Analyzing the Effect of Information Stagnancy on the Distributed Stochastic Algorithm

Extended Abstract

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ABSTRACT

Despite the fact that many real world problems change over time, many Distributed Constraint Optimization Problem (DCOP) algorithms assume that the problem is constant or changing at a negligible rate. In addition, these algorithms also assume that changes to the environment are instantaneously observable. However, in highly dynamic environments with communication delays, both of these assumptions can be violated resulting in problem solving with out-of-date information. In this study, we explore the relationship between environmental dynamics, information stagnancy, and solution quality in Dynamic DCOP problems. By using recent advances in the analysis of dynamic, distributed problems, we show that information stagnancy can be characterized and used to accurately predict the behavior of a protocol. To evaluate our finding, we use the Distributed Stochastic Algorithm (DSA) as a basis. Through extensive empirical testing, we show that the prediction function is accurate.

KEYWORDS

DCOP; Dynamic;Distributed Algorithms; Data Stagnancy; Constraint Optimization; Thermodynamics

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1 INTRODUCTION

Characterizing the performance of a distributed protocol is a difficult task. When operating on static problems, Distributed Constraint Optimization Problem (DCOP) protocols are usually measured using metrics such as their overall solution quality, local computation time, and network utilization. To evaluate a protocol, practitioners measure these quantities on numerous sample problems that are generated using parameters such as size, complexity, and difficulty. Evaluating even a simple protocol change can result in 10s of thousands of test runs consuming months of computation time. These measures are important, but their value is limited by the fact that many real world problems that are modeled as DCOPs change over time.

Recent advances in the analysis of DynDCOPs [3, 4] partial addressed these issues by modeling DynDCOPs as a thermodynamic systems. With this mapping in place, a protocol's performance on dynamic problems can be predicted based on how fast it converges onto a final solution for a static problem. This is a powerful tool as it addresses the need to account for the rate that an environment is changing the problem. However, it does not address how information stagnancy, caused by communication delays or protocol design, affects the final solution quality. In fact, because it models the performance of a protocol on static instances, it predicts the performance of a protocol under the assumption that changes to the environment are instantly known and taken into account. This presents an opportunity because it means that the impact of information stagnancy can be measured.

2 DYNAMIC, DISTRIBUTED CONSTRAINT OPTIMIZATION PROBLEMS (DYNDCOP)

A static (non-changing) DCOP problem $\mathbf{P} = \langle \mathbf{V}, \mathbf{A}, \mathbf{D}, \mathbf{C} \rangle$ is [5]:

- A set of n variables: $\mathbf{V} = \{v_1, \ldots, v_n\}$.
- A set of g agents: $\mathbf{A} = \{a_1, \ldots, a_g\}$.
- Discrete, finite domains for each variable: $\mathbf{D} = \{\mathbf{D_1}, \ldots, \mathbf{D_n}\}$.
- A set of m cost functions $\mathbf{C} = \{c_1, \ldots, c_m\}$, where each $c_i(d_{i,1}, \ldots, d_{i,j_i})$ is a function where $c_i : D_{i,1} \times \cdots \times D_{i,j} \rightarrow \{i | i \in \mathbb{N} \wedge 0 \leq i \leq c_{i,max}\}$.

With above definition, the objective is to find an assignment $\mathcal{S}^* = \{d_1, \ldots, d_n | d_i \in D_i\}$ that minimizes the sum of the cost.

Based on the work of Dechter and Dechter [1], a DynDCOP can be defined as a sequence of static problems $\{P_0, P_1, \ldots, P_n\}$. By defining $\mathbf{c_i^a}$ as a set of cost functions that are added and $\mathbf{c_i^r}$ as a set cost functions that are removed, we can say that $P_i = P_{i-1} + \mathbf{c_i^a} - \mathbf{c_i^r}$ [6]. It should be apparent that a cost function can be changed by simply removing it and adding it back in with a different cost table.

Formally, we can then define the change rate of a problem as [2] $rate = \frac{dP}{dt} = \lim_{\Delta t \to 0} \frac{P_{t+\Delta t} - P_t}{\Delta t}$

Making the rate of change for a DynDCOP problem over a time period Δt is [2] $rate = \frac{1}{\Delta t} \sum_{i=t}^{t+\Delta t} \frac{|c_i^a| + |c_i^r|}{2}$ where c_i^a and c_i^r are the added and removed cost functions respectively.

3 ANALYSIS MODEL

In 2017, Mailler et. al [4] developed a mapping from DynDCOP problems onto physical systems. However, their model did not take into account the impact that information delay had on the problems solvers. To understand this impact, we decided to modify the DSA protocol [7] to allow us to control the amount of delay

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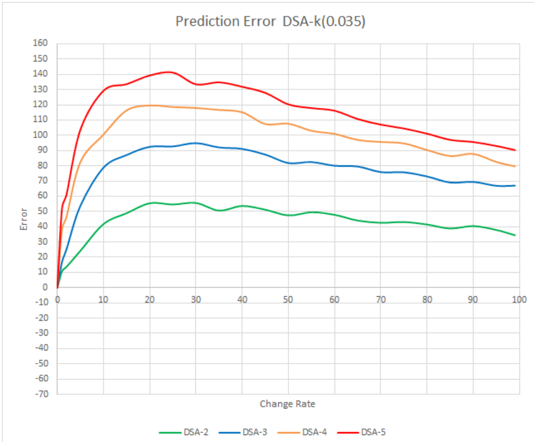

Figure 1: Prediction error for DSA-k for various values of k

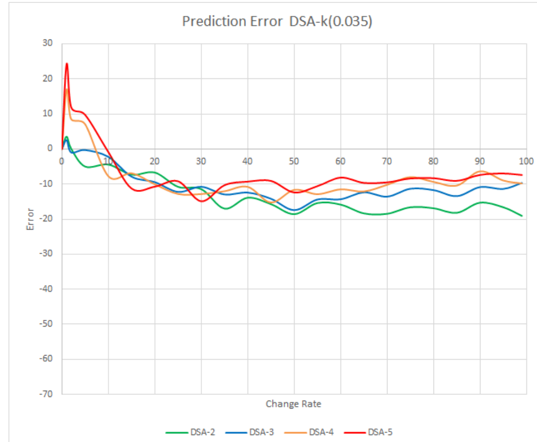

Figure 2: Comparison of predicted versus actual equilibrium points for DSA-k taking into account information stagnancy

in the protocol's information processing. The key difference lies is how often the agents takes cost function changes into consideration. This is controlled by a parameter value we call k. To evaluate the proposed model, we ran an empirical test using the DSA-k protocol where we varied the value for k from 2 through 5. These tests were conducted using $n = 100$ variables, $|D| = 3$, $p_1 = 0.035$, $< c_i = 5 >$ and a $rate$ that varied from 0 to 99. For each setting of k and $rate$, we conducted 30 experiments, each of 1000 steps, where the cost functions were altered, but not added or removed. The results of these tests can be seen in Figure 1. The results clearly show the impact that stagnant information has on the protocol. As the value of k is increased, a noticeable increase in the error can be seen.

With these results in mind, we revisited the equation for the change in energy caused by work. This equation has two principle components, the convergence rate, A and the convergence point, B. By definition, the convergence point is unaffected by delays in information because it represents the solution that the protocol will eventually obtain assuming infinite time. However, it should be clear that delays in processing updates would cause changes to the speed at which a protocol could reach that solution.

Using this reasoning, we speculated that the convergence rate is changed by a factor k. To include this finding, we altered the change work equation by multiply the convergence rate by the value k, which has the impact of slowing convergence. This can be seen in the equation $\frac{dE_W}{dt} = \frac{B-E}{kA}$. Then by combining the equations we reach a new equation to create a new equilibrium point equation that factors in the impact of information stagnancy. This is seen in the equation $E_0 = \frac{kAD+\frac{CB}{rate}}{kA+\frac{C}{rate}}$ In fact, the error for all of the values of k is nearly constant indicating that the error that does remain is probably caused the by order of the simulation cycle.

4 CONCLUSIONS

In this study we showed that the primary cause of prediction error for the equilibrium point of a protocol operating on a DynDCOP is information stagnancy. This error is created by the method used to characterize the converge rate of a protocol. However, this error can be corrected for by altering the equilibrium prediction equation. In addition, the error can be used to measure the impact that information delay has on the performance of a protocol.

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