RIM: Reputation-Based Incentives for Optimizing Service Pricing in Metaverse

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***Abstract*—Metaverse is the fusion of physical and virtual worlds, where users interact with the virtual world in real-time. To enhance the user experience *i.e.,* Quality of Experience (QoE), it is crucial to incorporate high-quality data, such as higher sampling rate and bit rate in real-time that encourages users to spend more time in the virtual environment. Internet of Things (IoT) devices that collect data for the Metaverse should be incentivized to collect high-quality data. Therefore, in this work, we propose the *Reputation based Incentives for Optimizing Service Pricing in Metaverse* (RIM) scheme by which rational smart devices can earn higher payoffs and increase their reputation by feeding high-quality data to the Metaverse system. Similarly, using RIM, Virtual Service Providers (VSPs) of the Metaverse system also earn more for collecting high-quality data from the environment by selecting the most suitable IoT devices based on their previous reputation. We fit RIM into the *Stackelberg-based Multi -leader and -follower gaming model*, which has *Stackelberg Equilibrium*. MATLAB-based simulation results demonstrate the effectiveness of RIM compared to other baseline schemes.**

***Index Terms*—Metaverse, IoT, Pricing, Stackelberg game.**

I. INTRODUCTION

METAVERSE is the next-generation internet-based platform that allows Metaverse Users (MUs) to virtually interact with the living and non-living entities of the physical world in real-time [1], [2]. Recent technologies, such as Virtual Reality (VR), Augmented Reality (AR), Digital Twin (DT), 5G communication, Artificial Intelligence (AI), and Blockchain, help the MUs to have real-time and seamless interaction with the three-dimensional (3D) virtual world [3]–[5]. Recently, Metaverse has gained attention of both academic and industrial researchers because of its huge applicability in different virtual event-based domains, such as smart industry, online education, gaming, meetings or conferences, shopping, virtual driving, social interaction, and more [6]–[10].

For real-time and seamless interaction of the physical and virtual worlds, the Metaverse system requires to integrate various technologies, such as sensing, communication and high computing devices [11], [12]. In Metaverse, the Internet of Things (IoT) devices and sensors (from now onward, we refer to them together as smart devices) collect information from the physical world. After that, this collected information is forwarded to high computing devices using fast and reliable communication technologies to create a digital replication of the physical world. As Metaverse is currently in a nascent stage, both Quality of Service (QoS) and Quality of Experience (QoE) will play a significant role in its future adoptation.

Individual and independent bodies own smart devices and can offer services to multiple Metaverse applications [13]. For instance, virtual driving training centres, city planners, road traffic analyzers, and online games can use an IoT camera next to a road. As a result, the owner of the IoT camera can choose the application they want to serve based on the monetary profit he/she earn from the Virtual Service Provider (VSP) that supports the application. In a Metaverse system, VSPs are responsible for various tasks such as data collection, managing resources in clouds or edge devices, and providing services to the MUs. Similarly, VSPs can select a smart device for data collection from the physical world based on the quality of previous data. This is because better quality data results in a higher QoE for MUs, which attracts more users and increases the revenue of the whole Metaverse system. Consequently, VSPs receive more incentives from the Metaverse system based on the service provided to MUs.

However, the transmission of high-quality data imposes high costs on smart devices, including those related to hardware, service time, and device lifespan. Consequently, many smart devices tend to offer low-quality data, which negatively impacts the performance of the Metaverse in terms of QoE. None of the existing works [13]–[17] considered the above-mentioned problem. Only the work in [18] considered the resource allocation problem considering the service cost as stated above *i.e.,* among the smart devices and VSPs. Although the work [18] considered the resource allocation problem among smart devices and VSPs, the authors only tried to maximize the profit of smart devices. The authors neither considered the quality of transmitted data nor the VSPs' profit while designing their resource allocation model. However, the owner of the smart devices could be selfish enough to transmit low-quality data to maximize their profit even though they receive high payments from the VSPs as collection and transmission of high-quality data cost more. On the other hand, VSPs prefer choosing smart devices for data collection. Therefore, it is imperative to establish a new service pricing scheme for data collection that maximizes the profit of both smart devices and VSPs and the quality of the collected data by considering various metrics, such as data quality, cost, and profit associated with data collection.

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A. Contribution

In this work, we propose *Reputation based Incentives for Optimizing Service Pricing in Metaverse* (RIM) model. Our proposed RIM model incentivizes smart devices to provide high-quality data by assigning more tasks and paying more to the devices with better reputation to maintain QoE. The RIM model also enables VSPs to choose and pay for smart devices based on the quality of data received while ensuring sufficient compensation for smart devices based on their reputation. None of the existing works considered reputation-based high-quality data collection in the literature. To obtain optimal solutions for VSPs and smart devices, we utilize *multi-leaders and multi-followers* based *Stackelberg gaming model* in which leaders *i.e.,* VSPs and followers *i.e.,* smart devices determine their strategies to maximize their profit while enabling desired quality of data. All leaders and followers decide the optimal *price per unit time*, *duration of service*, and *quality of data* in a non-cooperative manner to maximize their profit. We implement the proposed RIM model in MATLAB and conduct comparison-based numerical analysis to demonstrate its effectiveness and efficiency. Overall, this work contributes to developing a new service pricing for data collection that balances the profit of both smart devices and VSPs while ensuring high-quality data transmission. The overall contributions of this work are summarized as follows,

- We propose *Reputation based Incentives for Optimizing Service Pricing in Metaverse* (RIM) model to incentivize smart devices for providing high-quality data and allowing VSPs to choose smart devices based on previously received data quality while ensuring sufficient compensation, resulting in maintained QoE.
- We fit our proposed RIM model to a multi-leaders and multi-follower Stackelberg gaming model. Then, we prove that RIM meets the Stackelberg equilibrium point and has optimal solutions for VSPs and smart devices.
- Finally, the Stackelberg gaming-based RIM model is implemented in MATLAB, and numerical results show that both smart devices and VSPs can maximize their profit while maintaining the desired data quality compared to baseline schemes in the Metaverse system.

The rest of the paper is organised as follows. Section II discusses the related works on the resource allocation problem in Metaverse. In Section III, we describe the system model of RIM; in Section IV, we briefly discuss the formulation of Stackelberg gaming model. In Section V, we provide a brief analysis of numerical results with different parameter settings, and finally, in Section VI, we conclude this paper.

II. Related Work

The work in [13] studied the virtual education system in Metaverse and proposed a stochastic optimal resource allocation scheme to address the unified resource allocation problem between the VSPs and cyber resources *i.e.,* edge or cloud service. The authors performed numerical analysis and showed that their proposed scheme can allocate optimal resources adaptively depending on the users' demand probability. However, their work did not consider the complex environment, such as multiple VSPs and cyber resources. The work in [18] considered the resource allocation among the smart devices and VSPs during data collection from the real world. However, it only considered the profit maximization of the smart devices and did not consider the profit of the VSPs in their resource allocation problem. The authors in [15] proposed a sharding scheme to improve the complex interactions between a VSP and a group of MUs in a blockchain-based Metaverse architecture. The authors developed a Stackelberg game theory-based incentive mechanism considering the MUs' contributions in terms of computing power to the Metaverse. The work in [17] studied the interaction among the VSPs and the network infrastructure providers (InP), considering the utility of the VSPs as a function of MUs' QoE requirement.

It can be seen that the existing works neither considered the quality of data such as sampling rate (*i.e.,* a higher sampling rate captures more objects per frame) nor tried to maximize the individual profit of the VSPs and smart devices together. Therefore, establishing a new paradigm for optimal service pricing is essential so that all VSPs and smart devices can choose their optimal prices over data quality, which is neither too high nor too low, to maximize their profits. Hence, we consider the service allocation and pricing problem among the smart devices and VSPs in this work.

III. System Model

We consider a Metaverse system with a set of smart devices (e.g., IoT cameras) that perform similar activities, denoted by $I = \{1, \dots i, \dots, I\}$, and a set of VSPs denoted by $V = \{1, \dots v, \dots, V\}$. The V VSPs collect data from the physical world with the help of $i - th$ set of smart devices owns by single owner or IoT service provider (later, we consider it as smart device only) to update or synchronize the digital world with the physical world, providing real-time experience to the MUs. Let us assume that the VSP $v \in V$ wants to collect real-time data from the smart device $i \in I$ for a period of T_{vi}. The data collection period T_{vi} can be divided into several time slots, each of which has a duration of one hour, denoted by $T = \{1, \dots t, \dots, T_{vi}\}$. We use the same notation T_{vi} for denoting smart device i offers T_{vi} hours of service time to the VSP v. Note that i can change the quality of its transmitted data to v VSP at any given time.

The smart device i earns P_{vi} dollars ($) per hour (Hr) from the v VSP and spends C_{vi} $\$/Hr$ for collecting and forwarding best quality real-world data to the nearest cloud or edge device for storage and processing. For simplicity, we assume that C_{vi} includes all possible costs such as hardware, energy, communication, and deployment for collecting and transmitting such data. Note that the cost for collecting and transmitting data from the real world depends on the data quality, D_{vi}, that the smart device i transmits to VSP v. It can be further assumed that the smart device i can provide service for a few hours in a day, *i.e.,* $S_i \leq 24$ Hrs, considering the best quality of data. However, this service time S_i can be extended by compromising data quality. For example, if a UAV is used for data collection, it needs to recharge its battery after a specific interval. Furthermore, if the UAV collects data with a low sampling rate, it can save energy and, therefore, can extend its service time. So, we can write the quality of data transmission Q as a function of service time, S_i and the desired extended time, T_e, as follows.

$$Q = \frac{S_i}{S_i + T_e} \tag{1}$$

In Equation (1), Q degrades with the increasing value of T_e. Therefore, the smart device i aims to extend its service time per day by compromising the data quality so that it can earn more by giving maximum service time to the VSPs. The term $\frac{T_{vi}}{\sum_{j\in I} T_{vj}}$ defines the service time given by smart device i to VSP v w.r.t. other smart devices. The smart device i also needs to maintain high-quality data compared to other smart devices, $-i$ to get more service offers. Therefore, smart device i needs to compete to maintain its quality of data D_i as follows.

$$D_i = \frac{D_{vi}}{\sum_{j\in I} D_{vj}} \tag{2}$$

Therefore, we define the utility function of the smart device i as follows.

$$U_i = \sum_{v\in V} \left(P_{vi} - C_{vi}\ e^{D_i}\right) \frac{T_{vi}}{\sum_{j\in I} T_{vj}} \tag{3}$$

Similarly, v VSP can take service from any of the smart devices $i \in I$. Let us assume, the VSP v earns P_v $\$/Hr$ from the Metaverse system and needs to pay P_{vi} $\$/Hr$ to collect the data from smart device i such that $P_{vi} < P_v$. We adopt a reputation-based incentive mechanism by which VSP v decides to choose a smart device $i \in I$ based on the quality of data it has received from the smart device i. Using this reputation-based incentive mechanism, a smart device can earn higher payoffs only by transmitting high-quality data to maintain its reputation as VSPs assign more tasks and pay more to the smart devices which have higher reputations. For calculating the reputation of smart device i in front of VSP v (*i.e.,* R_{vi}), we assume that the smart device i transmits data to the VSP v at a rate of r_{vi} bits per second, and the expected data rate required for a specific task is R_v bits per second. The VSP calculates the quality of data received from the smart device as follows,

$$Q_{iv} = \frac{r_{vi}}{R_v} \tag{4}$$

Here, Q_{iv} represents the quality of data received from smart device i by VSP v, and it is calculated as the ratio of the actual data rate to the expected data rate. If the data quality is high, Q_{iv} will be close to 1, indicating that the smart device is transmitting data at a rate that meets or exceeds the required rate. On the other hand, if the data quality is low, Q_{iv} will be less than 1, indicating that the smart device is not transmitting data at the required rate. Once the data quality is calculated, the VSP uses this information to update the reputation score of the smart device. For this, VSPs maintain a weighted average of the quality of data received from the smart devices over a while and use this average to determine the reputation score. For instance, the reputation score of smart device i at VSP v can be updated as follows:

$$R_{vi}(t) = \alpha Q_{iv}(t) + (1-\alpha) R_{vi}(t-1) \tag{5}$$

Here, $R_{vi}(t)$ represents the reputation score of smart device i at VSP v at time t, and α is a weight parameter that determines the relative importance of the current quality of data versus the historical reputation score. The value of α can be set based on the desired trade-off between responsiveness to changes in data quality and stability of the reputation score over time. Note that smart devices can build trust over time by consistently providing high-quality data and meeting the expectations of the VSPs. This can help them establish a good reputation in front of the VSPs, which can lead to more service offerings and higher payoffs.

We also consider that VSP v can attract more smart devices to work (*i.e.,* provide service) for it only when the VSP v pays higher P_{vi} $\$/Hr$ compared to the other VSPs *i.e.,* $-v$ by sacrificing its profit. Therefore, each VSP v determines the payments within the strategy space $\{P_{vi} : 0 \leq P_{vi} \leq P^{\max}\}$ to maximize its profit. The value of $P^{\max}$ should be less than P_v, say $P^{\max} = 80\% P_v$ to save some profit. Considering all the above-mentioned conditions, we formulate the utility function of VSP v as follows.

$$\begin{aligned} U_v &= \sum_{i\in I} (P_v - P_{vi})\ T_{vi}\ M_{vi} \\ &= \sum_{i\in I} (P_v - P_{vi})\ (\frac{RST_v\ R_{vi}}{\sum_{j\in I} R_{vj}})\ M_{vi} \end{aligned} \tag{6}$$

where M_{vi} denotes the probability that smart device i chooses VSP v to offer its service, and it is calculated as follows,

$$M_{vi} = \frac{P_{vi}}{\sum_{j\in V} P_{vj}} \tag{7}$$

The term $T_{vi} = \frac{RST_v\ R_{vi}}{\sum_{j\in I} R_{vj}}$ in Equation (6) is used to assign service duration based on the value of R_{vi}, where RST defines the *Required Service Time* by the VSP v. Note that VSP v also gets incentives from the Metaverse system based on the service it has given earlier. Therefore, we update the values of P_{vi} and P_v based on the reputation of smart device i as follows.

$$P_{vi} = P_{vi}(1 + R_{vi}) \tag{8}$$

$$P_v = P_v(1 + R_{vi}) \tag{9}$$

Therefore, Equation (6) can be rewritten as follows,

$$U_v = \sum_{i\in I} (P_v - P_{vi})(1 + R_{vi}) T_{vi} \frac{P_{vi}}{\sum_{j\in V} P_{vj}} \tag{10}$$

The utility functions given in Equations (3) and (10) enable all I smart devices and V VSPs to maximize their profit.

Algorithm 1: Finding Optimal values for RIM

```
VSPs announce their latest decisions.
while VSPs' profit is changing do
    if a smart device then
        Find the optimal value.
        Announce decision.
    end if
    if an VSP then
        Find the optimal value.
        Announce decision.
    end if
end while
Final optimal prices for VSPs and smart devices
```

IV. Stackelberg Gaming based RIM Model

In the beginning, the V VSPs announce their *Required Service Time* (RST) and *payments per unit time* to the I smart devices. Based on this information, smart devices decide the service time and data quality for each VSP. Therefore, the interaction between the VSPs and the smart devices can be formulated as a multi-leader and multi-follower Stackelberg gaming model, denoted by G_{vi}. In G_{vi}, the VSPs act as *leaders* who declare their strategies first, which include RST and maximum payments per unit of time. Based on the information, the smart devices act as *followers* decide their strategies, including the service time and data quality to serve each VSP. Considering these scenarios, the multi-leader multi-follower Stackelberg gaming can be defined as follows,

$$Leader: \underset{P_{vi}}{\text{maximize}} \; U_v(P_v, P_{-v}, D_i) = \sum_{i \in I} (P_v - P_{vi})(1 + R_{vi}) T_{vi} \frac{P_{vi}}{\sum_{j \in V} P_{vj}}$$

$$Follower: \underset{T_{vi}, D_i}{\text{maximize}} \; U_i(T_i, T_{-i}, D_i, D_{-i}, P_{vi}) = \sum_{v \in V} (P_{vi} - C_{vi}\, e^{D_i}) \frac{T_{vi}}{\sum_{j \in I} T_{vj}}$$

such that

$$Leader: \sum_{i \in I} T_{vi} = RST$$

$$0 \leq P_{vi} < P^{\max}$$

$$Follower: T_{vi} \geq 0$$

$$\sum_{v \in V} T_{vi} \leq S_i$$

Lemma IV.1. *The utility function of each VSP, $v \in V$ in Equation (3), and the utility function of each smart device $i \in I$ in Equation (10) are strictly concave and the game G_{vi} has at least one Nash equilibrium point.*

V. Performance Analysis

In this section, we discuss the numerical results our proposed Stackelberg-based RIM model to validate its effectiveness. Algorithm 1 shows the steps to find the optimal solutions.

A. Simulation Setup

We use MATLAB on an Intel Xeon CPU 3.6 GHz system with 16GB RAM for simulation. We consider a group of 4 VSPs (*i.e.,* leaders) and 4 smart device owners or IoT sevice providers (*i.e.,* followers) with their respective initial inputs provided in Tables I and II to obtain different sets of results. We consider the same inputs for VSPs $V1$ and $V4$ except the expenses made by each VSP and VSP $V2$ provides minimum payoff to the smart devices and make less profit compared to other VSPs to understand different numerical results. Similarly, we assign different inputs to the smart devices to get different sets of results. For example, we assign the lowest reputation to the smart device $D2$ (Table I Reputation column). We also vary the payoff of the VSPs to see how it impacts the overall profit of both the VSPs and smart devices. Additionally, we show how smart devices can enhance their profit by upgrading their reputation in front of the VSPs. To compare our results with baseline schemes, we consider pair-wise allocation and greedy allocation, which are described below.

- **Pair-wise Allocation:** A VSP attempts to receive service from the smart device in the same ROW in Table II. For example, at first, $V1$ tries to obtain service from $D1$, and if $D1$ cannot provide the necessary service, then $V1$ tries to obtain service from $D2$, and so on. This process continues until $V1$ receives the required service. We can say this pair-wise allocation is an instance of random allocations.
- **Greedy Allocation:** It has two mode of operations. In the first mode, VSPs give the highest priority to smart devices that have high reputations. In other words, VSPs choose smart devices to receive their required services, and they are "*greedy*" about the reputation of the smart devices. In the second mode of operation, smart devices select the VSPs based on the profit they can make by providing services. The VSPs can not select the smart devices in this mode of operation.

Table I: Leaders' initial inputs

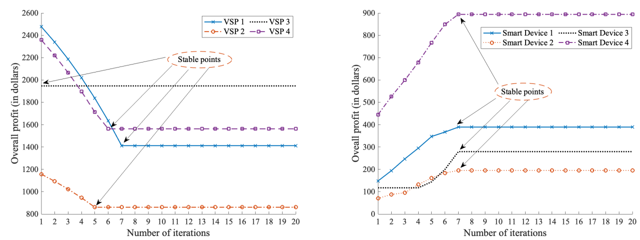
Leaders	Required Service	Earning ($/hr)	Expense ($/hr)				Reputation (0.5-1)			
			D1	D2	D3	D4	D1	D2	D3	D4
V1	9	220	100	100	100	100	0.7	0.5	0.8	1
V2	5	180	80	90	90	80	0.87	0.5	0.7	1
V3	6	350	190	210	310	190	0.7	0.5	0.8	1
V4	9	220	130	120	95	99	0.7	0.5	0.8	1

Table II: Followers' initial inputs

Followers	Capacity (in hours)	Earning ($/hr)				Cost ($/hr)			
		V1	V2	V3	V4	V1	V2	V3	V4
D1	10	100	100	100	100	70	70	70	70
D2	10	80	90	90	80	47	53	33	67
D3	8	190	210	310	190	120	100	192	110
D4	12	130	120	95	130	70	70	70	70

B. Simulation Results

The results are shown in Figure 1 to Figure 3. In Figures 1a and 1b, we show the profit of all the VSPs and smart devices over the iterations. As VSP $V2$'s earning is less compared to other VSPs, its profit is also less compared to the other VSPs. On the other hand, $V3$ provides the highest payoff, so it can immediately attract smart devices to work for it. In Figure 2a, we show the stable points of the VSPs when they receive their desired service from the smart devices over iteration. This figure shows that VSP $V3$ is the first VSP to attain its desired service (*i.e.,* in the $3rd$ iteration) from the smart devices because of its higher payoffs. Even though VSP $V4$ pays to the smart devices more than VSP $V1$, $V4$ profit is more because, at the beginning, it attracts more smart devices to work for by paying a high amount. So, VSP $V1$ needs to increase its payoffs to get services from smart devices. Hence, it receives less profit compared to VSP $V4$. We show the stable points in Figures 1a, 1b, and 2a, that denote the points when the Stackelberg equilibrium point is reached by all the leaders and smart devices. Therefore, no VSP or any smart device can increase its profit after these points.



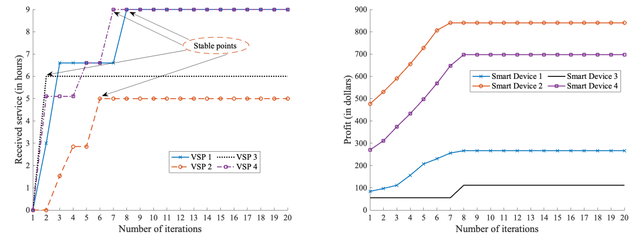
(a) Leaders' profit. (b) Follwers' profit.

Figure 1: Leaders and Followers' profit over the iterations

In Figure 1b, we show the profit obtained by all the smart devices. As follower $D2$ has less reputation in front of all the leaders compared to the other smart devices, it gets fewer service offers from the leaders, and so, needs to stay idle. It results in less profit obtained by $D2$. On the other hand, $D4$ attains the highest reputation, and so, all the leaders want service from $D4$. In brief, $D4$ attracts more leaders because of its reputation and so it receives the highest payoff (so, profit) among all the smart devices. Hence, using the proposed RIM model, the smart devices need to provide good quality data to get more service offers from the leaders.

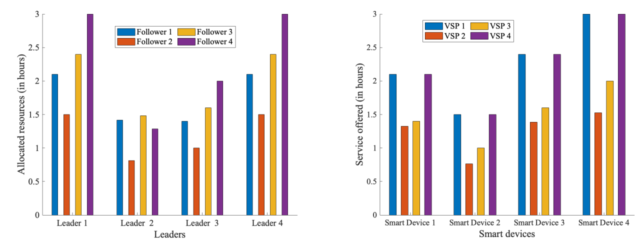
As mentioned above, Figure 2a shows when leaders obtained their desired services from the smart devices. As VSP $V1$ does not provide enough payoffs to the smart devices, hence, it has to increase its payoffs until the smart devices get satisfied to give service. So, it meets its stable point after several rounds of iterations. Please note that within an iteration, the VSPs and smart devices exchange their information.

In Figure 3a, we show the services obtained by each VSP from the smart devices, and in Figure 3b, we show the services offered by each smart device to the VSPs after reaching the Stackelberg equilibrium. In Figure 3a, we can see that all VSPs accept less service from smart device $D2$ because of its bad reputation and in Figure 3b, we can see that all the smart devices offer less service to the VSP $V2$ because of its less payoffs. Hence, using the RIM model, the VSPs need to make sufficient payments and the smart devices need to provide high-quality data to increase their profit.



(a) (b)

Figure 2: (a) Leader allocation to reach the stable points (b) Improvement in profit of the smart device 2.



(a) Leaders' allocation. (b) Follwers' allocation.

Figure 3: Leaders and Followers' allocation over the iterations.

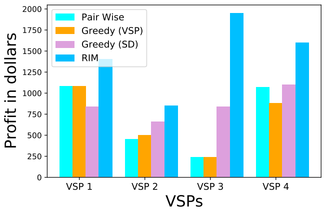
In Figure 2b, we show the improvement of the smart device 2's profit by increasing its reputation in front of all the VSPs. The results show that the smart device 2 improves its profit by improving its reputation.

In Table III, we provide the information regarding the number of iterations required to reach the Stackelberg equilibrium point. We also show the profits of the smart devices and VSPs concerning the percentage of increment of the payoffs of the VSPs in each iteration to reach the equilibrium point. As shown in Table III, VSPs and smart devices reach the equilibrium point quickly when each iteration increment increases as smart devices get their desired payoff in less time. However, when the increment of the payoffs made by the VSPs is very high, the smart devices have extra payoffs. Hence, the profits of the smart devices are more in this case. On the other hand, the VSPs' profit decreased as they increased their payments directly to some high values. When the increment of the payoffs made by the VSP is less in each iteration, the VSPs receive their desired service by paying less. So, in this case, the profit of smart devices is less. Note that as VSP V3 provides enough payoff from the beginning, its profit does not change the increment or decrement of the payoffs of the VSP

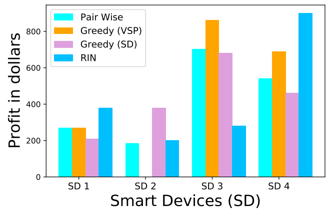
Table III: Change in profits of the VSPs and smart devices with respect to VSPs' payment increment

Increment in payoffs	Iterations	Profit of the VSPs ($)				Profit of the Smart devices ($)			
		1	2	3	4	1	2	3	4
5%	12	1609	852	1946	1583	360	174	258	880
10%	8	1412	860	1946	1562	389	194	279	893
20%	5	1472	692	1946	1444	399	209	316	941
50%	4	752	837	1946	877	464	220	477	1208

in each iteration.



(a)



(b)

Figure 4: Comparison-based results on the profit of the (a) VSPs and (b) Smart devices.

In Figure 4, we provide comparison-based results of the proposed scheme RIM. In Figure 4a, we can see that using RIM, all the VSPs can earn more profit compared to the baseline schemes such as Greedy and Random allocation. It is because the VSPs receive better quality data compared to other schemes, which helps them to earn more from the Metaverse system. However, in Figure 4b, we can see that all smart devices cannot earn more using the proposed RIM compared to other schemes. For example, in the smart device-based greedy approach, devices do not increase the quality of the transmitted data i.e. smart devices choose VSPs but VSPs cannot choose smart devices. Therefore, using this approach, $D2$ makes more profit compared to the RIM model by compromising data quality. The same $D2$ does not get a service offer from any of the VSPs when VSPs choose smart devices for data collection *i.e.,* using VSP-based greedy approach. However, using the RIM model, $D2$ gets some service offers from VSPs by improving the quality of data by compromising its own profit over time.

VI. Conclusion

In this work, we investigated the problem of high-quality data collection and optimal service pricing among VSPs and smart devices in a Metaverse system. To achieve this, we developed a RIM model to ensure the highest data quality was used in the Metaverse system while considering the individual profit of the VSPs and smart devices. To determine the optimal profit for both VSPs and smart devices while maintaining a standard quality of data in the Metaverse system, we utilized a multi-follower and multi-leader-based Stackelberg gaming approach, with VSPs as leaders and smart devices as followers. Finally, we obtained optimal solutions for VSPs and smart devices. We implement our proposed RIM model in MATLAB and perform numerical analysis. The numerical results show that RIM enables high-quality data transmission in the Metaverse system while satisfying the profit expectations of both VSPs and smart devices.

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