A Framework for Centralized Traffic Routing in Urban Areas

Matyáš Švadlenka[1,2] , **Lukáš Chrpa**[1]
[1]Czech Institute of Informatics, Robotics and Cybernetics, Czech Technical University in Prague
[2]Faculty of Electrical Engineering, Czech Technical University in Prague
svadlmat@fel.cvut.cz, chrpaluk@cvut.cz

Abstract

Dealing with the ever-increasing demand for traffic management is one of the main challenges of the 21st century. The issue is much more apparent in urban areas during rush hours. Traffic congestion causes economic losses due to delays and increased fuel consumption and, on top of that, is a major health risk. Intelligent centralized traffic routing is an important concept aiming at reducing traffic congestion in urban areas by more effectively utilizing road networks.

In this demo, we present a framework that, in a nutshell, integrates techniques for intelligent centralized traffic routing into the well-known SUMO simulator, so these techniques can be evaluated in realistic settings on real/realistic datasets. In particular, the framework automatically identifies "problematic" urban regions by analyzing historical traffic data, then simplifies the road networks by precomputing promising routes (for each considered traffic flow), and finally, leverages a planning-based approach to generate routes. Our framework is evaluated on a real dataset from Dublin's metropolitan area.

1 Introduction

Nowadays, traffic in urban areas is one of the major economic problems due to losses from traffic accidents and travel delays. In rush hours, the problem with traffic jams, road congestion, and travel delays is far more apparent. To give an example, the cost of congestion in London has exceeded £5 billion in 2020 in lost time and fuel consumption[1] and has become a major health threat [Chang *et al.*, 2019]. With the continuing growth of global urbanization, the problem of traffic congestion is expected to be exacerbated. Hence there is a need for intelligent traffic management techniques that can, at least to some extent, mitigate the problem. The introduction of highly innovative techniques such as *Connected Autonomous Vehicles* (CAV) has the potential to revolutionize the field as we have more options for designing intelligent traffic management techniques [Vallati and Chrpa, 2018].

Effective traffic management has to consider a global perspective on the controlled (urban) region to make good decisions about traffic signal configurations or vehicle routes. Distributed (decentralized) approaches for traffic signal control [Xie *et al.*, 2012] or dynamic vehicle routing [Wang and Niu, 2019] achieved promising results and are now being used in practice. Centralized approaches, in contrast, take the (global) perspective of a traffic control center and aim to optimize traffic for the whole controlled region. Notably, centralized approaches allow us to consider both the dynamic system optimal (DSO) principle [Merchant and Nemhauser, 1978] and the dynamic user optimal (DUO) principle [Friesz *et al.*, 1989] and to trade-off in between them. Centralized approaches, based on automated planning [Pozanco *et al.*, 2021; Gulić *et al.*, 2016], have been used, in cooperation with the SUMO simulator [Lopez *et al.*, 2018]. The generation of traffic light control strategies has also been tackled by using hybrid PDDL+ and numeric planning [Antoniou *et al.*, 2019; Vallati *et al.*, 2016; McCluskey and Vallati, 2017].

In the traffic routing problem, we face the alternative of decentralized and centralized computation mechanisms [Shahi *et al.*, 2020]. The former refers to accomplishing routing or rerouting tasks in closed vehicles or infrastructures, with benefits ranging from leveraged computation capacity to communication loads [Du *et al.*, 2014; Claes *et al.*, 2011]. The centralized approaches aim to provide the optimal routes for each vehicle from the global perspective, with the clear benefit of having a holistic vision of the controlled region. Yamashita *et al.* [2005] proposed a method that collects data about intended routes of the vehicles, based on the collected data it predicts future traffic intensity in the area, and the prediction is broadcasted back to the vehicles that update their routes according to the prediction. Recently, planning-based techniques for centralized traffic routing have been proposed and shown promising results [Chrpa *et al.*, 2019; Vallati *et al.*, 2021; Svadlenka and Chrpa, 2023; Svadlenka *et al.*, 2023].

In this demo, we present a framework that integrates techniques for intelligent centralized traffic routing into the well-known SUMO simulator [Lopez *et al.*, 2018] (initial work on the framework was recently published [Svadlenka and Chrpa, 2023]). The framework aims to evaluate central-

[1]https://www.london.gov.uk/press-releases/mayoral/cost-of-congestion-in-capital-revealed

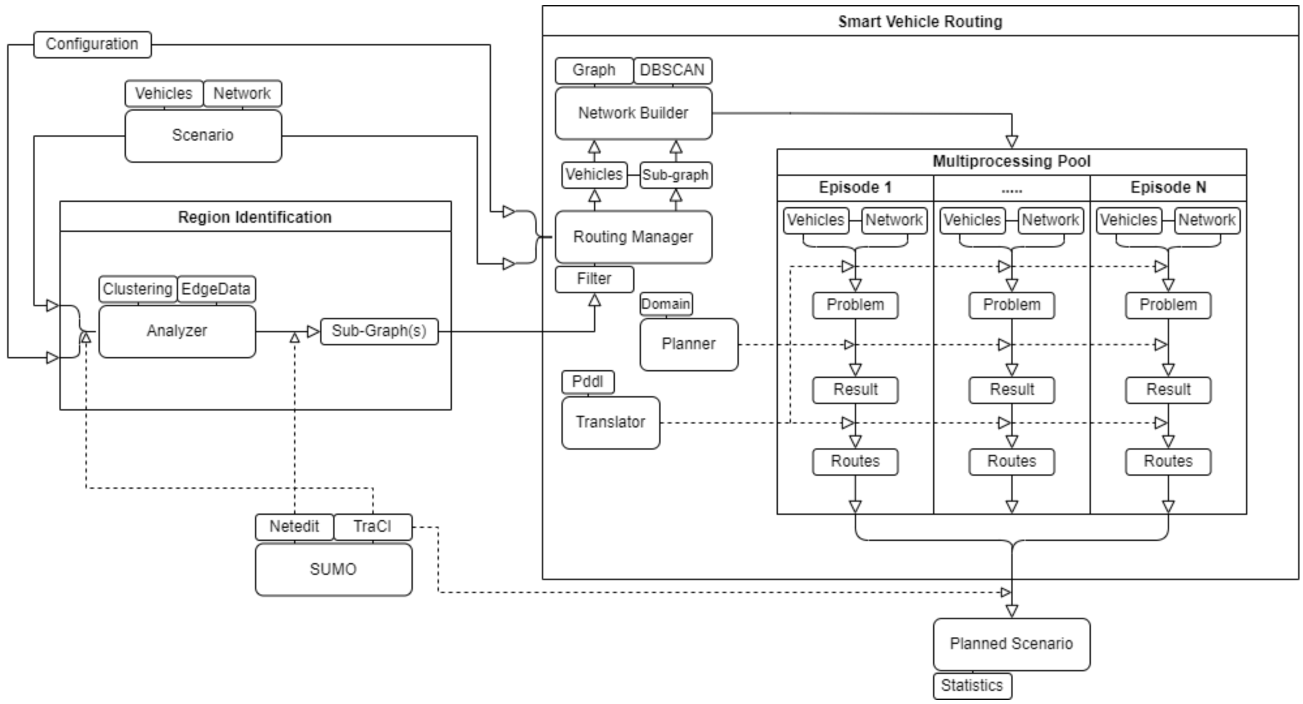

Figure 1: A diagram of the architecture of our framework for centralized traffic routing.

ized traffic routing techniques in realistic traffic conditions on real/realistic datasets. The framework provides the following functionality: (i) it automatically identifies "problematic" urban regions by analyzing historical traffic data, (ii) simplifies the road networks by precomputing promising routes (for each considered traffic flow) [Svadlenka *et al.*, 2023], and (iii) leverages a PDDL-based planning approach to generate vehicle routes [Chrpa *et al.*, 2019]. Our framework is (preliminarily) evaluated on a real dataset from Dublin's metropolitan area [Gueriau and Dusparic, 2020].

2 Centralized Traffic Routing Framework

The problem of effective centralized traffic routing is computationally demanding and hence it might not be feasible to tackle it in the whole metropolitan urban areas [Chrpa and Vallati, 2023]. Thus it is necessary to simplify the problem by focusing only on the most critical traffic flows in the most critical parts of the (whole) network.

The architecture of our framework for centralized traffic routing, depicted in Figure 1, is divided into three main parts: **region identification component** (left), **smart routing component** (right), and the **SUMO simulator** itself [Lopez *et al.*, 2018] (bottom left). Note that the architecture extends the one presented in [Svadlenka and Chrpa, 2023] by considering existing (real) datasets from larger metropolitan areas.

The region identification component processes a given SUMO scenario to identify "problematic" regions that are prone to traffic congestion. It analyzes historical statistical traffic data from the scenario (travel time, arrived and departed vehicles, etc.) in the considered road network. For each road segment, we compute *Congestion index* as $1 - \frac{t_f}{t_a}$ (where t_f is a free flow travel time, and t_a is an actual travel time). Then, we apply *Gravitational Clustering* [Wright, 1977] to identify the "problematic" regions that are prone to congestion. Gravitational Clustering is parametrized by the number of iterations and by the "merging radius". The identified "problematic" regions, as the result of the clustering, can be visualized in the framework, so an expert can either approve the result (i.e., the regions are reasonable) or change the parametrization of the clustering and generate a new result. The approved regions are then converted with Netedit (which is a part of the SUMO framework) into the graph-like format that we use in the routing component.

The smart routing component periodically takes vehicles from the scenario in advance of their arrival (30 seconds in this work) and filters out those that do not drive through any of the identified regions. For each *episode* that is specified by a given identified "problematic" region and a given 30-second timespan, we initially identify *traffic flows* specified by the point of origin, where the vehicles enter the region, and the point of destination, where the vehicles leave the region. For each traffic flow, we in a preprocessing step identify a road sub-network containing "smart" routes that are diverse enough and within a specified suboptimality bound [Svadlenka *et al.*, 2023]. In particular, a variant of the A* algorithm [Hart *et al.*, 1968] is used to identify routes that are within the specified suboptimality bound [Svadlenka and Chrpa, 2023] and then by using the DBSCAN algorithm [Ester *et al.*, 1996] we cluster the routes based on their similarity, which is measured by Jaccard Index (that measures similarity of sets). For each cluster, we consider only the shortest route as it achieved the most promising results [Svadlenka *et al.*,

	travel distance (m)	speed (m/s)	travel time (s)	waiting time (s)	time loss (s)
Original	1917.04	6.59	749.68	482.92	559.17
CTR	1909.99	6.76	581.55	324.42	397.48
DUO	1812.64	7.67	326.30	116.55	161.31

Table 1: Results of the simulation on Dublin dataset (rush hours). DUO (Dynamic User Optimal) refers to decentralized dynamic routing. CTR refers to our Centralised Traffic Routing approach. All quantities are averages per vehicle.

2023].

Each episode is then compiled into a PDDL model that, in a nutshell, encodes a planning task in which the vehicles, from considered traffic flows, have to be routed through the region such that the traffic intensity on road segments is minimized. Note that vehicles of each traffic flow can be routed only on pre-identified "smart" routes in the preprocessing and other (non-routed) vehicles are taken into account in the form of the occupancy of the road segments. More details about the PDDL model can be found in [Chrpa *et al.*, 2019]. To solve a PDDL planning task (to generate vehicle routed through the region in the given episode) we use the Mercury planner [Domshlak *et al.*, 2015]. To solve an episode, we imposed a time limit of 27 seconds (for "smart" routing and Mercury together) and, in the case, no solution is produced, the original routes of the vehicles are assigned.

In the final step, all planned vehicle routes are converted back into SUMO's representation (by replacing the parts of the routes of the vehicles going through the "problematic" regions). SUMO hence simulates how our centralized traffic routing affects the traffic both in the "problematic" regions as well as in the whole metropolitan area. The results of the simulation are exported into a file consisting of various statistics (e.g., average travel time, average travel distance).

3 Demonstration & Preliminary Results

The demonstration will focus on showing the functionality of our framework that aims at improving traffic conditions by centralized traffic routing. Resources and video demonstration can be found in the following repository[2].

For the demonstration, we consider a dataset from the metropolitan area of Dublin [Gueriau and Dusparic, 2020]. To emphasize the benefit of centralized traffic routing techniques, we have considered data from morning rush hour (between 7 am and 9 am), in which the traffic in the region is the most intense. In total, the data contain 45 181 vehicles out of which 6 177 were routed by centralized routing.

In our experiments, we have parametrized the Gravitational Clustering algorithm we use to identify "problematic" regions such that the merging radius was set to 8 meters (i.e., how close the clusters have to be to be merged into a larger cluster) and the number of iterations was set to 150. To speed up the convergence of the algorithm we have considered the weights of initial clusters (each cluster corresponds to a single road segment) as 10 times the value of the Congestion Index for particular road segments. For the "smart" route preprocessing, we have generated at most 3000 routes that are at most 1.2 times longer than the shortest route (for each traffic flow). Only traffic flows, in which the preprocessing identified at least 10 routes such that each route consisted of at least 3 road segments, were further processed by the DBSCAN clustering algorithm that was parametrized by setting the minimum distance (measured by Jaccard Index) between "diverse" routes (that cannot be in the same cluster) to 0.26 and the minimum cluster size of 2 routes. The routing of vehicles (of considered traffic flows) is done by an off-the-shelf planner Mercury [Domshlak *et al.*, 2015] (as mentioned in the previous section). The experiments were run Intel i7-8700 (3.2 GHz) and 4GB of RAM.

We have identified three "problematic" regions (in the whole Dublin metropolitan area) in which we have applied our Centralised Traffic Routing (CTR) approach (they are shown in the video presentation). Table 1 shows the results of the simulation (in a whole area). As can be seen, the use of CTR (in "problematic" regions) can improve the average travel time by about 22.5% with respect to the original traffic data. Of course, such a plain comparison might not reflect reality as many drivers routinely use modern SATNAV systems that dynamically adjust the route based on current traffic conditions. Hence, we have considered the "DUO" option in SUMO (setting the rerouting for each 30 seconds to align with the duration of the planning episode in the CTR approach) that, roughly speaking, considers the use of such SATNAV systems. Unsurprisingly, DUO improves the results by further 35%. A plain combination of CTR and DUO led to the same results as SUMO always replaced the routes generated by CTR with the DUO ones. Interestingly, when focusing only on the central "problematic" region, the average travel time for CTR was about 10% better than for DUO.

4 Conclusions

This demonstration presents a framework that, in a nutshell, integrates centralized traffic routing techniques into the SUMO simulator [Lopez *et al.*, 2018] in order to evaluate the techniques on real datasets. The framework has a modular architecture, so it allows embedding a new technique (e.g. for centralized traffic routing) without considerable implementation overheads.

The preliminary results achieved in the Dublin metropolitan area (in the morning rush hour) indicate that the use of centralized traffic routing techniques might complement the existing decentralized techniques that are used in modern SATNAV systems.

Future work will include the development and integration of more efficient centralized routing techniques, effective combination with DUO techniques, and integration of existing approaches for traffic light control (e.g. see [McCluskey and Vallati, 2017]).

[2] https://github.com/lchrpa/CTR-IJCAI24-demo.git

Acknowledgments

This research is supported by Czech Science Foundation (project no. 23-05575S), by the European Union under the project ROBOPROX (reg. no. CZ.02.01.01/00/22_008/0004590), and by the Grant Agency of the Czech Technical University (project no. SGS24/115/OHK3/2T/37).

References

[Antoniou *et al.*, 2019] Grigoris Antoniou, Sotiris Batsakis, John Davies, Alistair Duke, Thomas L. McCluskey, Evtim Peytchev, Ilias Tachmazidis, and Mauro Vallati. Enabling the use of a planning agent for urban traffic management via enriched and integrated urban data. *Transportation Research Part C: Emerging Technologies*, 98:284 – 297, 2019.

[Chang *et al.*, 2019] Kuang-Hsi Chang, Po-Yuan Hsu, Chun-Ju Lin, Cheng-Li Lin, Suh-Hang Hank Juo, and Chung-Ling Liang. Traffic-related air pollutants increase the risk for age-related macular degeneration. *Journal of Investigative Medicine*, 67(7):1076–1081, 2019.

[Chrpa and Vallati, 2023] Lukás Chrpa and Mauro Vallati. Centralised vehicle routing for optimising urban traffic: A scalability perspective. In *IEEE Intelligent Vehicles Symposium, IV 2023, Anchorage, AK, USA, June 4-7, 2023*, pages 1–6. IEEE, 2023.

[Chrpa *et al.*, 2019] Lukás Chrpa, Mauro Vallati, and Simon Parkinson. Exploiting automated planning for efficient centralized vehicle routing and mitigating congestion in urban road networks. In *Proceedings of the 34th ACM/SIGAPP Symposium on Applied Computing, SAC 2019*, 2019.

[Claes *et al.*, 2011] Rutger Claes, Tom Holvoet, and Danny Weyns. A decentralized approach for anticipatory vehicle routing using delegate multiagent systems. *IEEE Transactions on Intelligent Transportation Systems*, 12(2):364–373, 2011.

[Domshlak *et al.*, 2015] Carmel Domshlak, Jörg Hoffmann, and Michael Katz. Red-black planning: A new systematic approach to partial delete relaxation. *Artif. Intell.*, 221:73–114, 2015.

[Du *et al.*, 2014] Lili Du, Lanshan Han, and Xiang-Yang Li. Distributed coordinated in-vehicle online routing using mixed-strategy congestion game. *Transportation Research Part B: Methodological*, 67:1–17, 2014.

[Ester *et al.*, 1996] Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu. A density-based algorithm for discovering clusters in large spatial databases with noise. In *the Second International Conference on Knowledge Discovery and Data Mining*, pages 226–231, 1996.

[Friesz *et al.*, 1989] Terry L Friesz, Javier Luque, Roger L Tobin, and Byung-Wook Wie. Dynamic network traffic assignment considered as a continuous time optimal control problem. *Operations Research*, 37(6):893–901, 1989.

[Gueriau and Dusparic, 2020] Maxime Gueriau and Ivana Dusparic. Quantifying the impact of connected and autonomous vehicles on traffic efficiency and safety in mixed traffic. In *23rd IEEE International Conference on Intelligent Transportation Systems*, 2020.

[Gulić *et al.*, 2016] Matija Gulić, Ricardo Olivares, and Daniel Borrajo. Using automated planning for traffic signals control. *PROMET-Traffic&Transportation*, 28(4):383–391, 2016.

[Hart *et al.*, 1968] Peter E. Hart, Nils J. Nilsson, and Bertram Raphael. A formal basis for the heuristic determination of minimum cost paths. *IEEE Trans. Syst. Sci. Cybern.*, 4(2):100–107, 1968.

[Lopez *et al.*, 2018] Pablo Alvarez Lopez, Michael Behrisch, Laura Bieker-Walz, Jakob Erdmann, Yun-Pang Flötteröd, Robert Hilbrich, Leonhard Lücken, Johannes Rummel, Peter Wagner, and Evamarie Wießner. Microscopic traffic simulation using sumo. In *Proceedings of ITSC*, 2018.

[McCluskey and Vallati, 2017] Thomas Leo McCluskey and Mauro Vallati. Embedding automated planning within urban traffic management operations. In *Proceedings of the Twenty-Seventh International Conference on Automated Planning and Scheduling, ICAPS 2017, Pittsburgh, Pennsylvania, USA, June 18-23, 2017*, pages 391–399, 2017.

[Merchant and Nemhauser, 1978] Deepak K Merchant and George L Nemhauser. A model and an algorithm for the dynamic traffic assignment problems. *Transportation science*, 12(3):183–199, 1978.

[Pozanco *et al.*, 2021] Alberto Pozanco, Susana Fernández, and Daniel Borrajo. On-line modelling and planning for urban traffic control. *Expert Systems*, 2021.

[Shahi *et al.*, 2020] Gurpreet Singh Shahi, Ranbir Singh Batth, and Simon Egerton. Mrgm: an adaptive mechanism for congestion control in smart vehicular network. *International Journal of Communication Networks and Information Security*, 12(2):273–280, 2020.

[Svadlenka and Chrpa, 2023] Matyás Svadlenka and Lukás Chrpa. Towards a framework for intelligent urban traffic routing. In Michael Franklin and Soon Ae Chun, editors, *Proceedings of the Thirty-Sixth International Florida Artificial Intelligence Research Society Conference, FLAIRS 2023, Clearwater Beach, FL, USA, May 14-17, 2023*. AAAI Press, 2023.

[Svadlenka *et al.*, 2023] Matyás Svadlenka, Lukás Chrpa, and Mauro Vallati. Improving the scalability of automated planning-based vehicle routing via smart routes identification. In *8th International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2023, Nice, France, June 14-16, 2023*, pages 1–6. IEEE, 2023.

[Vallati and Chrpa, 2018] Mauro Vallati and Lukás Chrpa. A principled analysis of the interrelation between vehicular communication and reasoning capabilities of autonomous vehicles. In *Proceedings of ITSC*, pages 3761–3766, 2018.

[Vallati *et al.*, 2016] Mauro Vallati, Daniele Magazzeni, Bart De Schutter, Lukás Chrpa, and Thomas Leo McCluskey. Efficient macroscopic urban traffic models for reducing congestion: A PDDL+ planning approach. In *Proceedings of AAAI*, pages 3188–3194, 2016.

[Vallati *et al.*, 2021] Mauro Vallati, Enrico Scala, and Lukás Chrpa. A hybrid automated planning approach for urban real-time routing of connected vehicles. In *24th IEEE International Intelligent Transportation Systems Conference, ITSC*, pages 3821–3826. IEEE, 2021.

[Wang and Niu, 2019] Jianqiang Wang and Huimin Niu. A distributed dynamic route guidance approach based on short-term forecasts in cooperative infrastructure-vehicle systems. *Transportation Research Part D: Transport and Environment*, 66:23–34, 2019.

[Wright, 1977] W.E. Wright. Gravitational clustering. *Pattern Recognition*, 9(3):151–166, 1977.

[Xie *et al.*, 2012] Xiao-Feng Xie, Stephen Smith, and Gregory Barlow. Schedule-driven coordination for real-time traffic network control. In *Proceedings of ICAPS*, 2012.

[Yamashita *et al.*, 2005] Tomohisa Yamashita, Kiyoshi Izumi, Koichi Kurumatani, and Hideyuki Nakashima. Smooth traffic flow with a cooperative car navigation system. In Frank Dignum, Virginia Dignum, Sven Koenig, Sarit Kraus, Munindar P. Singh, and Michael J. Wooldridge, editors, *4th International Joint Conference on Autonomous Agents and Multiagent Systems (AAMAS 2005), July 25-29, 2005, Utrecht, The Netherlands*, pages 478–485. ACM, 2005.