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# Decentralization of Control Loop for Self-Adaptive Software through Reinforcement Learning

**Kishan Kumar Ganguly, Kazi Sakib**
**Institute of Information Technology**
**University of Dhaka, Dhaka, Bangladesh**

**Presented By**

Kishan Kumar Ganguly
Institute of Information Technology
University of Dhaka

# Presentation Outline

- Introduction
- Background
- Related Work
- Problem and Motivation
- Running Example
- Proposed Approach
- Experimental Evaluation
- Results
- Discussion
- Conclusion and Future Work

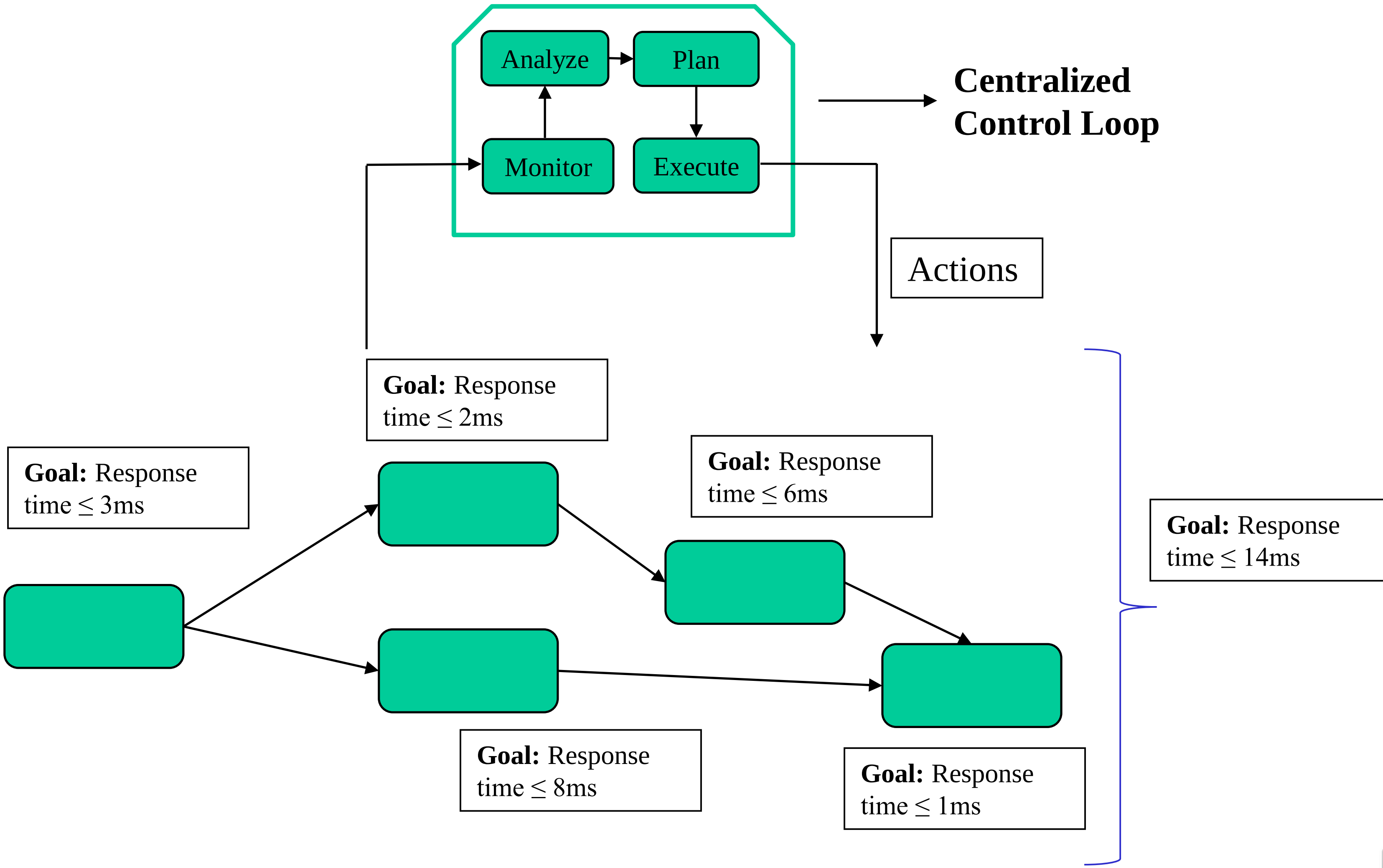
# Introduction

- Self-adaptive systems change their behavior at runtime to conform to their goals
- Goals are generally non-functional requirements
  - Response time
  - Throughput etc.
- Decentralization has become a widespread concept [1]
- Designing self-adaptive software with decentralized control loop is still a research challenge [1]–
  - A control loop helps to respond to the goal violation at runtime without interrupting its service

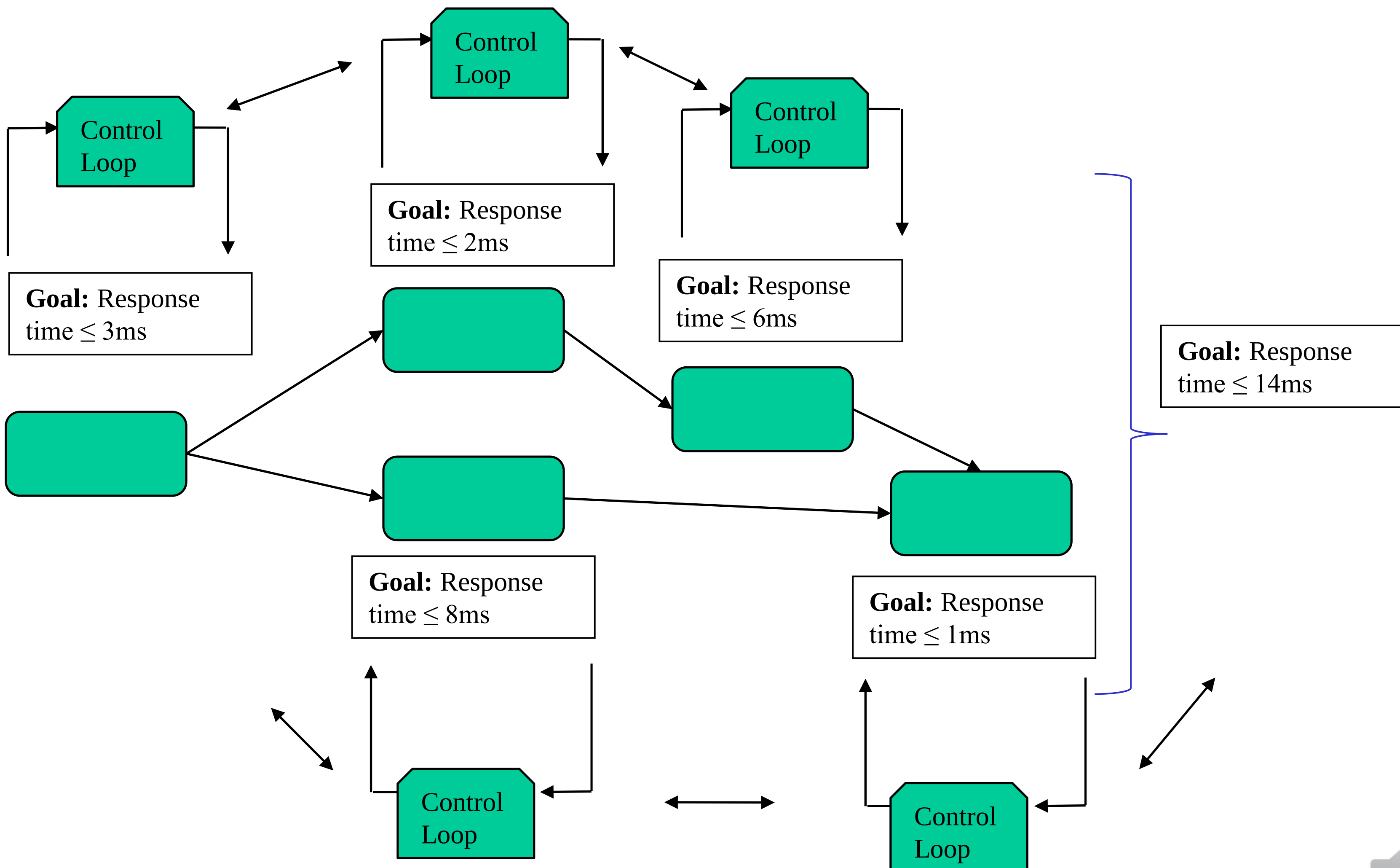
# Background

- In self-adaptive system with decentralized control loops, multiple control loops coordinate to satisfy some goals
- These goals can be divided as –
  - Local goal: component-level goal [2]
  - Global goal: system-level goal [2]
- A goal violation leads to –
  - Coordination of multiple control loop (information sharing) to take adaptation decisions
  - These adaptation decisions / actions are selection of variants (software variants with different configurations)
  - Adaptation decisions must satisfy local and global goals

# Background: Centralized Self-Adaptive Systems



# Background: Decentralized Self-Adaptive Systems



# Related Work

### Weyns et al. [4]

- Proposed a generic model for decentralized self-adaptive system
- It was highly abstract and did not explicitly address coordination of multiple control loops

### Sykes et al. [5]

- Proposed a distributed self-assembly approach
- Used aggregated gossip for coordination
- Lacked dynamism, used static strategies

### Schmerl et al. [13]

- Proposed five patterns for decentralized self-adaptation
- Facilitated further research into this domain

2010 — 2011 — 2013 — 2014 — 2016

### Grassi et al. [2]

- For self-adaptive service assembly
- Used gossip protocol for service specification dissemination
- Selected best service based on predefined utility
- Problem: static utility value

### Wang et al. [3]

- Dynamic service composition based on reinforcement learning
- Opponent model-based coordination
- Can be further improved using opponent model for both learning and action selection and updating weight of violated goal for more importance

### Caporuscio et al. [6]

- Performed TD learning on global quality functions of services to estimate their long term quality
- Service matching was performed by choosing the service that has maximum quality
- Local goals and coordination was not explicitly considered

# Problem and Motivation

**Problem**

- Writing static strategies or action selection rules, similar to some centralized control loops is not practical due to large state space
- In a specific state, action selection rules of a local control loop depend on the strategies followed by other control loops
- Reward functions (that calculate goal conformance [3]) need to be defined in such a way that these successfully capture both local and global goal violations

**Motivation**

- Reinforcement learning provides a great opportunity to introduce dynamism into the self-adaptive decisions
- Each local control loop needs to estimate the strategies used by other ones which can be done through an opponent model along with multiagent reinforcement learning
- The reward functions can be aggregated with a dynamic weight to provide more importance to the violated goals

# Running Example

- The Tele Assistance System (TAS) is a service-based system that provides medical service to patients [9]
- Three services are used –
  – MedicalAnalysisService – Checks the vital parameters of the patient and takes actions
  – DrugService – Change drug or dosage of the drug
  – AlarmService – Provides alarm in case of emergency
- MedicalAnalysisService variants with different configurations
  – MedicalAnalysisService1, MedicalAnalysisService2 and MedicalAnalysisService3
- AlarmService similarly has three variants

# Running Example

| Goal | Attribute | Goal Type | Goal Threshold |
|---|---|---|---|
| MedicalAnalysisService must have response time less than or equals 5.6 ms | Response Time | Local & Threshold | 5.6 |
| AlarmService must have response time less than or equals 5.2 ms | Response Time | Local & Threshold | 5.2 |
| MedicalAnalysisService must have failure rate less than or equals 0.12 | Failure Rate | Local & Threshold | 0.12 |
| AlarmService must have failure rate less than or equals 0. | Failure Rate | Local & Threshold | 0.1 |
| At least one service must have failure rate less than 0.08 | Failure Rate | Global & Threshold | 0.08 |
| Average cost per service must be minimized | Average Cost Per Service | Global & Minimization | - |

# Running Example

| Goal Attribute | Value Range | Corresponding Category |
|---|---|---|
| Failure Rate | [0, 0.002) | Low |
| | [0.002, 0.08) | Medium |
| | [0.08, 0.1) | High |
| | [0.1, ∞) | Extreme |
| Average Cost Per Service | [0, 2) | Low |
| | [2, 5) | Medium |
| | [5, ∞) | High |
| Individual Service Response Time | [0, 2.5) | Low |
| | [2.5, 5.2) | Medium |
| | [5.2, ∞) | High |

# Proposed Approach

- A state is represented by a specific combination of the different goal attribute values in different agents
  - *{{low,extreme},{high,high},{low}}* is a state that expresses that MedicalAnalysisService has low response time and extreme failure rate, AlarmService has high response time and failure rate and globally average cost per service is low
- An action is considered as choosing a specific variant
- The action set of a specific agent consists of all of its variants
- The joint action set is the action selection of all the agents
  - {{MedicalAnalysisService1, MedicalAnalysisService2, MedicalAnalysisService3},{AlarmService1, AlarmService2, AlarmService3}}

# Proposed Approach

- Reward functions measure goal conformance
- For minimization and maximization goal, if $G$ is the set of the values of a goal attribute, a reward function is defined as $R : G \rightarrow [0, 1]$
- For threshold goals, it is defined as $R : G \times T \rightarrow [0, 1]$
- The reward function value is restricted between 0 and 1

# Proposed Approach

- Reward functions for TAS –

Global
Failure Rate
Reward

$$r_{glf} = \begin{cases} \dfrac{(2 \times th_{glf} - min(f_r^1, f_r^2, \cdots, f_r^n))}{2 \times th_{glf}} & \text{if } (th_{glf} - min(f_r^1, f_r^2, \cdots, f_r^n)) > 0 \\ \dfrac{1}{2} - \dfrac{min(f_r^1, f_r^2 - 2 \times th_{glf}}{2 \times (1 - th_{glf})} & \text{if } (th_{glf} - min(f_r^1, f_r^2, \cdots, f_r^n)) \leq 0 \end{cases}$$

Local
Response
Time Reward

$$r_t = \begin{cases} \dfrac{2 \times th_t - t^i}{2 \times (th_{glf} - t^i_{max})} & \text{if } th_t - t^i > 0 \\ \dfrac{1}{2} - \dfrac{th_t - t^i + 1}{2 \times (th_t - t^i_{max} + 1)} & \text{if } th_t - t^i < 0 \\ \dfrac{1}{2} & \text{if } th_t - t^i = 0 \end{cases}$$

# Proposed Approach

- Reward functions for TAS –

Local Failure Rate Reward

$$r_f = \begin{cases} \dfrac{2 \times th_f - f^i}{2 \times (th_f - f^i_{max})} & \text{if } th_f - f^i > 0 \\ \dfrac{1}{2} - \dfrac{th_f - f^i + 1}{2 \times (th_f - f^i_{max} + 1)} & \text{if } th_f - f^i < 0 \\ \dfrac{1}{2} & \text{if } th_f - f^i = 0 \end{cases}$$

Average Cost Per Service Reward

$$r_{\overline{c}} = \frac{1}{\frac{1}{n} \sum_{i=1}^{n} \overline{c^i} + 1}$$

Total Reward

$$tot_r = 0.25 \times r_{glf} + 0.25 \times r_t + 0.25 \times r_f + 0.25 \times r_{\overline{c}}$$

Threshold-based reward functions provide [0, 0.5) values for goal violation and [0.5, 1] values for goal conformance

# Proposed Approach

- Weights need to be updated at runtime for providing more importance on reward function values indicating goal violation
- For example, consider four reward functions $r1$, $r2$, $r3$, $r4$
  - For reward values 0.7, 0.8, 0.3, 0.6, the total reward value is 0.6
  - For reward values 0.6, 0.8, 0.5, 0.5, the total reward value is also 0.6
  - The first reward value should be less than the second
- Solution –
  - The weight for 0.3 can be updated to 0.3542 from 0.25
  - The remaining weight 0.6458 can be equally distributed among the other three agents
  - The total reward value becomes 0.558

# Proposed Approach
# Action Selection through Q-Learning

**Algorithm 1** Algorithm for Multiagent Q-learning

$Q_i(s, a) \leftarrow 0, \forall s, a, i$
$decay \leftarrow d_f$
**while** $TerminationCondition \neq true$ **do**
  **for** $i = 1$ to $n$ **do**
    $a_i \leftarrow selectAction()$
    $a^{-i} \leftarrow receiveOtherAgentActions()$
    $a \leftarrow a_i \cup a^{-i}$
    *observe transitioned state* $s'$ *and reward* $r_i$
    **for** $i = 1$ to $n$ **do**
      $Q_i(s, a) \leftarrow Q_i(s, a) + \alpha \times [r_i(s, a) + \gamma \max_{a_i} Q_i(s', a_i) - Q_i(s, a)]$
      $\alpha \leftarrow \alpha - decay \times \alpha$
    **end for**
  **end for**
**end while**

# Proposed Approach
# Action Selection through Q-Learning

- An opponent model chooses the maximum next state strategy based on other agents' strategies [8]

$$Q_i(s, a_i) = \sum_{a^{-i} \in A_c^{-i}} P(s, a^{-i}) \times Q_i(s, a_i, a^{-i})$$

Opponent Model

$$P(s, a^{-i}) = \frac{F(s, a^{-i})}{\sum_{a^{-i'} \in A_c^{-i}} F(s, a^{-i'})}$$

# Proposed Approach
# Action Selection through Q-Learning

- The *ε-greedy* strategy is used for action selection
- This provides a balance between exploration and exploitation in Q-learning [11]
- *ε-greedy* strategy –

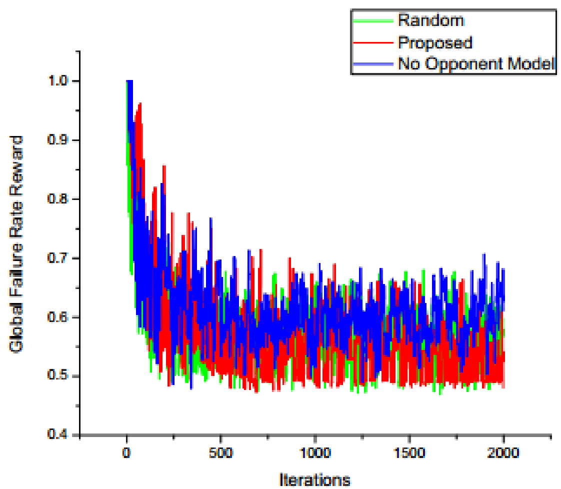
An ε value is prespecified where $0 \leq \varepsilon < 1$ → A value *p* between 0 and 1 is randomly selected → If $p < \varepsilon$, the agent chooses a random action → Otherwise, it selects the action with maximum Q-value in the current state

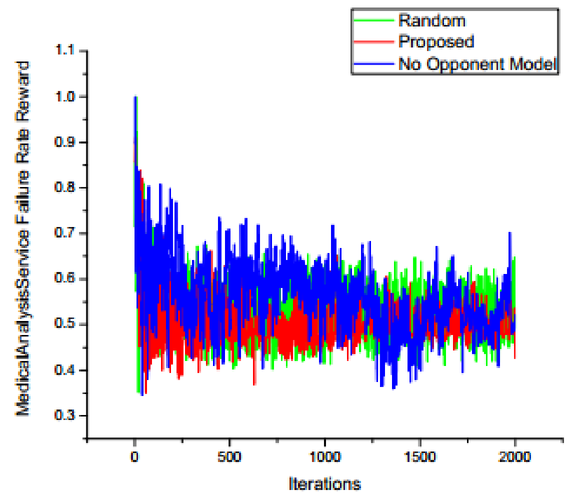
# Experimental Evaluation

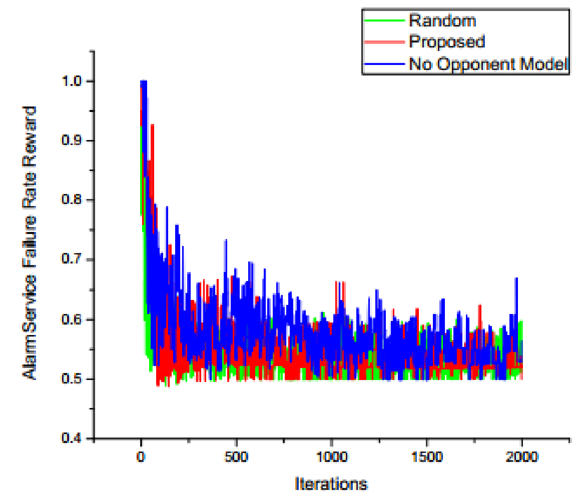
- The Tele Assistance System is used to evaluate the proposed approach
- It is extended to support decentralized adaptation by adding a control loop to each of the services
- The approach is compared to two techniques –
  – The first one chooses actions randomly
  – The second one learns and chooses actions based on maximum Q-values without considering opponent models
- Parameters –
  – $\alpha$, $\gamma$ and $\varepsilon$ were chosen to be 0.1, 0.9 and 0.8 respectively
  – A small number 0.001 was chosen as the decay factor
  – 1.25 was chosen as the value of *fr*

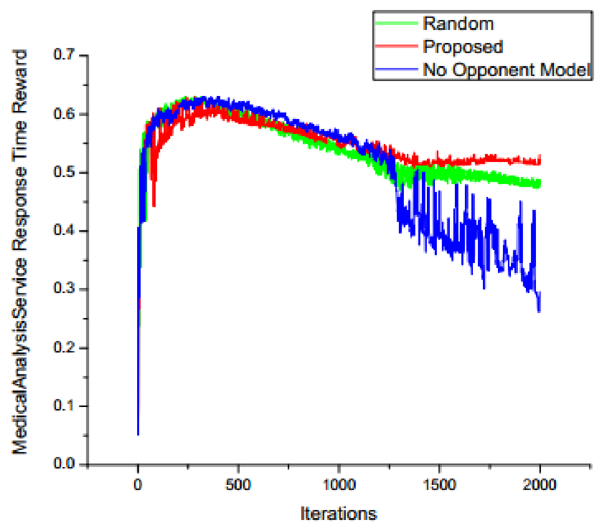
Chosen through empirical experimentation

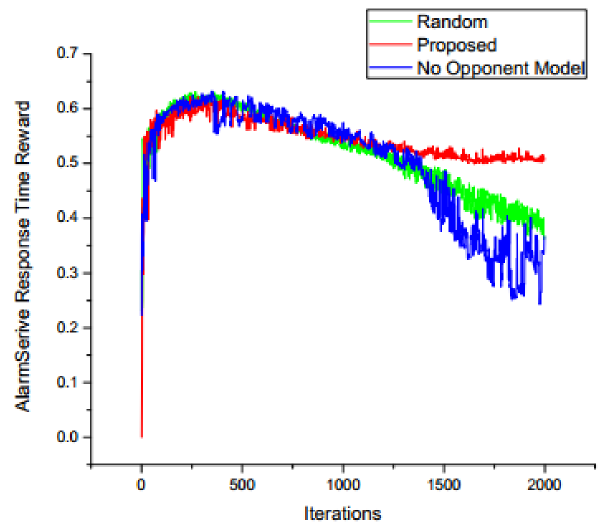
# Results: Comparison of Reward



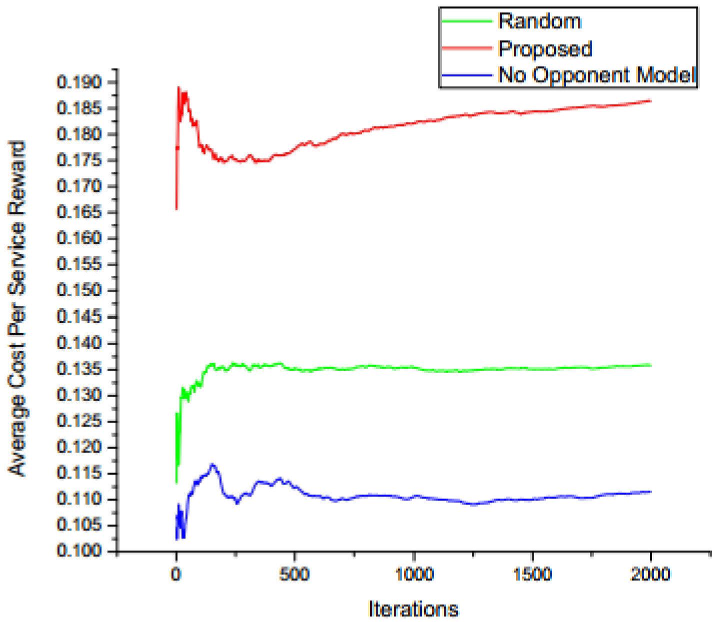



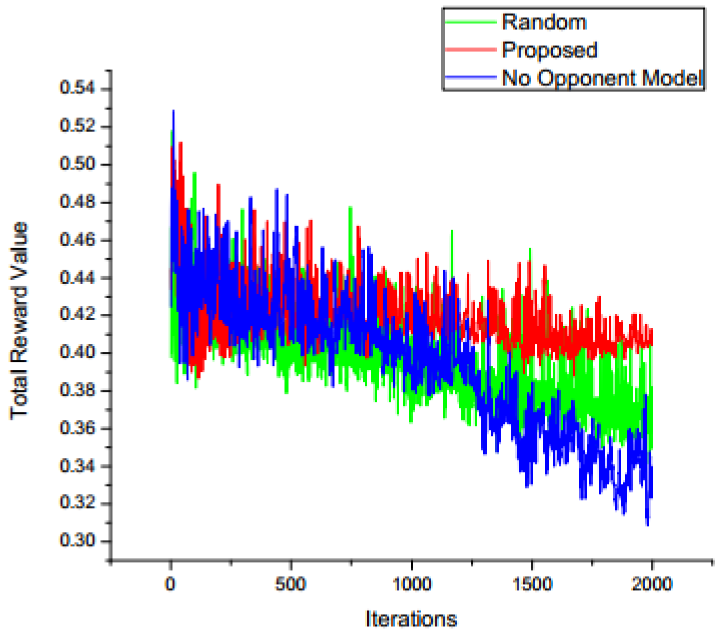



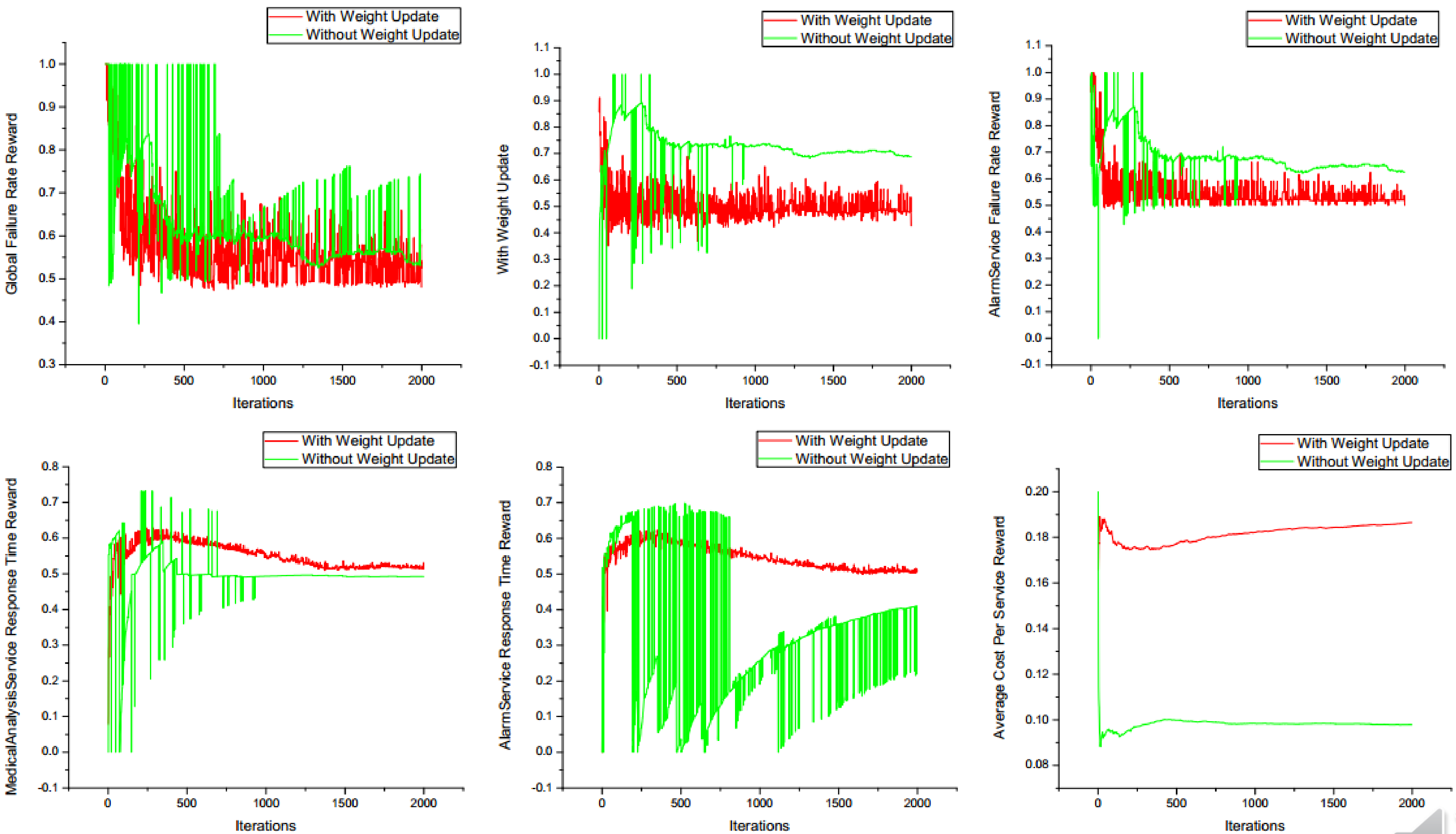



# Results: Comparison of Reward



# Results: Effectiveness of the Dynamic Weight Update Technique



# Discussion

- The reward values are over 0.5 in most cases which indicates adaptation
- Reward values are more stable and total reward values are higher when opponent model is considered
- The weight update mechanism supports adaptation of multiple goals as the reward values remain stable over time
- Q-learning over joint actions become computationally challenging in large scale systems
- A promising direction towards solving this problem can be the use of sparse cooperation Q-learning (future work) [12]

# Conclusion and Future Work

- A decentralized control loop for self-adaptive software has been proposed –
  - Considering other agent strategies
  - A better total reward calculation mechanism
- It was evaluated on a Tele Assistance System where it was observed that –
  - Reward stays over threshold
  - Reward values are stable over time
  - Both indicates successful self-adaptation
- Future Work –
  - Applying to large scale systems
  - Self-tuning the required parameters to achieve the highest reward
  - Tool support

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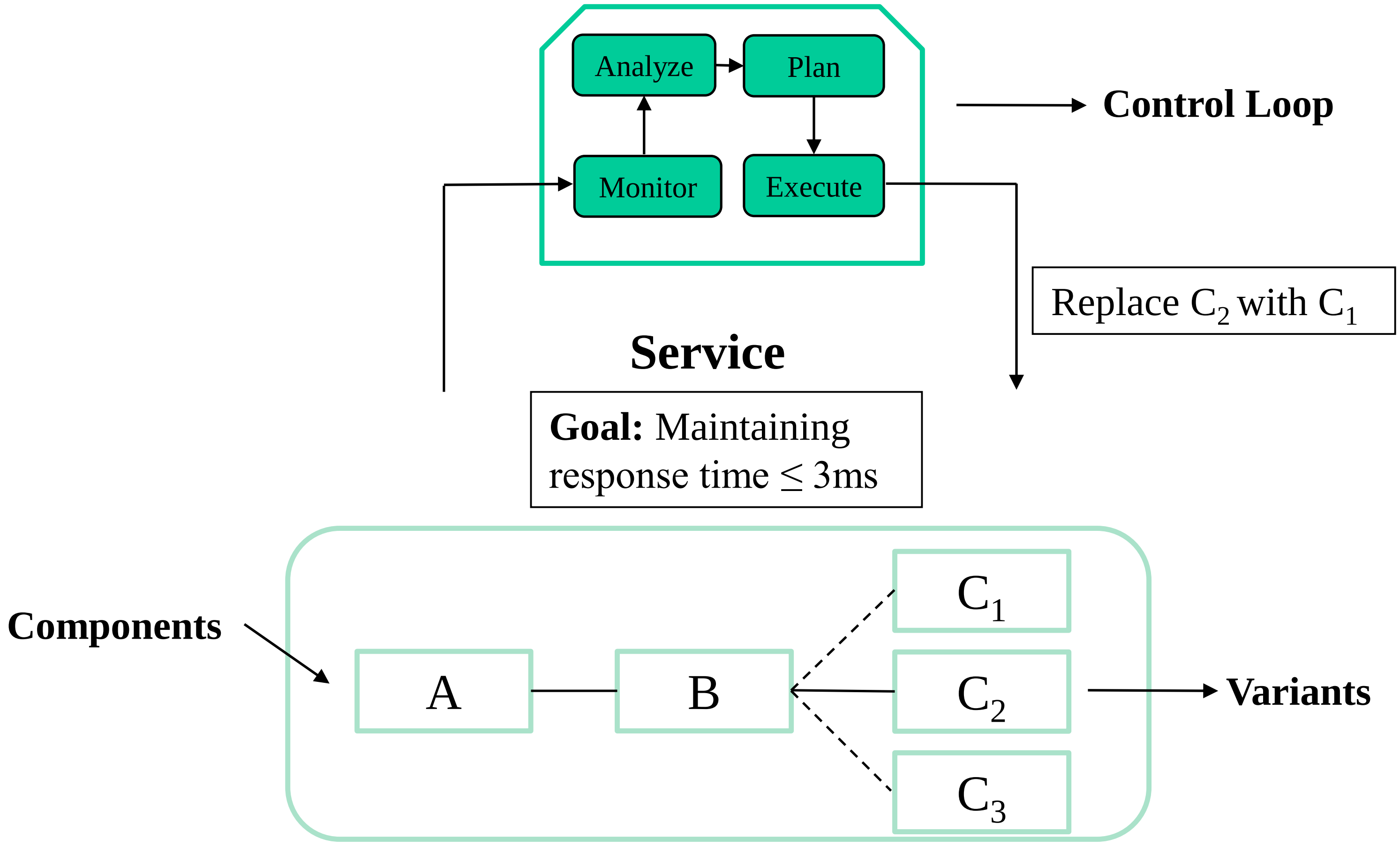
# Thank You

# Background: Action Selection



# Proposed Approach

**Lemma 1.** *Let $n_r, n_a$ be the total number of reward functions and the number of reward functions requiring weight update respectively. Let $r_i, th$ and $fr$ be the $i-th$ reward function value requiring weight update, reward function threshold and the fraction of the initial reward used to update the weight respectively. The weight of the $i-th$ reward function is updated with $\Delta w_i = k \times (th - r_i)$, where $k = \frac{1}{fr \times n_r \times (n_a \times th - \sum_{i=1}^{n_a} r_i))}$.*

- For the previous example –
  - $r_i = 0.3$
  - $th = 0.5$
  - $fr = 2.4$