Fair Food Delivery Trading System Based on Edge Computing and Stackelberg Game

Tao Wu[1](✉), Xuefeng Zan[2], Lei Xu[1], Yuang Chen[1], and Kai Liu[3]

[1] Georgia Tech Shenzhen Institute, Tianjin University, Shenzhen 518055, China
taowu@gatech.edu
[2] Sun Yat-sen University, Guangzhou 510275, China
[3] Shenzhen Securities Communication Co., Ltd., Shenzhen 518040, China

Abstract. Recent years have witnessed Food-as-a-Service (FaaS) facing challenges in delivery pricing. FaaS platform collects orders from restaurants and distributes them to delivery man (DM). The fairness of the pricing and distribution have raised attention. To improve the fairness of FaaS delivery order pricing and allocation, it is critical to design a trading system with a better order distribution rule and pricing model. This paper proposes a trading system with a fair pricing model based on the edge computing system. The Stackelberg model, a second-order game model, is deployed on the edge computing system for pricing. And a smart agent algorithm based on Deep Reinforced Learning (DRL) is used for optimization. The system realizes a balance of utilities of both restaurant and DM, and it also helps the DM supply meets the spatiotemporally dynamic demands. The results indicate that the system will carry on a fair and win-win FaaS delivery trading. The verification result shows the stability of Nash equilibrium in practice and proves that our system helps build a balance between utilities of restaurant and DM. Moreover, the simulation result illustrates the system's stability and real-time response performance, and the transaction result indicates that our system helps improve market fairness.

Keywords: Stackelberg game · Dynamic pricing · Edge computing

1 Introduction

Recent years have witnessed the rapid development of Food-as-a-Service (FaaS), along with the centralization of market. Nowadays, very few companies monopolize the market in a specific area, like Meituan monopolizing the China market and GrabFood occupying the Southeast Asia market. However, due to the lack of regulation governing the business, fairness and labor relationship of the business have attracted society's attention. In this paper, we focus on delivery trading fairness between the restaurant, platform and delivery man three parties and we wish to improve the food delivery trading fairness and the labor relationship by proposing a new generation of pricing system.

In this paper, we develop a pricing system with a game-theoretic formulation, operating on the blockchain with the help of DRL for optimization. To improve the fairness of

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the pricing model, we introduce a dynamic self-scheduling approach with the Stackelberg game model to the delivery pricing system.

For the game model, the Stackelberg game model, a second-order game model, indicates a well equilibrium. The game model realizes balanced utilities for both restaurant and DM, and the dynamic demands which are distributed spatiotemporally unbalanced is met. The blockchain is expected to check the qualification of DM before entering the market and organizes the order allocation by game model. DRL is chosen because of its efficiency for optimization.

The proposed system has the following three contributions,

1. The FaaS trading system operating on the consortium blockchain constructs a decentralized system with fog computing servers, which is open and fair, trustworthy, traceability, private and secure.
2. The second order Stackelberg game model realizes a balance between the restaurants and DM: Once receiving the order, DM's agent gives the pricing strategy at the beginning as the leader, then the restaurant reacts with the pricing strategy and give the purchase strategy.
3. Our pricing model and the order allocation system's stability can be verified by the Nash equilibrium test and the continuous order pricing and allocation simulation.

The remainder of this paper is organized as follows. Section 2 reviews related works and Sect. 3 presents the methodology. Section 4 analyzes the results from the proposed model, followed by Sect. 5, which covers an extensive discussion. Section 6 concludes the paper.

2 Related Works

The literature review will be done from the three perspectives, pricing model, takeaway food delivery pricing development and the system operation techniques.

Although price surging with dynamic multipliers is still the most popular solution in the industry [1], many novel pricing systems have been put forward, including game theorem. The game theorem is a good option because of its open and fair principle and has been deployed in many fields, including the carpooling pricing. In 2016, Li et al. proposed a carpooling trading system with a game model, which aimed to develop a dynamic pricing model considering the utilities of different passengers [2]. In 2019, Liu et al. proposed a Stackelberg Game Model to deal with Internet of Things (IoT) data trading [3]. An agent is proposed in this study to simply the multi-seller-single-user game process. The agent represents the seller side, which is the leader in the game model, and customers are the followers in the game model and decide the purchase amount based on the leader's previous price policy. Moreover, some models try to price more fairly by solving the unbalanced demand distribution. A game-theorem-based pricing model tries to identify and track the distribution of user demand for the individual social taxi, which helps release irrational pricing phenomenon by improving the cooperation efficiency of taxis [4]. Under the food delivery topic, people are just starting to use dynamic pricing model [5]. So far, little work has been performed on advanced pricing strategy application in the food delivery pricing.

Not like Software-as-a-Service or Mobility-as-a-Service, Food-as-a-Service is less used while discussing the online takeaway food order [6, 7]. However, the online food has developed greatly especially in the developing countries [8, 9]. The cheap human resource might be a potential reason for the flourishing FaaS market [10]. However, the fast-moving FaaS industry sees challenges in its labor relationship. Platforms outsource the delivery service to DMs, and there sees many conflicts between restaurants, customers and DMs [11]. The delivery pricing and order allocation fairness is one important topic needing discussion.

Computing power dramatic development supports a more efficient and economic information system, including the blockchain, Internet of Things, edge computing and cloud computing solutions [12–14]. One important reason we need edge computing and distributed system is to make a better usage of the edge computing resources, and blockchain can be used to record the usage and pay a reasonable return. Blockchain was initially a distributed ledger and then developed to carry information and trustworthy application [15], which has been introduced to the resources trading system based on the edge computing [16]. Blockchain system with debt-credit mechanism is also guaranteed by the clear systematic risk management [17], which helps improve the performance of the edge area trading. For system optimization, a smart agent based on deep reinforced learning (DRL), a novel machine-learning-approach algorithm, is widely deployed in edge computation because of its usability [17, 18]. And one author's work in the Mobility-as-a-Service trading system also provides insights in the pricing and model design [19].

3 Methodology

In this section, our model will be explained in divisions of the system:

1. Pricing model: Stackelberg game
2. Trading algorithm: DRL-based smart agent model
3. System operation: edge computing and blockchain

Furthermore, a situation statement will be given before our model.

3.1 Problem Statement

Today, FaaS is becoming more popular. Costumers order takeaway food with a mobile APP, and the platform behind the APP transmits orders to restaurant and assign DM to deliver it. To achieve the long-term interests of the business, the platform must balance utilities of 3 parties, improving their satisfaction and efficiency of the operation. The platform is also expected to regularize the trading, avoiding the conflicts between the three party. In this paper, we focus on the takeaway food delivery order pricing and allocation.

From a perspective of delivery, the outsourcing delivery market expands the potential delivery ability, so restaurants can choose the better (Normally with lower price, better feedback and shorter waiting time, as we assume that all the DMs follow the standard work rule) DM's service.

From the DM's side, he/she is trying to realize more salary by deploying a dynamic pricing system which meets the spatiotemporally dynamic customer demands. Moreover, DMs have to consider their competition as the high price may lose the order. To make the game-based pricing process more efficient, an agent operating on the blockchain is introduced as DM's intermediary trade agent. It operates the game process with the restaurant for each order on behalf of DMs, and it chooses the DM winner considering the users' utility and the supply situation.

Our expected platform operation process can be explained as follows (Fig. 1),

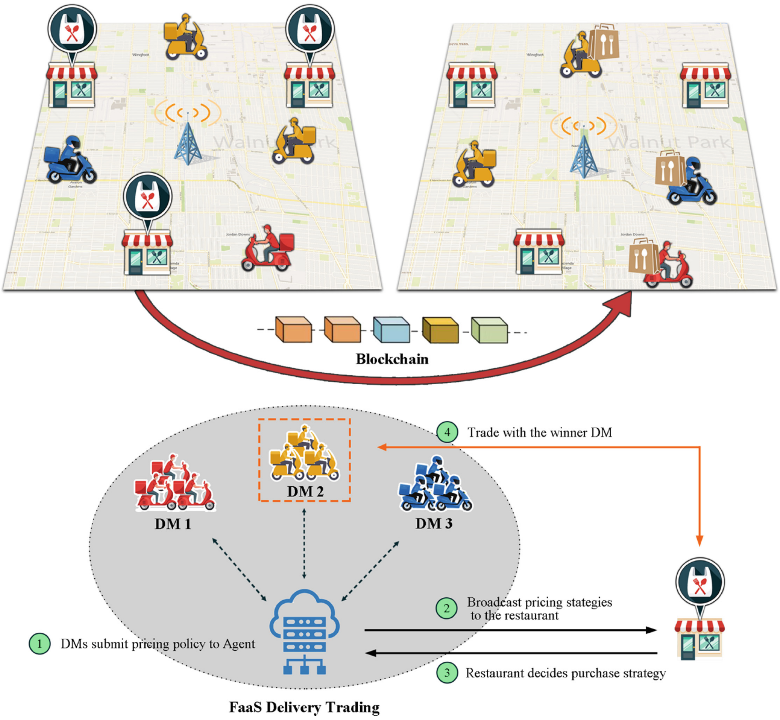

Fig. 1. Situation description

3.2 Stackelberg Game Based Pricing Model

In the hot area of the city and during the peak hours (e.g. central business district and lunch time), it is assumed that N DMs work and the set of DMs is defined as $\mathcal{N}$. Restaurants submit order delivery requests to the FaaS platform with delivery information (Table 1).

Table 1. Notation

Symbol	Definition
$\mathcal{N}$	Set of DMs
N	Number of DMs
Restaurant	
BU_i	Restaurant's utility of the trading
q_i	Quality to DM_i
$\tilde{q}_{-i}$	Average quality besides DM_i
x_i	Purchase intention of DM_i
ϑ_i	Feedback to DM_i
Delivery Man (DM)	
SU_i	DM_i's utility $\forall i \in \mathcal{N}$
c_i	DM_i unit base price (cost)
p_i	DM_i reported price
ω_i	DM_i competitive power
ω_{-i}	Average competitive power besides DM_i
π_i	DM_i market relatively competitive power
v_i	DM_i Arriving restaurant time
v_{-i}	Average arriving time besides DM_i

Then, quantitative utility models will be constructed both for the restaurant and the DM. The buyer utility and the seller utility are used to describe the interests of them.

The buyer's utility can be described by:

$$BU_i = \vartheta_i - p_i x_i \tag{1}$$

$$\vartheta_i = q_i \alpha ln(1 + x_i) \tag{2}$$

$$q_i = \ln\left(1 + \frac{\tilde{v}_i}{v_i}\right) \tag{3}$$

whereas the α is a strengthen factor of feedback. As the restaurant wishes to achieve a maximum utility, the goal of optimization is:

$$\underset{x_i}{maximize}\ BU_i \tag{4}$$

$$subject\ to\ x_i \in [0, 1], \forall i \in N \tag{5}$$

And the Seller's utility, DM's utility, can be described as,

$$SU_i = \pi_i x_i (p_i - c_i) \tag{6}$$

$$\omega_i = \frac{q_i - \log(N)}{p_i} \tag{7}$$

$$\pi_i = \frac{\omega_i}{\frac{1}{N}\sum_{j \in N} \omega_j} \tag{8}$$

As the DM_i wishes to achieve a maximum utility, the goal of optimization is:

$$\underset{p}{maximize}\ SU \tag{9}$$

$$subject\ to\ p_i \in \left[c_i, p_{max}\right], \forall i \in \mathcal{N} \tag{10}$$

3.3 Trading Algorithm

In this section, we propose resources trading algorithm including Stackelberg game and the optimization. The resources trading algorithm includes the following steps:

1. DM_i Decides its pricing policy: $P = (p_1, p_2 \ldots, p_i \ldots, p_N)$.
2. Restaurant decides its purchase intention based on the DM_i's pricing policy: $\boldsymbol{X} = (x_1, x_2, \ldots, x_i, \ldots, x_N)$.
3. Continue the game until the change is lower than the threshold value ξ.
4. The DM's agent chooses the DM_i with maximum buyer utility as the winner.
5. The restaurant trades with winner DM_i.

The pseudocode can be described as (Table 2),

Table 2. Trading algorithm based on Stackelberg game

1 :	**Initialize:** N DMs, M restaurant orders and Pricing policy change threshold ξ;
2 :	**For each** order in M **do**
3 :	Restaurant submits order to the agent, and agent broadcasts the order to DM_i.
4 :	**Repeat:**
5 :	**Action 1**: DM_i updates the pricing strategy, $\boldsymbol{p} = (p_1, p_2, \ldots, p_i), i \in \mathcal{N}$, to agent, and agent broadcasts price strategy $\boldsymbol{p}$ to the user (as the leader in the game).
6 :	**Action 2**: User feedbacks the purchase intention strategy, $\boldsymbol{x} = (x_1, x_2, \ldots, x_i), i \in \mathcal{N}$, based on the price strategy p_i (as the follower in the game).
7 :	**End for** Nash equilibrium achieved: $$\frac{\|\boldsymbol{p}^{j+1} - \boldsymbol{p}^{j}\|}{\|\boldsymbol{p}^{j}\|} \leq \boldsymbol{\xi} \quad (1)$$
8 :	DM_i is chosen by: $$\Pi = \max_{i \in \mathcal{N}}(SU_i) \quad (2)$$
9 :	The matchmaking trading between the DM winner and restaurant is made by the agent.

The agent's side optimization is done by the Deep Q-Learning Network [20]. The agent state space is defined as the restaurant's purchase intention and the price, and the action space is the price adjustment (with a little step of surging or discounting). The reward is decided by the seller utility increase due to the price adjustment.

After iterations, the price, purchase intention tends to converge and provide a stable and reasonable price as termination. The pricing policy renew, DQN reward design and the price adjustment (action space) are as follows,

$$p_i^j = a_i^j p_i^{j-1} \forall i, j \tag{13}$$

$$r_i^j = SU_i^j\left(x_i, p_i^j, p_{-i}\right) - SU_i^{j-1}\left(x_i, p_i^{j-1}, p_{-i}\right) \forall i, j \tag{14}$$

$$A_i^{\mathrm{j}} = \{0.98, 0.99, 1, 1.01, 1.02\} \forall i, j \tag{15}$$

Moreover, our parameter for DQN is chosen as follows (Table 3),

Table 3. DQN parameters

Parameter	Value
Learning rate	0.005
Reward decay	0.90
ϵ − greedy	0.95
Replace target iteration	200
Memory size	8000
Batch size	56

3.4 Distributed System on Blockchain

As the FaaS delivery demand varies with time and space, individual DM cruises around the city, targeted hot areas are distributed and variable. In another word, FaaS trading happens anywhere and anytime. Thus, the distributed and efficient edge computing hardware among the city also needs a distributed software for our trading game.

To operate our trading system, our system can be deployed on a blockchain with a consensus mechanism, Practical Byzantine Fault Tolerance (PBFT). Some nodes, known as leaders in PBFT, with better computing resources, take the responsibility of keeping the ledger. Most DMs' devices are followers of PBFT, and they take orders from the trading system. The blockchain leader is elected by Proof of Work (PoW) [21].

To avoid the attack from inside and outside, only verified nodes (Including edge servers, restaurant nodes and DM nodes) are allowed to operate on the blockchain. Each node operating on the blockchain holds an account with a digital signature generated by the Elliptic Curve Digital Signature Algorithm (ECDSA). The trade is done with the unique digital account, so the transactions' security and privacy improve.

Another reason for the blockchain and distributed system is to enhance the restaurant's link to the platform and enable restaurant's digital transformation. With the return from the blockchain, restaurants will be more likely to implement the digital FaaS system and work close with the platform, which benefits to the whole industry [22].

4 Results and Analysis

In this section, results will be posted and discussed. Two results will be illustrated, Nash equilibrium verification test and the 100-order continuous simulation. Additionally, the analysis will be given attached to the result.

All computations were performed using Python 3.7.4 on a Windows environment. We used Intel(R) Core i7-8550U CPU @1.80 GHz and 16 GB of RAM, which is close to the edge node computing resource.

4.1 Nash Equilibrium Computation

Consider a scenario, 4 DMs compete for an order and their arriving time ratio is t_{DM1}:t_{DM2}:t_{DM3}:t_{DM4} = 1:2:3:4. Our system's maximum game iteration is set as 1500 times. The Nash equilibrium is achieved in our set iteration times and indicates a fair result in Fig. 2 and Fig. 3.

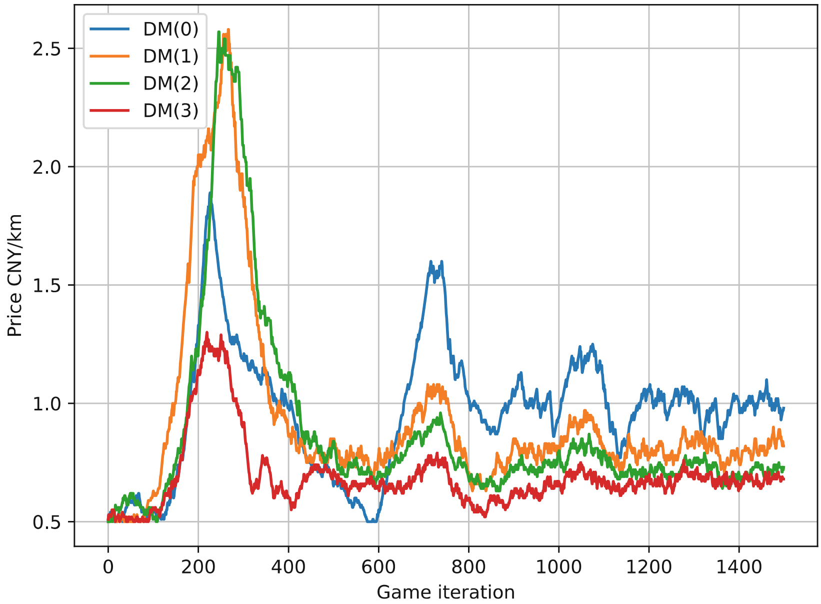

Fig. 2. Price equilibrium

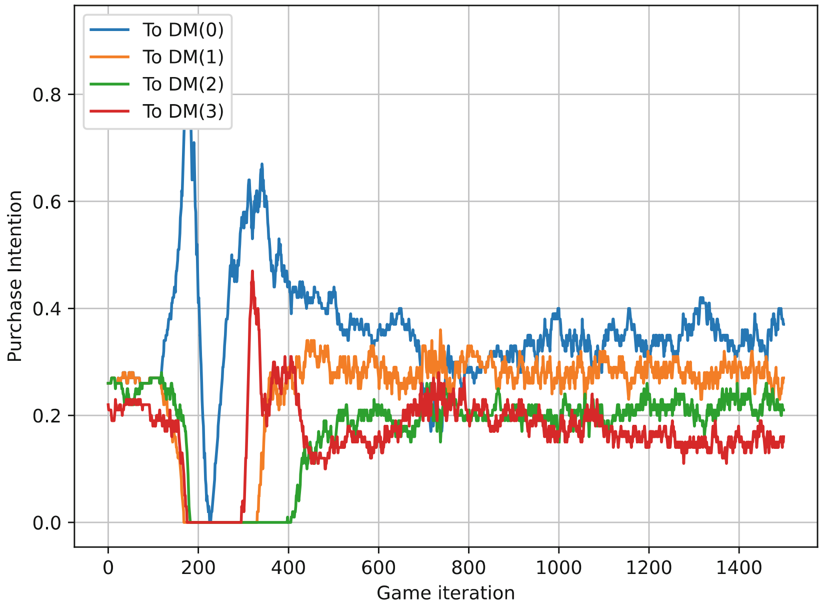

Fig. 3. Intention equilibrium

It can be seen that the fast-arriving DM has a significant advantage even if it charges for more, because it meets the food delivery's fast demand. The lead time results in the increases both in the purchase intention and the price, which protects the market's benign competition. And it sees that after 500 iterations the game converge, so we will only iterate for 500 times in the order simulation to reduce the system response time.

4.2 100-Order Continuous Simulation

In simulation, 4 groups of 100 DMs compete for orders and their arriving time ratio is $t_{DM\,1}$:$t_{DM\,2}$:$t_{DM\,3}$:$t_{DM\,4}$ = 1:2:3:4. To show that our model with DM competitive power consideration has a stable and reasonable pricing, we compare our competitive pricing to the independent pricing game (Baseline). Each order's game iteration is limited to 500. As the order is allocated to a DM, he/she leaves the game. The purchase intention and price change over the simulation area plotted in the Fig. 4 and Fig. 5.

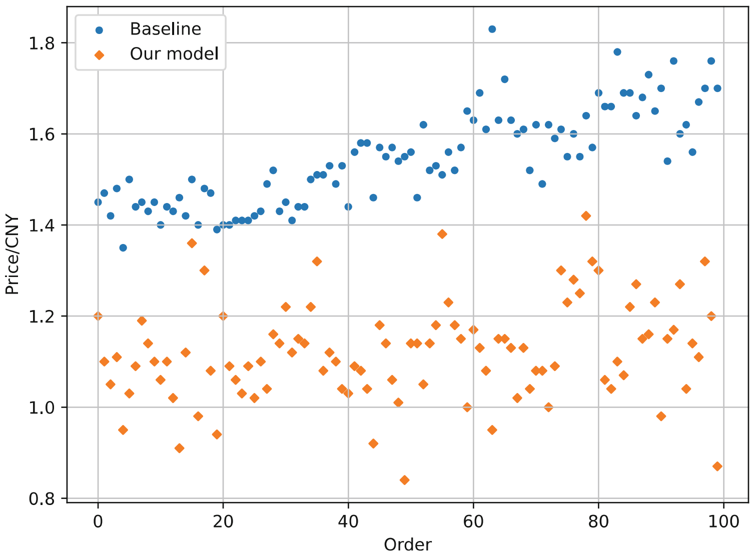

Fig. 4. Price change over the simulation

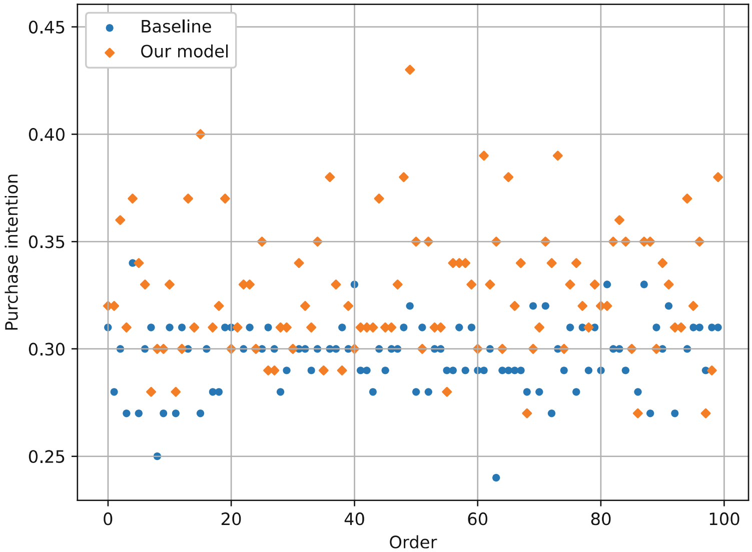

Fig. 5. Intention variability over the simulation

The Fig. 4 and Fig. 5 indicate that our competitive model provides a more stable and reasonable price than the baseline model. As competitive DMs win orders and leave the game, the average competitive power decreases so that the baseline model price sees a significant rise. Our model provides a significant transaction price fall and transaction purchase intention increase by allocating orders to the DMs with less arriving time. This action does not harm DMs interests, because they will save much time in this order. In conclusion, our model reduces the whole society's cost on the transportation by better order allocation. This is possible because farther DMs are hard to win the orders, which contributes to the system's long-term prosperity.

5 Discussions

Overall, studies in this paper establish a game theorem based dynamic pricing system which is deployable on the edge computing system. The stability of the pricing system is detailly verified, and the simulation experiment indicates the system's perfect performance. Moreover, the system does not rely on much computation, ensuring the availability of the distributed edge computation. As a result, our system is a smart combination of the edge computing hardware and the pricing game software.

Our model and result suggest a possibility of a future open FaaS delivery trading. The openness is guaranteed by the distributed system and the open consensus mechanism. Compared to the traditional center server plan, blockchain with distributed nodes provides a faster response. It saves the cost of communication with the help of edge computing nodes in the smart city.

One important future direction of the FaaS delivery trade is fairness. Only if one platform convinces its users, both DMs and restaurants, that the platform is fair can it operate its business for a long term. Our system introduces the game theorem with a clear and open policy for the pricing process. Compared to the existed surge price at the hot area plan, our plan provides a more reasonable price by introducing the interaction between restaurants and DMs to the pricing system. Thus, both restaurants and DMs do not worry about the unfair pricing due to the information gap. Our studies serve as a proof-of-concept that mobile APP makes a good use of edge computing resources.

On the other hand, the lack of real-world simulation is the main drawback of our studies, which reflects in two perspectives: lacking the order information and the limited parameters considered in our model. The real-world orders are much more complex than our simple simulation: real-world orders have different delivery requirements (e.g. different restaurants have variable requirements on delivery, including time sensitivity and weight limit) and any other potential factors not considered in our model. Thus, our model is better to verify other parameters' influence on the stability and the efficiency in the real-world order experiment. Real-world transaction experiment on the existed FaaS platform is the best choice. This experiment can be based on existing orders from the FaaS platform. Furthermore, it is also expected to carry on grayscale tests at some hot areas.

6 Conclusions and Further Work

This paper has proposed a novel FaaS trade system, possibly operating on the distributed edge computing system and blockchain. This study sets out to improve the fairness and security of FaaS trading, and the proposed system consists of dynamic pricing, order allocation and distributed ledger functions. Additionally, the smart agent with deep reinforced learning algorithm applied in the optimization provides a fast and stable convergence.

The results indicate that our system improves trading fairness in the hot area. DMs closer to the restaurant are more likely to win the game. Then, the simulation indicates our system's continuous performance. The investigation of our dynamic pricing system has shown that the game theorem deployment contributes to the fairness of the trade.

The major limitation of this study is the lack of real-world FaaS order simulation. Without real-world statistic data and test, the parameters are limited because other parameters, such as DM's reachability, are not considered because they lack knowledge of their correlation with price and purchase intention. An additional uncontrolled factor is a possibility that competition exists in the multi-FaaS-platform market.

More investigation of game theorem applied in the FaaS trade would be a fruitful area for further work. Moreover, different optimization methods are expected to be tried. More broadly, research is also needed to determine how other parameters influence the pricing and purchase decision. This work needs more understand of correlation between parameters and data support from the industry.

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