Two tales of platoon intelligence for autonomous mobility control: Enabling deep learning recipes

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Abstract
This paper surveys recent multiagent reinforcement learning and neural Myerson auction deep learning efforts to improve mobility control and resource management in autonomous ground and aerial vehicles. The multiagent reinforcement learning communication network (CommNet) was introduced to enable multiple agents to perform actions in a distributed manner to achieve shared goals by training all agents’ states and actions in a single neural network. Additionally, the Myerson auction method guarantees trustworthiness among multiple agents to optimize rewards in highly dynamic systems. Our findings suggest that the integration of MARL CommNet and Myerson techniques is very much needed for improved efficiency and trustworthiness.

KEYWORDS
auction, autonomous mobility control, deep learning, platoon, reinforcement learning

1 | INTRODUCTION

Autonomous mobility has emerged as a transformative innovation in a fast-paced world of technological advancements, and it promises to dynamically reshape numerous aspects of human life, including transportation, logistics, and surveillance [1]. These complex systems depend on advanced algorithms, sensors, and communication networks (Comments) to perform tasks smoothly and proficiently with their own objectives [2]. A crucial element supporting the successful functioning of these systems, particularly when operating as coordinated groups, is the efficient sharing of information among multiple mobility platforms.

Information exchange is essential for the seamless operation of a networked platoon regardless of whether it...
consists of autonomous vehicles navigating roadways or drones flying in coordinated patterns. Efficient and thorough data sharing facilitates collaboration among individual units, empowering them with agency to maintain formations, prevent collisions, and execute synchronized maneuvers [3]. Consequently, an effective information exchange system can considerably bolster the overall safety, dependability, and performance of autonomous fleets. In addition to ensuring safe and efficient operations, information exchange in platoon systems facilitates resource optimization and energy conservation and reduces negative environmental impacts. By sharing critical velocity, position, and route information, platoons can synchronize their movements and optimize their trajectories, ultimately resulting in decreased fuel consumption, emissions, and traffic congestion. This not only contributes to a more sustainable future but also helps organizations achieve their economic and environmental objectives.

In this study, we investigated two deep learning methods to address the challenges associated with managing and controlling autonomous mobility platoons: reinforcement learning (RL) and neural Myerson auctions. RL is a common artificial intelligence technique that enables autonomous agents to learn from their environment to accomplish specific objectives by maximizing their expected returns. When applied to autonomous mobility applications, RL can be used to derive optimal control strategies for maintaining safety, efficiency, and robustness in various traffic situations. Furthermore, to control a platoon, the use of a single-agent RL is not suitable because all agents operate identically when they are located in the same space and time with the same action-reward settings. Therefore, multiagent RL (MARL) algorithms should be utilized to ensure cooperation and coordination among agents [4-6]. Among the various MARL algorithms, this study considers a CommNet that is widely and actively used in modern distributed computing and networking applications. As such, centralized neural network training using multiagent states and actions is first conducted, followed by distributed execution while sharing the centralized trained neural network with multiple agents. This MARL technique encompasses centralized training and distributed execution (CTDE).

Neural Myerson auctions, an emerging approach in the field of mechanism design, combine the power of deep learning with a traditional Myerson auction framework. Among traditional auction mechanisms, the second-price auction (SPA) is widely used for truthfulness in trading and bidding. However, a major problem with SPA is the non-optimality of the auctioneer's revenue. To improve this, the Myerson auction utilizes the concept of virtual valuation, and according to recent advanced methods, the neural Myerson auction has emerged. This method effectively allocates resources among multiple autonomous vehicles while preserving incentive compatibility, leading to efficient and fair outcomes while preserving truthfulness.

By integrating CTDE-based MARL and neural Myerson auctions, a comprehensive solution for managing and controlling autonomous mobility platoons can be designed that address various challenges, ranging from vehicle cooperation and coordination to resource allocation among multiple agents.

The major contributions of this study are summarized as follows:

- The major CTDE-based MARL research trends are reviewed in terms of autonomous mobility control and platoon applications.
- The neural Myerson auction is illuminated in terms of multiuser resource allocation and scheduling techniques that require truthfulness among bidders.

The remainder of this paper is organized as follows. Sections 2 and 3.2 introduce the main concepts and CTDE-based MARL and neural Myerson auction applications for autonomous mobility control applications. Section 4 concludes the paper.

2 | CTDE-BASED MARL FOR AUTONOMOUS MOBILITY

2.1 | Legacy technologies

Cooperative and coordinated autonomous mobility controls have been studied in a variety of ways. Convex and linear optimization approaches [7] can preserve model optimality. However, drawbacks exist in that all optimization formulation and computation information is needed for each computation procedure, which is unrealistic. Furthermore, optimization and computation information should be shared without delays. Hence, a Lyapunov control-based approach that provides time-averaged utility maximization subject to stability has been considered [8-10]. As this approach is fully distributed, it is beneficial for multiple autonomous mobility control platforms. However, unexpected environmental dynamics cannot be overcome. Therefore, learning-based methods must be utilized.

2.2 | MARL basics

RL is a sequential decision-making strategy used in dynamic environments [11] and has shown superior
performance in autonomous mobility controls [12]. Agents trained with RL methods can adaptably react to environmental uncertainties. However, with MARL, multiple agents can affect the policy training of other agents. These nonstationarity challenges conventional RL-based approaches optimize control policies [13]. To overcome this challenge, many researchers have investigated ways to extend single-agent RLs to scenarios in which agents interact and cooperate. The CommNet approach [14] supports an advanced neural network architecture that allows agents to find optimal policies to achieve common objectives by sharing environmental information. Recent studies have shown the superior versatility of this approach. See Figure 1.

2.3 | CommNet

The interagent communications illustrated in Figure 2 include agents \(b_1, b_2, \ldots, b_n\) that each obtain partial observations \(o\) of their environment. The ground truth state \(s\) is then determined by the sequential decision-making and information sharing of all agents as states and observations are fed forward into the neural network. After encoding the input vector, hidden variable \(h^l\) passes through several \(L\)-dense layers that are fully connected to the next hidden layer. At each time step, a CommNet-based agent creates a communication variable \(c^l\) that averages the hidden variables of other agents for use in its next dense layer, except when explicitly sharing information. Hence, multiple agents cooperatively learn global neural network parameters. Before hidden and communication variables are provided to the subsequent layer, they are concatenated and activated with a nonlinear function, such as a rectified linear unit (ReLU), hyperbolic tangent, or Sigmoid function. As this process repeats, action probabilities are returned by decoding the hidden variable of the last dense layer using a SoftMax function. After policy training, multiple agents can then cooperatively achieve shared goals in a distributed manner using trained policies that do not require centralized controls or explicit coordination rules.

2.4 | Applications

For CommNet applications, cooperative and coordinated energy/power-scheduling algorithms for multiple agents are considered as energy-related discussions are the most important in power-hungry battery-operated mobility platforms. As such, charging-scheduling algorithms are discussed in Sections 2.4.1 and 2.4.2. Unmanned aerial vehicle (UAV) surveillance is another important task. As such, research for CommNet-based multi-UAV surveillance is presented in Section 2.4.3.

2.4.1 | Charging station scheduling for electric vehicles (EVs)

In the Industry 4.0 Revolution era, the demand for EVs is growing exponentially. EVs can control motor-driven

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**FIGURE 1** Representative papers utilizing CommNet for the cooperation of multiple agents in multifaceted MARL scenarios.
rotations without latency in an eco-friendly manner, which ensures they remain more suitable than conventional vehicles that rely on internal combustion engines. Furthermore, the electronic components of EVs have advantages over internal combustion engines in terms of analyzing vehicle data and diagnosing faults using low currents and voltages. To support the increasing production of EVs, a cost-efficient energy management system for EV charging stations (EVCSs) is needed based on supplier–consumer behaviors. When dealing with highly dynamic systems and real-time big data processing, conventional centralized optimization strategies will not work. For this reason, Shin and others proposed a CommNet-based optimization approach to manage vast amounts of data in a distributed manner by considering the state of energy storage systems and photovoltaic (PV) power production for EVCSs [15]. In their scenario, each EVCS can provide energy to EVs using its PV charger, but they share surplus energy with other EVCSs only after meeting its own demands. Using data-intensive performance evaluations, it was confirmed that each CommNet-based EVCS agent can jointly minimize the amount of energy purchased from private enterprises while tracking its energy state and price fluctuations throughout the day.

2.4.2 | Charging tower scheduling for UAV networks

Owing to their high agility and mobility, UAVs can assume flexible roles in a wide range of fields. However, an efficient UAV energy management system is vital, owing to the limited battery capacity of drones [16]. Jung and others proposed an optimization framework for joint charging scheduling and CommNet-based energy management assisted by cloud computing [17].
In their scenario, multiple charging towers provide charging services to UAVs during runtime operations in a decentralized manner based on a plug-and-play method. All charging towers act as independent RL agents that cooperatively develop individual policies to meet their own demands while maximizing the full network’s efficiency at the lowest costs. The resultant convex-optimal charging-scheduling scheme provided fair resource allocations.

2.4.3 | Surveillance for UAV networks

UAVs have also been used to support autonomous mobile surveillance systems [18]. Unlike conventional static closed-circuit monitoring system, UAVs provide on-demand surveillance by dynamically changing their locations. Moreover, they can monitor extreme environments in which ground access is prohibited. Nevertheless, UAVs still must overcome environmental uncertainties, such as collisions and battery discharge, while jointly managing coverage regions for service efficiency. To address this need, Yun and others proposed a CommNet-based multi-UAV positioning method in which a leader UAV is accompanied by multiple follower UAVs [19]. The leader makes decisions based on the observations of all UAVs, whereas non-leader UAVs make decisions based only on their own observations. In this study, UAVs monitored a large number of users with high video resolution by adaptively traversing two-dimensional trajectories and controlling video resolution. To investigate the cost of malfunctioning UAVs, the authors examined the tradeoff between surveillance areas and video resolution.

3 | DISTRIBUTED LEARNING FOR AUTONOMOUS MOBILITY

3.1 | Legacy technologies

Distributed resource allocation and scheduling in autonomous mobility control scenarios have been studied extensively in terms of convex optimization-based resource allocations [20-22] with the objective of guaranteeing optimality. However, distributed operations are not supportable as the information needed for optimization formulation and policymaking cannot be provided in advance. Notably, game theory-based approaches are useful as they can solve distributed optimizations under uncertainties [23,24]. However, game theory does not consider truthfulness, whereas auction-based approaches do. Additionally, the Lyapunov control-based approach has been considered based on the nature of distributed computations [8-10], but unexpected environmental dynamics cannot be handled.

3.2 | Auction basics

A conventional first-price auction (FPA) is a well-known algorithm in which a bidder who submits the highest bid value to the auctioneer or seller wins with the cost of paying the bid. Considering a scenario in which \( N \) bidders exist,

\[
b_1, \ldots, b_N,
\]

with an auctioneer, the bidders’ bid values are

\[
v_1, \ldots, v_N.
\]

The auctioneer selects the maximum bid value, \( v^* \), using

\[
v^* = \max\{v_1, \ldots, v_N\},
\]

and the winner bidder, \( b^* \), submits the bid value, \( v^* \). Supposing the second-highest bid value is \( v' \), the winning bidder, \( b^* \), does not need to pay the full bid amount, \( v^* \), because submitting a bid slightly higher than \( v' \) is sufficient to win the auction. Consequently, the individual bidders must be strategic when participating in FPA. However, the presence of untruthful bidders undermines the incentive capacity of the mechanism, rendering the FPA inefficient in competitive environments [25].

Another type of auction mechanism is the second-price auction (SPA), which functions similarly to the FPA in terms of selecting a winner. However, instead of paying the highest bid value, the winner pays the second-highest bid. SPA is widely regarded as a truthful auction mechanism [26,27] and is commonly used for resource allocations in distributed computing environments [28,29]. However, the SPA has a drawback in that it cannot achieve revenue optimality because the auctioneer receives only the second-highest bid value instead of the highest. Various approaches have been proposed to overcome this issue. Among these, the Myerson auction, which uses virtual valuations [26,30], commonly use monotonic increasing functions to numerically formulate virtual valuations. With the continued advancements in deep neural network (DNN) research, Myerson auction computation procedures can be approximated. As a result, this study proposes a DNN-based autonomous neural Myerson auction aerial delivery scheduling algorithm that leverages a DNN to compute virtual valuations.
3.3 | Neural Myerson auction for optimal delivery

This section discusses the use of deep learning-based auctions to maximize the expected revenue of surveillance drones while guaranteeing truthfulness and revenue optimality. A monotonic network is used for random sampling to approximate the pseudo-optimal revenue values. Additionally, allocation and payment networks are leveraged to determine the winning drone and payment amount, respectively. The detailed structures of monotonic networks (Section 3.3.1), allocation networks (Section 3.3.2), and payment networks (Section 3.3.3) are presented next.

3.3.1 | Virtual valuation function

A virtual valuation function in an auction network is represented by \( \phi_i \) [31]. The input bids, \( b_i \), of the delivery drones are transformed into \( \tilde{b}_i \) after passing through a monotonic network that performs max/min operations over several linear functions. The Monotonic network, \( \phi_i \), is composed of \( K \) groups of \( J \) linear functions, as defined next [31].

\[
\phi_i = \text{max} \left( \phi_i^1(\tilde{b}_1, \ldots, \tilde{b}_J, k) \right), \quad \forall i \in N.
\]

The final payment made by the winning drone to the auctioneer is calculated as follows:

\[
p_i = \phi_i^{-1}(p_i^0(\tilde{b})).
\]

3.3.4 | Neural network training and complexity

The neural architecture training parameters, \( w_{kj} \) and \( \beta_{kj} \), are trained using a set of valuation profiles with a loss function that minimizes negative Myerson auction revenue. The loss function \( \hat{R} \) is defined as

\[
\hat{R}(w, \beta) = -\sum_{i=1}^{N} \hat{g}_i^{(w, \beta)}(v_i)p_i^{(w, \beta)}(v_i).
\]

The results of the allocation and payment networks are used as training parameters, and a stochastic gradient descent optimizer is employed for the loss function, \( \hat{R} \). In conventional deep-learning procedures, training and inferencing are required. During training, positive time is needed for cost function minimization with iterative computations, such as stochastic gradient descent for backward propagation. Most studies have evaluated complexity as a measure of training time, which is approximately 5 min on an Intel i7 with eight cores and requires 16-GB of memory. However, during inferencing, a simple dense layer with trained optimal/approximate matrix and activation function computations are needed. Computation time comprises monotonic network computations at several layers, and the algorithmic complexity is scaled linearly. This can be represented as

\[
(O_M(m) + O_A(m)) \times NL,
\]

where \( O_M(m) \) and \( O_A(m) \) denote the computational complexity of the matrix operation for each layer [32], and \( m \) and \( NL \) denote the number of nodes and layers, respectively. After training, real-time execution in the inferencing phase can be performed within a few seconds.

3.4 | Auction properties

We have defined the characteristics of auction networks and truthfulness, including allocation rule \( g \) and payment.
rule \( p \). According to the Myerson theorem, truthful conditions IR and IC can be ensured.

**Theorem 1 (Myerson [33]).** For single-parameter environments with any set of strictly monotone functions \( \phi_1, \phi_2, \ldots, \phi_N \), the IR is an auction that assigns an item to the bidder with the highest virtual valuation, \( \phi_i(v_i) \), and the IC is the payment determined by the second-highest virtual valuation.

The neural architecture comprises \( K \) groups with outputs, \( t_1, t_2, \ldots, t_K \). Within each group, the number of hyperplanes is \( h_r \), where \( r \) ranges from 1 to \( R \). The hyperplane parameters are represented as

\[
\mathbf{w}(r, 1), \mathbf{w}(r, 2), \ldots, \mathbf{w}(r, h_r),
\]

and the entire set of weights and biases is given by matrix \( \mathbf{W} \). Group \( r \) produces an output,

\[
t_r(x) = \min_j(w(r, j) \cdot x + \theta(r, j)), 1 \leq j \leq h_r,
\]

and the final output is as follows:

\[
O_x = \max_{r} t_r(x).
\]

This is similar to the virtual method described in Section 3.3.1. If all weights in the first layer are positive, the network will satisfy increasing monotonicity, which is the condition of our system [34].

### 3.5 Applications

#### 3.5.1 Data delivery in UAV networks

Several studies have explored data-acquisition frameworks for sensor networks using drones to improve data collection efficiency. Say and others [35] proposed a priority-based frame-selection approach to reduce the number of redundant data transmissions between sensor nodes and drones. The algorithm in previous works [36,37] leveraged drones as mobile data collectors for randomly deployed sensor nodes. This study aims to jointly optimize the wake-up schedules of sensor nodes and the trajectories of drones to minimize the maximum energy consumption, thereby achieving min–max fairness. Gong and others [38] proposed an algorithm that minimizes the total flight times of drones while ensuring that each sensor uploads a certain amount of data. Additionally, Singhal and others [39] proposed an adaptive surveillance and event-telecast video-streaming service that uses drones employing WiFi-direct link scheduling and dynamic configuration settings to transmit data to ground control stations.

In this paper, we present an aerial data delivery scheduling approach that utilizes neural Myerson auction computations. This approach differs from previous studies in which delivery drones compete to transfer data directly. Our approach has an advantage over these approaches in that it enables data transmission sustainably in extremely poor conditions. Furthermore, our deep learning-based auction reduces costs by selecting the optimal delivery drone for the particular data collection process. Although our study is consistent with other studies on drone-based data delivery networks that consider the energy and coverage of drones as bid values, it distinguishes itself by enabling data delivery, even in the absence or destruction of communication infrastructures.

#### 3.5.2 Resource allocation in UAV networks

Auction-based approaches are a popular and effective method for solving resource allocation and scheduling problems in a distributed and truthful manner. However, uncertainty is inherent to auctioneer/seller and buyer/bidder valuation processes. That is, the auctioneer is uncertain about the true value offered by bidders in terms of the maximum amount that each bidder is willing to pay. If the auctioneers have complete information about the values, they can simply offer the object to the bidder with the highest value at or below the bid. However, bidders do not know the true values attached by other bidders, but knowing these values will not affect their worth [40]. Due to the large volume of economic transactions conducted through auctions, auction-based computations have been extensively studied for limited-resource and tough-scheduling problems [41]. Dai and others [42] examined a transportation problem aimed at reducing costs and increasing profits by collaborating with carriers on pick-up and delivery requests. Those authors introduced a price-setting combinatorial auction to solve this problem. In contrast, Marinescu and others [43] proposed a self-organizing architecture for large-scale cloud computing with a scalable combinatorial auction-based solution. In contrast, Coltin and others [44] presented an auction-based scheduling algorithm for enhancing the efficiency of item delivery between robots. The algorithm operates online and adjusts to new requests, dead vehicles, and shared information. Furthermore, an auction-based incentive mechanism for collaborative computational offloading that achieves near-optimal long-term social welfare was proposed in He and others [45].
The Myerson auction is one of the most efficient revenue-optimal single-item auction-based scheduling and resource allocation algorithms [33]. A DNN-based architecture can be used to numerically approximate a Myerson auction, which has led to the development of several wireless power transfer-based multidrone network and electric vehicle applications [26, 46]. Other DNN-based auctions have been used to solve resource allocation problems in edge computing and wireless virtualization scenarios [31, 32]. Moreover, the algorithm proposed in Kuo and others [47] addresses fairness concerns while maintaining high revenue and strong incentive guarantees by approximating auctions using deep learning.

4 | CONCLUDING REMARKS

This study investigated the challenges of autonomous mobility in a multiautonomous system with high system dynamics. First, we focused on a CTDE-based MARL algorithm that allows autonomous entities to pursue shared objectives and make decisions in a distributed manner based on their separate observations. We investigated several application studies based on CommNet, which is a popular CTDE-based MARL algorithm. Because MARL-assisted decision methods have difficulty guaranteeing all agents’ trustworthiness and achieving revenue optimality, we presented the neural Myerson auction, which efficiently allocates system resources to distributed autonomous entities, such as vehicles and UAVs, while achieving high revenues and strong incentives. Thus, we conclude that the integrated framework of the MARL and neural Myerson auction is powerful for efficiently controlling multiple agents with autonomous mobility and simultaneously pursuing trustworthy system.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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