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Autonomous bargaining agents: Redefining cloud service negotiation in hybrid ecosystems

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Abstract

With the historic rise in cloud computing, mega-enterprises are now more and more shifting their on-premises IT infrastructures to cloud environments. Even though such migration is being adopted more and more, there still remains a paucity of research focused on autonomous resource negotiation between cloud consumers and providers. The current paper introduces a complete designed framework for multi-party, multi-issue negotiation in cloud resource provision. It offers a sophisticated cloud marketplace in which resources are dynamically purchased and sold. It employs belief–desire–intention (BDI) model-based consumer and provider agents, which negotiate simultaneously on multiple axes. The negotiations employ a hybrid approach that integrates time-aware and resource-aware dynamic deadline methods for computing offers and counteroffers. In addition, the marketplace proposed herein also includes a behavior norm score mechanism and Reputation Index to build agents' mutual trust.

Keywords: Multi-Agent Systems; Automated Negotiation; Intelligent Systems; Cloud Computing

1 Introduction

Negotiation is a tactical communication where various groups attain a mutually agreed upon target towards a common overall target. Now, IT infrastructure growth is not limited to simply scaling on-premises data center equipment capacity anymore. Instead, organizations are employing multi-tenant environments like public cloud platforms to build hybrid cloud infrastructure strategies. e-negotiation creation is especially vital in the hybrid cloud computings.

A fine example of cloud negotiation is the Amazon AWS EC2 Marketplace, where customers can bid for EC2 Spot Instances. In developing an effective cloud marketplace, offering and counter-offering among parties is needed to create short- or long-term partnerships. To every negotiation among cloud providers and consumers, compliance with standard protocols and predetermined thresholds is necessary.

An agent here refers to an independent computational entity that interacts with the outside world and is adaptive as well as autonomous in order to fulfill its programmed goals. Belief–Desire–Intention (BDI) is one of the most researched smart agent design structures, and it models human cognitive capabilities and logical reasoning. BDI agents use real-time procedural reasoning systems (PRS) to undertake elaborate decision-making in dynamic cloud environments.

Hybrid cloud computing negotiation consists of an array of key features. It may be as simple as one-issue negotiation, like the cost of virtual machine resources, or multi-issue negotiation extending to considerations including memory allocation, storage capacity, and operating system image. The complexity is even higher when negotiations include non-functional ones like cloud Service-Level Agreements (SLAs). Cloud customers are able to negotiate at the same time with multiple providers, targeting some of the specific features that matter most to their business needs. But before

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negotiating, all stakeholders must agree on the terms of negotiation to establish cooperative partnerships. These partnerships emerge when multiple parties unite to achieve a shared business objective.

This paper presents a multi-party, multi-issue negotiation framework for BDI-based agents in a cloud marketplace. The agents learn incrementally through a sequence of successive rounds of negotiation, improving at making offers and adapting the changing dynamics of the negotiation to reach optimal bargains.

A typical illustration of negotiation in the cloud in practice is the Amazon AWS EC2 Marketplace, where users are able to bid for EC2 Spot Instances. The system enables customers to enjoy cloud resources at competitive rates while enabling cloud vendors to optimize the use of resources. Yet the existing cloud negotiation environment does not have a powerful, automated system that can effectively manage multi-party and multi-issue negotiations in a dynamic environment. There is a requirement for smart, adaptive negotiation protocols since cloud customers need the optimal mix of price, performance, SLAs, and other characteristics.

1.1 The Role of Intelligent Agents in Cloud Negotiation

To support efficient negotiation in cloud computing, autonomous software agents have been widely used. Intelligent agents are software programs to operate independently in a particular environment and make decisions based on specified goals, learned history, and current interactions. The agents should demonstrate elasticity (i.e., the capability to change resources dynamically) and self-governance (i.e., the capability to make autonomous decisions within specified negotiation rules and constraints).

Among the several agent-based paradigms, Belief–Desire–Intention (BDI) is one of the most researched and utilized paradigm in artificial intelligence (AI). BDI model is inspired by cognitive reasoning and deductive logic of humans to enable agents to behave intelligently in dynamic and interactive environments. BDI-based agents utilize:

- Beliefs: Input received about the environment and other negotiating parties.
- Desires: The objectives or goals the agent wants to fulfill.
- Intentions: The actions and plans the agent takes to do something based on its desires and beliefs.

The BDI agents dynamically modify their strategies, adapt their negotiation strategy, and react to counteroffers using Procedural Reasoning Systems (PRS), making them strongly appropriate for multi-issue, multi-party negotiations in cloud marketplaces.

1.2 Multi-Issue and Multi-Party Negotiation Challenges in Cloud Computing

Cloud negotiation is inherently complicated because there are various stakeholders and rich diversity in the subjects of negotiation. It can be straightforward one-issue negotiations—like agreeing on a price for a VM—or complicated many-issue negotiations considering various factors, including:

- Compute resources (CPU, memory, storage, GPU availability)
- Service-level agreements (uptime guarantees, support response times)
- Security and compliance (data encryption, regulatory compliance)
- Geographic placement of data centers and considerations of latency
- Contract length and pricing models (e.g., pay-as-you-go vs. reserved instances)

Furthermore, within a competitive cloud market, cloud customers would be able to negotiate simultaneously with multiple providers, comparing various offers based on their individual requirements and limitations. The process becomes even more complex when trust and reputation are brought into perspective, as customers and providers must be certain that their negotiated terms will be fulfilled reliably.

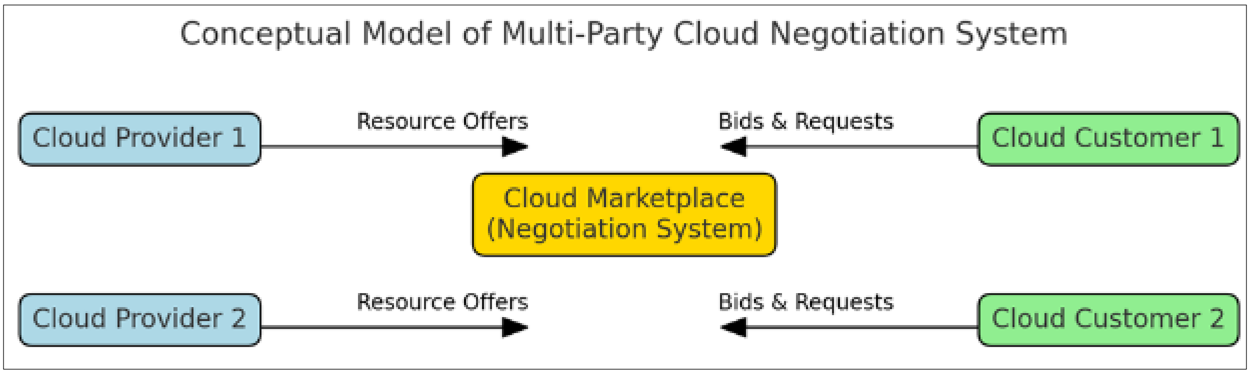

Figure 1 - diagram depicts the main constituents of a multi-party, multi-issue negotiation system

1.3 Explanation of Cloud Negotiation System Architecture

The above diagram depicts the main constituents of a multi-party, multi-issue negotiation system in a cloud marketplace. The system comprises:

1.3.1 Cloud Providers (Left Side)

- Cloud providers provide computing resources such as virtual machines, storage, and network.
- They negotiate by providing resources to the Cloud Marketplace.

1.1.1 Cloud Customers (Right Side)

- Customers order resources based on their application requirements.
- They place offers or orders via the marketplace and negotiate with numerous providers.

1.3.2 Cloud Marketplace (Center)

- It is the site for negotiation where intelligent automated agents haggle on one's behalf.
- It handles offers, counteroffers, and ultimate agreement between providers and customers.
- It implements trust measures, such as behavior norm scores and reputation indexes, to promote equity in trade.

1.3.3 Negotiation Process (Arrows)

- Providers send resource offers (prices, configurations, SLAs).
- Customers submit bids and requests (desired configurations, budgets).
- The marketplace brokers and negotiates, setting offers dynamically based on negotiation strategies set in advance, demand, and supply.

1.4 Building Trust in Cloud Marketplaces

Trust is extremely crucial in cloud-based negotiations. As negotiations are taking place in a decentralized setting where buyers and sellers might not have any previous experience, building trust and reliability mechanisms is of the highest priority. A cloud marketplace needs to include:

- Behavioral Norm Scoring: Scoring agents for their compliance with equitable negotiation practices.

- Reputation Index: A dynamic measure of an agent's past performance, agreement satisfaction, and dependability.

Through incorporating trust-building mechanisms, cloud negotiation platforms can avoid opportunistic behavior, facilitate equitable exchanges, and increase the efficacy of cloud marketplaces.

1.5 Contribution of This Paper

This paper presents a multi-party, multi-issue negotiation framework for cloud resource allocation. It uses BDI-based intelligent agents that dynamically negotiate according to changing market circumstances and previous interactions. Our framework includes time-based and resource-based dynamic deadline algorithms for enabling optimal offers and counteroffers by agents in competitive cloud environments. We also introduce a trust-enforcement mechanism that promotes transparency and accountability among cloud stakeholders.

1.5.1 The rest of the paper is organized as follows

- Section 2 gives an overview of the state of the art,
- Section 3 outlines the proposed model,
- Section 4 outlines the algorithmic approach
- Section 5 presents future directions, and
- Section 6 provides the conclusion.

2 Related work

Belief-Desire-Intention (BDI) programming paradigm has been extensively used to model intelligent agent's behavior by encapsulating three most basic cognitive elements:

- Beliefs: Model the perception and knowledge of the agent of its environment.
- Desires: Model the goal of the agent based on its current beliefs.
- Intentions: Model the commitment of the agent to a set of actions in order to achieve its goals.

Despite being widely used, classic BDI agents have been hampered by disadvantages, including learning rigidity, non-adaptability, and limited multi-agent coordination, as investigated in [4]. Solutions to the above have resulted in advanced BDI frameworks. For instance, dMARS (Distributed Multi-Agent Reasoning System) [5] combines Procedural Reasoning Systems (PRS) with the BDI framework, enabling learning and adaptive capabilities in dynamic scenarios. Equally, [6] improves BDI capabilities through the addition of distributed shared memory and messaging based on the network to allow for cooperative sharing of beliefs and performance in multi-agent environments. Through these features, BDI-based agents can now manage sophisticated, adaptive decision-making in very dynamic environments, e.g., cloud service negotiation.

2.1 Cloud Computing Negotiation Research

With the ongoing expansion in cloud computing [8], organizations at present have an extensive choice of providers of cloud service to choose from. Still, choosing the most cost-efficient and appropriate provider demands successful negotiation techniques. Until now, most of the research in this area has relied on negotiation of cloud Service-Level Agreement (SLA) [9–11].

For instance, the study in [9] examines SLA negotiation in grid computing, where service-level requirements are specified by a process owner and a cloud provider is chosen accordingly. Although this approach is efficient in handling non-functional requirements like SLA terms and compliance, the functional requirements like configurations of computing resources (CPU, memory, OS, storage) are not taken into account while handling multiple providers.

A multi-cloud negotiation strategy, for example, mOSAIC [10], has also been proposed as an agent-based one that is a middleware to negotiate on behalf of customers in clouds. The system, however, does not have fine-grained control over negotiation since it cannot dynamically modify the negotiation strategy according to customers' preferences or perform simultaneous multi-party, multi-issue negotiations. Our framework provides a proposed marketplace-based solution to these challenges by allowing BDI agents to rank negotiation topics, with importance weights on key issues and adapting their strategies dynamically.

2.2 The BDI Programming Paradigm in Intelligent Negotiation

The BDI model of the agent has its origins in philosophy and cognitive sciences, where decision-making is facilitated through three basic building blocks:

- Beliefs (B): The environment knowledge of the agent, gathered through observations and interactions.
- Desires (D): The agent's goals or objectives that the agent wants to realize.
- Intentions (I): The concrete actions the agent executes, based on its beliefs and desires.

Classical BDI-based agents have been widely studied in automated reasoning and decision-making fields [3]. The initial implementations, however, were plagued with some major flaws, including:

- Inadequate Learning and Adaptation: Initial fixed decision rules left them unable to learn from and adapt to changing environments.
- Limited Multi-Agent Cooperation: BDI agents had difficulty collaborating on problem-solving with multiple entities.

More advanced BDI architectures have been proposed by researchers to overcome these limitations, including:

- MARS (Distributed Multi-Agent Reasoning System) [5]:
- Tempts Procedural Reasoning Systems (PRS) with BDI principles.
- Enables adaptive learning and distributed agent coordination.
- Shared-Belief Multi-Agent Systems [6]:
- Expands traditional BDI models with distributed shared memory and network-based communication.
- Enables agents to dynamically share beliefs, enabling collaborative decision-making.

These developments have greatly enhanced the capability of BDI agents to act autonomously in dynamic, complex environments, making them perfectly suitable for automated cloud service negotiations.

2.2.1 Traditional vs. Adaptive Negotiation Strategies

The majority of the classic negotiating mechanisms are based on pre-determined rule-based policies, which are highly effective when dealing with one adversary. For instance, game theory-based negotiating protocols in [2, 12] promise a win-win solution. The strategy tends to make buyers and sellers compromise and results in lower overall utility.

Conversely, our method utilizes adaptive BDI-based agents that process every negotiation round in real time and dynamically adapt the strategy. This provides guarantee of achievement of agreements within a given time period, achieving optimal trade-offs between mutually incompatible priorities.

Related research in [13] offers a bilateral multi-issue negotiation framework in which sellers and buyers negotiate multiple issues at the same time. The drawback of this approach is that both parties must agree on all issues, resulting in prolonged and inefficient negotiations. In attempting to overcome this, the Belief-Goal-Plan (BGP) model [14] has been suggested to allow strategic adaptation while responding to an opponent's offer. However, it does not handle multilateral concurrent negotiations between multiple participants.

2.2.2 SLA-Based Cloud Negotiation

The majority of the previous studies on cloud negotiation have been centered on Service-Level Agreement (SLA) negotiation [9-11].

- Example: SLA Negotiation in Grid Computing [9]
- It enables customers of the cloud to describe SLA requirements from the perspective of a business process.
- It assigns them a cloud provider that satisfies the above requirements.
- It does not provide support for functional negotiations (e.g., choice of CPU, memory, storage).
- OSAIC Framework: Multi-Cloud Negotiation [10]
- Automatically negotiating on behalf of cloud buyers through an agency model based on cloud software.

2.2.3 Acts as middleware between consumers and producers of clouds.

Restriction: Does not have fine-grained control over negotiation, and customers are unable to dynamically adjust the negotiation preferences.

Our marketplace-based model, in contrast to these, supports dynamic, real-time multi-party negotiation, where BDI-based agents prioritize provided issues and adjust offers accordingly.

2.3 Time and Behavior-Driven Negotiation Strategies

Our approach, grounded in Faratin's time- and behavior-dependent negotiation model [15], improves the negotiation process by allowing agents to dynamically make concessions on secondary issues to facilitate faster agreements.

Compared to traditional two-party negotiation models that tend to lead to redundant interactions, our system employs a mutual interest-based filtering mechanism to ensure that:

- Only appropriate negotiation issues are considered, avoiding unnecessary interactions.
- Matches are formed based on shared preferences, maximizing resource utilization and minimizing overhead.

2.3.1 Multi-Issue and Multi-Party Negotiation Strategies

Cloud negotiation is where multiple parties negotiate multiple attributes at the same time. Conventional approaches have generally been:

2.3.2 Predefined Strategy-Based Negotiation

Predefined, rule-based methods are employed by some studies in cloud negotiation [2, 12]:

- Agents choose a pre-defined negotiation strategy (e.g., game-theory rules).
- Win-win but loses utility for both parties.

2.3.3 Adaptive BDI-Based Negotiation

2.3.3.1 Our method employs adaptive BDI agents, which:

- Assess each round of negotiation in real-time.
- Change their strategy dynamically to maximize utility.
- Ensure agreement is reached within a specified time frame.

2.3.3.2 Bilateral vs. Multilateral Negotiation Models

- Bilateral Multi-Issue Negotiation [13]
- Handles a single buyer and a single seller negotiating multiple parameters.
- Includes agreement on all issues, which leads to long negotiation times.
- Belief-Goal-Plan (BGP) Model [14]
- Provides multi-strategy negotiation, helping agents choose the best strategy dynamically.
- However, does not support multi-party, simultaneous negotiations.

2.3.3.3 Our Approach

- Supports multi-party negotiations by matching agents by common interests.
- Reduces negotiation overhead by enabling agents to dynamically prioritize issues.

2.4 Contributions Summary

Table 1 Approach , Strengths and Limitations

Limitations in Existing Research:

Approach	Strengths	Limitations
SLA-Based Negotiation [9-11]	Focus on SLA parameters	Does not negotiate functional parameters (CPU, memory, OS, storage)
Multi-Cloud Agency Model (mOSAIC) [10]	Middleware-based cloud negotiation	Lacks fine-grained control over negotiation issues
Predefined Strategy-Based [2, 12]	Ensures structured negotiation	Reduces negotiation flexibility
Bilateral Multi-Issue Negotiation [13]	Handles multiple issues	Leads to prolonged negotiation times
BGP Multi-Strategy Model [14]	Adapts strategy dynamically	Does not support multi-party negotiation

Whilst existing work has given the foundation for automated cloud negotiations, it is largely limited to bilateral SLA negotiations, pre-specified strategies, or agent-based middleware. Our suggested multi-party, multi-issue cloud negotiation framework offers the following foundational contributions:

- BDI-based adaptive agents that iteratively refine negotiation strategies.
- A cloud marketplace-driven strategy, enabling smart negotiation through weighted issue prioritization.
- Efficient agreement creation through a time- and resource-conscious dynamic deadline mechanism.
- Trusting and reputational unification with negotiation bottleneck simplification.

This paper throws open the possibility of scalable, smart cloud marketplaces where upper-level negotiations are dynamically managed by self-governing agents to provide overall increased efficiency for consumers and providers in the cloud.

3 System structure proposed

3.1 The system structure proposed has two main components

- The Cloud Marketplace – A centralized, decentralized marketplace where cloud vendors and consumers buy and sell, post offers, and negotiate service contracts.
- Cloud Agents – Self-managing BDI-based agents mimicking buyers and sellers dynamically negotiating, multi-issue negotiations.

As illustrated in Figure 2, the cloud marketplace supports the negotiation process through an advertisement repository, matchmaking facilities, a negotiation engine, and behavioral monitoring utilities to guarantee trust and efficiency of transactions.

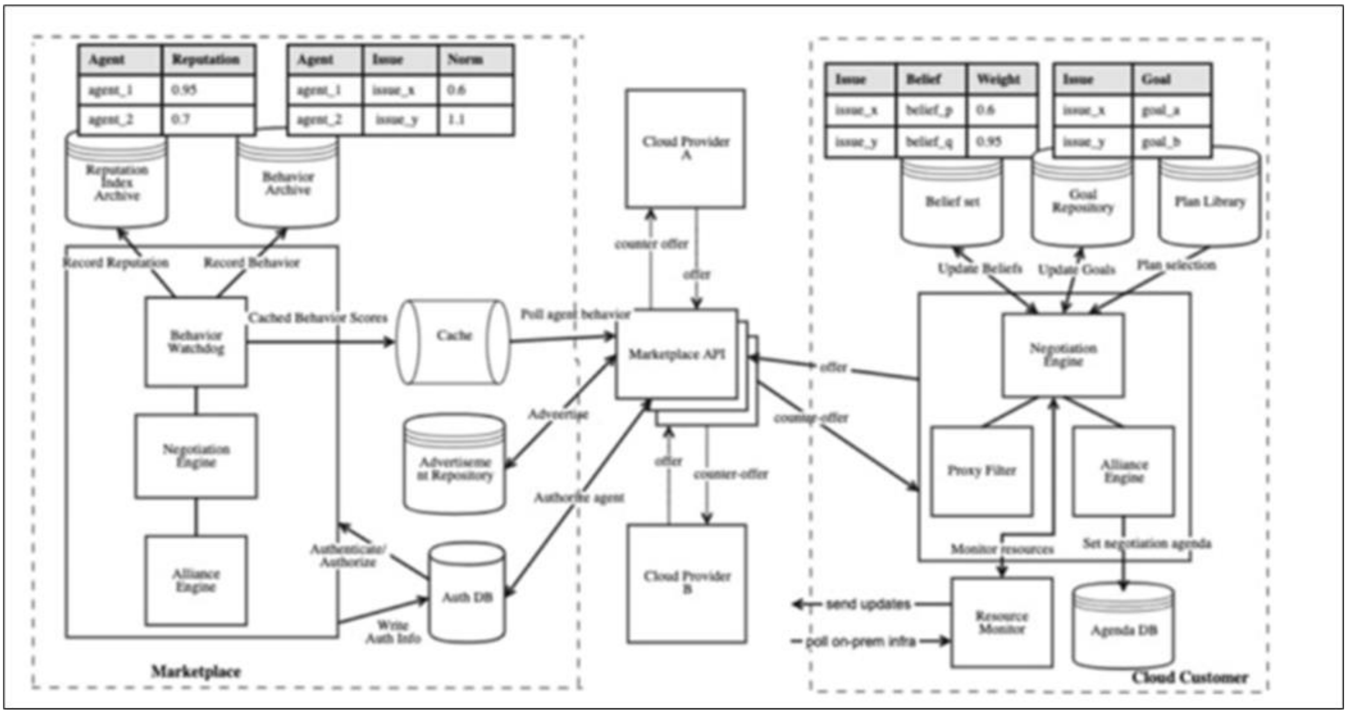

Figure 2 the cloud marketplace supports the negotiation process through an advertisement repository

3.2 Cloud Marketplace

Cloud Marketplace is a peer-to-peer market where cloud service consumers and producers list themselves, list requests for resources, and negotiate automatically. It supports:

- Buyers to identify the optimal cloud service provider according to cost, SLAs, and resource profile.
- Sellers to market their services and maximize their use of resources.

The marketplace uses Web Service Description Language (WSDL), XML, and Simple Object Access Protocol (SOAP) for its negotiation mechanism and related services. Additionally, a RESTful Marketplace API supports interactions upon user authentication.

3.3 Advertisement Repository and Agent Discovery

One of the most important parts of the marketplace is the advertisement repository, which holds:

- Agent information (cloud provider and client identities).
- Product information (computing capacities, prices, SLA terms).
- Negotiation information (Reputation Index, previous transactions).

When a cloud customer agent requests resources, it sends a Request for Quote (RFQ) with details:

- Desired compute/storage/network resources.
- Anticipated SLA parameters.

Minimum Reputation Index that the provider should achieve.

$$S = \begin{cases} B_a < 1, \text{where agent a tends to be headstrong} \\ B_a = 1, \text{where agent a tends to be linear} \\ B_a > 1, \text{where agent a tends to be conceder} \end{cases} \quad (1)$$

Periodic inquiries are made by other agents with the advertisement repository for matchmaking and statistics.

3.4 Alliance Engine: Smart Matchmaking Service

The Alliance Engine facilitates effective negotiation by:

- Denying irrelevant negotiation proposals – Not wasting interactions for matters in which there is no shared interest.

- RFQ matched customers and providers, Reputation Index, and joint issue priority.

Upon establishing a match, the Negotiation Engine drives the transaction with a commenceNegotiation message to both stakeholders and with a timestamp to capture time-based commitments.

3.5 Negotiation Engine: Core for Negotiation Process

Negotiation Engine conducts automated negotiation between cloud customer agents and provider agents.

3.5.1 Negotiation Workflow

- Initial offer made by provider agent.
- Customer agent analyzes the offer and makes counter-offer when necessary.
- Repeat the loop in negotiation rounds until:
- Agreement achieved, OR
- Time expired, aborting negotiation.

3.5.2 Negotiation Engine also executes

- Transaction logging – Records all transactions between agents for statistical purposes.

- Behavioral tracking – Supplies negotiation statistics to the Behavior Watchdog service for reputation scoring.

3.6 Behavior Watchdog and Reputation Index

In credibility establishment and building of trust within the market environment, the system employs:

3.6.1 Reputation Index (R) Calculation

- A rational number $0 \leq R \leq 1$, stored within the Reputation Index Archive.
- The more reliable agents with a better R-score have kept their word.
- Good reputation agents receive good-quality negotiation requests.

3.6.2 Behavior Norm Index (B) Calculation

- Pins down behavior pattern during negotiations for the purpose of tagging agents as:
- Headstrong ($Ba < 1$) – Not given to yielding during negotiations.
- Linear ($Ba = 1$) – Negotiates in balance.
- Conceder ($Ba > 1$) – Often adapts offers in order to seal deals quickly.

This will allow agents to be able to predict opponent moves and adjust accordingly.

3.7 Cloud Agents: BDI-Based Negotiation Entities

Customer and cloud provider agents are both grounded on the BDI (Belief-Desire-Intention) model. The agent holds:

- Beliefset (B) – Contains information regarding the current negotiation, which is constantly updated after each round.
- Goal Repository (D) – Specifies the agent's goals per problem (e.g., leasing a VM at the minimum cost).
- Plan Library (I) – Contains predefined plans, which the agent can run:
  - Offers
  - Counter-offers
  - Negotiation termination

Every negotiation problem is graded according to its significance to facilitate rational decision-making.

3.8 Negotiation Security and Validity

To prevent unauthorized deals and ensure proper negotiations alone, the system incorporates:

- Proxy Filter: Illegal Transaction Prevention
- Prevents out-of-time-limit counter-proposals by default.
- Protects the agents against malicious tampering with ongoing negotiations.

3.8.1 Handling of Multiple Negotiations

- AJents negotiate with multiple counterparties concurrently, prioritizing deals with greatest utility.
- The Alliance Engine manages metadata for ongoing negotiations in an Agenda Database.

3.9 Agent Negotiation Decision-Making

3.9.1 Negotiation Engine Service:

- Produces offers and counter-proposals.
- Evaluates competing proposals through strategic planning.
- Publishes RFQs and ads via the Marketplace API.
- Refers Beliefset, Goal Repository, and Plan Library by round.

3.9.2 Resource Monitor:

- Checks on-premise resource availability periodically.
- When resources are low, the agent gets aggressive in closing deals in a rush.

Conclusion

The above cloud marketplace-induced negotiation system involves a multi-party, multi-issue negotiation environment where BDI-based agents are self-adaptive, autonomous actors of adaptive real-time cloud service negotiations.

3.9.3 Key Innovations

- Self-adaptive, autonomous intelligent BDI-based agents for automated negotiations.
- Prioritization of sub-issues for effective agreement construction.
- Reputation Index and Behavior Norm score-based enforcement of trust mechanisms.
- Negotiation adaptation according to varying conditions of time requirements and real-time available resources.
- Rule-based secure enforcement of negotiation to avoid incorrect transactions.

By incorporating behavioral analytics, strategic adaptation, and smart matchmaking, this system enhances efficiency, equity, and dependability in the distribution of cloud resources.

4 Negotiation process

A cloud agent, prior to the commencement of a negotiation, specifies its preferences by defining:

- The importance weight (Wi) on every issue.
- The acceptable range of cost value (Ci) for every issue.
- The negotiation time limit (tmax), which ensures agreement within a time limit.

4.1.1 The negotiation takes place within the constraints:

The overall utility value (U) of the agent's proposal is calculated through the weighted sum:

This guarantees that the contribution of every issue to the final decision is according to the priorities of the agent.

4.2 Negotiation Response Strategy

In negotiation, an agent evaluates incoming offers and decides its response (R) based on utility assessment.

For a transaction between two agents (a and b) on issue i, an agent adheres to these rules:

- Accepting an Offer: If the offer Otn-1 received is greater than or equal to the agent's expected utility, the agent accepts it.

- Sending a Counter-Offer: If the offer received is less than the expected utility, the agent updates the cost value and sends a counter-offer.

- Terminating Negotiation: If after the negotiation time limit (tmax) a counter-offer is received, the negotiation is ended.

4.2.1 Mathematically, the agent's decision function R can be represented as:

The agent's primary goal is utility maximization in all the critical subjects. Agents employ adaptive counter-offer generation strategies for this reason.

4.3 Counter-Offer Generation Strategy

Counter-offer generation strategy is to increase the quality of the negotiation in a dynamic process. The hybrid approach followed is to employ both:

- Time-Dependent Tactics – Dynamic revision of offers based on proximity to deadlines.

- Resource-Dependent Tactics – Dynamic offer adjustment based on available processing resources.

4.3.1 Time-Dependent Strategy

A time-constrained negotiation strategy guarantees the making of deals in the specified timeframe (tmax). This is regulated by a time function f(t), and it ensures that:

Timely negotiations optimize obtaining the optimum offer.

As tmax gets closer, agents strategically offer concessions to secure the deal.

$$S = \begin{cases} B_a < 1, \text{where agent a tends to be headstrong} \\ B_a = 1, \text{where agent a tends to be linear} \\ B_a > 1, \text{where agent a tends to be conceder} \end{cases} \quad (1)$$

The formula of a counter-offer on issue i, from agent a to agent b at time tn, is:

Where the time function, which varies with time, must meet the following constraints (L):

This strategy makes an agent alter its position over time, delaying concessions initially but still allowing negotiations to finish on schedule.

4.3.2 Resource-Dependent Strategy

In addition to time-dependent strategies, the agent also dynamically changes its strategy according to available resources.

- Like a hardheaded approach when the opponent's resources are low, concessions are only granted when absolutely necessary.
- Like an early conceding approach when the agent requires resources as soon as possible in order to arrive at a rapid agreement.

Agents watch the behavior of their opponent and respond accordingly:

- When the opponent adopts a linear conceding strategy, the agent does the same to balance.
- When the opponent adopts an aggressive strategy, the agent responds by strategically modifying its counter-offers.

$$U = \sum_{i=1}^{n} C_i W_i \text{ where } \sum_{i=1}^{n} W_i = 1 \quad (2)$$

4.4 Calculation of Concession Rate

In case there is no agreement in the first three rounds, the concession rate (λ) is determined by the negotiation engine to control subsequent counter-offers.

4.4.1 The concession rate is calculated by analyzing past offers

Depending on λ, an agent selects its strategy:

- If $\lambda > 1$ → Opponent is conceding → The agent imitates the opponent's action.
- If $\lambda < 1$ → Opponent is hardheaded → The agent uses a conceding strategy to speed up agreement.
- If $\lambda = 1$ → Opponent has a linear strategy → The agent has a balanced negotiation style.

Through active concession trend analysis, agents learn in real-time to maximize successful negotiations.

$$\mathcal{R} = \begin{cases} \text{acquire}(a, b, O_i^{t_{n-1}}), & U_i(O_{i\,a\to b}^{t_n}) \le U_i(O_{i\,b\to a}^{t_{n-1}}) \\ \text{terminate}(a, b), & t_{co} > t_{\max} \\ \text{counter}(a, b, O_{i\,a\to b}^{t_n}), & \text{otherwise} \end{cases} \quad (3)$$

$$L = \begin{cases} 0 \le f_{i\,a}(t_n) \le 1, \text{ offer range} \\ f_{i\,a}(0) = C_{i\,a}(0), \text{ initial cost belief at time } 0 \\ f_{i\,a}(t_{\max}) = 1, \text{ at the time threshold} \end{cases} \quad (5)$$

$$\lambda = \frac{O_{i\,b\to a}^{t_n} - O_{i\,b\to a}^{t_{n-1}}}{O_{i\,b\to a}^{t_{n-1}} - O_{i\,b\to a}^{t_{n-2}}} \quad (6)$$

4.5 Hybrid Negotiation Approach Summary

Resource-Dependent Tactic\tChanges offers based on available resources\tWhen resource availability is changing

Hardheaded Strategy\tDelays concessions to maximize return\tWhen opponent is resource-constrained Conceder Strategy\tEmploying early concessions to speed agreements\tWhen quick resolution is needed Linear Matching Aligns opponent's concession behavior If opponent is employing a consistent strategy

Conclusion

- The presented negotiation model presents a time-resource-dependent hybrid strategy, guaranteeing:
- Time- and resource-dependent dynamically adaptive decision-making.
- Strategic counter-offering for maximizing agreement outcomes.
- Incentive-based concession-based adaptation reflecting opponent behavior.
- On-the-fly negotiation pattern evaluation without time-wasting delays.

The strategy improves cloud services negotiations to be more efficient, adaptable, and self-governing in dynamic cloud markets.

5 Future directions

This paper introduced a negotiation model for parallel, multi-party negotiations between various agents. The current model consists of predominantly a single IT infrastructure owner who is ready to scale resources up to the cloud. Real cloud setups are diversified with multiple microservices in a single infrastructure managing their own scaling requirements independently.

5.1 For our future study, we plan to:

5.1.1 Enlarge the model to accommodate microservices-based cloud negotiations

- Instead of a monolithic negotiation framework, microservices within an organization's infrastructure may negotiate on their own with different cloud vendors.

- This would enable granular, service-level scaling compared to monolithic infrastructure migration.

5.1.2 Establish a multi-agent framework

- Assign intelligent negotiation agents to individual microservices.
- Investigate how the autonomous agents can collaborate and scale the overall infrastructure dynamically.
- Investigate multi-agent learning mechanisms that enable the agents to learn from one another and improve decisions collectively.

5.1.3 Enhance multi-agent cooperation and communication

- Highlight distributed shared memory paradigms to enable agents to query and update shared negotiation knowledge.
- Prototype law-governed interaction models [20] for agent-to-agent communication to enable structured and rule-based negotiations.

These developments will make the negotiation model scalable and flexible, transforming it from an intra-agent transaction model to a multi-agent cloud-scalable system operating independently.

6 Conclusion

This research proposed a cloud marketplace-based autonomous negotiation system for hybrid clouds. The system allows multi-party, multi-issue negotiations to facilitate dynamic provider-customer transactions for resource allocation.

6.1 Some key contributions of this research include

6.1.1 Alliance Formation for Efficient Parallel Negotiation

- For avoiding redundant computation overheads, the model allows agents with the same objective to collaborate through alliances, thus facilitating easy parallel negotiations

6.1.2 Trust-Driven Cloud Marketplaces

- Agents are given the authority to give preference to transactions with credible counterparts, encouraging marketplace credibility.

6.1.3 Hybrid Time-Resource Deadline Algorithm

- The negotiating strategy integrates time-constrained and resource-driven decision-making, leading to better counter-offers and agreements in shorter times.

6.1.4 Scalable Cloud Resource Management

- It facilitates automated infrastructure scaling, wherein on-premises IT elements dynamically shift to cloud environments based on real-time negotiation outcomes.

6.2 Future Prospects

Though this paper establishes the foundation for intelligent agent-based negotiations, further studies aim at extending the model by:

- Enabling distributed learning among a team of agents.
- Allowing real-time interaction in a multi-agent cloud setting.
- Enabling self-optimizing negotiation approaches that adjust dynamically based on market directions and available resources.

With the integration of state-of-the-art AI-powered negotiation approaches, this model seeks to transform automated cloud scaling into an efficiency, flexibility, and responsiveness process in hybrid clouds.

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