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Maximizing Overall Service Profit: Multi-Edge Service Pricing as a Stochastic Game Model

Shengye Pang, Xinkui Zhao*, Jiayin Luo, Jintao Chen, Fan Wang, and Jianwei Yin

Abstract: The diversified development of the service ecosystem, particularly the rapid growth of services like cloud and edge computing, has propelled the flourishing expansion of the service trading market. However, in the absence of appropriate pricing guidance, service providers often devise pricing strategies solely based on their own interests, potentially hindering the maximization of overall market profits. This challenge is even more severe in edge computing scenarios, as different edge service providers are dispersed across various regions and influenced by multiple factors, making it challenging to establish a unified pricing model. This paper introduces a multi-participant stochastic game model to formalize the pricing problem of multiple edge services. Subsequently, an incentive mechanism based on Pareto improvement is proposed to drive the game towards Pareto optimal direction, achieving optimal profits. Finally, an enhanced PSO algorithm was proposed by adaptively optimizing inertia factor across three stages. This optimization significantly improved the efficiency of solving the game model and analyzed equilibrium states under various evolutionary mechanisms. Experimental results demonstrate that the proposed pricing incentive mechanism promotes more effective and rational pricing allocations, while also demonstrating the effectiveness of our algorithm in resolving game problems.

Key words: service pricing; game theory; incentive mechanism; Pareto improvement; equilibrium solution

1 Introduction

The forthcoming years anticipate a substantial surge in the web services market, propelled by several key factors: the escalating embrace of cloud/edge services, the burgeoning presence of IoT, and the mounting demand for automation and integration solutions. This industry flourishes amidst intense competition, with a growing number of participants aiming to pioneer innovative web services that address the expanding demands across various sectors such as healthcare, Internet of Things, media, finance, and smart cities, among others[1–6]. According to a report from MarketsandMarkets*, the global web services market is forecasted to ascend from 2.5 billion dollars in 2020 to 6.5 billion dollars by 2025, exhibiting a robust compound annual growth rate (CAGR) of 21.3%. In this process, the significance of service pricing in shaping the evolution of service markets has been duly acknowledged[7]. In unfettered market settings, service providers might prioritize their profits, deploying pricing strategies that detrimentally impact others' interests. Regrettably, these tendencies often trigger cutthroat competition, ultimately diminishing overall profitability. Further complexity infiltrates edge service

• Shengye Pang, Jiayin Luo, Jintao Chen, Fan Wang, and Jianwei Yin are with College of Computer Science and Technology, Zhejiang University, Hangzhou 310058, China. E-mail: pangsy@zju.edu.cn; fro_l@zju.edu.cn; chenjintao@zju.edu.cn; fanwang97@zju.edu.c; zjuyjw@cs.zju.edu.cn.
• Xinkui Zhao is with School of Software Technology, Zhejiang University, Ningbo 315048, China. E-mail: zhaoxinkui@zju.edu.cn.
∗ To whom correspondence should be addressed.
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*https://www.marketsandmarkets.com/Market-Reports/3d-imaging-market-998.html pricing scenarios due to factors like the scattered dispersion of edge service providers (ESPs) and regional disparities, intensifying the intricacies of pricing analysis. Consequently, this paper delves into elucidating the conundrum of service pricing within scenarios where multiple ESPs offer similar services to numerous edge service consumers (ESCs). In some cases, the location of the ESP may not align with the location of service deployment. Nevertheless, this misalignment will not diminish the research value of the pricing game presented in this paper.

With the rapid evolution of edge-side infrastructure, edge services have emerged as a focal point in the service market[8, 9]. Initially, transactions for edge services predominantly followed a one-to-one service customization model, wherein ESPs tailored services at the edge to meet specific user requirements. However, there has been a gradual transition in recent years toward a more generalized service transaction model as ESCs and ESPs have become increasingly active. For instance, data processing services catering to intelligent connected vehicles (ICV) provided by internet service providers (ISPs) at the edge can be commoditized for all smart car vendors while contending commercially with other ISPs. In this scenario, advantageous geographic positioning for ESPs enables them to offer superior services to a larger pool of ESCs, albeit potentially encountering higher service maintenance costs. Considerable research has delved into the intricate realm of service pricing. Within cloud computing, Wu et al.[10] have proposed an innovative approach rooted in value-based pricing. This method not only factors in the service's cost to a CSP but also gauges the extent to which a customer is willing to invest in the service. Meanwhile, Deng et al.[11] devised a resource bidding strategy for the edge side, employing a two-stage Steinberg game model. Their strategy aims to maximize the overall value for all entities operating at the edge. Regarding network service pricing, Ma[12] explored generic congestion-prone network services, investigating the usage-based pricing strategies adopted by service providers amid market competition. Additionally, Asheralieva et al.[13] formulated a model for resource management and pricing within the BaaS-MEC system. Their model represents a stochastic Stackelberg game featuring multiple leaders and incorporates incomplete information about the actions undertaken by leaders/BSs and followers/peers. Undoubtedly, these cutting-edge works are informative; however, there remains significant potential for optimizing the pricing matter of multi-edge services, and the task turns out to be non-trivial due to the following challenges.

Challenge 1: Modeling of the intricate pricing matter. Multi-edge homogeneous service pricing is a complex issue where participants' benefits are influenced by various factors. These factors encompass the distribution of ESPs and ESCs, preferences in service selection of ESCs, operational costs in different regions, and more. Pricing strategy formulation faces a dynamically complex market environment.

Challenge 2: Incentive-driven pricing game iterations. When participants formulate pricing strategies, in general, they tend to maximize their individual profits. This inclination could lead to the game gravitating towards a Nash equilibrium-like state, potentially resulting in a decrease in the overall profit of the service market.

Challenge 3: Resolution of complex game-theoretic problems. The multi-participant stochastic game model poses a complex multi-objective optimization challenge due to its non-differentiable optimization function. Consequently, closed-form equilibrium solutions are unattainable, rendering the use of analytical methods challenging for accurate solutions.

To effectively tackle the aforementioned challenges, this paper presents a comprehensive framework to address the multi-edge service pricing problem, encompassing a game modeling approach, an incentive mechanism, and a model-solving methodology. To tackle Challenge 1, we formalized a model for the participating entities in the game and devised credibility assessment and admission rules. Then, we transformed the multi-edge service pricing problem into a multi-participant stochastic game model and conducted an equilibrium existence proof. To tackle Challenge 2, our proposed service pricing incentive mechanism based on Pareto improvement, aims to elevate overall profits. To tackle Challenge 3, we present a three-stage enhanced Particle Swarm Optimization algorithm named TIAO-PSO in the final stage. By conducting adaptive optimization of the inertia factor based on search effectiveness across three stages, TIAO-PSO endeavors to determine equilibrium points before and after the application of incentive mechanisms through a comprehensive global search approach.

The primary contributions of this paper are as follows:

• We defined utility functions for game participants and designed pre-game ESP and service credibility assessment and admission rules.

• We establish a comprehensive model that elucidates the interplay among ESPs operating in diverse regions while pricing homogeneous edge services.

• Our proposed incentive mechanism utilizes Pareto improvement to steer the multi-edge service pricing game towards a Pareto optimal state, thereby maximizing overall profits.

• The introduction of TIAO-PSO, an enhanced Particle Swarm Optimization algorithm, designed to solve the intricate game model, facilitates a solution of equilibrium under various iterative strategies.

• Comparative experiments are conducted to demonstrate the effectiveness of the proposed incentive mechanism and game-solving algorithm.

The preliminary results of this work[14] have been published at the IEEE International Conference on Web Services (ICWS). The current study has undergone significant improvements and expansions in several crucial aspects: (1) At the problem modeling stage, we extended the formal definition of strategy, designed a credible evaluation and admission rules for ESPs and services, thereby reducing the impact of malicious behaviors on the service market. (2) At the stage of constructing the multi-participant stochastic game model, we bolstered the theoretical integrity by providing additional proofs regarding the existence and necessity of game equilibrium. (3) At the stage of equilibrium resolution, we augmented the model-solving algorithm based on the method proposed in the conference paper, further accelerating the iterative speed through an adaptive optimization mechanism. (4) We included an evaluation of the iterative process in our set of experimental metrics to better observe the trends in game iteration changes. (5) All sections have been revised and expanded with additional details to present a more comprehensive and refined discourse.

The remainder of this paper is structured as follows: Section 2 summarizes research on service pricing problems in different scenarios. Section 3 provides preliminary to achieve a better background understanding. In Section 4, We defined utility functions for game participants and designed pre-game ESP and service credibility assessment and admission rules. Section 5 formalizes the multi-edge service pricing problem based on stochastic game theory and designs a pricing incentive mechanism based on Pareto improvement. In Section 6, an enhanced PSO algorithm is proposed to solve and analyze the game model. In Section 7, comparative experiments are conducted to evaluate the effectiveness of the proposed methods. Finally, in Section 8 we summarize the main contributions of this paper and outline future research directions.

2 Related Work

In recent years, with the robust growth of the service market, service pricing has gradually emerged as a focal point in research. Studies on service pricing typically fall into three categories: those concerning issues within cloud computing scenarios, edge computing scenarios, and other specialized contexts.

In the context of cloud computing, service pricing necessitates service providers to contemplate various facets, including costs, competition, diverse user requirements, economic advantages, as well as the scalability and adaptability of services. Paul et al.[15] presented an analytical framework addressing the pricing of cloud service offerings, considering the operational costs accrued by the CSP to meet a given demand, the quality of service (QoS) provided, and the pricing strategies of other CSPs. Chatterjee et al.[16] introduced a dynamic and optimal pricing scheme tailored for provisioning Sensors-as-a-Service within sensor-cloud infrastructure. Nan et al.[17] delved into the study of optimal pricing strategies for a cloud service provider in a scenario involving incumbent and entrant entities, factoring in user upgrade costs and switching costs. Additionally, Wu et al.[10] proposed a novel approach rooted in value-based pricing, which not only accounts for the service cost but also considers the customer's willingness to pay.

In the context of edge computing, service pricing intricacies are intricately linked to the resource constraints of edge devices. Li et al.[18] delved into service selection within mobile cloud architecture, employing M/M/∞ queue and M/M/1 queue models to characterize PSP and ESP. Lyu et al.[19] introduced an innovative dynamic pricing scheme for edge computing services employing a two-layer reinforcement learning approach, comprising a pricing layer and a resource allocation layer. Deng et al.[11] used a two-stage Steinberg game model, devise a resource bidding strategy at the edge to maximize value for all involved parties in the edge ecosystem. Additionally, Roostaei et al.[20] implemented a game-based distributed scheme to jointly and dynamically allocate and price resources essential for effective offloading in a two-tier NOMA-based mobile system.

Other service pricing scenarios include specific offerings such as block-chain services, mobile data services, network services, and composite services, among others. Zhang et al.[21] delved into the study of mobile users' data usage behavior, factoring in the social network effect and congestion effect, thereby exploring pricing strategies for wireless providers in competitive environments. For generalized service composition, Wu et al.[22] proposed Vickrey-Clarke-Groves auction-based dynamic pricing strategies. Concerning network service pricing, Ma[12] examines usage-based pricing of service providers amidst market competition, focusing on generic congestion-prone network services. Additionally, Asheralieva et al.[13] modeled resource management and pricing within the BaaS-MEC system through a stochastic Stackelberg game framework, accounting for multiple leaders with incomplete information about actions of leaders/BSs and followers/peers. Additionally, tasks such as service discovery and recommendations are often based on the evaluation of service value[23, 24].

However, prevailing research on service pricing across diverse scenarios predominantly emphasizes the interaction between service providers and consumers. Regrettably, it neglects the competitive pricing dynamics among ESPs within edge scenarios, thus lacking an effective mechanism to optimize this competitive relation.

3 Preliminary

Game theory is a mathematical theory that studies the behavioral strategies of decision-makers in situations of mutual influence and interdependence. It involves researching conflicts, cooperation, competition, and interactions among participants, attempting to predict the actions they might take and decisions they might make. It aids in analyzing the optimal choices decision-makers might make in different scenarios and investigates optimal strategies and potential outcomes. In this section, we'll provide a brief formal explanation of two game concepts relevant to this paper to better acquaint readers with subsequent content.

3.1 Stochastic game

A stochastic game, often referred to as a Markov game, represents a form of dynamic game. Differing from strategic-form game and evolutionary game, a stochastic game integrates the variable state at each stage to delineate the ongoing scenario confronting all participants. Typically, a stochastic game MG involving m participants can be represented as a five-tuple.

$$\mathrm{MG} = \{H, S, \{A_i\}_{i\in m}, \{r_i\}_{i\in m}, P\} \tag{1}$$

where H represents the number of game iterations, S represents the set of states for all participants, A_i and r_i represent the strategy sets and reward function for the i-th participant respectively, and P represents for the set of transition probabilities.

In each stage of a stochastic game, the whole system occupies a state from the set of states. Subsequently, each participant, based on the current system state, selects an action from its feasible action space as their strategy. Once all participants have executed their actions, on one hand, depending on the current system state and the actions taken by all participants, the system undergoes a probabilistic transition from the current state to another in the subsequent stage. On the other hand, each participant receives an immediate reward as a consequence of their actions and the system's state transition. Specifically, when the state set S is a singleton, the random game degenerates into a repeated standard game. Thus, from this perspective, the random game extends the standard game into dynamic multi-stage and dynamic multi-scenario settings. When the set of participants contains only one, the random game degenerates into a standard Markov decision process. Consequently, from this standpoint, the random game further extends the Markov decision process from a single-agent system to a multi-agent system. These two analogies will better facilitate our understanding of the role that multi-participant stochastic game will play in the context of multi-edge service pricing.

3.2 Pareto improvement and Pareto optimality

A Pareto improvement refers to finding a strategy combination in a game where the profit for at least one participant increases without reducing the profits for any other participants. Consider a multi-participant game involving N participants, where each participant i has a strategy set $S = \{s_1, s_2, ..., s_N\}$. Each s_i represents the strategy chosen by i. Every participant has a utility function $u(s)$, representing their utility under strategy combination s. A Pareto improvement occurs if there exists another strategy combination s':

(1) Exist at least one participant i, $u'_i(s') > u\_i(s)$;

(2) For the other participant j, $u'_j(s') \geqslant u\_j(s)$.

In essence, if a strategy change enables at least one participant to achieve a better utility without causing a decrease or maintenance of utility for other participants, it qualifies as a Pareto improvement.

When no other strategy combination s' can enhance the utility for at least one participant without harming the utility of other participants, the scenario reaches a Pareto optimality state. At this point, no room exists for further Pareto improvements, signifying the optimal distribution of utility, where altering strategies cannot benefit any participants without causing harm to others.

4 Problem Formulation

In this section, we initially present a motivating example that illustrates the challenges of service pricing games encountered by various edge service providers. To precisely depict this dynamic, we proceed to model the participants involved in this game.

4.1 Motivating example

In Fig. 1, we endeavor to illustrate the complexity of the multi-edge service pricing issue using a scenario involving three regions, three edge service providers, and two edge service consumers, focusing on service localization. We take the example of ESP_1 situated in a locality where the ESC demand is higher, consequently incurring escalated maintenance costs, encompassing labor, utilities (water and electricity), and rent. Inter-regional service invocations introduce distance-based response latency, while distinct ESCs exhibit varying sensitivity levels to latency across different business functions. For instance, if ESP_1 sets higher pricing compared to ESP_2, ESC_1, which develops autopilot business, would still choose es_1 due to the nature of its business being sensitive to latency and its proximity to the deployment location of es_1. However, ESC_2, which is engaged in the food delivery business, chooses es_2 instead because it offers cost savings while minimizing potential business losses. While uninterrupted low latency is critical to the former, the latter can still function effectively even with a slightly longer service response. Benefiting from the pricing strategy of ESP_1, ESP_2 has gained a greater volume of service invocations. Consequently, ESP_2 might contemplate raising prices to augment revenue, while striving to retain customers or minimize customer attrition. However, this decision could potentially impact the choices of users invoking es_2 in Region 3, thereby influencing the pricing strategy of ESP_3. ESCs need to conduct a comprehensive evaluation of costs and profits associated with low-latency services at higher prices to make informed decisions. In essence, each pricing adjustment by each ESP is not an isolated

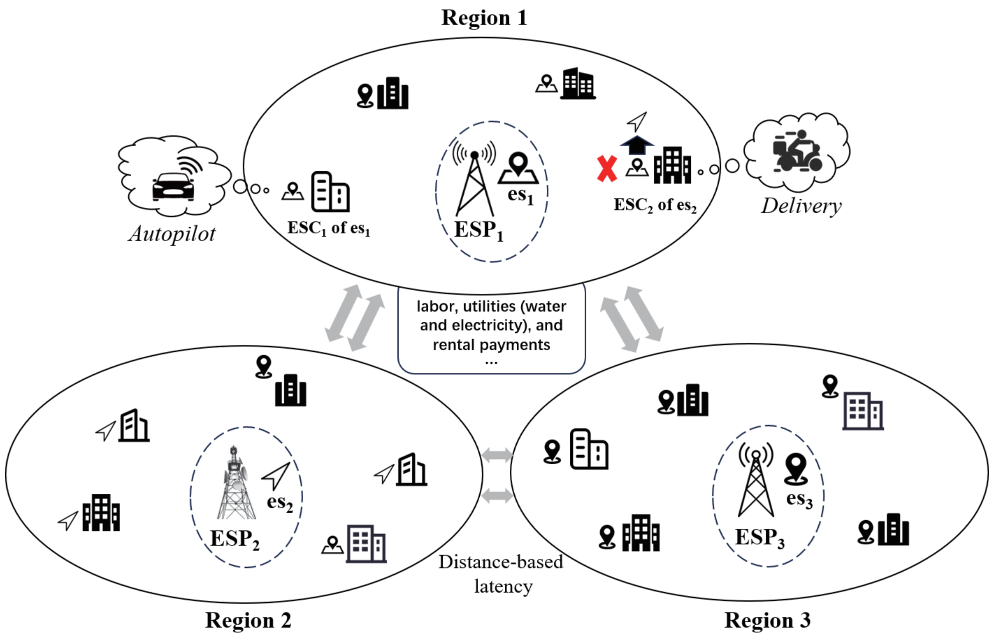

Fig. 1 Motivating scenario of homogeneous edge services provided by multi-ESPs.

action; rather, it can have a ripple effect on the global service pricing and invocation selection akin to the butterfly effect. As the scale of ESPs expands, the situation becomes even more intricate. Additionally, individual and global returns lack inherent correlation, further complicating the dynamics of the game.

Game theory is a mathematical theory that studies decision-making and predicts outcomes. In computer science, it is often applied to design algorithms and solve complex decision-making problems[29-31]. To accurately depict this game, it is essential to construct a multi-participant stochastic game model for multi-edge service pricing and analyze its evolutionary patterns. It is important to note in advance that we assume all ESCs are rational, meaning they opt for edge services that maximize their own profits.

4.2 Participant model

In this paper, the pricing game primarily occurs among ESPs that offer homogeneous services, while the invocation choices of different ESCs constitute the utility function of the ESP. Hence, we will first construct models for ESPs and ESCs.

4.2.1 Modeling ESP

In our proposed scenario, ESPs represent edge service providers situated in distinct regions offering identical functional edge services, denoted as $\text{ESP}=\{\text{esp}_1, \text{esp}_2,...,\text{esp}_n\}$, where n signifies the number of ESPs' regions. Let $\text{PR}=\{\text{pr}_1,\text{pr}_2,...,\text{pr}_n\}$ denote the pricing, $\text{PIT}=\{\text{pit}_1,\text{pit}_2,...,\text{pit}_n\}$ represent the total invocation count of services from each ESP, and $Z=\{z_1,z_2,...,z_n\}$ indicate the location vector of each region. The ESP model can be formulated as follows.

The primary revenue source for ESPs comes from fees paid by ESCs, denoted as $\text{ESP\_R}=\{\text{esp\_r}_1, \text{esp\_r}_2,...,\text{esp\_r}_n\}$, where esp_r_n represents the revenue of the ESP located in region n. The total revenue obtained by esp_m from all regions can be defined as $\text{esp\_r}_m=\sum_{i=1}^{n}\text{esc\_r}_{mi}$, where esp_r_{mi} signifies the revenue obtained by esp_m from region i. The esp_r_{mi} can be calculated as follows:

$$\text{esp\_r}_{mi}=\text{pit}_{mi}*\text{pr}_m \tag{2}$$

and

$$\text{pit}_{mi}=\sum\text{Count}_{\text{esc}_{i}\_m} \tag{3}$$

where $\text{Count}_{\text{esc}_{i}\_m}$ represents the number of times the ESC from region i invokes service from esp_m. Therefore, ESP revenue can be finally expressed as

$$\text{ESP\_R}=\left\{\sum_{i=1}^{n}\left(\sum\text{Count}_{\text{esc}_{i}\_1}\right)*\text{pr}_1,\sum_{i=1}^{n}\left(\sum\text{Count}_{\text{esc}_{i}\_2}\right)*\text{pr}_2,...,\sum_{i=1}^{n}\left(\sum\text{Count}_{\text{esc}_{i}\_n}\right)*\text{pr}_n\right\} \tag{4}$$

While the cost of the ESP could be influenced by the frequency of service invocations in practice, it isn't a primary factor in our model. As such, the daily maintenance cost of the ESP is regarded as a constant, predominantly determined by labor, utilities (water and electricity), and rental payments, denoted as ESP_C.

$$\text{ESP\_C}=\{\text{esp\_c}_1,\text{esp\_c}_2,...,\text{esp\_c}_n\} \tag{5}$$

$$\text{esp\_c}_1=\text{lab}_1+\text{uti}_1+\text{ren}_1\propto z_1 \tag{6}$$

Define the difference between ESP revenue and ESP cost in a period as ESP profit, donated as ESP_P.

$$\text{ESP\_P}=\text{ESP\_R}-\text{ESP\_C} \tag{7}$$

4.2.2 Modeling ESC

In the homogeneous service pricing game scenario, to streamline the model, we consider each ESC as exclusively engaging with a single edge service, simplifying the interactions. When an ESC utilizes multiple services, we handle it as multiple ESCs for calculations. This approach is solely aimed at simplifying the problem's complexity and will not alter the final result. We denote ESC as $\text{ESC}=\{\text{esc}_1, \text{esc}_2,...,\text{esc}_n\}$, with esc_n representing the set of ESCs in region n. The influence of distance on service response time is more prominent across different regions rather than within the same region. This is attributed to network latency, a key contributor to service response delays, which escalates with greater distances. In this paper, service response time is assumed to be consistent within the same region, whereas across regions, it is calculated based on the respective coordinates of each region. The ESCs within a region can be represented as a set: $\text{esc}_n=\{\text{esc}_{n1},\text{esc}_{n2},..., \text{esc}_{nm}\}$, each sharing the identical location vector specific to their region. During the service invocation process, ESCs choose the most suitable edge service provider considering factors like service pricing, the geographical proximity of the provider, and the demand for high-quality services in a particular business domain.

In general, the delay in service response tends to increase with the distance between ESC and ESP, influenced by network transmission characteristics. As the physical distance between ESP and ESC grows, data transmission encounters multiple routing devices, elevating the likelihood of network congestion in real-world network settings. Notably, network conditions widely vary across different geographical regions. In our experimental segment, we extensively tested services across 30 regions, deploying test nodes and collecting data to derive the probability distribution of inter-regional latency. When specific datasets were unavailable, we introduced a quadratic equation to approximate the link between invocation distance and response latency. This equation accounts for transmission and forwarding delays, regional disparities, and potential network congestion. The relationship between service response latency and distance can be expressed as a function:

$$\mathrm{RL} = \lambda_1 X^2 + \lambda_2 X + \lambda_3 \tag{8}$$

where RL represents the response latency due to distance, X represents the distance calculated by Z_n of esp_n and esc_n, The parameters λ_1, λ_2, and λ_3 are set based on the network conditions. These factors are taken into account to establish the ESC model.

To enhance the credibility of our proposed method, in the experimental section of this paper, we deployed the test service across multiple nodes spanning 30 regions. Extensive testing was conducted to derive the probability distribution of service response delays among these regions.

The ESC cost includes both the service invocation payment and any potential business losses resulting from response latency. Assuming that esc_{nm} selects esp_i as the edge service, the cost of service invocation can be formulated as follows:

$$\mathrm{esc}_{nm}\_\mathrm{c} = \mathrm{esc}_{nm}\_\mathrm{pay} + \mathrm{esc}_{nm}\_\mathrm{lose} \tag{9}$$

$$\mathrm{esc}_{nm}\_\mathrm{pay} = \mathrm{pit}_{i\_nm} * \mathrm{pr}_i \tag{10}$$

and

$$\mathrm{esc}_{nm}\_\mathrm{loss} = \alpha * \mathrm{RD} \tag{11}$$

where pit_{i_nm} represents the number of times esc_{nm} invokes the service from esp_i, and the parameter α is used to adjust the impact of service response latency on business losses. Similar to ESP_C, the revenue of esc_{nm} is treated as a constant denoted by $\mathrm{esc}_{nm}\_\mathrm{r}$.

Hence, define the difference between the revenue and cost of esc_{nm} in a given period as profit, donated as $\mathrm{esc}_{nm}\_\mathrm{p}$.

$$\mathrm{esc}_{nm}\_\mathrm{p} = \mathrm{esc}_{nm}\_\mathrm{r} - \mathrm{esc}_{nm}\_\mathrm{c} \tag{12}$$

4.2.3 Modeling pricing strategy

In the current scenario of multi-edge service pricing, service providers initiate changes in pricing strategies that prompt updates in the market state. For ESP_m, the strategy strat_m can be represented as $\{\mathrm{pr}_m, \mathrm{pr}_{m'}\}$, where pr_m represents the current price of ESP_m for services, and $\mathrm{pr}_{m'}$ represents the adjusted price after ESP_m modifies its service strategy. Consequently, ESCs will reassess based on the strategies of ESPs, selecting the ESP that maximizes their own profits, denoted as

$$\mathrm{esp}_m = \mathrm{argmax}(\mathrm{esc}_{nm}\_\mathrm{p}) \tag{13}$$

Therefore, $\mathrm{distr(ESP)} = \{c_1, c_2, \ldots, c_n\}$ represents the distribution of service invocations from different ESPs, where c_n signifies the count of ESCs invoking services provided by ESP_n. This distribution stems from the statistics derived from $\mathrm{argmax}(\mathrm{esc}_{nm}\_\mathrm{p})$. The eventual profit generated from the strategy alteration of ESPs can be expressed as

$$\mathrm{ESP}\_\mathrm{P}_m = \mathrm{distr(ESP)}_m * \mathrm{strat}_m \tag{14}$$

The analysis of multi-edge service pricing problem fundamentally involves identifying strategies that can lead to a particular state, often a strategy associated with some form of equilibrium. Therefore, the strategies to be solved can be represented as

$$\mathrm{strat} = \mathrm{state(Strat)} \tag{15}$$

where state(Strat) represents the strategy that enables the service transaction market to reach a specific state.

Figure 2 illustrates three models: ESP, ESC, and strategy, along with their fundamental elements and interactions. Initially, ESP initiates pricing strategy adjustments in response to the current state of the transaction market. Subsequently, this adjustment fundamentally alters the service unit price, thereby affecting ESP's revenue and ESC's cost. Following this, ESC, driven by maximizing profit, adapts service

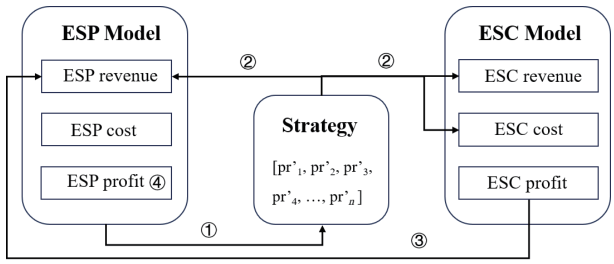

Fig. 2 Interaction between ESP and ESC through pricing strategy.

selections. This adjustment influences ESC_R through changes in service quality of service (QoS) and affects ESC_C through alterations in service unit price. This change ultimately reflects in the revenue of the relevant ESPs, culminating in an iterative process to arrive at the final ESP_P.

4.3 Credibility assessment and admission rule

To facilitate the normal conduct of multi-edge service pricing games within the market environment, it is essential to conduct credibility assessment of ESPs and services based on pricing behavior and service operational performance. By designing admission rules, we aim to eliminate potential factors that could adversely interfere with pricing games.

In service pricing games, besides the factors related to distance, ESCs typically consider the service level agreement (SLA) when choosing a service. The SLA defines the service provider's expected service level, performance metrics, and quality standards, often encompassing specific indicators like service availability, response times, and fault handling. Consequently, the credibility of a service is primarily assessed by observing whether its actual execution aligns with the commitments outlined in its claimed SLA. Let $C_s \in [0,1]$ represent the level of credibility we have in a service. Specifically, we assume that the QoS of a service is characterized by q metrics, where w_k represents the weight of the kth metric. After a period of time Δt, and assuming that it is the tth period since the beginning, observing whether the metrics in QoS meet the requirements specified in the SLA. Let C denote the set of metrics that are satisfied, and we calculate the trustworthiness of the service for this period as follows:

$$C_{s,t} = \frac{\sum_{k\in T} w_k}{\sum_{k=1}^{q} w_k} \tag{16}$$

Then the overall trustworthiness that aggregates trust values of t periods is defined as

$$C_s = \frac{\sum_{k=1}^{t} \mathrm{wt}_i T_{s,k}}{\sum_{k=1}^{t} \mathrm{wt}_k} \tag{17}$$

where wt_k denotes the weight of the k-th time period. Since time-based attenuation is a fundamental property that trust should meet, wt_k can be computed with a time-attenuation function:

$$\mathrm{wt}_k = \frac{1-(1-\lambda)^k}{\sum_{v=1}^{k}[1-(1-\lambda)^v]} \tag{18}$$

where $\lambda \in [0,1]$ is an adjustable positive constant in the system, and can be tuned accordingly.

Abnormal behaviors of an ESP, such as engaging in malicious pricing for unfair competition or falsely advertising SLAs for services, can significantly impact the pricing game process. Therefore, conducting trustworthy assessments of ESPs is crucial. Generally, the credibility of an ESP can be evaluated from two perspectives: malicious behavior and the services they offer.

To a large extent, the reputation of an ESP is reflected in the level of credibility in its services. Let c represent the total number of services provided by the ESP, and C be the collection among these c services that are deemed trustworthy. The number of times the i-th service is invoked is denoted as n_i. The overall credibility of the ESP's services is calculated as follows.

$$a(t) = \begin{cases} 1-\dfrac{t}{t_0} & \text{if } t \leqslant t_0, \\ 0 & \text{if } x > t_0 \end{cases} \tag{19}$$

$$C_e = \max\{0, C_{e,s} - \sum_{i\in \mathrm{MB}} a(t_i) p_{\text{type of } i}\} \tag{20}$$

where MB represents the list of harmful behaviors that ESP may exhibit, $C_{e,s}$ represents the initial trust value of ESP and $p_{\text{type of } i}$ denotes the severity of punishment for a specific type of malicious behavior. It is important to note that the specific design of MB and $p_{\text{type of } i}$ is beyond the scope of this study and will not be further discussed. Additionally, in subsequent modeling of game problems, an ESP offering multiple services will be regarded as multiple distinct ESPs to reduce model complexity.

In the multi-edge service transaction market, we only permit services and ESPs with a credit score higher than the specified threshold $\varepsilon_s/\varepsilon_e$ to participate in the pricing game. The ineligibility of a particular service will not render its affiliated ESP ineligible; however, the ineligibility of an ESP will result in the disablement of all associated services.

4.4 Architecture

In this paper, we introduce an incentive-driven architecture for service pricing game and resolution, aimed at addressing the multi-edge service pricing problem, showcasing a profit optimization scheme.

Initially, we illustrate the service pricing scenario, delineating the utility functions of key participants ESP and ESC, and describe the interaction between ESP and ESC by defining pricing strategy. Subsequently, we formulate the multi-edge service pricing problem as a multi-participant stochastic game model. We then devise an incentive mechanism based on Pareto improvement, fostering the evolution of the game towards a Pareto-optimal state. Finally, an enhancement to the PSO algorithm is proposed for equilibrium resolution within the game model. This architectural framework provides a comprehensive strategy to address the complex issue of multi-edge service pricing. By integrating closed-loop game-theoretic models and solution approach, the aim is to optimize profits while ensuring equitable participation among stakeholders, as depicted in Fig. 3.

5 Service Pricing as an Incentive-Driven Multi-Participant Stochastic Game

Hence, based on the motivating example presented, the multi-edge service pricing problem proposed in this paper can be modeled as a multi-participant stochastic game, as shown in Fig. 3 (Step 2). Among them, multiple edge service providers of homogeneous services can be viewed as multiple participants in the game. The current pricing strategy can be regarded as a state s, while all other possible pricing constitutes the state space S. The adjustment of service prices by ESP based on pricing strategy forms the action space A, and the reward r is the profit gained by ESP after adjusting the prices from ESC in Fig. 4. An essential aspect of this model lies in the assumption that each ESP operates as a perfectly rational entity, adjusting its pricing strategy according to the prevailing game state in order to maximize its utility function. Moreover, ESCs contribute to this process by offering environmental feedback, making rational decisions regarding service invocation. This iterative process persists until either convergence is achieved or the maximum number of iterations is surpassed.

The utility function of the game is equivalent to the profit of the ESP. For a given esp_n, the optimal strategy satisfies

$$\begin{aligned}
&\mathrm{pr}_n=\operatorname{argmax}\left(\sum_{i=1}^{n}\left(\sum \mathrm{Count}_{\mathrm{esc}_i_n}\right)*\mathrm{pr}_n-\mathrm{esp_c}_n\right),\\
&\text{subject to } \mathrm{Count}_{\mathrm{esc}_i_n}\in\left[0,\mathrm{Count}_{\mathrm{esc}_i}\right],\\
&\qquad \mathrm{pr}_n\in[\mathrm{pr}_{\min},\mathrm{pr}_{\max}],\\
&\qquad \mathrm{esp_c}_n\in[0,\mathrm{esp_c}_{\max}]
\end{aligned}\tag{21}$$

where $\mathrm{Count}_{\mathrm{esc}_i}$ represents the total number of ESCs in region i, while $\mathrm{pr}_{\min}$ and $\mathrm{pr}_{\max}$ represent the reasonable lower and upper limits of the edge service price.

In this game, each participant strives to make decisions that will enhance their interests. If each participant, given the decisions made by other participants, has maximized their interests, the game will reach a Nash equilibrium. Assuming that

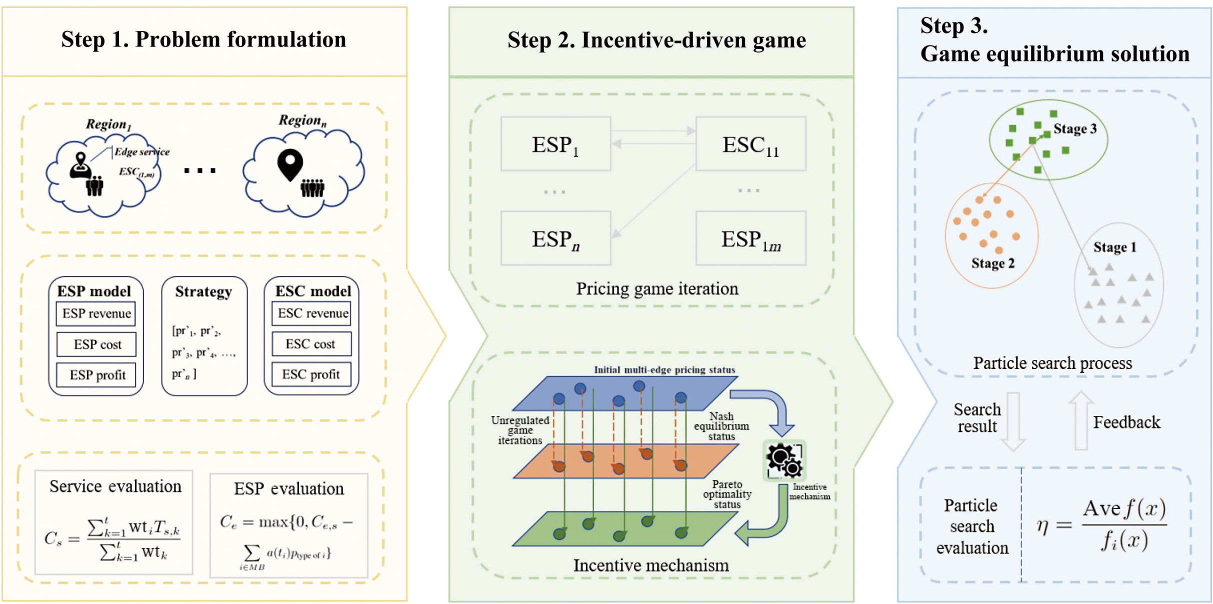

Fig. 3 Incentive-driven architecture for service pricing game and resolution.

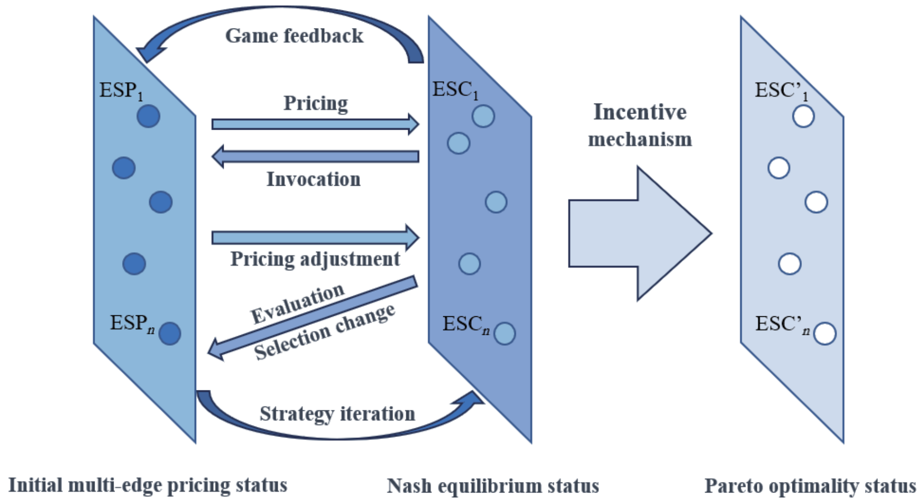

Fig. 4 Multi-edge service pricing as an incentive-driven multi-participant stochastic game.

$\mathrm{PR} = \{\mathrm{pr}_1, \mathrm{pr}_2, \ldots, \mathrm{pr}_n\}$ is the strategy combination adopted by all ESPs in the game, where pr_n represents the service pricing of esp_n.

Lemma 1 PR^* is a sufficient and necessary condition for the equilibrium solution of the game if and only if, for strategy pr_k of esp_k,

$$\mathrm{ESP\_P}_k(\mathrm{PR}^* \odot \mathrm{pr}_k) \leqslant \mathrm{ESP\_P}_k(\mathrm{PR}^*) \tag{22}$$

where $\mathrm{PR}^* \odot \mathrm{pr}_k$ represents that only ESP_k changes its strategy in PR^*, while the strategies of other ESPs remain unchanged.

Proof Given a mixed strategy state $s \in S$, for each $i \in N$, $\mathrm{pr}_i \in \mathrm{PR}_i$, define

$$\varphi_i, \mathrm{pr}_i(s) = \max\{0, \mathrm{ESP\_P}_i(s \odot \mathrm{pr}_i) - \mathrm{ESP\_P}_i(s)\} \tag{23}$$

which indicates the intention of esp_i to replace the strategy. The mapping function from s' to s can be defined as $f(s) = s'$, where

$$s_i'(\mathrm{pr}_i) = \frac{s_i(\mathrm{pr}_i) + \varphi_{i,\mathrm{pr}_i}(s)}{1 + \sum_{\mathrm{pr}_i' \in \mathrm{PR}_i} \varphi_{i,\mathrm{pr}_i}(s)}, \tag{24}$$

Because each $\varphi_i, \mathrm{pr}_i(s)$ is continuous and S is convex, the inference of Brouwer's fixed point theorem indicates that there must exist at least one fixed point s in f, for which the equation $f(s) = s'$ holds. Specifically, if the state s is a Nash equilibrium, then all φ would be equal to zero, and it can be proven that s is a fixed point of the function f. Conversely, for any fixed point s of the function f, since the expectation is linear, there must exist at least one strategy pr_i' in state s that satisfies $\mathrm{ESP\_P}_{i,a_i'}(s) < \mathrm{ESP\_P}_i(s)$. According to the definition of φ, it can be concluded that $\varphi_{i,a_i'}(s) = 0$. Since s is a fixed point of the function f, it follows that $s_i'(\mathrm{pr}_i') = s_i(\mathrm{pr}_i')$.

Based on reference Eq. (25), it can be concluded that for each i and $\mathrm{pr}_i' \in \mathrm{PR}_i$, $\varphi_{i,\mathrm{pr}_i'}(s) = 0$. That means no ESP can improve its expected utility by switching to a pure strategy. Therefore, according to Lemma 1, the state s is a Nash equilibrium. ■

In non-cooperative multi-participant stochastic games, each participant typically adopts a self-centric strategy, aiming to maximize their individual interests, irrespective of others' strategies. The resulting Nash equilibria are commonly embraced by all participants, as no one finds it advantageous to alter their strategy. While these equilibria embody a consensus reached by all participants within the prevailing circumstances, they do not consistently yield optimal profits for the entire game. Indeed, Nash equilibria frequently yield diminished profits for certain participants or the entire system. This limitation stems from their focus solely on locally optimal strategies, disregarding the potential gains from global collaboration. Consequently, the overarching benefits of cooperation might be undervalued. Using the frequently cited example of the prisoner's dilemma in game theory research, two suspects, after committing a crime, are arrested by the police and placed in separate rooms for interrogation. The police, lacking concrete evidence, are aware of both individuals' guilt. Each suspect is informed of the following consequences: if both deny involvement, each will be sentenced to one year in prison; if both confess, they will each receive an eight-year sentence; if one confesses while the other denies involvement, the one who confesses will be set free while the other will receive a ten-year sentence. Therefore, each prisoner faces the choice of confessing or denying involvement. However, irrespective of the accomplice's decision, the optimal choice for each prisoner is to confess: if the accomplice denies involvement and one confesses, they are set free, but if they deny involvement, they receive a one-year sentence, making confession preferable; if the accomplice confesses and one also confesses, they both receive an eight-year sentence, which is better than the ten-year sentence for denial. The payoff matrix for Prisoner A and Prisoner B is shown in Table 1. Consequently, both suspects choose to confess, resulting in an eight-year sentence each. Opting to deny involvement would lead to a one-year sentence for both, clearly indicating the superior outcome.

Pareto improvement refers to finding a strategy in a game where at least one participant's profit increases without reducing any other participant's profit. In a game, a strategy combination $\{a_1, a_2, ..., a_n\}$ is considered a Pareto improvement if and only if there exists a player j, for whom a particular alternative strategy $a'_j \in A_j$ is available, satisfying

$$u_j(a'_j, a_{\neg j}) \geqslant u_j(a_j, a_{\neg j}) \tag{25}$$

where $a_{\neg j}$ represents the strategy combination of all participants except j, and a_j is the strategy currently chosen by participant j. This inequality indicates that the participant's profit after changing the strategy to a'_j is greater than or equal to their profit under the current strategy.

Hence, this paper introduces an incentive-driven pricing mechanism rooted in Pareto improvement, enabling the game to achieve Pareto optimality, maximizing overall profits optimally, as depicted in Fig. 3 (Step 3). Pareto improvement denotes a scenario where game participants modify their strategies, leading to at least one participant's profit increment without compromising others' interests. Consequently, the ensuing constraint can be appended to Eq. (21):

$$\mathrm{pr}_n = \operatorname{argmax}\left(\sum_{i=1}^{n}\left(\sum \mathrm{Count}_{\mathrm{esc}_{i\_n}}\right) * \mathrm{pr}_n - \mathrm{esp\_c}_n\right), \tag{26}$$
$$\text{Subject to } \mathrm{esp\_r}_{\neg n} - \mathrm{esp\_r}'_{\neg n} \geqslant 0$$

Table 1 Prisoner's dilemma payoff matrix.

Prisoner A	Prisoner B	
	Confess	Deny
Confess	(−8, −8)	(0, −10)
Deny	(−10, 0)	(−1, −1)

where $\mathrm{esp\_r}'_{\neg n}$ and $\mathrm{esp\_r}_{\neg n}$ represent the profit of other ESPs before and after the price change of ESP_n.

Lemma 2 In a multi-participant stochastic game under the mixed strategy, there exists at least one Pareto Optimality solution.

Proof Given a multi-objective optimization problem: $F(x) = (f_1(x), f_2(x), ..., f_k(x))$, where x is the decision vector, $f_i(x)$ is the function of the i-th optimization objective, and k is the number of optimization objectives.

Assuming that there are no non-dominated solutions, all solutions are dominated by other solutions. This means that we can find a set of $\{a_1, a_2, ..., a_n\}$ such that x_{a_1} dominates x_{a_2} and x_{a_2} dominates x_{a_3}. However, this means that x_{a_1} dominates x_{a_n}, which is contradictory to the nature of multi-objective optimization problems. Because in multi-objective optimization problems, there cannot be a solution that makes all objective functions get the minimum or maximum. Therefore, a Pareto optimal solution must exist. ■

Lemma 3 If there is no solution for a pr_n in Eq. (26), then the multi-edge service pricing game is in a Pareto-optimal state.

Proof In game theory, a Pareto-optimal state refers to a situation where there is no improvement possible for at least one individual without causing harm to others. To prove that if there is no solution for a pr_n in Eq. (26), then the multi-edge service pricing game is in a Pareto-optimal state, we can utilize proof by contradiction.

From Eq. (26), it can be concluded that pr_n can improve the profit of at least one ESP while not decreasing the profits of other ESPs. Hence, pr_n being a solution to the Eq. (26) is equivalent to being an effective Pareto improvement. Assuming there is no Pareto-improving solution at a given state, yet the global state is not Pareto-optimal, meaning there exists an improvement benefiting at least one individual without harming others. According to the definition of Pareto optimality, this contradicts the assumption that there are no Pareto improving solutions. ■

6 Enhanced Heuristic Algorithm for Stochastic Game Solving

The multi-participant stochastic game model described above poses a complex multi-objective optimization challenge due to its non-differentiable optimization function. Consequently, closed-form equilibrium solutions are unattainable, rendering the use of analytical methods challenging for accurate solutions. The Nash Q-learning algorithm, introduced by Hu et al.[25], offered theoretical promise for addressing the outlined game problems by extending the Q-learning algorithm to non-cooperative multi-agent domains. In the context of causal inference and probabilistic graphical models, some research attempts to utilize probabilistic graphical models to model the interactions and influences within game theory[26]. However, its computational demands present a significant obstacle, especially in large-scale agent scenarios akin to those discussed in our study. In this paper, we introduce an enhanced algorithm called three-stage inertia weight adaptive optimization PSO (TIAO-PSO), which capitalizes on a staged adaptive optimization technique employing an inertia factor. Through iterative particle swarm optimization, our algorithm effectively converges towards game equilibrium solutions.

The classical PSO algorithm draws inspiration from the stochastic foraging behavior of birds[27]. In this algorithm, each particle embodies a potential solution to the problem, characterized by its position, velocity, and corresponding fitness value, serving as a quality metric. Navigating within the feasible solution space, each particle's movement —both direction and distance—is dictated by its velocity, influenced by both individual experience and collective swarm behavior. Post position update, the fitness value is computed, and individual as well as global extremes are tracked and recorded. With each iteration, we update the positions of both individual and global best points, persisting in iterations until an optimal solution is reached. In the process of pricing game of ESPs, at any given moment, the pricing strategies of all ESPs correspond to the positions of all particles in space, and the particle search process corresponds to the iterative process of service pricing. Therefore, the PSO algorithm is suitable for solving the equilibrium state of the game.

The quantity n of ESP represents the dimensionality of the search space in the algorithm, where h particles constitute a particle swarm denoted as $X=[x_1,x_2,...,x_h]$. The i-th particle's position in the n-dimensional space is denoted by a corresponding n-dimensional vector $x_i=[x_{i1},x_{i2},...,x_{in}]$, which also represents a possible solution to the game. The fitness value of each particle x_i can be calculated using the defined objective function. The i-th particle's velocity, denoted by $v_i=[v_{i1},v_{i2},...,v_{in}]$, represents its respective direction and magnitude. Individual and population extremum are respectively denoted as $\mathrm{ex}_i=[\mathrm{ex}_{i1},\mathrm{ex}_{i2},...,\mathrm{ex}_{in}]$ and $\mathrm{ex}_g=[\mathrm{ex}_{g1},\mathrm{ex}_{g2},...,\mathrm{ex}_{gn}]$.

During each iteration, the particle updates its position and velocity based on both individual and global extremum, which can be calculated as

$$v_{in}^{k+1}=\omega v_{in}^{k}+\mu_1 r_1(\mathrm{ex}_{in}^{k}-x_{in}^{k})+\mu_2 r_2(\mathrm{ex}_{gn}^{k}-x_{in}^{k}) \tag{27}$$

$$x_{in}^{k+1}=x_{in}^{k}+v_{in}^{k} \tag{28}$$

where ω represents the inertia weight, k represents the current number of iterations, v_{in} and x_{in} represents the velocity component and position component, respectively. ex_{in} represents the individual extremum, and ex_{gn} represents the global extremum. μ_1 and μ_2 are acceleration constants, $r_1,r_2\in[0,1]$ are random number. To regulate the search path of the particle, its velocity and position are limited to the interval $[-X_{\max},X_{\max}]$ and $[-v_{\max},v_{\max}]$. The fitness function for each particle is defined as

$$f(\ddot{X})=\sum_{i=1}^{n}\max\{\mathrm{ESP\_P}_i(\dot{X}\odot \mathrm{pr}_i)-\mathrm{ESP\_P}_i(\dot{X}),0\} \tag{29}$$

According to the game we construct, $f(\ddot{X})=0$ if and only if $\dot{X}$ is a Pareto optimality solution.

The PSO algorithm is greatly influenced by the parameter ω, which significantly impacts the precision and convergence speed of iterations. Specifically, higher values of ω often diminish the accuracy and convergence speed of the search process. Conversely, lower values of ω might cause the search to get trapped in local optima, resulting in "immaturity". The inertia weight linearly decreasing particle swarm optimization (ILPSO) algorithm has shown promising performance in addressing this issue[28]. However, a linearly decreasing setting for ω might not be optimal for our complex game model construction as it could potentially slow down the iterative convergence speed.

To tackle this challenge, this study introduces TIAO-PSO algorithm, building upon the foundations of the ILPSO algorithm, as illustrated in Fig. 5. Tailoring specific strategies to adjust the inertia factor in response to the distinct characteristics of the three stages during the iterative process of the model, we aim to achieve efficient and precise convergence.

Across three stages, our approach optimizes the ω parameter to refine the particle swarm optimization process. In Stage 1, a higher initial ω-value promotes

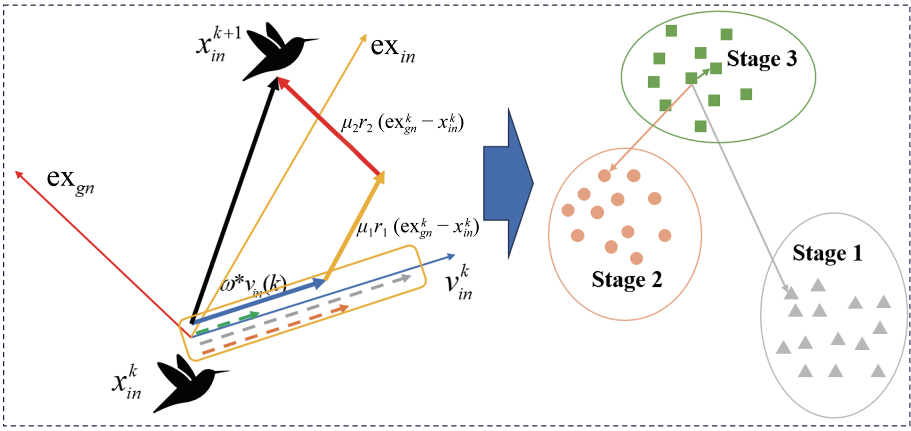

Fig. 5　Three-stage inertia weight adaptive optimization PSO.

an extensive global search among particles, gradually decreasing with each iteration to encourage broader exploration. Transitioning to Stage 2, our strategy incorporates an adaptive ω selection mechanism informed by particle fitness feedback. Notably, if a particle demonstrates improved fitness in the prior iteration, we augment its ω-value for the subsequent iteration. This fine-tuning mechanism amplifies individual particle fitness, enhancing the overall effectiveness of the search process. Finally, Stage 3 employs a lower ω-value to facilitate a more precise local search, expediting convergence. This strategic reduction in ω enhances the swarm's focus on exploiting local areas, accelerating convergence without compromising accuracy.

Therefore, the weight factor ω can be calculated as

$$\omega = \begin{cases} \eta * \omega_{\max} - \dfrac{\eta * k * (\omega_{\max} - \omega_{\min})}{k_{\max}}, & (\omega_2, \omega_1); \\ \left(1 - \dfrac{k}{k_{\max}}\right) * \omega_{\max} + \dfrac{k}{k_{\max}} * \omega_{\min}, & k \in \text{else} \end{cases} \tag{30}$$

$$\eta = \frac{\text{Ave} f(x)}{f_i(x)} \tag{31}$$

where η means that well-behaved particles will have higher inertia in the next iteration, ω_2 and ω_1 represent the baseline value of ω at the beginning and end of the second stage. Algorithm 1 describes the solution process of the edge service pricing game based on the proposed algorithm.

Algorithm 1　Game equilibrium searching algorithm

Require: $n, \text{nm}, Z_n, \text{esp\_c}_n, \alpha * \text{RD}, \omega, \text{Iteration}_k$, where n, nm denotes the number of regions and ESCs in region n, respectively

Ensure: Pricing strategies at the Pareto Optimality point

```
Initial each particle vector X_i, x_im ∈ [pr_min, pr_max]
while Pareto Optimality not found do
    Calculate the fitness value of each particle according to
    Eq. (29);
    Update ex_i, ex_g;
    if Iteration_k in stage_s then
        Update ex_i and ex_g
        Update v_in^k, x_in^k according to Eq. (33) in stage_s
    end if
    Update particle vector X_i
    Iteration_k=Iteration_k+1
    if Iteration_k = Ite_max then
        break while
    end if
end while
return X_i
```

7　Experimental Result

In this section, we introduce a dataset constructed using practical test and simulation data, accompanied by corresponding parameter configurations. Through this dataset, we scrutinize the impact of implementing an incentive mechanism on individual as well as collective profits within the pricing game. Furthermore, we conduct a comparative analysis among the TIAO-PSO algorithm, classic PSO, and ILPSO algorithms, showcasing the superior performance of the proposed algorithm in addressing the edge service pricing game problem.

7.1　Experimental setting

To substantiate the practical viability of our approach, we have collected actual statistical data encompassing utility costs, IT industry population metrics, and geographic coordinates for 30 regions. Complementing this, we positioned multiple test nodes across these regions, facilitating real-world tests. This deployment allowed us to acquire the latency probability distribution for inter-regional service invocations. From the perspective of scale, the dataset contains data from 30 ESPs and 2250 ESCs, along with 36 000 cross-region invocation test records. Figure 6 illustrates the relationship between service invocation popularity and cost across ten typical regions, indicating a predominantly positive correlation between the two factors.

Our algorithm's performance is managed through various parameters, encompassing the edge service pricing interval (strategy space), swarm size, the permissible range for inertia factor ω values, maximum iteration count $\text{Ite}_{\max}$, and acceleration constants μ. Augmenting the particle size enhances global search capabilities while maintaining manageable computational overheads. Properly configuring the strategy space prevents model entrapment in non-converging states. Setting a maximum iteration count $\text{Ite}_{\max}$ prevents unnecessary resource expenditure by ensuring algorithm termination. The acceleration constants optimize particle search directions, whereas the ω value significantly influences our approach's overall performance. Refer to Table 2 for a detailed presentation of the pivotal parameters utilized in our experiments.

7.2 Profit analysis

As a case study, Fig. 7 delineates the impact of incentives on overall profit. Given the non-uniqueness of equilibrium states in game theory[29–32], multiple sets of repeated experiments were conducted. The lines in the figure represent the average overall profit, while the shaded region indicates the profit fluctuation. Across varying ESP scales, ranging from 5 to 25, the proposed

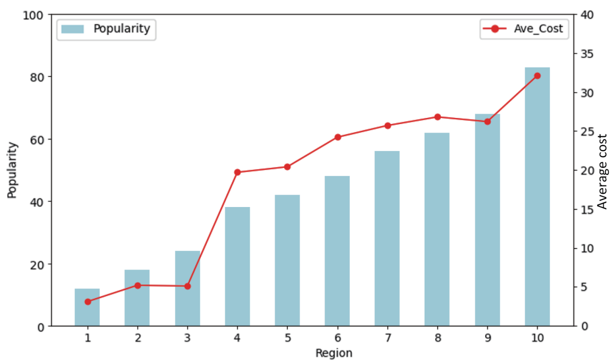

Fig. 6 Service invocation popularity and cost distribution.

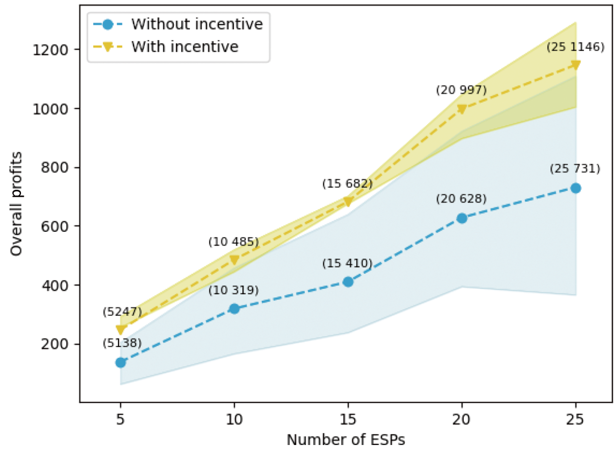

Fig. 7 Comparison of overall profits with different ESP scales.

Table 2 Parameter setting.

Parameter	Value
Edge service ceiling price	0.01/100 invocation
Edge service floor price	0.1/100 invocation
Swarm size	[50 300]
Maximum of inertia factor $\omega_{\max}$	0.8
Minimum of inertia factor $\omega_{\min}$	0.2
Maximum iteration num. $\text{Ite}_{\max}$	1000
Acceleration constants μ_1, μ_2	random(1, 2)
Latency impact factor α	10^{-4}
Maximum cost of ESP $\text{esp\_c}_{\max}$	50
Maximum particle velocity $v_{\max}$	0.003

incentive mechanism consistently generates higher overall profits compared to unregulated pricing. This outcome strongly substantiates the effectiveness of the proposed incentive mechanism in achieving optimized profits.

Furthermore, in Table 3, we calculate the Anarchist Losses of the pricing game without incentives. These losses signify potential adverse consequences or disadvantages stemming from an unregulated pricing game. Due to the non-uniqueness of solutions in both Pareto optimality and Nash equilibrium, extreme cases exist where the Nash equilibrium coincides with the Pareto optimality solution. Consequently, the data in the table reflects a unstable loss, but typically leaning towards positive values.

Table 3 Anarchist losses of different ESP scales.

Number of ESPs	5	10	15	20	25
Profits without incentive	138	319	410	628	731
Profits with incentive	247	485	682	997	1146
Anarchist loss	0.400	0.342	0.398	0.370	0.362

Figure 8 presents a comparative analysis of individual average profits post multiple convergence rounds with an ESP scale of 10. The visual representation distinctly illustrates the dynamic shifts in profits among the participating ESPs. Notably, the profits of eight ESPs showcased an evident surge under the new game equilibrium, portraying substantial enhancement. Conversely, a marginal decrease in profits was observed among only two ESPs within this equilibrium state. This indicates that incentive mechanisms generally ensure an increase in overall profits and the majority of individual profits rather than all individual profits. In the current experimental setup, the rate of increase in individual profits stands at 80%. Addressing the fairness aspect, a potential avenue lies in designing a compensatory mechanism to offset the losses incurred by these two ESPs. However, it is pertinent to note that this discussion of compensation mechanisms remains beyond the scope of this paper.

7.3 Iteration evaluation

To monitor the evolving trends in the iterative

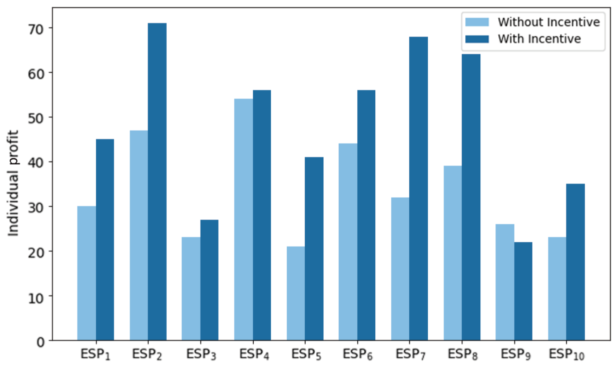

Fig. 8 Comparison of individual profit.

equilibrium of pricing games, we have introduced an iterative evaluation process incorporating two key observation metrics: absolute increment (AI) and relative increment (RI). Regarding the metrics, $AI=\{ai_1, ai_2, ..., ai_k\}$ portrays the variance in the overall game profit in comparison to the initial profit, primarily reflecting the cumulative trend of profit generated throughout the game until the current moment. Meanwhile, $RI=\{ri_1, ri_2, ..., ri_k\}$ showcases changes in the overall game profit concerning the profit from the previous iteration, emphasizing more localized and phased trends in alterations during the iterative process. Hence, ai_k and ri_k can be computed as

$$ai_k = esp\_p_k - esp\_p_1 \quad (32)$$

$$ri_k = esp\_p_k - esp\_p_{k-1} \quad (33)$$

where esp_p_k represents the profit that the target provider can obtain in the k-th round of pricing game iteration.

We extracted segments comprising 10 rounds of iteration each from both Nash iteration and Pareto iteration processes. Figure 10 illustrates the trends in profit changes for these two types of iterations. From the figure, it is evident that in the Nash iteration process, the overall profit does not consistently increase with each iteration, and the final profit might not necessarily surpass the initial state. This is inherent to the nature of Nash equilibrium – aiming for a stable state rather than the optimal one. On the other hand, in the Pareto iteration process, it is noticeable that the overall profit in each iteration consistently exceeds the previous one, ensuring the final profit is higher than the

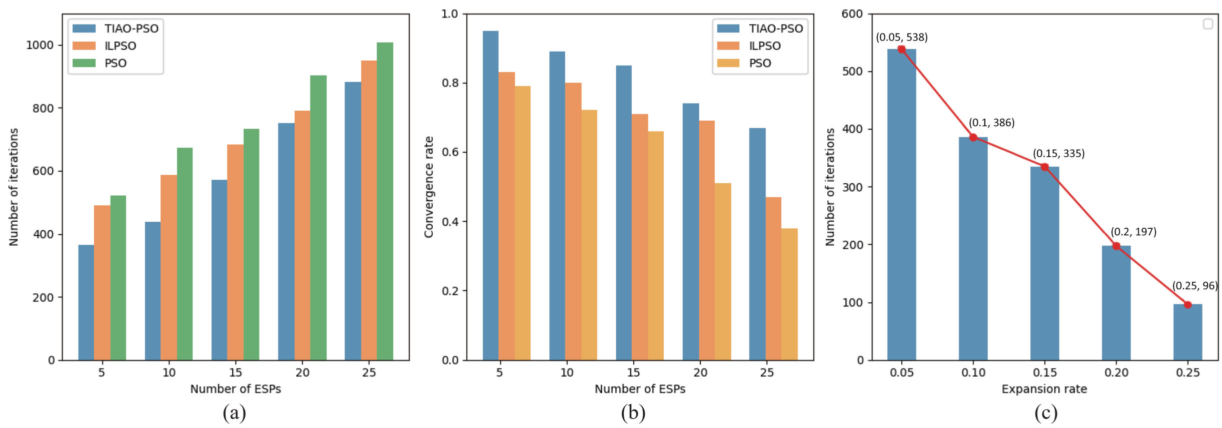

Fig. 9 Performance comparison between PSO, ILPSO, and TIAO-PSO. (a) Number of iterations under different ESP scale, (b) convergence rate under different ESP scale, and (c) number of iterations under relaxed Nash equilibrium criteria.

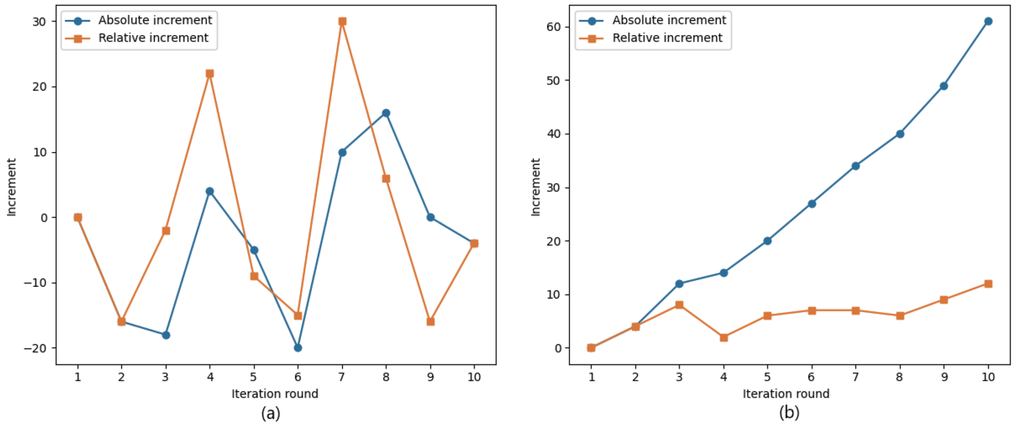

Fig. 10 Trend of overall profit change throughout the iterations of the game with/without incentive.

initial one. This aligns with the fundamental principle of Pareto improvement – striving for a balanced state at the peak profit.

7.4 Performance evaluation

Due to the increased complexity involved in attaining Nash equilibrium states as opposed to finding Pareto optimal states, we conducted a comparative analysis of three algorithms concerning their convergence efficacy in solving Nash equilibrium problems across varying ESP scales. Figure 9 portrays the convergence dynamics exhibited by these algorithms at diverse ESP scales. Within Figs. 9a and 9b, the x-axis signifies the ESP scale, the first y-axis represents the number of iterations necessary for the game model to converge, and the second y-axis showcases the average convergence rate observed over multiple experiments, indicating the proportion of games that eventually reached equilibrium states. Navigating high-dimensional spaces often encounters convergence hurdles. Hence, in our experiments, we constrained pricing strategy values to two decimal places and limited each particle to ten strategy options to ensure adherence to acceptable iteration constraints. The figure highlights that as the ESP scale expands, connoting a broader search space, the iteration count required for convergence also escalates, concurrently leading to a gradual decline in the convergence rate. In such scenarios, the proposed TIAO-PSO algorithm demonstrates superior performance in terms of both requisite iteration counts and achieved convergence rates.

The precise determination of Nash equilibrium often imposes substantial computational burdens, especially in the context of identifying Nash points within multi-participant stochastic games— an inherently complex task. In practical scenarios, game participants frequently only require a rough strategy determined by an approximate Nash equilibrium. In Fig. 9c, we witness the convergence dynamics of a pricing game involving 10 ESPs as we relax the criteria for Nash equilibrium. In this scenario, if an ESP modifies its strategy, maintaining ESP_P's growth rate within the expansion rate ensures its alignment with Nash equilibrium. To avert premature convergence in the model, we expand the strategy space into 50 dimensions. The figure notably portrays a marked reduction in iteration counts as the Nash criterion becomes less stringent. Furthermore, even amid an expanded search space, the algorithm consistently outperforms the strict Nash criterion.

8 Conclusion and Future Work

In this paper, we have enhanced the modeling representation of participants in the multi-edge service pricing problem, formulating this issue as a multi-participant stochastic game model centered around ESP profits as utility functions. To address the issue of unregulated pricing games leading to a decline in overall profits, we propose an incentive mechanism based on Pareto improvement. This mechanism aims to achieve optimal overall profits and includes an additional proof of the existence of Pareto-optimal solutions. Considering the complexity of iterative gaming models, we have enhanced the PSO algorithm. This enhancement involves optimizing the value of ω in three distinct phases, aimed at expediting the equilibrium state resolution process. Finally, we conducted experimental validation using a dataset constructed from cross-region service invocation tests and expanded experiment scale to observe potential scenarios of non-convergence. The numerical results substantiate the effectiveness of the proposed method.

Apart from the cases discussed in this paper, future research will notably focus on pricing issues concerning collaboration among multiple edge services to accomplish tasks at the edge. One key challenge involves assessing the contribution of each edge service to the task at hand. A common approach is to address multi-participant cooperative pricing problems based on the Shapley value, whereby the analysis involves assessing each participant's contribution to the overall coalition outcome and subsequently allocating profits accordingly. This method can offer insights into fair pricing strategies and foster collaboration among participants.

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Shengye Pang is working towards the PhD degree at College of Computer Science and Technology, Zhejiang University, Hangzhou, China. He received the BS degree in computer science from Tongji University, in 2015. His current research interests include blockchain and service computing.

Jiayin Luo is currently ardently pursuing the PhD degree at College of Computer Science and Technology, Zhejiang University, Hangzhou, China. He received the BS degree in computer science from Tongji University in 2021. His current research interests include service computing and distributed systems.

Fan Wang is currently pursuing the PhD degree at College of Computer Science and Technology, Zhejiang University, Hangzhou, China. She received the master degree in School of Computer Science, Qufu Normal University in 2021. Her research interests include big data analyses and recommendation system.

Xinkui Zhao is a ZJU 100-Young professor at Zhejiang University, China. He received the PhD degree from College of Computer Science and Technology at Zhejiang University in 2016. His research interests mainly include cloud-native technologies, edge computing, and service computing.

Jintao Chen is working towards the PhD degree at College of Computer Science and Technology, Zhejiang University, Hangzhou, China. She received the BS degree in Internet of Things from Central South University. Her research interests include service computing, service regulation, and machine learning.

Jianwei Yin received the PhD degree in computer science from Zhejiang University in 2001. He is currently a full professor with College of Computer Science, ZJU. His current research interests include service computing and business process management.