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Cordon-Metering Rules for Present-Day and Future Cities

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Cordon-Metering Rules for Present-Day and Future Cities

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Connected and Automated Vehicles (CAVs) play a pivotal role in alleviating urban road network congestion. This study adopts a macroscopic approach to identify strategies for using CAVs to ease traffic congestion and reduce energy consumption. Specifically, this study proposes an Area Transmission Model (ATM) based on Macroscopic Fundamental Diagram (MFD) suitable for city-level network applications. It also presents a macro-optimization control strategy that utilizes speed advisories to modulate traffic flow across the network, thereby ensuring effective congestion management and enhanced energy efficiency. By employing the city of Madison as a case study, the research examines the optimal speed advisory solution. This methodology demonstrates potential for improving traffic management practices, highlighting a promising path forward for optimizing urban transportation systems.</td></tr>
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Abbreviations and Acronyms

ATM	Area Transmission Model
AV	Automated Vehicle
CAV	Connected Automated Vehicle
CBD	Central Business District
LOS	Level of Service
MFD	Macroscopic Fundamental Diagram
MILP	Mixed-integer Linear Programming
MRC	Multi-rhythm Control
NICR	National Institute for Congestion Reduction
OSA	Optimal Speed Advisory
TTC	Total Travel Cost

Executive Summary

Connected and Automated Vehicles (CAVs), through real-time traffic information collection and collaborative communication, can assist vehicles in selecting optimal routes. Furthermore, they facilitate the adaptive adjustment of vehicle headways, a shorter headway can alleviate traffic congestion and reduce energy consumption. This study leverages a macroscopic perspective to explore strategies utilizing CAVs for reducing both traffic congestion and energy consumption. At its core, this study introduces the Area Transmission Model (ATM), a novel construct ingeniously derived from the Macroscopic Fundamental Diagram (MFD). This model is specifically tailored for expansive application across city-scale networks. Complementing this, a macro-optimization control strategy is proposed, employing speed advisories to effectively regulate traffic flow and enhance congestion management alongside energy efficiency within the network. Utilizing the city of Madison as a case study, this study critically assesses the efficacy of the proposed speed advisory solution. The findings underscore the significant potential of this methodology to refine traffic management practices, suggesting a strategic pathway towards the optimization of urban transportation systems, making it an invaluable contribution to the field of urban mobility and traffic management.

Chapter 1. Introduction

In recent years, urban traffic congestion has emerged as a significant challenge for cities worldwide (Desai et al., 2023), leading to increased travel time(Zhang et al., 2023), higher energy consumption(Lu et al., 2021), and elevated emissions (González-Aliste et al., 2023). The emergence of Connected and Automated Vehicles (CAVs) is poised to significantly alter the transportation landscape, offering a promising opportunity to address these challenges (Rahman and Thill, 2023; Ramezani and Ye, 2019; Seuwou et al., 2020). CAVs, through their ability to communicate with each other and with traffic infrastructure, enables the orchestration of traffic flow with unprecedented precision, optimizing route selection, and ensuring the efficient utilization of road networks. Through the strategic deployment of CAVs, it is conceivable to hold the potential to revolutionize traffic management and control systems, and significantly enhance the efficiency and sustainability of transportation systems.

In exploring the impact of introducing CAVs on the entire road network, existing research has been conducted from both micro-control and macro-control strategy perspectives. The majority of studies adopt a microscopic control viewpoint, investigating the effects of CAVs on traffic. These studies focus on road networks with a limited number of intersections, like corridor level (Mirbakhsh et al., 2023; Wan et al., 2024; Yu et al., 2019) or at the network level (Levin et al., 2017; Zhou et al., 2024; Zhu and Ukkusuri, 2015). Wang et al. (2020) proposed a control strategy that addresses intersection conflict resolution, multi-objective optimization within road segments, and the management of heterogeneous decision-making behaviors. Then validated through simulation in a network consisting of 6 intersections. Chu et al. (2020) proposed a Dynamic Lane Reversal-Traffic Scheduling Management scheme to determine the optimal timetable and routes for CAVs. Qian et al. (2021) proposed a method for optimizing the departure times, routes, trajectories, and intersection signal timings for CAVs, aimed at minimizing the total travel time within the network. This method was validated within a network containing 26 intersections. The existing research predominantly adopts a microscopic perspective, investigating the impact of proposed CAV control strategies on networks with a limited number of intersections. Consequently, this narrows their applicability in large-scale network research.

Some studies have been conducted from an integrated macroscopic and microscopic control perspective. Nguyen et al. (2022) proposed a bi-level control strategy that integrated system-optimal traffic flow control at the network level with individual CAV speed control at the link level. This was aimed at enhancing the overall throughput of CAVs within the network. The approach was validated on both a small-scale network (11 nodes) and a large-scale network (the Fort Worth transportation network, with 100 nodes). Furthermore, another bi-level strategy that combined network-level traffic signal timing design with link-level trajectory control of individual CAVs was also developed and validated within the network (Nguyen et al., 2023). Tajalli et al. (2021) proposed a method for coordinating traffic light control and optimizing the CAVs' speed at multiple intersections on urban road networks to maximize network throughput while simultaneously managing speed coordination. However, this method still only considers a limited number of intersections.

When the research extends to the big city level (with an increased number of intersections and nodes), the aforementioned methodologies may become ineffective in the context of large-scale network studies due to limited computational resources. Consequently, it becomes essential to adopt big network-level models from a macroscopic perspective.

There are some studies based on a macroscopic control perspective in the traffic control domain. These studies do not focus on the details of individual road segments or intersections; instead, they divide the city into distinct areas to study the characteristics of the entire network. Yang et al. (1994) first proposed a user equilibrium model for travel distribution in congested urban cores, intending to minimize the congestion travel time for each commuter. This study models the city consisting of a discrete freeway network and a two-dimensional continuum of densely packed surface streets. Utilizing the finite element method, the continuum of surface streets is segmented into a series of triangular areas, transforming the study problem into a nonlinear programming problem, to understand the traveler's route choice in continuous space when travel cost is a linear function of traffic flow density. The proposed method adopted a macroscopic perspective, foregoing the detailed network of surface streets. This approach effectively reduces computational demands by simplifying complex problems and streamlining the process of managing urban traffic flow. This approach is suitable for addressing localized congestion issues. Building on this foundation, scholars have explored a series of variants of continuous traffic equilibrium models based on the finite element method. These variations include solutions for customer facility choice (Ouyang et al., 2015; Wong and Sun, 2001), cordon-based congestion pricing (Ho et al., 2005) and multiple customer categories (Wai et al., 2003).

Additionally, the Macroscopic Fundamental Diagram (MFD) has been proposed as a method to study the macroscopic relationship between traffic flow and density within urban networks (Daganzo, 2007, 2005; Daganzo and Geroliminis, 2008). This approach captures and describes the average characteristics of the entire network from a macroscopic viewpoint, rather than focusing on the details of individual road segments or intersections. By providing a holistic understanding of urban traffic dynamics, MFD facilitates the analysis of overall network performance, enabling the development of more effective traffic management and planning strategies that consider the city-wide implications of traffic interventions. Some scholars have proposed perimeter control methods based on MFD (Aboudolas and Geroliminis, 2013; Geroliminis et al., 2013). These methods utilize MFD to analyze and optimize traffic distribution within a network, to maximize efficiency and minimize congestion throughout the urban area. The approaches introduced include control strategies based on perimeter control (Aalipour et al., 2019; Haddad and Mirkin, 2017), signal timing plans (De Jong et al., 2013; Hajiahmadi et al., 2013), model-free adaptive control driven by data strategies (Lei et al., 2020), and adaptive boundary feedback control(Haddad et al., 2021). This approach has also been applied in emerging transportation areas (Yang et al., 2018).

Following these thoughts, this study investigates macro-control strategies for managing CAVs in city-level networks. It introduces an approach that utilizes speed advisories to regulate the entire network’s traffic flow, sidestepping the complexity of micro-level modeling for specific intersections or lanes. By simplifying the control process, this method not only reduce computational demands but also effectively moderating traffic conditions. The strategic adjustment of CAV speeds on a network-wide scale is poised to alleviate congestion and cut energy consumption, thereby offering a scalable solution to traffic management challenges.

This study introduces three contributions to traffic management within city-level networks. Firstly, it proposes an Area Transmission Model (ATM) based on MFD, a discrete-time and discrete-space framework capable of calculating traffic flow in each area based on both current and historical area states. This model is particularly suited for modeling traffic flows in networks prone to congestion. Secondly, an optimized control strategy is developed, utilizing the constraints of ATM to fine-tune CAV speeds to minimize the total travel cost across the network. This cost is defined by two critical components: energy consumption and travel delay. Lastly, the city of Madison is employed as a practical use case to demonstrate the applicability and effectiveness of the proposed model and strategy. Through this empirical exploration, the study substantiates the potential of the ATM and the optimized control strategy to significantly enhance traffic management practices, underscoring their value as instrumental resources in the quest to ameliorate urban mobility.

This study is structured as follows. Chapter 2 elaborates methodology. Chapter 3 conducts numerical experiments to illustrate the validity of the established models. Finally, Chapter 4 concludes this study.

Table 1. Network-Level Control Studies

Reference	Network Scale	Control Strategy	Traffic Mode	Objective	Model	Solution Algorithm
(Yu et al., 2019)	Corridor	Microscopic	CAV	Reduce travel delay	Mixed-integer linear programming (MILP) model	Heuristic solution algorithm
(Levin et al., 2017)	Small-scale network	Microscopic	Automated Vehicles	Reduce travel time and energy consumption	Integer program for the conflict point simplification of the reservation-based model	Heuristic solution algorithm
(Chen et al., 2022)	Small-scale network	Microscopic	CAV	Reduce travel time and waiting time before entering the network	Multi-rhythm control (MRC) scheme (transfer to MILP)	Commercial solver
(Qian et al., 2021)	Small-scale network	Microscopic	CAV	Improve Traffic safety and efficiency	Mixed-integer nonlinear programs	Commercial solver
(Chu et al., 2020)	Small-scale network	Microscopic	CAV	Reduce travel time	Dynamic lane reversal-traffic scheduling management scheme	Distributed optimization scheme
(Wang et al., 2020)	Small-scale network	Microscopic	CAV	Reduce travel delay; Improve energy-saving and ride comfort	Autonomous crossing strategy, multi-objective trajectory optimization and composite strategy for route planning	Exact solution algorithm
(Zhou et al., 2024)	Small-scale network	Macroscopic	Human-driven Vehicle/CAV	Improve road network capacity	Nonlinear programming models (transfer to MILP)	Commercial solver
(Nguyen et al., 2023)	Large-scale network	Microscopic and macroscopic	CAV	Reduce total travel time	Microscopic: MILP model Macroscopic: linear programming models	Heuristic solution algorithm

Reference	Network Scale	Control Strategy	Traffic Mode	Objective	Model	Solution Algorithm
(Tettamanti et al., 2017)	Small-scale network	Microscopic and macroscopic	AV	Reduce headways and traffic emission	Microscopic level control：nonlinear model predictive control Macroscopic level control: segmentation function	Commercial solver
(Tajalli et al., 2021)	Small-scale network	Microscopic and macroscopic	CAV	Improve intersection throughput and reduce speed variations	Mixed-integer non-linear program	Distributed optimization scheme
(Nguyen et al., 2022)	Large-scale network	Microscopic and macroscopic	CAV	Reduce total travel time	MLIP	Commercial solver

Chapter 2. Methodology

2.1 Notation

To facilitate the understanding of the city-level network modeling, a summary of the notation has been compiled and presented in Table 2.

Table 2. Notation List

Parameters	Description
$\mathcal{J}$	Set of areas in the studied city, $i \in \{1,2,\cdots,I\}$.
$\mathcal{J}_i^-$	Set of upstream areas of area i.
$\mathcal{J}_i^+$	Set of downstream areas of area i.
$[0,T]$	Studied time horizon in continuous time.
$\mathcal{T}$	Studied time horizon in a discrete time interval, $t \in \{1,2,\cdots,\mathbb{T}\}$.
θ	Length of each time interval
$\bar{v}_{it}$	Average speed in area i at time interval t.
l_i	Length of area i.
ρ_i^c	Maximum permitted density under the free flow speed or critical density.
Q_i^M	Maximum flow of area i that occurs at critical density ρ_i^c.
ρ_i^{jam}	Jam density of area i.
$\bar{\omega}_i$	Average speed of area i at which congestion waves propagate upstream through the road under fully congested conditions.
α	Coefficient to convert energy consumption into cost.
β	Coefficient to convert time delay into cost.
$w_{ii'}$	Proportion of flow from area i that flows into area i'
q_{it}	Average flow rate into area i during the interval $[t, t+1)$, in vehicles per unit time.
ρ_{it}	Density of area i at time interval t.
TTC	Total cost of travel.
Intermediate variables	**Description**
s_{it}	Maximum flow that can be sent by area i at time t.
R_{it}	Maximum flow that can be received by area i at time t.
e_{it}	Energy consumption for all vehicles in area i in time interval t.
d_{it}	Time delay for all vehicles in area i in time interval t.
$U_{ii't}$	Number of vehicles flow from area i to area $i' \in \mathcal{J}_i^+$ at time t,
Decision variables	**Description**
v_{it}	Controlled speed in area i at time interval t.

2.2 Problem Statement

Consider a city-level network with one central business district (CBD). The city can be divided into a series of areas, and the set of areas is denoted by $\mathcal{I} = \{1,2,\cdots,I\}$, in which area 1 represents the CBD. In peak hours, people travel through the areas either from the suburbs to the CBD for work (i.e., morning peak hours) or from the CBD to suburbs for returning home (i.e., evening peak hours). We illustrate this with the City of Madison, a small-scale city as shown in Figure 1. The downtown area of the city, which includes the State Capitol and the University of Wisconsin-Madison, is a significant hub of activity. Readers can observe from the figure that the City of Madison is divided into 20 areas according to Alder Districts (https://cityofmadison.maps.arcgis.com/). Please note that both areas 2, 3, 6 and 19 encompass land and lake regions. In our subsequent analysis, we will focus on land-based traffic. However, to maintain the integrity of the Alder Districts, we will not exclude the lake portions from areas 2, 3, 6 and 19.

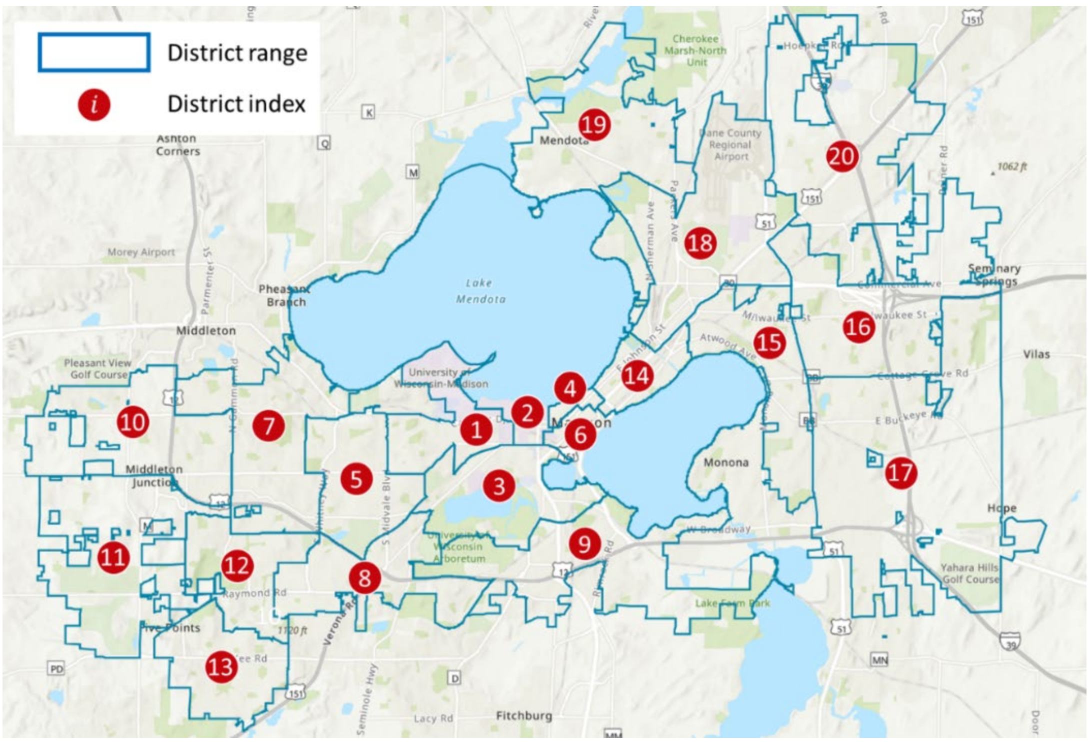

Figure 1. Problem illustration with the City of Madison.

Then, we consider the peak hours happened between $[0, T]$. For the convenience of the network modeling, the continuous study time $[0, T]$ is discretized into a set of identical time intervals, indexed by $\mathcal{T} \coloneqq \{0,1,2,\cdots,\mathbb{T}\}$, and the length of each time interval is $\theta \coloneqq T/\mathbb{T}$, where the time index $t \in \mathcal{T}$ maps to continuous time $t\theta$.

Each area owns traffic characteristics for any given time interval t, such as average travel speed $\bar{v}_{it}$, flow rate q_{it}, density ρ_{it}. Each area also has geometric-related characteristics, such as the average length for traveling through the area denoted by l_i, critical density ρ_i^c, jam density ρ_i^{jam}, shockwave speed ϖ_i, and maximum flow Q_i^M under ρ_i^c.

The vehicles traveling through the areas will produce energy consumption. Energy consumption for all vehicles traveling in area i in time interval t is denoted by e_{it}. e_{it} is a function of vehicle types (e.g., fuel-based vehicles or electric vehicles) and sizes (sedan, SUV, pickup, etc.). In addition, if congestion happens within area i, all vehicles traveling through the area will cause longer travel time than usual, and travel delay caused by congestion is denoted by d_{it}. To study the impacts of energy consumption and time delay together, coefficients α and β are introduced to convert the energy consumption and time delay to cost. The summation of the energy consumption cost and the time delay cost is the total travel cost (TTC) for the network.

We assume all vehicles operating in the network are CAVs, which means that the CAVs will exactly follow the speed advised by the traffic control center. This study is to find the optimal speed control strategies within each area, denoted by v_{it}. By controlling the CAVs within each area following the proposed optimal speed, we aim to minimize the TTC for the whole network considering energy consumption and travel delay.

2.3 Network Modeling

A novel ATM is proposed to model the network traffic. We use $\mathcal{I}_i^+$ to denote the set of downstream areas of area i. The traffic area density of area i at time $t+1$ equals the density of area i at time t plus the density change caused by in and outflows.

$$\rho_{\text{it}} = \rho_{i(t-1)} + \frac{T}{\mathbb{T}l_i}\left(q_{it} - \sum_{i' \in \mathcal{I}_i^+} U_{ii't}\right) \tag{1}$$

Similarly, we use $\mathcal{I}_i^-$ to denote the set of upstream areas of area i. The flow rate into area i at time t can be expressed as:

$$q_{it} = min\left(\sum_{i' \in \mathcal{I}_i^-} w_{ii'} S_{i't}\ , R_{it}\right) \tag{2}$$

$w_{ii'}$ is the proportion of flow from area i that flows into area i'. For a given i, $\sum_{i' \in \mathcal{I}_i^+} w_{ii'} = 1$. The value of $w_{ii'}$ for each given i' needs to be calibrated with real-world data. $\sum_{i' \in \mathcal{I}_i^-} S_{i't}$ is the maximum flow which can be supplied by upstream areas of area i under free flow conditions, at time t. S_{it} is the flow can be supplied by area i at time t:

$$S_{i't} = mi\,n\big(min(v_{i't}, v_{lim})\,\rho_{i'(t-1)}, Q_{Mi'}\big) \tag{3}$$

To track the number of vehicle flow from area i to area $i' \in \mathcal{I}_i^+$ at time t, we denote the variable $U_{ii't}$.

$$U_{ii't} = \begin{cases} w_{ii'} S_{i't}, if \displaystyle\sum_{i' \in \mathcal{I}_i^-} w_{ii'} S_{i't} < R_{it} \\ \dfrac{\sum_{i' \in \mathcal{I}_i^-} w_{ii'} S_{i't}}{R_{it}} \times w_{ii'} S_{i't}, if \displaystyle\sum_{i' \in \mathcal{I}_i^-} w_{ii'} S_{i't} \geq R_{it} \end{cases} \tag{4}$$

In addition, R_{it} is the maximum flow that can be received by area i under congested conditions, at the same time interval:

$$R_{it} = min\left(Q_{Mi}, \overline{\omega}\left(\rho_{jam} - \rho_{i(t-1)}\right)\right) \tag{5}$$

th this, vehicle conservation among different areas is modeled.

The objective of this study, TTC, is the summation of traffic energy consumption cost (i.e., e_{it}) and travel delay cost (i.e., d_{it}). The energy consumption is calculated with the theoretical models developed by Bottero et al., (2014),

$$e_{it} = \frac{T}{\mathbb{T}} q_{(i+1)t} * l_i F'(v_{it}) \tag{6}$$

where $F'(v_{it}) = F(v_{it})\left(1 + \varepsilon \frac{\mathbb{T}d_{it}}{T}\right)$ and $F(v_{it}) = \frac{W^* + Z\overline{v}_{it}^2}{\eta}$.

W^* denotes the resistance elements that are independent of speed. The W^* is associated with both the slope of the road section and the tire deformation. Z signifies the resistance elements that are contingent upon the square of the speed. It is associated with aerodynamics, tire deformation, pavement friction, and centrifugal forces. η, which represents a fixed performance coefficient, has been established at a value of 38% (Bottero et al., 2014). ε is a parameter dependent on the level of service (LOS) to account for acceleration and ε=0 if LOS A, ε=0.3 if LOS B-C, and ε=0.5 if LOS D-E.

The delay can be calculated as:

$$d_{i(t+1)} = \frac{T}{\mathbb{T}} q_{i(t+1)} \max\left(\frac{\rho_{i1} l_i + \sum_{t'=1}^{t} q_{it'} - Q_{Mi}(t-1)}{Q_{Mi}}, 0\right) \tag{7}$$

With this, TTC can be calculated as follows,

$$TTC \coloneqq \sum_{t=1}^{\mathbb{T}} \sum_{i=1}^{I} (\alpha e_{it} + \beta d_{it}) \tag{8}$$

where e_{it} and d_{it} are the energy consumption and travel delay for all vehicles traveling in area i in time interval t, and coefficients α and β are introduced to convert the energy consumption and time delay to cost.

2.4 Optimization Framework

To solve the proposed problem and find the optimal speed advisory in each area, an optimization-based method is adopted, and the problem is a mixed integer nonlinear programming model. The nonlinearity happened in both objective function (speed square) and constraints (nested min-max constraints). The problem will be solved by a commercial solver, Gurobi.

$$obj \coloneqq \min_{v} \sum_{t=1}^{\mathbb{T}} \sum_{i=1}^{I} (\alpha e_{it} + \beta d_{it}) \tag{9}$$

$$s.t.\ q_{i(t+1)} = min\left(\sum_{i' \in \mathcal{I}_i^-} w_{ii'} S_{i't}\ , R_{it}\right) \tag{10}$$

$$\rho_{i(t+1)} = \rho_{it} + \frac{T}{\mathbb{T}l_i}\left(q_{i(t+1)} - \sum_{i' \in \mathcal{I}_i^+} q_{i'(t+1)}\right) \tag{11}$$

$$S_{i't} = mi\,n(min(v_{i't}, v_{lim})\,\rho_{i't}, Q_{Mi'}) \tag{12}$$

$$R_{it} = min\left(Q_{Mi}, \overline{\omega}\left(\rho_{jam} - \rho_{it}\right)\right) \tag{13}$$

Chapter 3. Numerical Experiments

3.1 Toy Experiment

A simple toy experiment was conducted to illustrate the effectiveness of our proposed network modeling approach. This simulation experiment was implemented using Python and run on a PC equipped with an AMD Ryzen 7 5700G processor and 64.0 GB of RAM.

Table 3 shows the simulation settings. The simulation duration is 150 minutes. The toy experiment simulates the morning peak hour scenario, which means that during the simulation duration, individuals are commuting from suburban areas to the CBD for work/school, entailing that CAVs travel from the origin areas to the destination area.

Figure 2 displays the status of the areas at critical simulation intervals, before using the optimal speed advisory. It is observed that congestion, which begins to form and spread from the 2nd to the 40th minute, is generated. As the simulation progresses, several bottleneck areas become evident, moving from the outer to the inner areas. Notably, significant congestion develops in the downtown area at the 40th minute, aligning with both our expectations and previous experiences. This buildup of traffic is primarily due to the high volume of CAVs commuting from suburban origin areas to the downtown destination area, which mirrors typical urban rush hour patterns. The simulation reveals several bottleneck areas, where traffic flow transitions from the periphery towards the central zones, a common phenomenon as vehicles converge on high-demand downtown locations. The significant congestion observed in the downtown area by the 40th minute is anticipated based on both theoretical understanding and empirical observations of urban traffic dynamics. During peak rush hours, CBD experiences a surge in vehicle influx, leading to increased traffic density and slower speeds. The simulation's ability to replicate this pattern underscores the model's accuracy in reflecting real-world traffic behavior.

As the simulation continues, no new traffic enters the network after the 20th minute. In real-world terms, this could equate to the time when most commuters have already started their trip, significantly reducing the CAV entries into the urban network. The cessation of new traffic entering the network naturally leads to a gradual easing of congestion. Vehicles already within the network continue on their paths toward their destinations without the compounding effect of additional incoming traffic. This decrease in vehicle accumulation allows for more efficient use of available road space and facilitates smoother traffic flow. Over time, as vehicles reach their destinations, the density of cars on the road decreases. By the 120th minute, the simulation shows a dissipation of congestion, illustrating the network's return to a no-congested state. This outcome is a direct consequence of the strategic pause in new traffic entries, allowing the system to 'clear out' the existing congestion without the pressure of new vehicles adding to the burden.

Table 3. Simulation Settings

Simulation duration	150 minutes	**Jam density**	500 vehicle/km
Number of areas	20	**Free flow speed**	5 meter/second
# of origin areas	9	**Shockwave speed**	2 meter/second
Inflow rate (origin)	5 vehicle/minute	**Inflow duration**	20 minutes
# of dest. area	1		
Outflow rate (dest.)	10 vehicle/minute		

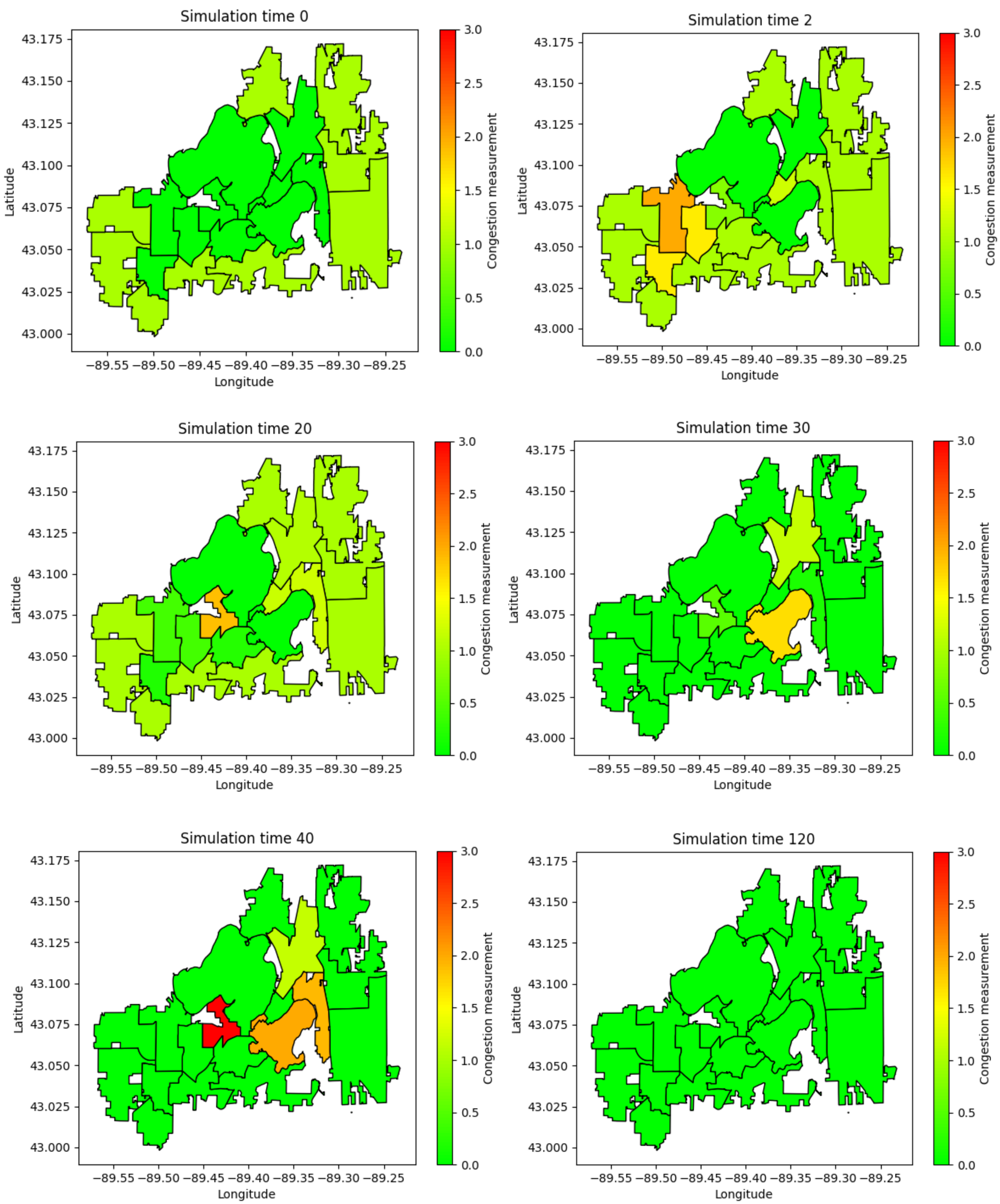

Figure 2. Simulation results before using the optimal speed advisory.

3.2 Toy Experiment with Optimal Speed Advisory

We implemented our proposed Optimal Speed Advisory (OSA) solution to mitigate traffic congestion within the same Python-based optimization model on our PC. To solve the model to optimality, we utilized the commercial solver Gurobi.

The effectiveness of this optimal speed advisory is evident in Figure 3, which shows area statuses at crucial simulation moments, keeping the same settings as our initial toy experiment. The sole distinction is that we will use the calculated OSA as a speed input for the CAVs in the simulation, ensuring that all CAVs within the network travel at the speed dictated by the OSA. The key difference observed between Figure 3 and Figure 2 is the absence of significant congestion during the simulation (like the 40th minute in the simulation before OSA), as traffic from outer areas flowed into the inner areas, illustrating the successful management of traffic transitioning from peripheral to central zones. In the simulation period, traffic density remained at acceptable levels across all areas, underscoring the efficiency and superior performance of our solution in mitigating traffic congestion. Throughout the duration of this refined simulation, traffic density maintained manageable levels across all regions, validating the efficacy and enhanced performance of our control strategy in alleviating congestion.

A detailed observation reveals that the most congested scenario emerged around the 20th minute; however, following this peak, congestion began to steadily dissipate, leading to a significant reduction in traffic density. By the 60th minute, the network had transitioned to a state of minimal congestion, a stark contrast to the situation without the control strategy, where congestion persisted until the 120th minute. Remarkably, with the OSA-based control strategy implemented, all traffic efficiently reached its destinations within just 60 minutes, effectively halving the time required in the initial experiment. This accelerated resolution of traffic congestion underscores the strategic advantage and operational efficiency introduced by the optimal speed advisory, showcasing a compelling case for its broader application in urban traffic management.

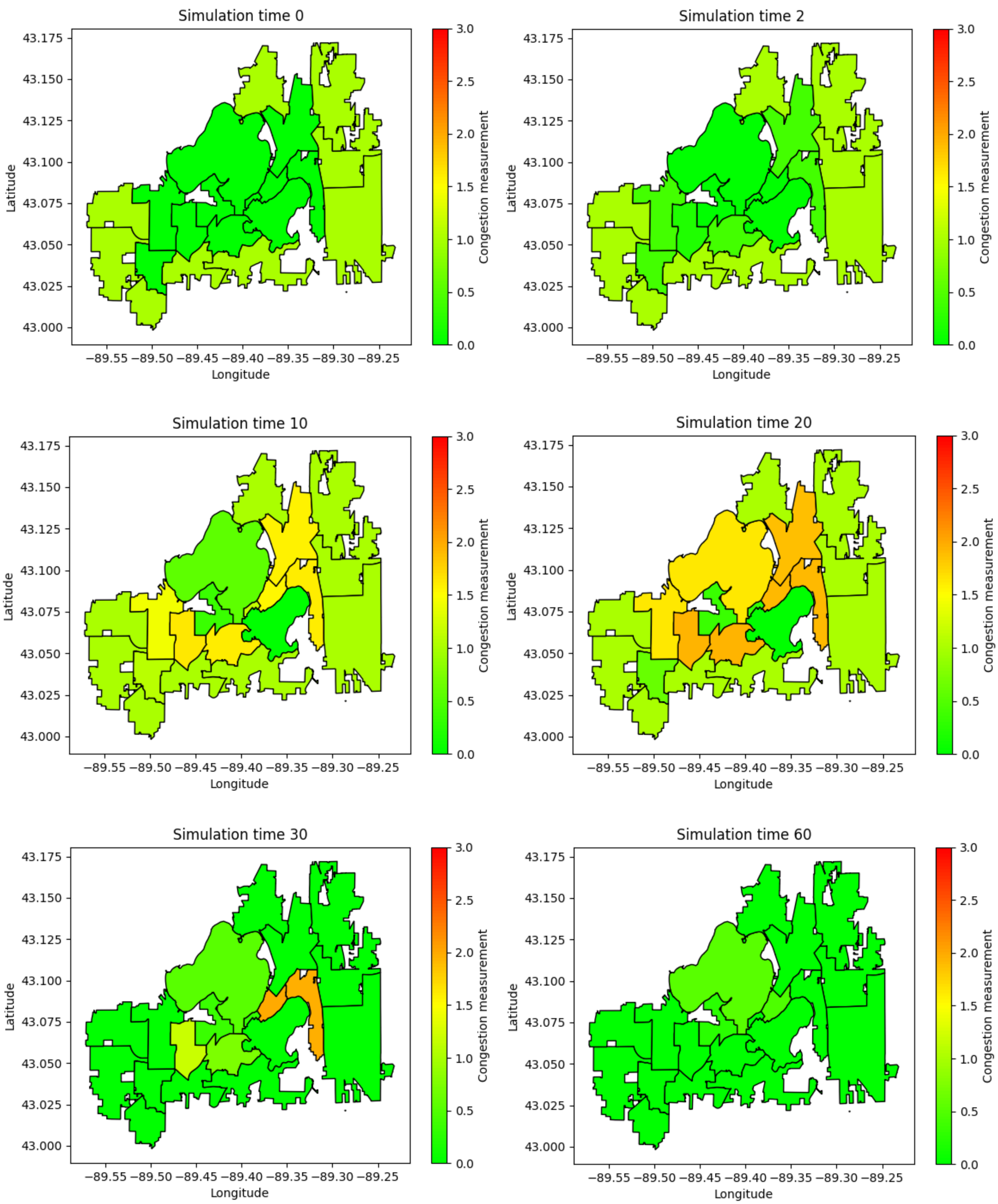

Figure 3. Simulation result after using the optimal speed advisory.

The data compiled in Table 4 offers a comprehensive qualitative comparison that underscores the significant enhancements enabled by our control strategy across a spectrum of critical metrics. These metrics not only cover aspects such as energy consumption and travel delay but also extend to congestion resolution time and specific congestion indicators, namely maximum and average traffic density within the simulation environment.

Specifically, for a 150-minute simulation, the proposed solution achieved a 30.1% reduction in overall energy consumption, a 23.7% decrease in total travel delay, a 50% reduction in total travel time, and a significant smoothing of traffic flow concerning maximum and average density in each area, suggesting a more evenly distributed traffic load and less pronounced peaks of congestion. These results highlight the exceptional efficacy of our proposed solution and point to the promising potential of these methods in enhancing system performance.

Table 4. Comparison between With and Without OSA

	With OSA	Without OSA
Energy Consumption	576.94 Gallons	825.02 Gallons
Travel Delay	5,008.0 seconds	6,560.5 seconds
Traffic Clear Time	60 seconds	120 seconds
Congestion Measurement	Max 2.32	Max 3.00
	Average 1.56	Average 1.87

Chapter 4. Conclusions

This study proposed an ATM based on MFD suitable for large-scale network applications and presented a macro-optimization control strategy that utilizes optimal speed advisories to modulate traffic flow across the network, thereby ensuring effective congestion management and enhanced energy efficiency. By employing the city of Madison as a case study, the research examines the optimal speed advisory solution. The deployment of our solution presents a highly effective strategy for mitigating traffic congestion, as demonstrated by the comprehensive comparison between simulations with and without the control strategy. Notably, the adoption of the strategy resulted in all traffic reaching its destination in half the time required by the scenario without the strategy, underscoring the strategy's effectiveness in optimizing traffic efficiency and reducing delays. The qualitative comparison further highlights the solution's capability to improve system performance across multiple dimensions, including a 30.1% reduction in energy consumption, a 23.7% decrease in total travel delay, and a notable improvement in congestion resolution, with traffic densities smoothed out to maintain maximum and average levels within acceptable bounds. This methodology demonstrates the potential for improving traffic management practices, highlighting a promising path forward for optimizing urban transportation systems.

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