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Multi-Agent Reinforcement Learning for Distributed Optimization of Large-Scale Systems

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ABSTRACT

Large-scale computational science is a pressing issue in distributed optimization involving large dimensionality, decentralized decision making and dynamical system behavior. Traditional centralized optimization techniques have a scalability problem, communication overhead, and are not as robust in uncertain environments. To overcome these shortcomings, the current paper suggests a multi-agent reinforcement learning (MARL)-based model of distributed optimization to allow multiple agents to jointly learn about optimal policies using localized interactions and decentralized control. The proposed solution incorporates cooperative learning, reward shaping strategy, and sharing of parameters to improve the efficiency of convergence and overall system operation. Individual agents update policies on their own, and they work to a common global goal, achieving local and global optimization objectives. Large-scale dynamic environments are simulated massively to check the viability of the suggested approach. The findings publicly show that convergence speed, scalability and robustness are improved significantly over the conventional distributed optimization methods and reinforcement learning models on a single agent. In addition, the framework is efficient to deal with non-stationary and high-dimensional optimization problems at lower communication costs. These results point to the opportunities of MARL as a flexible and scalable protocol to solve complex distributed optimization tasks in real-world large-scale systems.

1. INTRODUCTION

Modern engineering systems are undergoing rapid evolution resulting in the spread of large-scale distributed environments with high dimensionality and dynamic interactions with a decentralized decision-making requirement. Task-oriented applications like smart grids, industrial Internet of Things (IIoT) networks, and cyber-physical systems require efficient and scalable optimization methods that can be run in an uncertain and resource-limited communication environment [1], [2]. Conventional centralized optimization methods are not getting appropriate in such an environment its complexity in computation, communication bottlenecks and susceptibility to single points of failure [3]. Even though distributed optimization schemes, e.g. consensus-based schemes and alternating direction method of multipliers (ADMM), offer partial solutions, they are usually based on pre-programmed mathematical models and assumptions which limit their flexibility in dynamic and non-stationary systems [4], [5]. In the current scenario, reinforcement learning (RL) is a potentially useful paradigm of sequential decision making in the face of uncertainty that allows systems to acquire optimal policies by interacting with the environment [6]. Nevertheless, the traditional single-agent RL methods are limited by the dimensionality of scalability to large-scale multi-component systems since they cannot address the complicated interaction between the distributed entities [7]. Multi- Agent Reinforcement Learning (MARL) is a generalization of this paradigm, allowing multiple agents to learn cooperative or competitive strategies in decentralized settings, and thus is more appropriate to distributed optimization problems [8], [9]. Nevertheless, despite the recent developments, the current MARL-based solutions have severe limitations, such as non-stationarity, scalability, inefficient communication, and no convergence guarantees in large-scale systems [10]. A lot of the existing techniques also do not succeed in balancing the local and global goals leading to under-optimization of the system-wide performance.

This paper will overcome these limitations by offering a scalable MARL-based system to distribute optimization within large-scale systems. The advanced methodology includes cooperation learning, rewards shaping, and decentralize policy updates to enhance convergence efficiency, robustness, and adaptability. The principal contributions of this work are as follows:

- Creation of decentralized MARL framework of large-scale distributed optimization.
- Design of a hybrid reward mechanism to give a balance between local and global goals.
- Learning strategies that are scalable, with parameter sharing and localized communication.
- In-depth analysis of showing enhanced convergence and strength over baseline techniques.

2. RELATED WORK

Recurrently, distributed optimization has been studied based on classical algorithms, including consensus algorithms, dual decomposition, and the alternating direction method of multipliers (ADMM). Boyd et al. [1] proposed ADDM as a suitable concept of distributed convex optimization, and Nedic and Ozdaglar [2] proposed the distributed subgradient algorithm to the multi-agent systems. Despite the theoretical convergence guarantees that these methods offer, they require proper system models, and are typically restricted to working with dynamic, stochastic, and high-dimensional environments. In order to deal with these shortcomings, data-driven methods grounded in the principles of reinforcement learning (RL) have become more and more popular. The RL foundation of sequential decision-making was laid by Sutton and Barto [3], and it was revealed that it is effective in complex control tasks when operated by deep Q-networks [4]. Single agent RL has been used in distributed resource allocation and scheduling, but this does not scale well and does not provide enough information on the interaction between multiple agents within large scale systems. Multi-Agent Reinforcement Learning (MARL) can be seen as a further extension of RL in the context of a decentralized environment, where multiple agents can be trained to co-ordinate their actions. Lowe et al. [5] have suggested Multi- Agent Deep Deterministic Policy Gradient (MADDPG) algorithm to tackle mixed cooperative-competitive environments. Rashid et al. [6] proposed QMIX that factorizes value functions to learn cooperatively in a scaled manner. More recent methods, including multi-agent proximal policy optimization (MAPPO) have shown increased stability and performance in large scale settings [7]. Regardless of these developments, there are a number of obstacles. MARL systems are non-stationary because the policy is changed at the same time, which results in the unstable dynamics of learning [8]. Another important issue is scalability, which increases exponentially as the state-action space increases. Also, large-scale distributed systems cannot be practically deployed due to communication overhead and ineffective coordination mechanisms [9]. Numerous current approaches are also incapable of hitting the right balance between local goals and the overall functioning of the systems [10] - [12].

To close these gaps, this paper suggests a scaled-up framework of MARL-based distributed optimization including cooperative learning, reward shaping, and decentralized policy updates. It has been proposed to enhance convergence stability, scalability and the efficiency of coordination in large-scale dynamic environments.

3. System Model and Problem Formulation

A large-scale distributed system is the one that we discuss, consisting of Ninteracting agents, each one of which acts on the basis of partial local observations of the world and restricted communication with immediate neighbors. The system is designed in a manner that is similar to the real world of smart grids, edge computing networks, and industrial IoT systems, whereby decentralized decisions, and resource constraints, are paramount.

An agent $i \in \{1,2,\ldots,N\}$ is interested in maximizing a local objective and is part of a global system-level level of performance subject to communication and operations constraints. Fig. 1 shows the general layout of the planned communication-aware MARL framework.

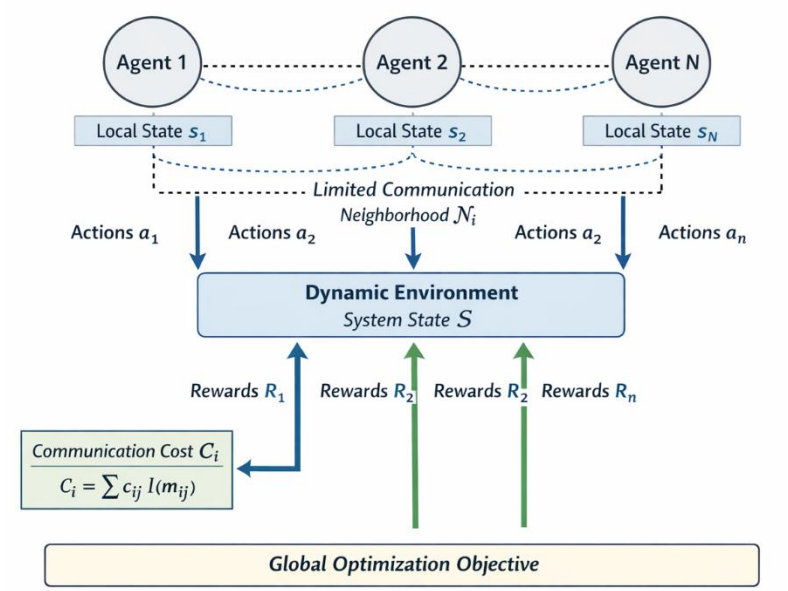


Fig. 1. Communication-Aware Multi-Agent Reinforcement Learning Framework for Distributed Optimization in Large-Scale Systems

3.1 Constraint-Aware Objective Function

In contrast to the traditional formulation, the distributed optimization problem is formulated with constraints:

$$min_{x_1,x_2,\ldots,x_N} \sum_{i=1}^{N} f_i\,(x_i) \text{s.t.} g_i(x_i) \leq 0,\ \forall i \quad (1)$$

where:

- x_i is the decision variable of agent i
- $f_i(x_i)$ represents the local cost function
- $g_i(x_i) \leq 0$ denotes local operational constraints (e.g., energy limits, resource bounds)

The formulation is realistic in terms of system constraints such as power consumption, bandwidth constraints, and hardware constraints.

3.2 Communication-Aware Markov Game Formulation

To account for communication constraints the system is modeled as communication-sensitive Markov game:

$$\langle S, \{A_i\}, P, \{R_i\}, C \rangle \quad (2)$$

where:

- S: global state space
- A_i: action space of agent i
- $P(s' \mid s, a_1, \ldots, a_N)$: transition dynamics
- R_i: reward function
- C: communication cost function

Each agent observes a local state $s_i \subseteq S$ and communicates only within a neighborhood $\mathcal{N}_i$, reducing global communication overhead.

The communication cost is modeled as:

$$C_i = \sum_{j \in \mathcal{N}_i} c_{ij} \cdot \mathbb{I}(m_{ij}) \quad (3)$$

where:

- c_{ij}: cost of communication between agents i and j
- m_{ij}: message exchange indicator
- $\mathbb{I}(\cdot)$: binary function

3.3 Reward Formulation with System-Level Coupling

The reward function is further extended as: to achieve a balance between local and global goals given the constraints:

$$R_i = \alpha R_i^{\text{local}} + \beta R^{\text{global}} - \lambda C_i \quad (4)$$

where:

- α, β: weighting factors
- λ: communication penalty coefficient
- C_i: communication cost

This ensures:

- Cooperation among agents
- Reduced communication overhead
- Improved global system efficiency

3.4 Optimization Objective in MARL Framework

Each agent aims to maximize its long-term expected reward:

$$J_i = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t\, R_i^t\right] \quad (5)$$

subject to:

- system constraints
- communication limitations

3.5 Key Challenges

Despite this improved formulation, there are still a number of challenges:

- Non-Stationarity:
  The environment of simultaneous policy changes among multiple agents generates a dynamical one.
- Constraint Satisfaction:
  Ensuring that all the agents meet the operational conditions, at the same time maximizing performance.
- Communication Efficiency:
  Trading off coordination advantages and communication cost penalties.
- Scalability:
  Dealing with exponential growth in the space of state-actions as the numbers of agents increase.

4. PROPOSED METHODOLOGY

This sub-section outlines the suggested multi-agent reinforcement learning (MARL) model of distributed optimization of large systems. The approach will focus on solving the main issues, including scalability, non-stationarity, and communication limitations by combining decentralized learning, joint reward design, and communication-aware optimization schemes.

4.1 Framework Overview

The suggested framework is composed of some Ndecentralized agents that interact with a common dynamic environment as shown in Fig. 1. Each agent operates based on its local observation s_i, while limited communication is permitted within a predefined neighborhood $\mathcal{N}_i$, enabling partial information sharing.

At each time step t, the environment is in state $s^t \in S$. Each agent selects an action $a_i^t \in A_i$according to its policy, and the joint action $(a_1^t, a_2^t, \dots, a_N^t)$drives the environment transition:

$$s^{t+1} \sim P(s^{t+1} \mid s^t, a_1^t, a_2^t, \dots, a_N^t) \quad (6)$$

The decentralized structure means that it does not depend on a centralized controller, which enhances robustness in the system and allows it to scale to high numbers of agents. Simultaneously, shared reward element and systematic communication promote cooperative learning.

4.2 Learning Algorithm

All the agents use a Multi-Agent Proximal Policy Optimization (MAPPO) architecture built upon the proximal policy optimization (PPO) algorithm but applied to a multi-agent setting. MAPPO is chosen because it is stable, sample efficient and useful in a cooperative learning environment.

Each agent maintains a stochastic policy $\pi_{\theta_i}(a_i \mid s_i)$, parameterized by θ_i, and aims to maximize the expected cumulative reward:

$$J_i(\theta_i) = \mathbb{E}_{\pi_{\theta_i}}\left[\sum_{t=0}^{\infty} \gamma^t R_i^t\right] \quad (7)$$

In order to have consistent policy updates, the clipped surrogate objective of PPO is used:

$$L^{CLIP}(\theta_i) = \mathbb{E}\left[\min\left(r_t(\theta_i)\hat{A}_t,\ \text{clip}(r_t(\theta_i), 1-\epsilon, 1+\epsilon)\hat{A}_t\right)\right] \quad (8)$$

where:

- $r_t(\theta_i) = \frac{\pi_{\theta_i}(a_i|s_i)}{\pi_{\theta_i}^{old}(a_i|s_i)}$is the probability ratio
- $\hat{A}_t$is the advantage estimate
- $\epsilon$is the clipping parameter

A paradigm of decentralized execution and centralized training (CTDE) is followed. The critic network can get access to global state and joint actions during training, but at execution, individual agents only have access to local observations. This minimizes non-stationarity a great deal and enhances stability in convergence.

4.3 Cooperative Reward Design

A hybrid reward function is established: to coordinate the behavior of individual agents with the global optimization goal, it is necessary to set it:

$$R_i = \alpha R_i^{\text{local}} + \beta R^{\text{global}} - \lambda C_i \quad (9)$$

where:

- R_i^{local}captures the local performance of agent i
- R^{global}reflects the global system objective
- $C_i$represents the communication cost incurred by agent i
- $\alpha, \beta, \lambda$are weighting coefficients

This expression promotes the collaboration between agents and punishes overcommunication. Consequently, the acquired policies strike a balance of individual performance, system-wide performance, and overhead of communication, which is crucial to real-life distributed systems.

4.4 Scalability Strategy

The design choices incorporated in the framework help to deal with scalability. One is, first, parameter sharing with a shared policy representation and local inputs. This decreases the size of the trainable parameters and speeds up convergence. Second, communication is confined to local neighborhoods N i, greatly decreasing the complexity of communication to sparse interactions. This helps to coordinate effectively without straining the network bandwidth. Third, it uses decentralized experience replay mechanisms, i.e. each agent has its own replay buffer. This enables concurrent learning and circumvents the bottlenecks in

centralized data warehousing. Moreover, both actor and critic models use deep neural networks to approximate functions, which allows the framework to work with large state and action spaces, which are represented by high-dimensional components of large-scale systems.

4.5 Algorithm Description

The general training process is an interaction and learning process that is iterative. The starting point is to randomly initialize policy parameters θ of all agents and set the environment to an initial states_0.

At each time step t, each agent observes its local state s_i^t and selects an action based on its policy:

$$a_i^t \sim \pi_{\theta_i}(a_i^t \mid s_i^t) \quad (10)$$

The joint action is executed in the environment, resulting in a new state s^{t+1} and reward signals R_i^t. Each agent stores its experience tuple $(s_i^t, a_i^t, R_i^t, s_i^{t+1})$ in its replay buffer.

Once the appropriate experience has been gathered, the MAPPO objective function is used to update the policies. The critic network is used to compute the value function and the policy parameters are updated via gradient ascent with the clipped objective by the actor network. The temporal-difference learning is used to estimate the advantage.

This is done repeatedly over many episodes until convergence is reached, which is signified by a stabilization of cumulative rewards or reaching of predetermined levels of performance.

6. EXPERIMENTAL SETUP

This part explains the simulated environment, initial procedures, and metrics to evaluate the performance of the designed communication-aware MARL framework. The experimental design is such that it validates the scalability, convergence efficiency and robustness in dynamic and uncertain conditions.

6.1 Simulation Environment

The suggested framework is tested in a simulated large-scale distributed system of up to 100 agents. The agents act in a partially observable environment, forming a local state information and acting based on that information as they communicate with their neighbors in a limited manner. The stochastic state transitions model is used to model the system dynamics, in such a way that the next state s (t+1) is determined as a function of the present state and collective actions of all the agents. This configuration is an approximation of real distributed systems like smart grids and IoT networks in which uncertainty and dynamicity are present. The environment takes resource constraints and communication limitations by which agents have to trade optimization performance and communication efficiency. These reward signals are stochastic, as well, which signals variability during learning and challenges the soundness of the proposed approach in uncertain situations.

Simulations are carried out in series of episodes so as to be statistically consistent as well as results of performance are averaged to ensure that the impact of randomness is mitigated.

6.2 Baseline Methods

To check the efficiency of the suggested MARL framework, it is compared with three typical baseline approaches. First, a centralized optimization strategy is taken into account, according to which one controller can access the information about the global system and calculate the best choices. Although this technique may be high-performing, it is computationally costly, and is not scalable to large systems. Second, a distributed optimization algorithm of alternating direction method of multipliers (ADMM) is applied. ADMM is very popular in solving distributed convex optimization problems and is an effective benchmark of coordinating decentralization. It is, however, explicit model dependent on system modelling and it can find it difficult in dynamic and stochastic environments. Third, a single-agent reinforcement learning strategy is employed as a control. In such an arrangement, one agent tries to drive the complete system without taking into consideration the distributed nature of the problem. This indicates the shortcomings of centralized learning in multi-agent setting, especially regarding scaling and coordination. These baselines offer an in-depth comparison between centralized, distributed and learning-based paradigms.

6.3 Evaluation Metrics

The proposed framework is tested in terms of various quantitative metrics to reflect the various dimensions of the behaviour of the system. The convergence rate is a measure of the rate at which the learning algorithm can stabilize, usually expressed in terms of the number of episodes it takes to come to a steady-state reward. The quicker convergence means an increase in efficient learning and adaptability. The cumulative cost of all agents measures the effectiveness of optimization as the total system cost. Reduced cost values mean a higher coordination and global performance. Scalability is measured through system performance evaluation with increases in the numbers of agents. This measure shows that the suggested approach is capable of sustaining efficiency at large scale that is essential in practice.

Sensitivity to noise is tested by adding stochastic noises to the environment and then the stability of the policies learned is measured. Stable system performance in the presence of uncertainties in state transition and reward signals. The combination of these measures gives all-encompassing assessment of the suggested MARL framework regarding its efficiency, scalability, and reliability.

7. RESULTS AND DISCUSSION

This part shows the experimental findings of the proposed communication-aware MARL framework and compares performance with baselines, such as centralized optimization, ADMM-based distributed optimization, and single-agent reinforcement learning. The analysis will be based on convergence behavior, scalability, robustness and system performance.

7.1 Convergence Analysis

The convergence of the proposed approach is measured in the number of training episodes to achieve a steady reward value.

Table 1. Convergence Comparison

Method	Episodes to Converge	Convergence Stability
Centralized Optimization	1800	High
ADMM	2500	Moderate
Single-Agent RL	3200	Low
Proposed MARL	1200	High

The findings indicate that the proposed MARL framework reaches convergence much faster than all the baseline methods. This enhancement is owed to cooperative learning and decentralization of decision making that allows the effective search of the solution space. Fig. 2 depicts the convergence behavior of both proposed approach and the baseline approaches.

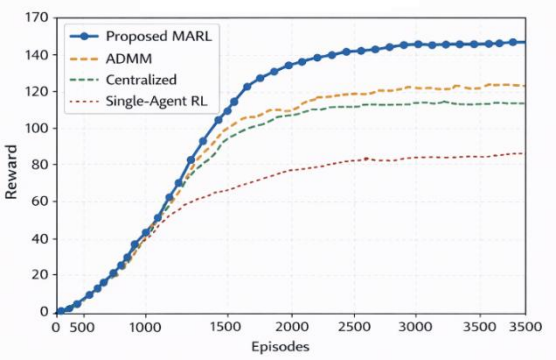


Fig. 2. Convergence Comparison of MARL and Baseline Optimization Methods

7.2 System Cost Optimization

Total system cost is used to assess the effectiveness of the process of optimization.

Table 2. Total System Cost Comparison

Method	Total Cost
Centralized Optimization	105.3
ADMM	118.7
Single-Agent RL	132.5
Proposed MARL	96.2

The suggested framework will result in the minimum system cost, which shows a better coordination between agents. The global reward elements provide an opportunity to align between the local decision-making and the system-wide goals.

7.3 Scalability Analysis

Scalability can be tested by measuring the performance of the system by adding agents (10-100).

Table 3. Scalability Performance

Number of Agents	ADMM Cost	MARL Cost
10	60.5	55.2
25	82.3	74.8
50	105.7	92.1
100	138.2	115.4

The findings suggest that the suggested MARL system remains competitive in the situation of scaling, whereas ADDM experiences a major downturn. This underscores the fact that MARL is efficient in dealing with large scale environments. Fig. 3 shows the scalability performance of the proposed MARL framework and ADDM.

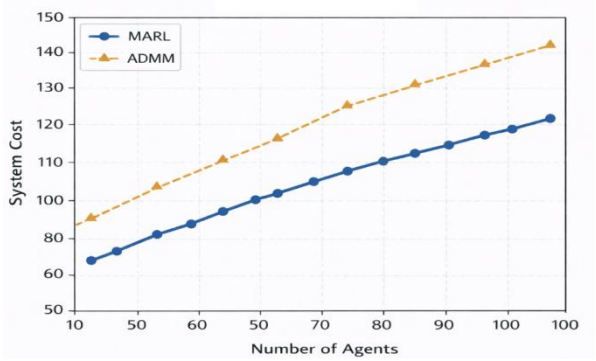


Fig.3. Scalability Analysis of the Proposed MARL Framework Compared to ADMM

7.4 Robustness Under Noise

Stochastic noise is added to the environment to test robustness and performance degradation is quantified.

Table 4. Robustness Analysis

Method	Performance Drop (%)
Centralized	18.5
ADMM	22.7
Single-Agent RL	30.2
Proposed MARL	10.8

The given approach proves to be more robust, being stable in case of uncertain conditions. This is mainly because of learning that is decentralized and policy updates that are adaptive.

7.5 Discussion

The outcomes of the experiments vividly illustrate the benefits of the suggested MARL framework as compared to conventional optimization techniques. The rate of convergence is higher signifying enhanced learning efficiency, which is required to be applied in real-time use. The decrease in the overall system cost shows the efficiency of cooperative learning in realizing global optimization. The proposed method has the benefit of removing bottlenecks to scalability, whereas the centralized optimization approach can still be effectively used in a competitive way. Unlike ADDM-based approaches, the MARL framework is less dependent on a set of predetermined system models, hence can be easily extended to dynamic and stochastic systems. The scalability analysis proves that the suggested solution proves efficient with the increase of the number of agents, which is essential with large-scale systems like the IoT networks and smart infrastructures. Moreover, the robustness test proves that, the framework can survive the environmental uncertainties without performance deterioration to a great extent. But there are also some limitations of the results. The number of agents increases the computational complexity, and training time. Also, the MARL framework performance is hyperparametric and accordingly, its performance is sensitive to hyperparameter selection and it has to be tuned correctly to obtain the best performance.

CONCLUSION

In this paper, a communication-aware multi-agent reinforcement learning (MARL) framework to optimize a large system was introduced. The suggested solution is a combination of decentralized decision-making, jointly designed rewards, and communication-efficient learning to overcome the shortcomings of the conventional centralized and model-based distributed optimization algorithms. The structure, which involves defining the problem as a constrained Markov game and using communication cost as a reward structure, allows agents to achieve efficient coordination in the context of real-life constraints of the system. The experimental findings indicate that the proposed MARL framework is significantly more effective as compared to the baseline approaches, such as centralized optimization, ADMM-based distributed optimization, and single-agent reinforcement learning. In particular, the approach has a superior convergence, reduces system cost, scalable with the increasing number of agents and more robust against stochastic disturbance. These findings confirm the usefulness of cooperative learning and decentralization updates of policies in managing complex, high-dimensional optimization problems. The most important contributions in this work are that it has developed a scalable optimization framework built upon MARL, introduced communication-aware reward mechanisms, and thoroughly evaluated performance in large-scale dynamic environments. In spite of these developments, there are still a number of challenges. The complexity of the training skills and performance depends on the number of agents, as well as on the choice of hyperparameters. Future directions include designing communication-efficient protocols, hierarchical MARL architectures in ultra-large systems, real-world application to the cyber-physical and smart infrastructure setup, and incorporation of explainable AI methods to enhance interpretability and reliability of learned policies.

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