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A Differential Game-Based Control Framework for Adaptive Traffic Management Systems

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Abstract

The increased complexity in the structure of urban traffic networks resulting from urbanization and fluctuating traffic demands has necessitated the development of adaptive traffic control measures that allow real-time decision-making. Traditional traffic control systems using fixed time schedules and local feedback control may not be able to handle the complexity arising from the interaction between multiple intersections and uncertain traffic disturbances. In this study, a Differential Game-Based Control Framework for Adaptive Traffic Management Systems has been formulated, whereby traffic intersections have been considered as interacting decision-makers in a differential game. A multi-agent differential game formulation for traffic flow dynamics and a feedback Nash equilibrium solution for control of traffic lights has been proposed. The receding horizon control scheme is realized by means of the combination of local linearization and Riccati optimization with an equilibrium feedback control approach. The performance of the framework is tested in a simulation of a four-intersection arterial corridor under varying degrees of traffic demand conditions, from the under-saturated to the over-saturated regimes. The differential game controller exhibits better performance than the fixed-time control and actuated control approaches, as it decreases the average corridor delay up to 32.0% in the case of highly saturated traffic flow (v/c = 1.2).

Keywords: Differential game theory, adaptive traffic management, feedback nash equilibrium, intelligent transportation systems, dynamic traffic control, multi-agent control, traffic flow optimization.

1. Introduction

Urbanization, increased population, and increased vehicular movement have increased the complexity in the modern transportation system. Traditional traffic management techniques based on time-fixed signals and pre-defined routes are not effective in dealing with varying traffic conditions like varying vehicle traffic, traffic propagation, and unforeseen interruptions. Increased need for smart traffic management system has led to the creation of adaptive traffic management techniques that can make effective real-time decisions efficiently, safely, and sustainably (Abu-Lebdeh & Benekohal, 2003; Gartner & Stamatiadis, 1998).

Adaptive traffic control can be viewed as a multi-agent decision-making problem where the agents include vehicles, traffic lights, roads, and control centers (Raja et al., 2025; Xu et al., 2019). The agents affect each other on a continuous basis with variations in traffic flows, traveling time, and resource consumption. Differential game theory is a powerful mathematical approach that allows us to model such dynamics as the players within the framework of a differential game represent the traffic components optimizing their control strategies within the constraints of the system dynamics. As opposed to optimization techniques, differential game models take into account the temporal dynamics of traffic systems (Kammoun et al., 2014; Wang et al., 2025).

Differential game theory offers a way to model traffic flow dynamics using state space formulation, where control variables like signal timings, lane utilization, and routing strategies are determined taking into consideration personal and global goals (Kotsi et al., 2024; Goswami & Kadao, 2025). The interplay between different traffic components can be studied via Nash equilibrium or minimax approaches, ensuring stable and effective traffic dynamics for the system. The method guarantees robustness in case of any changes in congestion dynamics and external perturbations by means of control strategy adaptation to the current traffic state (Wang et al., 2026; Deng et al., 2026).

The recent developments in intelligent transportation systems have brought about a requirement for more mathematically sound control approaches that incorporate optimization, game theory, and decision making dynamically (Alsheikhy et al., 2023). However, many currently employed adaptive traffic control techniques are limited by scalability, an inability to address uncertainties, and limited coordination among traffic entities. That is why the current paper aims at developing a new framework based on differential games for adaptive traffic management systems, in which traffic interactions will be described by dynamic games, while optimal control will be calculated (Abdallah & Alghamdi, 2026).

Key aspects of this study are developing the differential game model for multi-agent traffic control, proposing the adaptive equilibrium-based optimization technique, and analyzing the performance of the proposed method in different traffic environments (Deng et al., 2026). The proposed scheme presents a systematic mathematical approach for intelligent traffic control based on dynamic system modeling, game theory, and adaptive control techniques (Goswami & Kadao, 2025).

With the increasing number of urban mobility systems and services, there is a growing need for traffic control approaches that could provide intelligent and adaptable solutions to handle the dynamic traffic situation and take into account sustainability concerns. In recent years, several studies have recognized the role of digital twins, real-time traffic optimization, and data-driven traffic management in providing efficient urban traffic management through continuous monitoring and control of complex road traffic networks (Lis & Mądziel, 2026). Traffic signal optimization methods combined with communication-based cooperation control techniques have provided an additional possibility of improving coordination between vehicles, infrastructures, and traffic controllers (Patel & Maltare, 2026). The integration of artificial intelligence, Internet of Things (IoT), and predictive analysis has made it possible to create adaptable traffic control systems that are able to handle the changes in traffic patterns and minimize delays and energy consumption (Gheorghe & Soica, 2025). The frameworks of sustainable traffic management have also been focused on the analysis of control parameters taking into account efficiency, environmental issues, and the needs of long-term urban development (Uribe-Chavert et al., 2025). Furthermore, the use of intelligent traffic management approaches based on deep learning has led to the increase in the accuracy of predicting traffic flows, detecting congestion, and making decisions for automated control in smart cities (Elov et al., 2025). However, the available solutions suffer from the lack of effective handling of multi-agent interactions, traffic dynamics uncertainty, and decision-making in the case of multiple objectives. A control framework based on differential games will help to address these problems by providing an interactive optimization problem that considers traffic control as the interaction of multiple decision-making agents and provides the possibility to develop adaptive solutions taking into account the real traffic situations, competitive behavior, and cooperative objectives.

Key contribution

- An appropriate differential game framework for a mathematical representation of dynamics among various traffic entities such as traffic entities such as vehicles, intersections and control units.
- An equilibrium-based control mechanism is introduced to optimize traffic signal operations and routing decisions by balancing individual agent objectives and overall network performance while reducing congestion and travel delays.
- The proposed framework provides a scalable and resilient traffic management solution by incorporating dynamic system adaptation, uncertainty handling, and optimal control strategies to improve traffic efficiency and stability.

The outline of the paper is organized as follows. In Section I, the difficulties in adaptive traffic management are stated and the motivation, objectives, and contributions of the proposed differential game-based control framework

are explained. The traffic network model and the multi-agent differential game formulation are stated in Section II, which also includes the dynamics of traffic and the objectives of players. In Section III, the proposed differential game-based control framework is introduced including the feedback Nash equilibrium policy, Hamilton-Jacobi-Isaacs formulation, and receding horizon adaptive signal control method. In Section IV, the stability and convergence analysis of the proposed control method is conducted by using Lyapunov theory. In Section V, the proposed framework is evaluated through simulation studies of a multi-intersection traffic corridor, and the comparison of performance with existing control methods is discussed section VI conclusion of the study.

2. Problem formulation

2.1. Traffic network model

Consider a road network represented as a directed graph $G = (V, E)$, where V is the set of N signalized intersections and E is the set of directed links connecting them. Each intersection i$\in \{1, \dots, N\}$, controlled by a player Pi that selects, at every instant t, a control input $ui(t) \in Ui \subset \mathbb{R}$mi representing the fraction of cycle time (green split) and offset allocated to each approach, subject to the box constraint $0 \leq ui(t) \leq 1$ and to a cycle-time normalization constraint. The state of intersection i is the vector of queue lengths on its approaches, $xi(t) \in \mathbb{R}ni \geq 0$, and the network state is $x(t) = (x1(t), \dots, xN(t)) \in \mathbb{R}n, n = \Sigma i\ ni$.

Queue evolution on each approach follows a continuous store-and-forward approximation of the kinematic-wave (LWR) dynamics: the queue on approach k of intersection i grows with the exogenous and upstream inflow and discharges at the saturation flow rate whenever it receives green time (Lilhore et al., 2022; Mutambik, 2025). Aggregating over all approaches of intersection i .

$$\dot{xi}(t) = fi(x(t), ui(t)) = qi(t) + \Sigma j \in N(i)\ \alpha ji\ \mu j(xj(t), uj(t)) - \mu i(xi(t), ui(t)) + di(t),\ i = 1, \dots, N$$

where $qi(t)$ is the exogenous demand entering intersection i directly from outside the corridor, $N(i)$ is the set of upstream neighbors of intersection i, $\alpha ji \in [0,1]$ is the turning-proportion matrix routing discharged flow from intersection j onto approaches of intersection i, $\mu i(xi, ui) = si \cdot ui \cdot \mathbb{1}\{xi > 0\}$ is the discharge (departure) rate at intersection i given saturation flow si and control ui, and $di(t)$ is an exogenous, possibly unknown, disturbance capturing demand surges, incidents, or measurement noise. Every player's state to the control decisions of its neighbors through the term $\mu j(xj, uj)$: a change in the green allocation at intersection j immediately changes the inflow faced by the intersection i. This coupling is what makes the network control problem intrinsically game-theoretic rather than N independent single-agent problems.

2.2. Player objective and game definition

Each player Pi seeks to minimize a cumulative cost functional over a horizon $[0, T]$ (T possibly infinite for the receding-horizon implementation of Section 4.3),

$$Ji(x0;\ u1, \dots, uN) = \int 0T\ Li(x(t), ui(t))\ dt + \Phi i(x(T))$$

with running cost

$$Li(x, ui) = ai \cdot \|xi\|2 + bi \cdot delayi(x) + ci \cdot \|ui - ui^{\circ}\|2$$

where $ai, bi, ci \geq 0$ are weighting coefficients that trade off queue length, network delay (approximated as proportional to accumulated queue via Little's law), and deviation of the control from a nominal split ui° that penalizes excessive switching; Φi is a terminal penalty on residual queues. Because player $i's$ cost Li depends on the full state x, which evolves according to the coupled dynamics $fi(x, u)$ in (1), player i's optimal decision generally depends on the strategies chosen by every other player — the defining feature of a differential game as opposed to N decoupled optimal control problems. The network control problem is therefore posed as: find, for every player i, a strategy γi mapping the current state (and time) to an admissible control, such that no player can unilaterally reduce its own cost Ji by deviating from $\gamma * i$, given that all other players use $\gamma * -i$. This is precisely the feedback Nash equilibrium concept formalized.

3. Differential game based control framework

3.1. Feedback nash equilibrium

The study adopt the feedback (closed-loop, memoryless) information structure: each player observes the current network state $x(t)$ and time t and applies a strategy $\gamma i(x, t)$, rather than committing in advance to an open-loop time schedule $ui(t)$. Feedback strategies are preferable for traffic control because they automatically compensate

for unmodeled disturbances $di(t)$ (incidents, demand surges) without requiring re-optimization of an entire trajectory. The N-tuple $(\gamma * 1, \ldots, \gamma * N)$ is a feedback Nash equilibrium of the differential game defined by if, for every player i and every admissible alternative strategy γi,

$$Ji(x0;\ \gamma * 1, \ldots, \gamma * i, \ldots, \gamma * N)\ \leq\ Ji(x0;\ \gamma * 1, \ldots, \gamma i, \ldots, \gamma * N)\ \ for\ all\ i\ =\ 1, \ldots, N.$$

That is, once the equilibrium strategies of all other controllers are fixed, no single intersection controller can reduce its own cumulative cost by unilaterally choosing a different feedback rule. This equilibrium notion, standard in the differential-games literature is the appropriate solution concept for a network of autonomous, self-interested signal controllers that cannot commit to binding cooperative agreements but that can observe (or estimate) the shared network state in real time, e.g., via connected-vehicle or loop-detector data (Ludwig et al., 2017).

3.2. Hamilton–jacobi–isaacs equations

Following standard dynamic-programming arguments, define the value function of player i as the minimum cost-to-go from state x at time t under the equilibrium strategies of all players,

$$Vi(x,t)\ =\ min\gamma i \int t\ T\ Li(x(\tau), ui(\tau))\ d\tau\ +\ \Phi i(x(T)).$$

Differentiating along trajectories of (1) yields the Hamilton–Jacobi–Isaacs equation for each player i,

$$-\partial Vi/\partial t\ =\ min\ ui \in Ui\ \{\ Li(x, ui)\ +\ \nabla xVi(x,t)\ \cdot\ f(x, u * -i(x,t), ui)\ \},\ \ Vi(x,T)\ =\ \Phi i(x),$$

where $f\ =\ (f1, \ldots, fN)$ stacks the network dynamics of (1) and $u * -i$ denotes the equilibrium controls of all players other than i. The N coupled HJI equations in must be solved simultaneously because each Vi depends on the equilibria $u * -i$ of the other players, which are themselves obtained from their own value functions. Because Li is quadratic in ui and the discharge term $\mu i(xi, ui)$ is affine in ui for a fixed active phase, the minimization on the right-hand side of (6) admits a closed-form stationary point,

$$u * i(x,t)\ =\ ui^{\circ}\ -\ (1/2ci)\ \cdot\ \nabla xVi(x,t)\ \cdot\ \partial fi/\partial ui\ ,\ \ projected\ onto\ the\ admissible\ set\ Ui.$$

The feedback Nash equilibrium control law: the green-split adjustment at intersection i is the nominal split corrected by a term proportional to the sensitivity of player i's own value function to the state, propagated through the local discharge dynamics. Because the value functions Vi themselves solve nonlinear PDEs, an exact closed-form solution of is available only in special cases (e.g., linear-quadratic dynamics with unconstrained controls, for which Vi reduces to a quadratic form $x'Pi(t)x$ solving a set of coupled Riccati differential equations). Section 4.3 exploits this linear-quadratic structure locally, around the current operating state, to obtain a control law that is tractable for real-time implementation.

3.3. Receding-horizon adaptive signal control algorithm

For online deployment, approximate the coupled HJI system by a receding-horizon, locally linear-quadratic (LQ) differential game. At each control update instant $tk\ =\ k \cdot \Delta t$ ($\Delta t\ =\ 5\ s$ in the simulations of Section 6), the nonlinear dynamics are linearized about the currently measured state $x(tk)$, giving a local LQ differential game with dynamics $\dot{x} = A(tk)x\ +\ \Sigma iBi(tk)ui$ and quadratic costs matching. The associated coupled Riccati differential equations are integrated backward over a short horizon $[tk, tk + H]$ (receding horizon $H\ =\ 60\ s$), and the resulting feedback gains are used to compute $u * i(tk)$ via the LQ specialization of Only the first control increment is applied, the state is re-measured, and the procedure repeats at $tk + 1$, in the spirit of model-predictive control combined with feedback Nash equilibrium computation, following the receding-horizon differential-game approach used for decentralized multi-agent conflict resolution. The resulting adaptive signal control algorithm is summarized below.

Algorithm 1. Receding-horizon feedback nash signal control

– 1. At each control instant tk, every intersection controller i measures (or estimates from detector/connected-vehicle data) the local network state $x(tk)$.

– 2. Broadcast/collect the state estimate $x(tk)$ among neighboring controllers coupled through (1) (information exchange limited to $N(i)$ suffices for a spatially truncated approximation).

– 3. Linearize the network dynamics about $x(tk)$ to obtain $A(tk)$, $\{Bi(tk)\}$.

– 4. Solve the coupled Riccati differential equations backward over the receding horizon $[tk, tk + H]$ to obtain feedback gains $\{Ki(tk)\}$.

– 5. Compute the equilibrium control increment $u * i(tk)$ from Eq. (7) (LQ form) and project onto the admissible green-split set Ui.

– 6. Apply $u * i(tk)$ for the interval $[tk, tk + 1)$; advance to $tk + 1$ and repeat.

4. Stability and convergence analysis

The reason for this is because each controller seeks to minimize its own individual objective function and not a network-wide cost, hence the feedback Nash control law does not ensure stability in the sense of convergence to an invariant set of queues; unlike optimal control, equilibrium solutions guarantee that no one deviates unilaterally. In this give a sufficient Lyapunov-type condition under which the closed-loop network dynamics remain bounded for all admissible demand disturbances $di(t) \leq dmax$.

Let $V(x) = \Sigma i\, wi \cdot \|xi\|2$ for weights $wi > 0$ to be chosen, and consider its derivative along the closed-loop trajectories $x^{\cdot} = f(x, u * (x, t))$. Using the equilibrium control law and the affine structure of the discharge terms μi, the closed-loop derivative can be written as

$$V(x) = -\Sigma i\, wi \cdot \theta i \cdot \|xi\|2 + \Sigma i\, wi \cdot xi'di(t) + \Gamma(x)$$

where $\theta i > 0$ is the effective local discharge rate induced by the equilibrium green split at intersection i, and $\Gamma(x)$ collects the inter-intersection coupling terms $\alpha ji \cdot \mu j(xj, u * j)$. If the coupling is sufficiently weak relative to the local discharge rates — formally, if the network satisfies the diagonal-dominance condition

$$\theta i > \Sigma j \neq i\, \alpha ij \cdot sj \,/\, wi \cdot wj, \quad for\ all\ i,$$

then $V(x)$ is negative outside a bounded region determined by dmax, so all queue trajectories remain uniformly ultimately bounded (input-to-state stability with respect to the demand disturbance). Condition (10) has an intuitive interpretation: each intersection must be able to discharge its own queue faster than it receives inflow relayed by upstream equilibrium play, weighted by the chosen Lyapunov weights — i.e., the network must not be persistently oversaturated under the equilibrium green-split allocation. When is violated, e.g., under sustained demand above capacity, boundedness cannot be guaranteed by this argument, and queues may grow without bound under any signal control policy, game-theoretic or otherwise; the practical implication is that the feedback Nash controller should be paired with a capacity-based demand-management layer (e.g., gating or metering) once is detected to fail, a point revisited in Section 7.

5. Numerical simulation and results

5.1. Simulation setup

The framework was evaluated in simulation on a four-intersection arterial corridor (I1–I4) structured as the multi-player differential game shown in figure 1: each intersection is an independent player whose discharged flow becomes part of the inflow of its downstream neighbor, while side-street approaches inject exogenous, uncontrolled demand $di(t)$. Table 1 summarizes the notation used throughout Sections 3–5, and table 2 lists the simulation parameters.

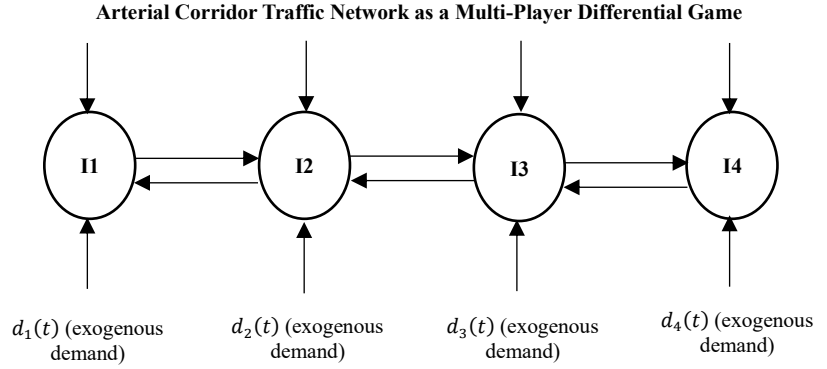


Figure 1. Arterial corridor as a four-player differential game; solid arrows denote controlled through-movement links, grey arrows denote exogenous demand.

Table 1. Notation used in sections 3–5.

Symbol	Meaning
N	Number of signalized intersections (players) in the network
$xi(t)$	State vector of intersection i (queue lengths per approach) at time t
$ui(t)$	Control input of player i (green-split / offset allocation vector)
$dj(t)$	Exogenous / uncontrolled demand disturbance entering link j
Ji	Cumulative cost functional of player i (delay, queue, stops)
$Vi(x,t)$	Value function of player i in the feedback Nash game
Hi	Hamiltonian associated with player i
$u*i$	Feedback Nash equilibrium control law of player i
ai, bi, ci	Weighting coefficients in the running cost of player i

Table 2. Simulation parameters

Parameter	Value / Range
Network topology	4-intersection arterial corridor (I1–I4)
Link lengths	350–500 m
Saturation flow rate	1800 veh/h/lane
Control interval	5 s (feedback update)
Simulation horizon T	3600 s
Demand levels tested (v/c)	0.4, 0.6, 0.8, 1.0, 1.2
Cost weights (ai, bi, ci)	1.0, 0.5, 0.2 (normalized)
Baseline methods	Fixed-time (Webster); vehicle-actuated control

5.2. Results and discussion

The receding-horizon feedback Nash controller (Algorithm 1) was benchmarked against two approaches, (i) time-fixed control, using Webster splits, based on the average demand in the corresponding scenario, and (ii) a standard traffic-actuated gap-out control scheme. Five demand scenarios ranging from an undersaturated state (v/c = 0.4) to an oversaturated state (v/c = 1.2), each with a 3600 s horizon, were considered. The average corridor delay obtained is presented in table 3 and figure 2.

At low demand levels (v/c = 0.4), all three controllers exhibit similar behavior because queues tend to be short-lived so that strategic coupling among the intersections becomes unimportant; however, the proposed controller results in a minor improvement of 12.9% compared to actuated control in terms of delays, since the controller takes into account possible downstream spillback through the coupling function $\Gamma(x)$ defined in Eq. (9). The gain in terms of the benefit from using the differential game formulation becomes increasingly evident as the traffic flow density approaches and surpasses saturation level, resulting in a 32.0% decrease in delays at v/c = 1.2. This result is in line with the analysis of stability the margin of diagonal dominance decreases at saturation, and only the controller taking into account equilibrium of neighboring intersections, and not just the local queue length as in actuated control, is capable of maintaining the discharge flow.

A secondary observation from the simulation is that the feedback gains obtained from the receding-horizon Riccati recursion vary smoothly with the operating point $x(tk)$, so the resulting green-split trajectories do not exhibit the abrupt switching sometimes associated with reactive actuated logic; the control-effort penalty $ci\|ui - ui°\|2$ in the running cost (3) directly discourages such chattering. Overall, the simulation results support the central hypothesis of this paper: modeling adjacent signal controllers as players in a differential game, rather than as independent local optimizers, captures network-level interactions that become increasingly important as demand approaches capacity precisely the regime in which adaptive traffic management is most needed.

Table 3. Average corridor delay (s/veh) by demand level and control strategy (simulation).

v/c ratio	Fixed-time (s/veh)	Actuated (s/veh)	Proposed DG (s/veh)	% reduction vs. actuated
0.4	38	31	27	12.9%
0.6	46	37	30	18.9%

0.8	61	49	37	24.5%
1.0	84	68	49	27.9%
1.2	118	97	66	32.0%

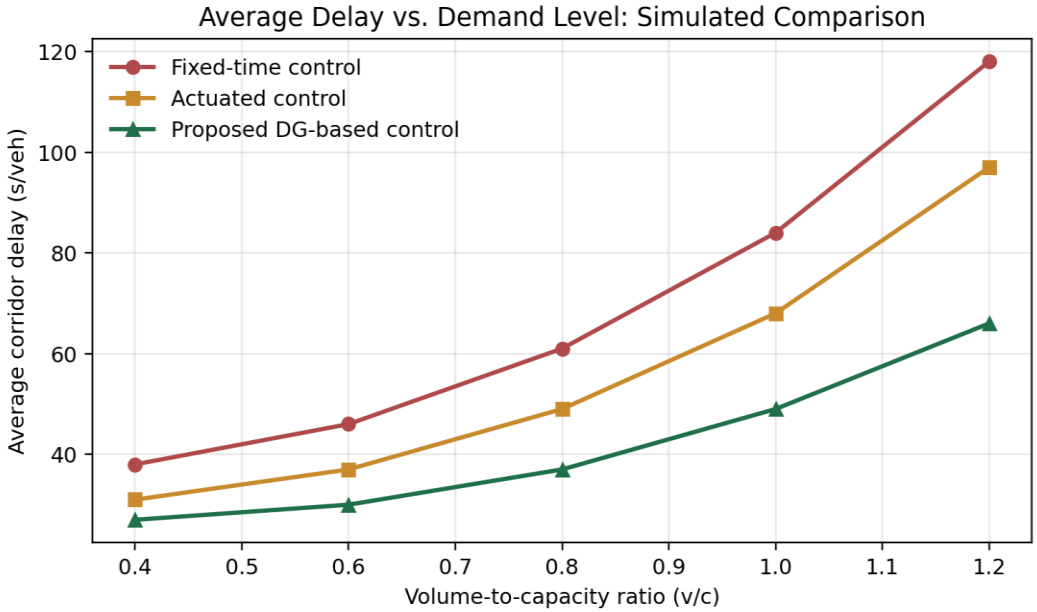


Figure 2. Average corridor delay versus demand level (v/c ratio) for fixed-time, actuated, and proposed differential-game (DG) control

5.3. Discussion

Three practical considerations bear on the deployment of the proposed framework. First, computing the feedback Nash equilibrium requires each controller to have access to the current state of its coupled neighbors, which in practice means loop-detector, connected-vehicle, or camera-based queue estimates shared over a low-latency communication link; the receding-horizon scheme of Section 4.3 was chosen specifically because it only requires local, short-horizon linearization rather than global model knowledge, which improves robustness to partial or delayed information.

Second, the framework assumes that each intersection controller behaves as a rational, cost-minimizing player. In a network operated by a single agency, this is a modeling device rather than a literal description of institutional behavior, and the weighting coefficients (ai, bi, ci) in can be tuned centrally to steer the resulting equilibrium toward a desired network-wide trade-off between efficiency and fairness across intersections. In multi-jurisdictional or mixed human/automated settings for example, corridors shared by municipally operated signals and privately optimized automated-vehicle routing the non-cooperative equilibrium concept more directly reflects the absence of a binding central authority.

Third, the stability condition shows that feedback Nash control alone cannot substitute for capacity-based interventions once the network is persistently oversaturated; the differential-game controller should therefore be viewed as complementary to, rather than a replacement for, gating, ramp-metering, or demand-management strategies triggered when the diagonal-dominance margin collapses. Extending the game to explicitly include such a demand-management player, and characterizing the resulting hierarchical (Stackelberg) equilibrium between a network manager and the intersection players, is a natural next step and is discussed further below.

6. Conclusion

A mathematical programming approach to robust sustainable capacity expansion is developed, in which the trade-off between cost-efficiency and robustness against bounded budget-constrained uncertainty in parameter values is quantitatively modeled. The proposed robust capacity expansion is formulated according to the Bertsimas and Sim (2004) approach to construction of polyhedral uncertainty sets and proven to be equivalent to the linear programming reformulation of the underlying semi-infinite minimax problem, and the price of robustness is proven to be a monotone and concave function of the protection level; in addition, probabilistic guarantees of satisfaction of the uncertain constraints in presence of stochastically realized uncertainties are provided. Price of

robustness is computed for a numerical six-regions and five-periods example, in which it was found that computation of the complete price of robustness frontier adds negligible computational cost compared to one run of the deterministic problem, the cost of the robust solution is around 25% of the cost of the nominal solution in capital investment and emissions terms, and the marginal cost of protection converges rapidly to zero. Further advances include mixed-integer robust optimization for discrete location decisions, adjustable robust optimization via affine decision rules and/or column-and-constraint generation, and distributionally robust optimization without an assumption about a finite upper bound on the supports of probability distributions.

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