Li et al. Journal of Cloud Computing (2022) 11:16
https://doi.org/10.1186/s13677-022-00286-6

Journal of Cloud Computing:
Advances, Systems and Applications

RESEARCH

Open Access

Agent-based multi-tier SLA negotiation for intercloud

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Abstract

The evolving intercloud enables idle resources to be traded among cloud providers to facilitate utilization optimization and to improve the cost-effectiveness of the service for cloud consumers. However, several challenges are raised for this multi-tier dynamic market, in which cloud providers not only compete for consumer requests but also cooperate with each other. To establish a healthier and more efficient intercloud ecosystem, in this paper a multi-tier agent-based fuzzy constraint-directed negotiation (AFCN) model for a fully distributed negotiation environment without a broker to coordinate the negotiation process is proposed. The novelty of AFCN is the use of a fuzzy membership function to represent imprecise preferences of the agent, which not only reveals the opponent's behavior preference but can also specify the possibilities prescribing the extent to which the feasible solutions are suitable for the agent's behavior. Moreover, this information can guide each tier of negotiation to generate a more favorable proposal. Thus, the multi-tier AFCN can improve the negotiation performance and the integrated solution capacity in the intercloud. The experimental results demonstrate that the proposed multi-tier AFCN model outperforms other agent negotiation models and demonstrates the efficiency and scalability of the intercloud in terms of the level of satisfaction, the ratio of successful negotiation, the average revenue of the cloud provider, and the buying price of the unit cloud resource.

Keywords: Multi-agent negotiation, SLA negotiation, Multi-tier negotiation, Cloud computing, Intercloud

Introduction

The cloud computing paradigm provides on-demand network access to configurable computing resources, and flexible deployment for fast delivery to cloud consumers [1] . One of the key features of cloud computing is providing elastic infrastructure by utilizing virtual technology for the illusion of infinite resources [2–5]. However, the resources of a single cloud provider are limited and cannot meet the diversity of service demand of all consumers [6]. When cloud providers might not have sufficient resources, they will reject the request of the consumer or cancel the low priority service, which will result in a loss of reputation and lead to reduced revenue in the market [7].

To overcome this problem, the traditional cloud computing model needs to evolve into an intercloud ecosystem to provide cloud interoperability to scale up the capacity of cloud resources based on open standard protocols [8]. Therefore, cloud providers should be able to trade their idle resources with each other to help to facilitate optimizing the utilization and to improve the cost-effectiveness of service [9, 10]. For instance, when the cloud service cannot completely satisfy the demand of some consumers in the intercloud environment, a provider could outsource resources for a higher profit. Similarly, a provider could rent unused resources to compensate for the cost of maintaining them for more benefit [7]. Therefore, cloud providers with diverse and heterogeneous resources can be grouped together and share their resources with each other to scale up their resource pools and contribute to an integrated solution for improved competitiveness [2, 11], which would provide the customer-tailored dynamic composition of cloud services to

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satisfy customers with the special quality of service (QoS) requirements [8, 12].

However, the intercloud model raises more challenges than the single cloud model in the market, because the intercloud model is a larger-scale distributed and interconnected system composed of individual cloud consumers and providers. Moreover, the intercloud consists of a competitive and cooperative multi-tier market [2, 13, 14], wherein the provider not only competes for the resource demand but also acts as the consumer to cooperate with other providers, resulting in a dynamic and on-demand federation cloud. Therefore, establishing a healthier and more efficient intercloud ecosystem, which needs an automatic market-oriented approach not only solves the conflict between consumers and cloud providers but also supports coordination among cloud providers to allow scalable resources.

In the cloud market, cloud services have emerged as catalysts of the trading market and have changed the traditional IT services model that brings consumers and providers together [15, 16]. During the service transaction process, cloud consumers must select and compare appropriate services from cloud providers in the market. Since cloud providers offer a variety of services with diverse characteristics, an automatic selection approach is necessary to save time and efficiently match demand. When a transaction is established, the cloud providers must immediately provide the service or resource according to the Service Level Agreement (SLA) [17, 18], which is a legal contract between the provider and consumer that defines demand according to Quality of Service (QoS) parameters, such as availability, response time and price. Service provision or resource allocation is a challenging issue for cloud providers, who aim to configure and deploy their virtualized resources from shared physical resources in a profitable manner. The deployed service needs to fulfill the request specification while attempting to avoid violating the SLA due to the overallocation of resources because of increasing consumer demand. Therefore, negotiations based on SLA act as a bridge between consumers' service selection and providers' service provision, and negotiation is a means of establishing an SLA and resolving conflicts between consumers and providers. During the negotiation process, providers evaluate whether sufficient resources are available to fulfill the SLA request, and consumers select the most suitable service within the budget. The cloud service is terminated when the expiration date specified in the SLA has been reached; additionally, conditions that violate the SLA may lead to termination of the cloud service. Figure 1 shows the lifecycle of a cloud service trading-based SLA.

Currently, agent-based approaches are widely used in cloud computing to solve the SLA negotiation problem [19–22], by providing efficient, flexible techniques to solve various distributed problems. The intercloud can be innately modeled as a multi-agent system, composed of the individual cloud provider and consumer as autonomous agents. These agents make their decisions independently but also work together to address

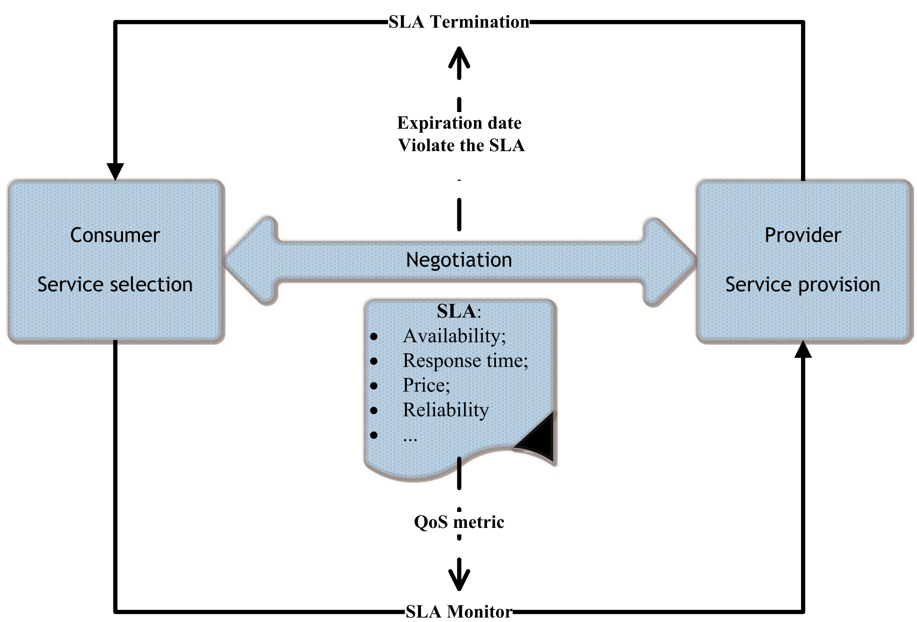

Fig. 1 Lifecycle of a cloud service trading-based SLA

distributed problems through automatic SLA negotiation. Moreover, the intercloud market consists of a two-tiered SLA negotiation framework of consumer-to-provider negotiation and provider-to-provider negotiation [3]. The consumer agent seeks more satisfying cloud services by negotiating with the provider agent, while the provider agent aims to increase revenue by delivering services themselves or contributing integrated services by negotiating with the agents of other providers [23].

However, agent negotiation presents challenges in creating a general framework for modeling a two-tiered multilateral and multi-issues SLA negotiation framework for the intercloud market. First, the decision-making process should not be managed by a central decision-maker. In particular, cloud providers need to dynamically establish ad hoc cooperative partners with competitive relationships [11], while the central entity arises the trust risks and becomes a bottleneck that hinders problem solving [5, 24]. Second, efficient coordination based on two-tiered negotiation requires all negotiators to understand the behavior of their opponents. However, uncertain and incomplete proposal information is exchanged during each tier negotiation [25, 26], so no agent has any a priori information to evaluate the solution for the mutually satisfactory outcome [27].

This paper aims to propose a multi-tier agent-based fuzzy constraint-directed negotiation (AFCN) model to support a fully distributed and autonomous approach for intercloud: consumer-to-provider negotiation and provider-to-provider negotiation. The novelty of the proposed multi-tier AFCN is the use of a fuzzy membership function to represent the preferences regarding issues such as imprecise QoS [28] (e.g., task completion time and price). During the negotiation, this information is shared between negotiating agents in a step-by-step process through the iterative exchange of offers and counteroffers. This added information sharing is of critical importance for the effectiveness of distributed coordination because it not only reveals the opponent's behavior preference but can also specify the possibilities prescribing the extent to which the feasible solutions are suitable for the agent's behavior. Moreover, this information can pass through and guide each tier of negotiation to generate a more favorable proposal that will improve the integrated solution capacity in the intercloud. The experimental results demonstrate that the proposed multi-tier AFCN mechanism outperforms other agent negotiation models and gives full play to the efficiency and the scalability of intercloud in terms of the level of satisfaction, the ratio of successful negotiation, the total revenue of PAs, and the buying price of unit cloud resources in the intercloud market.

The rest of this paper is organized as follows. Section 2 discusses related work. Section 3 describes our formulation of the negotiation of the intercloud problem and presents our proposed multi-tier AFCN model for intercloud. Section 4 describes the detailed multi-tier AFCN process. Section 5 evaluates the performance of our AFCN model, and Section 6 concludes the paper.

Related works

Intercloud refers to a mesh of clouds acting as an interconnected global "cloud of clouds" that is viewed as the natural evolution of a single cloud computing pattern [29]. The vertical supply chain and horizontal federation are two important types of intercloud models [30], as shown in Fig. 2. The vertical supply chain model supports interconnection among clouds at different levels of cloud stack layers (e.g., SaaS to IaaS), and this model may establish the settled federation based on prior agreements [31] without a competitive relationship. The horizontal federation model provides the interconnection among clouds of the same layer (e.g., IaaS to IaaS), and different cloud providers in a horizontal federation dynamically establish ad hoc cooperative partners with competitive relationships [11].

In such an intercloud environment, the market for trading arbitrary cloud services can be supported based on the SLA. With SLAs, consumers have more flexibility to switch among multiple providers [2], while providers can effectively change to other deployment service to meet the customer needs [32]. An SLA defines the QoS parameters [33], which include the functional and nonfunctional properties of cloud services. Functional properties detail what is offered. For instance, Amazon S3 provides storage services, Amazon EC2 offers computing services, and Microsoft SQL Azure (SQL Azure) provides database services. If functional properties fail, cloud consumers' requirements cannot be fulfilled. In contrast, nonfunctional properties detail how well a service is performed. For instance, Amazon S3 guarantees "a monthly uptime percentage of at least 99.9% during any monthly billing cycle". Here, an availability of at least 99.9%, which is one of the important nonfunctional properties of cloud services, is promised. QoS parameters are related to the cloud service layer (SaaS, PaaS, IaaS), except for generic issues such as the price and contract period. The CPU capacity, memory size, and response time are negotiated for IaaS services; the integration, scalability and number of licenses are negotiated for PaaS services; and for SaaS services, the issues involved are reliability, usability and availability.

Currently, the two main categories of methods used to solve the intercloud service selection or service provisioning problem are centralized and distributed methods.

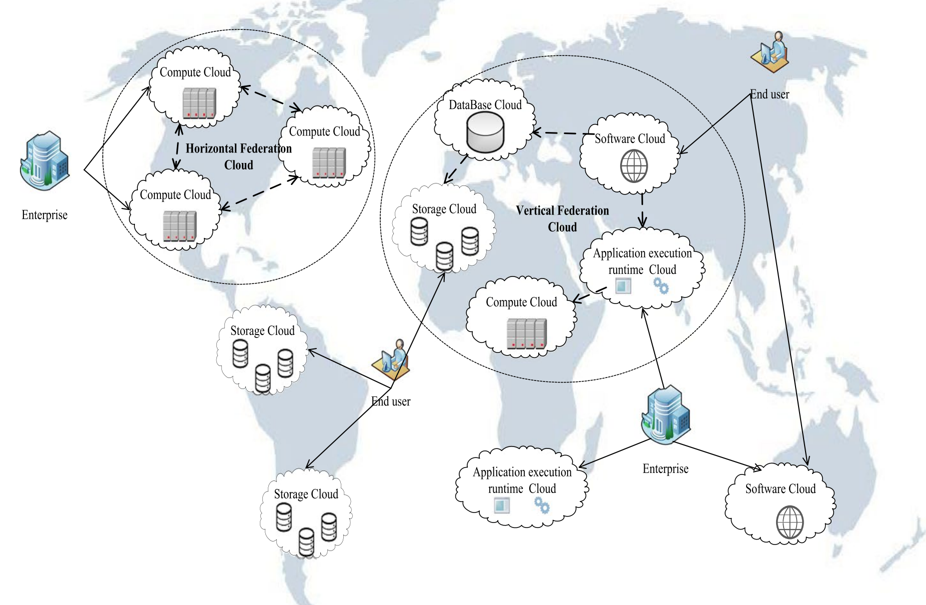

Fig. 2 Intercloud market

With centralized methods, such as genetic algorithms (GAs), ant colony optimization, and simulated annealing, one coordinator or broker [6, 25, 34] controls and decides on the resource provisioning process in the sense that full information sharing is often needed to achieve a near-optimal solution. Wen et al. [35] adopted GAs to dynamically partition scientific workflows over federated clouds to optimize the costs. Anastasi et al. [36] proposed a genetics-based broker to find the near-optimal solution to satisfy various QoS requirements of cloud consumers, which can scale up with hundreds of providers in the intercloud. Zhang et al. [37] adopted ant colony algorithms and complex network theory in open cloud computing federations to realize load balancing in a distributed system. However, centralized methods encounter great difficulties in offering sophisticated decision making and cannot address the intercloud scenario for the distributed service provision problem. Because these cloud providers are independent separate entities, each cloud provider prefers to achieve its optimal individual target rather than achieving the overall best performance of the entire system.

To support multi-issues negotiation in the cloud market, Patel et al. [38] proposed the double auction approach for improving the satisfaction levels of both sides. In the mobile edge cloud federation, Yadav et al. [39] proposed the profit maximized auction approach for efficiency in the price model. These agents bid for items and additional trusted broker agents called auctioneers evaluate the bids and determine the negotiation process by soliciting sensitive strategic information from both sides of the negotiation. These auction models are typically broker negotiation models, and a third-party broker agent of the broker model (i.e., the auction-based model uses an auctioneer agent) is used to solve conflicts among participant agents. However, a major problem with these approaches is that they are essentially centralized scheduling methods and often require sharing of strategic information that would not be revealed to opponents or even to a broker agent; thus, the central entity arises the trust risk and becomes a bottleneck that hinders problem solving.

On the other hand, the agent-based approach, which is characterized by decentralized computation and information processing, is more efficient, flexible, and adaptable to the intercloud market. An agent acts in pursuit of its party's own best interests but also seeks to cooperate with other agents to reach an agreement. When conflicts occur, agents use negotiation to relax, reconfigure, or compose the demand until a compromise is reached or negotiations are terminated. Hassan et al. [31] and Ayachi et al. [40] proposed an agent-based cooperative game-theoretic solution that is mutually beneficial to cloud providers in horizontal dynamic cloud federations, shows better resource allocation performance and requires minimal computation time. Sim [3] proposed an agent-based economic model for analyzing two-tier negotiation in dynamic intercloud, i.e., consumer-to-provider negotiation and provider-to-provider negotiation. The negotiation among providers is modeled as a coalition game for reaching Nash equilibrium. These game approaches assume that each agent has full knowledge of the space of possible deals and the fixed strategies and knows how to evaluate them, which is not appropriate for the decentralized intercloud environment.

Similar to the agent-based model of Sim [3], Siebenhaar et al. [41] proposed a multi-tier cloud negotiation model and adopted the time-dependent bargaining model to increase the flexibility for complex resource provisioning in a vertical cloud federation. Time-dependent, resource-dependent, and behavior-dependent models are three common types of bargaining strategies and are described by [21, 42]. These negotiation models exchange offers and counteroffers interactively to search for an agreement between the two sides. Dastjerdi et al. [21] and Zulkernine et al. [43] applied the time-dependent strategy for SLA negotiation. Wu et al. [20] and Sim [3] proposed an automated negotiation model that takes both time and market factors into account to address the dynamic cloud market environment. In the intercloud, Omezzine et al. [14], Adabi et al. [44] and Shojaiemehr et al. [45] proposed mixed strategies of time, market and behavior agent negotiation to enhance the success rate and satisfaction level of agents; these strategies take the opponent's behavior into account and the agents' behavior regarding making concessions is based on recorded post negotiation data.

These approaches allow the negotiating agents to ensure their satisfaction and avoid the risk of conceding everything to the opponent, thereby increasing their chances of achieving their optimal goals. However, currently, bargaining agents resolve conflicts through continued concessions until the value of issues overlaps or no further solutions can be found because the agent exchanges the uncertain and incomplete proposal information without knowing the agent's preference or utilities.

The proposed two-tiered AFCN model provides a unified framework and uses the fuzzy constraint not only to represent the QoS requirements that must be satisfied but also to specify the extent to which the solutions are suitable for both sides. This information effectively helps the negotiation to arrive at a consensus solution and gives full play to the efficiency and scalability of intercloud. Table 1 presents a summary of the aforementioned approaches.

Intercloud negotiation model

In the classic horizontal IaaS federation scenario, the cloud consumer (e.g., cloud end-user, enterprise application, and cloud application) submits Virtual Machine (VM) requests for task operation to multiple IaaS

Table 1 Summary of the aforementioned approaches

Work	Behavior model	Distributed model	Multi-tier model	Negotiation strategy	Negotiation protocol	Optimality evaluation metric
Wen et al. [35]	GA					cost
Anastasi et al. [36]	GA					cost, scalability
Zhang et al. [37]	Ant Colony					load balancing, scalability
Patel et al. [38]		√			double auction	success rate, profit
Yadav et al. [39]		√			auction	the level of satisfaction, profit
Hassan et al. [31] and Ayachi et al. [40]	Game	√				cost, profit, the level of satisfaction, scalability
Sim [3]	Game	√	√	time, market	bargaining	success rate, the level of satisfaction
Siebenhaar et al. [41]		√	√	time	CNP	the level of satisfaction
Dastjerdi et al. [21]		√		time	bargaining	profit, the level of satisfaction
Zulkenine et al. [43]		√		time	bargaining	the level of satisfaction
Wu et al. [20]		√		time, market	bargaining	cost, the level of satisfaction
Omezzine et al. [14]	GA	√	√	time, market and behavior	bargaining	profit, the level of satisfaction, success rate
Adabi et al. [44]		√		time, market and behavior	bargaining	
Shojaiemehr et al. [45]		√	√	time, market and behavior	bargaining	the level of satisfaction, negotiation speed
This paper	Fuzzy Constraint	√	√	time, market and behavior	bargaining	profit, the level of satisfaction, success rate, scalability

providers by specifying the service level objectives (SLOs) with performance metrics such as completion time, request resources, reliability and availability. These SLOs have a trade-off relationship with price and are regarded as issues in the negotiation process. According to the service requests of consumers, the provider provides access to the VM on a physical machine (PM) if the PM has the required resources available for the assigned task. The PM makes it possible to create virtual resources from a combination of CPU, memory, and storage. This paper focuses on a horizontal IaaS federation, wherein different cloud providers dynamically establish cooperative partners. If the provider in the IaaS federation cannot accommodate the service demand, the service can be outsourced to another provider. Thus, a cloud provider in a federation acts as both an infrastructure provider and a consumer.

The intercloud environment is composed of some large-, medium-, and small-sized federations, and even isolated cloud providers, and consists of a two-tiered negotiation model, as shown in Fig. 3. In the CA-to-PA negotiation tier, the cloud consumer agent (CA) starts a negotiation process for cloud resources with multiple provider agents (PAs). In the federation, a PA negotiating with a CA is named a home PA (hPA); the hPA will hide the internal information of the federation and can assemble cloud resources to provide a single access point for resources. When the hPA experiences potential insufficient resource capacity or needs to provide high-cost resources to meet service requests, the hPA can negotiate with other federation members named foreign PAs (fPAs) for additional resource capacity. In the intercloud, cloud providers need to dynamically establish ad hoc cooperative partnerships with competitive relationships. Thus, in the hPA-to-fPA negotiation tier, each hPA simultaneously negotiates with multiple fPAs to establish federation SLA contracts that comply with all SLA requirements. When some fPAs have the same replaceable service capacities, the negotiation result is determined by the negotiation strategy of agent. The fPAs do not interact directly with the CA in the two-tiered negotiation process. However, the fPAs also act as hPAs to receive requests from the CA. Therefore, we assume that the hPA must hide the CA's identity information in the hPA-to-fPA negotiation. If the negotiation is a success, a CA and PA pair will sign the consumer SLA contract, and the hPA will give notice to the selected fPAs to determine the final federation SLA. The negotiation model uses the symbol descriptions listed in Table 2.

In a decentralized intercloud environment, these agents are independent and have private interests and information; they make local decisions and reach a common satisfactory agreement based on agent negotiation. Meanwhile, these negotiating agents constitute a distributed two-tier network. Thus, a multi-agent system (MAS) model is developed to model the two-tier SLA negotiation problem (TSLAN).

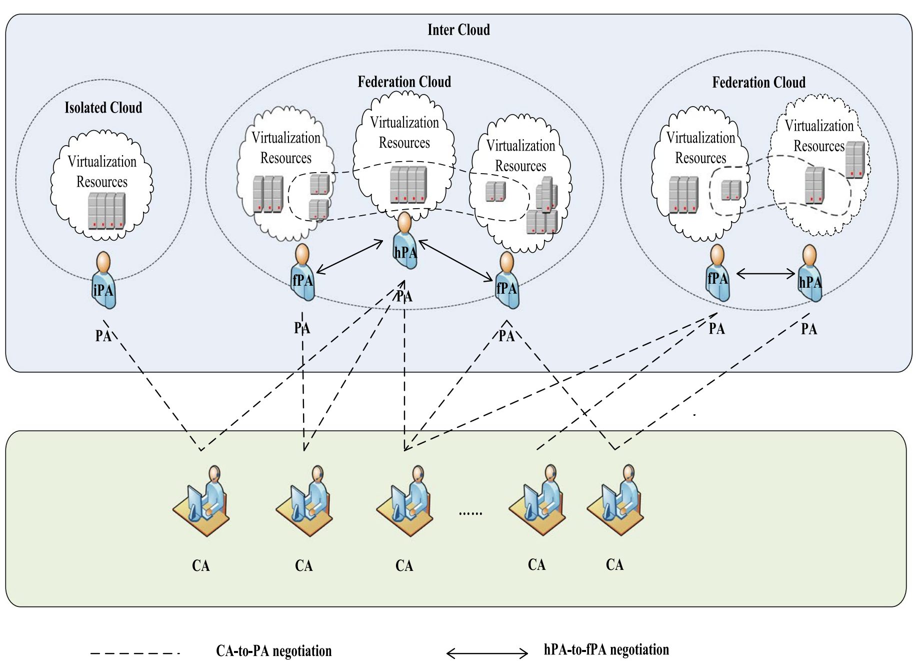

Fig. 3 Intercloud negotiation model

Table 2 Description of symbols

Symbols	Description
CA	Cloud provider agent.
PA	Cloud provider agent. iPA denotes the isolated Cloud providers, hPA is the home Cloud provider in the federation and fPA is the foreign Cloud provider in the federation.
$\Im$	Interrelations between two classes of agents.
$\mathfrak{L}$	The set of interrelations between hPA and fPA.
$\mathbf{U}$	The universe of discourse for the entire distributed fuzzy constraint network (DFCN).
$\mathbf{X}^k$	The tuple of non-recurring objects of the k^{th} agent.
$\mathbf{C}^k$	The set of fuzzy constraints of the k^{th} agent.
$\mathfrak{N}^k$	The fuzzy Constraint Network (FCN) of the k^{th} agent.
$\prod_{\mathfrak{N}^k}$	The intention of a fuzzy constraint network $\mathfrak{N}^k$, which is an n-ary possibility distribution.
$\overline{C_i^k}$	The cylindrical extension of $\mathbf{C}_i^k$ in the space $\mathbf{X}^k$.
$_\alpha \prod_{\mathfrak{N}^k}$	The $\alpha - level$ cut of $\prod_{\mathfrak{N}^k}$, which can be viewed as a set of solutions satisfying all constraints that are greater than or equal to an acceptable threshold α.
$\Psi^k(\mathbf{S})$	The aggregated satisfaction value (ASV) of the solution $\mathbf{S}$.
$F_l(\mathbf{S})$	The fuzzy membership function about the l^{th} issue of the solution $\mathbf{S}$.
ρ, δ, r, λ	The concession according to the own satisfaction degree, the responsive information of the opponent, the time constraint and the market factor, respectively.
$\varepsilon, \Delta\varepsilon, \varepsilon^*$	The threshold, concession value and new threshold, respectively.
$\mathbf{D}(\mathbf{A}, \mathbf{B})$	The distance measure between offer $\mathbf{A}$ and counter-offer $\mathbf{B}$.
$\boldsymbol{G}(\,)$	The distance measure function of two fuzzy sets.
$\mathbf{P}$	The set of feasible solutions.
$\boldsymbol{T}(\,)$	The appropriate measure function between a solution and the counteroffer.
$\mathbf{S}^*$	The prospective solution.
$\mathbf{A}^*$	The new offer, which is the marginal particularized possibility distribution in the space $\mathbf{X}^k$ of the k^{th} agent.
$\mathbf{X}^{k'}$	The tuple of non-recurring objects of the k^{th} agent in the second tier negotiation.
$\mathbf{C}^{k'}$	The set of fuzzy constraints of the k^{th} agent in the second tier negotiation.
$\rho', \delta', r', \lambda'$	The satisfaction, response, time and market factor of the second tier, respectively.
$\Delta\varepsilon'$	The concession value of the second tier.
$\mathbf{P}'$	The set of second tier feasible solutions.

Definition 1
The TSLAN problem can be modeled as a MAS, $(\mathbf{CA}, \mathbf{PA}, \Im, \mathfrak{L})$, which is a 4-tuple, where

- **CA** is a set of cloud consumer agents (CAs), each of which requests cloud service with a specified demand.
- **PA** is a set of cloud provider agents (PAs), each of which can benefit from selling services to the **CA**. There are three subsets of **PA**, $\mathbf{PA} = (\mathbf{iPA} \cup \mathbf{hPA} \cup \mathbf{fPA})$. The **iPA** subset includes isolated cloud providers with no interrelations with other providers in the intercloud; the federation cloud providers of the home PAs, **hPA**, can not only offer their own service to the CA but also purchase services from the other federation members, which are foreign PAs, which make up the **fPA** subset.
- $\Im$ is a set of interrelations between the consumer agent and provider agent **PA**; each interrelation, $\Im\, i, j, s$, specifies a QoS metric, s, that needs to be negotiated between the *ith* CA, **CA**i, and the *jth* PA, **PA** j.
- $\mathfrak{L}$ is a set of interrelations between **hPA** and **fPA**; each interrelation, $\mathfrak{L}_{p,q,o}$, specifies an object, o, that needs to be negotiated between the p^{th} hPA, $\mathbf{hPA}_p$ and the q^{th} fPA, $\mathbf{fPA}_q$.

According to Definition 1, the solution of TSLAN must satisfy all the constraints about the interrelation between $\Im$ and $\mathfrak{L}$. Therefore, agents must negotiate with each other to resolve conflicts about these constraints, and rational agents want a favorable integrated solution. The **hPA**, therefore, will play a critical role in reaching a satisfactory consensus for the TSLAN problem because it is the link between $\Im$ and $\mathfrak{L}$.

In fact, agent negotiation is naturally formulated through the use of distributed fuzzy constraint networks to discover the agent's intention for a common agreement. As shown in Fig. 4, each agent participating

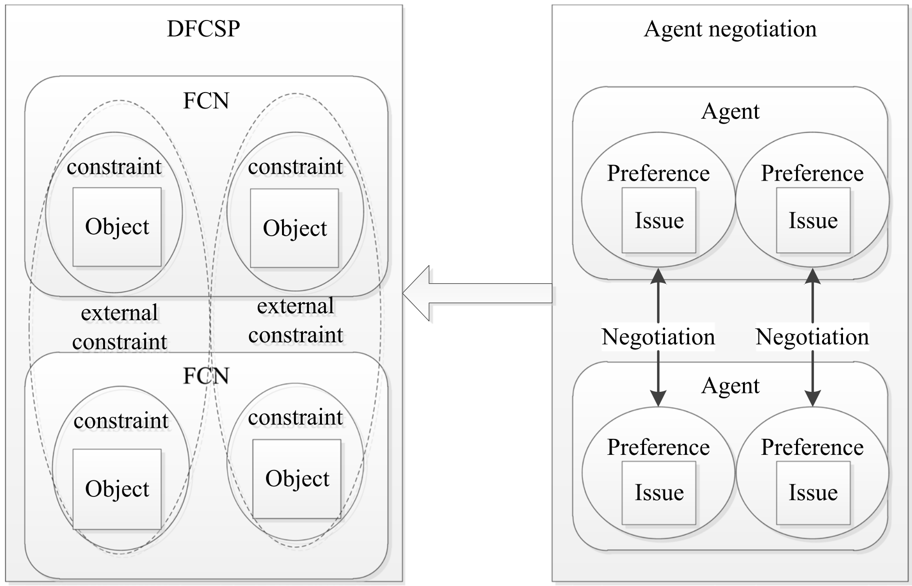

Fig. 4 Agent negotiation formulated by the DFCSP

in the negotiation can be represented as a fuzzy constraint network (FCN); negotiation among agents corresponds to constrained objects and the agent's demands and preferences can also be represented by fuzzy constraints. Therefore, the proposed TSLAN problem can be described as a distributed fuzzy constraint satisfaction problem (DFCSP) interlinked by inter-agent constraints in that an agreement is reached that satisfies all constraints, resulting in a mutually satisfactory outcome. The distributed FCN (DFCN) formulates the agent negotiation in searching for a solution to the DFCSP. Meanwhile, the CA-to-PA and hPA-to-fPA negotiations can be regarded as different tiers of the DFCN.

Definition 2

A DFCN, $(\mathbf{U}, \mathbf{X}, \mathbf{C})$, in an MAS, $(\mathbf{CA}, \mathbf{PA}, \Im, \mathfrak{L})$, can be defined as a set of FCNs, $\{\mathfrak{N}^1, \mathfrak{N}^2, \cdots, \mathfrak{N}^n\}$ [46, 47], where

- $\mathbf{U}$ is the universe of discourse for the entire DFCN;
- $\mathbf{X} = (\cup \mathbf{X}^k)$ is the set of all non-recurring objects in the DFCN, while $\mathbf{X}^k$ is a tuple of non-recurring objects of the k^{th} agent;
- $\mathbf{C} = (\cup \mathbf{C}^k)$ is the set of all fuzzy constraints about the objects $\mathbf{X}$ in the DFCN, and $\mathbf{C}^k$ is the set of fuzzy constraints that involves a set of internal or external fuzzy constraints among the objects in $\mathbf{X}^k$. The external fuzzy constraints of the first-tier agents are interrelated with $\Im$, while the external fuzzy constraints of the second-tier agents are interrelated with $\mathfrak{L}$;
- $\mathfrak{N}^k = \left(\mathbf{U}^k, \mathbf{X}^k, \mathbf{C}^k\right)$ represents the k^{th} agent is connected to other FCNs by a set of external constraints, $\mathbf{C}^k$, while $\mathbf{U}^k$ is the universe of discourse for an FCN.

The set of non-recurring objects, $\mathbf{X}^k$, of the k^{th} agent represents its beliefs, including the agent's attributes (e.g., the QoS metrics) and the knowledge of the environment (e.g., market conditions and negotiation time). The set of fuzzy constraints, $\mathbf{C}^k$, for the k^{th} agent corresponds to a set of restrictions (e.g., budget constraints, QoS preferences, resource capacity, and cost constraints). Moreover, the linking agent, hPA, has different beliefs and constraints for different tiers of negotiation; for example, on one hand, the hPA wants the maximum revenue from the CA, and on the other hand, it aims to achieve the minimum payment for the fPA.

Definition 3

According to Definition 2, the solutions to an FCN, $\mathfrak{N}^k$, represent the intentions of the agents, written as $\prod_{\mathfrak{N}^k}$, and defined as follows.

$$\prod\nolimits_{\mathfrak{N}^k} = \left(\overline{\mathbf{C}_1^k} \cap \cdots \cap \overline{\mathbf{C}_i^k} \cap \cdots \cap \overline{\mathbf{C}_m^k}\right) \tag{1}$$

where for each constraint $\mathbf{C}_i^k \in \mathbf{C}^k$, $\overline{\mathbf{C}_i^k}$ is the cylindrical extension in the space $\mathbf{X}^k$. $\prod_{\mathfrak{N}^k}$ is an n-array fuzzy possibility distribution for objects $\mathbf{X}^k$ that satisfies fuzzy constraints $\mathbf{C}^k$. Meanwhile, $_\alpha \prod_{\mathfrak{N}^k}$ is an $\alpha - level$ cut of $\prod_{\mathfrak{N}^k}$, which can be regarded as a set of solutions satisfying all constraints $\mathbf{C}^k$ that are greater than or equal to an acceptable threshold α. If $_{\alpha}\prod_{\mathbf{X}^k} = \Phi$, it is overconstrained with no solutions, and the agent will adjust the threshold α and use fuzzy constraint relaxation to reconfigure the ranges of the constraints to create new feasible solutions, thereby moving toward a satisfactory consensus solution for all constraints in the DFCN.

Negotiation model of a two-tiered AFCN

The two-tiered AFCN model considers each tier of negotiation behavior between the CA and PA or between the hPA and fPA and provides the main decision-making functionality. First, the agents evaluate the offers or counteroffers and decide whether to accept them. If the solution cannot be accepted by the agent, concessions are calculated through the opponent's responsive state and the intention. Then, a set of feasible solutions are generated with a lower intention based on the decision behavior, and a prospective solution is selected as a new offer/counteroffer. The exchange of offers/counteroffers continues until the termination conditions are met (e.g., the achievement of consensus or failure).

Behavior of the first-tier agent

During the first-tier negotiation, the CAs start their negotiation requests by proposing an ideal offer for cloud resources to the corresponding PAs. Then, the CAs and PAs continuously exchange offers and counteroffers until the negotiations terminate. The agent's behavior involves the following steps: solution evaluation, concession calculation, feasible solution generation, offer generation, and negotiation termination.

Step 1: solution evaluation

An agent's preferences are captured by a utility function based on utility theory. The utility function is formally defined by the aggregated satisfaction value (ASV). The ASV represents the preference over the combination of objects of the agent, and is transferred into a utility value that is used to evaluate the satisfaction of solution $\mathbf{S}$ to decide if an agreement has been reached or concession is necessary. The ASV of solution $\mathbf{S}$ for the k^{th} agent is defined as follows:

$$\Psi^k(\mathbf{S}) = \frac{1}{N_I}\sum_{l=1}^{N_I} F_l(\mathbf{S}) * w_l \tag{2}$$

where $F_l(\mathbf{S})$ is the fuzzy membership degree of the l^{th} issue of the solution, $\mathbf{S}$, N_I is the total number of issues that need to be negotiated and w_l is their respective weighting factors. The fuzzy membership function helps the agent flexibly estimate imprecise preferences about individuals or combinations of multiple issues.

Step 2: concession calculation

The concession strategy is used to calculate the concession to generate a new threshold with a lower intention toward a consensus. The concession strategy takes into account one's own satisfaction degree, the response degree by the opponent, the time factor, and the market factor [48, 49]. These four factors are defined as Satisfaction, Response, Time, and Market.

Satisfaction: The current solution is evaluated by the ASV and is regarded as the satisfaction degree, which is the accepted threshold of intention $_{\varepsilon}\prod_{\mathfrak{N}^k}$. Given the solution $\mathbf{S}$ from the last offer for intention $_{\varepsilon}\prod_{\mathfrak{N}^k}$, the satisfaction value ρ is defined by the ASV as follows:

$$\rho = \Psi(\mathrm{S}) \tag{3}$$

Response: The opponent responsive degree δ is regarded as the opponent's belief about offer $\mathbf{A}$ and the opponent's counteroffer $\mathbf{B}$ and is defined as follows.

$$\delta = 1 - \left(\frac{D(\mathbf{A}_{n-1}, \mathbf{B}_n) - D(\mathbf{A}_n, \mathbf{B}_n)}{D\left(\mathbf{A}_{n-1}, \mathbf{B}_{t,n}\right)}\right) \tag{4}$$

where $\mathbf{A}_{n-1}$ is the offer from the previous round. $\mathbf{A}_n$ and $\mathbf{B}_n$ are the offer and counteroffer in the current negotiation round, respectively. The distance measure $D(\mathbf{A}, \mathbf{B})$ is associated with the offer and counteroffer over the set of issues and is defined as follows:

$$D(\mathbf{A}, \mathbf{B}) = \frac{1}{N_I}\sqrt{\sum_{l=1}^{N_I} G\left(C_l^{\mathbf{A}}, C_l^{\mathbf{B}}\right)^2} \tag{5}$$

where G is the distance measure of two fuzzy sets, which are the possibility distributions of offer $\mathbf{A}$ and counteroffer $\mathbf{B}$ for each of the agent's negotiation issues. Euclidean distance is often adopted as the distance measure. $C_l^{\mathbf{A}}$ is the fuzzy constraint of the l^{th} issue to offer $\mathbf{A}$, and $C_l^{\mathbf{B}}$ is the fuzzy constraint of the same issue to counteroffer $\mathbf{B}$.

Time: The time constraint is the negotiation environment limit. The polynomial function proposed by [42] is used and is defined as follows:

$$r = q + 1(1-q)\left(\frac{n}{n_{\max}}\right)^{1/\beta} \tag{6}$$

where the variable n is the current round of negotiation and $n_{\max}$ indicates the deadline of the negotiation process. Parameter β is the used to control the slope, and q is a constant, that defines the initial concession at the beginning of the second-tier of negotiation ($n=0$).

Market: The market factor λ represents the market conditions, and is defined as follows:

$$\lambda = \frac{\mathbf{D}_n}{\overline{\mathbf{D}_n}} \tag{7}$$

where $\mathbf{D}_n$ is a distance function $D(\mathbf{A}, \mathbf{B})$ between the offer and counteroffer in the n^{th} negotiation round and $\overline{\mathbf{D}_n}$ represents the average distance value among all past negotiations.

An agent's satisfaction level represents the current agent's intention, the opponent's responsive state reveals the opponent's behavior preferences, and the market environments are the negotiation knowledge available for perceiving and reasoning. Then, the agent calculates the concession $\Delta\varepsilon$ as follows:

$$\Delta\varepsilon = \left(\mu_\rho(\rho) \wedge \ \mu_\delta(\delta) \ \wedge \ \mu_r(r) \wedge \ \mu_\lambda(\lambda)\right) \tag{8}$$

where $\mu_\rho(\rho)$, $\mu_\delta(\delta)$, $\mu_r(r)$ and $\mu_\lambda(\lambda)$ denote the desire for a concession according to the satisfaction value, the response degree of the opponent, time constraints, and market influence, respectively.

Then, the agent can determine the new behavior state ε^*, which is defined as follows:

$$\varepsilon^* = \varepsilon - \Delta\varepsilon \tag{9}$$

Accordingly, an agent generates feasible solutions and presents a new perspective solution, which is limited by the new behavior state ε^*.

Step 3: feasible solution generation

Given the intent ${}_{\varepsilon^*}\prod_{\mathfrak{N}^k}$ of the agent with the ε^* level cut, the task of generating a set of feasible solutions $\mathbf{P}$ is defined by the following expression:

$$\mathbf{P} = \left\{\mathbf{S}|\left(\mathbf{S}\in_{\varepsilon^*}\Pi_{\mathfrak{N}^k}\right) \ \wedge \ \left(\varepsilon^* \le \Psi^k(\mathbf{S}) \le \varepsilon\right)\right\} \tag{10}$$

The set of feasible solutions $\mathbf{P}$ is gradually explored in a partial solution space with satisfaction falling below a certain threshold, which allows agents to exploit the rational trade-off space among different issues, rather than a single point value, which is adopted by most bargaining models, or re-exploring proposals over the whole solution space. This ensures that agents move toward a more effective agreement, as the AFCN searches for consensus proposals and guides the behavior toward constraint-satisfying solutions [48].

Then the agent generates the best offer by selecting the most appropriate solution according to the latest counteroffer $\mathbf{B}$ of the opponent and the feasible solution set $\mathbf{P}$. An appropriate measure function is denoted as follows:

$$T(\mathbf{S}, \mathbf{B}) = \frac{1}{N_I}\sqrt{\textstyle\sum_{l=1}^{N_I}\left(\min\left(F_l(\mathbf{S}) \wedge \left(1 - G\left(C_l^{\mathbf{A}}, C_l^{\mathbf{B}}\right)\right)\right)\right)^2} \tag{11}$$

where $F_l(\mathbf{S})$ is the fuzzy membership function of the l^{th} issue of the solution $\mathbf{S}$. $C_l^{\mathbf{A}}$ and $C_l^{\mathbf{B}}$ are the possibility distributions for offer $\mathbf{A}$ and counteroffer $\mathbf{B}$ over the constraint of the l^{th} issue, respectively. Then, the solution with the maximum appropriateness $\mathbf{S}^*$ is proposed by ranking the feasible solutions $\mathbf{P}$, as follows:

$$\mathbf{S}^* = \max\left(T(\mathbf{S}, \mathbf{B})|\mathbf{S} \in \mathbf{P}\right) \tag{12}$$

However, if the agent achieves an additional solution from the second-tier, the agent must be integrated into the first-tier negotiation solution, and the maximum appropriateness solution $\mathbf{S}^*$ of the first-tier is proposed by ranking the feasible integrated solutions of the two tiers, as follows:

$$\mathbf{S}^* = \max\left(T\left(\mathbf{S} \wedge \mathbf{S}^{'*}, \mathbf{B}\right)|\mathbf{S} \in \mathbf{P}\right) \tag{13}$$

where $\mathbf{S}^{'*}$ is the appropriate solution for the second-tier.

Step 4: offer generation

A new offer $\mathbf{A}^* = \left(\mathbf{A}_1^*, \mathbf{A}_2^*, \ldots \mathbf{A}_p^*, \ldots, \mathbf{A}_{N_X}^*\right)$ is generated over the set of objects $\mathbf{X}^k$ about the N_X number of objects. Each element $\mathbf{A}_p^*$ is the marginal particularized possibility distribution in the space $\mathbf{X}^k$ and is defined by [46] as follows:

$$\mathbf{A}_p^* = \mathrm{Proj}_{\mathbf{X}_p^k}\left(P_t \ \cap \overline{\Pi}_{\mathbf{X}_1^k} \ \cap \ \overline{\Pi}_{\mathbf{X}_2^k} \ \cap \ldots \ \cap \overline{\Pi}_{\mathbf{X}_{p-1}^k} \ \cap \overline{\Pi}_{\mathbf{X}_{p+1}^k} \ \cap \ldots \ \cap \overline{\Pi}_{\mathbf{X}_{N_X}^k}\right) \tag{14}$$

where $\overline{\Pi}_{\mathbf{X}_p^k}$ is the cylindrical extension of $\Pi_{\mathbf{X}_p^k}$ in the space $\mathbf{X}^k$.

Step 5: termination

During the negotiation process, negotiation agents exchange offers and counteroffers until either one negotiation succeeds in reaching an agreement or all negotiations fail to find a solution. Then, successful negotiation occurs if the ASV of counteroffer $\mathbf{B}$ or the ASV of next round offer $\mathbf{S}^*$ exceeds the threshold. Negotiation success can be defined as follows:

$$\Psi\left(\mathbf{S}^*\right) \ge \varepsilon^* \ \text{ or } \ \Psi(\mathbf{B}) \ge \varepsilon^* \tag{15}$$

Otherwise, negotiation fails if the solution is empty or the negotiation resources are exhausted, such as if the threshold is less than 0 or the negotiation time runs out.

$$\mathbf{S}^* = \Phi \ \text{ or } \ \varepsilon^* \leq 0 \tag{16}$$

Behavior of the second-tier agent

The behavior of first-tier agents will affect and guide the behavior of second-tier agents; meanwhile, the results of second-tier negotiation can affect the outcome of upper-tier negotiations. In other words, the hPA links the first tier and the second tier, so the two-tier negotiations are not independent. Therefore, the behavior of hPA plays a critical role in achieving a better TSLAN outcome.

During the course of second-tier negotiation, the hPA should first pay attention to the dynamic behavior of the CA and flexibly form a dynamic set of objects with the expected constraint in the second-tier negotiation space. For the hPA-to-fPA negotiation, the hPA can use the average distance function $D(\mathbf{A}, \mathbf{B})$ to measure any object that needs to be negotiated in the second-tier, and the selected objects $\mathbf{X}^{k'}$ are defined as follows:

$$\mathbf{X}^{k'} = \left\{ \mathbf{X}_l^k | D(\mathbf{A}, \mathbf{B}) < \boldsymbol{G}\left(C_l^{\mathbf{A}}, C_l^{\mathbf{B}} \right) \right\} \tag{17}$$

where G is the distance measure of two fuzzy sets, which are the possibility distributions of the offer and counteroffer. $C_l^{\mathbf{A}}$ is the constraint of issue l for $\mathbf{A}$ from the first-tier negotiation, and $C_l^{\mathbf{B}}$ is the constraint of the same issue for counteroffer, $\mathbf{B}$.

The constraint C^k for the objects $\mathbf{X}^{k'}$ must consider one's own desire and the opponent's belief from the first-tier, as follows.

$$C^{k'} = \left\{ C_l^{k'} | C_l^{k'} = C_l^{\mathbf{A}} \wedge C_l^{\mathbf{B}} \right\} \tag{18}$$

Then, the hPA can start the second-tier negotiation with the fPAs in the federation. In addition, the fPAs regard requests from the hPA as having lower-priority demand than the requests of CAs because the second-tier negotiation always launches after the PAs schedule the requests of the CAs. The behavior of the second-tier agent includes the following steps: concession calculation, feasible solution generation, and negotiation termination.

Step 1: concession calculation

The negotiation result of the first-tier determines the final outcome and guides the second-tier negotiation behavior of the agent; for example, the market environment is affected by the consumer's demand and the whole federation's resource supply, and the response from the second-tier agent aims to satisfy the end consumer's demand. Therefore, the behavior of the second-tier agent must incorporate the belief about the concession factors from the first-tier and the current-tier negotiation environments to generate the second-tier margin of concession $\Delta\varepsilon'$, which is defined as follows:

$$\Delta\varepsilon' = \left(\mu_\rho\left(\rho \wedge \rho'\right) \wedge \ \mu_\delta\left(\delta \wedge \delta'\right) \ \wedge \ \mu_r\left(r \wedge r'\right) \wedge \ \mu_\lambda\left(\lambda \wedge \lambda'\right)\right) \tag{19}$$

where ρ', δ', r' and λ' represent the satisfaction, response, time, and market factors of the second-tier, respectively. The second-tier negotiation environment in the federation cloud results in different concession factors, such as the influence of the internal market of the federation on the market factor.

Step 2: feasible solution generation

Furthermore, the rational behavior of the hPA needs to contribute to a better-integrated appropriateness solution. Therefore, the set of second-tier feasible solutions $\mathbf{P}'$ should not only explore the second-tier solution space, but also aim for a better-integrated solution for the CAs. The feasible solution $\mathbf{P}'$ is defined as follows:

$$\mathbf{P}' = \left\{ \mathbf{S} | \left(\mathbf{S} \in {}_{\varepsilon'^*} \prod\nolimits_{\mathfrak{N}^{k'}} \right) \ \wedge \ \left(\varepsilon'^* \leq \Psi(\mathbf{S}) \leq \varepsilon' \right) \wedge \left(\varepsilon'^* > \varepsilon^* \right) \right\} \tag{20}$$

where the set of feasible solutions $\mathbf{P}'$ of the second-tier not only satisfies the threshold of the second-tier but also expects the satisfaction degree to be larger than the behavior state of the upper tier.

Step 3: termination

The termination of the second-tier is only suspended, as the final result needs to wait for the CA's notice. Therefore, when the second-tier negotiation succeeds in reaching an agreement, the fPA does not need to deploy the cloud service in time. In addition, even if all negotiations fail in this second-tier negotiation, the hPA may start a second new negotiation with these fPAs during the next round of the first-tier negotiation.

The final success for the second-tier negotiation can be defined as follows.

$$(\Psi(\mathbf{S}^*) \geq \varepsilon^* \ \text{ or } \ \Psi(\mathbf{B}) \geq \varepsilon^*) \text{ And } \left(\Psi\left(\mathbf{S}'^*\right) \geq \varepsilon'^* \ \text{ or } \ \Psi\left(\mathbf{B}'\right) \geq \varepsilon'^* \right) \tag{21}$$

Otherwise, the negotiation of the second-tier negotiation fails.

Figure 5 shows the complete two-tiered behaviors of the various types of agents. The two-tiered SLA negotiation is more complex because the hPA needs to collaborate with multiple fPAs simultaneously. During the negotiation process, each agent owns its own behavioral process with respect to receiving the proposal

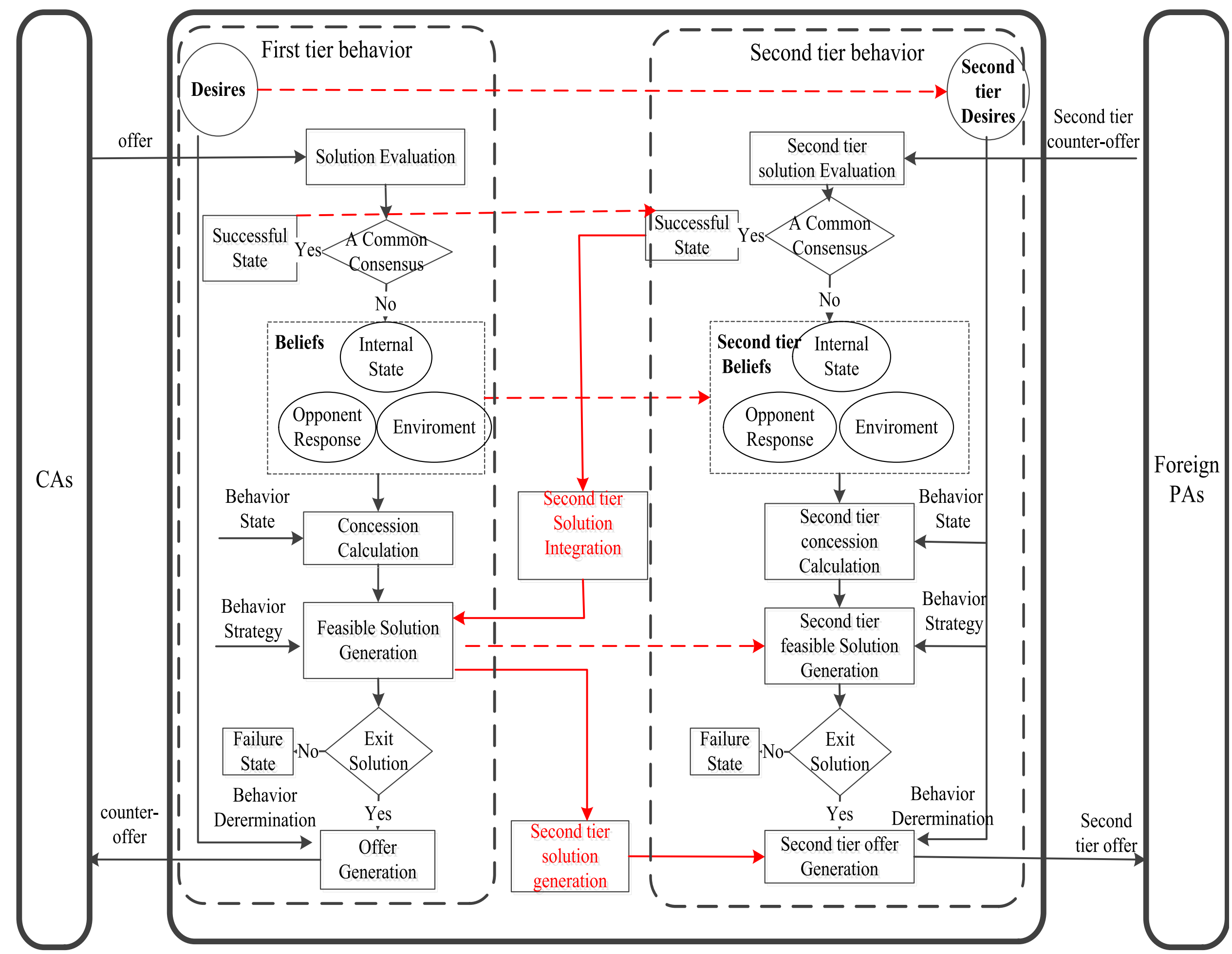

Fig. 5 Negotiation behavior of the two-tiered AFCN

and returning the counterproposal and uses individual desires to guide the negotiation behavior. Normally, the agent receives a proposal from the corresponding agents and then evaluates the solutions using Eq. (2). If consensus exists, the agent terminates the negotiations with a successful state using Eq. (15). Otherwise, the agent will make a concession and generate a set of feasible solutions **P** using Eq. (10) based on the relaxed new behavior state. This new behavior state is guided by the desire related to the satisfaction level ρ in Eq. (3), the opponent's responsive state δ in Eq. (4), the time factor r in Eq. (6), and the market factor λ in Eq. (7). Then, the agent proposes a new prospective solution $\mathbf{S}^*$ using Eq. (12) based on the counteroffer. Finally, the new solution is translated into a new offer $\mathbf{A}^*$ using Eq. (14), which is sent to the corresponding agents.

In addition, the behavior of the hPA is related to the following dual behaviors: the hPA waits for the offer and utilizes its own resources to immediately answer the request of the CA and generates a second-tier offer for renting services from multiple fPAs if its own capacity is not sufficient or if the utilization of its own capacity is not favorable based on the agent's intention. The hPA links the first tier and the second tier and must share information in the second-tier negotiation, such as the desire, behavior state, own solution, and state of termination from the first-tier, as represented by the dotted line in Fig. 5. During the second-tier negotiation process, initially, the hPA determines the issues to negotiate and the constraints using Eqs. (17) and (18), which are translated into the initial offer of the second-tier negotiation and are sent to the multiple fPAs. Then, the agent makes a concession based on Eq. (19), which considers all the factors of the two tiers. Based on the new behavior state, new feasible solutions are generated using Eq. (20). Finally, the agents terminate negotiation in the temporary successful or failed state and await the final result from the first-tier negotiation. However, if any consensus solution is agreed upon, the second-tier solution needs to be integrated into the first-tier negotiation solution, and the agent generates the appropriate solution using Eq. (13) rather than Eq. (12).

Negotiation protocol of the two-tiered AFCN

The negotiation protocol defines the common rules, communication messages, and communication sequence that govern the interaction between negotiating parties. The messages follow the Foundation for Intelligent Physical Agents-Agent Communication Language (FIPA-ACL) [50] standard because its formal semantics and interaction specifications can be used relatively easily to represent the fuzzy concept.

Figure 6 shows the sequence diagram of the negotiation process using UML, which describes the communication between any two lifelines of elements (agents) as a time-ordered sequence of agents' behavior. In UML, the vertical line represents the lifeline of the agent. The thin rectangle on the lifeline represents the activation, which describes the time period in which an operation is performed by the agent. The negotiated PA acting as the hPA splits the negotiation into two-tiered negotiations between multiple CAs and multiple fPAs. The CA-to-PA

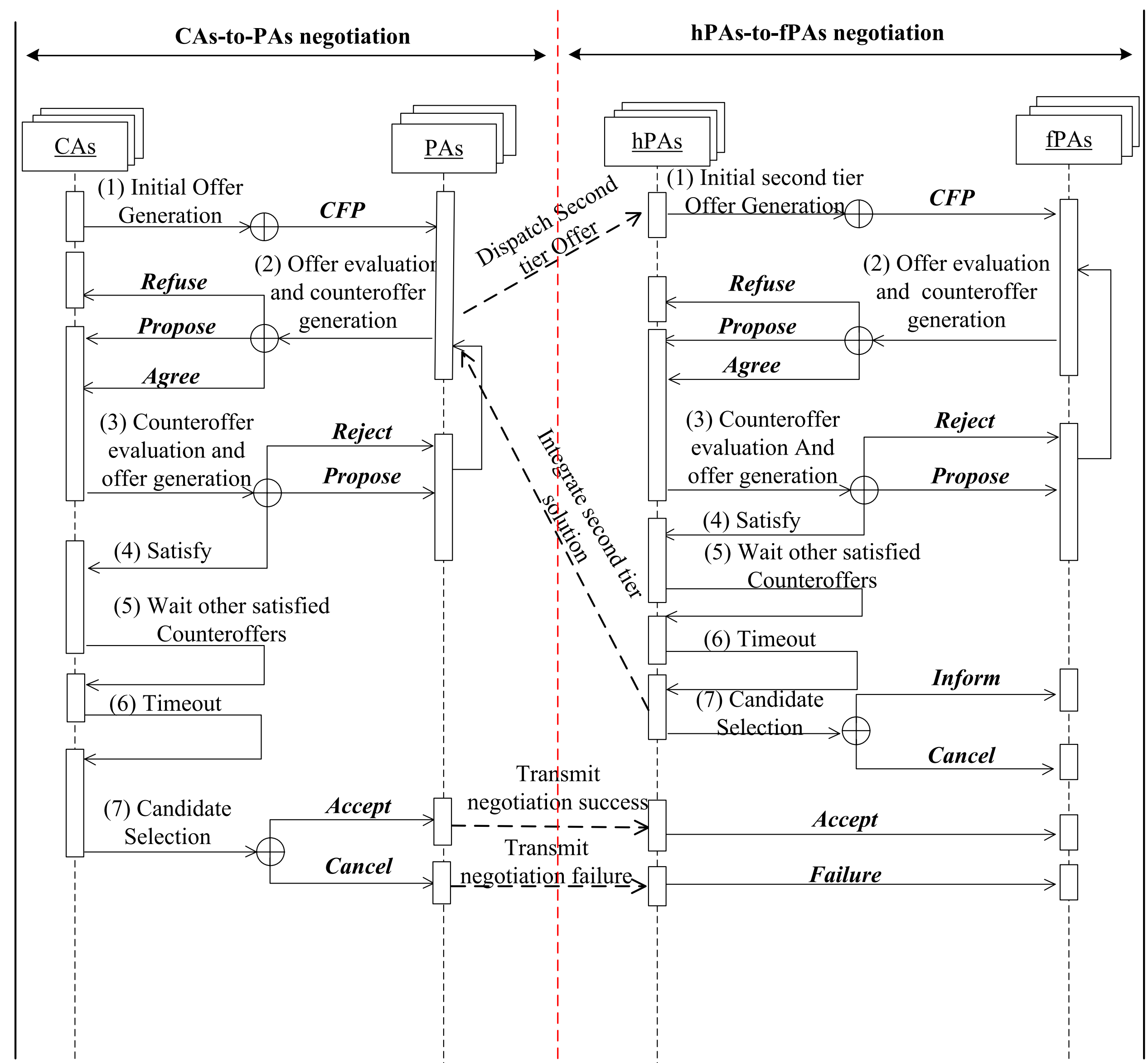

Fig. 6 Negotiation protocol of the two-tiered AFCN

negotiation process is related to the hPA-to-fPA negotiation process to synchronize the communication sequence until the hPA-to-fPA negotiation is complete. To avoid negotiation loops, we assume that the fPA does not transmit the offer from the hPAs to start a new hPA-to-fPA negotiation. In the CA-to-PA negotiation tier, the communication protocol can send the following six messages: ***CFP*** (call for proposal),***Propose***,***Agree***,***Refuse***, ***Accept***,***Reject***, and ***Cancel***. In the hPA-to-fPA negotiation tier, the communication protocol adds the ***Inform*** and ***Failure*** messages. The ***Inform*** message indicates that the hPA agrees with the counteroffer proposed by the fPA, while the result of the negotiation must wait for the CA's determination. The ***Failure*** message notifies the fPA that the result of the negotiation is a failure when the hPA receives the ***Cancel*** message from the CA.

At the beginning of a negotiation, the CA generates an initial offer and proposes a ***CFP*** message to send to the corresponding PAs to request cloud resources. Each PA evaluates the offer and may act as an hPA to dispatch the sub-offer and proposes a new ***CFP*** message to send to the fPAs for outsourcing. Before the hPA proposes a ***Propose*** message to send to the CA, it needs to make a counteroffer based on the results of all hPA-to-fPA negotiations. During the process of negotiation, the CA continuously bargains with multiple PAs through interactive ***Propose*** messages, in addition to bargaining between the hPA and fPA. Afterward, the ***Agree*** message from the fPA informs the hPA that a successful deal has been made, and the hPA can send the ***Inform*** message to the selected fPA to indicate that the result of the negotiation must wait for the CA's information. Thus, each PA finally proposes an ***Agree*** or ***Refuse*** message to send to the corresponding CA, and the CA selects the optimal counteroffer from the PA that agreed with the deal and sends an ***Accept*** message to the PA. Moreover, the CA sends a ***Cancel*** message to the other candidate PAs, and the hPA transmits the result of the negotiation and sends an ***Accept*** or ***Failure*** message to the corresponding fPAs. Accordingly, agreements are reached across the two tiers by means of the negotiations of each independent agent.

Figure 7 shows the algorithm of the negotiation process of a two-tiered AFCN. If the hPA received the offer from the CA, the hPA can start the second tier negotiation with the fPAs in the federation and propose a counteroffer based on the integrated solution of the two tiers (line 14–21). During the second tier negotiation process, the hPA proposes a ***Inform*** message to send to the fPA if the hPA reaches a consensus with the fPA. When the hPA receives the ***Accept*** message from CA, the hPA will send the ***Accept*** message to fPA simultaneously, which informs the final success for the second tier negotiation (line 37–39). Otherwise, the hPA received the ***Cancel*** message from the CA, and the hPA will send the ***Failure*** message to fPA (line 42–43). The process of two-tiered negotiation terminates.

Performance evaluation

To evaluate the performance of the proposed two-tiered AFCN model in the intercloud, experiments were implemented using the Java Agent Development Environment (JADE) platform, which is currently the most popular platform for developing MAs. Moreover, CloudSim [51], which is an appropriate toolkit to provide a comprehensive simulation basis that enables an on-demand model to perform an experiment for necessary facilities, parameters, and conditions related to evolving intercloud infrastructures [52, 53], was used as the cloud simulation platform.

In the simulation environment, there are ten IaaS providers, and each provider data center comprises 120 heterogeneous PMs. Each PM is modeled to have 10 CPU cores and 32 GB of RAM and 2 TB of storage. Specifically, the CPU performance for the first group of 30 PMs is set to 1000 million instructions per second (MIPS); the performance for the second group of 30 PMs is set to 2000 MIPS, and the performance for the final group of 30 PMs is set to 4000 MIPS. For example, the Amazon Elastic Compute Cloud (EC2) delivers different types of instances characterized by the size of the CPU (i.e., small, medium, or large).

The consumer submits resource requests to the simulated data center for task operation. Each request runs with a varied workload, which is modeled to generate a CPU load according to a uniformly distributed random variable with 1000–40,000 MIPS and a performance completion time according to a uniformly distributed random variable ranging between 10 and 20 minutes.

Ten negotiation rounds are allowed and the negotiation is terminated with a failure if no agreement is reached. The CAs and PAs had sufficient time to complete negotiation within 6 rounds in all experiments. The results are validated with a z-test, which shows that some experiments must be repeated at least 100 times to guarantee that the difference between the means is not significant (i.e., the value of $p > 0.05$). Therefore, for all experiments, 150 instances were randomly generated to assess the performance in each experiment.

To evaluate the performance of the two-tiered negotiation model in the intercloud market, the negotiation efficiency, such as a high degree of satisfaction and more agreement being reached for the negotiators is the most important property of the global outcome [54]. Thus, efficiency involves the combined ASV, and the ratio of successful negotiation, which is typically selected in most of the previous research [21, 43, 55]. In addition,

Algorithm: negotiation process of two-tiered AFCN

```
offer ← CA.initOffer()
CA sends CFP(offer) message to PA
while negotiation time limit is not exceeded
    PA evaluates the offer from CA
    if offer can be accepted then
        PA sends Agree() message to CA;
    elseif PA is not hPA then
        if negotiation is needed then
            PA sends Propose( counteroffer ) message to CA;
        elseif find not solution then
            PA sends Refuse() message to CA
        endif
    elseif PA is hPA then
        hPA negotiates with fPAs in the federation
        if any deal between hPA and fPA
            hPA sends Inform() message to fPA
            hPA integrates the second tier countoffer to first tier counteroffer
        endif
        hPA sends Propose( counteroffer ) message to CA;
    endif
    CA evaluates counteroffer from PA
    if counteroffer need negotiation then
        CA sends Propose(offer) message to PA;
    elseif can agree on counteroffer then
        CA adds the counteroffer to candidate list;
    elseif find no feasible solution about counteroffer then
        CA sends Reject() message to PA;
        if (PA is hPA) and (any deal exists between hPA and fPA) then
            hPA sends a new CFP() message to fPA;
        endif
    endif
    Wait other satisfied counteroffer until timeout
    CA evaluate the all counteroffer from candidate list
    if counteroffer is optimal then
        CA sends Accept() message to PA;
        if (PA is hPA) and (any deal exists between hPA and fPA) then
            hPA send Accept () message to fPA;
        endif
        terminate the negotiation with success;
    else
        CA sends Cancel() message to PA;
        terminate negotiation with failure;
    endif
endwhile
```

Fig. 7 Negotiation process of two-tiered AFCN for their private interests, the consumer agents aim to minimize the buying price, whereas provider agents aim to maximize revenue [56]. Thus, the local optimality of each agent is another desirable property and is domain-specific.

Moreover, since the demand and supply of the intercloud market can affect the performance of the negotiation model, scalability is an important feature in the intercloud market. The agent negotiation model should be designed to enlarge the scale of the cloud market or federation cloud. In addition, it should guarantee the best efficiency in matching the consumer's demand and provider's supply.

Performance comparisons among different negotiation models

Li [48] adopted the one-tiered AFCN for SLA negotiation in the traditional cloud market and outperformed other agent-based approaches, so we use that approach as a benchmark when we investigate the performance of two-tiered negotiation models. For the intercloud market, to evaluate the impact of the negotiation models and prove that the intercloud can deliver better service quality, the performance of two-tiered AFCN model (denoted as AFCN-AFCN) is compared with that of typical bargaining models used in the case of two-tiered SLA negotiation, including the model that considers the time factor proposed by Dastjerdi et al. [21], denoted as T-T, the model that considers the time and market factors proposed by Wu et al. [20], denoted as T_M- T_M, and the model that considers time, market and behavior factors proposed by Omezzine et al. [14] denoted as T_M_B- T_M_B.

All these bargaining models consider the time factor, and their time-dependent concession strategies are similar. To compare the rationality of the bargaining model, we select the same polynomial decision function, $t = q + (1-q)\left(\frac{r}{r_{\max}}\right)^{1/\beta}$, to determine how the values of an issue are automatically adjusted by the agents based on the time factor.

Figure 8 shows the average combined ASV derived from successful negotiation with a resource demand/supply ratio that is increasing from 0.1 to 1.5. The maximal average combined ASV is 2 (namely, the ASV of the CA is 1, and the ASV of the PA is 1). The average combined ASV decreases with an increasing resource demand/supply ratio because PAs have fewer available resources to satisfy the specific request from the CA. Moreover, the two-tiered AFCN-AFCN model in the federation cloud achieves the highest average combined ASV. The models that include behavior factors (AFCN-AFCN and T_M_B-T_M_B) in the federation always achieve a higher average combined ASV than that achieved without federation negotiation experience in the one-tier AFCN model. However, the T-T model achieves a lower average combined ASV than that achieved by the one-tier AFCN model because the time model achieves the worst solution for negotiators due to the substantial oscillation and excessive concessions when an agreement is approached. Moreover, when the demand/supply ratio varies from 1.2 to 1.5, the T_M-T_M model achieves a lower average combined ASV than the one-tier AFCN model because when the demand exceeds the supply, the PAs of the federation keep their ASV to maximize their profit, thereby reducing collaboration.

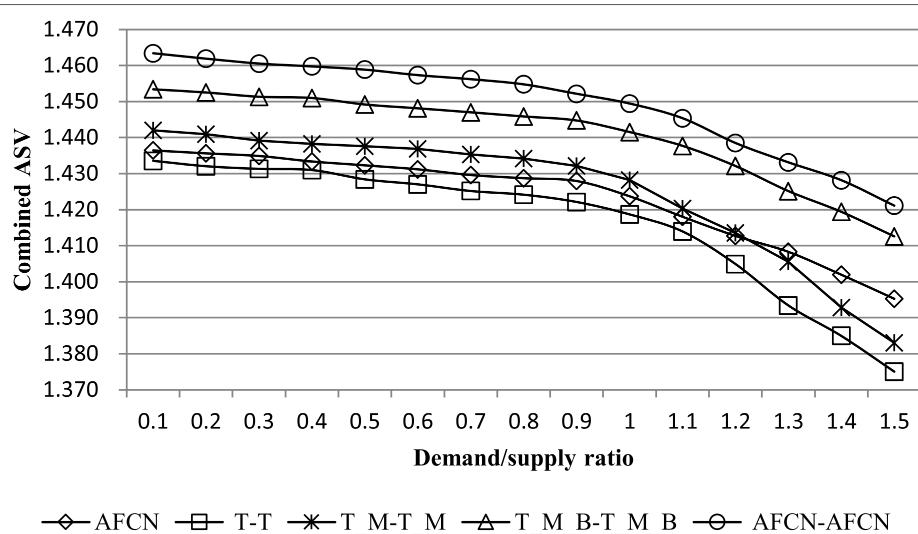

Fig. 8 Average combined ASV for different negotiation models

Table 3 shows the satisfaction level achieved by the CA or PA. As the demand/supply ratio increases from 0.1 to 1.5, the AFCN-AFCN model achieves a better ASV for the CA or PA than the other models used in the same tier negotiation. The T-T model is a fairer negotiation model, and the concession rates of CA and PA are similar because they reach an agreement in the same amount of negotiation time. The models involving the market factor (T_M, T_M_B, and AFCN models) are influenced by variation in the resource demand/supply ratio. When the demand is less than the supply, the PAs reduce their ASV to strive for a successful negotiation; when the demand is greater than the supply, the PAs will raise their ASV to maximize their profit.

Figure 9 shows that the ratio of successful negotiations decreases as the demand/supply ratio increases from 0.1 to 1.5. When the demand/supply ratio varies from 0.1 to 0.8, the success ratio is greater than 0.90 for all negotiation models with sufficient resources. Again, the AFCN-AFCN model achieves a higher success ratio than the two-tiered Time, T_M, and T_M_B models. However, as Fig. 9 shows, the one-tiered AFCN model achieves a

Table 3 Inequality degree between the CA and PA for different negotiation models

Demand/ Supply ratio	T-T			T_M-T_M			T_M_B-T_M_B			AFCN-AFCN		
	CA	PA	Inequality	CA	PA	Inequality	CA	PA	Inequality	CA	PA	Inequality
0.1	0.717	0.716	0.001	0.730	0.711	0.019	0.736	0.718	0.018	0.737	0.726	0.011
0.2	0.717	0.716	0.001	0.728	0.712	0.016	0.735	0.718	0.017	0.736	0.726	0.010
0.3	0.716	0.716	0.000	0.725	0.714	0.011	0.731	0.720	0.011	0.732	0.728	0.004
0.4	0.716	0.715	0.001	0.723	0.715	0.008	0.727	0.723	0.004	0.730	0.729	0.001
0.5	0.714	0.714	0.000	0.721	0.716	0.005	0.726	0.723	0.003	0.729	0.729	0.000
0.6	0.714	0.713	0.001	0.715	0.722	−0.007	0.722	0.726	−0.004	0.727	0.731	−0.004
0.7	0.713	0.712	0.001	0.712	0.723	−0.011	0.719	0.727	−0.008	0.725	0.732	−0.007
0.8	0.713	0.712	0.001	0.709	0.725	−0.016	0.717	0.729	−0.012	0.721	0.733	−0.012
0.9	0.712	0.711	0.001	0.704	0.728	−0.024	0.712	0.732	−0.020	0.718	0.734	−0.016
1.0	0.710	0.709	0.001	0.700	0.729	−0.029	0.704	0.737	−0.033	0.711	0.739	−0.028
1.1	0.707	0.706	0.001	0.688	0.732	−0.044	0.699	0.739	−0.040	0.705	0.740	−0.035
1.2	0.702	0.702	0.000	0.678	0.736	−0.058	0.691	0.741	−0.050	0.697	0.741	−0.044
1.3	0.697	0.696	0.001	0.669	0.736	−0.067	0.684	0.742	−0.058	0.691	0.743	−0.052
1.4	0.692	0.692	0.000	0.654	0.738	−0.084	0.677	0.742	−0.065	0.685	0.744	−0.059
1.5	0.688	0.687	0.001	0.646	0.736	−0.090	0.670	0.742	−0.072	0.677	0.744	−0.067

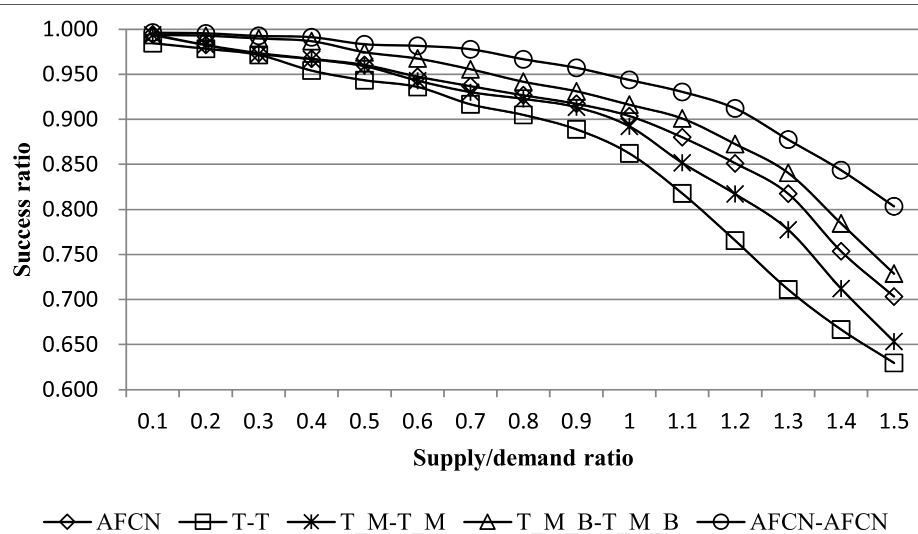

Fig. 9 Success ratio for different negotiation models

higher success ratio than the T_T model and T_M-T_M model. Market factors (e.g., the opportunity and competition factors) significantly affect the behavior of the T_M model, and the members of the federation become competitive in sharing resources, which results in a less successful negotiation in the federation.

Figure 10 shows that the buying price per unit resource of the CAs increases gradually as the demand/supply ratio increases from 0.1 to 1.5 because PAs can allocate fewer resources and experience increased costs. Again, the AFCN-AFCN two-tiered negotiation model achieves the lowest price per unit resource of the CAs and outperforms the other models for demand/supply ratios from 0.1 to 1.5. However, when the demand/supply ratio varies from 0.6 to 1.5, the T_M-T_M model achieves a higher buying price than the one-tier AFCN model. Furthermore, the T-T model achieves the highest price per unit resource.

Figure 11 shows the average revenue of the PAs derived from successful negotiations as the demand/supply ratio varied from 0.1 to 1.5. As indicated in Fig. 11, the AFCN-AFCN model outperforms the other models in terms of average revenue. Additionally, the T_M-T_M model achieves higher average revenue than the

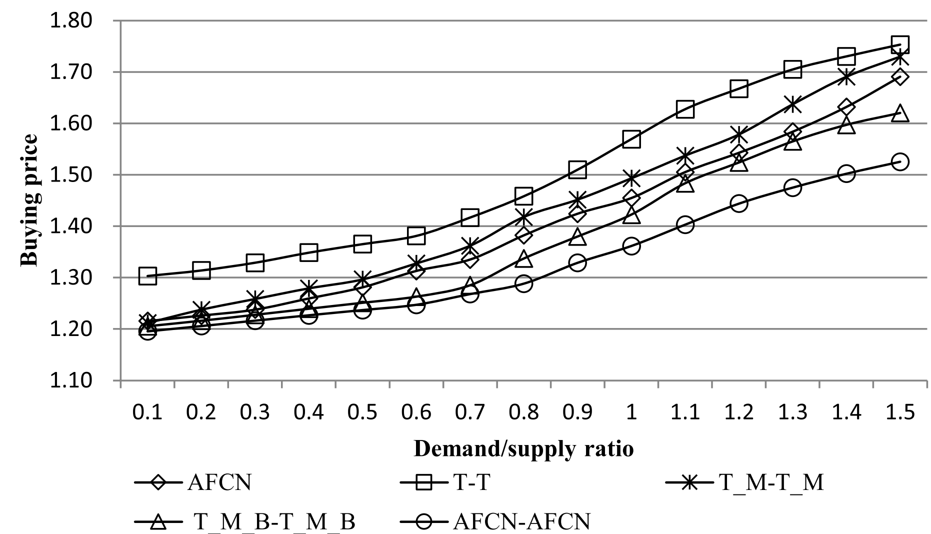

Fig. 10 Buying price for different negotiation models

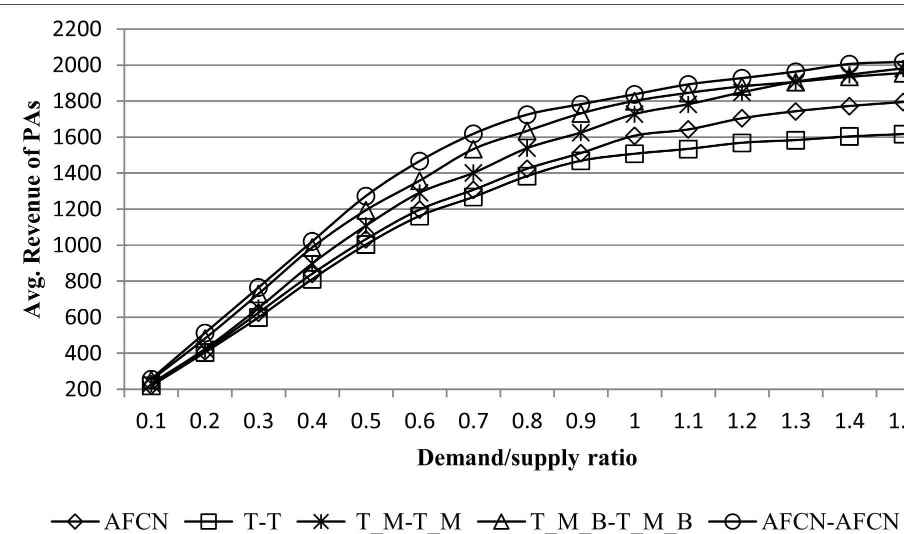

Fig. 11 Average revenue of PAs for different negotiation models

T_M_B-T_M_B model when the demand/supply ratio varies from 1.3 to 1.5.

Thus, a one-tiered AFCN can achieve a higher average combined ASV than the T-T model and a higher success ratio than the T-T and T_M-T_M models. These results show that some bargaining negotiation models (Time, T_M, T_M_B) are unable to give full play to the intercloud efficiency because these models resolve conflicts through continued concessions until the values of all issues overlap and further possible solutions cannot be found.

The market-driven agents within the T_M, T_M_B, and AFCN models are utility-maximizing agents, and an agent seeks its own interests based on making minimally sufficient concessions [57]. However, the T_M model focuses on the numbers of competitors and patterns to represent the market factor influence. The T_M_B and AFCN models take into account the behavior of the opponent agent, which is a major factor in interpreting and processing to guide the agent's behavior to improve the satisfaction level and avoid the risk of conceding everything to the opponent, thus increasing their chances to achieve their best goals.

Moreover, the AFCN represents the opponents' behavior information using a fuzzy membership function to evaluate the proposal, and to specify the possibilities prescribing the extent to which the feasible solutions are suitable for both sides. As a consequence, the experimental results demonstrate that the negotiation performance can be improved by employing the two-tiered AFCN model.

Performance comparisons between federation and isolated providers

The real intercloud environment is composed of some large, medium, and small federations and even isolated cloud providers. To evaluate the impact of federation PAs and isolated PAs in the case of the intercloud market, the number of providers in the federation is considered a simulation parameter, and the performance of 50% federation PAs (the federation consists of half of the providers) adopting the different two-tiered negotiation models (T-T, T_M-T_M, T_M_B- T_M_B, AFCN-AFCN) and isolated PAs adopting the one-tiered negotiation models (T, T_M, T_M_B, AFCN) is compared in terms of the success ratio and total revenue of PAs.

Figure 12 shows that the success ratio decreases gradually as the demand/supply ratio increases from 0.1 to 1.5. The federation provider always achieves a higher success ratio than the isolated PA. Moreover, a federation provider adopting the AFCN model achieves the highest success ratio. Isolated PAs need to provide a better solution than federation PAs to achieve successful negotiation, which results in a lower success ratio. However, as the demand increases, the PAs of the T_M-T_M federation allocate resources more cautiously, which leads to the federation PAs achieving approximately the same success ratio as that achieved by isolated PAs.

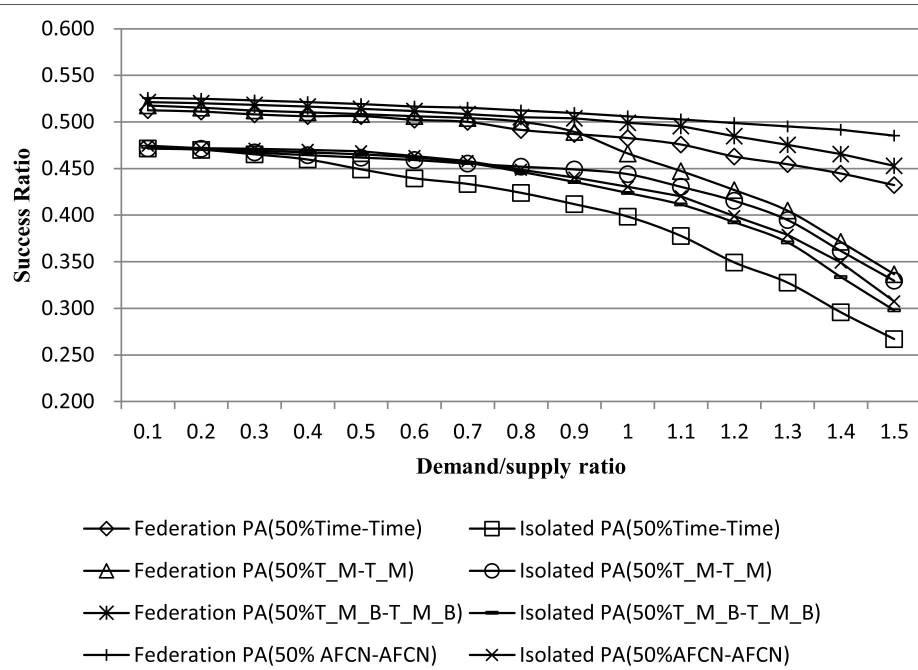

Fig. 12 Success ratios of federation and isolated PAs for different negotiation models

Table 4 shows the average revenue of the PAs derived from successful negotiations as the demand/supply ratio varies from 0.1 to 1.5. Again, the federation provider always achieves higher revenue than the isolated provider, and the federation provider adopting the AFCN model achieves the highest revenue. For the same reason, in term of the success ratio, the isolated provider adopting the Time model achieves lower revenue than when the T_M, T_M_B, and AFCN models are adopted..

Scalability comparisons among different negotiation models

To evaluate the scalability of the negotiation model, the experiments evaluate the scalability performance in terms of how many providers participate in the federation. Hence, we varied the number of PAs from 10 to 200. As the demand/supply ratio increases from 0.1 to 1.5, the number of cloud consumers dynamically increases simultaneously.

Figure 13 shows the average combined ASV derived from successful negotiation with the resource demand/supply ratio increasing from 0.1 to 1.5. Figure 13(a), (b), (c), and (d) show that the performances of the Time, T_M, T_M_B and AFCN models varied as the number of providers increased from 10 to 200. The average combined ASV decreases with an increasing resource demand/supply ratio because the PAs have fewer available resources to satisfy the specific request from the CA. Meanwhile, the average combined ASV increases with the number of PAs for all negotiation models because a large number of PAs can offer more diverse resource capacity to satisfy a large number of specific QoS demands from CAs. When the demand/supply ratio varies from 0.1 to 1.0, the Time model achieves less growth in terms of the average combined ASV as the number of PAs increases. In contrast, the T_M model achieves less growth when supply is short. For the behavior negotiation models with PA variation, T_M_B and AFCN always continue to increase as the demand/supply ratio varies from 0.1 to 1.5, while the AFCN model achieves the highest scalability in terms of the combined ASV.

Figure 14 shows that the ratio of successful negotiations decreases as the demand/supply ratio increases from 0.1 to 1.5, while the success ratio increases as the number of PAs increases for all negotiation models. The T_M_B and AFCN behavior models show an increase in the success ratio as the number of PAs increases. The Time model achieves obvious scalability when the demand/supply ratio varies from 1.0 to 1.5 due to the more diverse service capacity. However, the T_M model shows a small variation in the success ratio as the number of PAs changes when the demand/supply ratio varies from 1.0 to 1.5 because all PAs allocate resources more strictly as the demand/supply ratio increases.

Figure 15 shows that the buying price of unit resources increases gradually as the demand/supply ratio increases from 0.1 to 1.5. The buying price decreases with an increasing number of PAs for all negotiation models. However, the Time model shows an indistinct decrease in the buying price as the number of providers increases, while the T_M model achieves obvious scalability when the demand/supply ratio increases from 0.1 to 1.0. Again,

Table 4 Avg. revenue of federation and isolated PAs for different negotiation models

Demand/ Supply ratio	T-T		T_M-T_M		T_M_B-T_M_B		AFCN-AFCN	
	Federation	Isolated	Federation	Isolated	Federation	Isolated	Federation	Isolated
0.1	237	214	269	245	272	251	**282**	256
0.2	453	432	498	482	527	497	**557**	503
0.3	660	628	743	673	789	725	**806**	746
0.4	890	822	1032	904	1089	946	**1158**	977
0.5	1080	997	1279	1083	1316	1092	**1437**	1154
0.6	1276	1181	1488	1280	1528	1306	**1664**	1347
0.7	1435	1311	1638	1388	1719	1483	**1817**	1534
0.8	1518	1402	1767	1544	1828	1592	**1964**	1644
0.9	1613	1513	1847	1676	1925	1682	**2047**	1736
1.0	1665	1579	1933	1767	1997	1780	**2136**	1813
1.1	1714	1616	1997	1884	2031	1809	**2197**	1894
1.2	1731	1631	2043	1938	2078	1838	**2267**	1928
1.3	1744	1665	2108	2033	2132	1853	**2299**	1947
1.4	1768	1682	2129	2084	2171	1894	**2343**	1979
1.5	1793	1698	2159	2098	2198	1921	**2388**	2011

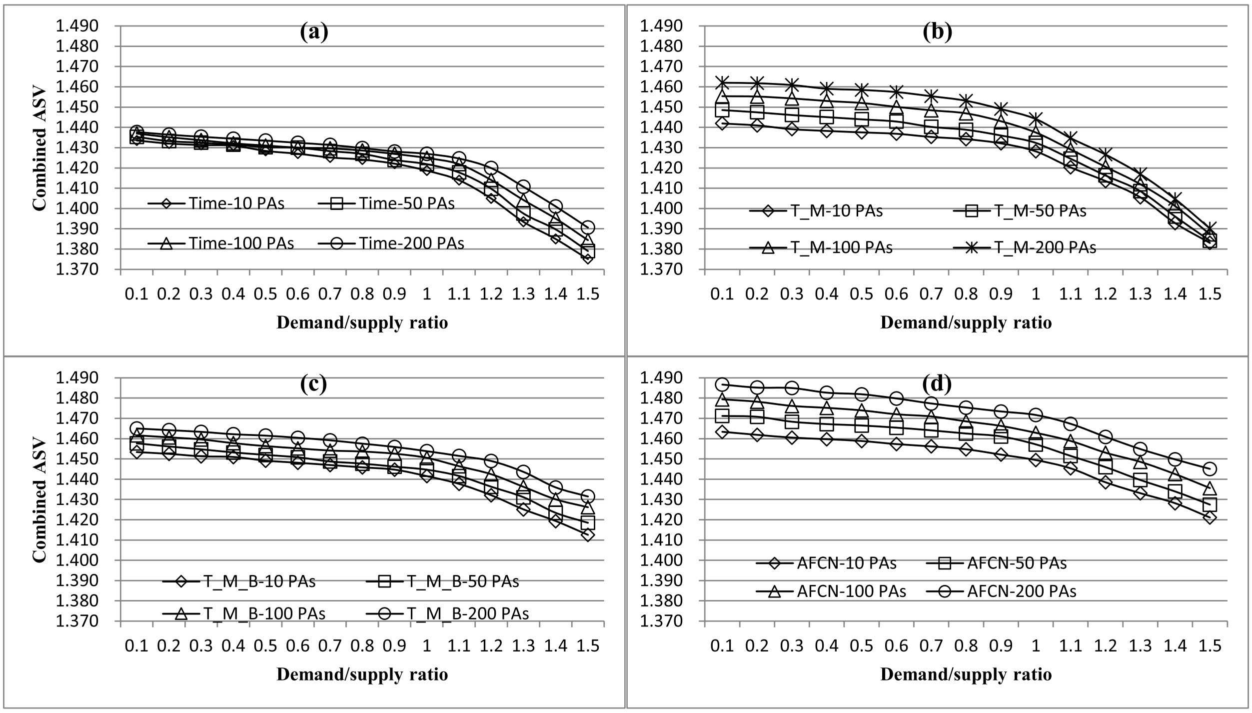

Fig. 13 Average combined ASV for different numbers of PAs

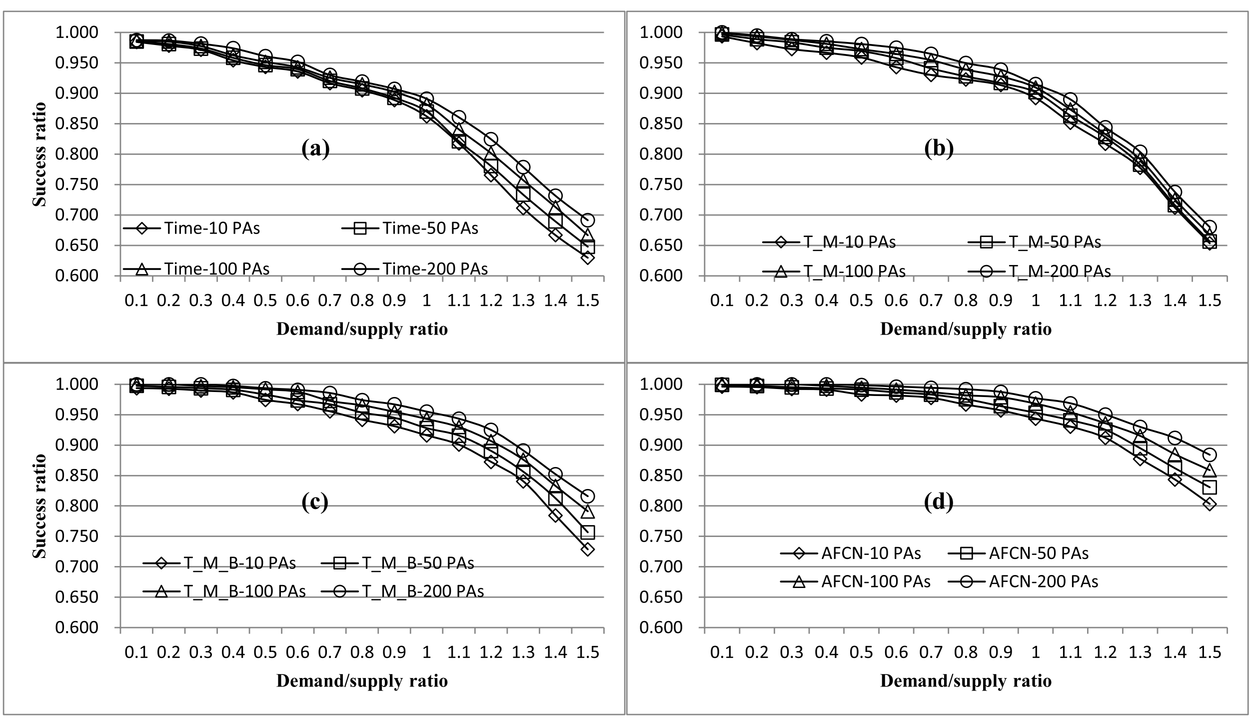

Fig. 14 Success ratio for different numbers of PAs

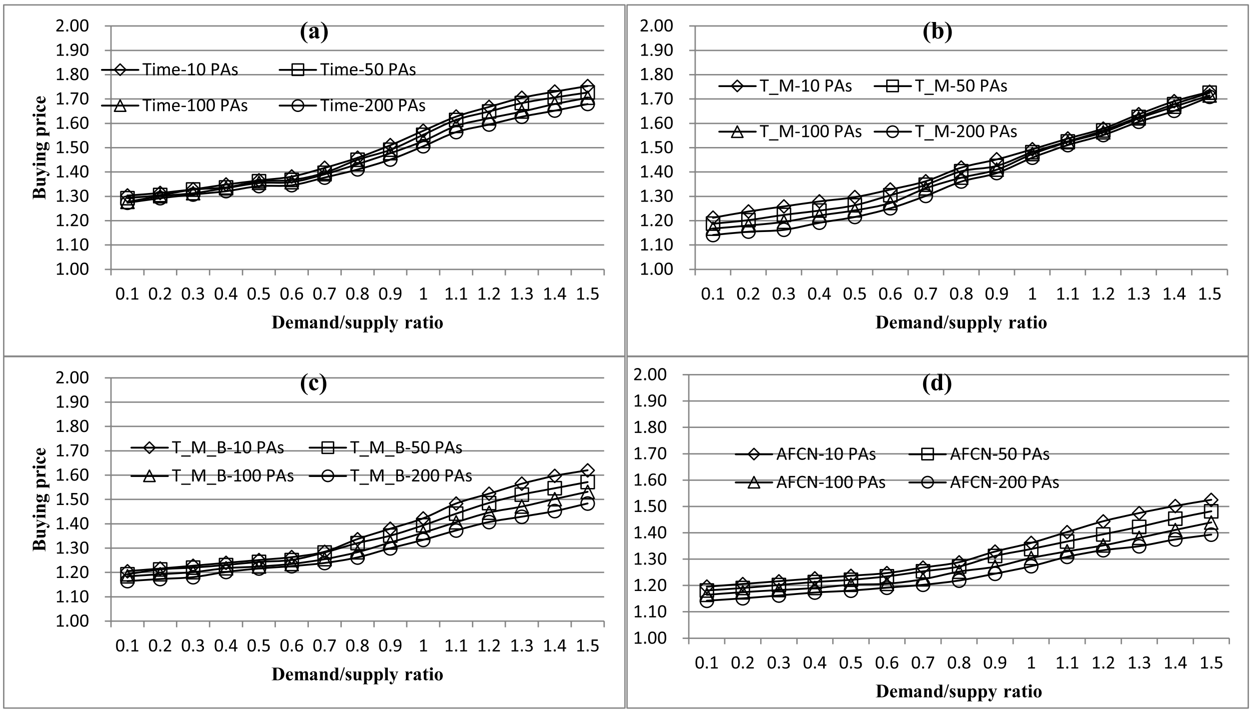

Fig. 15 Buying price for different numbers of PAs

the T_M_B and AFCN can maintain higher scalability in terms of the buying price as the number of PAs increases.

Figure 16 shows that the average revenue of the PAs increases gradually as the demand/supply ratio increases from 0.1 to 1.5. The average revenue increases with an increasing number of PAs for all negotiation models. The Time model achieves less growth in terms of average revenue. However, the T_M model cannot maintain growth in terms of average revenue as the number of PAs changes. When the demand/supply ratio varies from 1.0 to 1.5, the T_M model shows reduced scalability due to the lower success ratio. Again, the T_M_B and AFCN behavior models maintain remarkable scalability in terms of average revenue as the number of PAs increases.

According to the experimental results and performance comparisons, the negotiation strategy of the agents impacts the performance of the two-tiered negotiation. For the Time model, time is a predominant factor adopted to guide behavior, which is not suitable for the time insensitivity of automated negotiation. However, the Time model makes fixed and continued concessions based on the time function until the values of the issues overlap, which results in solutions that are worse than those achieved by the other models due to the greater oscillation and excessive concessions when an agreement is approached. For the two-tiered Time-Time model, the outcome of the second-tier is not able to promote the performance of the overall negotiation. Therefore, the one-tiered and two-tiered Time model provides little support for the efficiency and scalability of the federation. This support is achieved simply because a large number of PAs or federation members can offer more diverse resource capacity to satisfy a large number of specific QoS demands from CAs. However, when CAs and PAs adopt the concession strategy with the same concession rate, the Time model is a fairer negotiation model, as Table 3 indicates.

The behavior of the T_M model and that of the two-tiered T_M-T_M model significantly affect the variation of the demand/supply ratio. When the demand is less than the supply, PAs or federation PAs always propose desirable service to induce purchases. This approach can efficiently improve the success ratio and support the scalability of the intercloud market. However, as the demand/supply ratio increases, the PAs allocate the resources more strictly, and the federation market between the hPA and fPA becomes increasingly competitive in terms of sharing resources; thus, resource waste is avoided and more resources are provided to allocate. Therefore, the negotiation solution is better than that achieved by the Time model. However, the model results in a higher price per unit resource of the CAs than that of the other models. Therefore, in cases of short supply, the T_M model cannot support efficient scalability of the federation.

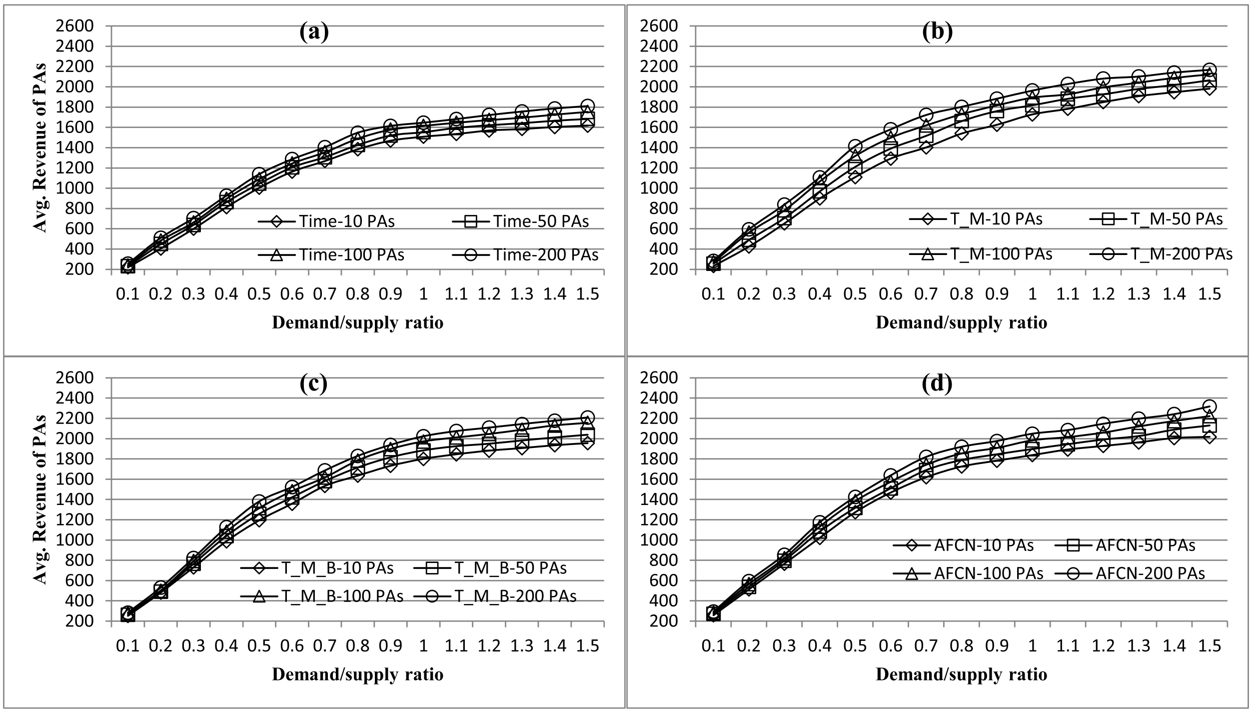

Fig. 16 Average revenue for different numbers of PAs

The T_M_B model considers not only time and market factors but also the behavior of the opponent agent. The opponent's behavior is stored in the local database and is a major factor used in interpreting and processing when guiding the agent's behavior to improve the satisfaction level and avoid the risk of conceding everything to the opponent, thereby increasing the probability of achieving the optimal goals. Thus, the two-tiered T_M_B-T_M_B model can increase the chance of achieving a better solution via second-tier negotiation. Therefore, the T_M_B model achieves better negotiation performance and scalability than the two-tiered Time and T_M models.

However, these aforementioned bargaining negotiation agents are unable to give full play to the efficiency and scalability of the intercloud market. This is because no agent has a priori information about the feasible solutions of other agents or any possible agreements just exchanging the uncertain and incomplete information regarding the proposal without the agent's preference or utilities, which affects the decision-making behavior for generating better solutions in the two-tiered negotiation.

The agents of the proposed AFCN model are endowed with beliefs about the market environment and the opponent's behavior. During the negotiation process, an agent makes an offer/counteroffer via iterative constraint adjustment and relaxation; it considers its own self-interest, as well as its opponents' behavior, which together guides the behavior of the agent and represent the global goal the agents want to achieve. The proposed offer/counteroffer, which is expressed by the fuzzy membership function, represents not only a set of acceptable solutions but also the possibility for conflict. Based on the ranking of the solutions obtained through the application of fuzzy constraints, a set of feasible solutions can be further refined based on preferences through the application of a satisfaction value threshold acceptable to both sides, which enables an agent to ensure that the proposed offers/counteroffers converge efficiently toward a satisfactory global solution. Moreover, the behavior of first-tier agents can affect and guide the behavior of second-tier agents, and the beliefs and intentions of agents in the first-tier negotiation and second-tier negotiation are linked.

As a consequence, the experimental results demonstrate that the two-tiered AFCN model can improve the efficiency and scalability of intercloud negotiation.

Conclusion

This paper proposes an agent-based multi-tier negotiation model called AFCN to perform two-tiered negotiations that facilitate intercloud performance. In contrast to the other agent negotiation model, the multi-tier AFCN has the following important aspects:

- A unified framework of agent negotiation with fuzzy constraints: The multi-tier AFCN provides a unified framework for all constraints, objectives, preferences and relations within and among agents to improve the flexibility and efficiency of negotiation to solve resource provision problems in the intercloud markets.
- Distributed and safe: In comparison to the other broker negotiation models, the multi-tier AFCN model supports a many-to-many bargaining negotiation infrastructure and provides a fully distributed and autonomous approach that does not require a third-party agent to coordinate the negotiation process. The AFCN can facilitate the exchange of messages without requiring the sharing of sensitive strategic information or private information to a third-party mediator.
- More efficient solution based on information sharing: By sharing limited and fuzzy membership functions through the iterative exchange of offers and counter-offers between negotiated agents (CAs and PAs, hPAs and fPAs) in a step and step process, AFCN enables them not only to reveal the opponent's behavior preference, but also to specify the possibilities prescribing the extent to which the feasible solutions are suitable for both agents' intents. Moreover, this information can pass through to and guide each tier of negotiation to generate a more favorable proposal, which avoids potential conflicts and more effectively reaches a satisfactory consensus. Thus, the multi-tier AFCN can improve the negotiation performance and the integrated solution capacity in the intercloud.

The experimental results demonstrate that the proposed multi-tier AFCN model outperforms other agent negotiation models and gives full play to the efficiency and scalability of the intercloud in terms of the level of satisfaction, the ratio of successful negotiation, the average revenue of the cloud provider, and the buying price of the unit cloud resource.

This paper demonstrates that the two-tiered AFCN is suited for SLA negotiation in the horizontal IaaS federation. However, it has some limitations for the vertical supply chain federation because the issues are different in each negotiation tier. Nevertheless, some fuzzy-based rule inference techniques can be incorporated to transform issue on decision making during the negotiation process.

Future research can address the behavior-based learning model embedded in the multi-tier AFCN model to assist the agent in generating more favorable proposals. The learning model can further explore the opponent's uncertain beliefs, including the preferences, behavior strategy and state, especially for the next feasible proposal. Some studies have proposed neural network learning, Bayesian learning, evolutionary behavior learning and deep learning to learn the opponent's uncertain behavior and to improve the utility value and the success ratio. Therefore, it is important to evaluate the performance of various learning models integrated in the AFCN.

Moreover, SLA renegotiation allows agents to change the established SLA to a new agreement; for example, to meet the peak demand or failure that occurs, the process and storage capacity need to be resized in terms of the VM dynamic migration or service replaceability by the federation members to maintain service continuity. The SLA renegotiation framework will support all cases in the dynamic intercloud market. Therefore, it is necessary to add SLA renegotiation activity to the SLA management life cycle.

Acknowledgments
The authors would like to thank the staff and postgraduate students at the School of Computer and Information Engineering of Xiamen University of Technology for their assistance and valuable advice.

Authors' contributions
Shunzhi Zhu is the corresponding author and contributed to the "Intercloud negotiation model", "Negotiation model of two-tiered AFCN", and "Performance evaluation" sections. Lin Li contributed to all of the manuscript sections. Li Liu and Kaibiao Lin contributed to the "Related works" section and the "Intercloud negotiation model" section. Linsha Huang and Shibiao Lv contributed to the overall architecture of the proposed execution environment. All authors have read and approved the manuscript.

Funding
This work was supported in part by the Natural Science Planning Project of Fujian Province under Grant 2020J01264, the Fujian Province Science and Technology Plan Project under Grant 2019J05123, the Joint Funds of 5th Round of Health and Education Research Program of Fujian Province under Grant 2019-WJ-41, and the Science and Technology Planning Project of Fujian Province under Grant 2020H0023.

Availability of data and materials
Not applicable.

Declarations

Competing interests
The authors declare that they have no competing interests.

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Received: 22 June 2021 Accepted: 13 April 2022
Published online: 28 June 2022

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