Analysis of Business Model of Co-Creation Digital-Twin City Using Evolutionary Game

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***Abstract*—Digital twins that predict various phenomena in the real world by collecting a wide variety of data from the real world and simulating them in cyberspace are attracting attention. The *City Digital Twin* is a digital twin that uses various environmental data of living environments and urban areas to predict the future state and conditions of the society in which people live. The co-creation digital twin is a digital twin that collects data from *city dwellers*, and the co-creation digital twin is attracting attention as a method to realize an city digital twin that requires a wide variety of data. The platform operator collects data from residents, performs simulations, and provides various prediction results. In the co-creation digital twin, the business model of how to provide incentives to residents for providing data is the key to realizing a sustainable city digital twin. In this paper, we examine possible business models for co-creation digital twin platform. We then use evolutionary game theory, which can analyze the dynamic relationships among stakeholders using differential equations, to examine what kind of business model for co-creation digital twin platform is desirable.**

***Keywords*-digital twin; evolutionary game theory**

I. Introduction

Digital twin is a concept proposed by Michael Greaves of the University of Michigan in 2002, which uses Internet-connected devices to obtain information in real space and reproduce the environment of real space in cyberspace. It is a mechanism that enables monitoring and simulation by constructing a twin in digital space that is a counterpart of the real world. The urban digital twin, which applies the digital twin to cities, has been attracting attention in recent years, and the progress of IoT sensor technology and 5G will enable advanced analysis and simulation by collecting various data in real time and visualizing the data in a three-dimensional space, not only on a flat map, which has been difficult to superimpose in the past.

Visualization of data that was previously difficult to superimpose not only on a flat map but also in a three-dimensional space will enable advanced analysis and simulation. By feeding back the results to various devices in real time, the QoS (Quality of Service) of a city can be upgraded and the quality of life of city residents can be improved. The fields of application are diverse, including disaster prevention, urban planning, mobility, energy, nature, wellness, education, work styles, and industry [1]. Digital twins are becoming an essential tool for realizing smart cities[2][3]. In Japan, there is a project called PLATEAU, promoted by the Ministry of Land, Infrastructure, Transport and Tourism, to create 3D city models of all Japanese cities and convert them into open data [4]. Finland has set goals of achieving carbon neutrality by 2035 and recycling all waste by 2050, and is using a digital twin called Helsinki 3D to simulate the impact of different policies and individual decisions on achieving these goals. The digital twin, Helsinki 3D, is being used to simulate the impact of different policies and individual decisions on achieving them [5]. Research is also being done to allow users to report feedback on planned urban changes through interactive interactions [6]. Continuously collecting all kinds of up-to-date information on cities is considered to be limited by the efforts of only the operators and local governments that provide urban services. The key is to be able to continuously collect a wider range and variety of information through the voluntary and active participation of city residents. In this way, city residents and others become data providers, and by providing data to the digital twin and conducting simulations, the digital twin that brings benefits to the data providers is called co-creation digital twin. However, there are no examples of co-creation digital twins in Japan or overseas [7]. The purpose of this paper is to contribute to the realization of co-creation digital twins by identifying a desirable business model for a co-creation digital twin platform. Section II describes related research, and Section III summarizes the evolutionary game. Section IV applies the evolutionary game to a co-creating urban digital twin, Section V presents the numerical evaluation results, and Section VI summarizes the entire paper.

II. Related Works

A. Modeling Co-Creation Digital Twin

Watababe et al. modeled a co-creation urban digital twin using a cooperative game [8]. They modeled a data transaction by a cooperative game focusing on the data consumer, i.e., service provider, side, as a preliminary study. Assuming that the value of the offered data varies with the size of data and that there are multiple data consumers who wish to trade, each data consumer can reduce the amount paid by cooperating with each other. However, they did not consider strategies and policies on the part of the operators collecting data and providing them to the urban digital twin platform.

B. *Incentive Models for Participatory Sensing*

Many models have been studied for incentives in participatory sensing systems (PSS) [9][10][11][12][13]. Participatory sensing is generally a crowdsourcing method for people to analyze, share, and mutually benefit from the information and knowledge collected from their daily lives. Motivating people to participate in sensing phenomena in their surroundings and reporting them to a dedicated server is a key factor in the success of the system. Since users are not expected to participate voluntarily, an incentive model is proposed.

In addition, when the quality of the sensing data differs, an incentive model that accounts for the difference in quality is needed. Multi-attribute auctions have been proposed to address this problem. With traditional financial incentives, the need to determine the price expected by users is recognized as a challenge, as different people have different price expectations and the effort required to collect and transmit data varies.

There are many factors to be considered in the incentive for participatory sensing, such as the quality of data as well as the price expected by the user. For this reason, it has been proposed to use multi-attribute auctions for participatory sensing. In this multi-attribute auction, additional attributes can be incorporated into the auction in addition to price. In the presence of price- and quality-dependent goods, the seller whose condition maximizes the buyer's utility function after all bids wins[14].

III. Evolutionary Game

In replicator dynamics, individuals in a population are considered to play against a randomly selected opponent with a certain probability in unit time, leaving behind a number of offspring determined by the gain and dying themselves. The degree of adaptation of each strategy is defined as the expected number of offspring when that strategy is used, and the gain of a strategy is defined as the increase or decrease in the expected value from the base value. The strategies of the parent and the offspring are assumed to be the same, and the convergence point to be reached is derived depending on the stability of the convergence point and the initial state by constructing and solving differential equations for the change in the number of individuals using each strategy during a small time δt. The most basic form is when there are two strategies A and B, and only two sets of players are considered. When i and j are the groups, i.e., strategies to be used, to which two randomly selected players belong, the gain g_{ij} is defined as the rate of increase or decrease in the number of individuals in each strategy group after the battle between these two players. That is, g_{ij} is the expected rate of increase or decrease in the number of players in strategy group i after a player in strategy group i plays against a player in strategy group j. When the share, i.e., ratio, of players using strategy A is x, the probability that a player in player set A plays against a player using strategy A or B is x and $1-x$, respectively, so the average gain u_a per battle for a player in player set A is $u_a = xg_{aa} + (1-x)g_{ab}$. Similarly, the average gain u_b per battle for the players in player set B is $u_b = xg_{ba} + (1-x)g_{bb}$. The average gain u per battle for all players is $u = xu_a + (1-x)u_b$, and the following differential equation holds for x.

$$\frac{dx}{dt} = (u_a - u)x \tag{1}$$

Therefore, by solving this differential equation for any initial value of x, x at any time t can be obtained.

IV. Evolutionary Game Applied to Co-Creation Urban Digital Twin

A. *Assumptions*

In a co-creation city digital twin, data providers who are residents receive incentives in return for providing data to the digital twin platform. The platform performs a simulation using the received data, provides the simulation results of the digital twin to the service provider, and receives a fee for using the digital twin. The service provider provides services to residents and cities. In this paper, we examine how to incentivize platforms. Since it is considered burdensome for a platform to collect data, conduct simulations, and provide incentives, this paper assumes that a broker, i.e., middleman, exists between the platform and the data provider, as shown in Figure 1. The broker is in charge of collecting data from data providers and granting incentives, allowing the platform to concentrate on running simulations. It is also possible to collect a variety of data through multiple types of brokers offering different incentives. Since it is the residents, i.e., individuals, who receive the service, the incentive should be a monetary incentive. We assume that there is one platform, many brokers, and many data providers. The service provider wants the platform to collect more information at a lower cost, the broker wants to increase its profit, and the data providers wants to purchase the data at a higher price. Therefore, the optimal behavior of each player is for the broker to choose the incentivization strategy that maximizes his profit, and for the data provider to choose the broker that increases the amount of money he receives. In this paper, the optimal behavior of the service provider is not considered because we focus on the incentive allocation method. The number of brokers using each strategy changes as brokers join and exit the market.

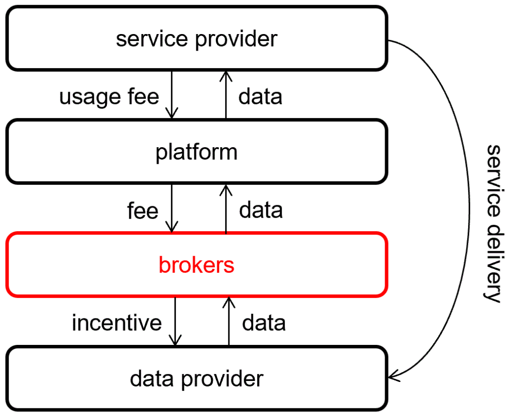

Figure 1. Co-creation digital twin model

B. Modeling

The data of a data provider is evaluated by the broker in terms of data quality and quantity. Let Q_i and V_i denote the quality and quantity of the data of data provider i, respectively, and assume that Q_i and V_i follow a bivariate normal distribution with mean and standard deviation of $(\mu_q,\ \sigma_q)$ and $(\mu_v,\ \sigma_v)$, respectively. We define ρ as the correlation coefficient between Q_i and V_i. Here, we consider two type of brokers: QP (quality prioritized) and VP (volume prioritized). QP brokers assign more weight to the quality of data, whereas VP brokers assign more weight to the volume, i.e., quantity, of data. We define α_{QP} and α_{VP} as the weights of each broker type on the quality of data in QP and VP, and the weights on the quantity of data of each broker type are $1-\alpha_{QP}$ and $1-\alpha_{VP}$. The fee that the data provider i gets from the broker s is obtained by the following equation.

$$p(s,i) = \alpha_s q_i + (1-\alpha_s)v_i \tag{2}$$

The data provider i compares the fee $p(QP,i)$ offered by the QP broker and the fee $p(VP,i)$ offered by the VP broker, and chooses the higher one. Let ϵ_{QP} denote the probability of selecting QP, i.e., the percentage of data providers who receive more money if they select QP. Let r be the expected value of the revenue the broker earns from each data provider, and assume it is constant. Let c_s be the average incentive paid to one data provider by the broker using broker strategy s. The c_s is obtained by averaging over only the fees selected by the number of data providers choosing each strategy. The expected profit per broker is then $r-c_s$. The total number of data providers W is fixed, and the simultaneous probability density of q and v in the set of W data providers is $D(p,v)$. When data providers are free to contract with either QP or VP, ϵ_{QP} is obtained by

$$\epsilon_{QP} = \int\int D(p,v)U\big(\psi_1(p,v) < \psi_2(p,v)\big)dpdv, \tag{3}$$

and the probability ϵ_{VP} of choosing VP is $\epsilon_{VP} = 1-\epsilon_{QP}$. The set of brokers of QP is denoted as $\boldsymbol{M}_1$ and that of VP as $\boldsymbol{M}_2$. The number of brokers in $\boldsymbol{M}_s$ is x_s $(s=1,2)$. The convergence value of x_s is derived for a game in which two brokers selected at random compete for the user's prize in a number of iterations when there are a large number of brokers. The model is a population model and a non-target game. Replicator dynamics is used to analyze the change in the number of brokers using each differentiation strategy over time. However, while replicator dynamics assumes that, as a result of each battle, players who have engaged in the battle die and their offspring are born, when applied to brokers, the dynamics of continuation, withdrawal, and new entry of the broker's cocreation-type digital twin data collection service are considered to occur.

In replicator dynamics, it is necessary to directly affect the number of players by the results of battles between players, but in this case, the results of battles between brokers will appear in the difference in the number of users acquired, which does not directly imply a change in the number of brokers using each strategy. Therefore, it is necessary to introduce a mechanism to reflect the number of acquired data providers in the change in the number of brokers. Therefore, we define a gain function $\phi(\pi)$, which represents the rate of increase or decrease of the number of brokers using each strategy as a result of one battle between brokers, as a function of the profit π determined by the expected number of users to be acquired. If $\phi(\pi)$ is greater than 1, it means that brokers using the strategy are likely to continue the service and that there are many new brokers who use the strategy. On the other hand, if $\phi(\pi)$ is less than 1, it means that brokers using the strategy are likely to exit the market and there are few new brokers using the strategy. If π_0 is the lower limit of the minimum profit that the broker needs to earn to continue its business, the gain function $\phi(\pi)$ satisfies $\phi(\pi_0)=0$. Furthermore, $\phi(\pi)$ increases monotonically with increasing π, and the rate of increase of $\phi(\pi)$ is large near π_0 and decreases as π moves away from π_0. Furthermore, it is assumed that $\phi(\pi) \to L\ (-L)$ asymptotically approaches $\phi(\pi) \to L\ (-L)$ in the limit of $\pi \to \infty\ (-\infty)$. As a function of $\phi(\pi)$ satisfying these requirements, we use the hyperbolic tangent $\tanh x = (e^{2x}-1)/(e^{2x}+1)$. That is, $\phi(\pi)$ is given by

$$\phi(\pi) = L \cdot \tanh\Big(\frac{\pi-\pi_0}{z}\Big), \tag{4}$$

where Z is a constant parameter that scales the value of π according to the order of π_0. In addition, π_0 is set to the average profit obtained from X data providers, which is obtained by the following equation:

$$\pi_0 = (r - \frac{c_1+c_2}{2}) * X. \tag{5}$$

When the profit π is π_0, $\phi(\pi_0) = 0$ and $\phi(\pi)$ increases monotonically with increasing π. Using the gain function

$\phi(\pi)$, the differential equation for the broker number is numerically calculated by the RungeKutta method. We define π_{ij} as the expected value of the profit that an broker with $\boldsymbol{M}_i$ can obtain when it plays against an broker with $\boldsymbol{M}_j$. Assuming that each user chooses a subscriber by comparing two brokers chosen at random, the total number of brokers is $x_1 + x_2$, so any two brokers will compete on average for $2W/(x_1 + x_2)$ of users. Therefore, when MVNOs of different types compete against each other, π_{ij} is obtained by the following equation:

$$\pi_{12} = \frac{2(r - c_1)W\epsilon_Q P}{x_1 + x_2}, \tag{6}$$

$$\pi_{21} = \frac{2(r - c_2)W(1 - \epsilon_Q P)}{x_1 + x_2}. \tag{7}$$

On the other hand, assuming that when brokers of the same type play against each other, each broker wins each user with a probability of 50%, and we have

$$\pi_{11} = \frac{(r - c_1)W}{x_1 + x_2}, \tag{8}$$

$$\pi_{22} = \frac{(r - c_2)W}{x_1 + x_2}. \tag{9}$$

The gain g_{ij} when the broker of $\boldsymbol{M}_i$ plays against the broker of $\boldsymbol{M}_j$ is ϕ, and

$$g_{ij} = \phi(\pi_{ij}) = L \cdot \tanh\Big(\frac{\pi_{ij} - \pi_0}{z}\Big). \tag{10}$$

Since each broker plays against the broker of $\boldsymbol{M}_s$ with probability $x_s/(x_1+x_2)$, the expected gain G_s of the broker of $\boldsymbol{M}_s$ in one match is

$$G_s = \frac{x_1}{x_1 + x_2} g_{s1} + \frac{x_2}{x_1 + x_2} g_{s2}. \tag{11}$$

The following equation is obtained from G_s. Using G_s, the following simultaneous differential equations for x_1 and x_2 are satisfied

$$\frac{dx_1}{dt} = G_1 x_1 = \frac{x_1^2}{x_1 + x_2} g_{11} + \frac{x_1 x_2}{x_1 + x_2} g_{12}, \tag{12}$$

$$\frac{dx_2}{dt} = G_2 x_2 = \frac{x_1 x_2}{x_1 + x_2} g_{21} + \frac{x_2^2}{x_1 + x_2} g_{22}. \tag{13}$$

Since π_{ij} is a constant, the values of x_1 and x_2 at arbitrary time t can be calculated by giving initial values of x_1 and x_2 using a numerical solution method such as Runge-Kutta method.

V. Numerical Evaluation

In this section, we show numerical results of the proposed model obtained by computer simulations.

A. Simulation Condition

The initial values of the number of brokers of QP type and VP type are $x_1^{(0)}$ and $x_2^{(0)}$, respectively, the step width of the Runge-Kutta method is h, and the parameters used are summarized in Table I. Assuming that a fraction of the population will be data providers in a large city, we set $W = 100,000$. Assume that there is a difference in the quality and quantity value of data, we set $\mu_q = 11$ and $\mu_v = 10$.

Table I
Setting values of parameters used in evaluation

variable	value	variable	value	variable	value
W	100,000	$x_1^{(0)}$	10	$x_2^{(0)}$	10
ρ	0.8	μ_q	11	σ_q	2.5
r	15	μ_v	10	σ_v	2.5
X	5000	z	10000	L	1

B. Selection Probability

For convenience, we set the weights for the quality of data for both broker types so that the sum of the weights for both broker types is 1. That is, for an arbitrarily given α_{QP}, we set α_{VP} to $\alpha_{VP} = 1 - \alpha_{QP}$. In Figure 2, we plot ϵ_{QP}, the probability that each data provider selects QP-type broker against α_{QP} when changing α_{QP} in the unit of 0.01. ϵ_{QP} took a constant value of about 0.27 when α_{QP} was between 0.01 and 0.49, and ϵ_{QP} took a constant value of about 0.73 when α_{QP} was between 0.51 and 0.99. When α_{QP} was 0.5, ϵ_{QP} was 0.5.

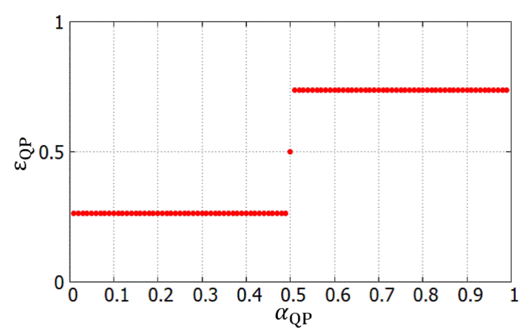

Figure 2. ϵ_{QP}, QP broker selection probability of data providers, against α_{QP}, weight for quality of data in QP type broaker

To investigate the reason why ϵ_{QP} took a constant value in wide range of α_{QP}, Figure 3 shows a scattergram of the incentive that each data provider received from each of the QP and VP brokers when the weights set by each type of broker were extremely different, i.e., $\alpha_{QP} = 0.99$ and $\alpha_{VP} = 0.01$. Data providers plotted below the straight line $x = y$ selected QP brokers, and the ratio of these data providers was about 0.7. Figure 4 shows a scattergram of the incentive received by each data provider from each type of broker when the weights set by both types of brokers were almost identical, i.e., $\alpha_{QP} = 0.51$ and$\alpha_{VP} = 0.49$. Figure 5 shows an enlarged graph around the center of Figure 4. From these figures, we confirmed that the probability that data providers selected brokers of type QP was about 0.7, even when there was no difference between the weights of the two types of brokers. Thus, as long as $\alpha_{QP} > \alpha_{VP}$, ϵ_{QP} was constant no matter how the weights of both types of brokers were set, and we obtained the results shown in Figure 2.

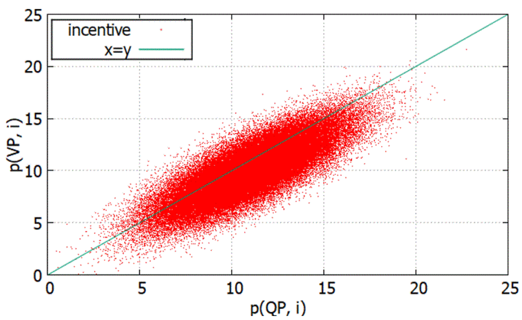

Figure 3. Scattergram of incentives received by each data provider from brokers of each type when setting $\alpha_{QP} = 0.99$ and$\alpha_{VP} = 0.01$

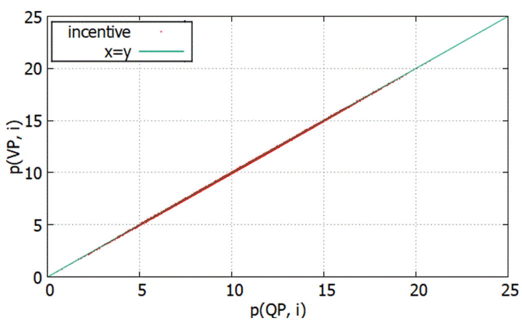

Figure 4. Scattergram of incentives received by each data provider from brokers of each type when setting $\alpha_{QP} = 0.51$ and $\alpha_{VP} = 0.49$

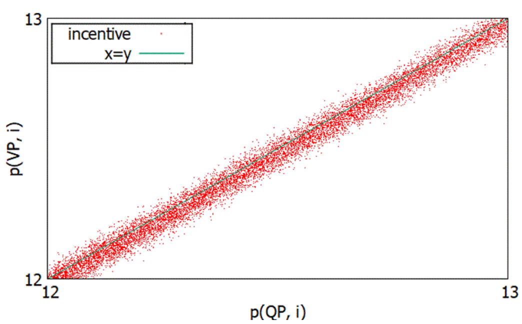

Figure 5. Enlarged scattergram of incentives received by each data provider from brokers of each type when setting $\alpha_{QP} = 0.51$ and $\alpha_{VP} = 0.49$

C. Time Series of Number of Brokers of Each Type

By definition, QP brokers are quality-oriented and will set α_{QP} to $\alpha_{QP} > 0.5$, while VP brokers are quantity-oriented and will set α_{QP} to $\alpha_{QP} < 0.5$. Therefore, we consider four evaluation scenarios shown in Table II, and the time evolution of the number of brokers of each type is evaluated.

As mentioned in the previous section, ϵ_{QP}, the probability of selecting a QP broker by data providers, was always about 0.73 when α_{QP} was greater than 0.5. In all the four scenarios, $\alpha_{QP} > 0.5$, so ϵ_{QP} was about 0.73 on all the four scenarios. Figures 6-9 show the time series of the number of brokers of each type in each of the four scenarios. In all the scenarios, the QP brokers were dominant because the QP selection probability ϵ_{QP} exceeded 0.5, and the number of VP brokers m_2 initially increased, followed by decreasing and eventually reaching zero. When $\alpha_{QP} > \alpha_{VP}$, the market was always eventually occupied by the QP brokers, no matter what the weights were set to. Whenμ_q was greater than μ_v, the selection probability of QP, ϵ_{QP}, was larger than 0.5. When $\mu_q = 10$ and $\mu_v = 11$, i.e., inverting the importance of quality and quantity of data, and reversing the weight settings for QP and VP, m_1 and m_2 were reversed in these graphs.

In these four evaluation scenarios, although there was no significant difference in the time series of m_1, the number of brokers of QP type, and m_2, the number of brokers of VP type, there was a difference in the time it took for m_2 to reach 0. This is related to the difference in profit: when α_{QP} was close to the lower limit of 0.5 in QP's broker strategy, QP's profit was about 4.5, and when α_{QP} was close to the upper limit of 1, QP's profit was about 3.7. When α_{QP} was close to the upper bound of 1, the profit of QP was about 3.7. The larger the value of α_{QP} was, the more the incentive paid to data providers was affected by the data quality value. In a situation where the average μ_q of data quality was larger than the average μ_v of quantity, the larger α_{QP} was, the larger the amount paid by the QP broker to the data provider was. Therefore, the larger α_{QP} was, the smaller the profit of the QP brokers.

Table II
EVALUATION SCENARIOS

scenario	α_{QP}	α_{VP}
scenario A	0.99	0.01
scenario B	0.99	0.49
scenario C	0.51	0.01
scenario D	0.51	0.49

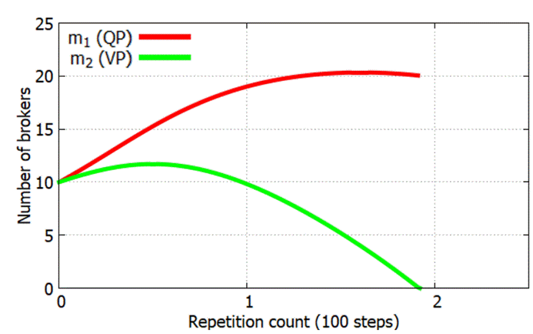

Figure 6. Time series of number of brokers (scenario A)

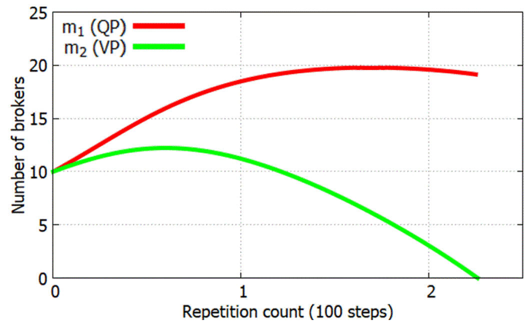

Figure 7. Time series of number of brokers (scenario B)

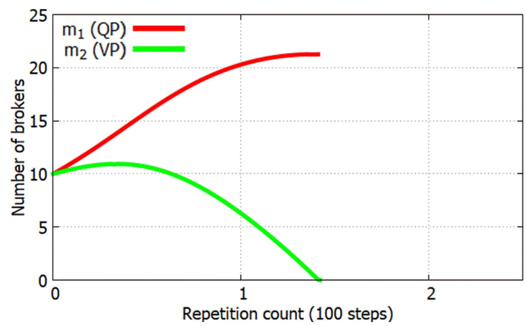

Figure 8. Time series of number of brokers (scenario C)

Since it is desirable for multiple types of brokers to continue to exist in the market for stable co-creation digital twin operations, the larger the weights α_{QP} and α_{VP} of scenario B, the longer both types of brokers will survive. Also, a smaller broker profit means that the data provider received a larger amount of money, so scenario B was less profitable with a QP that was chosen by about 73% of the data providers. This means that the attractiveness to many data providers will increase. By the way, the VP broker on the disadvantaged side naturally increases α_{VP} because it is motivated to remain in the market, while the QP broker on the advantaged side decreases α_{QP} because it prefers to occupy the market himself. The QP broker is motivated to reduce α_{QP}. Therefore, a mechanism that gives the QP broker an incentive to increase α_{QP} is needed.

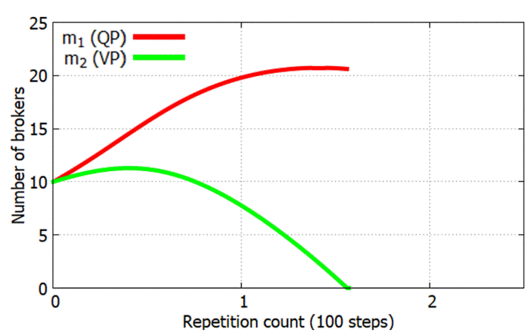

Figure 9. Time series of number of brokers (scenario D)

VI. Conclusion

In order to realize a co-creation urban digital twin, we investigated methods of providing incentives to broker data providers and quantitatively evaluated the number of brokers using each strategy type using an evolutionary game. By computer simulation, we confirmed the transition of the number of brokers when changing the weights in the quality-first vs. quantity-first case, and clarified a better weight setting method for realizing a co-creation digital twin. In the future, we plan to subdivide the data elements.

Acknowledgment

This work was supported by JSPS KAKENHI Grant Number 23K28078 and 23K21664.

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