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Towards a Unifying Multilateral Cloud Negotiation Strategy

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Abstract— **In a Cloud business model, consumers pay Cloud providers for consumption of computing capabilities and the allocation of resources often requires consumers and providers to establish service contracts through negotiation. This paper reports the preliminary findings in devising a unifying strategy for supporting price negotiation among multiple consumers and multiple providers in Cloud resource allocation. The contributions of this work include i) comparing the negotiation functions of various existing negotiation strategies, ii) implementing the various negotiation strategies in an agent-based testbed, and iii) empirically comparing the performance of a family of multilateral negotiation strategies. Even though the negotiation functions of these negotiation strategies are composed of different mathematical functions, experimental results show that they have equivalent properties. It can be deduced that despite adopting different market-driven strategies that are studied in this work, agents make similar amounts of concessions under different respective market situations.**

Index Terms—**Multiagent system, software agent, automated negotiation, Cloud resource allocation, Cloud commerce.**

I. Introduction

Cloud computing is a new and emerging computing paradigm that aims to provide ubiquitous access to on-demand data, storage, and computing capabilities that are dynamically configured. A Cloud computing system consists of a collection of inter-connected and virtualized computers dynamically provisioned as one or more unified computing resource(s) through negotiation of service-level agreements (*SLAs*) between Cloud providers and consumers [1]. Whereas there is incentive in the form of profit for Cloud resource providers to offer their resources for consumption by users, consumers can avoid having to own and maintain expensive IT infrastructures by leasing resources from providers. Since consumers and providers may have different objectives, policies, and requirements, negotiation is needed to resolve their differences. However, to date, state-of-the-art approaches in Cloud computing provide very limited support for dynamic *SLA* negotiation [1].

In a Cloud business model, many consumers may compete for the same computing resources and many Cloud providers may compete to provide the resources to consumers. This paper presents a *market-driven negotiation strategy* for supporting price negotiation among multiple consumers and multiple providers in Cloud resource allocation (Section II). While section III reviews existing multilateral negotiation strategies, section IV compares the common properties among these negotiation strategies. Section V reports empirical results comparing the performance of various existing multilateral negotiation strategies. Section VI summarizes the empirical results which suggest that the market-driven strategy is a unifying strategy.

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II. A Market-Driven Negotiation Model

A. Market-driven Negotiation Strategy

Automated negotiation can be viewed as a group decision-making process with two or more agents actively making concessions to achieve a compromise. In a Cloud resource market where multiple consumers compete for computing resources and Cloud providers compete to provide resources, a *market-oriented approach* for regulating the supply and demand of Cloud resources is appropriate. To model the dynamic pricing of Cloud resources, this research adopts a *market-driven negotiation strategy* [2-4] that will take into consideration the market dynamics of a Cloud resource market. When making concessions, a *market-driven agent* (*MDA*) takes into consideration factors such as time, opportunity, and competition. An *MDA* determines the appropriate amounts of concessions using a combination of three negotiation functions: time (*T*) function, opportunity (*O*) function, and competition (*C*) function.

The *T* function is defined as follows:

$$T(t,\tau,\lambda) = 1 - (t/\tau)^{\lambda}$$

where t is the current trading round, τ is the deadline, and λ is an *MDA*'s time preference. *MDAs* have different time preferences (e.g., negotiators with different time preferences may have different concession rates with respect to time). With infinitely many values of λ, there are infinitely many possible strategies in making concessions with respect to remaining trading time. In [2-4], an *MDA*'s *T* function can be categorized into three classes: *conservative*, *linear*, and *conciliatory* that correspond to the conceding slowly, conceding at a constant rate, and conceding rapidly, respectively.

The *O* function $\boldsymbol{O}(n, v_t^{B\rightarrow Sj}, \langle w_t^{Sj\rightarrow B}\rangle)$ determines the amount of concession based on (i) outside options or trading alternatives (i.e., number of trading partners n) and (ii) differences in utilities generated by the proposal of an agent B ($v_t^{B\rightarrow Sj}$) and the counter-proposals of its trading partner(s) ($\langle w_t^{Sj\rightarrow B}\rangle = \{w_t^{S1\rightarrow B}, .., w_t^{Sn\rightarrow B}\}$, where $\{S_1, \ldots, S_n\}$ is the set of trading partners) [2-4]. When determining opportunity, Sim showed in [3] that if there is a large number of trading alternatives, the likelihood that an agent proposes an offer that is potentially close to an *MDA*'s offer may be high. However, it would be difficult for the *MDA* and any of its trading partners to reach a consensus if none of the so many options are viable (i.e., there are large differences between the proposal of the *MDA* and the counter-proposals of all its trading partners). On this account, $\boldsymbol{O}(n, v_t^{B\rightarrow Sj}, \langle w_t^{Sj\rightarrow B}\rangle)$

determines the probability of obtaining a utility $v_t^{B\to Sj}$ with at least one of its n trading partners by considering the notion of *conflict probability* p_c defined as follows:

$$p_c = (v_t^{B\to Sj} - w_t^{Sj\to B}) / (v_t^{B\to Sj} - c^B)$$

p_c is a ratio of difference between two utilities. c^B=0 is the worst possible utility for B when the negotiation ends in conflict. While $v_t^{B\to Sj} - w_t^{Sj\to B}$ measures the cost of *B accepting a trading partner* S_j*'s last offer* (the difference between the (counter-)proposals of B and S_j), and $v_t^{B\to Sj} - c^B$ measures the cost of *provoking a conflict*. Mathematical derivation and detailed analyses of p_c and $\boldsymbol{O}(n, v_t^{B\to Sj}, \langle w_t^{Sj\to B}\rangle)$ can be found in [2-3]. The general idea is that if the probability of reaching a consensus on its own terms is high (respectively, low), an *MDA* should make a smaller (respectively, larger) amount of concession.

The ***C*** function determines the amount of competition faced by an *MDA* by determining the probability that it is not being considered as the most preferred trading party. Since *MDAs* are utility maximizing agents, an *MDA* is more likely to reach a consensus if its proposal is ranked the *highest* by some other agent. Suppose an agent ***B*** has m-1 competitors $\{B_2,\dots, B_m\}$ and n trading parties $\{S_1,\dots, S_n\}$. The probability that ***B*** is *not* the most preferred trading party of *any* S_j (where $S_j \in \{S_1,\dots, S_n\}$) is $(m-1)/m$. Hence, the probability that ***B*** is *not* the most preferred party of *all* $S_j \in \{S_1,\dots, S_n\}$ is $\left[(m-1)/m\right]^n$. In general, the probability that ***B*** is considered the *most preferred* trading party by at *least one* of $S_j \in \{S_1,\dots, S_n\}$ is:

$$C(m,n) = 1 - \left[(m-1)/m\right]^n$$

where m and n are respectively the numbers of buyer agents (including ***B***) and seller agents at round t.

B. Multilateral Negotiation Protocol

The Cloud negotiation protocol for specifying the negotiation activities between consumer agents and Cloud provider agents is given as follows:

- Negotiation proceeds in a series of rounds.
- Consumer and provider agents negotiate by making proposals in alternate rounds.
- Multiple consumer-provider agent pairs can negotiate deals simultaneously.
- When an agent makes a proposal, it proposes a deal from its space of possible deals (e.g., consisting of the most desirable price, the least desirable (reserve) price, and those prices in between). Typically an agent proposes its most preferred deal initially.
- If no agreement is reached, negotiation proceeds to the next round. At every round, an agent determines its amount of concession based on the *MDA* strategy.
- Negotiation between two agents terminates 1) when an agreement is reached, or 2) with a conflict when one of the negotiation agents' deadline is reached.

III. Existing Multilateral Negotiation Models

Whereas there is very limited support for Cloud resource negotiation in the literature, Sim [5] surveyed state-of-the-art negotiation strategies and protocols of Grid resource negotiation. The difference between Cloud computing and Grid computing is that whereas most Grids adopt a batch-mode to allocate physical and dedicated resources to users governed by a queuing system, Clouds are more oriented towards using dynamic, real-time resource allocation, allowing resources to be shared by all users simultaneously (e.g., as Virtual Machine instances) [6]. Whereas the testbeds for simulating the scheduling of Cloud and Grid resources will be different, from an automated negotiation perspective (the main focus of this work), the price negotiation mechanisms for Cloud and Grid resources are related. Some of the closely related negotiation mechanisms surveyed in [5] are as follows.

A. Multilateral Negotiation Model by Lang

Lang [7] proposed a multiple-attribute Grid negotiation mechanism. In [7], an agent determines the amount of concession by considering both time and market factors.

An agent makes concession in each negotiation round i by modifying its offer using a time function $\Delta_i(\pi)\in[0,1]$, such that:

$$\Delta_i(\pi) = \left(\frac{t - t_0}{t_{crit}(\pi)}\right)^{\beta_i(\pi)}$$

where π is an agent's belief about the current state about the real world, $t = \{0, 1, 2,\dots\}$, t_0 refers to the time index when t=0, and $t_{crit}(\pi)$ is an agent's negotiation deadline. With respect to time, an agent can adopt an *aggressive* strategy which maintains its bid/offer until almost its deadline, a *defensive* strategy which rapidly concedes to its reservation value (e.g., its least preferred price), or simply a *neutral* strategy which concedes linearly.

Additionally, a service agent determines its "market power" π_{power_j} by taking into account the ratio of 1) N_{pro}^j (the number of supply advertisements for the same competing service) and 2) $N_{pro}^j + N_{con}^j$ (the total number of advertisements published in the entire system), where N_{con}^j is the total number of request advertisements from consumers.

B. Bilateral Negotiation Model by Lawley

Lawley et al. [8] investigated the use of negotiation agents for identifying mutually acceptable terms among information publishers (providers) and consumers of message notification services in Grid computing. The strategies in [8] are determined using a combination of time-dependent and resource-dependent functions [9]. The time-dependent negotiation function $f^A(t)$ of an agent in [8] is given as $f^A(t) = k^A + (1-k^A)\left(\frac{\min(t,\tau)}{\tau}\right)^{\frac{1}{\psi}}$ where t is a discrete trading (negotiation) time indexed by $\{0,1,2,\dots\}$, τ is the deadline of agent A, $\psi\in\mathbb{R}^+$ (i.e., $\psi\geq 0$) represents A's time preference, and k^A is a constant that, when multiplied by the size of the interval $[IP^A, RP^A]$, determines the price to be offered in the first proposal of A. (IP^A and RP^A are respectively the initial and reserve prices of A). Even though there are infinitely many strategies for agents (since there are infinitely many values of ψ), the strategies of agents in [8] can be categorized into *Bouleware*, *Linear*, and *Conceder* tactics [9] (which correspond to the aggressive, neutral, and defensive strategies, respectively) that determine the amounts of concessions based on the fraction of remaining time.

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Using a resource function to determine the amount of resource consumption, resource-dependent functions, consisting of Patient, Steady, and Impatient tactics, generate proposals based on how a particular resource (e.g., remaining bandwidth) is being consumed. Agents become more conciliatory as the quantity of resource diminishes.

C. *Multilateral Negotiation Model by Ghosh*

Ghosh et al. [10] considered the issue of load balancing in a mobile computational Grid by proposing a fair pricing strategy and an optimal static job allocation scheme. The pricing strategy considers factors such as resource constraints, time discount factor, "market price", the expected counter-proposal of an agent's opponent, and (i) the perceived probability $P_x^{O_x}(acc)$ that an agent's opponent will accept its proposal O_x, (ii) the perceived probability $P_x^{O_x}(rco)$ that an agent's opponent will reject its proposal O_x but negotiation will continue as the opponent will make a counter-proposal, and (iii) the perceived probability $P_x^{O_x}(rbd)$ that an agent's opponent will reject its proposal and negotiation breaks down (i.e., terminates without an agreement).

IV. Common Properties

Although negotiation functions such as time-dependent functions and other market-driven functions such as opportunity and competition functions in [2-4] appear to have surface dissimilarities, a closer examination by Sim [5] reveals that they have strong resemblance.

Table 1 compares the time-dependent functions in [2-4], [7], and [8] in terms of three major classes of concession making strategies and highlights the common features of the three different time functions in [2-4], [7], and [8]. By highlighting the similarities of these time functions, Table 1 aims at providing agent designers with some guidelines on the common properties of the mathematical functions when modeling devaluation of resources. For instance, all functions in [2-4], [7], and [8] can be used to model 1) concessions made with respect to time, and 2) different attitudes of agents toward time [e.g., a patient (respectively, an impatient) agent can adopt either the Boulware or the conservative or the aggressive strategy (respectively, the Conceder or the conciliatory or the defensive strategy)].

To model market dynamics in their concession making strategies, Sim [2-4], Lang [7], and Ghosh [10] take into consideration factors such as opportunity, probability of an opponent accepting a bargainer's offer, competition, and "market power." Table 2 compares the opportunity and competition functions of [2-4], [7], [10] in terms of making less (respectively, more) concessions in favorable (respectively, unfavorable) market conditions and shows the similar concession making properties of the opportunity functions in [2-4] and [10] and the competition functions in [2-4] and [7]. By highlighting the similarities of these opportunity and competition functions, Table 2 aims at providing agent designers with some guidelines on their common properties when modeling market conditions.

V. Multilateral Cloud Negotiation Testbed

Sim's *MDA* strategy (section II.A), Lang's strategy (section III.A), Lawley's strategy (section III.B), the Ghosh strategy (section III.C), and the multilateral Cloud negotiation protocol (section II.B) are implemented in a multilateral Cloud negotiation testbed using *JADE* (*Java Agent DEvelopment framework*). The testbed consists of 1) a set of Cloud resources, 2) a set of resource consumers, 3) a set of middleware consisting of Cloud negotiation agents (provider agents and consumer agents) acting as intermediaries between resource providers and consumers, 4) a market controller, 5) a service registry, and 6) a resource trading record directory. The inputs to a consumer agent (respectively, provider agent) consist of the initial price, reserve price, and negotiation deadline of the consumer (respectively, provider). Consumer agents and provider agents negotiate among themselves following the multilateral negotiation protocol in section II.B. Whereas the service registry is a repository of resource information, the resource trading record directory is a database for documenting the outcomes of Cloud resource negotiation. The market controller simulates the trading of Cloud resources in a Cloud resource market by 1) generating consumer agents and provider agents, 2) controlling their entrance to and exit from the Cloud resource market, and 3) recording the results of the negotiation outcomes between consumer and provider agents in the resource trading record directory.

VI. Empirical evaluation

A. *Objectives*

Experiments were conducted to evaluate the multilateral negotiation strategy in a Cloud service market by comparing the performance of agents adopting the 1) *Sim's MDA* strategy, 2) *Lang*'s strategy, 3) *Lawley*'s strategy, and 4) *Ghosh*'s strategy in three types of Cloud service markets: consumer-favorable, balanced, and consumer-unfavorable.

B. *Experimental Settings*

The input parameters of consumer and provider agents for the experiments are shown in Table 3. Additionally, consumer-to-provider ratios of {1:3, 1:5, 1:10}, {1:1}, and {3:1, 5:1, 10:1} were used to simulate *consumer-favorable*, *balanced*, and *consumer-unfavorable* markets, respectively. These ratios were simulated by fixing the number of provider agents at 250 and varying the number of consumer agents.

Table 1. Time-dependent Functions

References	**Time function**	Slow decreasing	Constant decreasing	Fast decreasing
Sim [2-4]	$T(t,\tau,\lambda) = 1 - (t/\tau)^{\lambda}$	*Conservative* (λ>1)	*Linear* (λ=1)	*Conciliatory* (λ<1)
	t is the current trading time, τ is the deadline, and λ is an agent's time preference.			
Lawley et al. [8]	$f^{A}(t) = k^{A} + (1-k^{A})\left(\frac{\min(t,\tau)}{\tau}\right)^{\frac{1}{\psi}}$	*Boulware* (ψ<1)	*Linear* (ψ=1)	*Conceder* (ψ>1)
	t is a discrete negotiation time indexed by {0,1,2,…}, τ is the deadline of agent A, and ψ is A's time preference.			
Lang [7]	$\Delta_i(\pi) = \left(\frac{t - t_0}{t_{crit}(\pi)}\right)^{\beta_i(\pi)}$	*aggressive* ($\beta_i(\pi)$>1)	*Neutral* $\beta_i(\pi)$=1	*defensive* $\beta_i(\pi)$<1
	π is an agent's belief about the current state about the real world, t = {0, 1, 2,… }, t_0 refers to the time index when t=0, $t_{crit}(\pi)$ is an agent's negotiation deadline, and $\beta_i(\pi)$ is an agent's time preference.			

Table 2. Market-driven Functions

References	**Opportunity Function**	Favorable Market (Makes less concession)	Unfavorable Market (Makes more concession)
Sim [2-4]	$\boldsymbol{O}(n, v_t^{B\to Sj}, \langle w_t^{Sj\to B}\rangle)$	$\boldsymbol{O}(n, v_t^{B\to Sj}, \langle w_t^{Sj\to B}\rangle) \to 1$	$\boldsymbol{O}(n, v_t^{B\to Sj}, \langle w_t^{Sj\to B}\rangle) \to 0$
	$\boldsymbol{O}(n, v_t^{B\to Sj}, \langle w_t^{Sj\to B}\rangle)$ is the probability of reaching a consensus at an agent's own terms. $\boldsymbol{O}(n, v_t^{B\to Sj}, \langle w_t^{Sj\to B}\rangle)$ depends on: 1) n - number of trading alternatives, and 2) differences in utilities between agent B's proposal and each trading partner S_j's proposal.		
Ghosh et al. [10]	$P_x^{O_x}(acc)$	$P_x^{O_x}(acc) \to 1$	$P_x^{O_x}(acc) \to 0$
	$P_x^{O_x}(acc)$ is the perceived probability that agent x's opponent will accept its proposal O_x. $P_x^{O_x}(acc)$ depends on the number of opponents with proposed prices higher than the "market price".		
References	**Competition Function**	Favorable Market (Makes less concession)	Unfavorable Market (Makes more concession)
Sim [2-4]	$C(m,n) = 1 - [(m-1)/m]^{n}$	*Little* competition $C(m,n) \to 1$	*stiff* competition $C(m,n) \to 0$
Lang [7]	$\pi_{power_j} = \begin{cases} 1 - 2 \times \pi_{GCA.ratio_j}, & for\ provider \\ 2 \times \pi_{GCA.ratio_j} - 1, & for\ consumer \end{cases}$	*high* "market power" $\pi_{power_j} \to 1$	*low* "market power" $\pi_{power_j} \to -1$
	$\pi_{GCA.ratio_j} = \frac{N_{pro}^{j}}{N_{pro}^{j} + N_{con}^{j}}$, $\pi_{power_j} \in [-1,1]$ N_{pro}^{j} is the number of supply advertisements for the same competing service, and $N_{pro}^{j} + N_{con}^{j}$ is the total number of advertisements published in the entire system.		

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Table 3. Settings of Experiment 2

Input Parameters	Settings			
	Consumer		Provider	
Initial Price	$IP_{CA} \in [1,15]$		$IP_{PA} \in [66,80]$	
Reserve Price	$RP_{CA} \in [66,80]$		$RP_{PA} \in [1,15]$	
Sim-MDA Strategy	*Conciliatory*	$\lambda_{CA}=0.3$	*Conciliatory*	$\lambda_{PA}=0.3$
	Linear	$\lambda_{CA}=1.0$	*Linear*	$\lambda_{PA}=1.0$
	Conservative	$\lambda_{CA}=3.0$	*Conservative*	$\lambda_{PA}=3.0$
Lang Strategy	*Defensive*	$\beta_i(\pi)_{CA}=0.3$	*Defensive*	$\beta_i(\pi)_{PA}=0.3$
	Neutral	$\beta_i(\pi)_{CA}=1.0$	*Neutral*	$\beta_i(\pi)_{PA}=1.0$
	Aggressive	$\beta_i(\pi)_{CA}=3.0$	*Aggressive*	$\beta_i(\pi)_{PA}=3.0$
Lawley Strategy	*Conceder*	$1/\psi_{CA}=0.3$	*Conceder*	$1/\psi\lambda_{PA}=0.3$
	Linear	$1/\psi_{CA}=1.0$	*Linear*	$1/\psi_{PA}=1.0$
	Boulware	$1/\psi_{CA}=3.0$	*Boulware*	$1/\psi_{PA}=3.0$
Deadline	$\tau_{CA} \in [20, 40]$		$\tau_{PA} \in [20, 40]$	
CPU resource (resource units)	500~5000		5000~20000	
Storage resource (resource units)	250~2500		2500~10000	

C. Performance Measures

Two performance measures were used: 1) average utility and 2) success rate.

Utility: A consumer agent's utility function is defined as follows:

$$U_{CA}(P_{Agr}) = \frac{RP_{CA} - P_{Agr}}{RP_{CA} - IP_{CA}} + u_{\min}$$

where IP_{CA} and RP_{CA} are the consumer agent's initial and reserve prices, P_{Agr} is the agreement price of both the consumer and broker agents, and u_{min} is the minimum utility that a consumer agent receives for reaching a consensus at RP_{CA}. For the purpose of experimentation, the value of u_{min} is set to 0.1. A consumer agent receives a utility of zero if it cannot reach a consensus with any provider agent before its deadline.

A provider agent's utility function is defined as follows:

$$U_{PA}(P_{Agr}) = \frac{P_{Agr} - RP_{PA}}{IP_{PA} - RP_{PA}} + u_{\min}$$

where IP_{PA} and RP_{PA} are the provider agent's initial and reserve prices and u_{min} is the minimum utility that *PA* receives for reaching a consensus at RP_{PA}. For the purpose of experimentation, the value of u_{min} is defined as 0.1. Similarly, a provider agent receives a utility of zero if it cannot reach a consensus with any consumer agent before its deadline.

Success rate: Success rate is determined by N_{succ}/N_{total}, where N_{succ} is the number of successful negotiations and N_{total} is the total number of negotiations (including unsuccessful negotiations).

D. Experimental Results

Even though the average utilities and success rates for both consumer and provider agents were recorded, space limitation precludes all results from being included here.

Figs. 1 and 2 show the average utilities and success rates of consumer agents adopting time-dependent negotiation strategies for consumer-to-broker ratios of 1:10, 1:5, 1:3, 1:1, 3:1, 5:1, and 10:1. Figs. 1 and 2 *only* show the results when consumer agents adopt the slow conceding time-dependent strategy (i.e., the Sim's conservative strategy, the Lawley's Boulware strategy and the Lang's aggressive strategy). Empirical results for agents adopting the slow conceding strategies (conciliatory, conceder and defensive) and the linear (neutral) strategies were also obtained. However, due to space limitation, they cannot be included here.

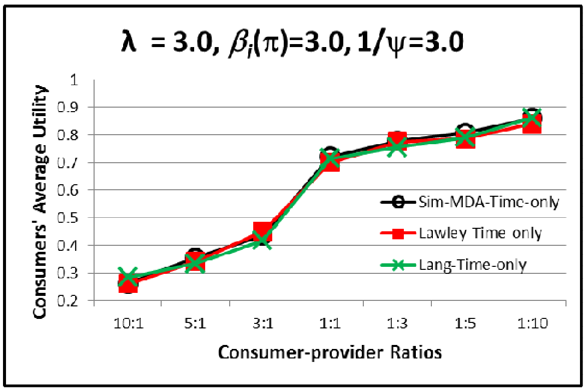

Fig. 1 Average utilities of consumer agents adopting time-only strategies

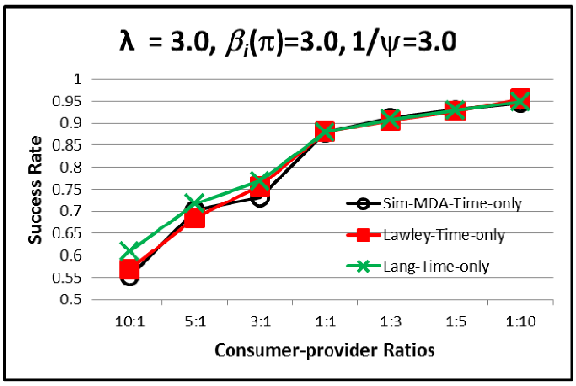

Fig. 2 Success rates of consumer agents adopting time-only strategies

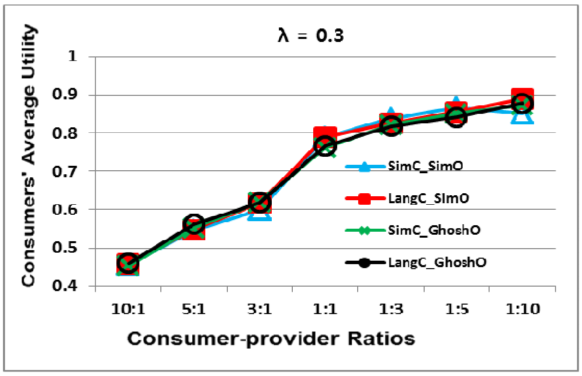

Fig.3 Average utilities of consumer agents adopting market-driven strategies

Figs. 3 and 4 show the average utilities and success rates of consumer agents adopting market-driven negotiation strategies for consumer-to-broker ratios of 1:10, 1:5, 1:3, 1:1, 3:1, 5:1, and 10:1. In Figs 3 and 4, the results of four different market-driven strategies composed using the Sim-Time-function (conciliatory strategy) and 1) the Sim-Competition function and Sim-Opportunity-function (SimC_SimO), 2) the Lang-Competition function and Sim-Opportunity-function (LangC_SimO), 3) the Sim-Competition function and Ghosh-Opportunity-function

(GhoshC_SimO) and 4) the Lang-Competition function and Ghosh-Opportunity-function (LangC_ GhoshO) are plotted.

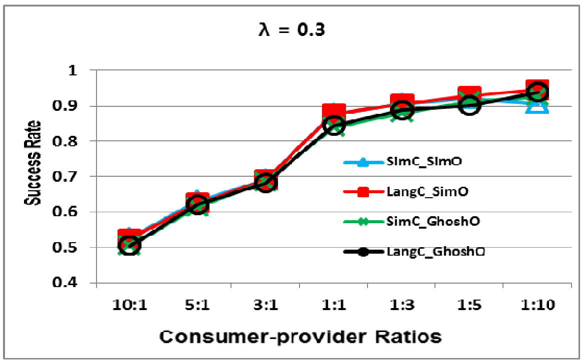

Fig.4 Success rates of consumer agents adopting market-driven strategies

E. Observations

From Figs. 1 to 4, the following observations are drawn.

Observation 1: Consumer agents adopting the Sim-Time-only, Lawley-Time-only, and Lang-Time-only strategies achieved almost the same average utilities in favorable, balanced, and unfavorable markets.

Analysis: From Figs. 1 and 2, it can be seen that consumer agents adopting all the three time-dependent strategies achieved almost the same average utilities and success rates for all the consumer-provider ratios. Even though the time-dependent function in Sim [2-4], Lang [7] and Lawley [8] are composed of very different mathematical functions, it can be deduced that agents adopting the three strategies make similar amounts of concessions under different respective market situations.

Observation 2: Consumer agents adopting the SimC_SimO, LangC_SimO, GhoshC_SimO, and LangC_GhoshO strategies achieved almost the same average utilities in favorable, balanced, and unfavorable markets, respectively.

Analysis: From Figs. 3 and 4, it can be seen that consumer agents adopting all the four market-driven strategies achieved almost the same average utilities and success rates for all the consumer-provider ratios. Since the four market-driven strategies were composed using different permutations of opportunity functions and competition functions from Sim [2-4], Lang [7] and Ghosh [10], the results suggest that the opportunity functions in Sim and Ghosh and the competition functions in Sim and Lang have equivalent properties. It can be deduced that agents adopting the opportunity functions in Sim and Ghosh (respectively, the competition functions in Sim and Lang) react to different respective market situations by making similar amounts of concessions.

VII. CONCLUSION

This work compares the common properties of a family of negotiation strategies and conducted a series of experiments to study the performance of these strategies. Despite using a family of negotiation strategies that are composed of different opportunity and competition functions, agents make similar amounts of concessions under different respective market situations.

The results in observation 1 suggest that an agent designer can achieve similar negotiation results under different respective market situations by 1) replacing the corresponding negotiation strategy in Lang [7] with a time-dependent negotiation strategy in Sim [2-4] and vice-versa and 2) replacing the corresponding negotiation strategy in Lawley [8] with a time-dependent negotiation strategy in Sim [2-4] and vice-versa.

The results in observation 2 suggest that an agent designer can achieve similar negotiation results under different respective market situations by adopting a negotiation strategy to 1) replace the competition function in Lang [7] with the competition function in Sim [2-4] and vice-versa, 2) replace the competition function in Ghosh [10] with the opportunity function in Sim [2-4] and vice-versa, 3) use different permutations of the competition functions in either Sim or Lang and opportunity functions in either Sim or Ghosh.

These results suggest that Sim's *MDA* strategy (which consists of time, opportunity and competition functions) is a unifying strategy. For instance, a designer can construct a negotiation strategy equivalent to Lang's negotiation strategy using a time function in Sim to model a corresponding time function in Lang and Sim's competition function to replace Lang's competition function. A designer can also construct a negotiation strategy equivalent to Ghosh's strategy by replacing the Ghosh opportunity function with the Sim opportunity function.

This paper only reports the preliminary findings and preliminary results of this work. The author hopes to report detailed mathematical analyses and a complete set of experimental results in a future paper.

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REFERENCES

[1] R. Buyya et al. Cloud Computing and Emerging IT Platforms: Vision, Hype, and Reality for Delivering Computing as the 5th Utility. Future Generation Computer Systems, Vol. 25, No. 6, pp. 599-616, Jun. 2009.
[2] K. M. Sim. Equilibria, Prudent Compromises, and the "Waiting" Game. IEEE Transactions on Systems, Man and Cybernetics, Part B: Cybernetics, Vol. 35, No. 4, Aug. 2005, pp. 712-724.
[3] K. M. Sim. A Market-driven Model for Designing Negotiation Agents. In Computational Intelligence, Special issue in Agent Technology for E-commerce, vol. 18, no. 4, pp. 618–637, 2002.
[4] K. M. Sim and C.Y. Choi. Agents that React to Changing Market Situations. IEEE Trans. Syst., Man Cybern B: Cybernetics, Vol. 33, No. 2, April 2003, pp. 188-201.
[5] K. M. Sim, "Grid resource negotiation: Survey and new directions," IEEE Trans. Syst., Man, Cybern. C, Appl. Rev., vol. 40, no. 3, pp. 245–257, May 2010.
[6] I. Foster et al. Cloud Computing and Grid Computing 360-Degree Compared. Proc. Grid Computing Environments Workshop, 2008. GCE '08, Nov. 12-16, 2008, pp. 1-10.
[7] F. Lang. Developing dynamic strategies for multi-issue automated contracting in the agent based commercial grid. in Proc. IEEE Int. Symp. Cluster Comput. Grid (CCGrid05), Workshop Agent-Based Grid Econ., Cardiff, U.K., May 2005, pp. 342–349.
[8] R. Lawley, M. Luck, K. Decker, T. Payne, and L. Moreau. Automated negotiation between publishers and consumers of grid notifications. Parallel Process. Lett., vol. 13, no. 4, pp. 537–548, 2003.
[9] P. Faratin, C. Sierra, and N. R. Jennings. Negotiation decision functions for autonomous agents. Int. J. Robot. Auton. Syst, vol. 24, no. 3, pp. 159– 182, 1998.
[10] P. Ghosh, N. Roy, S. Das, and K. Basu. A pricing strategy for job allocation in mobile grids using a non cooperative bargaining theory framework. J. Parallel Distrib. Comput., vol. 65, no. 11, pp. 1366–1383, Nov. 2005.

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