STAIRS 2012
K. Kersting and M. Toussaint (Eds.)

doi:10.3233/978-1-61499-096-3-125

Adaptive Negotiation for Resource Intensive Tasks in Grids

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Abstract. Automated negotiation is especially important when tasks, which require many resources, enter a Grid where resources are scarce. The level of *resource scarcity* dynamically changes in a Grid and the client's negotiation strategy has to adapt to this *dynamism*. In addition, we consider the *non-transparency* of a Grid with respect to a client. That is, a client is only able to observe proposals sent to it by the Grid resource allocator (GRA) but it does not have direct knowledge about availability of Grid resources. In our work, the client's strategy is to estimate the dynamism in a Grid by inferring the criteria influencing the GRA's proposals, and to adapt to this dynamism using fuzzy control rules. These rules define whether the client has to make smaller or larger concessions towards the GRA considering Grid dynamism. The simulation results show that a client who applies our *adaptive negotiation strategy* can obtain higher utility and significantly reduce the number of failed negotiations comparing to a client who applies the non-adaptive negotiation strategy.

Keywords. Grid dynamism, resource scarcity, non-transparent Grid, negotiation, adaptive strategy

1. Introduction

Increasingly large amounts of computing resources are required to execute large-scale resource demanding tasks. For example, Ghanem et al. [1] state that current air pollution sensors can produce data every two seconds, with approximately 8GB of data per sensor per day. However, in reality, it is not possible to process an unbounded amount of data because the resources are bounded in terms of their capacity and operating time. A Grid environment can be suitable for the effective processing of such data streams, as it may possess more processing power than a single supercomputer, cluster or workstation. Moreover, the sources of such data streams can be geographically distributed and a Grid allows processing them in a distributed way [2]. Although recent work [2, 3] shows good performance, it does not fully take into account preferences and requirements of a client and resource provider when they allocate resources to execute these tasks, applying matching algorithms that adjust to client requirements and the amount of available

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resources, which can lead to delays and inaccuracy of processing these tasks in the case of high dynamism and resource scarcity in the Grid. Here, automated negotiation can facilitate better matching of preferences and requirements between clients and resource providers.

In our scenario, we consider a *bilateral* negotiation in the *non-commercial* Grid where a Grid resource allocator (GRA) negotiates with a client over resources to perform the client's tasks. The GRA is assumed to have full knowledge of resources in the Grid, but incomplete knowledge of clients (e.g. their utility functions). It acts on behalf of all resource providers in negotiation with clients where the resource providers are organisations or private users. The GRA and client are considered to be *autonomous agents* [4, 5] which act on behalf of human users. We assume that the clients are *self-oriented*, i.e. they aim to obtain *optimal* resources for their own tasks, but they do not care about other clients' tasks. Considering the situation when resources are scarce and highly dynamic, we assume that the GRA aims to provide resources to those clients who need them the most. We believe that the clients who are more conceding with respect to the GRA need resources the most. These clients can obtain resources faster and avoid the situation when resources are *exhausted*. In a highly dynamic and large-scale Grid, information about resource availability and demand may not be available for the clients (or it may be too uncertain). Therefore, we assume that the clients are not aware of resource dynamism in the Grid, i.e. the Grid is considered to be *non-transparent* in respect to the clients. Moreover, the GRA does not intend to disclose its negotiation parameters (e.g. reservation value, the deadline of negotiation) because it aims to persuade clients to be more conceding in the case of resource scarcity.

A central argument of this paper, and one that informs our negotiation strategy, is that changes in the opponent's preferences (negotiation parameters) have to be not only learned (observed), but the reasons for those changes have to be taken into consideration by a client. The contribution of our paper is a client's negotiation strategy for a single negotiation which adapts to the Grid dynamism considering

- the Grid resources can be exhausted during negotiation;
- the Grid resources are scarce and highly dynamic;
- the client does not have certain knowledge about Grid dynamism;
- the client is not aware of the GRA's negotiation parameters.

This paper is organised as follows. The related work is discussed in Section 2, the formal model is described in Section 3, our adaptive negotiation strategy is presented in Section 4, the experimental results are discussed in Section 5, and the conclusions and future work are summarised in Section 6.

2. Related Work

Much research has been conducted in the field of automated negotiation in the Grid and related fields (e.g. e-commerce). Some is mostly focused on mechanisms of resource allocation (scheduling or load balancing) [6–8], while our primary interest lies in the negotiation strategies that can be applied by a client (buyer) to benefit from negotiation [9–17]. Many authors state that *the dynamism of environment* in the Grid, e-marketplace, etc. has to be taken into account by a negotiator to find the better outcome. Much work

[9, 13, 18–24] proposes negotiation strategies that adapt to the environment's dynamism, opponent's behaviour, etc. with incomplete (uncertain) information.

Narayanan and Jennings [13] assume that agents (buyer/seller) are not aware of their opponent's negotiation parameters (i.e. deadline of negotiation and reservation value), but they also assume that they have *probabilistic knowledge* about the transition of environment from one state to another. This probability varies over time because of the environment's dynamism. In the extended work of Narayanan and Jennings [22], the agent does not have a probabilistic knowledge about the environment's dynamism, but it has a specific number of hypotheses about the distribution of probabilities of the possible changes in the opponent's strategy which are updated during negotiation. Although their learning algorithm allows the agent to calculate the optimal payoff in a reasonable time with incomplete knowledge about the opponent, it depends on the *successful negotiations* which number could be insufficient if resources can be exhausted during negotiation (i.e. negotiation fails).

Sim et al. [16] propose the learning algorithm which allows an agent to estimate opponent's reservation value (price). Authors also describe a mechanism of estimation of the opponent's negotiation deadline considering opponent's proposals and the estimated reservation price. This work has been improved by Gwak and Sim [11] in respect to the learning algorithm. However, both these papers do not focus on the issue of high dynamism of the opponent's reservation value and its impact on the agent's estimations. They also do not take into account that resources can be exhausted during negotiation.

Hindriks et al. [18, 19] consider the situation when the opponent's preferences are not available for an agent. The authors propose an algorithm which enables the agent to learn the *opponent's preferences* in terms of the values of negotiated issues and the importance of each issue. Although this work proposes the comprehensive framework for modelling the opponent's preferences for multiple issues during a single negotiation, it does not explicitly focus on connection between the dynamism of environment and the opponent's behaviour. However, this connection can be relevant in the specific situation, e.g. the *greedy (selfish)* behaviour of the GRA can be caused by the level of resource scarcity, but not its own intentions to be "greedy" in respect of the clients.

Sim [14, 15] describes the *Market-Driven Agent (MDA)* which considers multiple *trading partners*, multiple *competitors* and *time constraints*. Ren et al. [23] extend the MDA to enable it working in the open and dynamic environments with the *uncertain outside options*. The outside options denote the possible trading partners which enter or may enter the e-market. Ren et al. assume that at most n trading partners (and m competitors) may join or leave the e-market in the next round of negotiation. However, the number of resources or clients which may join or leave the Grid is not usually bounded or predictable. Therefore, these estimations may not be applicable for the Grid.

An et al. [9] propose the heuristic-based negotiation strategies for one-to-many negotiation with an effective *commitment/decommitment* mechanism. In general, this mechanism implies that the agents are able to make *tentative* agreements with their opponents as well as to break these agreements with a penalty fee if the more profitable agreement was made. Although An et al. assume incomplete knowledge, the number of trading partners and competitors, and the distribution of the reservation value (price) of the trading partners are known to the agent. In this paper, we aim to solve the problem of resource scarcity and non-transparency of the Grid in the case of high resource dynamism estimating the criteria which affect the GRA's behaviour.

3. Formal Model

3.1. Tasks and Utility Function

In our model, a client aims to perform N tasks in the Grid. A task is the specification of an executable (piece of software)[2] that describes how this executable must be run in the Grid. That is, each task $Task_i$ comprises the name of the executable $Name_i$, the minimum resource R_i^{min} and the optimal resource R_i^{opt} required to run this executable. The client requires only one type of Grid resources for each executable, e.g. CPU time. That is, the task is described as:

$$Task_i = \left(Name_i, R_i^{min}, R_i^{opt}\right), \;\; R_i^{min}, R_i^{opt} \in \mathbb{R}, \tag{1}$$

We assume that the acceptable resource range $\left[R_i^{min}, R_i^{opt}\right]$ can be different for different executables but the deadline of negotiation t_{dl}^{Cl} for these executables is the same for all, but is not submitted to the GRA. In this way, the client tries to avoid the situation when the GRA might persuade the client to concede because the client's deadline is approaching. All tasks are embedded in one job $Job = \{Task_1, ..., Task_i, ..., Task_N\}$ which is submitted to the GRA. We assume that the client submits only one job to the Grid. The failure of negotiation is considered as the worst outcome for the client when it gains 0 utility. The client gains utility U_i which is between 0 and 1 for task i if this task obtains resource R_i from the acceptable range $\left[R_i^{min}, R_i^{opt}\right]$, i.e. $U_i : R_i \rightarrow \; [0,1]$. Consequently, the closer R_i is to R_i^{opt}, the higher the client utility. We also assume that the client gains utility $U_i > 0$ if $R_i = R_i^{min}$, and the client gains utility $U_i = 1$ if $R_i \geq R_i^{opt}$. The degree of non-linearity ξ of the utility is defined by the client and it is considered the same for all tasks, i.e. the tasks are *homogeneous*.

For example, assume the tasks that process climate data within a building depend on the dimensions of a particular room in terms of the amount of resources. However, these tasks are homogeneous in terms of their objectives, i.e. the processing of climate data. The utility function U_i for each task increases according to ξ, starting from utility k^{ξ} when $R_i = R_i^{min}$, towards the utility 1 when $U_i = R_i^{opt}$. The minimum utility which can be gained by a client for task i if negotiation was successful is equal to k^{ξ} and it is considered the same for all tasks. Consequently, the utility for task i is presented as:

$$U_i = \begin{cases} 0, & R_i < R_i^{min}; \\ \left(\frac{(1-k)\times R_i + k\times R_i^{opt} - R_i^{min}}{R_i^{opt} - R_i^{min}}\right)^{\xi}, & R_i^{min} \leq R_i < R_i^{opt}; \\ 1, & R_i \geq R_i^{opt}, \end{cases} \tag{2}$$

The aggregated client utility U_{Client} for N tasks is presented as the normalised sum of N utilities gained by the client.

$$U_{Client} = \frac{1}{N}\sum_{i=1}^{N} U_i. \tag{3}$$

[2]For instance, the executable may comprise code to perform a statistical analysis of data streams.

3.2. Proposals and Negotiation Protocol

A *proposal* denotes a message sent from one agent to another, containing an offered resource for a particular task. The proposal Pr_i comprises the name of the corresponding executable $Name_i$ (i is the identifier of the corresponding task) and the offered resource R_i.

$$Pr_i = (Name_i, R_i), \quad R_i \in \mathbb{R}. \tag{4}$$

A set of proposals denotes $S = \{Pr_1, ..., Pr_i, ..., Pr_N\}$ for all tasks in one job. If the proposal is accepted, the offered resource R_i in Eq. (4) is substituted with the token "ACCEPT". If the proposal is rejected (i.e. the deadline is reached or the resources are exhausted), the offered resource R_i in Eq. (4) is substituted with the token "REJECT". The negotiation finishes when the proposals for all tasks were accepted or rejected. In our work, we adopt the *alternating proposals protocol* [25] in which the pair of negotiators exchange proposals in turns. Each negotiator may *accept* the opponent's proposal, *generate* the counter-proposal or *reject* the opponent's proposal without generating a counter-proposal. That is, the last option means that the negotiator quits negotiation.

4. Adaptive Negotiation Strategy

Negotiation usually has a *time constraint*, e.g. a client has to launch its tasks in a reasonable period of time. Therefore, a client and the GRA adopt a time-dependent negotiation strategy [10] in which a value of the proposed resource depends on the approaching negotiation deadline. The negotiation starts at t_0 and then a client and the GRA exchange their proposals each round of negotiation j which is initiated each time unit t. If the negotiator's deadline is reached, it proposes its *reservation value*. The reservation value is a minimum resource for a client and maximum resource for the GRA which they are willing to accept. A negotiation finishes when the deadline of a client t_{dl}^{Cl} or the GRA t_{dl}^{GRA} is reached, or resources are exhausted. The negotiation deadline denotes the maximum possible number of time units in which the negotiation can continue.

Both the negotiators have their own *negotiation intervals* for each task. That is, a client starts negotiation from an optimal resource within its interval and then it moves towards its minimum resource, while the GRA starts from its minimum resource and moves towards its maximum resource during negotiation. The client's negotiation interval is $\left[R_i^{opt}, R_i^{min}\right]$ for each task i (see Eq. (1)), while the GRA's negotiation interval $\left[G_i^{min}, G_i^{max}\right]$ is considered to be within the client's interval, i.e. $G_i^{min} \geq R_i^{min}$ and $G_i^{max} \leq R_i^{opt}$. These constraints are based on the two corresponding assumptions, that is the GRA has no reason to offer a resource that cannot be accepted by the client nor a resource that is larger than the client's optimal resource because of resource scarcity.

The time-dependent strategy [10] comprises three time-dependent tactics which are determined by the coefficient $\beta_{i,j}^{Cl}$ for the client and $\beta_{i,j}^{GRA}$ for the GRA. These coefficients can be different for each particular task i and they can be changed in any negotiation round j. Considering that the client proposes resource $R_{i,j}^{Cl}$ and the GRA proposes resource $R_{i,j}^{GRA}$, the time-dependent strategies for the client and the GRA are presented as:

$$R_{i,j}^{Cl} = R_i^{opt} + \left(\frac{t-t_0}{t_{dl}^{Cl}}\right)^{\beta_{i,j}^{Cl}} \times \left(R_i^{min} - R_i^{opt}\right). \tag{5}$$

$$R_{i,j}^{GRA} = G_i^{min} + \left(\frac{t-t_0}{t_{dl}^{GRA}}\right)^{\beta_{i,j}^{GRA}} \times \left(G_{i,j}^{max} - G_i^{min}\right). \tag{6}$$

In Eqs. (5) and (6), $\beta_{i,j}^{Cl} > 1$ denotes *greedy* tactic, i.e. the client makes larger concessions when its negotiation deadline is approaching, comparing to the earlier negotiation rounds; $0 < \beta_{i,j}^{Cl} < 1$ denotes *generous* tactic, i.e. the client makes smaller concessions when its negotiation deadline is approaching, comparing to the earlier negotiation rounds; and $\beta_{i,j}^{Cl} = 1$ denotes *indifferent* tactic, i.e. the client makes the same concessions during negotiation (the same tactics are applied by the GRA). We assume that the GRA's reservation resource $G_{i,j}^{max}$ decreases and its tactic $\beta_{i,j}^{GRA}$ becomes less generous when the amount of available resources decreases and vice versa. Consequently, the GRA's reservation resource and tactic can vary from one round to another, while the client changes only its tactic $\beta_{i,j}^{Cl}$ to adapt to the GRA's dynamism.

4.1. Client's Estimation of Grid Dynamism

We assume that a client does not have certain knowledge of the GRA's reservation value and tactic. Consequently, a client is only able to observe the GRA's proposals and it must make a decision based on these proposals. We described a mechanism which allows the client to estimate the GRA's tactic and the change of its reservation resource on the next negotiation round after these parameters were changed, i.e. during the two rounds of negotiation.

In general, the estimation of the GRA's tactic is based on the increment between the GRA's offered resource in the previous and current rounds of negotiation [11]. For instance, this increment rises slowly if the GRA applies a greedy tactic and it rises fast if the GRA applies a generous tactic in the early negotiation rounds. Consequently, the increment does not change from round to round if the GRA applies an indifferent tactic. We consider that the client knows the current GRA proposal $R_{i,j}^{GRA}$, the previous GRA proposal $R_{i,j-1}^{GRA}$ and the first GRA proposal G_i^{min}. In this way, it compares the increments of the previous and the current GRA's proposals in respect to the first GRA's proposal. Applying Eq. (6) for the rounds j and $j-1$, the GRA's tactic for task i in round j can be estimated as:

$$\beta_{i,j}^{GRA} = \ln\left(\frac{R_{i,j}^{GRA} - G_i^{min}}{R_{i,j-1}^{GRA} - G_i^{min}}\right) / \ln\left(\frac{j}{j-1}\right). \tag{7}$$

However, this estimation has a limitation, i.e. it is not applicable when the GRA's tactic changes in the current negotiation round because the increments $R_{i,j}^{GRA} - G_i^{min}$ and $R_{i,j-1}^{GRA} - G_i^{min}$ are not comparable in this case. When the GRA's tactic is estimated, a client can use Eq. (7) to predict the GRA's proposed resource in the next round of negotiation $R_{i,j+1}^{pred}$. If the actual GRA proposal $R_{i,j+1}^{GRA}$ in round $j+1$ is significantly different from the predicted $R_{i,j+1}^{pred}$, the client assumes that the GRA's tactic and reservation resource were changed. In this case, a client aims to estimate the change of the GRA's reservation resource because this value explicitly reflects the change of the resource availability. That is, the GRA's reservation resource is the maximum resource which a client might obtain.

According to Eq. (7), the client has to know in which round the GRA offers its reservation resource to estimate its increment in respect to G_i^{min}, i.e. it has to know the GRA's negotiation deadline. In our current work, the client assumes that the GRA's deadline is equal to its own deadline. In this way, if negotiation round k is the round when the GRA offers its reservation resource, then $k = t_{dl}^{Cl}$. Consequently, our estimation of the change of the GRA's reservation resource is limited to the case when the GRA's and client's deadlines are equal (or the GRA's deadline is known to the client). According to Eq. (7), a client is able to estimate the expected increment $R_{i,k}^{pred} - G_i^{min}$ (where $R_{i,k}^{pred} = G_{i,k}^{max}$) of the GRA's reservation resource in the next negotiation round. A client is also able to estimate the actual increment $R_{i,k}^{GRA} - G_i^{min}$ (where $R_{i,k}^{GRA} = G_{i,k}^{max'}$) in that round when the GRA's reservation resource was changed. Then, the ratio of these two increments is calculated as described in Eq. (8).

$$\frac{R_{i,k}^{GRA} - G_i^{min}}{R_{i,k}^{pred} - G_i^{min}} = \left(\frac{k}{j+1}\right)^{\beta_{i,j+1}^{GRA} - \beta_{i,j+1}^{pred}} \times \left(\frac{R_{i,j+1}^{GRA} - G_i^{min}}{R_{i,j+1}^{pred} - G_i^{min}}\right), \tag{8}$$

where $\beta_{i,j+1}^{pred}$ and $\beta_{i,j+1}^{GRA}$ are the expected and actual GRA's tactics in round $j+1$. We also can describe the estimation in Eq. (8) in percentage $\delta_{i,j+1}$ comparing it to this estimation in the previous round j when the GRA's reservation resource was not changed.

$$\delta_{i,j+1} = \left(\frac{G_{i,k}^{max'} - G_i^{min}}{G_{i,k}^{max} - G_i^{min}} - 1\right) \times 100\%. \tag{9}$$

4.2. *Client's Adaptation to Dynamism*

The client has to adapt to the Grid dynamism based on the intuition which is outlined by Narayanan and Jennings [13]. If resources become more scarce (i.e. the GRA's reservation resource decreases), then the client becomes *more generous* towards the GRA to avoid a failure of negotiation. If resources become less scarce (i.e. the GRA's reservation resource increases), then the client becomes *less generous* towards the GRA aiming to reach a better agreement. However, the estimation of the change of the GRA's reservation resource (see Eq. (8)) is not precise leading to the uncertainty of the client about this change. Therefore, the client judges the change of resource availability in *fuzzy terms*, i.e. it has a particular level of confidence that the GRA's reservation resource was significantly decreased or increased. Consequently, the client cannot be certain which tactic can be considered "less" or "more" generous in respect to this change of resource availability. Therefore, we use *fuzzy logic* to deal with this client's evaluation. Assume that X is a non-fuzzy set in which x is a generic element of this set [26, 27]. A fuzzy set A is the subset of X which is defined ('characterised') by a *membership function* $\mu_A(x)$. This function denotes the *degree of membership* of x in A and $\mu_A(x) : x \in X \rightarrow [0,1]$.

In our work, a fuzzy mechanism consists of the three stages: fuzzification, inference and defuzzification. In the *fuzzification* stage, the two input parameters $\delta_{i,j}$ and $\beta_{i,j}^{Cl}$ are fuzzified, i.e. their degree of memberships are calculated for the corresponding fuzzy sets (see Figure 1). Three fuzzy sets are designed for $\delta_{i,j}$ which denote decrease "D", zero "Z" and increase "I". In Figure 1(a), "D" and "I" show the client's level of confidence

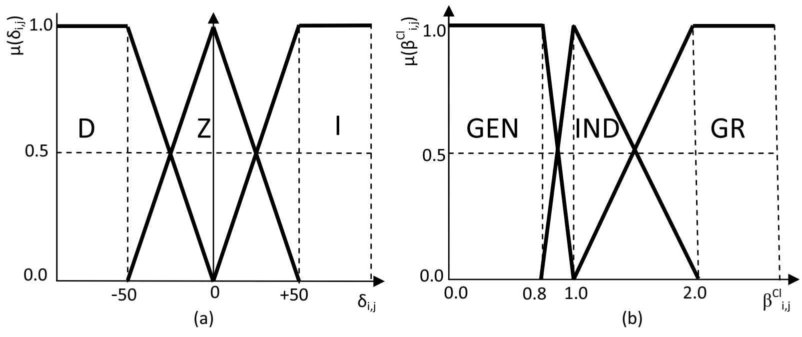

Figure 1. Input membership functions for (a) $\delta_{i,j}$ and (b) $\beta^{Cl}_{i,j}$.

that the GRA's reservation resource is significantly changed and "Z" shows that it is not significantly changed. That is, the $x-axis$ depicts the value of $\delta_{i,j}$ and the $y-axis$ depicts its degree of membership. In Figure 1(b), we demonstrate three fuzzy sets for the client's tactic $\beta^{Cl}_{i,j}$, i.e. generous "GEN", indifferent "IND" and greedy "GR". Each of these sets denotes the client's level of confidence that its tactic belongs to the one of the corresponding tactics when the change of resource availability is uncertain for the client. The $x-axis$ depicts the value of $\beta^{Cl}_{i,j}$ and the $y-axis$ depicts its degree of membership.

The output of the client's deliberation should be a percentage η that its current value of $\beta^{Cl}_{i,j}$ should change to avoid failure of negotiation and/or improve client utility. That is, $\beta^{Cl'}_{i,j} = \beta^{Cl}_{i,j} \times \left(1 + \frac{\eta\%}{100\%}\right)$ where $\beta^{Cl'}_{i,j}$ is the modified client's tactic. We believe that in highly dynamic Grid environments, the client does not have enough information to estimate the precise relations between input parameters (resource availability, client's tactic) and output parameter (change of client's tactic). Moreover, different Grid environments may have a different effect on η because of the different characteristics. Therefore, we designed the client's output in fuzzy terms where the output membership function (see Figure 2) shows the client's level of confidence that its tactic has to be changed in a particular way (e.g. "medium increase"). We also believe that the small fluctuations of resources should not affect client's tactic significantly because the risk of resource exhaustion is uncertain. We described five fuzzy sets, i.e. large decrease "LD", medium decrease "MD", small change "SC", medium increase "MI" and large increase "LI" which intuitively denote the level of the client's tactic change.

In the *inference* stage, fuzzy control rules connect the fuzzified input values and the output fuzzy value. For example, if $\delta_{i,j}$ is decreased (D) and $\beta^{Cl}_{i,j}$ is greedy (GR), then $\beta^{Cl}_{i,j}$ has to be "large decreased" (LD). These control rules are (i) if D and GEN then MD; (ii) if D and IND then MD; (iii) if D and GR then LD; (iv) if Z and GEN then SC; (v) if Z and IND then SC; (vi) if Z and GR then SC; (vii) if I and GEN then LI; (viii) if I and IND then MI; (ix) if I and GR then MI. These control rules correspond to the intuition of client adaptation to the dynamism which are mentioned above in this section. If the value of $\beta^{Cl}_{i,j}$ decreases (i.e. "MD" and "LD"), it means that the client becomes more generous for the cases when the resource availability decreases ("D"). If the value of $\beta^{Cl}_{i,j}$ increases ("MI" and "LI"), it means that the client becomes less generous for the cases when the resource availability increases ("I"). If the resource availability was not changed

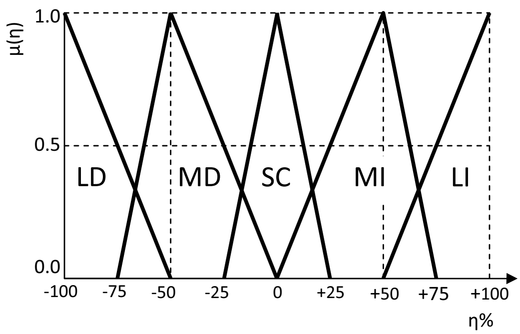

Figure 2. Output membership functions for $\eta\%$.

significantly ("Z"), the value of $\beta_{i,j}^{Cl}$ also does not change significantly ("SC"). We apply Mamdani's *Min-Max* inference method [26] because it is computationally effective for the small number of control rules (we have 9 fuzzy control rules). As a result of the inference stage, the output membership function for $\eta\%$ is truncated, i.e. the area where the output crisp value can lie becomes more narrow. In the *defuzzification* stage, we calculate a crisp value of $\eta\%$ by applying the conventional *centre of gravity* method (COG) mentioned in Runkler and Glesner [28] which is compatible with the Mamdani's type of fuzzy controllers. Consequently, the resulting $\eta\%$ is the centroid of area of the truncated output membership function. A client applies this fuzzy mechanism each round of negotiation to generate a counter-proposal.

5. Evaluation

We evaluate our adaptive negotiation strategy in comparison with non-adaptive negotiation strategy in which a client's tactic does not respond to the Grid dynamism. In contrast, our negotiation strategy adapts to the dynamism by estimating changes in the GRA's negotiation parameters. To evaluate the *effectiveness* of our strategy, we calculated the average client utilities and the average number of failed negotiations for 100 tasks over 100 runs (see Figure 3). Each negotiation took 100 rounds and the initial tactics for the client and GRA were assumed to be indifferent (see Eq. (5)). We also consider only linear client utility function in our current experiments.

To test our strategy, we tried to determine how our strategy works in the case of the more or less random Grid dynamism. In Figures 3 and 4, the probability of tendency denotes that the next change (increase/decrease) of the amount of available resources is in the same direction (positive/negative) as the previous change. Consequently, if the probability is 1, it means that each next change of the resource availability will be the same by direction (not by value) as its previous change. This case denotes the strongest *tendency* in the Grid dynamism and a probability of 0 denotes the highest *randomness* (opposite to the tendency) in the Grid dynamism. The GRA's reservation resource and tactic that reflect the dynamism of the resource availability are generated randomly for each task and can vary from task to task. We also assume that the GRA's reservation resource may increase or decrease per negotiation round by at most 5% of the client's optimal resource for the task.

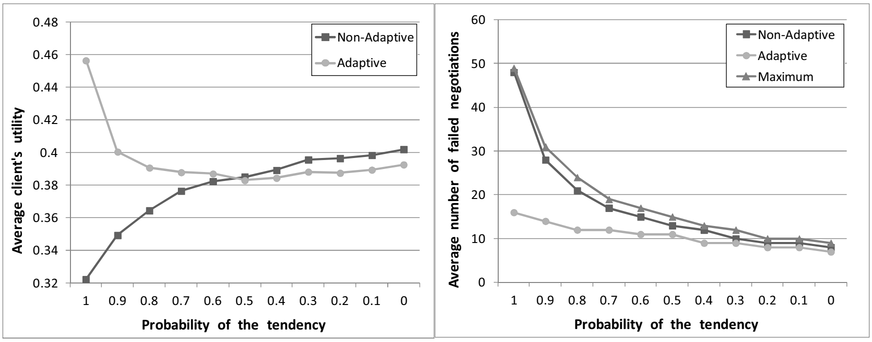

Figure 3. The experiment where approximately half of the tasks may fail to obtain resources.

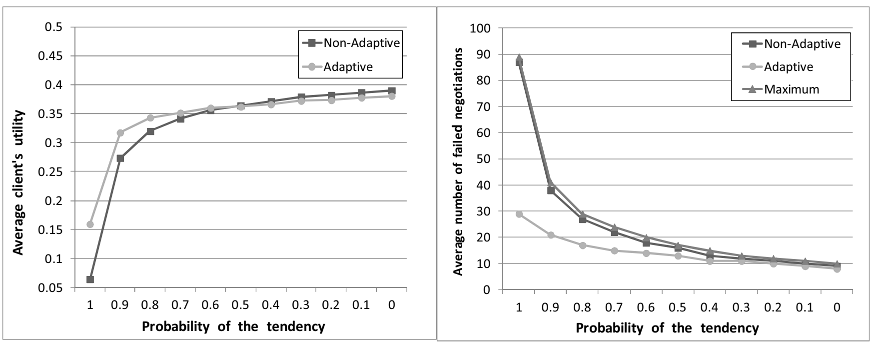

Figure 4. The experiment where approximately all tasks may fail to obtain resources.

Our negotiation strategy aims to avoid failure when resources are exhausted. Therefore, we conducted an experiment in which approximately half of the tasks may fail to obtain resources (see Figure 3) and another in which approximately all tasks may fail to obtain resources (see Figure 4) for the different levels of tendency in the Grid. In both experiments, our adaptive negotiation strategy significantly reduces the number of failed negotiations in comparison with the non-adaptive strategy. The "Maximum" labels in Figures 3 and 4 denote the maximum possible number of tasks which may fail to obtain resources because resources have been exhausted. It has to be noted that our strategy shows significantly better utility than the non-adaptive one in the cases of the stronger tendency. However, in the cases of the higher randomness, our strategy does not show improvements in utility compared to the non-adaptive one. Intuitively, it is not possible to adapt to random dynamism. In the adaptive strategy, the client becomes more generous when resources decrease and less generous when resources increase. If the client becomes less generous and then more generous, its tactic will be close to the indifferent one which is applied by the non-adaptive client. Therefore, the adaptive client utility is close to the non-adaptive client utility for these cases.

The significant difference between two experiments mentioned above is observed for the cases of stronger tendency of the dynamism, i.e. when the probability of the tendency lies in the interval from 1 to 0.6. The client utility for the adaptive strategy in Figure 3 tends to decrease, while this utility in Figure 4 tends to increase during the interval mentioned above. In the second experiment, the client utility for the adaptive strategy is significantly lower than in the first experiment because the number of failed negotiations is significantly higher. Moreover, the client utility for the probability of tendency, which is equal to 1, rapidly decreases or increases compared to all other tendencies in both experiments. This is because this case is more influenced by the decrease or increase of resources than all other cases. In summary, the advantage of our adaptive negotiation strategy is that it significantly reduces the number of failed negotiations and improves client utility for those cases when the dynamism is less random.

6. Conclusions and Future Work

In this paper we introduced our adaptive negotiation strategy for a client to negotiate with the Grid resource allocator (GRA) about resources for multiple tasks. That is, our strategy adapts to the high dynamism in the Grid by estimating the GRA's reservation resource and tactic in the case of ignorance of Grid dynamism. The adaptation is implemented with fuzzy control rules which specify whether the client should become less or more generous in respect to the GRA. We evaluated our adaptive strategy for the different tendencies of the Grid dynamism (increase/decrease of resources) in terms of client utility and the number of failed negotiations. We also compared our strategy to a non-adaptive one which does not change its tactic in response to the Grid dynamism. The simulation results show that our strategy outperforms the non-adaptive one with respect to the client utility and the number of successful negotiations for the cases of less random dynamism. In cases of more random dynamism, our strategy still shows better result in terms of the number of successful negotiations. In our future work, we intend to improve our strategy in terms of learning the tendency (direction) and speed (value per round) of Grid dynamism and compare it to alternative adaptive negotiation strategies. We also aim to allow a client to estimate its opponent's deadline of negotiation. Moreover, we intend to focus not only on resource intensive tasks, but on tasks which have to be processed continuously.

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