# Learning-Based Policy Design for Resource Planning and Pricing in Heterogeneous Multi-Leader–Multi-Follower Systems

Doctoral Consortium

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## ABSTRACT

This PhD project studies policy design for competitive resource planning in congestion-sensitive systems, with EV charging as a motivating application. Prior work develops game-theoretic models of pricing and infrastructure decisions that incorporate congestion and non-EV demand. The next phase focuses on decentralised multi-leader–multi-follower games with heterogeneous agents. Competing providers and users learn simultaneously, leading to non-stationary dynamics. The goal is to analyse emergent equilibria and efficiency using learning-in-games and multi-agent reinforcement learning.

## KEYWORDS

Policy Design, Multi-Leader–Multi-Follower Games, Heterogeneous Agents, Competitive Resource Planning, EV Charging

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## 1 INTRODUCTION AND MOTIVATION

Many real-world resource allocation settings involve competing providers and strategic users interacting over scarce, congestible resources, including transportation, energy, cloud services, and online markets. In such environments, providers must anticipate both competitors' strategies and users' responses to prices and congestion. In Stackelberg game settings, users act as followers who make strategic decisions without revealing their preferences, creating significant uncertainty for leaders (providers) when planning resources and setting prices under competition and incomplete information. However, existing models often assume a single or non-competing leader and homogeneous followers, and therefore fail to capture settings in which multiple competing leaders independently design pricing and planning policies while facing heterogeneous followers with private preferences. Moreover, the dynamic interaction between competing leaders and adaptive followers and its implications for equilibrium behaviour and system efficiency remain poorly understood.



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This research aims to address these limitations by studying decentralised resource planning and pricing in competitive and heterogeneous environments. A motivating application is Electric Vehicle (EV) charging networks, where multiple charging station providers (leaders) compete through pricing, capacity, and placement in response to heterogeneous drivers (followers) and congestion, exemplifying a multi-leader–multi-follower system.

While EV charging is the motivating domain, the modelling and learning questions apply more broadly to congestion-sensitive markets with competing providers and heterogeneous users, such as cloud, energy, and mobility systems.

## 2 BACKGROUND AND RESEARCH GAP

Prior work on EV charging networks studies pricing competition using Stackelberg models, ranging from single-provider settings to multi-leader price competition [9, 10, 15]. Network-aware pricing incorporates spatial structure, congestion, and traffic assignment, but typically assumes fixed station locations and homogeneous users [8, 12]. Other work departs from explicit game-theoretic formulations and examines joint placement and pricing, often via bilevel models in which a new entrant anticipates future price competition [1], but abstracts from detailed driver behaviour in traffic networks. Reinforcement learning approaches have also been proposed to address pricing and placement in large-scale networks [11]; however, these typically assume fixed or non-strategic competitors and provide limited insight into equilibrium behaviour under competition. Overall, existing approaches do not capture settings in which heterogeneous user preferences are private and revealed only through behaviour, while demand and congestion are coupled through the network. This gap motivates the next phase of the research, which focuses on decentralised policy design for pricing and resource planning in competitive, heterogeneous multi-agent environments.

## 3 PROGRESS TO DATE

This research to date has focused on modelling and analysing strategic interactions in EV charging networks under structured but progressively richer assumptions, addressing several gaps in the literature. In the first phase, we studied the joint optimisation of charging station placement and pricing from the perspective of a single provider. Drivers' decisions were modelled using connected congestion games, where individual costs captured travel time and queueing delay—both arising from the congestion game formulation—as well as charging fees. By jointly optimising placement and pricing under both atomic [4] and non-atomic [3, 5] formulations, we showed that explicitly accounting for the interaction between congestion and pricing yields improved outcomes compared to single-parameter optimisation. In the second phase [6], the framework was extended to incorporate additional sources of realism by accounting for multiple competing charging station owners and adaptive non-EV (non-follower) traffic. The analysis examined how non-followers affect pricing and planning decisions within a Stackelberg setting. The interaction between providers and drivers was formalised as a three-level Stackelberg game (Figure 1), in which a potential entrant first selects station locations, providers then compete on prices, and drivers respond by choosing routes and charging options under congestion alongside non-EV traffic. The results demonstrate that omitting non-EV traffic leads to systematic misestimation and distorted pricing and infrastructure planning decisions—an issue typically overlooked in the existing literature. This work provides a unified framework that motivates subsequent extensions to capacity planning and heterogeneous driver behaviour.

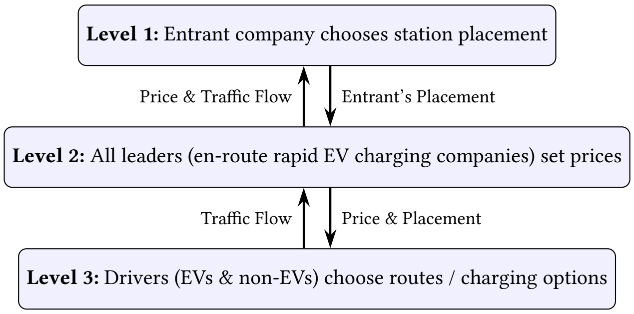


**Figure 1: Schematic of the three-level hierarchical game. The figure summarises the completed tri-level entrant Stackelberg model and serves as a conceptual precursor to the next phase, which generalises this structure to a decentralised multi-leader–multi-follower learning framework developed in three stages.**

## 4 PROPOSED RESEARCH

The proposed research studies decentralised policy design in competitive multi-leader–multi-follower systems with adaptive agents, with a focus on EV charging networks. The core components are:

**Follower modelling: a)** Heterogeneous EV drivers are modelled as learning agents with private preferences over charging mode, price, queueing congestion, travel time, and range anxiety. **b)** Preferences are revealed only through behaviour and equilibrium outcomes, and are not directly observed by providers.

**Leader policy design: a)** Charging providers act as competing leaders who independently design pricing (and later capacity and planning) policies under incomplete information. **b)** Leaders anticipate strategic responses from heterogeneous followers and rival providers, whose interactions jointly determine demand, congestion, electricity usage, and provider utilities.

**Learning framework: a)** Multi-agent reinforcement learning (MARL) is employed to jointly learn leader policies and follower strategies where analytical solutions are intractable. **b)** Simultaneous learning induces non-stationarity, complicating equilibrium analysis [14]. A learning-in-games perspective offers a principled framework for studying emergent equilibria in MARL [2].

**Equilibrium and performance evaluation:**
**a)** Learning outcomes are evaluated using equilibrium proxies: (1) Regret-based diagnostics for coarse correlated equilibria and no-regret learning. (2) Best-response exploitability measures for approximate Nash equilibria.
**b)** System-level performance is assessed in terms of social cost, congestion, and provider profit.

**Positioning relative to prior work: a)** Extends existing RL-based approaches for EV charging that focus primarily on pricing [7]. **b)** Goes beyond MARL studies of competitive charging providers [13] by explicitly modelling heterogeneous, strategic users interacting through congestion.

***Challenges:*** Several challenges arise in this setting. Designing policies for pricing, capacity, and placement under incomplete information is challenging because both leader and follower strategies evolve through learning. To address these systematically, the research is structured in stages:
**Stage A:** Pricing-only competition with heterogeneous followers, under fixed placement and capacity. Evaluation will use equilibrium proxies suitable for learning dynamics (e.g., approximate Nash or coarse correlated equilibrium).
**Stage B:** Extension to joint pricing and capacity decisions, still with fixed station locations.
**Stage C:** Incorporation of placement.

The core deliverables of the project are: **1)** A game-theoretic model capturing heterogeneous follower behaviour. **2)** A learning-based approach for competing leaders. **3)** Systematic empirical evaluation of emergent equilibria and system-level efficiency under competition.

## 5 RESEARCH QUESTIONS AND GUIDANCE SOUGHT

This research studies learning and competition in decentralised multi-leader–multi-follower systems. The key research questions and areas where expert guidance is sought are:

**(1) Learning under private heterogeneity:** How can competing leaders learn pricing (Stage A), capacity (Stage B), and placement (Stage C) policies when follower preferences are private and revealed only through behaviour? *Guidance sought:* selecting suitable MARL frameworks for simultaneous leader–follower learning without over-scoping.

**(2) Equilibrium characterisation under learning:** Which equilibrium proxies (e.g., approximate Nash or coarse correlated equilibrium) best characterise outcomes induced by simultaneous learning? *Guidance sought:* identifying equilibrium notions that remain meaningful in non-stationary competitive environments.

**(3) Efficiency of decentralised competition:** What efficiency loss arises from decentralised competition, and how does it vary across heterogeneity, congestion, and demand regimes? *Guidance sought:* defining robust metrics for system-level efficiency and stability.

**(4) Choice of learning paradigms:** Which classes of MARL methods (e.g., no-regret, two-timescale, or mean-field approaches) are most reliable in this setting, and why? *Guidance sought:* understanding which learning dynamics offer the best balance between empirical stability and theoretical interpretability.

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