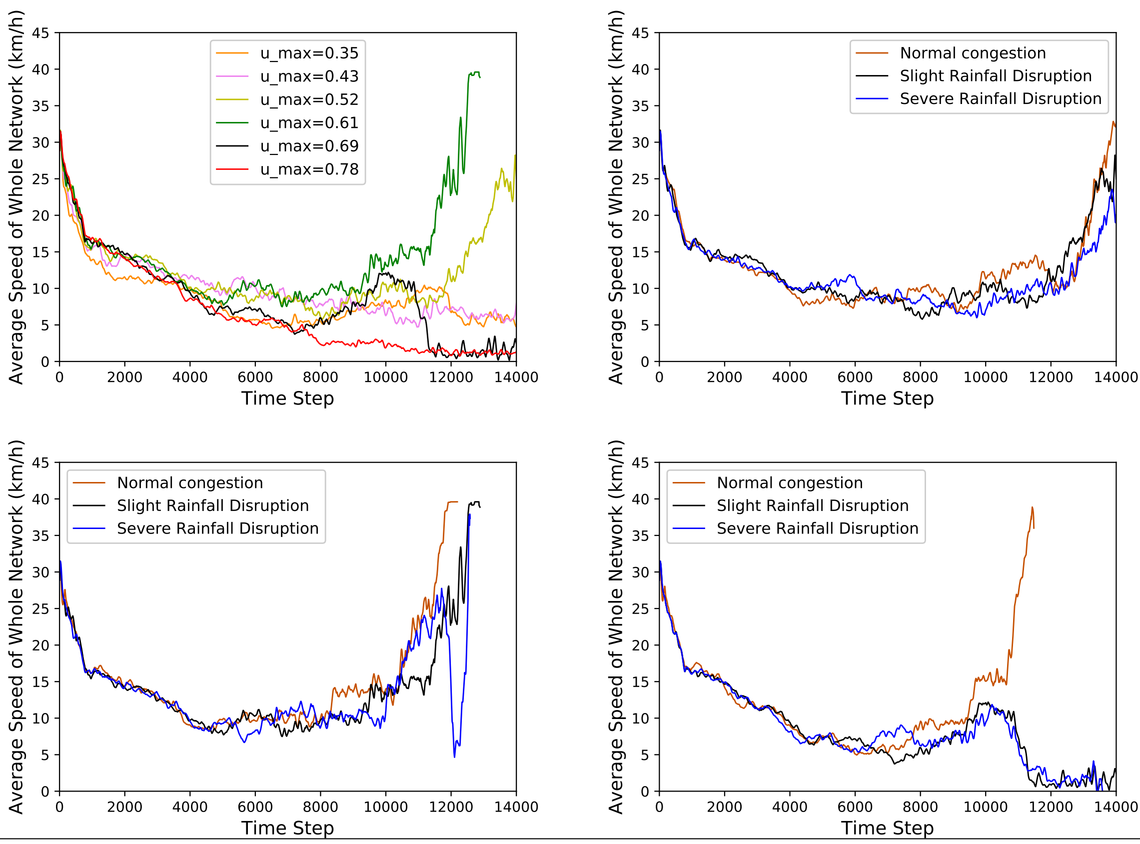


Figure 4: Comparison between different $u$max under rainfall disruption scenarios: (a) different $u_{\max}$ under slight disruption; (b) $u_{\max}$=0.52; (c) $u_{\max}$=0.61; (d) $u_{\max}$=0.69.



case presented earlier, $u_{\max} = 0.52$ is not the one that performs best, it can however handle the congestion induced by the severe rainfall well; note that capacity of flowing vehicles is reduced to approximately 7000 vehicles, which is close to the maximum accumulation of $u_{\max} = 0.52$ under the daily congestion. Furthermore, we demonstrate some quantitative results in Table 2; it is worth mentining that $u_{\max} = 0.61$ achieves the best performance in terms of average speed in both daily congestion and rainfall disruption scenarios. The goal of this study differs from previous as it aims at improving urban mobility, but also help the system recover from disrupted states as fast as possible; to this end, there is a trade-off between traditional traffic metrics (e.g. total delay) and system resilience and reliability. It is also a new attempt to do perimeter control in microscopic simulation with consideration of IoV environment, in which vehicles not only act as sensors but also reroute via real-time information.

Table 2: Comparison between different $u_{\max}$ under rainfall disruption

	Average Speed (km/h)	Timestep $<$ 10km/h	R_F ($t = 11000$)	R_F ($t = 12000$)
Slight disruption				
$u_{\max}$=0.52	13.02	6797	0.11	0.23
$u_{\max}$=0.61	14.25	4119	**0.37**	**0.73**
$u_{\max}$=0.69	8.31	9328	0.24	0.02
Severe disruption				
$u_{\max}$=0.52	12.78	6007	0.23	**0.20**
$u_{\max}$=0.61	13.36	3901	**0.64**	0.08
$u_{\max}$=0.69	8.78	9376	0.19	0.01

4 Conclusions

With the current rapid urbanization, traffic congestion becomes a daily issue in our cities, while this problem becomes even more critical when combined with external disruptions, such as heavy rainfall. Moreover, improper management might not ameliorate congestion but rather lead to a cascading system failure. In this paper, a resilience-based perimeter control strategy is proposed with the purpose of regulating the protected network in such a way that it can rapidly recover to a normal (uncongested) state. A case study in the central area of Nanjing, China, was performed in the microsimulation enviromnment SUMO with IoV environment. Results show that, in this case study, (a) $u_{\max} = 0.61$

demonstrates good mobility performance in both daily congestion and disruption events; (b) $u_{\max} = 0.52$ is the one that can realize rapid and steady recovery in severe rainfall disruption. The capacity of vehicles circulating in the network is crucial for the choice of $u_{\max}$ in this resilience-based perimeter control design. To the authors best knowledge, this is the first work that conducts perimeter control for resilience enhancement. It is also a novel attempt to apply perimeter control in microscopic simulation with IoV environment, which is a crucial issue for future urban traffic management. Future work will deal with cooperative perimeter control when the desired PN is relatively large and shows spatial heterogeneous properties.

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