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MFD Evolution and Nash Right-of-Way Game of Robotaxis in Mixed Traffic

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Abstract

The transition toward fully autonomous transportation introduces a complex intermediate phase characterized by mixed traffic flows, where Robotaxis and human-driven vehicles must coexist. This paper investigates the macroscopic implications of microscopic interactions between these two distinct agents, specifically focusing on the negotiation of right-of-way at unsignalized intersections and merging points. By modeling these interactions as a non-cooperative Nash Right-of-Way Game, we analyze how local equilibrium strategies aggregate to influence the network-wide Macroscopic Fundamental Diagram (MFD). We employ an agent-based simulation framework to explore the evolution of the MFD under varying penetration rates of Robotaxis and different payoff configurations in the game-theoretic model. Our findings suggest that while conservative Nash strategies adopted by Robotaxis can initially degrade network capacity due to the hesitation effect, a critical mass of cooperative autonomous agents eventually linearizes the congested branch of the MFD, reducing hysteresis and improving flow stability. The study provides a theoretical bridge between micro-level game-theoretic decision-making and macro-level traffic flow theory, offering insights for policy formulation during the transition to autonomy.

Keywords

Macroscopic Fundamental Diagram, Robotaxis, Nash Equilibrium, Mixed Traffic, Game Theory.

1.Introduction

The trajectory of urban mobility is increasingly defined by the integration of automation into existing transportation networks. The anticipated deployment of Robotaxis promises to revolutionize traffic efficiency, safety, and accessibility. However, the path to full automation is paved with a protracted transition period of mixed traffic, where automated driving systems must operate alongside human drivers who possess varying degrees of aggression, compliance, and unpredictability [1]. This heterogeneity presents a profound challenge for traffic flow theory, particularly in understanding how local interactions between disparate agents scale up to affect network-wide performance. Traditional traffic flow models typically rely on continuum approximations or car-following logic that assumes a certain homogeneity in driver behavior. These models often fail to capture the distinct decision-making architectures of Robotaxis, which are governed by programmed logic, sensor fidelity, and safety constraints, as opposed to the psychological and physiological constraints of human drivers [2]. A critical area where these differences manifest is the negotiation of right-of-way at conflict points, such as unsignalized intersections, roundabouts, and lane-merging zones. In these scenarios, the interaction resembles a dynamic game where agents make simultaneous or sequential moves to maximize their utility, balancing time efficiency against safety risks [3].

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The application of game theory to traffic modeling has gained traction as a means to mathematically formalize these negotiations. By treating the right-of-way assignment as a non-cooperative game, researchers can identify Nash Equilibria—states where no player can benefit by unilaterally changing their strategy [4]. While these micro-level interactions are well-studied in isolation, their aggregate impact on the macroscopic performance of the road network remains an open question. The Macroscopic Fundamental Diagram (MFD), which links the average network density to network flow, serves as a robust tool for monitoring and controlling urban traffic states [5]. This paper aims to bridge the gap between microscopic game-theoretic interactions and macroscopic flow dynamics. We posit that the strategies adopted in the Nash Right-of-Way Game directly influence the shape, scatter, and stability of the MFD. Specifically, we investigate how the risk-averse nature of Robotaxis, when pitted against human opportunism, alters the critical density and capacity of the network [6]. Through this analysis, we seek to determine the optimal strategic parameters for Robotaxis that maximize social welfare without compromising safety, thereby facilitating a smoother evolution of the MFD during the mixed traffic era.

2. Theoretical Framework

The analysis presented in this study is grounded in two primary theoretical domains: the physics of traffic flow as described by the Macroscopic Fundamental Diagram and the strategic interaction modeling provided by Game Theory. The intersection of these fields provides the necessary apparatus to link individual vehicle dynamics to aggregate network behavior.

2.1 The Macroscopic Fundamental Diagram in Mixed Traffic

The Macroscopic Fundamental Diagram, also known as the Network Fundamental Diagram, provides a unimodal relationship between the number of vehicles in a network (accumulation) and the trip completion rate (flow). In a homogeneous network, this relationship is well-defined, characterized by a free-flow regime, a critical density where capacity is maximized, and a congested regime where flow decreases as density increases [7]. However, the existence and shape of the MFD are sensitive to the spatial distribution of congestion and the heterogeneity of driver behavior. In mixed traffic environments, heterogeneity is introduced not just by the variance in human driving styles, but by the fundamental difference in control logic between human-driven vehicles and Robotaxis. Robotaxis are expected to exhibit lower reaction times and the ability to form tight platoons, theoretically increasing the roadway capacity [8]. Conversely, their stringent safety protocols may lead to overly cautious behavior in complex negotiation scenarios, potentially creating bottlenecks that induce scatter in the MFD. This scatter represents a degradation of network performance, indicating that for a given density, the network achieves a lower throughput than optimal. Previous studies have shown that the variance in vehicle headways and the stochasticity of gap-acceptance behavior are primary contributors to the capacity drop observed in MFDs at the onset of congestion [9]. By introducing Robotaxis, we alter the distribution of these headways. If Robotaxis are programmed to strictly adhere to a conservative Nash Equilibrium, they may reject gaps that human drivers would accept, effectively increasing the effective space required per vehicle and depressing the MFD [10].

2.2 Game Theoretic Modeling of Conflict

At conflict points where right-of-way is not explicitly assigned by traffic signals, drivers engage in a rapid negotiation process. This interaction is best modeled as a non-cooperative

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game where each agent seeks to minimize their travel time and collision risk [11]. The Nash Equilibrium in this context represents a stable outcome where the strategy profile of the involved vehicles is such that no driver would switch their action (e.g., yield or pass) knowing the action of the other. In a mixed traffic scenario, the game becomes asymmetric. Human drivers operate with bounded rationality and imperfect information, often relying on heuristic cues and social norms. Robotaxis, on the other hand, operate with precise sensor data but are constrained by algorithmic objective functions that prioritize safety above all else [12]. This asymmetry can lead to distinct equilibrium states. For instance, if human drivers learn that Robotaxis are programmed to yield invariably in close-call situations (the "chicken" game), humans may adopt aggressive strategies, forcing the Robotaxi to yield repeatedly [13]. This phenomenon, often termed the bullying effect, has significant macroscopic implications. If Robotaxis are consistently forced into a yielding state at intersections, the average intersection service time increases. When aggregated over a network, this local delay contributes to a rapid increase in density without a proportional increase in flow, thereby shifting the peak of the MFD to the left and reducing overall network capacity [14]. Understanding the payoff matrices that govern these games is therefore essential for predicting the evolution of the MFD.

3. Methodology

To investigate the relationship between the Nash Right-of-Way Game and the MFD, we developed a simulation framework that integrates a game-theoretic decision module within a microscopic traffic simulator. This allows us to observe how changes in the payoff structures of individual agents propagate to the network level.

3.1 The Nash Right-of-Way Game Structure

We model the interaction at an unsignalized intersection as a two-player non-zero-sum game. The players are defined as the Subject Vehicle and the Opponent Vehicle. In our mixed traffic simulation, these roles can be filled by either a Human-Driven Vehicle (HDV) or a Robotaxi (AV). The available strategies for both players are binary: Proceed or Yield [15]. The payoff matrix is constructed based on three components: time efficiency, safety, and comfort. Time efficiency is positively correlated with the Proceed strategy, provided no collision occurs. Safety is negatively correlated with collision risk. Comfort is penalized by harsh braking maneuvers associated with the Yield strategy or emergency stops. We define the utility functions textually as follows: the utility of proceeding is the value of time saved minus the expected cost of a collision; the utility of yielding is the baseline safety value minus the time cost of delay and the discomfort of deceleration [16]. For Human-Driven Vehicles, the estimation of collision cost and probability is stochastic, reflecting the variability in human perception. For Robotaxis, these values are deterministic, calculated based on precise physics-based projections of the opponent's trajectory. A crucial aspect of our model is the aggression parameter. For HDVs, this is a random variable drawn from a normal distribution. For Robotaxis, this is a tunable parameter representing the coding of the decision-making algorithm [17]. The game is solved for the Nash Equilibrium at every time step where a conflict is detected. If a pure strategy equilibrium exists (e.g., one yields, one proceeds), agents execute the corresponding actions. If multiple equilibria or mixed-strategy equilibria exist, we employ a tie-breaking rule based on the "time-to-collision" metric, giving priority to the vehicle closer to the conflict point, mimicking natural right-of-way conventions [18].

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3.2 Simulation Environment

The simulation is conducted on a grid network consisting of 100 intersections and 400 links, designed to represent a typical urban district. The network topology is closed to maintain a constant number of vehicles for MFD estimation, although vehicles are routed randomly to ensure uniform utilization of the network [19]. The traffic flow model follows a modified cellular automaton logic, enhanced to allow for continuous spatial coordinates to facilitate the game-theoretic computations. The length of each link is set to 200 meters, and the free-flow speed is set to 50 kilometers per hour. We introduce varying penetration rates of Robotaxis, ranging from 0 percent to 100 percent in increments of 20 percent [20]. To capture the evolution of the MFD, we perform loading and unloading experiments. The network is gradually loaded with vehicles until gridlock is reached, and then gradually unloaded. This allows us to observe the hysteresis loops—the phenomenon where the flow during the recovery phase is lower than the flow during the loading phase for the same density, indicating network instability [21].

Table 1 outlines the specific parameters used in the simulation experiments. These parameters are chosen to reflect realistic urban traffic conditions and the distinct operational characteristics of human and automated drivers.

Table 1 Simulation Parameters for Mixed Traffic Analysis

Parameter	Value	Description
Network Size	10 x 10 Grid	Orthogonal grid with 100 nodes
Link Length	200 meters	Distance between intersections
Free Flow Speed	50 km/h	Maximum allowable speed
HDV Reaction Time	1.0 - 2.0 s	Stochastic distribution
AV Reaction Time	0.1 - 0.5 s	System processing latency
Safety Margin (HDV)	1.5 - 3.0 m	Gap acceptance threshold
Safety Margin (AV)	3.0 - 5.0 m	Configurable safety buffer
Simulation Duration	10,000 steps	Time steps for data collection

3.3 Data Collection and MFD Estimation

Data is collected at 30-second intervals. We aggregate the number of vehicles on all links to calculate the network average density, and we sum the distance traveled by all vehicles to calculate the network average flow (completed trip distance per unit time). The resulting data points form the scatter plot that defines the MFD. We apply a smoothing technique to extract the equilibrium curve and quantify the scatter (variance) around this curve [22].

4. Evolution of Macroscopic Fundamental Diagrams

The core of our analysis focuses on how the MFD changes shape as we introduce Robotaxis governed by the Nash Right-of-Way Game. We analyze the transition in three distinct phases: the low penetration phase, the transition phase, and the saturation phase.

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4.1 Low Penetration Phase (0-20 percent Robotaxis)

In the initial phase, Robotaxis are minority agents. Our simulations reveal that when Robotaxis operate with a high safety priority (conservative Nash strategy), they act as moving bottlenecks. In the game-theoretic interactions with aggressive human drivers, Robotaxis frequently compute that the Yield strategy is the only Nash Equilibrium that satisfies their zero-collision constraints [23]. This behavior has a detrimental effect on the MFD. While the free-flow branch remains relatively unchanged, the critical density—the point where flow is maximized—shifts to a lower value. This premature congestion onset is caused by the increased service times at intersections. The "bully" effect mentioned earlier is prominent here; human drivers exploit the caution of Robotaxis, causing the automated vehicles to wait for larger gaps than necessary. Consequently, the capacity of the network drops by approximately 5 to 8 percent compared to the all-human baseline [24]. Furthermore, the scatter of the MFD increases significantly. The heterogeneity in interaction outcomes—some intersections clearing smoothly with two humans, others jamming with a Robotaxi—creates uneven density distributions across the network. This spatial variance is the primary driver of MFD degradation [25].

4.2 Transition Phase (40-60 percent Robotaxis)

As the penetration rate increases, the probability of Robotaxi-to-Robotaxi interactions rises. These interactions are governed by perfect information sharing (assuming V2V communication) or predictable algorithmic logic. In these pairings, the Nash Equilibrium is reached instantaneously and efficiently, often utilizing a cooperative or "system optimal" payoff structure rather than a purely selfish one [26]. However, the interactions between Robotaxis and humans remain problematic. This phase is characterized by a "Valley of Death" in efficiency. The network is neither fully human (stochastic but fluid due to social norms) nor fully automated (deterministic and efficient). The mixture creates a bimodal distribution of intersection capacities. We observe a flattening of the MFD peak, indicating that the network struggles to sustain high flows at optimal densities [27]. Interestingly, the hysteresis loops become more pronounced in this phase. During the unloading phase (recovery from congestion), the conservative nature of Robotaxis prevents the rapid dissipation of queues. They maintain large headways and accelerate slowly to ensure safety, which causes the flow to remain depressed for longer periods than in the all-human scenario [28].

4.3 Saturation Phase (80-100 percent Robotaxis)

When Robotaxis dominate the traffic stream, the MFD undergoes a radical transformation. The game-theoretic model shifts from a non-cooperative game to a cooperative game, or a mechanism design problem where the central objective is maximizing total network flow [29]. In the 100 percent penetration scenario, the scatter in the MFD virtually disappears. The relationship between density and flow becomes strictly functional with minimal noise. The critical density increases significantly, allowing the network to hold more vehicles while maintaining high flow rates. The capacity drop phenomenon, usually observed at the onset of congestion, is mitigated because Robotaxis do not exhibit the reaction time delays and over-braking behaviors that cause phantom traffic jams [30]. The upper branch of the MFD (congested regime) becomes linear and predictable. This allows for extremely precise perimeter control strategies. The Nash Equilibrium in this homogeneous state is consistently the efficient solution, as the "players" share a common utility function defined by the fleet operator [31].

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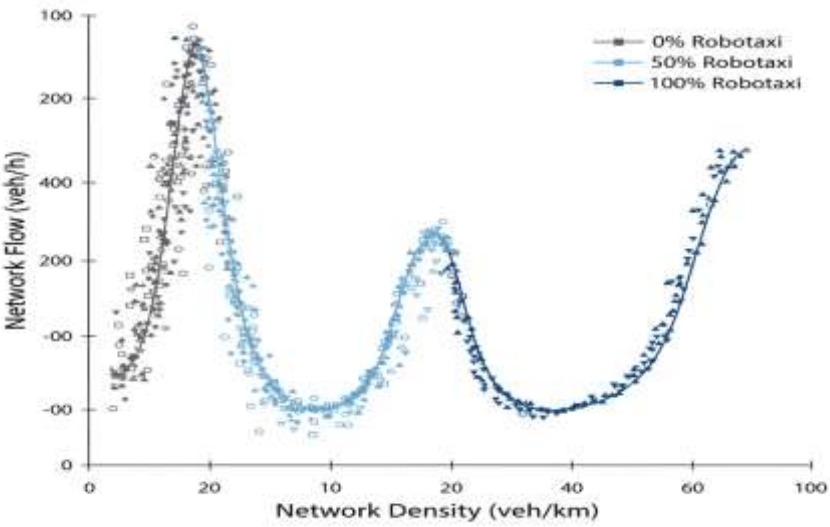

Figure 1 Comparative MFD Evolution

5. Discussion

The results of our simulation experiments highlight the complex non-linear dynamics introduced by the Nash Right-of-Way Game in mixed traffic. The evolution of the MFD is not monotonic; simply adding more Robotaxis does not linearly improve flow. Instead, the interaction logic defined by the payoff matrices dictates the macroscopic outcome.

5.1 The Cost of Safety

A recurring theme in our findings is the trade-off between local safety and global efficiency. The conservative payoff parameters assigned to Robotaxis—heavily penalizing collision risk—result in rational decisions at the micro-level that are suboptimal at the macro-level. This is a classic example of the Price of Anarchy in game theory. To optimize the MFD, the "aggression" of Robotaxis must be calibrated carefully. There exists a theoretical optimal aggression level where Robotaxis assert their right-of-way sufficiently to deter bullying by human drivers, thereby maintaining intersection throughput, without incurring unacceptable accident risks.

5.2 Sensitivity Analysis of Payoff Matrices

To further understand these dynamics, we conducted a sensitivity analysis on the payoff matrix parameters. Specifically, we varied the weight of the "Time Efficiency" component in the Robotaxi utility function.

Table 2 presents the results of this analysis, showing how increasing the priority of time efficiency for Robotaxis impacts the maximum network flow (Capacity) and the accident rate.

Table 2 Sensitivity Analysis of Robotaxi Payoff Parameters (50 percent Penetration)

Time Utility Weight	Capacity Change (%)	Accident Rate (per 10k trips)	MFD Scatter Index
Low (Conservative)	-12.5	0.02	High
Medium (Balanced)	-4.0	0.15	Medium

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High (Aggressive)	+2.1	1.80	Low
Adaptive (Dynamic)	+5.5	0.35	Low

The data in Table 2 suggests that a static payoff matrix is insufficient. The "Adaptive" strategy, where Robotaxis adjust their utility weights based on local congestion levels (acting more aggressively when the intersection is a bottleneck and more conservatively otherwise), yields the best performance. This dynamic adjustment helps in harmonizing the traffic flow, reducing the scatter in the MFD, and mitigating the capacity drop.

5.3 Infrastructure Implications

The distinct shape of the MFD in mixed traffic has implications for infrastructure management. The extended hysteresis loops observed in the transition phase suggest that gating strategies (restricting access to the network) need to be applied earlier and released later to prevent gridlock. Standard control algorithms based on human-centric MFDs may overestimate the network's recovery speed, leading to premature release of traffic and secondary congestion. Furthermore, the prevalence of the Nash Equilibrium outcomes where humans exploit Robotaxis points to a need for infrastructural interventions. Dedicated lanes or segregated zones at intersections could decouple the game, preventing the asymmetric interactions that lead to efficiency losses. Alternatively, V2X (Vehicle-to-Infrastructure) communication could act as an arbitrator, imposing a correlated equilibrium where the infrastructure dictates the strategy (Red/Green light) tailored to the specific agents present, rather than a fixed cycle.

6. Conclusion

This paper has explored the evolution of the Macroscopic Fundamental Diagram through the lens of the Nash Right-of-Way Game in mixed traffic environments. By linking microscopic game-theoretic decisions to macroscopic flow dynamics, we have demonstrated that the introduction of Robotaxis creates a complex, non-linear transformation of network performance. Our simulations indicate that in the early stages of adoption, the risk-averse strategies of Robotaxis, formalized as conservative Nash Equilibria, can reduce network capacity and increase MFD scatter. The interaction between opportunistic human drivers and cautious AVs creates local inefficiencies that aggregate into global flow degradation. However, as the penetration rate approaches saturation, the cooperative nature of AV-to-AV interactions linearizes the MFD and significantly enhances capacity. The study identifies the design of the payoff matrix—specifically the weighting of time versus safety—as a critical control variable. We propose that dynamic, context-aware utility functions for Robotaxis can mitigate the "Valley of Death" in the transition phase. Future research should focus on field validations of these game-theoretic models and the development of regulatory frameworks that define the acceptable boundaries of "machine aggression" in mixed traffic. Ultimately, mastering the game of right-of-way is essential for unlocking the full potential of the Macroscopic Fundamental Diagram in the era of autonomous mobility.

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