An Adaptive Strategy for Resource Allocation with Changing Capacities

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Abstract. In this paper, we study a class of resource allocation problems with changing resource capacities. The system consists of competitive agents that have to choose among several resources to complete their tasks. The objective of the resource allocation is that agents can adapt to the dynamic environment autonomously and make good utilisation of resources. We propose an adaptive strategy for agents to use in the resource allocation system with time-varying capacities. This strategy is based on individual agent's experience and prediction. Simulations show that agents using the adaptive strategy as a whole can adapt effectively to the changing capacity levels and result in better resource utilisation than those proposed in previous work. Finally, we also investigate how the parameters affect the performance of the strategy.

Keywords: Experience, Prediction, Attitude, Attractiveness.

1 Introduction

Resource allocation is an important problem that has attracted much research interest. It has been studied extensively and theoretically in a wide range of domains. In a multi-agent resource allocation system, different agents compete for different limited resources to complete their tasks. The objective of resource allocation is to find an allocation that is feasible and optimal, which means that the resources are fully utilised and all agents are able to complete their tasks so that the social welfare of all agents are maximised.

The approach for solving resource allocation problems may be either centralised or distributed. For the centralised approach [1,2], a central controlling authority or resource management decides on the final allocation of resources among agents. The centrilised allocation mechanism can be complex and the problem can be NP-complete [3]. For the distributed approach [4,5,6,7], agents may cooperate or act independently of one another. They can coordinate explicitly or implicitly with one another to achieve a consensus on the allocation of resources. No centralised allocation mechanism is needed in this approach.

Based on these two approaches, a lot of work has tackled the resource allocation problems with constant capacities [2,7,8]. However, in the real world, the capacities of resources may change with time. Galstyan et al. [9] study a class of resource allocations with changing capacities. They model the situation

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as a Minority Game and propose an approach for solving this kind of resource allocation game. Although this approach is distributed and agents can adapt to the dynamic environment autonomously, there are still some inadequacies in their approach. First, agents make decisions based on their neighbors' actions, which is local information. Second, the strategies which are generated randomly at the beginning prescribe agents' actions. The actions cannot change during the game. These may cause that this approach can not be applied to the allocation of resources with different changing capacities.

One objective in decision-making problems is to maximise utility [10]. However, human behaviors may violate this rule as many experiments show [11]. The reason behind is that people have attitudes towards risk according to Prospect Theory [11]. Moreover, attitudes can be changed by favorable or unfavorable experiences according to the theory of Conditions of Learning in psychology [12]. Based on these two theories, we design an adaptive strategy for agents to use in the resource allocation system. Using this strategy, each agent has an attitude towards a choice and makes decisions based on its experience and prediction. Simulations show that this strategy has better performance than those proposed in previous work in terms of resource utilisation.

The remainder of the paper is organised as follows. In Section 2, we give an overview of the related work in the resource allocation problem. In Section 3, we present the adaptive strategy. In Section 4, we implement various simulations and compare our result with some related work for performance evaluation. We also discuss how the parameters affect the strategy's performance. In the last section, we conclude the paper and present some possible future work.

2 Related Work

In recent years, there have been a lot of work on resource allocation techniques. The two main approaches are centralised [1,2,3] and distributed [4,5,6,7]. In this section, we introduce some related work on a class of resource allocation that can be formulated as a game in an idealistic environment.

Arthur [13] introduces the El Farol Bar problem, which is a widely studied example of complex adaptive systems. In this problem, each agent makes an independent decision every week on whether to attend the bar. If the number of agents that attend the bar does not exceed the bar's capacity, the agents that attend the bar will feel enjoyable. Later, Challet and Zhang [14] introduce Minority Game as a simplified formal version of the El Farol Bar problem. In this game, an odd number of agents have to choose between two sides in order to be on the minority side. Each agent uses a number of predictors to make the decision and keeps track of the predictors. Due to lack of space, we refer readers to [15] for further details.

Another approach for tackling the resource allocation problem is proposed by Galstyan et al. [9] who study the resource allocation games with time dependent capacities. They propose that agents use a set of strategies to decide which resource to choose and use a simple reinforcement learning scheme to update the accuracy of strategies. A strategy is a lookup table based on the actions of agents' neighbors at the previous time step and suggests agents to choose which resource at this time step. At each time step, each agent chooses the strategy with the highest score to make the decision. At the end of each time step, each agent assesses the performance of its strategies, adding (subtracting) a point if the strategy has predicted the winning (losing) choice. The winning (losing) choice is that the resource the agent chooses is not overloaded (overloaded). Their results indicate that for a certain number of neighbors, the system of agents can adapt effectively to some changing capacity levels.

Lam and Leung [8] propose an adaptive strategy for resource allocation modeled as minority game. The strategy is based on the history information h and the net payoff u_x for choosing a resource x. The history information h is the ratio of the number of times that a resource x is not overloaded over the size of the history H. Each agent has an initial attitude a_x towards a choice. At each time step, each agent calculates the attractiveness $((1 - a_x) \times h + a_x \times u_x)$ of each resource to make the decision and chooses the resource with the largest attractiveness. At the end of each time step, each agent updates its attitudes as follows. If the agent chose to use a resource x and the resource was not overloaded, then a_x is increased by a_+; if the agent chose to use a resource x and the resource was overloaded, then a_x is decreased by a_-. Simulations show that agents using the adaptive strategy are able to make good utilisation of resources with constant capacities.

3 An Adaptive Strategy

3.1 Problem Specification

We consider the following resource allocation problem. There are Q available resources, each having different capacities $C = \{C_1, ..., C_Q\}$ and a set $A = \{A_1, ..., A_N\}$ of N agents. The capacity of one resource is referred to the total units of the resource. Each agent has one task to execute at each time step. All agents compete for the resources to execute their tasks. Each task only needs one unit of resources and occupies one time step to complete. The resources can be shared by multiple agents. The capacities of the provided resources can be constant, but they generally vary over time. The total amount of capacities is equal to or greater than the number of agents at any time, which means that there are always sufficient resources. At the end of each time step, each agent completes its task if it chooses a not overloaded resource. If the number of agents choosing the resource is less than or equal to the capacity of the resource, then the resource is not overloaded. Otherwise, the resource is overloaded. In this case, not all agents choosing the resource can complete their tasks. We are only interested in the case of sufficient resources in this paper because this case can make it possible that all agents are able to complete their tasks.

In the system, there is no central information or no communication among agents. The only information available to all agents for making a resource choice decision are the history information from the past resource allocation records and the capacities of the resources during the previous time steps. A past resource allocation record is a record of whether a resource is under-utilised or over-utilised at the previous time step. A correct decision means that an agent chooses a not overloaded resource. The system can be considered as a multi-choice game, i.e. each of N agents decides to choose one of the Q resources at each time step. It is a new start of the game after each time step since the system completes a resource allocation for each time step.

The objective of the resource allocation problem is to make good utilisation of resources in the dynamic environment. Dynamics means that capacities of resources vary over time. Good utilisation of resources means that the resources are little under-utilised or over-utilised. Agents in the system need to be able to coordinate themselves well, so that they can adapt effectively to the dynamic environment.

3.2 An Adaptive Strategy

Based on the work by Lam and Leung [8], we propose an adaptive strategy for agents to use in the resource allocation problem with changing capacities. Using this strategy, each agent keeps an experience for each resource. It records the number of correct decisions it has made for each resource statistically. If an agent makes decisions only based on its experience, it will choose the resource which is not overloaded most of time in the past. The *experience* e_r^t for resource r at time step t is defined as follows:

$$e_r^t = \frac{n_r^t}{t} \tag{1}$$

where n_r^t is the number that the agent chooses resource r and resource r is not overloaded till time step t. For example, at time step t, the system has proceeded for 10 time steps, and the number of the agent choosing a not overloaded resource r is 6, then the value of experience for resource r is $e_r^t = \frac{6}{10}$.

Each agent also keeps a prediction for each resource. The prediction for a resource is the ratio of the current predicted capacity of the resource over the total amount of capacities of all resources. If an agent makes decisions only based on its prediction, it will choose the resource with the largest predicted capacity. The *prediction* p_r^t for resource r at time step t is defined as follows:

$$p_r^t = \begin{cases} \frac{C_r^t}{\sum_{i=1}^{Q} C_i^t} & t = 1 \text{ or } t = 2 \\ \frac{[C_r^{t-1} + (C_r^{t-1} - C_r^{t-2})] \times f}{\sum_{i=1}^{Q} C_i^{t-1}} & t > 2 \end{cases} \tag{2}$$

where C_r^t is the capacities of resource r at time step t, C_i^t denotes the capacity of resource i at time step t, and f is a scaling factor. At time step $t = 1$ and $t = 2$, we assume that the current predicted capacity of each resource is equal to its current capacity. At time step $t > 2$, the current predicted capacity is approximated by a linear function of the previous resource capacities.

Inspired by Prospect Theory [11], we associate to each agent an attitude towards a choice. Actually, some agents may rely more on the experience and some may rely more on the prediction. To model this phenomenon, we introduce an attitude $a_r \in [0, 1]$ as a weight to calculate the weighted value of the experience e_r^t and the prediction p_r^t. If an agent's attitude is close to 0, the agent is more experience-relying and it tends to choose the resource which is not overloaded most of the time. If an agent's attitude is close to 1, the agent is more prediction-relying and it biases the selection towards the resource with the largest capacity. The weighted value is called the attractiveness of the resource. The resource with the largest value of attractiveness is the most attractive to agents. So at each time step, each agent chooses the resource with the highest value of attractiveness. Formally, an agent calculates the *attractiveness* $attr_r^t$ of resource r at time step t as follows:

$$attr_r^t = (1 - a_r^t) \times e_r^t + a_r^t \times p_r^t \tag{3}$$

where a_r^t is the attitude for resource r at time step t.

By the theory of Conditions of Learning in psychology [12], attitudes will be changed by favorable or unfavorable experiences. So agents using the proposed adaptive strategy adjust their attitude a_r^t adaptively. At the end of each time step, each agent updates its attitudes: if the agent has chosen the resource and the resource is not overloaded, then the attitude for the resource a_r^t is increased by a_Δ. If the agent has chosen the resource and the resource is overloaded, then a_r^t is decreased by a_Δ. a_Δ is an adjusting rate. The adjusting rate is important to agents' adaptation. Without it, agents cannot adapt to the environments.

Galstyan et al. [9] introduce the deviation of resource utilisation from the optimal resource utilisation as a measure of efficiency. The cumulative deviation for the number of agents choosing the resource A_i^t from the capacity of the resource C_i^t over a certain time is defined as follows:

$$\sigma_i^2 = \frac{1}{T} \sum_{t=t_0}^{t_0+T} (A_i^t - C_i^t)^2 \tag{4}$$

The average deviation over Q resources is as follows:

$$\sigma_{tot}^2 = \frac{1}{Q} \sum_{i=1}^{Q} \sigma_i^2 \tag{5}$$

We use the average deviation as a quantitative measure criterion for resource utilisation in the following experiments.

In the situation that the capacities of some resources may be very large and some may be very small, the prediction of the small capacity may weigh very little when compared with the value of the experience in the calculation of attractiveness. So we introduce the scaling factor f to reinforce the value of the prediction. In the following experiments, we can see that the appropriate scaling factor can help to achieve lower average deviation of resource utilisation.

4 Experimental Evaluation

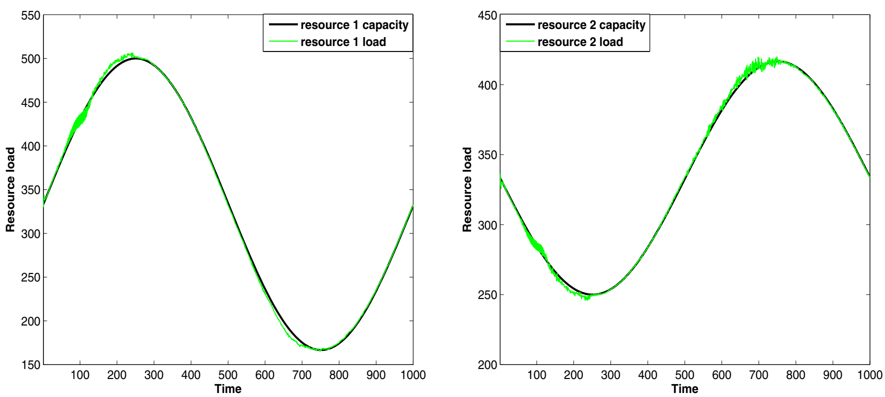
4.1 Simulations

In this section, we investigate the overall performance of the system in dynamic environments where agents use the proposed adaptive strategy described in Section 3. We investigate the performance of the adaptive strategy not only in the same experiment setting as [9], but also in other experiment settings. We define the number of agents choosing the resource as the resource load. The good overall performance is that the resource load follows the resource capacity well, which results in little under-utilisation or over-utilisation of resources.

First, we examine the resource allocation problem using the proposed adaptive strategy in the same experiment setting (Experiment Setting 1) as [9]. The number of agents is $N = 1000$ and the number of resources is $Q = 3$. The total amount of capacities of the three resources is $C = 1000$. The capacity of the first resource varies over time: $C_1^t = (\frac{1}{3} + \frac{1}{6}\sin\frac{2\pi t}{T}) \times C$; the capacity of the second resource varies over time: $C_2^t = (\frac{1}{3} - \frac{1}{12}\sin\frac{2\pi t}{T}) \times C$, where the periodicity is $T = 1000$. The capacity of the third resource is $C_3^t = C - C_1^t - C_2^t$.

We plot the time series of resource load for only two resources since the third one is fully determined by the first two. To account for agents' heterogeneity, the attitudes a_r for each agent are generated randomly. The adjusting parameters for all agents are $a_\Delta = 0.01$. The scaling factor is $f = 4$. For each simulation, we take 100 independent trials and average the results. The simulation results are shown in Fig. 1. It can be seen that the resource load follows the resource capacity very well, which means that the number of agents choosing a particular resource is always close to the capacity of the resource. This results in very little under-utilisation or over-utilisation of resources.

Next we investigate the performance of the adaptive strategy in other experiment settings with different changing functions. The slopes of changing functions in [9] are changing all the time, while the slopes of changing functions below are



(a) Resource 1 (b) Resource 2

Fig. 1. Resource load using the adaptive strategy under Experiment Setting 1

not always changing, but keep constant for some time and then change to other slopes for another time. The capacities of the first and second resources vary as follows (Experiment Setting 2):

$$C_1^t = \begin{cases} 100 + 0.5 \times t & 1 \leq t \leq 200 \\ 200 + (t - 200) & 200 < t \leq 400 \\ 400 + 2 \times (t - 400) & 400 < t \leq 600 \end{cases}$$

$$C_2^t = \begin{cases} 800 - 2 \times t & 1 \leq t \leq 200 \\ 400 + (t - 200) & 200 < t \leq 400 \\ 200 - 0.5 \times (t - 400) & 400 < t \leq 600 \end{cases}$$

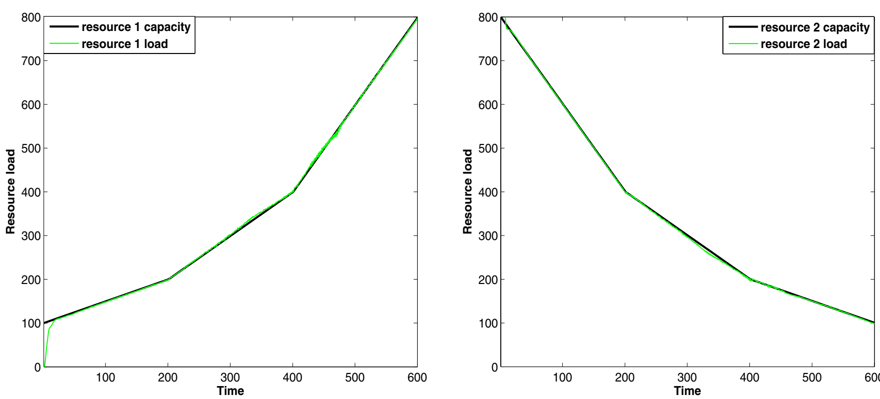
Another experiment setting is more complicated. The changing functions have both changing slope and constant slope. The purpose is to investigate how agents using the adaptive strategy perform in different situations. The capacities of the first and second resources vary as follows (Experiment Setting 3):

$$C_1^t = \begin{cases} (\frac{2}{5} + \frac{1}{12} \sin \frac{2\pi t}{T}) \times C & 1 \leq t \leq 500 \\ 400 & 500 < t \leq 700 \\ 400 + (t - 700) & 700 < t \leq 950 \\ 650 + (t - 950) & 950 < t \leq 1200 \end{cases}$$

$$C_2^t = \begin{cases} (\frac{2}{5} - \frac{1}{12} \sin \frac{2\pi t}{T}) \times C & 1 \leq t \leq 500 \\ 400 & 500 < t \leq 700 \\ 400 - (t - 700) & 700 < t \leq 950 \\ 150 + (t - 950) & 950 < t \leq 1200 \end{cases}$$

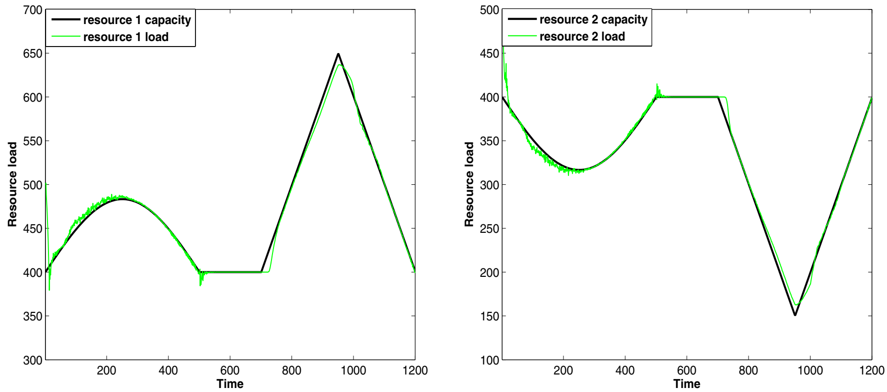
where the periodicity is $T = 1000$.

We implement the simulations using the adaptive strategy for these two situations. The adjusting parameters for all agents in Experiment Setting 2 are



(a) Resource 1 (b) Resource 2

Fig. 2. Resource load using the adaptive strategy under Experiment Setting 2



(a) Resource 1 (b) Resource 2

Fig. 3. Resource load using the adaptive strategy under Experiment Setting 3

$a_\Delta = 0.02$. The scaling factor is $f = 6$. In Experiment Setting 3, $a_\Delta = 0.02$ and $f = 4$. The attitudes for each agent are also generated randomly. The results are shown in Fig. 2 and Fig. 3 respectively. We can see that agents also follow the changes in the capacity levels very effectively.

To measure the performance of the system quantitatively, we use Equation (5) to calculate the average deviation of resource utilisation for each of the three experiments. The results are shown in Strategy 1 column of Table 1. These numbers are very small which indicate that the system is very close to the optimal allocation. The results suggest that the adaptive strategy enables agents to make good use of the resources in systems with time-varying capacities adaptively.

Table 1. Average deviation

Experiment	Strategy 1	Strategy 2	Strategy 3
1	372.2851	14233.49	18220.76
2	431.4749	12030.83	17823.87
3	267.4422	13990.60	32395.81

4.2 Comparisons with Related Work

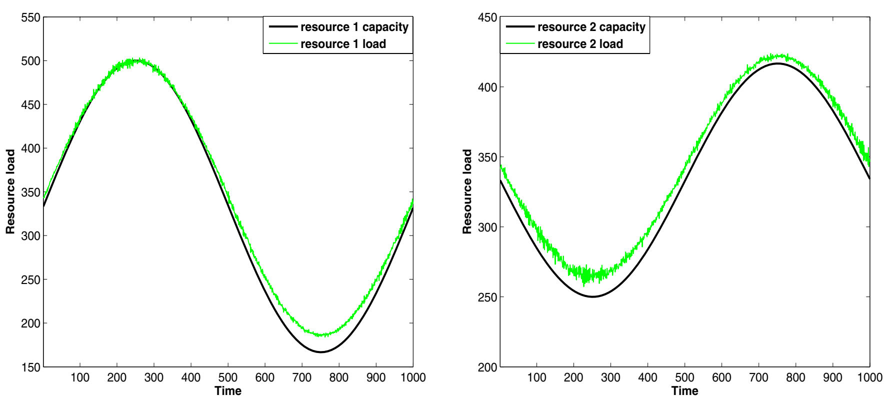
In this section, we conduct the simulations in the above three experiment settings using other strategies. First, we implement the simulations using Lam and Leung's strategy. The strategy of Galstyan et al. is another approach. We use their strategy to do the simulations. Also, we compare the simulation results with the results using the proposed adaptive strategy. We want to investigate that whether the system using the proposed adaptive strategy can make better utilisation of resources than other strategies.

Comparision with Lam and Leung's strategy. Using Lam and Leung's strategy [8] described in Section 2, agents' initial attitudes towards each resource are generated randomly. The adjusting parameters for all agents are $a_+ = a_- = 0.02$. The size of the history is $H = 5$. Lam and Leung [8] consider the payoff of choosing a not overloaded resource as the preference over the resource. They generate the preferences for each agent randomly in their simulations. The preferences are fixed once they are generated.

We plot the time series of resource load using Lam and Leung's strategy with preference. The results are shown from Fig. 4 and Fig. 6. It can be seen that the resource load also does not follow the resource capacity very well. The average deviations of resource utilisation are shown in Strategy 2 column of Table 1. Also, we can see that the average deviations using Lam and Leung's strategy with preference are much larger than those using the proposed adaptive strategy. This may be because the preferences are fixed once they are generated rather than change with time. As the capacities are varying over time, the preferences do not contain any information about capacities. This may lead to that the collective behavior of agents cannot adapt to the dynamic environments very effectively. So Lam and Leung's strategy [8] may work very well in static environments, but not very well in dynamic environments.

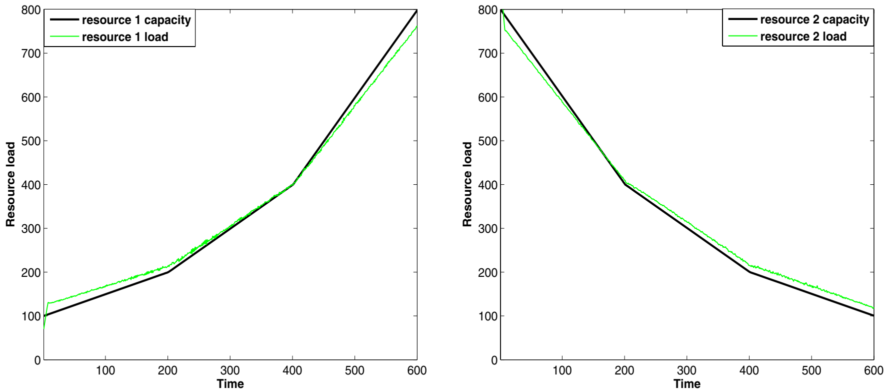
Comparison with the strategy of Galstyan et al. In the simulations using the strategy of Galstyan et al. [9], each agent randomly chooses two neighbors ($K = 2$) and also randomly generates two strategies ($S = 2$), which means the actions that suggest agents which resource to choose at the next time step are also generated randomly. Each agent's neighbors are fixed throughout the game, but neighbors' actions are updated at the end of each time step.

The simulation results are shown from Fig. 7 and Fig. 9. It can be seen that agents using Galstyan et al.'s strategy do not adapt effectively to the dynamic environments. The average deviations shown in Strategy 3 column of Table 1 are also much larger than those using the proposed adaptive strategy. The reason



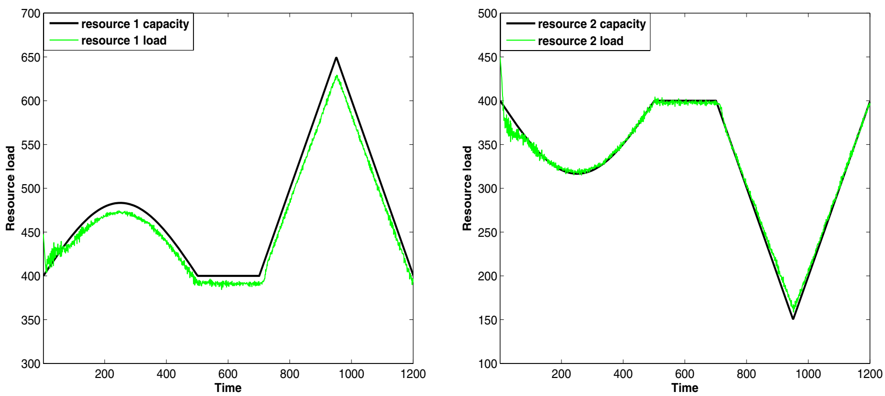
(a) Resource 1 (b) Resource 2

Fig. 4. Resource load using Lam and Leung's strategy under Experiment Setting 1



(a) Resource 1 (b) Resource 2

Fig. 5. Resource load using Lam and Leung's strategy under Experiment Setting 2



(a) Resource 1 (b) Resource 2

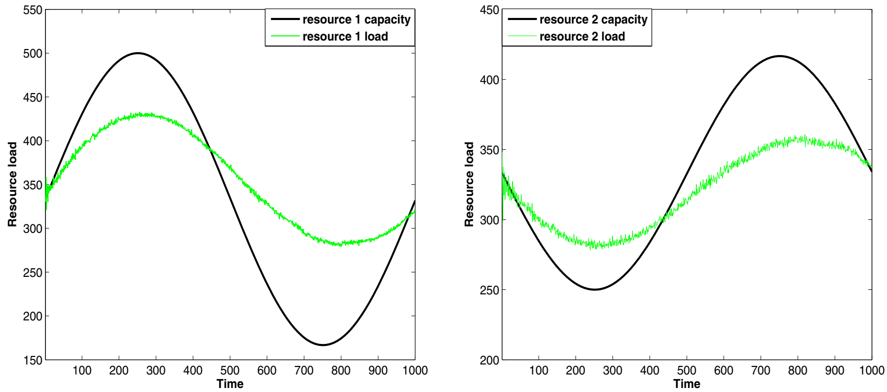
Fig. 6. Resource load using Lam and Leung's strategy under Experiment Setting 3

behind may be that the strategies do not change once they are generated. Agents are limited to choose the resources appearing in the strategies. Another possible reason is that the strategies are randomly generated at the beginning, which is not sensible.

From the comparisons, we can conclude that the proposed adaptive strategy performs better than Lam and Leung's strategy [8] and the strategy of Galstyan et al. [9] in terms of resource utilisation.

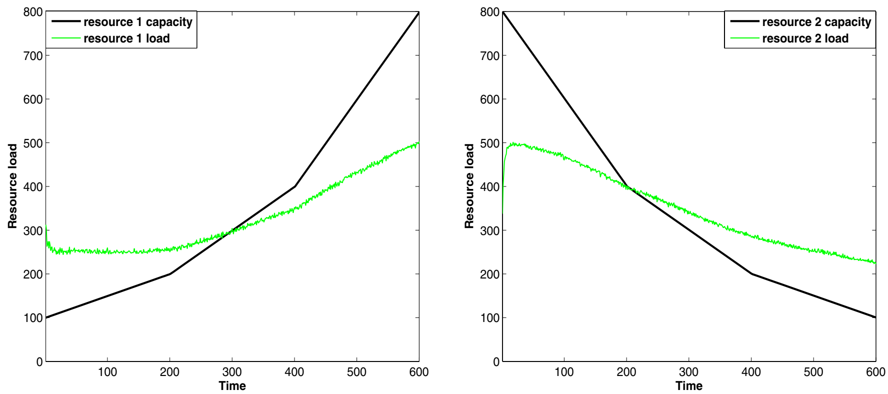
4.3 Discussions

In this paper, we present an adaptive strategy for agents to use in the resource allocation system. Our approach is applicable to multi-agent systems where agents have a choice among several resources with time-varying capacities. However, one issue of this approach is that the strategy is parameterised by the adjusting rate



(a) Resource 1 (b) Resource 2

Fig. 7. Resource load using the strategy of Galstyan et al. under Experiment Setting 1

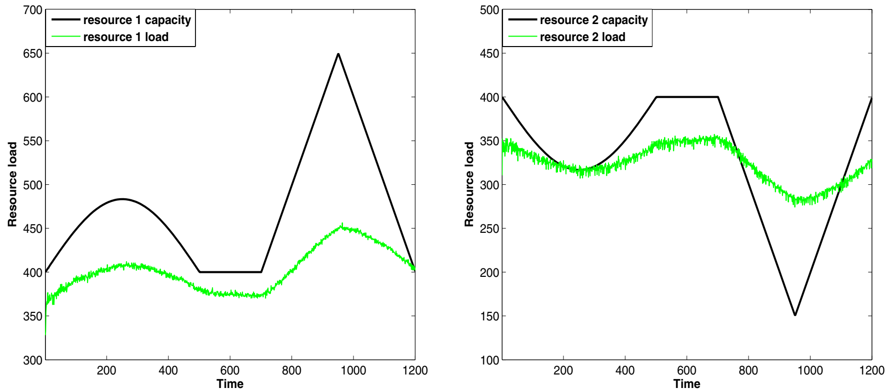


(a) Resource 1 (b) Resource 2

Fig. 8. Resource load using the strategy of Galstyan et al. under Experiment Setting 2

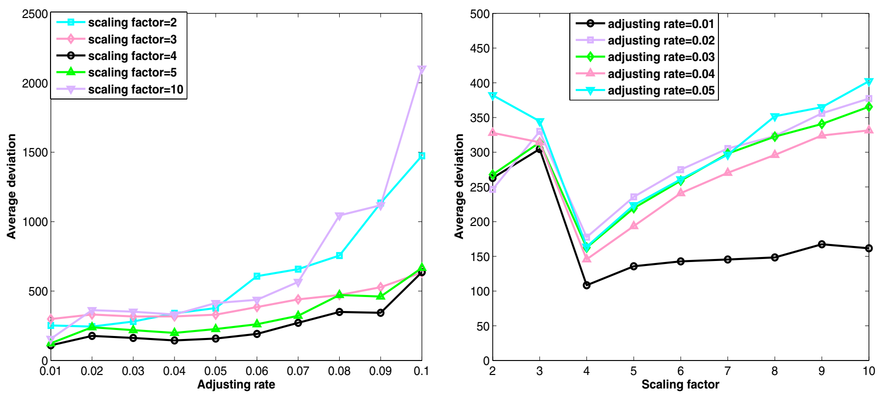
and the scaling factor in calculating the attractiveness of the resource. In this section, we focus on investigating how the adjusting rate and the scaling factor affect the performance of the strategy.

In Experiment Setting 1 using the adaptive strategy, we plot the average deviation of resource utilisation versus the adjusting rate with different scaling factors in Fig. 10(a). The adjusting rate ranges from 0.01 to 0.1. The scaling factor ranges among 2, 3, 4, 5 and 10. From this figure, we can see that when the scaling factor is fixed, larger adjusting rate results in larger average deviation. The minimal average deviation occurs at the point with the adjusting rate equal to 0.01. In Fig. 10(b), we plot the average deviation of resource utilisation versus the scaling factor with different adjusting rates. The scaling factor ranges from 2 to 10. The adjusting rate ranges from 0.01 to 0.05. From this figure, we can see that when the adjusting rate is fixed, the point with the scaling factor equal to 4 is a transition point. The system reaches the minimal average deviation at



(a) Resource 1 (b) Resource 2

Fig. 9. Resource load using the strategy of Galstyan et al. under Experiment Setting 3



(a) (b)

Fig. 10. Average deviation

this point. From these two figures, we can see that the appropriate parameters for Experiment Setting 1 are the adjusting rate equal to 0.01 and scaling factor equal to 4. Other parameters result in larger average deviations.

It is important to set the appropriate parameters. If the adjusting rate is too large, agents may over-adapt to the dynamic environments. On the other hand, if the adjusting rate is too small, agents may not adapt fast enough to the dynamic environments. For the scaling factor, if it is too large, it may cause the value of the prediction to dominate the value of the experience in the calculation of the attractiveness; if the scaling factor is too small, it may have little effect on the value of the prediction.

We study the system experimentally in different situations with a wide range of parameters. The parameters for the experiments in Section 4.1 have been tuned and lead to the minimal average deviations of resource utilisation. However, the relationship between the appropriate parameters and the changing capacities still needs further investigation. Still another interesting question is how we may characterise the system, such as the changing law of the capacities.

5 Conclusions and Future Work

In this paper, we propose an adaptive strategy for agents to use in the resource allocation system with time-varying resource capacities. We investigate the performance of the system using the strategy in different dynamic environments. The simulation results demonstrate that agents using the proposed adaptive strategy as a whole can adapt very effectively to the changing capacity levels and result in very little under-utilisation or over-utilisation of resources.

We also compare our strategy with other strategies. The results show that agents using the proposed adaptive strategy are able to make better utilisation, i.e. the average deviations of resource utilisation from the optimal allocation are smaller than those of related work. However, the strategy is parameterised by the adjusting rate and the scaling factor. How to determine the values of these parameters is of interest and we are going to investigate it further. On the other hand, we are also going to investigate the characterisation of the time-varying resource capacities.

In this paper, we have assumptions that each task only needs one unit of resources to complete in one time step. In real resource allocation systems, the situation may be more complicated. Each agent may have multi-task and each task may need more than one unit of resources to complete in more than one time step. The resources may not be available if some tasks already occupy them. So another aspect of future work is to extend the adaptive strategy in more complicated environments, such as resource allocation problems in load balance [6][16].

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