Parameter Estimation of Macroeconomic Agent-Based Models Using Evolutionary Computation

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Abstract: This study reports the estimation of model parameters for a macroeconomic agent-based model (ABM) using evolutionary computation methods. In an ABM, the parameter settings of the model are important in terms of verifying the validity of its outputs, because the parameter settings are closely related to these outputs, and determining whether the set parameters are appropriate. Conventionally, model parameters are qualitatively set by researchers based on values confirmed from empirical studies in related fields. However, in recent years, attempts to quantitatively determine model parameters using metaheuristic methods and Bayesian estimation-based methods have become widespread. In this study, we attempted to estimate time-varying parameters using a real-coded genetic algorithm, a type of evolutionary computation method, based on an inverse simulation method, which has not been used in macroeconomic ABM parameter estimation. The analysis confirmed that parameter estimation works well when the economic conditions to be assimilated are simple, whereas it is difficult when economic conditions change in a short time, such as before and after economic shocks.

1 INTRODUCTION

This study reports the estimation of model parameters for a macroeconomic agent-based model (MABM) using evolutionary computation methods. When developing an agent-based model (ABM), one of the most important issues for researchers is whether the parameters of the model are appropriate. In addition to the appropriateness of the parameters, parameter settings are important in terms of verifying the validity of the outputs of the developed ABM, because parameter settings are closely related to the outputs of the ABM (Fagiolo, 2018). Although researchers generally set model parameters qualitatively by referring to values confirmed in empirical studies in related fields, attempts to quantitatively determine model parameters using metaheuristic methods or Bayesian estimation have become widespread in recent years (Delli Gatti, 2020). In this study, based on the inverse simulation method proposed by (Kurahashi, 1999) as a parameter estimation method, we attempted to estimate the time-varying parameters of an economic simulator using a real-coded genetic algorithm (RCGA), a type of evolutionary computation method that has never been used for ABM parameter estimation in the macroeconomic field to our knowledge. According to the analysis results, we confirmed that parameter estimation works well when the economic conditions to be assimilated are simple, whereas it is difficult to estimate parameters when the economic conditions change in a short time, such as before and after economic shocks.

2 RELATED STUDIES

2.1 MABM

As a germ of research using ABMs in macroeconomic analysis, some of the early studies were conducted around 1960; however, it was not until the mid-2000s that the use of ABMs became widespread. In particular, when the financial crisis occurred in 2008, there was a movement to review economic analysis methods, partly because the crisis could not be predicted using conventional analysis methods. Thus, the effectiveness of ABMs was recognized, and their use expanded (Fagiolo, 2012).

While various models have been developed and proposed in macroeconomic analysis utilizing ABMs, a research paper that organized MABMs developed since the 2000s (Dawid, 2018) identified seven major

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MABMs/frameworks and summarized the characteristics of each. One of these seven frameworks, complex adaptive trivial systems (CATS), is frequently used in studies focusing on emergent aspects of the macroeconomy. (Caiani, 2016) proposed a benchmark model as a basis for various analyses of the CATS framework. (Obata, 2023) listed a macroeconomic approach, a sector-specific approach, and an input–output approach as approaches for developing an ABM to analyze the propagation of the impact of economic shocks and developed a novel MABM based on the benchmark model in (Caiani, 2016), utilizing the strengths of each approach. In this study, analysis is performed using a model that is an improved version of the MABM developed in (Obata, 2023). The model details are presented later.

2.2 Parameterization of ABM and Inverse Simulation Method

The setting of model parameters for ABMs is one of the most important issues that researchers pay attention to when developing ABMs. In MABM research, the validation of model parameters is typically conducted by empirically confirming whether the output and state of the model reproduce the stylized fact. In recent years, attempts to estimate parameters using quantitative methods have increased, but no established quantitative parameter estimation method exists (Delli Gatti, 2020). Quantitative model parameter estimation methods include metaheuristic methods and methods based on Bayesian estimation such as particle filters ((Grazzini, 2017), (Lux, 2022)).

Although attempts to estimate model parameters quantitatively are new to the field of MABM, various methods have been used in ABM research as a whole for more than 20 years. The inverse simulation method proposed by (Kurahashi, 1999), (Kurahashi, 2013) is a pioneering study that attempted quantitative parameter estimation. A typical simulation involves developing a model with several parameters, setting the parameters, running the simulation, and adjusting the parameters based on the simulation results. Conversely, the inverse simulation method involves the following process to solve a large-scale inverse problem:

1. designing a model with many parameters that represents the real world
2. setting up the evaluation function
3. simulation using evaluation function as objective function
4. evaluation of the obtained initial parameters

Inverse simulation employs evolutionary computation methods represented by genetic algorithms (GAs) as parameter search methods. According to (Kurahashi, 2013), there are two approaches to the inverse simulation method: one is to use it as inductive inference, and the other is to use it as deductive inference. This study attempts to estimate the parameters of MABMs using an inverse simulation method while adopting the former inductive reasoning approach.

2.3 Evolutionary Computations and RCGA

Evolutionary computations are multipoint search methods wherein the computational algorithm is inspired by the evolution of organisms and swarm behavior to perform solution search. The common features are as follows: the population of search points are processed in parallel and the population is changed, there is some kind of interaction among the search points, stochastic actions are used to change the population, and competitive actions work among the search points, such as survival of the fittest.

A GA is a type of evolutionary computation that incorporates the concept of natural selection, wherein organisms that adapt to their environment survive and those that fail to adapt die. It has the following characteristics: (1) no assumption of differentiability of the objective function is required, and (2) a global search is possible. Although bit coding of 0 and 1 has long been used as the genotype in GAs, when solving optimization problems with real-valued parameters, the phase structure of the genotype space may significantly differ from that of the phenotype space, the real number space. Therefore, a child generated from two-parent individuals close to each other in the phenotype space may not necessarily be generated in the neighborhood of its parent in the phenotype space, even if it is in the neighborhood of its parent in the genotype space.

An RCGA, which treats real-coded vectors as genotypes, responds to these remarks (Wright, 1991). Because an RCGA directly manipulates real-coded vectors by crossover, it can generate sub-populations in the neighborhood of the parent population in the phenotype space. Therefore, compared with conventional binary coding, the solution search efficiency for real-coded problems is significantly improved. There are various methods for RCGAs; however, in this study, we use the distance-weighted exponential natural evolution strategy (DX-NES)(Fukushima, 2013), a method that incorporates the concept of natural gradients. The literature reports that DX-NES improves the performance of solution search as well as addresses issues such as the bad scalability of the search area.

3 ABOUT MABM USED IN THIS STUDY

The MABM used in this study (hereinafter referred to as the "current model") is the improved version of the MABM developed by (Obata, 2023) (hereinafter referred to as the "reference model"), which has been improved by introducing the concept of capital goods, etc. . In this section, we explain the main differences from the reference model and discuss the simulation results using the current model.

3.1 Major Differences Between Reference and Current Models

The concept of capital equipment, which is one of the remaining limitations of the reference model, is introduced into the current model. All firms use capital equipment to produce their products. The productivity of capital equipment, μ_k, which represents the number of products that can be produced per piece of capital equipment, is set at 1.5 for all firms and all capital equipment. The labor capital equipment ratio, ι_k, which represents the maximum number of capital equipment that a worker can be equipped with, is 6.4. These two values were set referring to (Caiani, 2016). Thus, the maximum number of products that a worker can produce in one step is $1.5*6.4=9.6$. The durability period of capital equipment, η_k, was set to 20 steps (equivalent to 5 years in the real world). This was determined by referring to the table of useful lives of major depreciable assets published by the National Tax Administration Agency of Japan. The firms determine the desired number of capital facilities assumed for the current period using the following formula.

$$K^D_{fi,t} = (1+g^D_{fi,t})K_{fi,t-1} \quad (1)$$

$$g^D_{fi,t} = \gamma_1 \frac{pcfr_{fi,t-1}-\bar{r}}{\bar{r}} + \gamma_2 \frac{u^D_{fi,t-1}-\bar{u}}{\bar{u}}, \quad (2)$$

where $K^D_{fi,t}$ denotes firm i's desired number of capital facilities in period t, $g^D_{fi,t}$ denotes the desired capital facility growth rate, and $K_{fi,t-1}$ denotes the number of capital facilities owned in period $t-1$. γ_1, γ_2, $\bar{r}$, and $\bar{u}$ denote constants and are set to 0.01, 0.02, 0.03, and 0.90, respectively. These values are taken from (Caiani, 2016). $pcfr_{fi,t-1}$ denotes the net asset cash flow multiplier for firm i in period $t-1$, where the total capital equipment held is added to the calculation of net assets, as defined in the reference model. The investment amount of capital equipment purchased in each period is not reflected in the operating cash flow calculation because it is a capital transaction. Therefore, the operating cash flows in the reference and current models are the same. The net asset cash flow multiples in the current model are as follows:

$$pcfr_{fi,t} = \frac{OCF_{fi,t}}{NW_{fi,t-1}} \quad (3)$$

$$NW_{fi,t} = \text{reference models' } NW_{fi,t} + KV_{fi,t} \quad (4)$$

where $KV_{fi,t}$ denotes the total value of capital facilities owned by firm i in period t. The capital equipment owned by firm i is assumed to be depleted by $1/\eta * \nu_{\eta k}$ in each period. Firm i orders the quantity of capital equipment it wishes to own, i.e., $1/\eta_k * K^D_{fi,t} * (1+g^D_{fi,t})$, in each period. However, the ability to procure capital equipment based on the quantity ordered depends on the availability of sufficient products for capital equipment. The mechanism for ordering and procuring capital equipment is based on (Poledna, 2023), where the required quantity of capital equipment is aggregated by the industry attribute of the firms, and the products produced by each firm are provided according to its share of product sales in the industry to which it belongs in the immediately preceding period, rather than directly between individual firms with supplier–customer relationships, as in the case of product sales. Thus, a firm provides the products it produces in proportion to its share of product sales in its industry in the previous period. Although the percentage of the products of each industry comprising a unit of capital equipment can be set differently for each industry, in the setting of the current model, the percentage of the products of each industry comprising a unit of capital equipment is assumed to be equal. The maximum quantity of products that a firm can provide for capital equipment in each period is limited to 3% of the quantity of products manufactured in the period. How many products a firm can produce depends on the number of workers and intermediate input materials it has in the reference model; however, in the current model, it also depends on the number of capital facilities it has.

$$y^{max}_{fi,t} = min\{mat_{1,fi,t}/inpq_{fi,1}, mat_{2,fi,t}/inpq_{fi,2}, \cdots, mat_{n,fi,t}/inpq_{fi,n}, \mu_k\iota_k N_{fi,t}, \mu_k K_{fi,t}\},$$

where $mats_{,fi,t}$ denotes the quantity of intermediate input materials s in stock for firm i in period t. $inpq_{fi,s}$ denotes the quantity of intermediate input materials required by firm i to produce a unit of product, and $N_{fi,t}$ denotes the number of workers employed by firm i in period t. Because of the introduction of the capital equipment concept in the current model, the method of updating product markups has changed from that in the reference model. The product markup is the percentage that firm i adds to the product manufacturing cost uc when setting the product price p in step t, and their relations can be expressed as $p_{fi,t} = uc_{fi,t} * (1 + mu_{fi,t})$. In the reference model, the only criterion for increasing or decreasing the product markup is whether the product inventory ratio exceeds the threshold value ν. However, in the current model, we introduced a capital equipment utilization criterion, $u_{threshold}$, and added another condition indicating whether $u_{threshold}$ is more than 95%. This is done to avoid raising the product markup when the product inventory ratio becomes low under the condition of low facility utilization. The current model differs from the reference model in many other ways because of the introduction of the capital equipment concept (e.g., the capital equipment sales volume is reflected in the calculation of expected product sales volume). However, these are minor changes and will not be explained here.

3.2 Simulation Results

This section reports the simulation results with the model parameters based on the reference model.

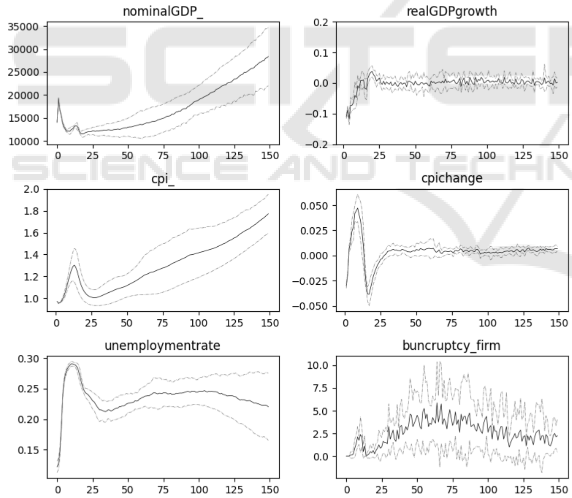

Figure 1: Mean and standard deviation of each indicator value obtained from ten trials of simulation up to 150 steps.

Figure 1 plots the mean value and ±1 standard deviation of the results of each trial, excluding the two trials wherein the economy collapsed, after running the 150-step simulation ten times. The price index is calculated by taking the weighted average of the average prices of firm and household products. According to the transition in nominal GDP, the standard deviation is within a small range in the early stage of the simulation; subsequently, the standard deviation gradually increases. This movement is similar to that of the reference model. As a common trend observed in the other index values, the standard deviations are within a small range in the first 10–20 steps of the simulation. In the subsequent steps, the standard deviations of the price index, unemployment rate, and the number of corporate bankruptcies gradually increase, whereas the standard deviations of the real GDP growth rate and the rate of change in the price index exhibit a slight tendency to increase until steps 60-80; however, thereafter, they remain within a narrow range. In the early stages of the simulation, the results of each simulation are similar to those of the reference model even though the degree of movement is significant, partly due to the initial settings. According to the standard deviation of the real GDP growth rate and the price index change rate, the simulation results were mixed until approximately the 80th step, after which each simulation reached a similar economic state. Excluding the initial stage by the 35th step, where output fluctuations were significant, the average values per step (standard deviation in parentheses) were as follows: nominal GDP growth rate was approximately 0.73% (0.68%), price inflation rate was 0.47% (0.14%), real GDP growth rate was approximately 0.26% (0.68%), and GDP growth rate was approximately 0.26% (0.68%). (0.68%) and an unemployment rate of 23% (0.63%). These levels are close to the reference model's nominal GDP growth rate of approximately 0.86% (0.9%), price inflation rate of 0.43% (0.08%), real GDP growth rate of approximately 0.44% (0.9%), and unemployment rate of 19% (3.3%).

4 PARAMETER ESTIMATION METHOD BY EVOLUTIONARY COMPUTATION

Based on the MABM simulation results discussed in the previous section, it takes approximately 80 steps for the model behavior to converge to similar behavior in each simulation. Therefore, when estimating model parameters in evolutionary computation, the results of simulation runs of up to 100 steps are used as initial conditions with some buffer, and the model parameters estimated using evolutionary computation are reflected in the computation process of the simulation after the 100th step.

As the parameter estimation method, DX-NES is adopted, which is an evolutionary computation method that has high solution search performance and can achieve the optimal solution with fewer individual evaluations. The parameters of DX-NES are set according to the reccomendation of (Fukushima, 2013), except for the number of individuals explained later.

In the MABM parameter estimation in this study, the evaluation values of the RCGA individuals depend on the results of the MABM simulations. Therefore, it is necessary to run MABM simulations to obtain individual evaluation values, which is computationally expensive. DX-NES is suitable for the case in this study. According to (Fukushima, 2013), because DX-NES allows parallel execution of the solution evaluation value calculation, the calculation time per generation does not significantly change even when the number of individuals to be generated is increased to the extent that parallel computing resources permit. In this case, as the number of individuals generated increases, the number of generations required to find the optimal solution generally decreases. Considering the available machine specifications, the number of individuals to be generated and evaluated per generation is set to 28.

The value of each individual is evaluated on the basis of the absolute error between the time series of each social indicator value to be assimilated and the time series of social indicator values obtained from the output of MABMs. The absolute error rather than the squared error is used because we do not want to focus on outliers in the output of the time series but rather on the overall direction of the social indicator values to be assimilated. The first step in the process of calculating specific evaluation values is to select the social indicators to be assimilated. In this study, three indicators were selected: real GDP growth rate, nominal GDP growth rate, and price index growth rate. Next, the MABM simulation is run for 101-124 steps, using the set of MABM parameters represented by the genes of each individual in the evolutionary computation, and the social index values are calculated on the basis of the output. The reason why 24 MABM simulation steps are performed is that the economic situation in an MABM artificial society does not change immediately after each step, and there is a lag until the impact of the parameters generated by evolutionary computation is reflected in the economic situation. Even after the economic situation is reflected, we cannot confirm whether the economic situation is stable until a certain length of time has passed. Finally, the absolute error between the social indicator value to be assimilated and the social indicator value obtained from the MABM is calculated, and the sum of the absolute errors of the three social indicator values is used as the individual's evaluation value. However, if the value of the gene of each individual deviated from the initially set upper and lower limits, the MABM simulation was not performed, the absolute value of the value exceeding the upper and lower limits was calculated for all genes possessed by each individual, and the sum of these values multiplied by 100,000 was used as the evaluation value for each individual as a penalty.

5 VALIDATION OF PARAMETER ESTIMATION RESULTS

Because the MABM used in this study has many parameters, optimization using evolutionary computation is performed for parameters that affect agent behavior, excluding the setting parameters, such as the number of agents, and parameters with external variables in the economic environment, such as policy interest rates and tax rates.

5.1 Parameter Estimation Results

Table 1 shows the parameters estimated for parameter optimization. For these parameters, the analysis was performed in two patterns, one assuming stable economic growth and the other assuming economic downturn.

In the case of stable economic growth, the parameters were optimized using evolutionary computation five times using time-series data with 24 consecutive steps of 0.80% nominal GDP growth, 0.40% price index increase, and 0.40% real GDP growth as the transition of social indices to be assimilated to these parameters. Conversely, in the case of an economic downturn, the parameters were optimized using evolutionary computation five times using time-series data with 24 consecutive steps of -0.40% nominal GDP growth rate, -0.20% price index growth rate, and -0.20% real GDP growth rate as the social indicators to be assimilated.

Table 2 shows the mean of the estimated values of all individuals in the last generation of each trial for both stable economic growth and downturns. Two parameters for the capital equipment rate, $u_{threshold}$ and $\bar{u}$, were estimated to have lower values for stable growth. Because one condition for raising the markup is for the capital equipment utilization rate to be above $u_{threshold}$, a lower $u_{threshold}$ is more likely to promote a higher markup, leading to the conclusion that prices are more likely to raise in the stable growth case. $\bar{u}$ denotes the threshold for increasing the facility growth rate, and the lower the $\bar{u}$, the more likely that the facility growth rate will increase. Because increasing the number of facilities and the quantity of products produced leads to economic growth, it is natural that the estimated value of $\bar{u}$ is smaller

Table 1: List of model parameters to be estimated.

ν	estimated inventory to product sales volume ratio	0.10	1.00	0.00
λ	weight of previous period's values in the current period forecast	0.25	1.00	0.00
$u_{threshold}$	One of the thresholds at which the markup is raised. Raise the markup if capital equipment utilization is above this threshold and other conditions are also met	0.95	1.00	0.50
$\bar{r}$	One of the factors that determine the capital equipment growth rate. If the profit margin is above this value, the capital equipment growth rate may be increased.	0.03	0.20	0.00
$\bar{u}$	One of the factors that determine the capital equipment growth rate. If the capital equipment utilization rate is above this value, the capital equipment growth rate can be increased.	0.90	1.00	0.50
$\gamma 1$	One of the factors that determine the capital equipment growth rate. Adjustment terms for profit margins.	0.01	0.10	0.00
$\gamma 2$	One of the factors that determine the capital equipment growth rate. Adjustment term for capital equipment utilization.	0.02	0.10	0.00
$ratio_{wfc}$	Adjustment rate coefficient for the number of workers.	0.50	1.00	0.00
α_{in}	One of the factors that determine household consumption expenditure. Coefficient of household income.	0.40	1.00	0.00
α_{nw}	One of the factors that determine household consumption expenditure. Coefficient of household assets.	0.25	1.00	0.00

for stable growth. $adaptive\lambda$ denotes a parameter that affects each agent's calculation of expectations, controlling the weight between the actual and expected values one period ago. The larger the $adaptive\lambda$, the greater the weight of the performance of the previous period. Therefore, a larger $adaptive\lambda$ may be more likely to continue the previous period's situation; however, whether this has a positive or negative effect on the economy depends on the situation.

We review the evolution of economic indicators that reflect the parameters estimated by evolutionary computation in each economic situation. Figure 2 shows the evolution of each social indicator value for stable growth. The graphs of all social indicators are perfectly consistent up to the 100th step because the common economic situation is read into the parameter estimation up to this step. The 101st step and beyond show that nominal GDP is rising steadily and the unemployment rate is declining. The mean value (standard deviation) of each indicator value is as follows. The mean (standard deviation) of each indicator value was +0.96% (+0.44%) for nominal GDP growth, +0.82% (+0.08%) for price index growth, and +0.14% (+0.39%) for real GDP growth. Figure 3 shows the same values for the economic downturn. In Figure 3, the nominal GDP growth rate is flat immediately after the 100th step, which is different from the case of stable economic growth. The other major differences from the stable growth case are the large angle of the price index and the fact that the unemployment rate, on average, remains flat. The nominal GDP growth rate was +0.49% (+0.56%), the price index change rate was +0.92% (+0.14%), and the real GDP growth rate was -0.43% (+0.52%), resulting in lower nominal and real GDP growth rates than those in the case of stable growth. Although the rate of price index change exceeded the level of stable growth, because the three social index values were used to generate the individual valuation values, it may have been easier to increase the individual valuation values by reducing the errors in the two GDP growth rates, even if the error in the rate of price index change increased. This is an example of how evolutionary computation may search for extreme solutions when there are multiple social indicators to be assimilated during parameter optimization. How to set the values of the social indicators to be assimilated is for future studies.

Table 2: Parameter estimation results.

Parameters	Stable growth	Downturn
ν	0.31	0.32
$adaptive\lambda$	0.31	0.37
$u_{threshold}$	0.68	0.75
$\bar{r}$	0.12	0.14
$\bar{u}$	0.71	0.73
$\gamma 1$	0.01	0.02
$\gamma 2$	0.03	0.04
$ratio_{wfc}$	0.33	0.28
α_{in}	0.34	0.30
α_{nw}	0.30	0.33

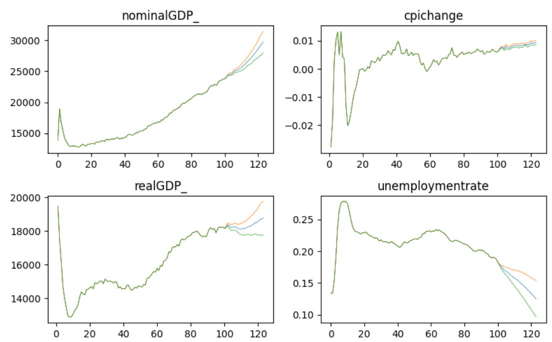

Figure 2: Mean and standard deviation of transition of each indicator value in stable growth case.

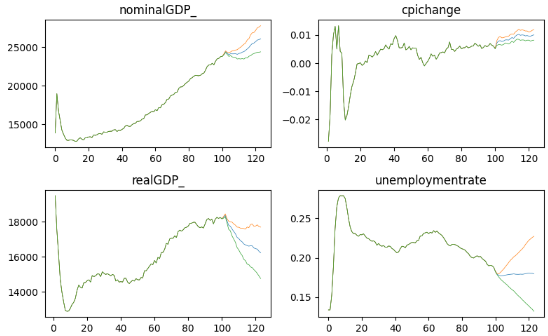

Figure 3: Mean and standard deviation of transition of each indicator value in downturn case.

5.2 Parameter Estimation in Cases Where Economy Moves up and down in the Short Term

Next, we tested whether appropriate parameter estimation can be performed even when the economy moves up and down in the short term. When an economic shock occurs, the economic situation changes both before and after the shock. Therefore, it is necessary to check whether the model parameters change because of changes in the economic situation. Therefore, assuming that there are ups and downs in the economy, we prepared time-series data for a period of stable growth before the economic shock, a period of rapid economic decline, and a period of recovery after the shock was resolved; we conducted parameter optimization. The initial eight steps of the time-series data assumed stable growth, with nominal GDP growth of 0.80%, price index growth of 0.40%, and real GDP growth of 0.40%, followed by a shock period for eight steps with nominal GDP growth of -0.60%, price index growth of -0.20%, and real GDP growth of -0.40%. Thereafter, the shock resolution period for four steps is assumed during which the nominal GDP growth rate, price index inflation rate, and real GDP growth rate hover at 0.00%. Eventually, the economy returns to a period of stable growth in four steps. We also performed parameter estimation for ten parameters in the case of business fluctuations. Table3 presents the results of parameter optimization for the business fluctuation case. For reference, the results for stable growth and economic downturn from the previous section are also included. Table3 shows that many parameters are between the two cases of stable growth and economic downturn, or close to them.

After the 101st step in the case of business fluctuations, the nominal GDP growth rate was +0.64% (+0.51%), the price index growth rate was +0.79% (+0.07%), and the real GDP growth rate was -0.13% (+0.47%). The simulation results fall between stable growth and economic downturn, implying that the estimation results capture the business fluctuation situation to some extent. Figure 4 shows the evolution of each indicator simulated using the estimated parameters for the business fluctuation case.

Table 3: Parameter search results for fluctuation case.

Parameters	business fluctuation	(Reiterated) Stable growth	(Reiterated) Downturn
ν	0.22	0.31	0.32
$adaptive\lambda$	0.38	0.31	0.37
$u_{threshold}$	0.69	0.68	0.75
$\bar{r}$	0.12	0.12	0.14
$\bar{u}$	0.72	0.71	0.73
$\gamma 1$	0.02	0.01	0.02
$\gamma 2$	0.05	0.03	0.04
$ratio_{wfc}$	0.43	0.33	0.28
α_{in}	0.44	0.34	0.30
α_{nw}	0.29	0.30	0.33

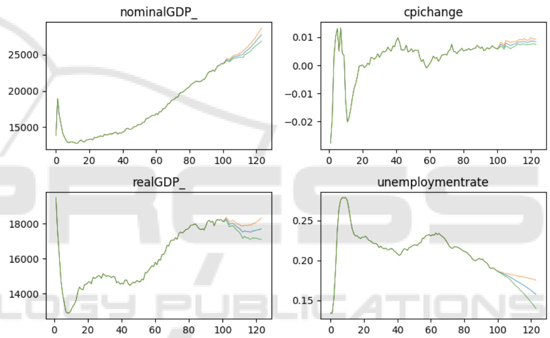

Figure 4: Mean and standard deviation of transition of each indicator value in business fluctuation case.

Although the average values alone do not reveal this, according to the output of individual simulators, for example, there are cases wherein real GDP, after leveling off, exhibits an upward trend in the second half of the period and cases wherein it exhibits a downward trend in the middle of the period and levels off in the last half, indicating that some of the characteristics of the business fluctuation cases are captured. However, overall, the economic transition was different from the ups and downs in the economy. It is difficult to fit short-term upward and downward movements when the model parameters are fixed throughout the simulation period.

6 CONCLUSION

In this study, we attempted to estimate the parameters of MABMs, which is an important issue when using an ABM, by RCGA. Conventionally, researchers have set the parameters of ABMs by referring to stylized facts. However, in recent years, an increasing number of studies have attempted to estimate the parameters of ABMs using quantitative methods such as heuristic methods or Bayesian estimation-based methods. In this study, we attempted to estimate time-varying model parameters using evolutionary computation methods based on the concept of the inverse simulation method proposed by (Kurahashi, 1999). From the experimental results, we confirmed that parameter estimation by evolutionary computation works well in cases where the economic transition to be assimilated is stable. On this basis, we confirmed that parameter search using evolutionary computation works well as an inverse simulation method. Conversely, we confirmed that it is difficult to estimate appropriate parameters in cases where the economic situation to be assimilated changes in the short term. One reason for this may be that it may be difficult to fit the economic fluctuations in the short term with fixed model parameters.

One of our future tasks will be to develop a more appropriate method of measuring the evaluation values of individuals in evolutionary computation. Currently, the absolute error is calculated for multiple social indicators to be assimilated, and the sum of these values is used as the individual's evaluation value. However, it may be more appropriate to use a single social indicator. As described in the previous section, it is difficult to evaluate parameters when multiple indicators are used, some of which are good while others are not. The second issue is to develop a method for capturing changes in parameter values in the short term. In the analysis of this study, the economic simulator was run for 24 steps to evaluate each individual. The parameters used in the simulation reflected the parameters estimated by evolutionary computation in the economic simulator only at the beginning of the simulation, and the reflected parameters were then continued. This is because the genes of each individual in the RCGA corresponded to each MABM parameter. We would like to confirm as a future issue whether it is possible to capture changes in parameter values in cases wherein economic conditions change in the short term by setting genes corresponding to each parameter at each point in time.

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