



A macroscopic Game-Theoretic Model Predictive Control framework for emergency vehicle prioritization in urban traffic networks

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ABSTRACT

Efficient Emergency Vehicle (EV) prioritization in congested urban networks remains a critical challenge for smart city infrastructure, as traditional preemption methods often trigger secondary congestion and network instability. This paper proposes a decentralized, macroscopic Game-Theoretic Model Predictive Control (GTMP) framework designed to facilitate rapid EV movement while preserving overall traffic equilibrium. The core of the proposed architecture integrates a weighted non-cooperative game with a potential function structure within a receding-horizon Model Predictive Control (MPC) structure, allowing each intersection to act as an autonomous agent that strategically allocates green-time allocations among competing traffic phases. By assigning dynamic priority weights to EV-serving approaches, the controller proactively clears queues and minimizes stop-and-go behavior. The framework is validated using high-fidelity SUMO simulations initialized with real-world traffic data from Dublin, Ireland, across varying demand profiles, including a 50% flow increase to simulate heavy traffic saturation. Experimental results demonstrate that the GTMP framework significantly outperforms both Fixed-Time and Classical MPC strategies. Specifically, it achieves substantial reductions in Average Suffering Red-lights, Average Time Loss, and Average Stop Count, while markedly enhancing Average Speed for emergency vehicles. Notably, under heavy traffic conditions, GTMP maintains robust performance, reducing Average Waiting Time by over 20% in scenarios where standard MPC baselines experience severe congestion and degraded traffic performance. Furthermore, the framework demonstrates an adaptive capability to manage concurrent EV arrivals through strategic multi-player negotiations. Owing to its decentralized structure, the proposed approach shows promising scalability and robustness properties in the conducted simulation studies, making it suitable for large-scale, real-time urban traffic control applications.

1. Introduction

Urban transportation systems around the world are increasingly challenged by rising traffic demand and network congestion, which adversely affect travel time reliability, energy consumption, and environmental sustainability. Beyond these well-documented impacts, congestion poses critical safety and social risks by delaying response times of Emergency Vehicle (EV) category, including ambulances, fire trucks, and police units, whose timely arrival is often a matter of life and death (Yu et al., 2022; Hao et al., 2024; Sysoev et al., 2025). Despite their importance, conventional traffic signal control strategies, such as fixed-time plans, actuated control, and rule-based preemption,

often struggle to accommodate the dynamic and sporadic presence of EVs without inducing excessive disruption to surrounding traffic streams (Yu et al., 2022; Chen et al., 2024).

Achieving a balance between minimizing EV travel time and preserving overall network stability, therefore, necessitates advanced control methodologies capable of proactive, anticipatory decision-making under uncertainty. In recent years, Model Predictive Control (MPC) has emerged as a powerful framework for urban traffic management due to its ability to explicitly account for system dynamics, constraints, and future demand evolution (Ren et al., 2022; Menelaou et al., 2019). In parallel, game-theoretic approaches have gained increasing attention

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as an effective means of modeling strategic interactions and conflicting objectives among multiple traffic entities, providing a rigorous mathematical foundation for cooperative and competitive decision-making in decentralized traffic environments (Abdelghaffar et al., 2016; Abdelghaffar and Rakha, 2019). The integration of these two paradigms offers a promising avenue for addressing emergency-aware traffic signal control in complex urban networks.

In our recent work, an adaptive-robust traffic signal control framework based on Linear Matrix Inequalities (LMIs), disturbance feed-forward compensation, and CAV-aware adaptation was developed to improve network performance under uncertain traffic conditions (Abdi et al., 2026). While that study focused on robust queue regulation through feedback-based control synthesis, the present work investigates a fundamentally different paradigm by integrating MPC and game-theoretic decision-making for Emergency Vehicle (EV) prioritization in urban traffic networks.

1.1. EV priority and network safety dynamics

The rapid response of EVs, including police units, ambulances, and fire services, is a cornerstone of urban public safety, where even marginal reductions in travel time can significantly decrease fatality rates in critical incidents. However, the operational mode of these vehicles, characterized by the use of lights and sirens and the frequent bypassing of traffic signals, introduces profound safety risks. Empirical evidence indicates that police vehicles, for instance, are 1.8 times more likely to be involved in crashes when operating in emergency mode compared to normal transit, with factors such as intersection geometry and adverse weather further exacerbating these risks (Missikpode et al., 2018). Data mining approaches have revealed that fatal emergency crashes are often tied to complex interactions between risky driving attributes, such as speeding and lack of seatbelt usage during emergency responses, while nonfatal injuries are predominantly associated with angle collisions at urban intersections (Hossain et al., 2023). These findings underscore the inherent trade-off between the urgency of rescue missions and the safety of both first responders and civilian road users.

To mitigate these risks while maintaining response efficiency, the paradigm of traffic management has shifted toward connected and software-defined environments. A connected infrastructure (V2X) facilitates better interaction between vehicles, where specific connectivity configurations, such as Rear Vehicle Single-Connected (RCV), have been shown to effectively reduce lateral collision risks and speed fluctuations during emergency-induced lane changes (Lyu et al., 2024). Within this context, a vehicle headway of approximately 30 m has been identified as a critical threshold to balance safety requirements with traffic efficiency. Furthermore, the emergence of Software-Defined Traffic Light Preemption (SD-TLP) allows for a transition from localized, rigid preemption to global, knowledge-based routing. By integrating real-time traffic data from across the city, these frameworks can select optimal rescue routes and preemptively clear intersections, thereby shortening rescue times while minimizing the resulting disruption to the broader urban network (Bagheri et al., 2024).

Beyond centralized preemption, recent advancements have explored multi-agent cooperative control to optimize the dual objectives of safety and efficiency. Innovative frameworks utilizing Deep Reinforcement Learning (DRL) now integrate traffic state prediction with signal and speed modules to dynamically adapt both signal timing and vehicle velocities at intersections (G. Zhang et al., 2025). Such systems leverage multi-objective reward functions to minimize conflicts and waiting times, demonstrating superior performance as the penetration rate of Connected and Automated Vehicles (CAVs) increases. However, the reliability of these interventions often hinges on the stability of long-range communication. To address this, cross-scale frameworks have been proposed that couple communication network feedback with traffic control layers. By employing distance-to-delay backtracking

and barrier consensus control, these systems can proactively dissipate incipient traffic jams and eliminate stop-and-go waves caused by unpredictable human behaviors, potentially enhancing driving safety by over 50% even in mixed traffic environments (Wu et al., 2026). Despite these technological strides, the seamless prioritization of EVs within a decentralized, predictive horizon remains a complex challenge, particularly in ensuring that proactive congestion mitigation does not induce systemic instability.

1.2. Game-theoretic frameworks for decentralized traffic control

The management of urban traffic intersections has evolved from centralized, rigid timing plans toward decentralized and adaptive architectures that treat traffic phases or road segments as autonomous decision-making agents. Within this context, game theory has emerged as a rigorous mathematical framework for analyzing the interactive and often conflicting objectives of traffic participants (Ahmad and Al-Fagih, 2023). Recent advancements emphasize that game-theoretic models are not only capable of capturing microscopic vehicle interactions and macroscopic flows (Qin et al., 2024) but also resolving the social dilemmas inherent in mixed traffic, where competitive behaviors by human drivers can degrade system efficiency (Li et al., 2026).

A significant portion of decentralized control research leverages cooperative game theory, particularly the Nash Bargaining (NB) solution, to resolve competition for green time. However, the efficacy of these frameworks increasingly depends on human-machine cooperation strategies. Research has shown that driving styles, ranging from aggressive to conservative, significantly influence decision-making in mixed traffic; for instance, aggressive AV strategies can induce riskier human maneuvers, necessitating adaptive game-theoretic policies that foster trust and predictability (Zhang et al., 2025c). To address these uncertainties, trust-aware decision frameworks have been developed that utilize multi-vehicle coalition games to dynamically estimate human trust levels, thereby optimizing cooperative maneuvers during complex tasks like lane-changing and merging (Pan et al., 2026).

The application of game theory also extends to uncontrolled environments and vulnerable road user protection. At unsignalized slip lanes and crosswalks, non-cooperative simultaneous games, such as the Quantal Response Equilibrium (QRE), have proven superior to traditional Nash models in predicting the crossing intentions of pedestrians and yielding behaviors of motorists (Arafat et al., 2025; Amini et al., 2024). Beyond interaction modeling, the establishment of careful and competent reference driver models via reinforcement learning has become essential for safety assessment in high-stakes scenarios like highway merging, providing a benchmark for autonomous system performance (Wang et al., 2024).

To further enhance resilience, hybrid architectures now combine Multi-Agent Systems (MAS) with self-learning mechanisms. Integrated frameworks that couple DRL for signal control with speed planning modules for CAVs have demonstrated the ability to simultaneously optimize safety and throughput at isolated intersections (G. Zhang et al., 2025). Furthermore, to prevent network-wide failures, cross-scale collaboration frameworks now integrate communication constraints into traffic control, using multi-layer strategies to proactively dissipate congestion clusters before they escalate into safety hazards (Wu et al., 2026). Additionally, the incorporation of individual risk perception fields into Nash game structures has enabled more precise modeling of driver-automation shared steering, capturing the subtle adaptations at both control and planning levels (Guo et al., 2025). While these decentralized approaches offer high scalability, their extension to specifically prioritize EV navigation within predictive horizons while maintaining network equilibrium remains an area of active investigation.

In addition to game-theoretic approaches, a substantial body of literature has addressed decentralized control problems using cooperative distributed optimization frameworks. These methods typically aim to minimize a global objective through coordinated decision-making

among agents under shared constraints, often with provable convergence guarantees. For instance, distributed formation matching and constrained optimization strategies have been proposed for large-scale multi-agent systems (Wu et al., 2023), while other works have developed distributed algorithms for constrained optimization over time-varying communication graphs with convergence guarantees (Luan et al., 2023). More recent studies have also considered uncertainty-aware distributed optimization under unknown distributions (Wu et al., 2024), as well as fixed-time convergence schemes for distributed convex optimization (Chen et al., 2021). While these cooperative frameworks offer strong theoretical guarantees and systematic coordination mechanisms, their applicability in urban traffic signal control may be limited by the need for communication, coordination overhead, and global information exchange, particularly in large-scale networks.

1.3. MPC and interaction-aware planning

MPC has become a cornerstone in autonomous vehicle research due to its inherent ability to handle multi-variable constraints and optimize future system states. Beyond trajectory accuracy, recent safety-oriented frameworks have focused on predicting the safety impact of automated vehicles on vulnerable road users by analyzing reaction times and accident statistics. Recent in-depth investigations into autonomous vehicle (AV) crash causations have identified that system functions, driver behaviors, and kinematics, specifically factors like longitudinal acceleration and the activation of AEB/ACC, are critical predictors of injury severity (He et al., 2026). To enhance the predictive horizon of MPC, online adaptive learning approaches are now employed to forecast the microscopic behavior of multi-type traffic participants. These methods integrate Extended Kalman Filters (EKF) for real-time trajectory correction, ensuring that the MPC planner can adapt to evolving conditions in dynamic transportation hubs without intensive retraining (M. Li et al., 2025).

The integration of game theory into MPC frameworks has facilitated the development of interaction-aware motion planners that can navigate complex multi-agent environments. In mixed autonomy scenarios where human-driven vehicles (HDVs) and CAVs coexist, a significant challenge involves predicting and mitigating the impact of aggressive human behaviors, such as sudden cut-in lane changes near signalized intersections. Cyber-physical system (CPS) perspectives suggest that two-stage methods, combining meso-scale decision-making with micro-scale safety control, can safeguard the right-of-way for CAVs and optimize traffic efficiency despite rule-violating maneuvers by human drivers (Wang et al., 2025). Furthermore, two-layer architectures have been proposed where the upper layer manages coalitional formation to improve computational efficiency, while the lower layer employs Stackelberg game-based frameworks and data-enabled predictive control to enhance robustness against human uncertainty during multi-vehicle interactions (Chen et al., 2025).

Advanced motion planning also necessitates learning the underlying preferences of other road users. End-to-end trainable architectures that hybridize neural networks with game-theoretic reasoning have been designed to reveal agent preferences from past joint trajectories and map them to local Nash equilibria. Such models allow for the prediction of interaction-aware future trajectories in merging scenarios, ensuring that downstream decision-making remains tractable and sound (Geiger and Strathle, 2021). For emergency scenarios where motion stability is critical, specialized frameworks utilize collision-free area calculations and time-varying Nonlinear Model Predictive Control (NMPC) to select safe terminal states and generate feasible avoidance trajectories (Gong et al., 2025). Moreover, the paradigm of intelligent defensive driving has been introduced to upgrade standard planners by integrating formalized expert knowledge and safety triggers, allowing AVs to anticipate potential risks in long-tail high-uncertainty scenarios (Zhang et al., 2026).

For freeway traffic management, hierarchical schemes often couple macroscopic PDE-based flow models with microscopic ODE-based platoon dynamics. In these multi-scale frameworks, high-level MPCs generate reference values for platoon velocity and length based on event-triggered logic, which are then tracked by medium-level distributed MPC and low-level robust integral sliding mode controllers to compensate for nominal model mismatches and improve fuel consumption (Ferrara et al., 2022). In the domain of bottleneck management, such as ramp merging and uncontrolled intersections, decentralized human-like control strategies have been developed using stochastic potential games. These frameworks characterize the uncertainty of human actions and minimize the accumulated cost of potential functions over a time horizon using MPC. Distributed algorithms are frequently employed to solve these optimization problems in parallel, thereby reducing the computational burden while enabling CAVs to take more reasonable actions compared to conservative driving strategies (Jing et al., 2025).

Similarly, dynamic bargaining game theory has been applied to stochastic distributed MPC (SDMPC) for ramp metering. By fusing fixed detector measurements with Connected Vehicle (CV) data via adaptive Kalman filters, these controllers negotiate local optimization problems based on expected costs and constraints, outperforming deterministic models in terms of equity and effectiveness (Heshami and Kattan, 2021). Recent research has also extended MPC to manage integrated traffic assignment and signal control (CAC) for mixed networks. For specialized environments like freeway tunnels, variable speed limit (VSL) control strategies based on model-based reinforcement learning (MBRL) have been developed. These systems incorporate safety perception through real-time crash risk prediction, using safety-trigger mechanisms to reduce frequent speed changes and significantly enhance both safety and efficiency (Jin et al., 2024).

For dense traffic scenarios, Branch MPC (BMPC) has been introduced to account for the uncertain equilibrium strategies, such as Nash or Stackelberg, adopted by surrounding vehicles. By combining search-based behavior planning with matrix games for gap selection, BMPC frameworks exploit tree structures to enhance numerical efficiency during automated lane merging (L. Zhang et al., 2024). The challenge of human-machine shared control vehicles (HSCVs) further complicates interactive control. Frameworks that integrate brain emotional learning models with distributed MPC (DMPC) allow for the dynamic allocation of control authority between the driver and the automation system based on driving safety fields. These methods enable safe interaction with surrounding vehicles by stopping dangerous human operations while considering personalized driving styles (Zhou et al., 2024).

In the context of vehicle platoons, systematic frameworks for cooperative obstacle avoidance (OA) utilize centralized decision-making to determine overtaking maneuvers, while distributed lateral controllers track reference trajectories through linear time-varying MPC (LTV-MPC). Tailored iterative control logic is often added to improve the accuracy of these LTV-MPC algorithms in varying scenarios (Gong et al., 2023). Furthermore, generalized potential games have been proposed to model shared collision avoidance constraints among multiple road users, where the resulting optimal control problems are solved online using augmented Lagrangian methods (Evens et al., 2022). Finally, addressing the specific oscillations caused by smoother CAV trajectories at signalized intersections, decentralized lane-change-aware trajectory optimization models have been developed. By linearizing complex nonlinear constraints related to car-following and lane-changing, these models can be solved efficiently to improve travel time, safety, and fuel consumption, even when the market penetration of CAVs is low (Yao and Li, 2021).

1.4. Mixed traffic dynamics and cooperative maneuvers

The integration of CAVs into existing road networks introduces complex interaction dynamics, as these systems must coexist with Human-Driven Vehicles (HDVs) for the foreseeable future. A fundamental challenge in this mixed environment is the resolution of social dilemmas,

where AVs must balance cooperative maneuvers against competitive human behaviors. Recent evolutionary game-theoretic (EGT) models, calibrated via Social Value Orientation (SVO) metrics, suggest that AV policies with moderate egoism and opponent-aware sociality are more evolutionarily stable, achieving population-level dominance while mitigating the overall social dilemma in mixed flows (Li et al., 2026). Beyond local interactions, management of bidirectional capacity and tidal flows has evolved toward lane-free paradigms and dynamic lane reversal to improve road utilization (Malekzadeh et al., 2025).

Lane-changing maneuvers represent one of the most significant sources of conflict. To address this, trust-aware game-theoretic frameworks (e.g., TGLD) have been developed to model interactions based on the estimated trust levels of human drivers. By dynamically estimating an HDV's trust during interactions, AVs can select cooperative maneuvers that minimize disruption to surrounding vehicles and enhance the predictability of their own behavior (Pan et al., 2026). From a cyber-physical system (CPS) perspective, this requires multi-scale strategies where micro-scale algorithms ensure driving safety while meso-scale decision-making suppresses traffic efficiency degradation caused by aggressive human cut-ins (Wang et al., 2025; Zhu et al., 2023).

The complexity of these interactions is further amplified at road bottlenecks such as freeway continuous merging areas. Integrated coordinated control frameworks now utilize bi-level programming to manage both traffic risks (e.g., crash and congestion risk) and energy consumption by coordinating Variable Speed Limit (VSL) and Ramp Metering (RM) strategies (W. Zhang et al., 2025). To validate the effectiveness of these maneuvers, careful and competent reference driver models (e.g., CCMD2) are increasingly used as benchmarks. These models, developed through interpretable reinforcement learning, ensure that AVs achieve safety performance levels that exceed those of expert human drivers in challenging highway merging scenarios (Wang et al., 2024).

A key innovation in addressing mixed autonomy is the development of cross-scale collaboration frameworks (e.g., CNC-CM). By integrating traffic control with communication networks, these systems can utilize micro-level barrier consensus to restrain disruptive human lane-changing and macro-level delay-corrected cruising control to eliminate stop-and-go waves (Wu et al., 2026). Such proactive congestion mitigation has been shown to enhance driving safety by over 54% by dissipating incipient traffic jams before they escalate into safety hazards (Wu et al., 2026).

Furthermore, environmental factors and infrastructure types dictate mixed traffic dynamics. In adverse weather, cellular automata models combined with game theory have revealed that increasing CAV penetration significantly improves traffic capacity (Gong et al., 2022). Cooperative route guidance utilizing macroscopic fundamental diagrams (MFD) and Stackelberg-evolutionary games can also optimize network-wide flow updates (Qian et al., 2025). At unsignalized intersections, hierarchical strategies involving strategy bargaining seek Pareto-optimal crossing orders to improve comfort and safety (Wang et al., 2021; Jing et al., 2024). Finally, lane-change-aware trajectory optimization models are essential to address "cut-in incentives", allowing CAVs to proactively restrain discretionary lane changes by human drivers while preserving the benefits of traffic smoothing across signalized intersection approaches (Yao and Li, 2021).

1.5. Advanced learning, energy efficiency, and multi-agent coordination

The final frontier in decentralized traffic management involves the integration of advanced learning algorithms with energy-conscious coordination mechanisms to address the multi-dimensional challenges of modern urban networks. Multi-agent reinforcement learning (MARL) has emerged as a particularly promising tool in this regard, offering an adaptive and decentralized alternative to traditional rule-based or optimization-based methods. Recent multi-objective deep reinforcement learning (DRL) approaches have expanded this paradigm by

concurrently optimizing safety, efficiency, and decarbonization at intersections. By utilizing Dueling Double Deep Q Network (D3QN) frameworks, these systems have demonstrated the ability to reduce carbon emissions by 4% while simultaneously decreasing traffic conflicts, highlighting the necessary trade-offs between throughput and environmental sustainability (G. Zhang et al., 2024).

In the context of unsignalized intersections, game-theory-inspired algorithms are being developed to replace traditional control systems. Beyond standard vehicle-to-vehicle negotiation, modern frameworks now incorporate the complex dynamics of human-pedestrian interaction. For instance, deep maximum entropy inverse reinforcement learning (DMIRL) combined with game theory allows for the development of reliable simulation models that capture pedestrian crossing behaviors at unsignalized crosswalks, ensuring that autonomous agents respect the rights of vulnerable road users (VRUs) in uncontrolled environments (W. Li et al., 2025). Furthermore, two-step DRL frameworks have been proposed to specifically protect VRUs by dynamically switching between traditional signal phases and modified versions that implement protected/prohibited right-turn (PPRT) strategies based on real-time pedestrian presence detected through CV data (Ren et al., 2025).

The coordination of large-scale networks also necessitates the integration of traffic assignment with signal control (CAC). To move beyond rigid dynamics, innovative DRL-based cooperative control frameworks have been constructed that unify signal timing and speed modules. By merging traffic state prediction models with current observational data, these agents can learn optimal signal policies and then feed this data into speed planning modules to optimize CAV velocities. Such co-optimization not only stabilizes driving volatility but also significantly amplifies traffic efficiency as CAV penetration rates increase (G. Zhang et al., 2025). Similarly, for urban expressways, multi-agent deep reinforcement learning (MADRL) combined with potential games has proven effective in balancing equity among multiple on-ramps while improving system-wide throughput (Lin et al., 2025).

Beyond pure traffic flow, the safety of complex socio-technical systems has become a critical research priority. Collaborative safety mechanisms based on game theory are now being used to model the interference between human decisions and automated systems. These frameworks, such as personalized human-machine shared driving (HMSD) systems, utilize obstacle avoidance path planning tailored to individual driving styles. By quantifying styles through clustering, these systems can provide customized assistance that reduces driving load and enhances trust, especially for cautious drivers, while maintaining vehicle stability through reliable interaction models (Pan and Zheng, 2025).

The scalability of these intelligent systems is further supported by advancements in cross-scale traffic-communication control. By establishing a feedback response mechanism between the traffic layer and the communication network, researchers have developed algorithms to ensure timely and reliable command delivery even under unstable long-range communication conditions. This multi-layer approach proactively dissipates incipient traffic jams, reducing crash risk by over 54%, before they escalate into large-scale hazards in mixed traffic environments (Wu et al., 2026).

Finally, the transition toward fully autonomous networks is supported by two-mode agent architectures that utilize both independent Q-learning and cooperative game theory. These hybrid systems allow intersection agents to operate independently under normal conditions but switch to cooperative modes to prevent network saturation during periods of high congestion (Abdoos, 2020). Such collaborative strategies are essential for ensuring that localized optimizations do not lead to systemic failures, ultimately providing a robust foundation for the next generation of intelligent transportation systems.

1.6. Transit signal priority, phase transition mechanisms, and performance evaluation

Transit Signal Priority (TSP) has been widely studied as an effective mechanism for improving the operational efficiency of public transport systems at signalized intersections. Recent advances have moved beyond vehicle-based prioritization toward more refined and adaptive formulations. For instance, [Lee and Wang \(2022\)](#) propose a person-based adaptive signal control framework with cooperative TSP, where both infrastructure and in-vehicle systems interact in real time to reduce passenger delays. Similarly, [Yang and Fan \(2023\)](#) investigate TSP strategies in CV environments and demonstrate that optimized priority schemes can significantly reduce transit delays while mitigating adverse impacts on other traffic streams. In addition, the integration of TSP within decentralized control frameworks has been explored in [Xu et al. \(2022\)](#), where a max-pressure controller is extended to incorporate transit priority while preserving network stability. Conditional and data-driven TSP strategies have also been developed, such as the CV-based approach in [Cvijovic et al. \(2022\)](#), which dynamically triggers priority requests based on vehicle states and passenger-related criteria. More recent learning-based approaches further enhance adaptability by incorporating passenger occupancy and real-time system feedback into the prioritization process ([Yang and Fan, 2025](#)).

Alongside prioritization strategies, the design of signal transition mechanisms and phase-switching dynamics plays a critical role in determining overall traffic performance. Traditional signal control formulations often neglect the impact of phase-switching losses and intergreen periods, which can significantly affect system efficiency under high demand. To address this limitation, recent studies have explicitly incorporated phase-transition effects into control design. For example, [Zoabi et al. \(2025\)](#) propose a dynamic max-pressure formulation that accounts for phase-switching gaps and adaptive phase durations, improving robustness under varying traffic conditions. Similarly, [Sun et al. \(2025\)](#) introduce enhanced phase-switching models that incorporate switching losses and dynamic green-time adjustments, demonstrating notable reductions in delay and queue lengths. These works highlight the importance of accurately modeling transition dynamics to ensure realistic and efficient signal control policies, particularly in decentralized and adaptive frameworks.

In parallel, a substantial body of research has focused on the estimation and evaluation of traffic performance metrics, which are essential for both control design and benchmarking. Queue length and travel delay are among the most widely used indicators of intersection performance. For instance, [Abutahoun et al. \(2025\)](#) develop a computationally efficient framework for queue length estimation using discrete-event simulation, enabling accurate representation of stochastic traffic dynamics. Similarly, [Almutairi et al. \(2024\)](#) propose a network-level delay estimation methodology based on real-time traffic measurements, providing a scalable approach for evaluating control strategies. Furthermore, advanced traffic signal performance measures (TSPMs) have been introduced in [Dobrota et al. \(2023\)](#) to better capture capacity utilization and operational efficiency under varying traffic conditions. These studies underscore the importance of reliable performance metrics in assessing the effectiveness of modern traffic signal control approaches.

1.7. Research gaps and main contributions

The extensive body of literature reviewed in the preceding sections demonstrates significant progress in decentralized traffic control, game-theoretic decision-making, MPC and mixed traffic coordination. Nevertheless, a careful examination of these studies reveals several critical gaps that motivate the present work.

First, although game-theoretic approaches have been widely adopted for traffic signal control, the majority of existing studies formulate games either at the level of individual vehicles, signal phases,

or traffic movements. Vehicle-level games primarily target microscopic interaction scenarios such as lane changing, ramp merging, and gap acceptance, while phase-based games focus on allocating green time among competing movements at an intersection. In contrast, the strategic role of urban road segments or links as macroscopic decision-making entities remains largely unexplored. As a result, current game-theoretic formulations often struggle to bridge the gap between high-level network flow dynamics and real-time signal control decisions in dense urban environments.

Second, while MPC has proven highly effective for both traffic signal optimization and interaction-aware motion planning, its integration with game theory in urban traffic networks remains fragmented. Existing MPC-based traffic control schemes typically assume cooperative or centralized optimization structures, whereas game-theoretic MPC formulations are predominantly confined to microscopic vehicle interactions. Consequently, there is a lack of unified frameworks that combine macroscopic traffic prediction with strategic decision-making among competing traffic entities in a decentralized manner.

Third, EV prioritization has been extensively studied, yet most existing approaches rely on rule-based preemption, heuristic green extensions, or centralized priority mechanisms. These methods often treat EVs as exogenous disturbances rather than endogenous agents that alter the strategic landscape of the traffic network. As a result, the presence of EVs is rarely embedded directly into the optimization objectives or payoff structures of decentralized traffic controllers, limiting the ability of existing systems to balance emergency response efficiency with network-wide stability.

Fourth, despite increasing interest in decentralized and scalable traffic control architectures, many advanced game-theoretic and MPC-based solutions still depend on centralized coordination, global state information, or corridor-level optimization. Such requirements reduce practical deployability in large urban networks, where communication constraints and computational scalability are critical concerns. Fully decentralized frameworks that rely solely on local macroscopic information at each intersection remain relatively underrepresented in the literature.

Finally, a significant portion of existing studies validate their methods using synthetic demand profiles or simplified benchmark networks. While these evaluations provide valuable insights, they may not fully capture the complexity and stochasticity of real-world urban traffic systems, particularly under emergency scenarios.

Motivated by these gaps, this paper proposes a decentralized macroscopic game-theoretic MPC framework for urban traffic signal control with explicit consideration of EVs. In the proposed formulation, each incoming urban link is modeled as a strategic player that competes or cooperates for green time based on macroscopic traffic states and the presence of EVs. The resulting game is embedded within a predictive control structure that optimizes signal timings over a finite horizon, enabling proactive and anticipatory decision-making. The control architecture is fully decentralized, as each intersection operates solely based on locally observable traffic conditions without reliance on a central coordinator. Furthermore, the effectiveness of the proposed approach is evaluated using real-world traffic data from Dublin city, ensuring practical relevance and realism. By explicitly minimizing key performance indicators for EVs, including average travel time, fuel consumption, time loss, waiting time, and stop count, this work advances the state of the art in emergency-aware urban traffic control while maintaining efficient network operation and scalability.

The rest of the paper is structured as follows: Section 2 provides a detailed description of the macroscopic modeling approach used to represent urban traffic dynamics. Section 3 introduces the integration of MPC with game-theoretic principles, providing a detailed formulation of the proposed control framework. Section 4 presents the experimental setup used to evaluate the proposed control framework, using real-world traffic data from Dublin, Ireland. Section 5 discusses the results of the experiments, providing a comprehensive analysis of the effectiveness of the proposed framework, and Section 6 concludes the paper with a summary of the contributions and findings, followed by suggestions for future research directions.

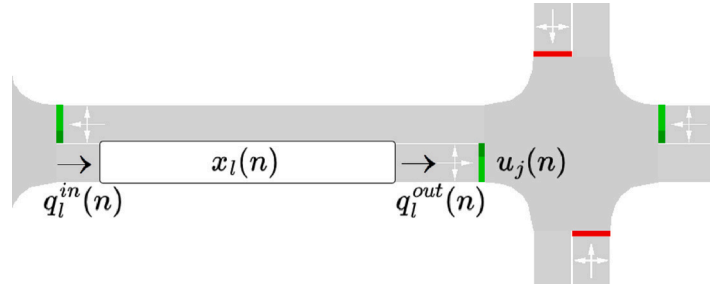


Fig. 1. Illustration of the variables to model traffic flow at an intersection.

2. Macroscopic modeling of urban traffic dynamics

This section presents a macroscopic representation of urban traffic dynamics tailored for predictive and decentralized signal control. The adopted modeling abstraction focuses on aggregated vehicle accumulations at intersection approaches, which enables scalable control design while preserving the essential dynamics required for network-level coordination and EV prioritization. Rather than tracking individual vehicle trajectories, the model describes traffic evolution through flow conservation principles evaluated at signal phase transition events.

Consider a signalized intersection with multiple incoming streets. Let $x_l(n)$ denote the number of vehicles accumulated on incoming street l at the macroscopic decision index n . The index n corresponds to signal phase transition events, such as green-to-red or red-to-green switches, rather than uniform time sampling instants. This event-driven formulation allows signal timing decisions to be updated only when meaningful control actions occur. It is important to note that the macroscopic state $x_l(n)$, representing vehicle accumulation, is not necessarily measured directly in practice, but can be reliably estimated using available sensing and data sources. In particular, loop detectors, traffic cameras, and CV technologies can provide real-time measurements of flow, speed, and occupancy, which can be used to infer traffic density and accumulation levels. Furthermore, model-based estimation techniques, such as observer-based methods or filtering approaches, can exploit the flow conservation structure in Eq. (1) to reconstruct the state from measured inflow and outflow data. This makes the proposed framework compatible with existing traffic sensing infrastructures. In addition, due to the receding-horizon feedback nature of MPC, the control strategy remains robust to moderate estimation errors, as the optimization is repeatedly updated using the latest available measurements.

The evolution of traffic accumulation on each street is governed by a conservation relationship that accounts for departing traffic during green phases and incoming demand from upstream links. Accordingly, the state update equation for street l is given by:

$$x_l(n+1) = x_l(n) - q_l^{\text{out}}(n)u_j(n) + q_l^{\text{in}}(n), \quad (1)$$

where $q_l^{\text{in}}(n)$ and $q_l^{\text{out}}(n)$ represent the inflow and outflow rates associated with street l , respectively. The control variable $u_j(n)$ denotes the effective green duration allocated to signal phase j that serves street l during event n , including clearance intervals. It is notable that $q_l^{\text{out}}(n)$ represents the effective discharge flow, which is obtained from real-time measurements and reflects both saturation conditions and signal actuation. An illustration of the parameters in a street connected to an intersection, related to Eq. (1), is shown in Fig. 1.

A complete signal cycle is realized over two consecutive events. Although the duration of individual green phases may vary, the total cycle duration is fixed and denoted by cycle time, CT . As a result, the allocated green times satisfy:

$$\sum_{j=1}^M u_j(n) = CT, \quad (2)$$

where M denotes the number of independent signalized movements at the intersection.

By stacking the traffic accumulations of all incoming streets into a single state vector:

$$X(n) = [x_1(n) \quad \dots \quad x_N(n)]^T, \quad (3)$$

the macroscopic traffic dynamics can be expressed in the compact form as shown in Eq. (4), that they are governed by the principle of flow conservation, whereby the number of vehicles on each incoming link evolves as the difference between inflow and outflow over each decision interval. This modeling approach is consistent with the well-established store-and-forward framework for urban traffic networks (Tettamanti et al., 2013), which provides a tractable and scalable representation of traffic evolution at the network level.

$$X(n+1) = AX(n) + B(n)U(n) + q^{\text{in}}(n), \quad (4)$$

where $U(n) = [u_1(n), \dots, u_M(n)]^T$ collects the green time allocations and $q^{\text{in}}(n)$ denotes the vector of incoming demands.

The state transition matrix is given by $A = I_N$, reflecting the accumulation-based nature of the model. The input matrix $B(n) \in \mathbb{R}^{N \times M}$ captures the mapping between signal phases and incoming streets, with elements defined as:

$$[B(n)]_{lj} = \begin{cases} -q_l^{\text{out}}(n), & \text{if phase } j \text{ discharges street } l, \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

The macroscopic traffic model is subject to a set of physical and operational constraints. Vehicle accumulations are bounded by street storage capacities, while green durations are limited by operational considerations. These constraints are expressed as:

$$0 \leq x_l(n) \leq x_{\text{max}}, \quad (6)$$

$$u_{\text{min}} \leq u_j(n) \leq u_{\text{max}}, \quad (7)$$

$$\Delta u_{\text{min}} \leq \Delta u_j(n) \leq \Delta u_{\text{max}}. \quad (8)$$

The constraints on the control increments $\Delta u_j(n)$ are introduced to prevent abrupt variations in green-time allocations between consecutive signal cycles. This smoothness requirement reflects practical operational considerations and improves driver expectancy and safety. In particular, when no EV is detected, the controller is discouraged from producing sudden and aggressive re-allocations of green time, leading instead to gradual and predictable adaptations. In emergency scenarios, these constraints still allow sufficient flexibility for prioritization, while avoiding disruptive signal behavior.

In this control architecture, explicit hard boundaries on the maximum link storage capacities in Eq. (6) are deliberately relaxed within the optimization layer to avoid infeasibility under severe traffic demand surges or near-saturation conditions. Instead, potential boundary violations are incorporated into the objective function through heavily penalized penalty terms. According to the constrained MPC framework established by Mayne et al. (2000) and Rawlings et al. (2020), this formulation is equivalent to a soft-constrained MPC scheme employing slack-like variables. The resulting optimization structure improves the practical solvability of the local control problem at each receding-horizon step and reduces the likelihood of optimization failure under uncertain and highly congested traffic conditions.

Table 1

Summary of variables, descriptions and units used in the proposed framework.

Variable	Description	Unit	Variable	Description	Unit
$x_l(n)$	Vehicle accumulation on incoming street l at decision event n	vehicles	$q_l^{\text{in}}(n)$	Inflow rate entering street l	vehicles/s
$q_l^{\text{out}}(n)$	Effective discharge (outflow) rate from street l	vehicles/s	$u_j(n)$	Effective green time allocated to signal phase j	s
CT	Signal cycle time	s	M	Number of signal phases	–
N	Number of incoming streets (state dimension)	–	$X(n)$	State vector of vehicle accumulations	vehicles
$U(n)$	Control input vector (green time allocations)	s	$B(n)$	Input (discharge) matrix mapping phases to streets	–
x_{max}	Maximum storage capacity of a link	vehicles	$u_{\text{min}}, u_{\text{max}}$	Minimum and maximum allowable green times	s
$\Delta u_{\text{min}}, \Delta u_{\text{max}}$	Bounds on variation of green times	s	N_p	Prediction horizon length	cycles
N_c	Control horizon length	cycles	$X_{k n}$	Predicted state at step k given information at n	vehicles
$U_{k n}$	Predicted control input at step k	s	$\mathbf{X}$	Stacked predicted state vector over the horizon	vehicles
$\mathbf{U}$	Stacked control vector over the horizon	s	$\mathcal{A}, \mathcal{B}$	Prediction matrices in MPC formulation	–
$q^{\text{in}}(n)$	Vector of incoming traffic demands	vehicles/s	$\mathbf{q}^{\text{in}}$	Stacked inflow vector over prediction horizon	vehicles/s
Q, R	Weighting matrices in MPC cost function	–	X^{ref}	Reference state (desired accumulation level)	vehicles
ρ	Global EV priority weighting parameter	–	$E_{k n}$	EV-related performance vector	vehicles
S_{EV}	Selection matrix for EV-related states	–	W_{EV}	Weighting matrix for EV prioritization	–
α_l	Weight on queue length for player l	–	β_l	Weight on control effort for player l	–
ϕ_l	EV priority weight for player l	–	$\delta_l^{\text{EV}}(n)$	Indicator of EV presence on street l	binary
Γ	Phase-to-street mapping matrix	–	γ_{ij}	Element of mapping matrix (phase-street relation)	–
J_l	Cost function of player l	–	Φ	Potential (aggregate) cost function	–

At the network level, intersections operate in a decentralized fashion, with each controller computing its own signal timing decisions based solely on local measurements. Nevertheless, macroscopic updates are synchronized at the end of each cycle of duration CT , ensuring consistent state measurements and control execution across the network. This decentralized architecture significantly enhances scalability, as the computational complexity grows linearly with the number of controlled intersections and no global traffic state or centralized coordination is required. As a result, the proposed framework can be readily deployed over large-scale urban networks while supporting real-time implementation and robust traffic-operational performance under increasing traffic demand and emergency events.

Although the proposed framework adopts a fully decentralized structure with no explicit communication among neighboring intersections, coordination across the network emerges implicitly through traffic flow propagation and state coupling. Specifically, the inflow term $q_l^{\text{in}}(n)$ in Eq. (1) captures the effect of upstream signal decisions on downstream intersections. When an upstream intersection releases a vehicle platoon, the downstream intersection observes this as an increase in incoming flow in subsequent decision steps. In the presence of an EV, this increase in inflow is coupled with the activation of EV-related priority weights in the local cost function, leading to adaptive green-time allocation that favors the approaching EV. As a result, a form of corridor-level coordination naturally arises without requiring explicit synchronization or information exchange between controllers. This implicit coordination mechanism enables scalable deployment while still supporting progressive EV movement across multiple intersections.

For clarity and ease of reference, Table 1 summarizes all key variables used throughout the paper, along with their physical interpretations and units.

3. Predictive and game-theoretic signal control framework

This section establishes the methodological link between the predictive control framework and the strategic interactions among competing traffic streams. First, a constrained MPC formulation is introduced to compute optimal green-time allocations over a finite horizon while explicitly accounting for macroscopic traffic dynamics and operational constraints. Subsequently, a game-theoretic layer is embedded within the MPC structure to capture the decentralized and competitive nature of incoming approaches at signalized intersections, with particular emphasis on EV prioritization. This integrated formulation enables predictive, smooth and strategically consistent signal control decisions.

3.1. MPC formulation for urban traffic signals

Regarding Eq. (4), consider an MPC prediction horizon of length N_p . Let n denote the current signal decision event. The predicted state and input sequences over the horizon are defined for $k = 0, \dots, N_p - 1$ as:

$$X_{k|n} \triangleq X(n+k), \quad U_{k|n} \triangleq U(n+k), \quad (9)$$

where, by definition, $X_{0|n} \triangleq X(n)$ represents the measured macroscopic state at the current decision event. The stacked prediction for the state trajectory over the horizon can be written in compact form. To this end, define the stacked state and input vectors as:

$$\mathbf{X} \triangleq \begin{bmatrix} X_{1|n} \\ X_{2|n} \\ \vdots \\ X_{N_p|n} \end{bmatrix} \in \mathbb{R}^{N \cdot N_p}, \quad \mathbf{U} \triangleq \begin{bmatrix} U_{0|n} \\ U_{1|n} \\ \vdots \\ U_{N_p-1|n} \end{bmatrix} \in \mathbb{R}^{M \cdot N_p}, \quad (10)$$

where N denotes the dimension of the macroscopic state vector (e.g., the number of controlled incoming links or accumulations), and M denotes the number of control inputs (e.g., green time allocations or signal phases) at each decision event. The control horizon is denoted by N_c , which specifies the number of future control moves that are explicitly optimized within the MPC framework. In this work, a full-degree-of-freedom configuration is considered, i.e., $N_c = N_p$, meaning that each prediction step has an independent control variable. This removes any input blocking structure and allows full flexibility in green-time allocation over the prediction horizon.

The stacked vector of predicted incoming demands and the block prediction matrices $\mathcal{A} \in \mathbb{R}^{(N \cdot N_p) \times N}$ and $\mathcal{B} \in \mathbb{R}^{(N \cdot N_p) \times (M \cdot N_p)}$, are defined as follows.

$$\mathbf{q}^{\text{in}} \triangleq \begin{bmatrix} q^{\text{in}}(n) \\ q^{\text{in}}(n+1) \\ \vdots \\ q^{\text{in}}(n+N_p-1) \end{bmatrix}, \quad \mathcal{A} \triangleq \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^{N_p} \end{bmatrix}, \quad (11)$$

$$\mathcal{B} \triangleq \begin{bmatrix} B(n) & 0 & \dots & 0 \\ AB(n) & B(n+1) & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N_p-1}B(n) & A^{N_p-2}B(n+1) & \dots & B(n+N_p-1) \end{bmatrix} \quad (12)$$

Here, A denotes the macroscopic state transition matrix introduced in (4), while $B(\cdot)$ represents the (possibly time-varying) discharge or control effectiveness matrix, which depends on local traffic conditions such as saturation flows and turning ratios. The block-lower-triangular structure of $\mathcal{B}$ captures the cumulative effect of current and future control actions on the predicted traffic states over the MPC horizon.

With these definitions, the predicted state evolution over the horizon can be expressed compactly as:

$$\mathbf{X} = \mathcal{A} \mathbf{X}(n) + \mathcal{B} \mathbf{U} + \mathbf{Q}^{\text{in}}, \quad (13)$$

where $\mathbf{Q}^{\text{in}} \in \mathbb{R}^{N \times N_p}$ denotes the appropriately shifted stacked inflow vector constructed from $\mathbf{q}^{\text{in}}$. Since the discharge matrix $B(\cdot)$ depends on local traffic conditions and may vary across decision events, the matrix B is time-varying and is recomputed at each event n . In practice, when future traffic conditions are uncertain, suitable approximations (e.g., $B(n+k) \approx B(n)$ over the horizon) may be adopted without loss of generality. It is important to note that the outflow term $q_i^{\text{out}}(n)$ is treated as a measured and state-dependent quantity in this study. In particular, when a queue is present, the outflow is assumed to be equal to the saturation flow rate, while under uncongested conditions it is limited by the upstream demand. Therefore, $q_i^{\text{out}}(n)$ inherently captures the effect of both signal timing and traffic conditions, as reflected in the state update equation. Moreover, although $q_i^{\text{out}}(n)$ may implicitly depend on the green-time allocation $u_j(n)$ and the evolving traffic state, the discharge matrix $B(n)$ is recomputed at each control step using the most recent measurements. The approximation $B(n+k) \approx B(n)$ over the prediction horizon is adopted to preserve the convexity and tractability of the MPC optimization problem, which is a common and well-established practice in traffic control applications (Tettamanti et al., 2013). This receding-horizon update mechanism mitigates potential mismatches between the predicted and actual traffic evolution.

The primary control objective is twofold: (i) to reduce overall network congestion and delay, and (ii) to explicitly prioritize EVs traveling along specific incoming links. To this end, the following quadratic stage cost is defined at prediction step k :

$$\begin{aligned} \ell(X_{k|n}, U_{k|n}) = & (X_{k|n} - X^{\text{ref}})^T Q (X_{k|n} - X^{\text{ref}}) \\ & + U_{k|n}^T R U_{k|n} + \rho E_{k|n}^T W_{\text{EV}} E_{k|n}, \end{aligned} \quad (14)$$

where $Q \geq 0$ and $R > 0$ are symmetric weighting matrices, X^{ref} denotes a reference accumulation vector corresponding to desired operating conditions, and $\rho > 0$ is a scalar parameter that amplifies the priority assigned to EVs. Since the primary control objective is to mitigate traffic congestion, the reference accumulation X^{ref} to zero in the proposed framework, effectively steering the system toward minimal queue lengths on all controlled approaches.

The vector $E_{k|n} \in \mathbb{R}^{N_{\text{EV}}}$ captures EV-related macroscopic performance measures and is defined as a linear mapping of the predicted accumulations:

$$E_{k|n} = S_{\text{EV}} X_{k|n}, \quad (15)$$

where $S_{\text{EV}} \in \{0, 1\}^{N_{\text{EV}} \times N}$ is a selection matrix identifying the incoming links that currently serve EV routes. The matrix $W_{\text{EV}} \geq 0$ weights the relative importance of different EV-related components, enabling the controller to penalize congestion and delay experienced by EVs more heavily than regular traffic. Both S_{EV} and W_{EV} may be updated online to reflect changes in EV routes or priorities.

The finite-horizon cost minimized at each decision event n is defined as:

$$J_{N_p}(X(n), \mathbf{U}) = \sum_{k=0}^{N_p-1} \ell(X_{k|n}, U_{k|n}), \quad (16)$$

where the inclusion of $k=0$ explicitly accounts for the current state $X_{0|n} = X(n)$ in the cost function.

At each decision event n , the controller solves the following constrained finite-horizon optimal control (CFHOC) problem:

$$\mathbf{U}^* = \arg \min_{\mathbf{U}} J_{N_p}(X(n), \mathbf{U}) \quad (17a)$$

$$\text{s.t. } \mathbf{X} = \mathcal{A} \mathbf{X}(n) + \mathcal{B} \mathbf{U} + \mathbf{Q}^{\text{in}}, \quad (17b)$$

$$0 \leq X_{k|n} \leq x_{\max}, \quad k = 1, \dots, N_p, \quad (17c)$$

$$u_{\min} \leq U_{k|n} \leq u_{\max}, \quad k = 0, \dots, N_p - 1, \quad (17d)$$

$$\Delta u_{\min} \leq U_{k|n} - U_{k-1|n} \leq \Delta u_{\max}, \quad k = 1, \dots, N_p - 1, \quad (17e)$$

$$\sum_{j=1}^M u_{j,k|n} = CT, \quad k = 0, \dots, N_p - 1, \quad (17f)$$

where $x_{\max}$ denote physical storage limit of the links, $u_{\min}$ and $u_{\max}$ represent operational bounds on green times. Constraints (17c)–(17e) enforce physical and operational limits, while (17f) guarantees a fixed cycle time at each decision step. When the stage cost is quadratic and all constraints are affine, the CFHOC problem (17) reduces to a convex quadratic program (QP) that can be solved efficiently in real time. However, when logical or integer constraints are incorporated (e.g., phase-compatibility, minimum green enforcement, or discrete signal decisions), the resulting problem becomes a mixed-integer quadratic program (MIQP). In this work, both formulations are admissible depending on the level of modeling detail, and the computational framework can accommodate either case.

Following the receding horizon principle, only the first optimal control input $U_{0|n}^*$ is applied to the system, after which the optimization is repeated at the next decision event using updated traffic measurements. Issues related to practical solvability, soft-constrained optimization and traffic-operational performance under high-demand and emergency scenarios are discussed in subsequent sections.

It is notable that, in urban traffic networks governed by store-and-forward dynamics, stability is commonly interpreted from a traffic-engineering perspective as maintaining bounded queue lengths and acceptable network operation over time, rather than asymptotic convergence to a fixed equilibrium point (Wang et al., 2022). This interpretation is motivated by the inherently time-varying, stochastic and non-stationary nature of traffic demand, which acts as a persistent external disturbance.

In the proposed framework, link storage constraints are handled through a soft-constrained formulation, whereby violations are penalized in the objective function rather than enforced as strict hard constraints. Such formulations are widely adopted in constrained MPC to improve optimization robustness and practical feasibility under uncertainty (Mayne et al., 2000; Rawlings et al., 2020). Consequently, the controller is able to maintain a feasible optimization problem in a broad range of congestion scenarios while reducing the risk of grid-lock and optimization breakdown. We further note that the proposed decentralized game-theoretic MPC formulation does not incorporate terminal costs, terminal invariant sets or other theoretical ingredients that are commonly employed to establish formal recursive feasibility and closed-loop stability guarantees in MPC. Instead, the proposed methodology is evaluated from a traffic-control perspective, where its effectiveness is assessed through its ability to maintain bounded vehicle accumulations, prevent excessive queue growth and sustain efficient network operation under stochastic traffic conditions. It should be emphasized that our proposed framework is evaluated from a traffic-operational perspective. Although bounded queue evolution and favorable congestion-management behavior are observed in the conducted simulations, no formal proof of recursive feasibility or closed-loop stability in the MPC sense is provided in this work. Consequently, the reported results should be interpreted as empirical evidence of traffic-operational effectiveness rather than theoretical guarantees of MPC stability or recursive feasibility.

For benchmarking purposes, a classical MPC controller is implemented as a baseline. It is important to emphasize that the CMPC approach adopted in this study follows the same decentralized control architecture as our proposed framework. In particular, each intersection independently solves a local MPC optimization problem based solely on its own macroscopic state measurements and predicted inflows, without requiring global network information or centralized coordination. The key distinction between classical MPC and Game-Theoretic MPC lies in the formulation of the cost function. In the classical MPC baseline, a single aggregated objective function is minimized,

aiming to reduce overall congestion and control effort, without explicitly modeling the competitive interactions among incoming traffic streams or incorporating adaptive priority weights for EVs. As a result, all approaches are treated uniformly, and EV prioritization is only indirectly reflected through the state penalty terms. Decentralized and distributed MPC formulations of this type have been widely investigated for large-scale urban traffic networks. For example, hierarchical and distributed MPC frameworks have been proposed to address scalability and computational challenges while preserving local decision-making capabilities (Zhou et al., 2016). The classical MPC implementation in this work is consistent with such decentralized predictive control strategies, but does not include the game-theoretic coordination layer introduced in our proposed Game-Theoretic MPC framework.

3.2. Game-theoretic coordination within MPC for EV prioritization

While the MPC formulation in the previous subsection provides a predictive and constraint-aware optimization framework, it relies on a single aggregate objective function defined at the intersection level that aggregates network-level performance criteria. However, traffic dynamics at signalized intersections are inherently driven by competing demands among incoming streets, particularly under emergency scenarios where certain approaches must be prioritized. To explicitly capture these strategic interactions, a game-theoretic layer is embedded within the MPC framework, allowing each incoming street to be modeled as a rational decision-making agent whose objectives are aligned with, but not identical to, the global control goal.

Consider a single signalized intersection with N incoming streets. Each incoming street $l \in \mathcal{N} = \{1, \dots, N\}$ is modeled as a strategic player in a non-cooperative, static game that is repeatedly solved at each MPC update. The objective of each player is to influence the allocation of green time in order to reduce its own predicted congestion over the finite MPC horizon.

The control decisions at the intersection are expressed in terms of phase-based green times:

$$\tilde{U}_{k|n} = [u_{1,k|n}, \dots, u_{M,k|n}]^T \in \mathbb{R}^M, \quad (18)$$

consistent with the macroscopic dynamics in Eq. (4) and with the notation introduced in Section 3.1. Since streets are served by one or more signal phases, the effective green time associated with street l at prediction step k is defined as a linear mapping of the phase green times:

$$u_{l,k|n} = \sum_{j=1}^M \gamma_{lj} u_{j,k|n}, \quad (19)$$

where $\gamma_{lj} \in \{0, 1\}$ (or more generally $\gamma_{lj} \in [0, 1]$ if partial phase-sharing is allowed) indicates whether phase j discharges vehicles from street l . In matrix form, for a given k we can write:

$$\mathbf{u}_{k|n} = \Gamma \tilde{U}_{k|n}, \quad (20)$$

where $\mathbf{u}_{k|n} = [u_{1,k|n}, \dots, u_{N,k|n}]^T \in \mathbb{R}^N$ and $\Gamma \in \{0, 1\}^{N \times M}$ has entries γ_{lj} .

Accordingly, the strategy of player l is defined as its implied green-time trajectory over the MPC horizon:

$$\mathbf{u}_l \triangleq [u_{l,0|n} \quad u_{l,1|n} \quad \dots \quad u_{l,N_p-1|n}]^T \in \mathbb{R}^{N_p}, \quad (21)$$

which is induced by the joint phase-based control sequence $\mathbf{U} \in \mathbb{R}^{M N_p}$. All players are assumed to have access to local macroscopic state measurements $X(n)$ and predicted inflows $\mathbf{q}^{\text{in}}$, resulting in a complete-information game solved repeatedly in a receding-horizon fashion.

Each player l minimizes an individual cost function that reflects both congestion on its own approach and the presence of EVs. Over the MPC horizon, the cost function of player l is defined as:

$$J_l(X(n), \mathbf{U}) = \sum_{k=0}^{N_p-1} \ell_l(X_{k|n}, U_{k|n}), \quad (22)$$

where the stage cost $\ell_l(\cdot)$ is given by:

$$\ell_l(X_{k|n}, U_{k|n}) = \alpha_l x_{l,k|n}^2 + \beta_l u_{l,k|n}^2 + \rho_l \delta_l^{\text{EV}}(n) x_{l,k|n}^2. \quad (23)$$

In the above, $x_{l,k|n}$ denotes the l th component of $X_{k|n}$ (i.e., the predicted accumulation on street l at step k), $\alpha_l \geq 0$ penalizes accumulation on street l , and $\beta_l > 0$ penalizes large allocations of green time to street l (discouraging oscillatory or excessive allocations). The indicator variable $\delta_l^{\text{EV}}(n) \in \{0, 1\}$ denotes the presence of an EV on street l at decision event n ; it is evaluated at the decision event and applied across the horizon in the present formulation. (For finer modeling one may use $\delta_{l,k}^{\text{EV}}(n)$ to indicate presence within prediction step k , i.e. allow EV presence to vary across the horizon; both representations are admissible and the text above uses the shorthand $\delta_l^{\text{EV}}(n)$ for clarity).

The first term penalizes congestion on street l , while the second term discourages excessive green-time allocation and prevents oscillatory control actions. When an EV is present, the third term significantly increases the marginal cost of congestion through the weight $\rho_l \gg \alpha_l$, thereby assigning a strategic advantage to the EV-serving street. This formulation treats EVs as endogenous components of the traffic system whose presence reshapes the strategic incentives of the players, rather than as external disturbances handled through ad-hoc preemption rules. The parameters $\alpha_l, \beta_l, \rho_l$ may be tuned per-approach to reflect geometric and operational heterogeneity (e.g., lane counts, saturation flows).

The proposed formulation naturally accommodates scenarios with multiple EVs, including both simultaneous and staggered arrivals at an intersection. This is achieved through the EV-dependent weighting term $\rho_l \delta_l^{\text{EV}}(n)$ in the cost function, which can be activated for multiple approaches at the same decision event. In such cases, competing EV-serving approaches are implicitly prioritized through their respective weights, and the resulting equilibrium reflects a trade-off among their demands within the shared green-time constraints. Therefore, the framework does not rely on explicit rule-based conflict resolution, but instead resolves multi-EV interactions endogenously through the optimization structure.

The proposed framework adopts a weighted non-cooperative game structure, in which each incoming street (player) minimizes its own cost function subject to shared physical constraints. Priority differentiation among competing approaches is represented through weighting parameters embedded in the player cost functions, particularly through the parameter ρ_l associated with EV presence. These weights modulate the relative importance of competing objectives and bias the equilibrium solution toward EV-serving approaches when necessary. Furthermore, the interaction among players is resolved through a potential-function formulation, where the aggregate cost function serves as a surrogate for computing a Nash equilibrium. This transformation enables the equilibrium to be obtained by solving a single quadratic optimization problem while preserving the decentralized and strategic interpretation of the original multi-player game. It is important to note that this formulation does not imply a centralized control architecture. Instead, the optimization can be carried out at the intersection level using locally available information, and coordination across the network emerges implicitly through traffic-flow interactions and the receding-horizon structure of the MPC scheme.

It is important to distinguish the proposed formulation from cooperative distributed optimization approaches commonly found in the literature. In cooperative frameworks, agents jointly minimize a shared global objective function, typically relying on iterative coordination, consensus mechanisms, or information exchange across the network. Such methods often provide strong theoretical guarantees, including

convergence and optimality, under suitable assumptions (Wu et al., 2023; Luan et al., 2023; Wu et al., 2024; Chen et al., 2021). In contrast, the proposed formulation adopts a non-cooperative game-theoretic perspective. This choice is motivated by the intrinsic characteristics of signalized intersections, where incoming traffic streams inherently compete for limited green time. As a result, their objectives are not fully aligned, particularly in the presence of EVs, which introduce asymmetric prioritization requirements.

From a modeling standpoint, the non-cooperative formulation provides a natural representation of these competing objectives without requiring explicit coordination or global information. Furthermore, it enables a scalable and fully decentralized implementation, where each intersection operates based on local state measurements and predicted inflows. Coordination across the network emerges implicitly through traffic flow interactions and the receding-horizon structure of the MPC scheme, rather than through explicit communication. Therefore, while cooperative approaches offer strong theoretical properties, the non-cooperative formulation adopted in this work is better aligned with the decentralized, competitive, and resource-constrained nature of urban traffic signal control.

A Nash equilibrium is defined as a strategy profile $\mathbf{U}^*$ such that no street can unilaterally reduce its cost:

$$J_l(X(n), \mathbf{U}^*) \leq J_l(X(n), (\mathbf{u}_l, \mathbf{U}_{-l}^*)), \quad \forall \mathbf{u}_l \in \mathcal{U}_l, \quad (24)$$

for all $l \in \mathcal{N}$, where $\mathbf{U}_{-l}^*$ denotes the strategies of all players except l , and $\mathcal{U}_l$ denotes the admissible strategy set for player l (induced by the MPC input bounds and the cycle-sum constraint).

Under the quadratic cost structure in Eq. (23) and the affine MPC constraints, the resulting game may admit an exact potential function under additional structural conditions on the parameters. In particular, define the aggregate cost:

$$\Phi(X(n), \mathbf{U}) = \sum_{l=1}^N J_l(X(n), \mathbf{U}). \quad (25)$$

If the per-player costs are derived from a common quadratic form (i.e., if the state-weighting and input-weighting matrices across players are consistent with a single global quadratic cost, and the mapping from phase-level inputs $U_{k|n}$ to street-level inputs $u_{l,k|n}$ is linear via Γ), then Φ acts as an exact potential: minimizers of Φ coincide with Nash equilibria of the game. A sufficient structural condition is that there exist matrices Q and R (used in Section 3.1, Eq. (14)) and a selection matrix S_{EV} such that:

$$\sum_{l=1}^N \alpha_l x_{l,k|n}^2 = (X_{k|n} - X^{\text{ref}})^\top Q (X_{k|n} - X^{\text{ref}}), \quad (26)$$

$$\sum_{l=1}^N \beta_l u_{l,k|n}^2 = \tilde{U}_{k|n}^\top R \tilde{U}_{k|n}, \quad (27)$$

where the second equality holds when:

$$R = \Gamma^\top \text{diag}(\beta_1, \dots, \beta_N) \Gamma. \quad (28)$$

Under these identifications and if ρ_l and W_{EV} are chosen consistently so that:

$$\sum_{l=1}^N \rho_l \delta_l^{\text{EV}}(n) x_{l,k|n}^2 = \rho E_{k|n}^\top W_{EV} E_{k|n}, \quad (29)$$

with $E_{k|n} = S_{EV} X_{k|n}$ and appropriate choice of ρ and W_{EV} , the aggregate player cost equals the MPC stage cost defined over the aggregated system in Eq. (14). In this case, the game is an exact potential game, and the minimizer of Φ is a Nash equilibrium. We emphasize that these are sufficient (but not necessary) structural conditions; when they do not strictly hold, the aggregate cost Φ remains a useful approximate potential and can still be used as a convex surrogate to compute coordinated allocations that reflect strategic incentives.

Consequently, when the structural conditions above are met (or approximately satisfied in practice), the equilibrium green-time allocation

can be obtained by solving the following convex optimization problem:

$$\min_{\mathbf{U}} \sum_{l=1}^N J_l(X(n), \mathbf{U}), \quad (30)$$

subject to the MPC constraints (17b)–(17f). Under the quadratic cost structure and affine constraints, the resulting optimization problem is a convex QP when all decision variables are continuous. However, if logical or integer constraints are introduced to capture signal phase relationships or operational rules, the problem becomes an MIQP. Therefore, the formulation should be understood as a QP/MIQP framework depending on the level of abstraction and implementation details.

The potential function in Eq. (25) coincides with the finite-horizon MPC objective defined in Eq. (16) when the parameter-identification conditions above hold, ensuring full consistency between the game-theoretic and MPC formulations. Strategic interaction among streets is therefore resolved directly over the predicted state trajectory in Eq. (13), and EV prioritization emerges naturally through the elevated congestion penalties on EV-serving links. At each decision event n , the equilibrium solution $\mathbf{U}^*$ is computed and only the first control input $U_{0|n}^*$ is applied to the system. The game is then reformulated at the next event using updated traffic measurements, yielding a receding-horizon game-theoretic MPC scheme.

By modeling incoming streets as strategic players, the proposed formulation establishes a direct connection between macroscopic traffic dynamics and decentralized decision-making. EVs are explicitly embedded within the strategic structure of the game, allowing priority to be granted in a predictive and smoothly adaptive manner. The resulting framework incorporates shared MPC constraints to promote operational consistency and coordinated signal allocation while balancing emergency response performance and overall network efficiency.

The algorithm of the proposed MPC Game-Theoretic control scheme can be defined now. The proposed control strategy follows a decentralized, event-driven, and receding-horizon workflow, which can be summarized as follows:

1. **Local State Measurement:** At each signal decision event n , each intersection controller locally measures the macroscopic traffic state, including vehicle accumulations on incoming streets and the presence of EVs on specific approaches.
2. **Prediction Model Construction:** Using the current macroscopic state $X(n)$ and predicted incoming demands, a finite-horizon prediction model is constructed based on the macroscopic traffic dynamics over a prediction horizon of length N_p .
3. **MPC Problem Formulation:** A constrained MPC optimization problem is formulated, such as physical storage limits and smoothness constraints on green-time variations between consecutive cycles.
4. **Game-Theoretic Embedding:** Incoming streets are modeled as strategic players whose individual cost functions penalize predicted congestion and assign elevated priority to EV movements. This interaction induces a non-cooperative game with a potential function structure.
5. **Equilibrium Computation:** Under the quadratic cost structure and affine constraints, the resulting potential game reduces to a convex quadratic program. Solving this program yields a Nash equilibrium corresponding to the optimal green-time allocation for the current decision event.
6. **Receding-Horizon Implementation:** The optimization is performed over a prediction horizon of length N_p and a control horizon of length $N_c \leq N_p$. In the simulation studies reported in this paper, the control horizon was selected equal to the prediction horizon ($N_c = N_p$), resulting in full-degree-of-freedom optimization over the entire prediction interval. At each signal decision event, only the control actions corresponding to the first N_c steps are implemented, while the remaining predicted actions

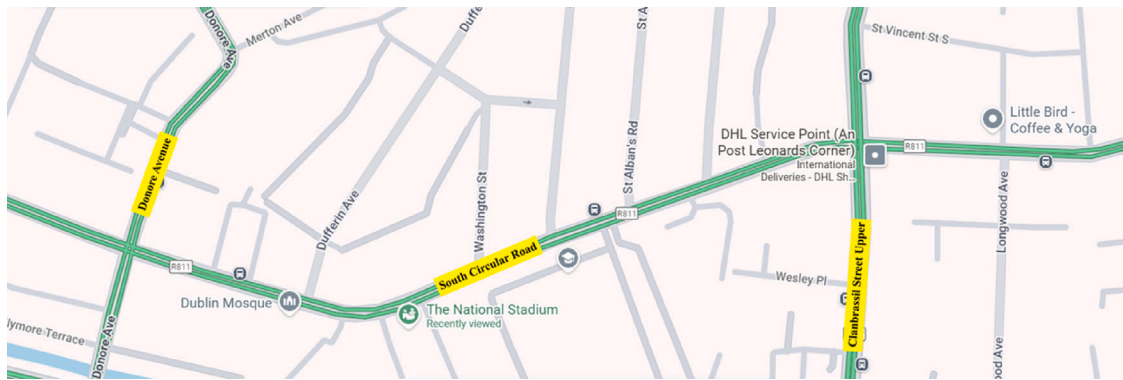


Fig. 2. The study area ($53^{\circ}19'54.2''N$, $6^{\circ}16'42.4''W$) and the instrumented approaches used in the experiments, as shown in the map. Green highlighted streets, including Donore Avenue, South Circular Road, and Clanbrassil Street Upper, represent the experimental region. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

are discarded. The optimization problem is then reformulated at the next decision event using updated traffic measurements, in accordance with the receding-horizon control principle.

7. **Event-Driven Update:** At the next signal decision event, updated traffic measurements are acquired and the entire procedure is repeated.

Through this iterative process, the proposed framework yields a decentralized, predictive, and smoothly adaptive signal control strategy. EV prioritization emerges endogenously through elevated congestion penalties on EV-serving approaches, without resorting to explicit signal preemption or rule-based overrides.

4. Experimental results

This section provides a comprehensive evaluation of the proposed Predictive and Game-Theoretic Signal Control (GTMP) framework. The performance of the decentralized controller is assessed through high-fidelity simulations that replicate real-world traffic conditions. The empirical foundation of this study is built upon open-access traffic datasets from Dublin, Ireland, specifically reflecting the traffic dynamics recorded in May 2025 (Smart Dublin Regional Team, 2025).

In the experimental region, we have modeled a stochastic emergency demand profile with a frequency of 5 to 10 vehicles per hour (veh/h). This range is selected to reflect a moderately high yet plausible emergency demand scenario in urban environments. Specifically, a rate of 5 veh/h corresponds to approximately one EV every 10–12 min on a given corridor, which already represents a demanding operational condition. To further stress-test the proposed control framework under more challenging conditions, the upper bound is increased to 10 veh/h, corresponding to an EV approximately every 6 min. This allows the evaluation of the controller under both isolated and overlapping emergency vehicle scenarios. This range represents a realistic operational load for urban emergency corridors, allowing the controller to be evaluated under both isolated and overlapping emergency intervention scenarios. The study area includes corridors such as Donore Avenue, South Circular Road, and Clanbrassil Street Upper. The geographical coordinates and the specific instrumented approaches are illustrated in Fig. 2.

In this study, all approaches are modeled as single-lane roads. This modeling choice is adopted to isolate and evaluate the core mathematical logic of intersection-level signal control and EV prioritization, without introducing additional complexity from multi-lane lane-changing dynamics. Consequently, human driver-level tactical interactions, specifically yielding mechanics, emergency lane-clearing maneuvers and behavioral responses to sirens, are omitted from the current simulation setup.

At each intersection, vehicles are allowed to perform three standard movements: left-turn, through and right-turn. Turning movements are incorporated through predefined routing probabilities, ensuring realistic macroscopic traffic distribution across outgoing links. EVs are embedded within the regular traffic stream and follow the same movement rules as other vehicles. Their arrivals are generated according to a stochastic process, allowing for both isolated and overlapping EV scenarios. This setup enables the evaluation of the proposed control framework under potential conflict conditions, where multiple EVs may simultaneously request priority at the same or adjacent intersections. It is worth noting that while a single-lane abstraction is adopted in this study for clarity and tractability, the proposed framework can be extended to multi-lane configurations. In this context, the term “realistic traffic conditions” used throughout this study refers specifically to realistic demand patterns, stochastic vehicle arrivals and empirically motivated traffic flow data, rather than a full microscopic representation of roadway geometry and driver behavior. Therefore, the adopted simulation framework should be interpreted as a controlled and simplified environment designed for isolating and evaluating the effects of the proposed control methodology. This extension would allow the incorporation of lane-changing behavior and more detailed traffic interactions, which we consider as a direction for future work.

To evaluate the proposed macroscopic control logic within a realistic microscopic environment, we utilize the Simulation of Urban MObility (SUMO) package (Lopez et al., 2018). It is important to note that the simulation framework is designed to emulate realistic field measurement conditions. In particular, the macroscopic state variables (vehicle accumulations and flows) used by the controller are derived from simulated sensor measurements, such as loop detectors and vehicle trajectory data available within the SUMO environment. These measurements are consistent with data typically obtainable from real-world traffic sensing systems such as loop detectors, cameras and V2X-enabled infrastructure. While the present study assumes accurate state information for control evaluation purposes, this corresponds to a best-case sensing scenario and allows us to isolate and assess the effectiveness of the proposed control strategy. The impact of measurement uncertainty and sensor noise is not explicitly modeled in this work and is left for future investigation. SUMO provides the necessary multi-modal traffic simulation capabilities to model the interaction between regular vehicles and EVs with high precision. Regarding vehicle interaction behavior, all vehicles in the simulation follow the default microscopic behavior models implemented in SUMO, including car-following and lane-changing dynamics. In this setup, EVs are not explicitly granted right-of-way by surrounding vehicles through cooperative maneuvers such as yielding or lane clearing. Instead, EV priority is realized exclusively at the signal control level through adaptive green-time allocation. This modeling choice is intentional and aligned

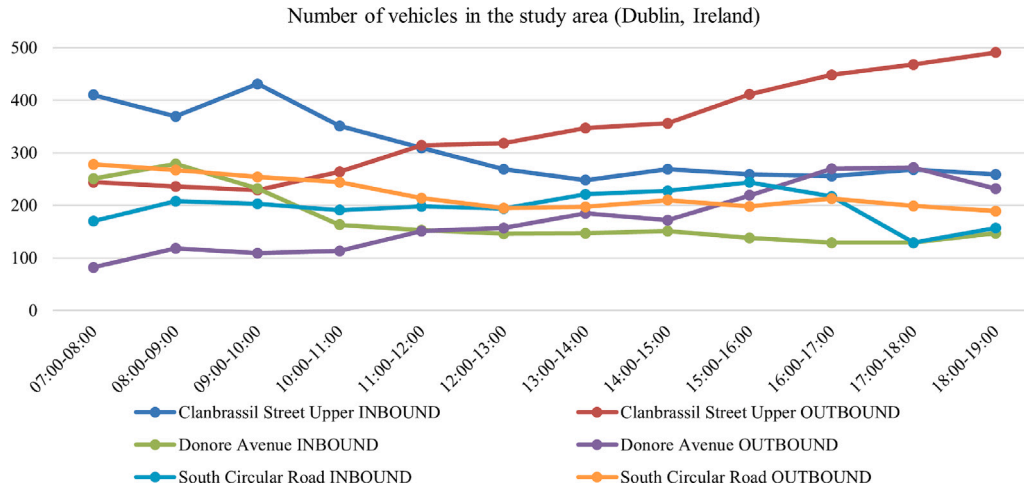


Fig. 3. Traffic flow measurements in the study area (Dublin, Ireland) from 07:00 to 19:00, May 2025. The data represents the number of vehicles recorded on key approaches, and were used for initializing SUMO simulations.

with the macroscopic scope of the present study, where the objective is to evaluate the effectiveness of the proposed control strategy independently of detailed behavioral assumptions. As such, driver-level interactions, including explicit yielding responses to EVs, are not modeled in this work. The simulations are initialized using traffic flow measurements recorded between 07:00 and 19:00, as depicted in Fig. 3.¹ These profiles ensure that the controller is tested under varying levels of congestion, from morning peaks to off-peak periods.

The operational parameters and configuration values used in both the simulation environment and the optimization layer are summarized in Table 2. These values, including cycle times and green duration bounds, are selected based on the actual signal plans implemented in the Dublin network to ensure a fair comparison. To further justify the selected values of the prediction and control horizons, it is important to note that the choice of N_p and N_c is supported both by empirical observations in the literature and by the computational structure of the proposed game-theoretic MPC framework. In particular, sensitivity analyses reported for store-and-forward urban traffic systems under demand uncertainty demonstrate that increasing the prediction or control horizon beyond a few signal cycles does not yield significant performance improvements and may in fact degrade performance due to accumulated prediction uncertainty and stochastic fluctuations in turning movements and demand patterns (Tettamanti et al., 2013). Moreover, since the proposed framework relies on a repeated game-theoretic optimization at each signal cycle, increasing N_p or N_c would significantly increase the dimensionality of the potential game and lead to a disproportionate rise in computational burden, which is undesirable for real-time implementation.

Consistent with the above discussion, the choice of short prediction and control horizons in Table 2 is mainly driven by the event-based formulation of the proposed framework. In this study, each decision step corresponds to a full signal cycle with duration $CT = 123$ s. Therefore, the selected prediction horizon effectively spans approximately 4 min, which is a meaningful time scale for urban traffic signal control. From a practical perspective, traffic demand in urban networks is inherently uncertain, and accurate prediction beyond 2–3 cycles is generally unreliable. As a result, extending the prediction horizon does not necessarily improve performance and may even degrade control effectiveness due to accumulated prediction errors.

Furthermore, the proposed formulation does not reduce to an LQR-type controller. Despite the short horizon, the optimization problem

Table 2

Simulation parameters and configuration values.

Parameter name	Symbol and value
Cycle time duration	$CT = 123$ s
Yellow time duration	$YT = 3$ s
Total green budget per cycle	$CT - YT = 120$ s
Minimum green time duration	$u_{\min} = 40$ s
Maximum green time duration	$u_{\max} = 80$ s
All initial green times	$U(0) = 60$ s
Minimum per-cycle change	$\Delta u_{\min} = -10$ s
Maximum per-cycle change	$\Delta u_{\max} = 10$ s
Prediction horizon	$N_p = 2$ cycles
Control horizon	$N_c = 2$ cycles

includes state and input constraints, inter-cycle coupling constraints, and a game-theoretic structure, all of which preserve the key characteristics of constrained MPC. The selected horizon therefore represents a trade-off between prediction reliability and computational efficiency, particularly given the additional complexity introduced by the game-theoretic component.

To demonstrate the efficacy of the proposed control framework, we conduct a comparative analysis against three baseline control strategies:

- **GTMP** (Proposed): The Decentralized Game-Theoretic Model Predictive Control framework. This method treats each approach as a strategic player in a weighted non-cooperative game, utilizing a prediction horizon to anticipate EV arrivals and adjust green times dynamically.
- **PRMP** (EV Preemption): A rule-based emergency vehicle preemption strategy, in which the signal controller overrides the normal operation upon EV detection and immediately grants or extends green time to the EV-serving approach. While this approach ensures rapid EV passage, it may disrupt overall traffic flow due to abrupt phase changes and lack of predictive coordination.
- **CMPC** (Classical MPC): A standard macroscopic Model Predictive Control baseline. This approach optimizes green times based on a global cost function without the EV-specific priority weights embedded in the cost function.
- **FT** (Fixed-Time): A traditional non-adaptive control strategy using pre-timed signal plans. This represents the legacy system without real-time responsiveness to fluctuating traffic or emergency requests.

It is important to emphasize that the proposed **GTMP** framework is inherently scalable to different network geometries and traffic

¹ The SUMO parameter settings for the Dublin scenario can be accessed via: <https://github.com/Arshia-Abdi/SUMO-Parameters-Set>.

configurations. Since the control structure is decentralized, each intersection independently optimizes its incoming approaches based on locally defined phase structures and traffic states. This design allows the framework to be directly extended to intersections with arbitrary geometries, including multi-leg intersections, asymmetric layouts and varying turning movement configurations. Specifically, the phase-link relationship matrix (denoted as $B(n)$ in the formulation) can be redefined for each intersection to capture the corresponding signal phases and movement conflicts. Furthermore, EV movements are not restricted to predefined routes or specific turning patterns. EVs are treated as part of the traffic stream with dynamically assigned priority weights, allowing the controller to accommodate different movement types (e.g., through, left-turn or right-turn) without requiring structural modifications to the control algorithm. As a result, the proposed framework is not limited to the specific case study presented in this paper and can be generalized to a wide range of urban traffic networks.

The primary objective of this study is to facilitate the rapid movement of EVs while preserving overall network performance and minimizing disruption to regular traffic. To this end, a set of Key Performance Indicators (KPIs) is defined, including both EV-specific metrics and network-wide performance measures:

- **Average Fuel Consumption (AFC):** The mean fuel consumed by EVs, estimated via SUMO's environmental emission models, reflecting the impact of frequent stops and accelerations.
- **Average Suffering Red-light (ASR):** The average number of times that EVs on the network face red lights.
- **Average Waiting Time (AWT):** The average duration EVs spend in a halted state (speed ≤ 0.1 m/s) at intersection approaches.
- **Average Travel Time (ATT):** The mean duration required for an EV to traverse the entire study area.
- **Average Time Loss (ATL):** The mean difference between the actual travel time and the time the EV would have taken at the free-flow speed.
- **Average Speed (AVS):** Average speed of EVs in the traffic network.
- **Average Queue Length (AQL):** The average number of vehicles accumulated on incoming links over time, representing congestion levels experienced by all vehicles in the network.
- **Average Stop Count (ASC):** The average number of times an EV was forced to stop completely before clearing the intersection.
- **Total Throughput (TTP):** The total number of vehicles that successfully traverse the network during the simulation period, reflecting the overall efficiency and capacity utilization of the traffic system.
- **Total Delay (TDL):** The cumulative delay experienced by all vehicles compared to their free-flow travel times, providing a network-wide measure of inefficiency.

By evaluating these KPIs across the four control scenarios, we aim to quantify the improvements provided by the game-theoretic integration in reducing the operational delay and environmental footprint of emergency services in a high-density urban setting. To evaluate the dynamic responsiveness of the proposed GTMPC framework, Fig. 4 illustrates a comprehensive temporal analysis of one of the network streets over a 12-hour simulation period based on Dublin's real traffic data. The figure is structured into three synchronized panels, providing a multi-layered view of the control efficacy.

The top panel presents the signal timing per cycle. It is observed that the green time duration is not static but fluctuates dynamically between $u_{\min} = 40$ s and $u_{\max} = 80$ s. This variation is the direct result of the underlying optimization mechanism, where the controller re-evaluates the priority weights of each link at every cycle based on predicted accumulation and detected EV presence.

The middle panel displays vehicle trajectories, where the distinction between regular traffic (cyan) and EVs (red) is visualized. A key

observation here is the smoothing effect on EV trajectories. When an EV enters the link, the slope of its trajectory often remains relatively constant, indicating a reduction in stop-and-go behavior. This is further clarified in the zoomed-In View (12:15-13:15). During this window, the controller detects an EV arrival and immediately adjusts the corresponding priority weight. As shown in the zoomed timing plot, the green interval is extended (near cycle 170 and 175) to ensure the EV clears the intersection without facing a considerable red-light delay.

The bottom panel illustrates the vehicle count on the related street. The zoomed section reveals that during the prioritization of EVs, the regular vehicle accumulation is managed such that the queue does not exceed the critical storage capacity of the link. This demonstrates that the GTMPC does not merely clear the way for EVs by ignoring other traffic, but rather finds a strategic equilibrium that facilitates emergency passage while limiting congestion growth and preserving overall traffic performance.

Specifically, in the zoomed-in interval (12:15–13:15) in Fig. 4, the precise synchronization between the green time extensions and the EV trajectory slopes proves that the predictive nature of the MPC layer allowed the system to allocate green time just in time, reducing the ASC and AFC for the emergency car, as it avoids unnecessary deceleration cycles. The quantitative performance of the proposed GTMPC framework is evaluated against FT, CMPC and PRMP scenarios. The numerical results, summarized in Table 3 and visualized in Fig. 5, demonstrate that the integration of a game-theoretic weighting mechanism in the non-cooperative formulation into the MPC structure yields superior outcomes.

As illustrated in Fig. 5, the GTMPC strategy consistently outperforms the alternatives. In addition to EV-specific improvements, the proposed framework also demonstrates strong performance at the network level. In particular, the AQL is reduced to 7 under GTMPC, compared to 8.54 in FT and 9.09 in PRMP, indicating a substantial alleviation of congestion. Moreover, the TDL is significantly reduced to 210571.01 s, corresponding to a considerable improvement over both CMPC and PRMP. Importantly, the TTP remains effectively unchanged (with a slight improvement of 0.05% under GTMPC) across all scenarios, confirming that the proposed prioritization strategy does not compromise the overall capacity of the network. Specifically, the ATT for EVs under GTMPC is significantly reduced compared to the FT scenario. This improvement is primarily attributed to the predictive weighting mechanism, which anticipates EV arrivals and adjusts the green-time allocation to clear the path before the vehicle reaches the intersection. A key driver of this efficiency is the ASR metric; the GTMPC reduces the average number of red lights encountered to 1.96, ensuring high continuity for emergency responders.

Environmental efficiency is another key highlight of the proposed method. The AFC is reduced under GTMPC control, compared to FT and CMPC. By minimizing the number of complete stops, ASC, and the associated idling time, GTMPC facilitates a smoother flow for EVs, which is reflected in the lower fuel consumption too. Furthermore, the ATL shows a marked improvement, and the AWT reaches its lowest recorded value. Consequently, the AVS reaches its peak at 7.83 m/s under GTMPC, confirming that the system maintains a higher velocity profile throughout the network. These results indicate that while CMPC offers marginal improvements over the static FT control, the addition of the game-theoretic layer in GTMPC provides the necessary strategic edge to prioritize high-priority agents while avoiding excessive congestion and preserving efficient traffic operation. These improvements are achieved without degrading overall traffic conditions, as evidenced by the simultaneous reduction in AQL and TDL at the network level. To further quantify the impact of the proposed decentralized controller, we analyze the relative percentage improvements of the CMPC and GTMPC strategies over the baseline FT scenario. The relative changes across all performance indicators are summarized in Table 4 and visualized in Fig. 6.

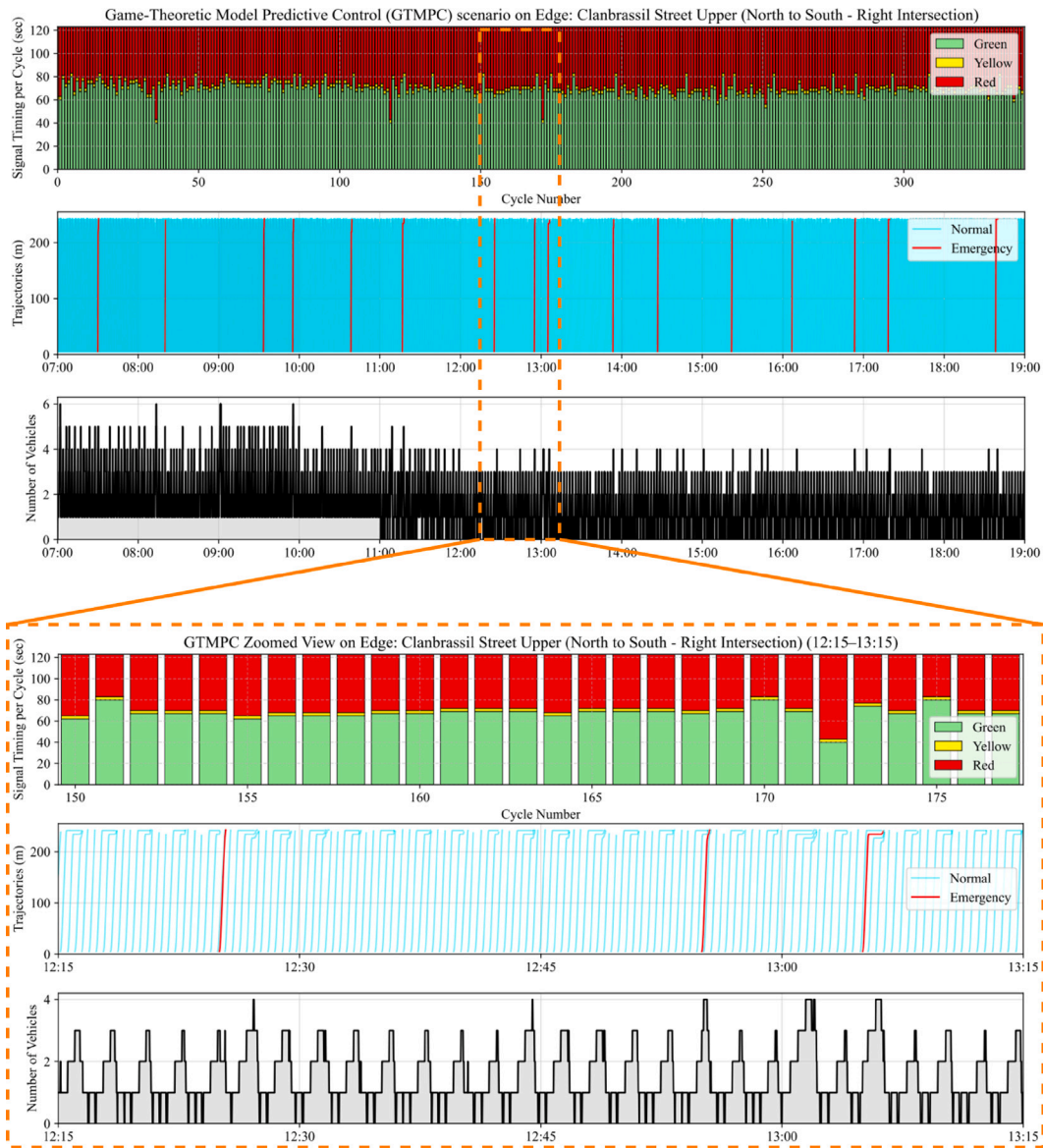


Fig. 4. Illustrative example of the Game-Theoretic Model Predictive Control (GTMPC) with real data of Dublin city. The top panel shows signal timings per cycle, with color coding for green, yellow, and red phases. The middle panel illustrates vehicle trajectories, with emergency vehicles highlighted. The bottom panel presents the number of vehicles per cycle, with the zoomed-in section showing a detailed view of the selected time period (12:15 to 13:15). The zoomed-in view provides more granular insight into the control actions and vehicle behavior during this critical period. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 3

Values of KPIs for each control scenario. (The columns correspond to the control scenarios: Fixed-Time (FT), Classic Model Predictive Control (CMPC), EV Preemption (PRMP) and Game-Theoretic MPC (GTMPZ)).

Parameter name	FT	CMPC	PRMP	GTMPZ
Average fuel consumption (kg)	96.63	96.26	92.41	93.51
Average suffering red lights	2.29	2.15	1.88	1.96
Average waiting time (s)	19.57	19.11	15.96	16.58
Average travel time (s)	107.93	106.91	101.85	103.84
Average time loss (s)	48.1	46.98	42.96	43.91
Average speed (m/s)	7.52	7.79	8.08	7.83
Average queue length	8.54	7.91	9.09	7
Average stop count	2.3	2.29	2.1	2.14
Total throughput	10 864	10 868	10 861	10 869
Total delay (s)	359 084.62	272 063.35	310 865.24	210 571.01

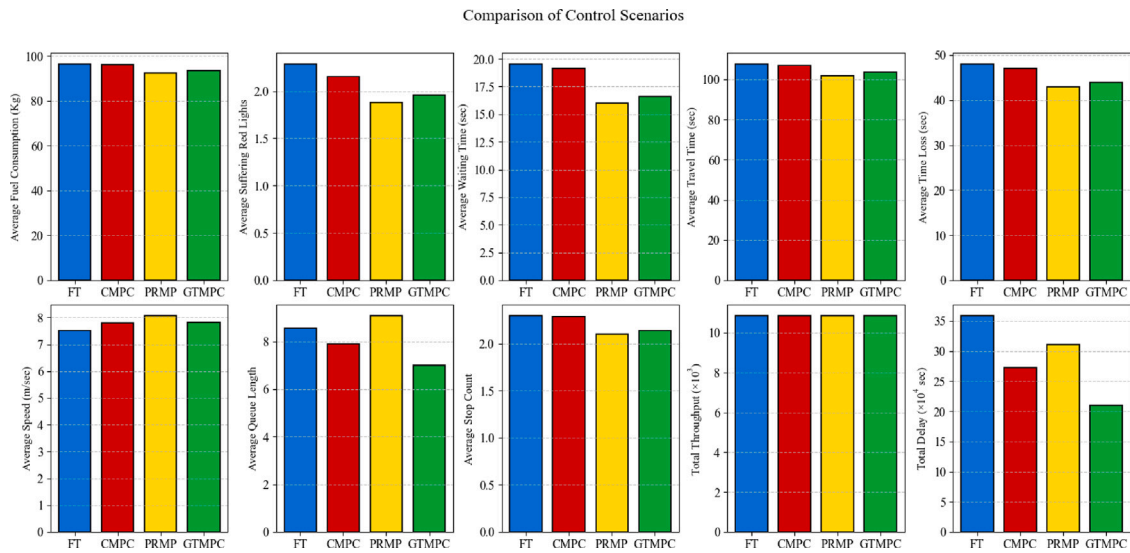


Fig. 5. Comparison of traffic control scenarios: **Fixed-Time (FT)**, **Classical MPC (CMPC)**, **EV Preemption (PRMP)** and **Game-Theoretic MPC (GTMPC)**. The figure presents the average values of various performance metrics, including AFC (km), ASR, AWT (s), ATT (s), ATL (s), AVS (meters per second), AQL, ASC, TTP and TDL (s) for each control scenario.

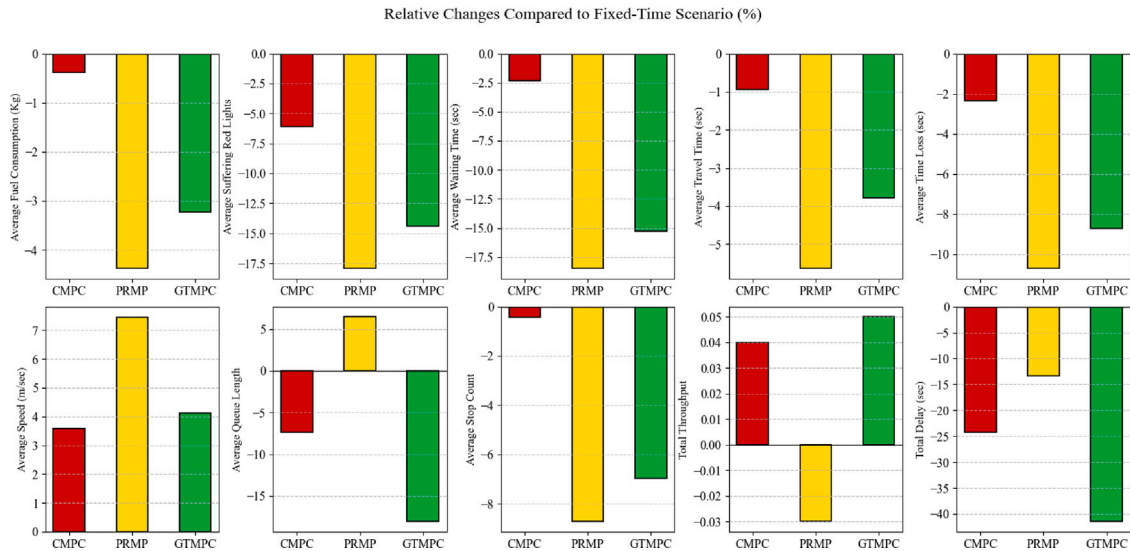


Fig. 6. Relative changes (%) in performance metrics compared to the **Fixed Time (FT)** scenario. The figure presents the relative percentage changes in AFC, ASR, AWT, ATT, ATL, AVS, AQL, ASC, TTP and TDL parameters for three control strategies: **Classical MPC (CMPC)**, **EV Preemption (PRMP)** and **Game-Theoretic MPC (GTMPC)**.

Table 4

Relative results indicating the percentage change compared to the Fixed-Time (FT) control scenario.

Parameter name	CMPC	PRMP	GTMPC
Average fuel consumption (kg)	-0.38%	-4.37%	-3.23%
Average suffering red lights	-6.11%	-17.90%	-14.41%
Average waiting time (s)	-2.35%	-18.45%	-15.28%
Average travel time (s)	-0.95%	-5.63%	-3.79%
Average time loss (s)	-2.33%	-10.69%	-8.71%
Average speed (m/s)	3.59%	7.45%	4.12%
Average queue length	-7.38%	6.44%	-18.03%
Average stop count	-0.43%	-8.70%	-6.96%
Total throughput	0.04%	-0.03%	0.05%
Total delay (s)	-24.23%	-13.43%	-41.36%

The empirical data reveals that while the **CMPC** approach offers minor gains, the **GTMPC** framework provides a substantial leap in

operational efficiency for EVs. Most notably, the ASR experienced a profound reduction of 14.41% under **GTMPC**, marking the most significant improvement among all indicators and validating the framework's ability to effectively provide green waves for emergency vehicles. Similarly, the ATL experienced a significant reduction of 8.71% under **GTMPC**, which is nearly four times the improvement achieved by **CMPC** (2.33%). From a network-wide perspective, the proposed **GTMPC** achieves a remarkable 41.36% reduction in TDL and an 18.03% reduction in AQL, outperforming both **CMPC** and **PRMP**. Notably, the TTP remains nearly unchanged (0.05% increase), indicating that the improvements are achieved through more efficient traffic management rather than reduced demand or restricted flow.

Another critical finding is the 6.96% reduction in ASC for **GTMPC**. In contrast, **CMPC** only achieved a marginal 0.43% reduction in this metric. The ability of **GTMPC** to significantly lower the number of complete stops (ASC) is vital for emergency response, as every full stop not only increases the risk of accidents at intersections but also contributes

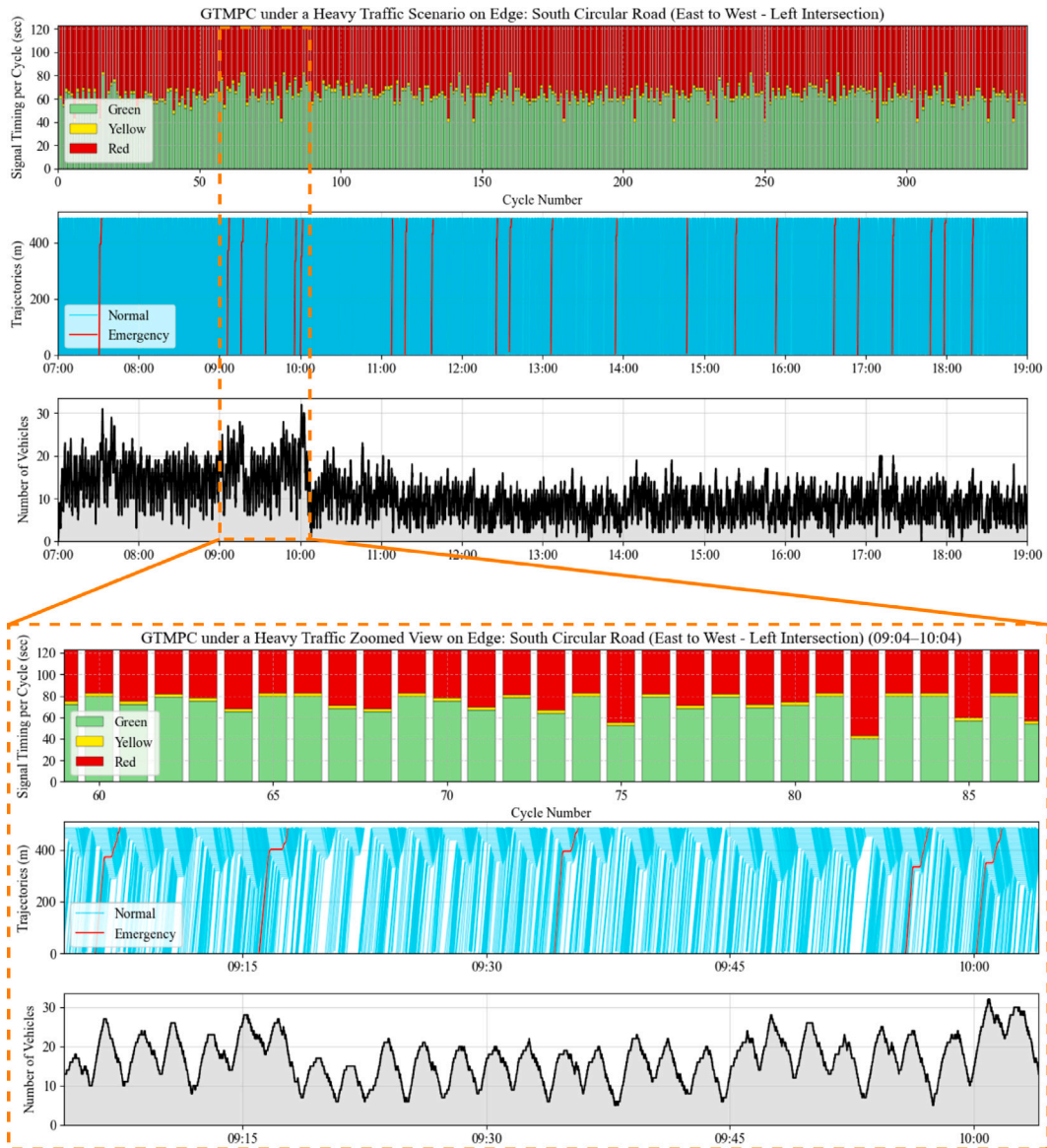


Fig. 7. Illustrative example of the GTMPC in heavy traffic condition based on real data of Dublin city. The top panel shows signal timings per cycle, with color coding for green, yellow, and red phases. The middle panel illustrates vehicle trajectories, with emergency vehicles highlighted. The bottom panel presents the number of vehicles per cycle, with the zoomed-in section showing a detailed view of the peak-hour (09:04 to 10:04). The zoomed-in view provides more granular insight into the control actions and vehicle behavior during this critical period. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

to the 3.23% decrease in AFC. Furthermore, the AVS showed a robust improvement of 4.12%, outperforming the 3.59% gain of the **CMPC** baseline.

The relative performance in ATT further cements the superiority of the proposed method, showing a 3.79% improvement. As shown in the bar charts of Fig. 6, the consistent downward trend across delay-related metrics and the upward trend in AVS under the **GTMPC** scenario prove that the decentralized non-cooperative decision-making mechanism logic is far more effective than global objective optimization in handling the high-priority requirements of EVs while simultaneously improving overall traffic efficiency and maintaining efficient network performance.

Since the overall performance of any signal control strategy strongly depends on the traffic demand in the network, we further challenge the proposed **GTMPC** framework by evaluating it under heavy traffic conditions. To replicate a high-density urban environment where both EV prioritization and overall traffic efficiency are critically stressed, we

utilize the real-world Dublin traffic data while scaling the flow of each approach by 50%. This increased demand not only tests the controller's ability to maintain EV priority under near-saturation conditions, but also provides a rigorous benchmark to evaluate its impact on network-wide performance. In particular, additional system-level KPIs, including AQL, TTP and TDL are analyzed to assess whether the prioritization mechanism mitigates congestion propagation and preserves acceptable traffic-operational conditions under heavy demand.

To evaluate the dynamic responsiveness of the proposed framework under these conditions, Fig. 7 illustrates a comprehensive temporal analysis of the network. As shown in the zoomed-in section of Fig. 7 (09:04 to 10:04), this period represents the peak-hour congestion where the queue length on the instrumented approaches reaches its maximum. In this scenario, EVs are frequently forced to stop behind residual queues. Despite the heavy saturation, the **GTMPC** logic attempts to dynamically allocate additional green time through the dynamic re-allocation of green time based on priority weights to dissipate the

Table 5

Values of KPIs for each control scenario in heavy traffic condition. (The columns correspond to the control scenarios: FT, CMPC, PRMP and GTMPC).

Parameter name	FT	CMPC	PRMP	GTMPC
Average fuel consumption (kg)	105.78	101.61	98.83	96.97
Average suffering red lights	2.48	2.45	1.95	1.99
Average waiting time (s)	23.45	25.15	21.44	20.11
Average travel time (s)	125.48	118.63	109.82	111.9
Average time loss (s)	68.48	61.67	58.79	54.91
Average speed (m/s)	6.18	6.53	7.17	6.92
Average queue length	16.35	14.43	17.86	13.75
Average stop count	2.48	2.45	2.35	2.41
Total throughput	16 262	16 263	16 259	16 266
Total delay (s)	462 887.47	362 671.82	379 121.8	288 996.66

Comparison of Control Scenarios (in heavy traffic)

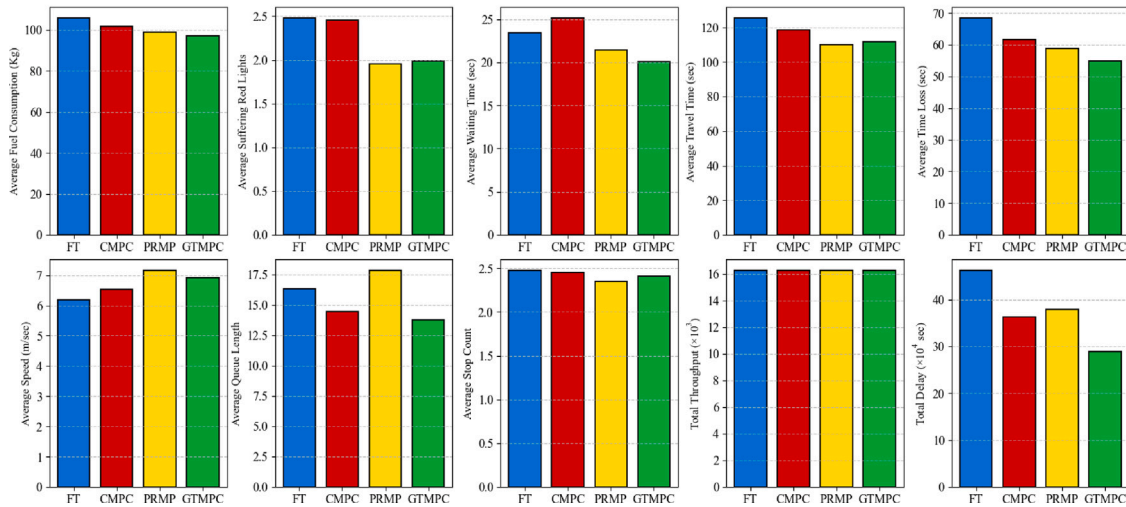


Fig. 8. Comparison of traffic control scenarios in heavy traffic condition: **FT**, **CMPC**, **PRMP** and **GTMPC**. The figure presents the average values of various performance metrics, including AFC (Kilograms), ASR, AWT (seconds), ATT (seconds), ATL (seconds), AVS (meters per second), AQL, ASC, TTP and TDL (seconds) for each control scenario.

queue ahead of the EV, even if a full non-stop passage is not physically possible due to the sheer volume of regular traffic. At the same time, the controller regulates queue growth on non-prioritized approaches, preventing excessive spillback and maintaining acceptable operating conditions across the network despite the high demand.

The quantitative results for the heavy traffic scenario are summarized in [Table 5](#) and visualized in [Fig. 8](#). To provide a more granular view of the performance gains, the relative percentage improvements of **CMPC** and **GTMPC** over the **FT** baseline are presented in [Table 6](#) and [Fig. 9](#). The empirical data highlights a critical distinction between the controllers under heavy demand. While the **CMPC** strategy struggles to manage the increased waiting time, showing a 7.25% increase in AWT compared to the **FT** scenario, the **GTMPC** framework achieves a significant reduction of 14.24%, demonstrating its ability to maintain EV mobility even under saturation. From a network-wide perspective, the advantages of the proposed framework become even more evident. The AQL is reduced to 13.75 under **GTMPC**, compared to 16.35 in **FT** and 17.86 in **PRMP**, indicating a substantial mitigation of congestion levels. Similarly, the TDL is significantly decreased by 37.57% relative to the baseline, outperforming both **CMPC** and **PRMP**. Importantly, the TTP remains effectively unchanged across all scenarios, confirming that the improved performance is achieved through more efficient traffic management rather than restricting network flow. These results collectively demonstrate that the proposed prioritization mechanism not only benefits EVs but also enhances overall traffic conditions under heavy demand.

Furthermore, **GTMPC** continues to demonstrate strong performance in mobility continuity, reducing the ASR by 19.76%, significantly outperforming the marginal 1.21% improvement of **CMPC**. The AVS also

Table 6

Relative results in heavy traffic condition indicating the percentage change compared to the **FT** control scenario.

Parameter name	CMPC	PRMP	GTMPC
Average fuel consumption (kg)	−3.94%	−6.57%	−8.33%
Average suffering red lights	−1.21%	−21.37%	−19.76%
Average waiting time (s)	7.25%	−8.57%	−14.24%
Average travel time (s)	−5.46%	−12.48%	−10.82%
Average time loss (s)	−9.94%	−14.15%	−19.82%
Average speed (m/s)	5.66%	16.02%	11.97%
Average queue length	−11.74%	9.24%	−15.90%
Average stop count	−1.21%	−5.24%	−2.82%
Total throughput	0.01%	−0.02%	0.02%
Total delay (s)	−21.65%	−18.10%	−37.57%

reaches 6.92 m/s under **GTMPC**, corresponding to an 11.97% increase over the baseline. Even under saturated conditions, the proposed method achieves a 19.82% reduction in ATL and an 8.33% reduction in AFC, confirming that the prioritization mechanism remains effective without inducing excessive stop-and-go behavior. From a broader system perspective, the simultaneous reduction in AQL and TDL further verifies that these improvements are not achieved at the expense of regular traffic. Instead, the results indicate that the proposed framework enhances both EV performance and overall network efficiency in a balanced and scalable manner.

To empirically justify the selected prediction horizon, a sensitivity analysis was conducted under the heavy traffic scenario. The prediction horizon was varied from one to six signal cycles while keeping

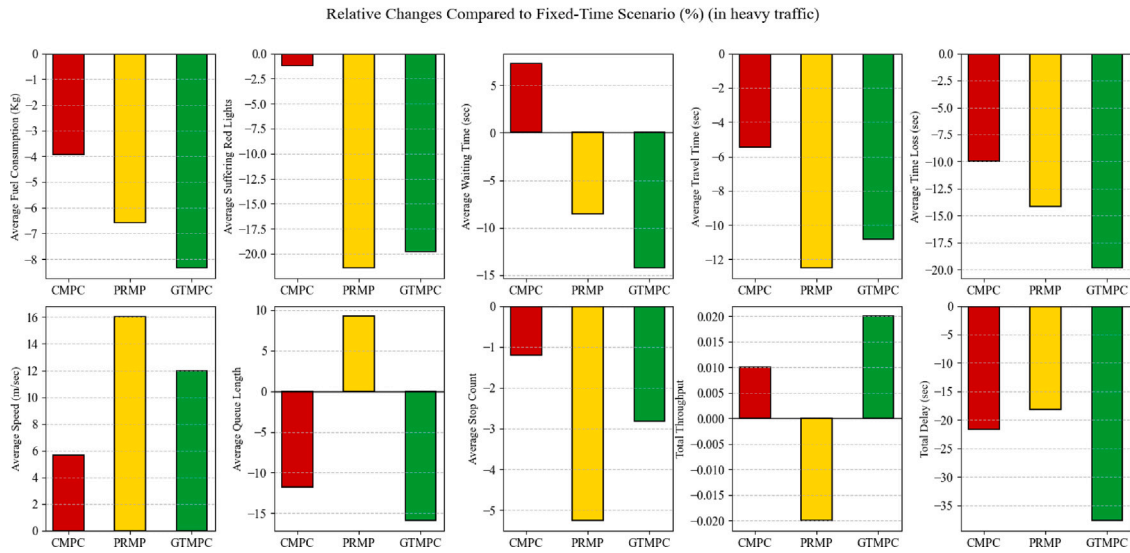


Fig. 9. Relative changes (%) in performance metrics compared to the **FT** scenario in heavy traffic condition. The figure presents the relative percentage changes in AFC, ASR, AWT, ATT, ATL, AVS, AQL, ASC, TTP and TDL parameters for three control strategies: **CMPC**, **PRMP** and **GTMPC**.

Table 7

Sensitivity analysis of the prediction horizon under heavy traffic conditions ($N_p = N_c$).

Parameter	$N_p = 1$	$N_p = 2$	$N_p = 3$	$N_p = 4$	$N_p = 5$	$N_p = 6$
Average waiting time (s)	21.61	20.11	21.14	21.35	22.50	22.59
Average travel time (s)	113.41	111.90	117.04	121.98	124.04	126.72
Average speed (m/s)	6.87	6.92	6.30	6.35	6.24	6.13
Average stop count	2.39	2.41	2.51	2.51	2.55	2.61
Maximum computation time (s)	0.4601	0.1550	0.5159	1.5546	2.0493	3.4391
Minimum computation time (s)	0.0062	0.0099	0.0158	0.0192	0.0238	0.0452
Average computation time (s)	0.0135	0.0246	0.0498	0.0584	0.0605	0.1119
Total computation time (s)	8.9979	10.3645	19.8785	38.8939	40.2921	74.4921

the remaining controller settings unchanged. The obtained results are summarized in Table 7. It can be observed that the best overall traffic performance is achieved for $N_p = 2$. Specifically, this configuration yields the lowest AWT (20.11 s), the lowest ATT (111.90 s), and the highest AVS (6.92 m/s). Increasing the prediction horizon beyond two cycles does not improve performance. On the contrary, both ATT and AWT gradually increase, while the AVS decreases. This behavior is consistent with the fact that traffic demand and turning movements become increasingly uncertain over longer prediction horizons, reducing the accuracy of future state estimations.

From a computational perspective, increasing the prediction horizon significantly increases the optimization burden. The average computation time rises from 0.0246 s at $N_p = 2$ to 0.1119 s at $N_p = 6$, while the maximum observed computation time increases from 0.1550 s to 3.4391 s. Since the proposed framework repeatedly solves a game-theoretic optimization problem at every signal cycle, such growth in computational effort is undesirable for real-time deployment. Therefore, $N_p = 2$ represents the best trade-off between traffic performance and computational efficiency for the considered urban emergency-priority scenario, and is consequently adopted throughout the remainder of this study.

A critical question regarding the operational reliability of the proposed system is the handling of multiple EVs arriving at an intersection simultaneously from different approaches. The decentralized **GTMPC** framework is inherently designed to handle such strategic conflicts through a multi-player weighted non-cooperative game formulation. When concurrent EVs are detected, each approach containing an EV is assigned a high priority weight within the cost function. In cases of simultaneous detection on conflicting phases, the optimization problem balances these competing priorities through the shared constraints on green time, resulting in an allocation that minimizes the aggregate cost

while respecting all active demands. This mechanism eliminates the need for explicit rule-based prioritization and ensures that multi-EV conflicts are resolved consistently within the optimization framework.

Furthermore, when EVs arrive with a temporal offset, the predictive nature of the MPC layer enables the controller to allocate green time to the first EV while anticipating the arrival of subsequent EVs. In such staggered scenarios, the priority weights evolve dynamically based on the system state, effectively prioritizing the approach associated with the most critical condition at each decision step. Even under fully saturated conditions, the game-theoretic equilibrium ensures that this prioritization does not lead to a total collapse of regular traffic flow on other links. By mitigating excessive congestion while providing a fair strategic compromise, the **GTMPC** ensures the system remains robust in the presence of overlapping emergency requests, maximizing the operational speed for all high-priority agents involved.

5. Discussion

The proposed decentralized, macroscopic **GTMPC** framework for EV prioritization in urban traffic networks demonstrates a significant advancement over traditional methods, such as **FT** and **CMPC**. The results of the simulation study, conducted on real-world traffic data from Dublin, Ireland, showcase the effectiveness of the **GTMPC** approach in addressing the critical challenges of emergency vehicle navigation through congested urban traffic networks. Specifically, the integration of new performance indicators, such as ASR and AVS, provides a deeper insight into how game-theoretic weighting mechanism facilitates a green corridor effect, reducing the number of red-light encounters and maintaining a higher velocity profile for EVs.

In addition to EV-oriented improvements, the inclusion of network-level performance indicators provides a more comprehensive assessment of the proposed framework. The results indicate that the **GTMPC**

not only enhances EV mobility but also improves overall traffic conditions. In particular, the observed reductions in AQL and TDL, along with the preservation of TTP, confirm that the prioritization mechanism does not induce adverse effects on regular traffic flow.

In contrast to centralized approaches, where traffic control decisions are made based on global state information, the decentralized nature of **GTMP**C ensures that each intersection operates independently, relying on local traffic measurements. This decentralized structure enhances the framework's scalability and demonstrates favorable traffic-operational performance across the considered scenarios, making it suitable for deployment in large-scale urban networks. From a network-level perspective, this decentralized architecture does not eliminate coordination, but rather shifts it from explicit communication to implicit interaction through traffic dynamics. In particular, upstream control actions directly influence downstream states via flow propagation, enabling a self-organized coordination mechanism that supports smoother EV progression along corridors. The absence of a central coordinator reduces communication requirements and minimizes the risk of bottlenecks, ensuring that the system can handle increasing traffic demand and emergency events effectively.

Despite these advantages, it is important to acknowledge a potential limitation of the proposed decentralized implicit-coordination mechanism. Since downstream intersections rely on locally observed traffic states and flow propagation rather than explicit inter-intersection communication, a propagation delay may arise in corridor settings. In particular, a downstream controller can only adapt its green-time allocation after detecting the upstream discharge or the EV-induced inflow at its own approach, rather than proactively anticipating the EV arrival through explicit corridor-level coordination. In contrast, explicit corridor-level or network-wide EV progression strategies can enable earlier anticipation and synchronization of signals along the corridor. However, such approaches typically require higher communication and coordination effort and their performance is more dependent on the reliability of centralized or inter-sectional information exchange.

The proposed framework instead prioritizes scalability, distributed implementation and local robustness by avoiding explicit communication requirements. Importantly, due to the receding-horizon nature of the **GTMP**C formulation, downstream controllers continuously re-optimize their decisions as new traffic information becomes available, which helps to rapidly adapt to EV-induced disturbances once they are observed, thereby reducing the practical impact of the inherent coordination delay. This property is particularly important when considering the interaction between prioritized EVs and regular traffic streams. The results suggest that local decision-making, guided by adaptive priority weights, is sufficient to maintain efficient traffic operation and controlled queue growth without requiring centralized coordination or explicit flow balancing mechanisms.

The comparative analysis reveals that while **CMPC** offers marginal improvements over **FT** control in normal conditions, and **PRMP** provides strong immediate prioritization for EVs, both approaches exhibit notable limitations. In particular, **PRMP** tends to disrupt regular traffic flow by introducing abrupt signal preemption, which can lead to increased queue formation and instability under high demand. In contrast, the proposed **GTMP**C framework achieves a more balanced trade-off by incorporating EV prioritization within a predictive and game-theoretic optimization framework. So, the integration of game theory into the predictive framework yields a substantial leap in operational efficiency. The equilibrium-based optimization process allows for a structured allocation of green time among competing traffic phases, ensuring that EVs are given priority without unduly compromising the flow of regular traffic.

To further clarify the source of performance improvements, an ablation-style interpretation of the results can be drawn by comparing the three benchmark strategies. The **CMPC** baseline represents a predictive control framework without explicit EV-priority weighting or game-theoretic interaction, thereby serving as a reference for

purely optimization-based coordination. In contrast, the **PRMP** strategy introduces strong EV prioritization through preemption, but lacks predictive capability and coordination, often resulting in disruptions to regular traffic flow. The proposed **GTMP**C framework effectively combines these two aspects by embedding EV-priority weighting within a predictive and game-theoretic structure. The comparison with **CMPC** indicates that the inclusion of adaptive priority weights and strategic interaction significantly enhances EV-related performance metrics. Meanwhile, the comparison with **PRMP** demonstrates that prioritization alone is insufficient, as the absence of predictive coordination leads to degraded network-level performance. Therefore, the observed performance gains of the **GTMP**C framework can be attributed to the synergistic effect of predictive control and game-theoretic prioritization, rather than to EV weighting alone.

This is further supported by the network-level metrics, where reductions in AQL and TDL demonstrate that the proposed approach mitigates congestion propagation while preserving system throughput. Unlike preemption-based strategies, which may locally favor EVs at the expense of global performance, the proposed method maintains a consistent balance between competing traffic demands.

The improvement is most evident in the ASR metric, where **GTMP**C consistently achieves the highest reduction in red-light stops, thereby minimizing the dangerous stop-and-go cycles that typically impede emergency responses. It is also noteworthy that the **GTMP**C approach performs well under varying traffic conditions, as evidenced by the experimental results obtained from the high-fidelity SUMO simulations. The framework effectively adapts to both peak and off-peak traffic conditions, maintaining a consistently high AVS even when the network is scaled to 150% of its original flow. Notably, this robustness extends beyond EV-specific metrics. The consistent reduction in TDL and controlled queue growth under heavy traffic conditions indicate that the framework effectively prevents congestion spillback and maintains acceptable traffic-operational conditions across the network.

The prediction horizon of the MPC framework, combined with the real-time detection of EVs, allows the system to anticipate and manage fluctuations in traffic demand, ensuring that emergency vehicles can navigate through congested intersections without significant delays. This strategic edge is further validated by the fact that **GTMP**C reduces time loss and fuel consumption more effectively than global objective optimization, as it treats each approach as a rational agent with adaptive priority weights.

A critical aspect of the operational reliability of the proposed system is the handling of multiple EVs arriving at an intersection simultaneously from different approaches. The decentralized **GTMP**C framework is natively designed to handle such strategic conflicts through its multi-player weighted non-cooperative game structure. When concurrent EVs are detected, each instrumented approach containing an EV is treated as a high-priority player in the game. In cases of simultaneous detection on conflicting phases, the weighting mechanism treats them as agents with equal priority weights, balancing the green time budget to minimize collective delay and ensuring neither vehicle faces a disproportionate red-light duration. This endogenous conflict resolution mechanism eliminates the need for heuristic or rule-based coordination strategies, allowing the system to scale naturally with the number of simultaneous EV requests.

Furthermore, if EVs are detected with a temporal offset, the predictive nature of the MPC layer allows the system to allocate a green extension to the first EV while simultaneously planning the optimal phase transition for the second. In this staggered arrival context, the priority weights dynamically adapt, granting temporary higher power to the approach with the EV closest to the intersection to clear the junction, followed immediately by a phase adjustment for the second vehicle. Even under fully saturated conditions, the game-theoretic equilibrium ensures that this prioritization does not lead to a total collapse of regular traffic flow on other links. By limiting congestion growth while providing a fair strategic compromise, the **GTMP**C ensures the system remains robust in the presence of overlapping emergency requests, maximizing the operational speed for all high-priority agents involved.

6. Conclusion and future works

In this paper, we proposed a decentralized macroscopic Game-Theoretic Model Predictive Control (**GTMP**C) framework designed to prioritize EVs within urban traffic networks. The framework integrates a game-theoretic non-cooperative formulation with Model Predictive Control (MPC) to address the dynamic and competing demands between regular traffic and emergency vehicles. By modeling each intersection as a strategic player in a weighted non-cooperative game, the **GTMP**C approach provides decentralized control that adjusts green-time allocations based on local traffic conditions and predictive horizons.

The empirical evaluation of the **GTMP**C framework, using real-world traffic data from Dublin, Ireland, demonstrates its superior performance over traditional traffic control strategies, including Fixed-Time (**FT**) and Classical MPC (**CMPC**) approaches. The results indicate that **GTMP**C provides substantial reductions in key performance metrics, most notably in the Average Suffering Red-lights (ASR) and Average Waiting Time (AWT), which saw improvements of up to 14.41% and 15.28% respectively in standard conditions. Furthermore, the framework successfully increased the Average Speed (AVS) of EVs to 7.83 m/s, ensuring a continuous green corridor effect that minimizes dangerous stop-and-go cycles. Importantly, the proposed framework achieves these improvements without degrading overall traffic conditions. The inclusion of network-level KPIs demonstrates that the **GTMP**C reduces congestion (as reflected by AQL), significantly lowers TDL, and maintains nearly unchanged TTP, confirming that EV prioritization is achieved in a system-efficient manner.

Our findings also highlight the exceptional robustness of the **GTMP**C framework under heavy traffic conditions. While the **CMPC** baseline struggles during peak saturation, even leading to a 7.25% increase in waiting time, and **PRMP** may introduce disruptions due to abrupt signal preemption, particularly under high-demand conditions, the proposed **GTMP**C maintains its efficacy, achieving a 14.24% reduction in AWT and a 19.76% decrease in ASR compared to the **FT** scenario. From a network-wide perspective, the framework achieves a substantial reduction in Total Delay (up to 37.57%) and a significant decrease in Average Queue Length, while maintaining nearly unchanged throughput. These results confirm that the proposed approach scales effectively under high demand and preserves overall traffic performance. Additionally, the decentralized multi-player game structure proved capable of managing concurrent EV arrivals through dynamic adaptation of priority weights, ensuring fair and efficient passage for multiple high-priority agents without destabilizing the macroscopic flow. This scalability and real-time responsiveness enhance the feasibility of deploying the **GTMP**C framework in large-scale urban networks where centralized coordination is often impractical.

It is important to emphasize that the evaluation in this study is conducted under a simplified corridor representation, which is commonly adopted in macroscopic traffic control research to ensure analytical tractability and to isolate the effects of the proposed control methodology. While the simulation captures realistic traffic demand patterns and stochastic EV arrival processes derived from real-world data, it does not explicitly model multi-lane interactions, detailed driver behavior, or lane-changing dynamics. Therefore, the results should be interpreted within this modeling scope. Extending the proposed framework to fully detailed urban networks would require additional modeling of microscopic traffic behaviors and more comprehensive validation under heterogeneous driving conditions. These aspects are beyond the scope of the present study and are identified as important directions for future research and real-world deployment.

Building upon the findings of this research, several directions for future studies are identified to further enhance the resilience and capability of the proposed framework. In particular, although the proposed framework is structurally capable of handling simultaneous and staggered multi-EV arrivals through its priority-weighted formulation,

the present study does not include a dedicated and systematic quantitative evaluation of such conflict scenarios. Future work will focus on designing controlled multi-EV experiments to systematically assess the performance of the framework under varying levels of conflict intensity, including simultaneous arrivals on competing phases and high-density emergency traffic conditions. A promising extension involves the integration of Vehicle-to-Infrastructure (V2I) communication protocols to provide the MPC layer with high-fidelity, real-time trajectory data, enabling a transition from macroscopic accumulations to precise, microscopic vehicle-level prioritization. Another important direction for future research is the incorporation of cooperative driving behaviors at the microscopic level. In particular, modeling explicit yielding mechanisms, lane-clearing strategies and driver response to approaching EVs would enable a more realistic representation of traffic interactions. Integrating such behavioral models with the proposed macroscopic control framework would allow for a comprehensive multi-scale evaluation of EV prioritization strategies. Furthermore, the application of Reinforcement Learning (RL) could be explored to achieve autonomous and adaptive tuning of the priority weights and penalty parameters, allowing the controller to evolve based on historical traffic patterns and varied emergency severity levels. The scope of the game-theoretic model could also be broadened to a multi-modal context, incorporating public transit and active transportation as strategic players within the game-theoretic framework to ensure holistic urban mobility. Additionally, considering the global shift toward electrification, embedding energy-aware constraints for electric emergency fleets into the optimization loop would facilitate a more sustainable response mechanism. Finally, investigating the robustness of the **GTMP**C framework under realistic measurement conditions will be an important direction for future work. In particular, incorporating sensor noise, partial observability, and state estimation techniques (e.g., Kalman filtering or observer-based approaches) into the control loop would enable a more comprehensive evaluation of the framework under practical deployment scenarios. This extension would allow the assessment of the sensitivity of the proposed controller to measurement uncertainty and data imperfections commonly encountered in real-world traffic systems.

CRedit authorship contribution statement

Arshia Abdi: Writing – original draft, Visualization, Software. **Bijan Moaveni**: Validation, Methodology, Conceptualization. **Tamás Tettamanti**: Writing – review & editing, Writing – original draft, Methodology, Conceptualization.

Declaration of AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used the Grammarly tool in order to check and improve the English grammar. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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