Decentralized Multi-Agent Reinforcement Learning in Average-Reward Dynamic DCOPs

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Abstract

Researchers have introduced the *Dynamic Distributed Constraint Optimization Problem* (Dynamic DCOP) formulation to model dynamically changing multi-agent coordination problems, where a dynamic DCOP is a sequence of (static canonical) DCOPs, each partially different from the DCOP preceding it. Existing work typically assumes that the problem in each time step is decoupled from the problems in other time steps, which might not hold in some applications. Therefore, in this paper, we make the following contributions: (*i*) We introduce a new model, called *Markovian Dynamic DCOPs* (MD-DCOPs), where the DCOP in the next time step is a function of the value assignments in the current time step; (*ii*) We introduce two distributed reinforcement learning algorithms, the Distributed RVI Q-learning algorithm and the Distributed R-learning algorithm, that balance exploration and exploitation to solve MD-DCOPs in an online manner; and (*iii*) We empirically evaluate them against an existing multi-arm bandit DCOP algorithm on dynamic DCOPs.

Introduction

Distributed Constraint Optimization Problems (DCOPs) are problems where agents need to coordinate their value assignments to maximize the sum of the resulting constraint utilities (Modi et al. 2005; Petcu and Faltings 2005a; Yeoh and Yokoo 2012). They are well-suited for modeling multi-agent coordination problems where the primary interactions are between local subsets of agents, such as the distributed scheduling of meetings (Maheswaran et al. 2004), the distributed allocation of targets to sensors in a network (Farinelli et al. 2008), the distributed allocation of resources in disaster evacuation scenarios (Lass et al. 2008), and the distributed coordination of logistics operations (Léauté and Faltings 2011a).

Unfortunately, DCOPs only model static problems or, in other words, problems that do not change over time. In the above-mentioned coordination problems, various events that change the problem can occur. As a result, researchers have extended DCOPs to *Dynamic DCOPs*, where the problem can change over time (Petcu and Faltings 2005b; 2007; Lass, Sultanik, and Regli 2008; Sultanik, Lass, and Regli 2009; Zivan, Glinton, and Sycara 2009). Researchers have thus far taken an *online* approach by modeling it as a sequence of (canonical) DCOPs, each partially different from the DCOP preceding it, and solving it by searching for a new solution each time the problem changes. However, existing work typically assumes that the problem in each time step is decoupled from the problems in other time steps, which might not hold in some applications.

Therefore, in this paper, we introduce a new model, called *Markovian Dynamic DCOPs* (MD-DCOPs), where the DCOP in the next time step is a function of the value assignments in the current time step. Similar to existing work on dynamic DCOPs, we assume that the agents in MD-DCOPs are not aware of the underlying transition functions and, thus, need to solve the problem in an online manner. Specifically, we introduce two reinforcement learning algorithms, the distributed RVI Q-learning algorithm and the distributed R-learning algorithm, that use a multi-arm bandit strategy to balance exploration (learning the underlying transition functions) and exploitation (taking the currently believed optimal joint action). We empirically evaluate them against an existing multi-arm bandit DCOP algorithm on dynamic DCOPs.

Background: DCOPs

A *distributed constraint optimization problem* (DCOP) (Modi et al. 2005; Petcu and Faltings 2005a; Yeoh and Yokoo 2012) is defined by $\langle \mathcal{X}, \mathcal{D}, \mathcal{F}, \mathcal{A}, \alpha \rangle$, where $\mathcal{X} = \{x_1, \ldots, x_n\}$ is a set of *variables*; $\mathcal{D} = \{D_1, \ldots, D_n\}$ is a set of finite *domains*, where D_i is the domain of variable x_i; $\mathcal{F} = \{f_1, \ldots, f_m\}$ is a set of binary *reward functions* (also called *constraints*), where each reward function $f_i : D_{i_1} \times D_{i_2} \mapsto \mathbb{N} \cup \{-\infty, 0\}$ specifies the reward of each combination of values of variables x_{i_1} and x_{i_2} that are in the function's scope; $\mathcal{A} = \{a_1, \ldots, a_p\}$ is a set of *agents* and $\alpha : \mathcal{X} \rightarrow \mathcal{A}$ maps each variable to one agent. Although the general DCOP definition allows one agent

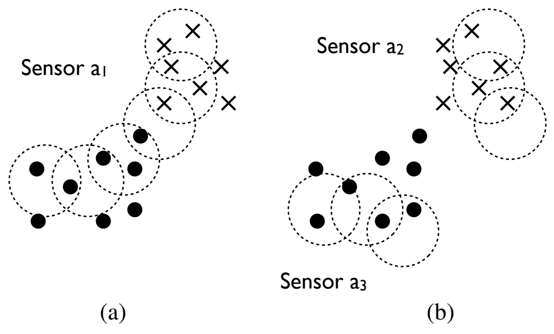

Figure 1: Sensor Network Example

to own multiple variables as well as the existence of k-ary constraints, we restrict our definition here in the interest of clarity. We will thus use the terms "agent" and "variable" interchangeably. A solution is a value assignment for a subset of variables. Its reward is the evaluation of all reward functions on that solution. A solution is *complete* iff it is a value assignment for all variables. The goal is to find a reward-maximal complete solution.

Motivating Domain

We motivate our work by a sensor network application, where a group of sensors need to coordinate to track targets in a grid. Figure 1 illustrates this problem, where there are three sensors a_1, a_2, and a_3, and two targets t_1 and t_2. The possible locations of target t_1 are denoted by "X's" and the possible locations of target t_2 are denoted by filled circles. The possible areas that sensor a_1 can scan are denoted by dotted circles in Figure 1(a), and the possible areas that sensors a_2 and a_3 can scan are denoted by dotted circles in Figure 1(b). Therefore, sensor a_2 can only track target t_1, sensor a_3 can only track target t_2, and sensor a_1 can track both targets.

Each target has an associated reward if it is found by any one sensor and a larger reward if it is found by two sensors. The reward is also location dependent – it is larger in locations of higher importance. The sensors need to coordinate with one another to decide which areas they would each like to scan at each time step for an infinite horizon. Additionally, the targets can observe the areas scanned by the sensors in the current time step, which will influence its choice of location to move to in the next time step. The sensors do not know how the targets decide to move.

If the sensors need to coordinate for a single time step only, and there is no uncertainty in the target movements, then one can represent this problem as a (canonical) DCOP, where the sensors are agents, the areas that a sensor can scan are its domain values, and the coordination between sensors to track each target is represented as a constraint.

Markovian Dynamic DCOPs

We now introduce the Markovian Dynamic DCOP (MD-DCOP) model. At a high level, an MD-DCOP can be visualized as a sequence of (canonical) DCOPs with one (canonical) DCOP at each time step. The variables $\mathcal{X}$, domains $\mathcal{D}$, agents $\mathcal{A}$, and ownership mapping α of the initial DCOP remains unchanged across all time steps, but the reward functions $\mathcal{F}$ *can* change and is a function of the global joint state $\mathbf{s}$ at the current time step. The problem transitions from one global joint state to another in the next time step according to a pre-defined joint transition probability function, which is a function of the values of the agents in the current time step. In this paper, we assume that the agents do not know this underlying joint transition probability function.

In more detail, an MD-DCOP is defined by a tuple $\langle \mathbf{S}, \mathbf{D}, \mathbf{P}, \mathbf{F} \rangle$, where

- $\mathbf{S}$ is the finite set of global joint states. $\mathbf{S} = \times_{1 \leq i \leq m} \mathbf{S}_i$, where $\mathbf{S}_i$ is the set of local states of reward function $f_i \in \mathcal{F}$. Each global joint state $\mathbf{s} \in \mathbf{S}$ is defined by $\langle \mathbf{s}_1, \ldots, \mathbf{s}_m \rangle$, where $\mathbf{s}_i \in \mathbf{S}_i$.
- $\mathbf{D}$ is the finite set of global joint values. $\mathbf{D} = \times_{1 \leq i \leq n} D_i$, where $D_i \in \mathcal{D}$ is the set of local values of variable x_i. Each global joint value $\mathbf{d} \in \mathbf{D}$ is defined by $\langle d_1, \ldots, d_n \rangle$, where $d_i \in D_i$. We also use the notations $\mathbf{D}_i = \langle d_{i_1}, d_{i_2} \rangle$, where $d_{i_1} \in D_{i_1}$ and $d_{i_2} \in D_{i_2}$, to denote the set of local joint values of variables x_{i_1} and x_{i_2} that are in the scope of reward function $f_i \in \mathcal{F}$ and $\mathbf{d}_i \in \mathbf{D}_i$ to denote an element of this set.
- $\mathbf{P}$ is the finite set of joint transition probability functions that assume conditional transition independence. $\mathbf{P} = \times_{\mathbf{s},\mathbf{s}' \in \mathbf{S}, \mathbf{d} \in \mathbf{D}} P(\mathbf{s}' \mid \mathbf{s}, \mathbf{d})$, where $P(\mathbf{s}' \mid \mathbf{s}, \mathbf{d}) = \Pi_{1 \leq i \leq m} P_i(\mathbf{s}'_i \mid \mathbf{s}_i, \mathbf{d}_i)$ is the probability of transitioning to joint state $\mathbf{s}'$ after taking joint value $\mathbf{d}_i$ in joint state $\mathbf{s}$. In this paper, we assume that the underlying joint transition probably functions are *not known* to the agents a priori.
- $\mathbf{F}$ is the finite set of joint reward functions. $\mathbf{F}(\mathbf{s}, \mathbf{d}) = \sum_{1 \leq i \leq m} f_i(\mathbf{s}_i, \mathbf{d}_i)$, where $f_i(\mathbf{s}_i, \mathbf{d}_i)$ is the reward of taking joint value $\mathbf{d}_i$ in joint state $\mathbf{s}_i$.

This model bears a lot of similarities with factored Markov decision processes (MDPs) (Boutilier, Dearden, and Goldszmidt 2000; Guestrin et al. 2003), multi-agent MDPs (Boutilier 1999) and decentralized MDPs (Bernstein et al. 2002), which we discuss in detail in the Related Work section.

In our sensor network example, if constraint f_i represents the coordination between sensors s_1 and s_2 to track target t_1, then each state $\mathbf{s}_i$ represents the possible locations of target t_1; each value $\mathbf{d}_i$ represents a pair of areas that the agents s_1 and s_2 can scan; the probability function $P_i(\mathbf{s}'_i \mid \mathbf{s}_i, \mathbf{d}_i)$ represents the movement strategy of target t_1; and the reward function $f_i(\mathbf{s}_i, \mathbf{d}_i)$ denotes the joint reward of sensors in those zones if they took joint movement $\mathbf{d}_i$ in state $\mathbf{s}_i$.

A solution to an MD-DCOP is a global joint policy $\Pi : \mathbf{S} \mapsto \mathbf{D}$ that maps each global joint state $\mathbf{s} \in \mathbf{S}$ to a global joint value $\mathbf{d} \in \mathbf{D}$. The objective of an MD-DCOP is for the agents to assign a sequence of values to their variables (to learn the underlying transition probability function and explore the state space) and converge on a global joint policy that together maximizes the expected average reward:

Definition 1 *The expected average reward of an MD-*

DCOP policy Π found using exploration strategy Φ is

$$\lim_{T\to\infty} \frac{1}{T}\,\mathbb{E}\left[\sum_{t=0}^{T-1}\sum_{i=1}^{m} f_i(\mathbf{s}_i, \mathbf{d}_i^t)\right] \tag{1}$$

where $\mathbf{d}_i^t$ is the local joint value for local state $\mathbf{s}_i$ at time step t. Let t^* be the time step in which all the agents converged on the global joint policy Π. Then, $\mathbf{d}_i^t$ is the local joint value defined by the exploration strategy Φ for $0 \le t < t^*$, and it is the local joint value given by the global joint policy Π for the global joint state $\mathbf{s}$ for $t^* \le t$.

Distributed RVI Q-Learning

Since the underlying transition probability functions of MD-DCOPs are not known to the agents a priori, there is a clear need for algorithms that trade off exploration vs. exploitation. In this paper, we explore reinforcement learning methods to solve this problem. Specifically, we extend the (centralized) RVI Q-learning and (centralized) R-learning algorithms to solve MD-DCOPs in a distributed way.

(Centralized) RVI Q-Learning

The Relative Value Iteration (RVI) Q-learning algorithm (Abounadi, Bertsekas, and Borkar 2001) was developed to solve average-reward single-agent Markov decision processes (MDPs), but it can be tailored to solve MD-DCOPs in a centralized fashion. It is one of the more popular learning algorithms as it does not make any assumptions on the underlying model of the problem and its convergence is guaranteed for any arbitrary exploration strategy (Abounadi, Bertsekas, and Borkar 2001). We now describe its operations using the notations defined above.

Step 1: Let time step $t = 0$. Initialize (say to 0) the Q values $Q^t(\hat{\mathbf{s}}, \hat{\mathbf{d}})$ for all global joint states $\hat{\mathbf{s}} \in \mathbf{S}$ and global joint values $\hat{\mathbf{d}} \in \mathbf{D}$.

Step 2: Let the current global joint state be $\mathbf{s}$. Choose the global joint value $\mathbf{d}$ based on some exploration strategy or converged policy. Let the immediate joint reward of choosing this value in this state be $\mathbf{F}(\mathbf{s}, \mathbf{d})$, and let the next resulting global joint state be $\mathbf{s}'$.

Step 3: Update the Q values using the following rule:

$$\begin{aligned} Q^{t+1}(\mathbf{s}, \mathbf{d}) = Q^t(\mathbf{s}, \mathbf{d}) + \gamma(t)\big[\mathbf{F}(\mathbf{s}, \mathbf{d}) + \max_{\mathbf{d}'\in\mathbf{D}} Q^t(\mathbf{s}', \mathbf{d}') \\ - Q^t(\mathbf{s}, \mathbf{d}) - Q^t(\mathbf{s}^0, \mathbf{d}^0)\big] \end{aligned} \tag{2}$$

where $\gamma(t)$ is a diminishing step-size schedule of stochastic approximation satisfying

$$\sum_{t=1}^{\infty} \gamma(t) = \infty \quad \text{and} \quad \sum_{t=1}^{\infty} \gamma(t)^2 < \infty \tag{3}$$

and $(\mathbf{s}^0, \mathbf{d}^0)$ is the initial state and value pair.

Step 4: Repeat Steps 2 and 3 until convergence.

Algorithm Description

While the (centralized) RVI Q-learning algorithm has been shown to be a general and powerful technique to solve average-reward (centralized) Markov decision processes (MDPs), there is no work done on how to adapt it to solve a decentralized constraint-based version of infinite-horizon average-reward MDPs, otherwise known as MD-DCOPs, in a *distributed* manner. We now describe how to do so.

We first show how the update rules in Step 3 of the (centralized) Q-learning algorithm can be done in a distributed manner. Observe that each global Q value can be decomposed into local Q values:

$$Q^t(\mathbf{s}, \mathbf{d}) \leftarrow \sum_{i=1}^{m} Q_i^t(\mathbf{s}, \mathbf{d}_i) \tag{4}$$

where each local Q value $Q_i^t(\mathbf{s}, \mathbf{d}_i)$ is associated with reward function f_i. Then, Equation 2 can be decomposed into the following for each reward function f_i:[1]

$$\begin{aligned} Q_i^{t+1}(\mathbf{s}, \mathbf{d}_i) = Q_i^t(\mathbf{s}, \mathbf{d}_i) + \gamma(t)\big[f_i(\mathbf{s}_i, \mathbf{d}_i) \\ + Q_i^t(\mathbf{s}', \mathbf{d}_i' \,|\, \mathbf{d}_i' \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^t(\mathbf{s}', \mathbf{d}')) \\ - Q_i^t(\mathbf{s}, \mathbf{d}_i) - Q_i^t(\mathbf{s}^0, \mathbf{d}_i^0)\big] \end{aligned} \tag{5}$$

The diminishing schedule $\gamma(t)$ is the same as the schedule in the centralized version.

There are two obstacles that prevent this equation from being updated in a completely distributed fashion. The first obstacle is that the local Q-value functions are functions of the global joint states, and each agent is only aware of the local state of each of its constraints. In our algorithm, before updating the local Q values, we require each agent to broadcast the local state of each of its constraints to all other agents. As a result, each agent can construct the global joint state.

The second obstacle is that there is one term for which a global optimization method is required. It is the term for which an argmax over the entire set of global joint values $\mathbf{D}$ is required:

$$\mathbf{d}_i' \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^t(\mathbf{s}', \mathbf{d}') \tag{6}$$

To solve this term in a distributed manner, we map the problem into a canonical DCOP, where the utilities in the DCOP equal the local Q values, and solve it using any off-the-shelf DCOP solvers. For example, in order to identify the local joint values $\mathbf{d}_i'$ in Equation 6, we set the reward $f_i(\mathbf{d}_i) = Q_i^t(\mathbf{s}', \mathbf{d}_i)$ of the canonical DCOP to equal the local Q value. Then, once the agents solve this canonical DCOP, the agents can update their Q values according to Equation 5 in a distributed fashion. In our experiments, we use DPOP (Petcu and Faltings 2005a) to solve this canonical DCOP.

One can view the operation of broadcasting the local states as similar to broadcasting the full DCOP structure to all agents. As a result, this operation will likely result in the loss of privacy, which can be a concern in some multi-agent applications (Greenstadt, Pearce, and Tambe 2006; Greenstadt, Grosz, and Smith 2007). However, we believe that our approach is very suitable for problems, such as our sensor network example, where all the agents are indeed completely cooperative and have no privacy concerns.

[1] With a slight abuse of notations, we use the symbol "$\in$" to mean an element of a vector instead of an element of a set.

Since each Q value $Q_i^t(\mathbf{s},\mathbf{d}_i)$ is associated with two agents, specifically the agents that are in the scope of the reward function f_i, there needs to be an agreement on which agent should maintain and update these values. We let the lower priority agent (the child or the pseudo-child in the constraint tree) maintain these values.

While this distributed RVI Q-learning algorithm can converge with any arbitrary exploration strategy, we describe a multi-arm bandit strategy. For each time step t, the agents choose their values that together maximizes the sum of the utilities over all constraints, whereby the reward of a local joint value $\mathbf{d}_i' \in \mathbf{D}_i$ for the current joint state $\mathbf{s}$ for reward function $f_i \in \mathcal{F}$ is defined by:

$$f_i(\mathbf{d}_i') = Q_i^t(\mathbf{s},\mathbf{d}_i') + \sqrt{2\ln t \frac{|\mathbf{D}_i|}{n^t(\mathbf{d}_i')}} \tag{7}$$

where $n^t(\mathbf{d}_i')$ is the number of times the joint value $\mathbf{d}_i'$ has been chosen in the previous time steps. The problem then corresponds to finding the new value $\mathbf{d}_i$ according to:

$$\mathbf{d}_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} \sum_{i=1}^{m} f_i(\mathbf{d}_i' \,|\, \mathbf{d}_i' \in \mathbf{d}') \tag{8}$$

In order to solve this problem, we can again map this problem into a canonical DCOP, where the utilities in the DCOP are defined in Equation 7, and solve it in a distributed way. The agents continue to use this exploration strategy until convergence, after which, they use the converged strategy.

Theoretical Properties

In this paper, we consider MDPs where a joint state can transition to any other joint state with non-zero probability, that is, the MDP is *unichain*. We are going to show the decomposability of the value function of a unichain MDP, thereby leading us to the property that the Distributed RVI Q-learning algorithm converges to an optimal solution. The detailed proofs for the lemma and theorems below are in the supplemental attachment.

It is known that there always exists an optimal solution for a given unichain MDP and this solution can be characterized by the $V^*(\mathbf{s})$ value:

Theorem 1 ***(Puterman 2005)*** *There exists an optimal Q-value $Q^*(\mathbf{s},\mathbf{d})$ for each joint state $\mathbf{s}$ and joint action $\mathbf{a}$ in an average-reward unichain MDP with bounded reward function satisfying:*

$$Q^*(\mathbf{s},\mathbf{d}) + \rho^* = \mathbf{F}(\mathbf{s},\mathbf{d}) + \sum_{\mathbf{s}'} P(\mathbf{s}',\mathbf{s},\mathbf{d}) \max_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}',\mathbf{d}') \tag{9}$$

Additionally, there exists a unique V-value $V^*(\mathbf{s}) = \max_{\mathbf{d}\in\mathbf{D}} Q^*(\mathbf{s},\mathbf{d})$ for each joint state $\mathbf{s}$ such that

$$V^*(\mathbf{s}) + \rho^* = \max_{\mathbf{d}\in\mathbf{D}}[\mathbf{F}(\mathbf{s},\mathbf{d}) + \sum_{\mathbf{s}'} P(\mathbf{s}',\mathbf{s},\mathbf{d})V^*(\mathbf{s}')] \tag{10}$$

with $V^*(\mathbf{s}^0) = 0$ for any initial state $\mathbf{s}^0$.

To help us prove the decomposability of the value function, we first show the decomposibility of average reward ρ^* of a given optimal policy.

Lemma 1 *For a given unichain MDP, the optimal average reward $\rho^* = \sum_{i=1}^m \rho_i^*$ can be decomposed into a sum of local average rewards ρ_i^* for each reward function $f_i \in \mathcal{F}$.*

Proof Sketch: For a given unichain MDP, there always exists a stationary distribution $P^\pi(\mathbf{s})$ of the global joint state $\mathbf{s} \in \mathbf{S}$ in the limit, where π is the converged global joint policy. Hence, we have the existence of

$$\rho_i^\pi = \sum_{\mathbf{s}\in\mathbf{S}} P^\pi(\mathbf{s}) f_i(\mathbf{s}_i,\mathbf{d}_i \,|\, \mathbf{s}_i \in \mathbf{s}, \mathbf{d}_i = \pi(\mathbf{s}))$$

for each reward function $f_i \in \mathcal{F}$. ■

From the decomposability of average reward given by Lemma 1 and the characteristic of V^* value given in Theorem 1, we now prove the decomposability of V^* as follows:

Definition 2 *$\bar{P}_i(\mathbf{s}',\mathbf{s},\mathbf{d}_i)$ is the probability of transitioning to joint state $\mathbf{s}'$ from joint state $\mathbf{s}$ given joint value $\mathbf{d}_i$ and other values following policy Φ with $V_j^*(\mathbf{s}_j^0) = 0$ for each reward function $f_j \in \mathcal{F}$.*

Theorem 2 *There exists $V_i^*(\mathbf{s}) = Q_i^*\big(\mathbf{s},\mathbf{d}_i \mid \mathbf{d}_i \in \operatorname{argmax}_{\mathbf{d}\in\mathbf{D}} Q^*(\mathbf{s},\mathbf{d})\big)$ and ρ_i for each reward function $f_i \in \mathcal{F}$ under an optimal policy $\Phi(\mathbf{s}) = \mathbf{d}_i \in \operatorname{argmax}_{\mathbf{d}\in\mathbf{D}} Q^*(\mathbf{s},\mathbf{d})$ such that*

$$\begin{aligned} V_i^*(\mathbf{s}) + \rho_i^* &= f_i(\mathbf{s}_i,\mathbf{d}_i \,|\, \mathbf{s}_i \in \mathbf{s}, \mathbf{d}_i \in \operatorname*{argmax}_{\mathbf{d}\in\mathbf{D}} Q^*(\mathbf{s},\mathbf{d})) \\ &+ \sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}',\mathbf{s},\mathbf{d}_i \,|\, \mathbf{d}_i \in \operatorname*{argmax}_{\mathbf{d}\in\mathbf{D}} Q^*(\mathbf{s},\mathbf{d}))\, V_i^*(\mathbf{s}') \end{aligned} \tag{11}$$

and $V^*(\mathbf{s}) = \sum_i V_i^*(\mathbf{s})$.

Proof Sketch: We do not show how to decompose $Q^*(\mathbf{s},\mathbf{d})$ into $Q_i^*(\mathbf{s},\mathbf{d}_i)$ but only show that there exists such a decomposition. The proof is based on the uniqueness of an optimal solution for any unichain MDP, which is given by Theorem 1.

Step 1: We first propose a modified MD-DCOP and decompose it into a set of subproblems, where each subproblem is an MD-DCOP with the transition probabilities identical with the original MD-DCOP, but the reward functions for each joint state $\mathbf{s}$ and joint value $\mathbf{d}_i$ are defined as follows:

$$\bar{f}_i(\mathbf{s},\mathbf{d}_i) = \begin{cases} f_i(\mathbf{s}_i,\mathbf{d}_i \,|\, \mathbf{s}_i \in \mathbf{s}) & \text{if } \mathbf{d}_i \in \operatorname{argmax}_{\mathbf{d}\in\mathbf{D}} Q^*(\mathbf{s},\mathbf{d}) \\ -C & \text{otherwise} \end{cases} \tag{12}$$

where C is a very large constant.

Step 2: We now show the existence of the decomposed Q-values $\bar{Q}_i^*(\mathbf{s},\mathbf{d}_i)$ for each reward function f_i. First, set the policy of every other variable that is not in the subproblem defined by reward function f_i to their respective optimal policy in the original MD-DCOP. Also set the transition probabilities $\bar{P}_i(\mathbf{s}',\mathbf{s},\mathbf{d}_i)$ according to the premise of Theorem 2 and set the reward functions $\bar{f}_i(\mathbf{s},\mathbf{d}_i)$ according to Equation 12.

According to Theorem 1, there exists a decomposed Q-value $\bar{Q}_i^*$ for this subproblem such that

$$\bar{Q}_i^*(\mathbf{s},\mathbf{d}_i) + \rho_i^* = \bar{f}_i(\mathbf{s},\mathbf{d}_i)$$

$$+\sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}_i)\, \bar{Q}^*_i\big(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}' \in \mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}')\big) \quad (13)$$

where ρ^*_i corresponds to the local average reward of the subproblem, as shown in Lemma 1.

Step 3: Next, we show that the global optimal Q-values (sum of the decomposed optimal Q-values) of the modified MD-DCOP is the same as the global optimal Q-values of the original MD-DCOP. For the globally optimal joint value $\mathbf{d}^* = \operatorname{argmax}_{\mathbf{d}\in\mathbf{D}} Q^*(\mathbf{s}, \mathbf{d})$, let $\mathbf{d}^*_i$ to denote the local joint value in $\mathbf{d}^*$, $\bar{Q}^*(\mathbf{s}, \mathbf{d}^*) = \sum_i \bar{Q}^*_i(\mathbf{s}, \mathbf{d}^*_i)$, and $\bar{\mathbf{F}}(\mathbf{s}, \mathbf{d}^*) = \sum_i \bar{f}_i(\mathbf{s}, \mathbf{d}^*_i)$. Summing over all subproblems, we get

$$\begin{aligned}
&\bar{Q}^*(\mathbf{s}, \mathbf{d}^*) + \rho^* \\
&\quad = \sum_i \Big[\bar{Q}^*_i(\mathbf{s}, \mathbf{d}^*_i) + \rho^*_i\Big] \\
&\quad = \sum_i \Big[\bar{f}_i(\mathbf{s}, \mathbf{d}^*_i) \\
&\qquad + \sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}^*_i)\, \bar{Q}^*_i(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}'))\Big] \\
&\quad = \sum_i \bar{f}_i(\mathbf{s}, \mathbf{d}^*_i) \\
&\qquad + \sum_{i,\mathbf{s}'} \Big[\bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}^*_i)\, \bar{Q}^*_i(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}'))\Big] \\
&\quad = \bar{\mathbf{F}}(\mathbf{s}, \mathbf{d}^*) \\
&\qquad + \sum_{\mathbf{s}'} \Big[P(\mathbf{s}', \mathbf{s}, \mathbf{d}^*) \sum_i \bar{Q}^*_i(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}'))\Big] \\
&\quad = \bar{\mathbf{F}}(\mathbf{s}, \mathbf{d}^*) + \sum_{\mathbf{s}'} \Big[P(\mathbf{s}', \mathbf{s}, \mathbf{d}^*) \max_{\mathbf{d}'\in\mathbf{D}} \bar{Q}^*(\mathbf{s}', \mathbf{d}')\Big] \qquad (14)
\end{aligned}$$

This equation is in the form of Equation 9, which characterizes $\bar{Q}^*(\mathbf{s}, \mathbf{d}^*)$ as a solution to the modified problem. Additionally, one can also show that the Q-value $Q^*(\mathbf{s}, \mathbf{d}^*)$ of the original problem is also a solution to the modified problem using the same process as in Equation 14. Since $V^*(\mathbf{s})$ is unique according to Theorem 1, it must be the case that $V^*(\mathbf{s}) = Q^*(\mathbf{s}, \mathbf{d}^*) = \bar{Q}^*(\mathbf{s}, \mathbf{d}^*)$.

Step 4: Finally, we show how to decompose the global optimally Q-values, which concludes the proof. We define the decomposed Q- and V-values for $\mathbf{d}^*_i$ as follows:

$$\begin{aligned}
Q^*_i(\mathbf{s}, \mathbf{d}^*_i) + \rho^*_i &= f_i(\mathbf{s}_i, \mathbf{d}^*_i) \\
&\quad + \sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}^*_i)\, \bar{Q}^*_i(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}'))
\end{aligned} \qquad (15)$$

$$V^*_i(\mathbf{s}) = Q^*_i(\mathbf{s}, \mathbf{d}^*_i) \qquad (16)$$

We now show that $Q^*_i(\mathbf{s}, \mathbf{d}^*_i) = \bar{Q}^*_i(\mathbf{s}, \mathbf{d}^*_i)$:

$$\begin{aligned}
Q^*_i(\mathbf{s}, \mathbf{d}^*_i) &= f_i(\mathbf{s}_i, \mathbf{d}^*_i) - \rho^*_i \\
&\quad + \sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}^*_i)\, \bar{Q}^*_i(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}')) \\
&= \bar{f}_i(\mathbf{s}_i, \mathbf{d}^*_i) - \rho^*_i \\
&\quad + \sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}^*_i)\, \bar{Q}^*_i(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}')) \\
&= \bar{Q}^*_i(\mathbf{s}, \mathbf{d}^*_i) \qquad (17)
\end{aligned}$$

Therefore,

$$\begin{aligned}
&V^*_i(\mathbf{s}) + \rho^*_i \\
&\quad = Q^*_i(\mathbf{s}, \mathbf{d}^*_i) + \rho^*_i \\
&\quad = f_i(\mathbf{s}_i, \mathbf{d}^*_i) + \sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}^*_i)\, \bar{Q}^*_i(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}')) \\
&\quad = f_i(\mathbf{s}_i, \mathbf{d}^*_i) + \sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}^*_i)\, Q^*_i(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q^*(\mathbf{s}', \mathbf{d}')) \\
&\quad = f_i(\mathbf{s}_i, \mathbf{d}^*_i) + \sum_{\mathbf{s}'} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}^*_i)\, V^*_i(\mathbf{s}') \qquad (18)
\end{aligned}$$

Finally, we now show that the V-value $V^*(\mathbf{s})$ is a sum of its decomposed components $V^*_i(\mathbf{s}, \mathbf{d}^*_i)$:

$$\begin{aligned}
V^*(\mathbf{s}) &= \bar{Q}^*(\mathbf{s}, \mathbf{d}^*) \\
&= \sum_i \bar{Q}^*_i(\mathbf{s}, \mathbf{d}^*_i) \\
&= \sum_i Q^*_i(\mathbf{s}, \mathbf{d}^*_i) \\
&= \sum_i V^*_i(\mathbf{s}, \mathbf{d}^*_i) \qquad (19)
\end{aligned}$$

which concludes the proof. ■

As a result of the existence of the local value $V^*_i(\mathbf{s})$ and the non-expansive property of the Q update, we can derive the convergence proof of our distributed RVI Q-learning algorithm:

Theorem 3 *The Distributed RVI Q-learning algorithm converges to an optimal solution.*

Proof Sketch: Let $\mathbf{d}$ denote the global joint value taken by all the variables in the current iteration, and $\mathbf{d}_i$ denote the local joint value taken by variables in the scope of reward function f_i. Additionally, let $\mathbf{s}$ denote the current global state, and $\mathbf{s}'$ denote the next global state as a result of taking the joint value $\mathbf{d}$.

Now, let H_i be the mapping defined by

$$\begin{aligned}
(H_i Q_i)(\mathbf{s}, \mathbf{d}_i) &= f_i(\mathbf{s}, \mathbf{d}_i) \\
&\quad + \sum_{\mathbf{s}'_i} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}_i) Q(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} Q(\mathbf{s}', \mathbf{d}')) - \rho_i \\
&= f_i(\mathbf{s}, \mathbf{d}_i) + \sum_{\mathbf{s}'_i} \bar{P}_i(\mathbf{s}', \mathbf{s}, \mathbf{d}_i) V(\mathbf{s}') - \rho_i
\end{aligned}$$

with $V(\mathbf{s}') = Q(\mathbf{s}', \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname{argmax}_{\mathbf{d}'\in\mathbf{D}} Q(\mathbf{s}', \mathbf{d}'))$. Since H_i is non-expansive, that is,

$$\|H_i Q_i - H_i Q'_i\|_\infty \le \|Q_i - Q'_i\|_\infty$$

and the corresponding ODE of $H_i Q_i$

$$\dot{Q}_i(t) = H_i(Q_i(t)) - Q(t)$$

has at least one solution according to Theorem 2, Q_i thus converges to the optimal value Q^*_i using the result by Abounadi, Bertsekas, and Borkar (2001). ■

Distributed R-Learning

We now describe how to extend the (centralized) R-learning algorithm to solve MD-DCOPs in a distributed way.

(Centralized) R-Learning

One of the limitations of the (centralized) RVI Q-learning algorithm is that it rate of convergence can be slow in practice. As a result, researchers developed the R-learning algorithm (Schwartz 1993; Mahadevan 1996), which can be seen as a variant of the Q-learning algorithm. Unfortunately, the convergence of this algorithm has not been proven to the best of our knowledge. Nonetheless, it has been shown to work well in practice.

The operations of the R-learning algorithm are very similar to that of the RVI Q-learning algorithm, except that it maintains R values $R^t(\mathbf{s}, \mathbf{d})$ and average utilities ρ^t instead of Q values $Q^t(\mathbf{s}, \mathbf{d})$ for each time step t. These values are updated using the following rules:

$$\begin{aligned} R^{t+1}(\mathbf{s},\mathbf{d}) \leftarrow & R^t(\mathbf{s},\mathbf{d})(1-\beta) + \beta\big[\mathbf{F}(\mathbf{s},\mathbf{d}) - \rho^t \\ & + \max_{\mathbf{d}'\in\mathbf{D}} R^t(\mathbf{s}',\mathbf{d}')\big] \qquad (20) \\ \rho^{t+1} \leftarrow & \rho^t(1-\alpha) + \alpha\big[\mathbf{F}(\mathbf{s},\mathbf{d}) \\ & + \max_{\mathbf{d}'\in\mathbf{D}} R^t(\mathbf{s}',\mathbf{d}') - \max_{\mathbf{d}'\in\mathbf{D}} R^t(\mathbf{s},\mathbf{d}')\big] \qquad (21) \end{aligned}$$

where $0 \leq \beta \leq 1$ is the learning rate for updating the R values and $0 \leq \alpha \leq 1$ is the learning rate for updating the average reward ρ.

Algorithm Description

Like the global Q values, each global R value and average reward can be decomposed into local R values and local utilities:

$$R^t(\mathbf{s},\mathbf{d}) \leftarrow \sum_{i=1}^{m} R_i^t(\mathbf{s}_i,\mathbf{d}_i) \qquad \rho^t \leftarrow \sum_{i=1}^{m} \rho_i^t \qquad (22)$$

where local R value $R_i^t(\mathbf{s}_i, \mathbf{d}_i)$ and local average reward ρ_t^i are associated with reward function f_i. Then, Equations 20 and 21 can be decomposed into the following for each reward function f_i:

$$\begin{aligned} R_i^{t+1}(\mathbf{s}_i,\mathbf{d}_i) \leftarrow & R_i^t(\mathbf{s}_i,\mathbf{d}_i)(1-\beta) + \beta\big[f_i(\mathbf{s}_i,\mathbf{d}_i) - \rho_i^t \\ & + R_i^t(\mathbf{s}_i',\mathbf{d}_i' \,|\, \mathbf{d}_i' \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} R^t(\mathbf{s}',\mathbf{d}'))\big] \qquad (23) \\ \rho_i^{t+1} \leftarrow & \rho_i^t(1-\alpha) + \alpha\big[f_i(\mathbf{s}_i,\mathbf{d}_i) \\ & + R_i^t(\mathbf{s}_i',\mathbf{d}_i' \,|\, \mathbf{d}_i' \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} R^t(\mathbf{s}',\mathbf{d}')) \\ & - R_i^t(\mathbf{s}_i,\mathbf{d}_i' \,|\, \mathbf{d}_i' \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} R^t(\mathbf{s},\mathbf{d}'))\big] \qquad (24) \end{aligned}$$

The learning rates $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$ are the same as the learning rates in the centralized version.

One of the differences here is that, unlike local Q value functions, the local R value and average reward functions are functions of *local* states $\mathbf{s}_i$ instead of *global* joint states. Therefore, there is no need for agents to broadcast the local states of their constraints to the other agents in the distributed R-learning algorithm. However, there are now two terms for which a global optimization method is required. They are:

$$\mathbf{d}_i' \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} R^t(\mathbf{s},\mathbf{d}') \qquad \mathbf{d}_i' \in \operatorname*{argmax}_{\mathbf{d}'\in\mathbf{D}} R^t(\mathbf{s}',\mathbf{d}') \qquad (25)$$

Similar to distributed Q-learning, we can solve for each of these terms in a distributed manner by mapping the problems into canonical DCOPs. Once the agents solve the two canonical DCOPs that correspond to solving Equation 25, they can update their R values and average utilities according to Equations 23 and 24 in a distributed fashion. Finally, we let the agents in this algorithm use the same multi-arm bandit exploration strategy as that in distributed Q-learning.

Related Work

Related DCOP Models: In a *Stochastic DCOP* (S-DCOP), each constraint $f_i : D_{i_1} \times D_{i_2} \rightarrow P(x_{i_1}, x_{i_2})$ now specifies a probability distribution function of the reward as a function of the values of the variables $x_{i_1}, x_{i_2} \in X$ in the scope of the function (Atlas and Decker 2010; Nguyen, Yeoh, and Lau 2012). Another close extension is the DCOP under Stochastic Uncertainty model (Léauté and Faltings 2011b), where there are random variables that take on values according to known probability distribution functions. In these problems, the goal is to find a complete solution that maximizes the expected sum of all utilities. MD-DCOPs are similar to S-DCOPs in that the reward of each value combination in a constraint is stochastic. However, the stochasticity is due to the change in the underlying joint state of the problem instead of having the reward function explicitly represented as a probability distribution function.

In an *Uncertain DCOP* (U-DCOP), the probability distribution reward functions are not known a priori to the agents. Thus, the agents need to strike a balance between exploration (learning the underlying probability distribution functions) and exploitation (taking the currently believed optimal joint action). A simpler version of this problem is one where the reward of each value combination is a number instead of a distribution function (Jain et al. 2009; Taylor et al. 2010).[2] In these problems, the goal is to maximize the expected cumulative reward over the time horizon. Researchers have introduced a regret minimizing algorithm, called HEIST, that uses a multi-arm bandit strategy to solve this problem (Stranders et al. 2012). MD-DCOPs are similar to U-DCOPs in that learning is required and the algorithms need to balance exploration and exploitation. However, in MD-DCOPs, the agents need to learn the state transition functions but, in U-DCOPs, the agents need to learn the reward function.

Finally, in a *Dynamic DCOP* (D-DCOPs), the problem can change over time (Petcu and Faltings 2005b; Sultanik, Lass, and Regli 2009; Yeoh et al. 2011). A typical model of a dynamic DCOP is a sequence of (canonical) DCOPs with changes from one DCOP to the next one in the sequence. In these problems, the goal is to solve each (canonical) DCOP at each time step. Other related extensions include a continuous-time model where agents have deadlines to choose their values (Petcu and Faltings 2007), a model where agents can have imperfect knowledge about their environment (Lass, Sultanik, and Regli 2008), and a model where the constraint graph can change as a function of the value assignments in the previous time step (Zivan,

[2]Researchers have called the former model MAB-DCOP and the latter model DCEE. We use the term U-DCOPs as a generalization of both models.

Glinton, and Sycara 2009). MD-DCOPs are similar to D-DCOPs in that the problem changes over time. However, the changes in MD-DCOPs are restricted to changes in the underlying state of the problem, while the changes in D-DCOPs include other forms, such as addition/removal of agents/variables/constraints.

Related MDP Models: *Markov Decision Processes* (MDPs) have been shown to be effective models for planning under uncertainty involving a single decision maker. Researchers have thus extended these models to treat multi-agent coordination problems. One such model is the *Multi-agent MDP* (Boutilier 1999), where the action space is factored into actions for each agent. Another model is the *Factored MDP* (Boutilier, Dearden, and Goldszmidt 2000; Guestrin et al. 2003), where in addition to the factored action space, the overall reward function is also factored into rewards among subgroups of agents. There is also the *Decentralized MDP* (Dec-MDP) (Bernstein et al. 2002), where the global state is also factored into local states for each agent. Lastly, a *Transition-Independent Dec-MDP* (TI-Dec-MDP) (Becker et al. 2004) is a subclass of Dec-MDPs, where the transition from one local state to the next is independent of the local states and actions of all other agents.

The MD-DCOP model can be viewed as part of this family of algorithms. Like all the above algorithms, it too assumes a factored action space. Like factored MDPs, it too assumes that rewards are factored into agent subgroups, where each agent subgroup is the scope of agents in a constraint. Like Dec-MDPs, it too assumes that the global state is factored, but the state is factored into local states for each constraint instead of each agent. Like TI-Dec-MDPs, it too assumes that the transition from a local state to the next is independent of the local states. However, unlike TI-Dec-MDPs, MD-DCOPs assume a different general form of transition independence, which we call *constraint-based transition independence*: the transition of a local state of a constraint to the next local state is independent of the local states of other constraints but is dependent on the joint actions of the agents in the scope of the constraint associated with that local state.

While there is a large body of work on applying coordinated reinforcement learning on Factored MDPs (Guestrin, Koller, and Parr 2001; Guestrin, Lagoudakis, and Parr 2002; Kok and Vlassis 2006; Teacy et al. 2012) and Dec-MDPs (Zhang and Lesser 2011; 2013), they typically optimize the expected cumulative reward over a finite horizon or the expected cumulative *discounted* reward over an infinite horizon. In contrast, we optimize the *average* expected reward over an infinite horizon. We believe that for infinite horizon problems, optimizing the average expected reward fits more naturally with many multi-agent applications, where achieving a goal in a future time step is as important as achieving it in the current time step. For example, in our sensor network application, detecting an intruder next week should not be any less valuable than detecting an intruder today. In some cases, optimizing the average expected reward is harder and the motivation for using discounted utilities is mostly a convenience, not a better match with the real objective. It is well known that discount factors are often selected arbitrarily despite the fact that they could affect the final policy. These considerations underscore the importance of developing methods for optimizing the average expected reward.

To the best of our knowledge, the only work that optimizes the average expected reward in this family of problems is by Petrik and Zilberstein (2007). The main differences are that the assumption of transition independence is different for the two models, as described above; they use a centralized approach (a mixed integer linear program) while we use a distributed approach; and they assume that the underlying joint distribution is known while we do not.

Experimental Results

In addition to the distributed Q- and R-learning algorithms described above, we also implemented another version of the distributed Q-learning algorithm, where we maintain a Q-value $Q_i(\mathbf{s}_i, \mathbf{d_i})$ for each local state $\mathbf{s}_i \in \mathbf{S}_i$ instead of each global state $\mathbf{s} \in \mathbf{S}$. The update rule is thus:

$$\begin{aligned} Q_i^{t+1}(\mathbf{s}_i, \mathbf{d}_i) = Q_i^t(\mathbf{s}_i, \mathbf{d}_i) + \gamma(t)\big[f_i(\mathbf{s}_i, \mathbf{d}_i) \\ + Q_i^t(\mathbf{s}'_i, \mathbf{d}'_i \,|\, \mathbf{d}'_i \in \operatorname*{argmax}_{\mathbf{d}' \in \mathbf{D}} Q^t(\mathbf{s}'_i, \mathbf{d}')) \\ - Q_i^t(\mathbf{s}, \mathbf{d}_i) - Q_i^t(\mathbf{s}^0, \mathbf{d}_i^0)\big] \end{aligned} \tag{26}$$

We call this version the Decomposed Distributed Q-learning algorithm. Like the distributed R-learning algorithm, this algorithm does not have any convergence guarantees.

We compare the above three algorithms to Multi-Arm Bandit DCOP (MAB-DCOP) (Stranders et al. 2012), a regret-minimizing algorithm that seeks to maximize the expected cumulative reward over the time horizon in a DCOP with reward uncertainty. We run our experiments on a 64 core Linux machine with 2GB of memory and evaluate the algorithms on our motivating sensor network domain.

We vary the number of agents $|\mathcal{A}|$ and the number of constraints $|\mathcal{F}|$ by varying the topology of the sensor network. We used a 4-connected grid topology, where each sensor has a constraint with each sensor in its four cardinal directions. We fixed the number of rows in the grid to 3 and varied the number of columns from 1 to 4. We also varied the number of values per agent $|D_i|$ of each agent a_i from 4 to 8 and the number of local states per constraint $|\mathbf{S}_i|$ from 2 to 10.

We make the following observations about the results shown in Figure 2:

- Figures 2(a–b) show the convergence rate of the four algorithms. In the bigger problem, the Distributed Q algorithm ran out of memory due to the large number of global joint states. In the smaller problem, it finds worse solutions than the other algorithms, but that is likely due to its slow convergence rate as it is guaranteed to converge to the global optimum. The results also show that both decomposed versions of the Q- and R-learning algorithms performed better than MAB-DCOP, which is not surprising as MAB-DCOP was not designed to solve MD-DCOPs and thus does not exploit the assumption that the underlying transitions are Markovian.
- Figures 2(c–e) show the final solution quality of the algorithms. We omitted Distributed Q in the latter two figures as it ran out of memory. In general, MAB-DCOP

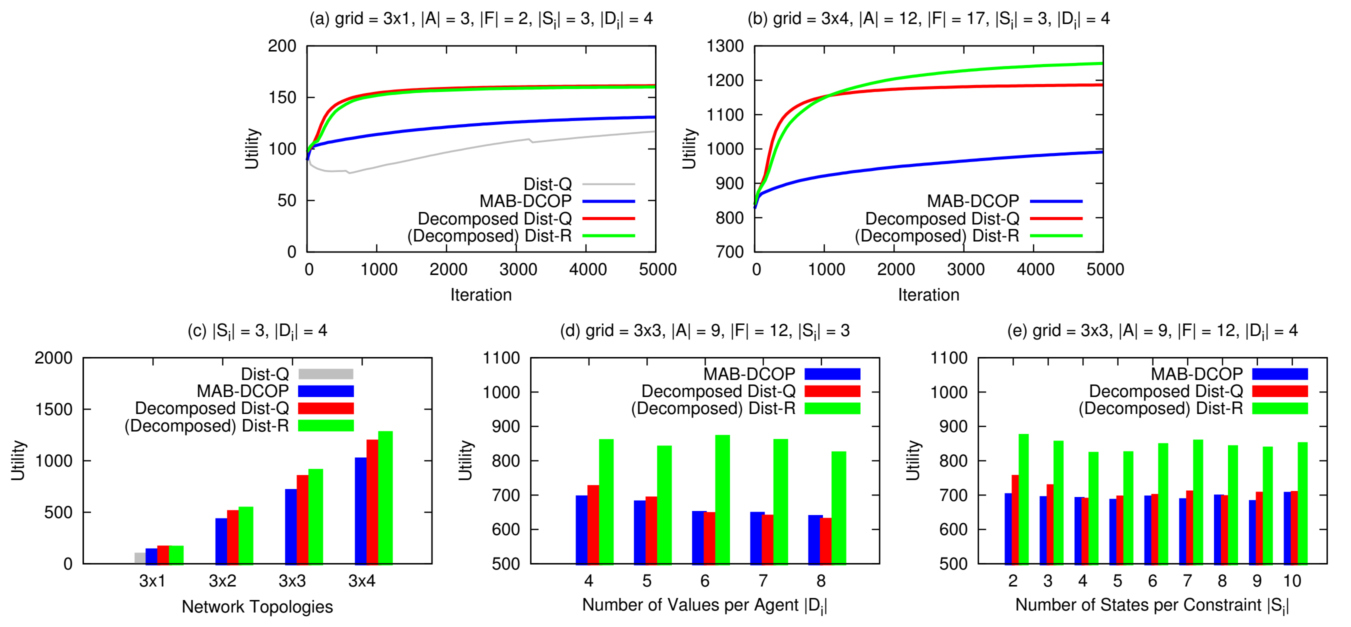

Figure 2: Experimental Results

and the Decomposed Distributed Q-learning algorithm performed equally well and the Distributed R-learning algorithm performed the best. These results thus affirm that the conclusions found for the centralized versions of the reinforcement learning algorithms, where the centralized R-learning algorithm was found to perform better than the centralized Q-learning algorithm (Mahadevan 1996), also hold for the distributed case.

Conclusions

The Dynamic DCOP formulation is attractive as it is able to model various multi-agent coordination problems that dynamically change over time. Unfortunately, existing work typically assumes that the problem at each time step is independent of the problems in the other time steps. This assumption does not hold in problems like our motivating sensor network domain, where the choice of value assignments (i.e., actions by the agents) in one time step can affect the problem in the next time step. In this paper, we take the first step towards capturing this inter-dependence, by introducing the Markovian Dynamic DCOP (MD-DCOP) model, where the underlying transition functions are Markovian. We also introduce several distributed reinforcement algorithms to solve this problem, and show that they outperform MAB-DCOP, a regret-minimizing multi-arm bandit algorithm, for a range of sensor network problems.

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