Quantitative Evaluation of the Energy System in an Adaptive Network Architecture

Guidance

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Abstract

In the future network, a large number of users and many kinds of devices connect through computer networks. In such a situation, the central server cannot control the whole system. Therefore, self-organizing autonomous networks, which are also called adaptive network systems, have been proposed, and the bio-net was suggested to realize an adaptive network system. Bio-net is a model of a network system to which biological behavior is applied. The bio-net consists of platforms and Cyber-Entities (CEs) describing service etc. The bio-net is a self-organizing autonomous system in which each CE judges by itself how to behave based on the evaluation by users. If users evaluate the grade of service of a CE to be low, the CE may be killed. Therefore, in order to understand the bio-net, we have to understand the relation between the user evaluation of the CE and the death rate of the CE. Note, however, that there is no study to estimate this relation quantitatively.

In this thesis, we model the evolution of the energy level of a CE by a Markov chain to estimate the death rate of the CE quantitatively, where the user evaluation is represented by a select probability. Thus, the death rate is considered as the first passage time to a particular state corresponding to zero energy. For a special case of a random walk, we explicitly derive the death rate and the mean first passage time to death. Further, using those results, we provide some numerical results and show that the death rate can be estimated in an arbitrary situation. Furthermore, we propose a way to decide whether a CE makes its copy, moves to another platform or does nothing, based on the estimation of the death rate.

Contents

1 Introduction

In the future, we will get to be able to take information through networks wherever and whenever we stay. We think networks are able to offer a new kind of services to connect all information systematically. In order to offer such services, computer networks work and gather information from all over the world and adapt services to it. In such a network, huge members are connected in the computer network such as not only users and computers but many kinds of devices like censers, home electric appliances, cars and so on. We ask for the network scalability and we cannot control the whole network with the consolidate management at the central control server. In order to adapt network services to user requests, we need networks, which can make self-originated, self-made and self-organized services. In this study, we attempt to develop an adaptive network with these two conditions: One is a complete self-moved distributed network, each of whose nodes gathers information and behaves according to it. The other is a self-organized network, in which we attempt to get rid of any central control systems and to organize services automatically.

As an adaptive networks system, some people [2, 7] suggested a bio-net that includes the feature of biological behavior in computer networks. The nature and biological world have the features mentioned above. Namely, the nature has an adaptive feature, scalability, availability and so on, and the nature can make any necessary kinds of patterns automatically. In the nature and biological world, each creature behaves according to a simple policy of his own. However, combining these behaviors leads to a complicated behavior like organization or society. Therefore the nature and biological world have the diversity and behave well without any central control systems even when something occurs. The bio-net attempts to realize the formulation of the above-mentioned biological behaviors in adaptive computer network systems. It consists of two parts, Cyber-Entities (CEs) and platforms. CEs correspond to many kinds of movable network elements such as devices, software, contents and users who receive, use and evaluate services on the network. On the other hand, platforms correspond to the basis of networks, such as communication link, router, CPU, buffer resource and so on.

CEs behave on a platform and offer their services, which is similar to an individual's function in the biological world. Individuals cooperating with one another can perform even a complex function that cannot be performed only by each individual. For this reason, a CE is not only a service itself but also the element of complex services in the bio-net. Self-sustaining CE behavior fitting the environment occurs through interactions among CEs and develops the complex services.

In the bio-net, users who accept services offered by CEs evaluate the grade of these services. We consider that CEs, which users often use, are necessary and get high user satisfaction. On the other hand, we consider that CEs, which users rarely use, are needless and get low user satisfaction. If there are some CEs, which get high user satisfaction, it is better to enlarge these CE services. The way to enlarge services is that high user satisfactory CEs make their copies and spread them to other platforms in the network. On the other hand, CEs whose user satisfaction is low are deleted from the network. We call the latter event CE death and call this mechanism *natural selection*. The natural selection is an evolutionary process and it is the same as the real biological world because natural selection implies that what cannot correspond to the environment becomes to death. We attempt to progress services. Only good services leave on the network to do the service emergent evolution, making copies of satisfactory CEs and natural selection. As the result, we are able to develop an adaptive network system matching the user request in a huge network.

To build in the natural selection mechanism, we introduce the concept of *energy* [1]. When a CE offers a service to other CEs, the CE gets the energy from them. When a CE uses the runtime resource of his platform or accepts services from other CEs, the CE spends some amount of energy as a consideration for the cost. Energy needs for a CE to be alive. We assume that when CE energy becomes zero, the CE gets to be killed and cannot continue to offer his service. Energy for CE corresponds to money for us. Therefore, as CEs live on the network, CEs have to offer their services that users often use and get much energy. Note that the purpose for CEs to live is to get energy as much as possible. Thus every CE considers how to get more energy and behaves accordingly.

Because each platform needs many useful CEs, it evaluates CEs based on the user evaluation. Platforms try to increase useful CEs and to decease useless CEs. In addition, each platform needs to all kinds of CEs to be able to catch up with the change of the environment or user requests. To realize this, each platform has to control how much energy it gets from CEs as a system using cost and how much energy it gives to CEs as a reward when they are used often.

Whether natural selection adequately occurs or not strongly depends on how to make rules to exchange energy. Therefore whether platforms can control CEs autonomously or not is equivalent to how well we keep the balance of energy flow. Each platform has its own policy that decides which CE the platform attempts to be killed as a natural selection. If the platform policy is not good, it is possible that the platform cannot control CEs, e.g., many useful CEs get to be death or countless CEs are made.

The purpose of the energy system is to make the mechanism that useful services (i.e., CEs) are living and useless services are killed in an adaptive network system. Therefore we have to consider what policy for each CE/platform we make and how we decide the amount of energy flow under this policy. However, there were some problems on the past study of energy system. In the past study, we qualitatively decided the rule of each CE giving and receiving energy when we design a network. The relation between the mechanism of CE death and the rule of giving and receiving the energy was not able to estimate unless we performed simulation experiments. That is, there are not any quantitative evaluation methods. Thus, in this study, we analyze the energy flow and propose the quantitative method of evaluation of the energy system.

The initial energy of a newly created CE is closely related to its death rate. If the initial energy is shortage, a useful CE perhaps gets to be killed. On the other hand, if the initial energy is too much, a useless CE continues to live for a long time. To solve these problems, we take the following approach. We assume that the network designer can control only two parameters:

- The function as a rule of energy flow between CEs and between CE and platform, and
- the amount of the initial energy.

In these parameters, we can include the policy, how a CE or platform behaves. We model the evolution of the energy level of a CE by an absorbing Markov chain and develop a way to estimate the death rate under the above assumptions.

CEs can sense other CEs and learn what happens at the neighborhood to get information of a network or platform resources [6]. In addition, CEs can change their own rules to fit the environment autonomously. We call this function *behavior*. Note that some behaviors such as migration and replication were proposed [2, 8].

Migration is the behavior that a CE moves to a neighbor platform. Platforms connect with one another and make graph networks. CEs can move only to the connected platforms at migration. Recall that each platform controls the amounts of energy receiving from CEs and giving to CEs by its own policy. On the other hand, each CE behaves to get energy as much as possible. Therefore it is a natural idea of migration that a CE moves to a neighbor platform on which it can offer the service more often and get more energy.

By using the quantitative evaluation of the death rate, we propose a policy of migration. Namely, a CE compares the death rates when it moves and when it does not move, and if the CE finds it is able to get more energy than before, it does the migration.

Replication is the behavior that a CE makes a copy and becomes two CEs to make their service popularize. When a CE replicates, the access rate of the service of each CE decreases temporarily because more CEs to offer the same service exist in the network than before. The amount of energy is also divided and when we focus on one of the CEs, the amount of energy decreases. Therefore, it is not a good way to replicate without any thinking because both the access rate and energy amount decrease. In this study, we propose a rule to use the death rate before replication and after replication.

The rest of this thesis is organized as follows. In section 2, we model the evolution of the energy level of a CE by an absorbing Markov chain. In section 3, we consider a special case, a random walk, of the model in section 2 and derive the death rate and the mean first passage time to death explicitly. In section 4, we provide some numerical results. Finally, the conclusion and future works are provided in section 5.

2 Markov Chain Modeling

We attempt to estimate the CE death rate.

For the purpose, we focus one CE. We attempt to estimate the CE death rate based on the amount of the current CE energy, the function of energy flow and the frequency of using the CE.

We settle the time when users access to the CE by the user intention of using it. From the viewpoint of a CE, user accesses occur at random. We assume that user accesses to the CE occur probabilistically.

2.1 Functions of Energy Flow

There exists energy flow between CEs, and between a CE and its platform. From the viewpoint of a CE, there are the following four types of energy flow:

I The CE receives some amount of energy from other CEs, E_{fromCE}, as a service reward when it offers the service to other CEs.

II The CE receives some amount of energy from its platform, E_{fromPT}, as a reward energy when it runs the service logic or users think of the CE as a good service.

III The CE gives some amount of energy to other CEs, E_{toCE}, as a service cost when it is served by other CEs.

IV The CE gives some amount of energy to its platform, E_{toPT}, as a resource cost.

The amounts of these energy flows are determined by some rule. We describe this rule as a function. These energy exchanges occur probabilistically depending on the user access rate.

Therefore, we write these:

I $\Pr(E_{fromCE})$ is the probability of receiving some amount of energy from other CEs.

II $\Pr(E_{fromPT})$ is the probability of receiving some amount of energy from a platform.

III $\Pr(E_{toCE})$ is the probability of giving some amount of energy to other CEs.

IV $\Pr(E_{toPT})$ is the probability of giving some amount of energy to a platform.

These amounts of energy depend on the policy of each platform and each CE. In this study, we qualitatively define a suitable function in advance. To make it clear, we assume that these four events are independent.

We think of these four types of energy flow as two energy flows, input energy that a CE receives, and output energy that a CE gives.

First, we consider the input energy that a CE receives. Input energy includes two types of energy flows, E_{fromCE} and E_{fromPT}. We denote the amount of energy by $E_{in}(= E_{fromCE} + E_{fromPT})$. We regard E_{in} as the amount depending on many kinds of elements: other CEs, the time and so on. The CE gets E_{in} when users use it. However, the time when the CE gets the energy is after the CE offers the service to users because of delay.

Next, we consider output energy that a CE gives. Output energy also includes two types of energy flows, E_{toCE} and E_{toPT}. We denote the amount of energy by $E_{out}(= E_{toCE} + E_{toPT})$. We also regard E_{out} as the amount depending on many kinds of elements. The CE gives E_{toPT}, the resource cost, at every time step since it always uses resources. Therefore, we let $\Pr(E_{toPT}) = 1$. E_{toCE} occurs probabilistically since this energy is the reward when the CE is very often used or when the CE accepts some special thanks from users. Therefore E_{out} occurs probabilistically.

To receive or give energy occurs probabilistically when the CE serves or is served. The energy for the resource cost of its platform occurs on every time step.

Now we are able to think that the amount of energy, $E_{IN} - E_{OUT}$, occurs with probability p. For example,

case	increase or decrease energy	probability
all cases happen	$E_{fromCE} + E_{fromPT}$ $-E_{toCE} - E_{toPT}$	$\Pr(E_{fromCE}) \Pr(E_{fromPT})$ $\cdot \Pr(E_{toCE})$
case I and II occur	$E_{fromCE} + E_{fromPT}$ $-E_{toPT}$	$\Pr(E_{fromCE}) \Pr(E_{fromPT})$ $\cdot\{1 - \Pr(E_{toCE})\}$
case I and III occur	E_{fromCE} $-E_{toCE} - E_{toPT}$	$\Pr(E_{fromCE})\{1 - \Pr(E_{fromPT})\}$ $\cdot \Pr(E_{toCE})$
case II and III occur	E_{fromPT} $-E_{toCE} - E_{toPT}$	$\{1 - \Pr(E_{fromCE})\} \Pr(E_{fromPT})$ $\cdot \Pr(E_{toCE})$
case I occurs	$E_{fromCE} - E_{toPT}$	$\Pr(E_{fromCE})\{1 - \Pr(E_{fromPT})\}$ $\cdot\{1 - \Pr(E_{toCE})\}$
case II occurs	$E_{fromPT} - E_{toPT}$	$\{1 - \Pr(E_{fromCE})\} \Pr(E_{fromPT})$ $\cdot\{1 - \Pr(E_{toCE})\}$
case III occurs	$-E_{toCE} - E_{toPT}$	$\{1 - \Pr(E_{fromCE})\}\{1 - \Pr(E_{fromPT})\}$ $\cdot \Pr(E_{toCE})$
nothing occurs	$-E_{toPT}$	$\{1 - \Pr(E_{fromCE})\}\{1 - \Pr(E_{fromPT})\}$ $\cdot\{1 - \Pr(E_{toCE})\}$

From this example, we find out that we can denote the increasing or decreasing energy by $E_{IN} - E_{OUT}$ with probability p.

2.2 Transition Probability Matrix

In order to estimate the death rate, we describe the evolution of the CE energy using a discrete time Markov chain. The amount of energy is the function of receiving and giving energy, and the evolution depends on the user access rate. The reason why we attempt to describe "discrete time" is that this system is on event driven system and we can get more useful information than we describe it in continuous time. We are already known that the formulation of continuous time Markov chains can change to the corresponding discrete time Markov chains. The state of the Markov chain is the amount of energy, which is also discrete for the same reason.

The transition probability, p_{ij}, denotes the energy state of a CE transferred from i to j at the next transition.

The ith row jth column of transition probability matrix is p_{ij}.

The transition probability matrix about the energy state is

$$\boldsymbol{P} = \begin{bmatrix} p_{00} & p_{01} & p_{02} & \cdots \\ p_{10} & p_{11} & p_{12} & \cdots \\ p_{20} & p_{21} & p_{22} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}. \tag{1}$$

When the current energy state is i and we describe $E_{IN} - E_{OUT} = \Delta E$, then the transition probability is $p_{ij} = p$ (p was defined in section 2.1) such that $j - i = \Delta E$. If there does not exist j such that $j - i = \Delta E$, $p_{ij} = 0$.

The energy amount 0 is the absorbing state of the CE death. Therefore, once the energy amount of a CE gets to 0, the CE cannot get some energy again.

We rewrite the transition probability matrix.

$$\boldsymbol{P} = \begin{bmatrix} 1 & 0 & 0 & \cdots \\ p_{10} & p_{11} & p_{12} & \cdots \\ p_{20} & p_{21} & p_{22} & \cdots \\ \vdots & \vdots & \vdots & \ddots \\ p_{N0} & p_{N1} & p_{N2} & \cdots \end{bmatrix}. \tag{2}$$

In the row, we describe the function concerned with the increasing or decreasing energy amount as the probability distribution.

2.3 Death Rate Estimation

It is impossible to calculate n power elements of the probability matrix which has infinite elements. We simplify the $N \times N$ elements matrix. (N is large enough.) This system has the absorbing state at the upper threshold N. For a sufficient large N, when a CE reaches the state of energy E_N, the CE lives forever since CE has about an infinity amount of energy. We define the state E_N is absorbing.

We can define the transition probability matrix:

$$\boldsymbol{P} = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ p_{10} & p_{11} & p_{12} & \cdots & p_{1N-1} & p_{1N} \\ p_{20} & p_{21} & p_{22} & \cdots & p_{2N-1} & p_{2N} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{N0} & p_{N1} & p_{N2} & \cdots & p_{NN-1} & p_{NN} \\ 0 & 0 & 0 & \cdots & 0 & 1 \end{bmatrix}. \tag{3}$$

We can rewrite this transition probability matrix:

$$\boldsymbol{P} = \begin{bmatrix} 1 & \boldsymbol{0} & 0 \\ \boldsymbol{P}_0 & \tilde{\boldsymbol{P}} & \boldsymbol{P}_N \\ 0 & \boldsymbol{0} & 1 \end{bmatrix}. \tag{4}$$

The probability to absorb the state i $(= 0, N)$ after n steps is $\tilde{\boldsymbol{P}}^{n-1}\boldsymbol{P}_i$. The probability to absorb the state i $(= 0, N)$ eventually is $(\boldsymbol{I} - \tilde{\boldsymbol{P}})^{-1}\boldsymbol{P}_i$.

When we focus the state after enough long time, we consider the limit $\lim_{N\to\infty} \boldsymbol{P}^N$. Since the matrix is the form of a discrete Markov chain with absorbing states, the elements of $\lim_{N\to\infty} \boldsymbol{P}^N$ is all 0 except the first and last columns.

2.4 Migration and Replication Strategies

In this section, we focus a CE, and we judge whether it moves another platform or not from the estimated death rate.

When we attempt to judge the migration, we can consider each kind of service. We consider the competition between the CE that we attempt to judge and other CEs that offer a similar service. We assume that competition does not occur with other kinds of services. We focus on one kind of CEs, which offer the same service. CEs can move to the connected platforms. When a CE moves, some amount of energy needs as a cost energy. We describe the amount of energy as E_{mcost}. We define $\boldsymbol{P}$ as the transition probability matrix before moving. We define $\boldsymbol{Q}$ as the transition probability matrix after moving.

We recommend the policy we compare the death rates before and after migration. If the latter rate is smaller, the CE moves to another platform. Namely,

1. For M enough large, we calculate $\boldsymbol{P}^M$. We also calculate $\boldsymbol{Q}^M$.
2. The energy before moving is i, the energy after moving is $i - E_{mcost}$.
3. We compare between $\boldsymbol{P}^M_{i\ 0}$ before move and $\boldsymbol{Q}^M_{i-E_{mcost}\ 0}$ after moving.
4. The condition of migration is $\boldsymbol{P}^M_{i\ 0} > \boldsymbol{Q}^M_{i-E_{mcost}\ 0}$.

Next we consider the replication. After the replication, one of the CE moves another platform by migration forcibly since two CEs of the same kind are made and since the purpose of replication is to spread the service. The amount of energy after replication is half of the original amount of energy because of the concept to divide to two CEs. The platform can receive some amount of energy as a cost to make a copy if it needs.

When we consider replication, we assume the followings. After a CE makes a copy, the copy CE moves to another platform. The CE can move only to the connected platforms. When the CE makes a copy, the CE needs some energy as a cost. We denote this cost energy by E_{rcost}. This includes the migration cost of the copy CE. And in the same way as migration, we describe the transient probability matrix before replication as $\boldsymbol{P}$, after replication as $\boldsymbol{Q}$.

About the rule of replication, we propose the follow policies:

Rule1: The probability that both CEs are killed after replication is smaller than the death rate before replication.

Rule2: The sum of probabilities multiplied the number of living CEs is bigger than the living rate before replication.

Namely,

1. If the amount of energy before replication is i, the amount of energy after migration is $\frac{1}{2}(i - E_{rcost})$.
2. We compare the following probabilities: $\boldsymbol{P}^M_{i\ 0}$ is the death rate before replication, $\boldsymbol{P}^M_{\frac{1}{2}i-E_{cost}\ 0}$ is the probability that the CE does not migrate after making copy and $\boldsymbol{Q}^M_{\frac{1}{2}i-E_{rcost}0}$ is that the copy CE migrates.
3. The condition of replication is:

$$
\begin{aligned}
\boldsymbol{P}^M_{i0} &> \boldsymbol{P}^M_{\frac{1}{2}i-E_{cost}0}\boldsymbol{Q}^M_{\frac{1}{2}i-E_{rcost}0}, \text{ for rule1,} \\
1-\boldsymbol{P}^M_{i0} &< 2\cdot(1-\boldsymbol{P}^M_{\frac{1}{2}i-E_{cost}0})(1-\boldsymbol{Q}^M_{\frac{1}{2}i-E_{rcost}0}) \\
&\quad +\{1-\boldsymbol{P}^M_{\frac{1}{2}i-E_{cost}0}\boldsymbol{Q}^M_{\frac{1}{2}i-E_{rcost}0}-(1-\boldsymbol{P}^M_{\frac{1}{2}i-E_{cost}0})(1-\boldsymbol{Q}^M_{\frac{1}{2}i-E_{rcost}0})\}, \text{ for rule2.}
\end{aligned}
$$

3 Analysis of a Simplified Markov Chain

When we describe the system by a Markov chain, as we show previously, we can describe any functions that take positive integers. In this section, we consider a simplified system. When the CE is used, the CE receives the $+a$ energy, otherwise CE receives the -1 energy, in other words, the CE gives 1 energy. We consider this system since it seems to distinguish between death and living clearly. In order to distinguish "death" and "living" clearly,

- Users use the CE. $\rightarrow$ the CE gets energy.
- Users do not use CE. $\rightarrow$ the CE loses energy.

It seems that we can achieve the purpose with this simple model. We define a is discrete, since we can get more information than we define a as continuous. The purpose in this section is to consult how the CE behaves.

This system is called a random walk [3, 4]. When we formulate this function, we can calculate the result explicitly.

3.1 Transition Probabilities

When the input function is $+a$, the output function is -1, we can show the special case of the Markov chain in the proceeding section. We define q as the select probability for a CE to receive the energy.

$$
\begin{aligned}
p_{i+a\ i} &= q \qquad (i = 1, 2, ..., N-a), \\
p_{N\ i} &= q \qquad (i = N-a+1, ..., N), \\
p_{i-1\ i} &= 1-q \qquad (i = 1, 2, ..., N).
\end{aligned}
$$

Thus the transition probability matrix is given by

$$
\boldsymbol{P} = \begin{bmatrix}
1 & 0 & 0 & \cdots & \cdots & \cdots & \cdots & 0 & 0 \\
1-q & 0 & \cdots & \cdots & 0 & q & 0 & \cdots & 0 \\
0 & \ddots & 0 & \cdots & \cdots & 0 & \ddots & 0 & \vdots \\
\vdots & 0 & 1-q & 0 & \cdots & \cdots & 0 & q & 0 \\
\vdots & \ddots & 0 & 1-q & 0 & \cdots & \cdots & 0 & q \\
\vdots & \ddots & \ddots & 0 & \ddots & 0 & \cdots & 0 & \vdots \\
\vdots & \ddots & \ddots & \ddots & 0 & 1-q & 0 & 0 & q \\
\vdots & \ddots & \ddots & \ddots & \ddots & 0 & 1-q & 0 & q \\
0 & \cdots & \cdots & \cdots & \cdots & 0 & 0 & 0 & 1
\end{bmatrix}. \tag{5}
$$

Let $g_z(a, q)$ denote the probability that the CE energy eventually becomes 0 given the initial energy is z. Note that q is the probability that CE gets energy $+a$, and $1-q$ is the probability that the CE looses the energy 1.

We can describe the recurrence formula:

$$g_z(a,q) = (1-q)g_{z-1}(a,q) + qg_{z+a}(a,q). \tag{6}$$

We solve under the condition $g_0(a,q) = 1, g_{N+a+1}(a,q) = ... = g_{N+2a}(a,q) = 0$.

Thus, (see Appendix A.1)

$$g_n(a,q) = \prod_{k=0}^{n-1} b_k \qquad (n = 1,2,...,N), \tag{7}$$

where

$$b_n = \tfrac{(1-q)}{1-qb_{n+1}b_{n+2}...b_{n+a}} \qquad (n = 0,1,...,N-1), \tag{8}$$
$$\text{where } b_N, b_{N-1}, ..., b_{N+a-1} = 1-q.$$

3.2 Generating Function

We consider the generating function [3]. Now the state of energy is z $(0 < z < N+a)$. $u_{z,n}$ is the death probability after n time step. We introduce the generating function

$$U_z(s) = \sum_{n=0}^{\infty} u_{z,n}s^n. \tag{9}$$

We then have (see Appendix A.2)

$$U_n(s) = \prod_{k=0}^{n-1} b_k \qquad (n = 1,2,...,N), \tag{10}$$

where

$$b_n = \tfrac{(1-q)s}{1-qsb_{n+1}b_{n+2}...b_{n+a}} \qquad (n = 0,1,...,N-1), \tag{11}$$
$$\text{where } b_N, b_{N-1}, ..., b_{N+a-1} = (1-q)s.$$

3.3 The Mean Time until CE Death

The duration until CE death has some finite mean D_z [3]. We calculate the mean until the energy amount of CE gets to 0 or reaches N.

If the condition is the same as section 3.1, then we can describe

$$D_z = (1-q)D_{z-1} + qD_{z+a} + 1. \tag{12}$$

We solve this under the initial condition, $D_0 = 0$ and $D_{N+a+1}...D_{N+2a} = 0$.

We then have (see Appendix A.3)

$$D_n = \sum_{l=1}^{n-1} \prod_{k=l}^{n-1} b_k c_{l-1} + c_{n-1} \qquad (n = 1,2,...,N), \tag{13}$$

where

$$b_n = \frac{1-q}{1-qb_{n+1}b_{n+2}...b_{n+a}} \qquad (n = 0, 1, ..., N-1), \tag{14}$$

where $b_N, b_{N-1}, ..., b_{N+a-1} = 1 - q$

$$c_n = \frac{q(\sum_{l=n+2}^{n+a} \prod_{k=l}^{n+a} b_k c_{l-1} + c_{n+a}) + 1}{1 - q \prod_{k=n+1}^{n+a} b_k} \qquad (n = 0, 1, ..., N-1), \tag{15}$$

where $c_N, c_{N-1}, ..., c_{N+a-1} = 1$.

3.4 Behavior Condition

Migration

To evaluate the migration, we consider the following conditions. We define $a = A/n$ as an input energy flow, where A denotes the maximum amount of energy. n is the number of CEs. The platform receives the 1 energy from every CE as an output energy flow. We define the following two patterns as an access rate. The first is that the platform give to CEs at a unit time, and the access rate R to the platform and CE access rates are given equally, that is, R/n. The second is that the access rate to CE is constant, and even when the CE moves, the CE access rate does not change.

We compare between the CE death rate before and after migration. If we find out the CE death rate after migration is smaller, the CE moves to the platform.

First, we consider the first case. Before the migration, E is the energy amount of the CE. R is the sum of the access rate of all CE. A is the sum of energy amount that platform gives to CE. And n is the number of CE on the platform. After the migration, E' is the energy amount of the CE ($E' = E - x$, x is energy as a cost when CE moves.). R' is the sum of the access rates of CEs. A' is the sum of energy amount that platform gives to CEs. And n' is the number of CE on the platform. The death rate before migration is $g_E(R/n, A/n)$. The death rate after migration is $g_{E'}(R'/n', A'/n')$. Thus the CE migrates if

$$g_E(R/n, A/n) \quad > \quad g_{E'}(R'/n', A'/n'). \tag{16}$$

Second, we consider the case of the constant access rate, where the access rate does not change even if the CE moves. We define r as the access rate of a CE. The death rate before migration is $g_E(r, A/n)$. The death rate after migration is $g_{E'}(r, A'/n')$.

Thus the CE migrates if

$$g_E(r, A/n) \quad > \quad g_{E'}(r, A'/n'). \tag{17}$$

Migration judgment is performed every pre-defined time interval, for example every one-day. This timing is integer times as long as the duration of energy exchange.

To select the migration platform, we calculate the death rate about every connected platform. If inequality (16) or (17) holds in plural platforms, the CE selects the platform with the largest $g_{E'}$.

If there exist multiple CEs of the same kind in one platform, one of them migrates. We can consider many ways which CE we select, for example, we select the CE randomly. In this study, in advance, we decided the parameter that shows the order of precedence. We decided the parameter depending on how long each CE exists.

Replication

In this study, when a CE replicates, one of the CEs remains at the original platform, but the other one moves to another platform that is the best condition for the CE.

The condition is the same as the migration rule. We define $a = A/n$, as an input energy flow. The platform receives 1 from every CE as an output energy flow. We define the access rate to the platform and CE access rate divides equally the access rate to the platform.

The condition to replicate is:

Rule1: The probability that both CEs are killed after replication is smaller than the death rate before replication.

Rule2: The sum of twice the probability that both CEs live and the probability that either CE lives is bigger than the living rate before replication.

Before replication and migration, E is the energy amount of CE. R is the sum of the access rate of each CE. A is the sum of energy amount that platform gives to the CE when it is CE selected. And n is the number of CE on platform.

After the replication, $\frac{E-y}{2}$ is the energy amount of the non-moving CE, which stays on the same platform (y is energy as a cost when CE replicate.). R, A and n do not change.

After the replication, about the moving CE, $E' = E - y$ is the energy amount of CE where y is energy as a cost when CE replicates. R' is the sum of the access rate of CEs. A' is the sum of energy amount that platform gives to the CE when it is selected. And n' is the number of CE on the platform.

In this case, we can describe the death rate before replication is $g_E(R/n, A/n)$, the death rate of non-moving CE after migration is $g_{(E-y)/2}(R/n, A/n)$ and the death rate of moving CE after migration is $g_{(E-y)/2}(R'/n', A'/n')$.

Therefore, a CE replicates if

$$\begin{aligned}
1 - g_E(R/n, A/n) &< 1 - g_{(E-y)/2}(R/n, A/n) g_{(E-y)/2}(R'/n', A'/n'), \text{for rule1}, \\
1 - g_E(R/n, A/n) &< 2 \cdot (1 - g_{(E-y)/2}(R/n, A/n))(1 - g_{(E-y)/2}(R'/n', A'/n')) \\
&\quad + \{1 - g_{(E-y)/2}(R/n, A/n) g_{(E-y)/2}(R'/n', A'/n') \\
&\quad\ - (1 - g_{(E-y)/2}(R/n, A/n))(1 - g_{(E-y)/2}(R'/n', A'/n'))\}, \text{for rule2}.
\end{aligned}$$

We consider the same condition of migration such as the judgment time of replication and the way of platform selection.

4 Numerical Analysis

4.1 Death Rate

As we state in the section 3.1, we calculate $g_z(a, q)$ of a CE, where the initial energy of the CE is z. The CE gets $+a$ energy with probability q, and -1 energy with probability $1 - q$. $g_z(a, q)$ is the death rate when behavior does not occur and the Markov chain time-homogeneous.

We consider the relation between the death rate $g_z(a, q)$ and the select probability q for various values of parameter a. We set the threshold N to be 10000. The vertical axis shows death rate and the horizontal axis shows select probability q in Figures 1, 2, 3.

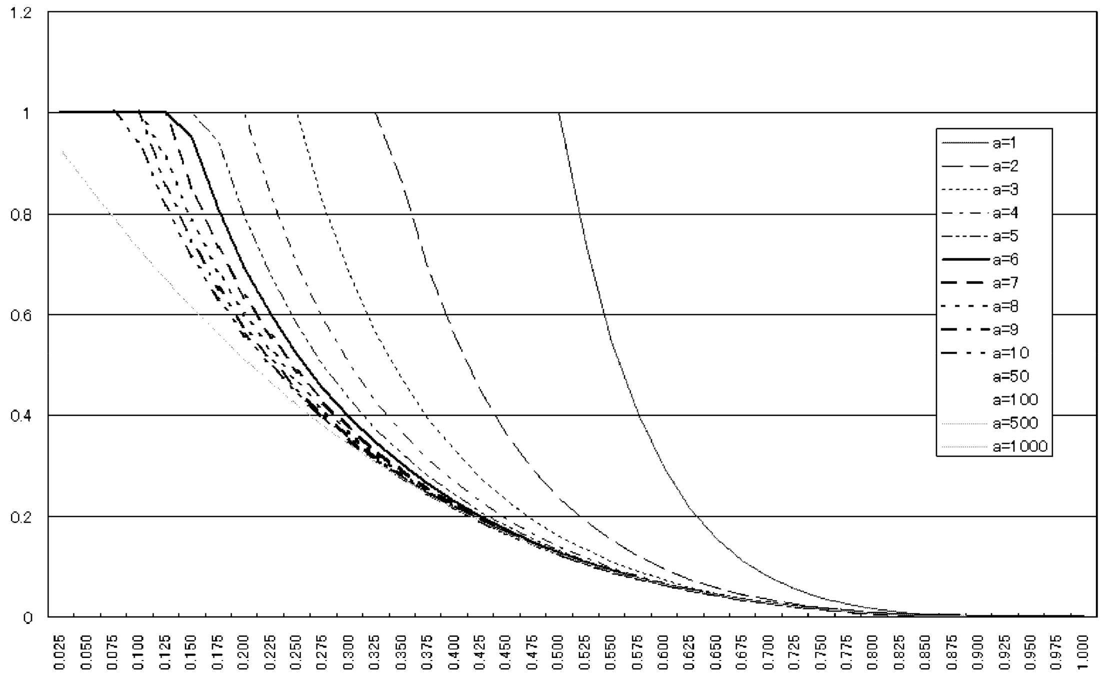

Figure 1: Death rate (initial energy 3).

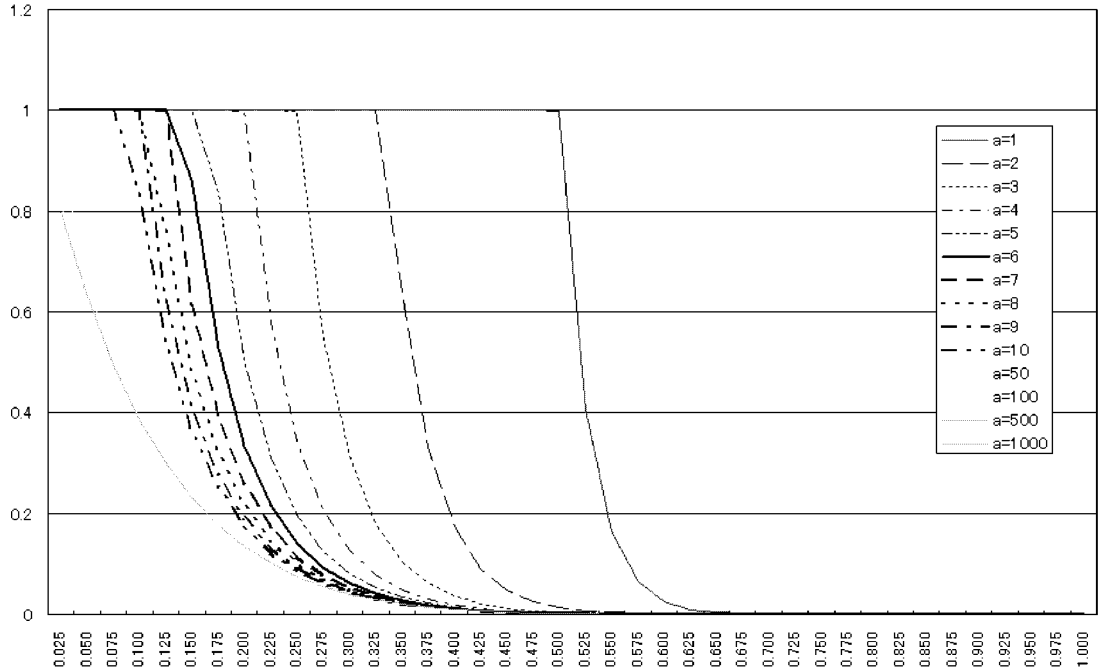

Figure 2: Death rate (initial energy 9).

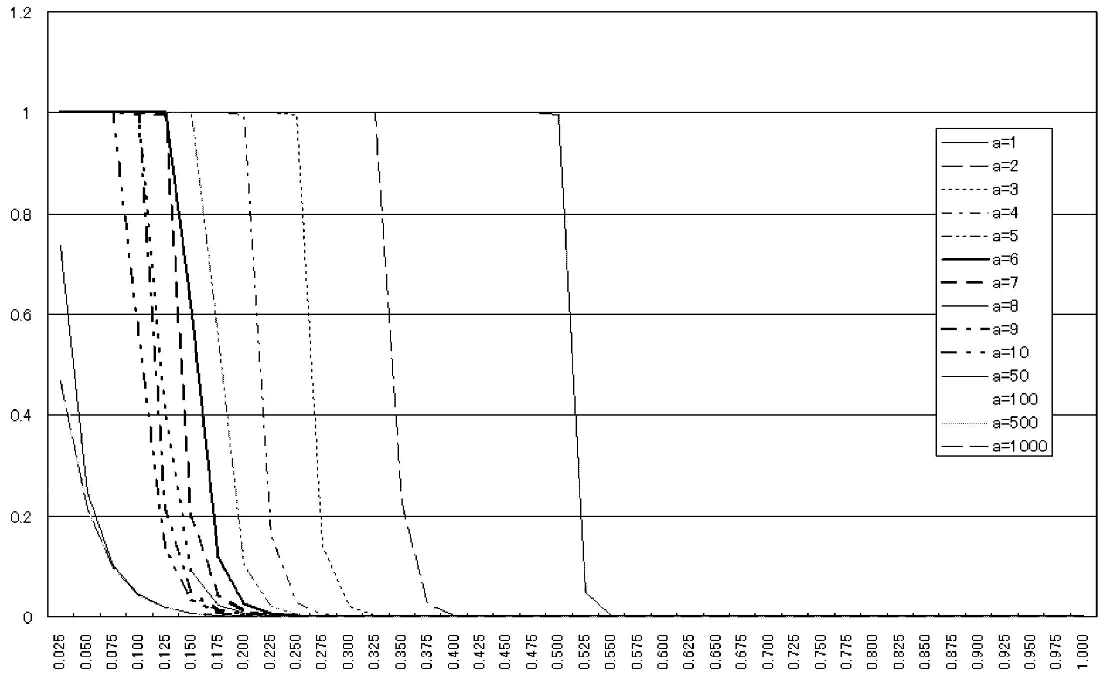

Figure 3: Death rate (initial energy 30).

From these figures, we observe that radical change of the death rate from 1 to 0 at some value of q which is different for a. If we change the value of a, we can change the value of q at which this radical change occur.

The platform has a wishing select probability q. A good system is that if the select probability of a CE is lower than the wishing probability, then the CE is killed. From these figures, if we change the parameter a, then for any select probability q, we can distinguish between to kill or not to kill.

Next we show some simulation results obtained by a simulator of the bio-net network. The vertical axis shows death rate (the number of dead CEs/ the total number of CEs) and the horizontal axis shows the select probability.

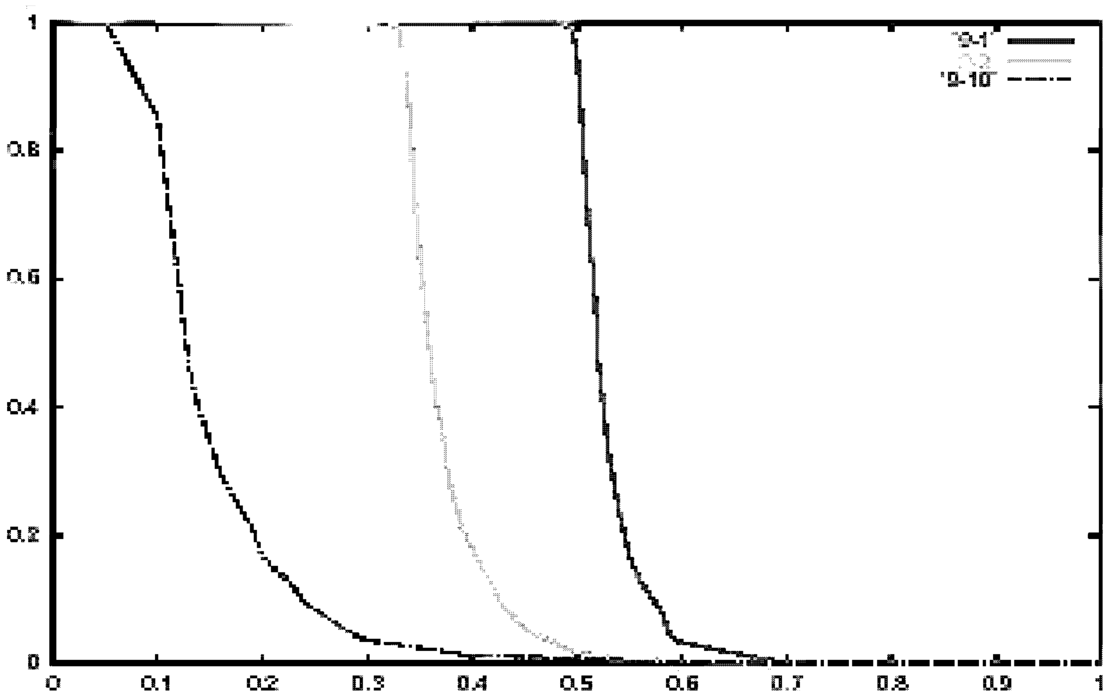

Figure 4: Death rate by simulation (initial energy 9).

We find that the simulation results coincide with the analytical results. Thus we conclude that the energy system in the bio-net can be well modeled by the Markov chain in section 3.

4.2 The Relation between Initial Energy and Death Rate

We consider the relation between the initial energy z and death rate $g_z(a, q)$ with $q = 0.8$, while changing the value of a. We assume here that there is no behavior. The threshold N is set to be 10000 in this part. In figure 5, the vertical axis shows the death rate and the horizontal axis shows the initial energy.

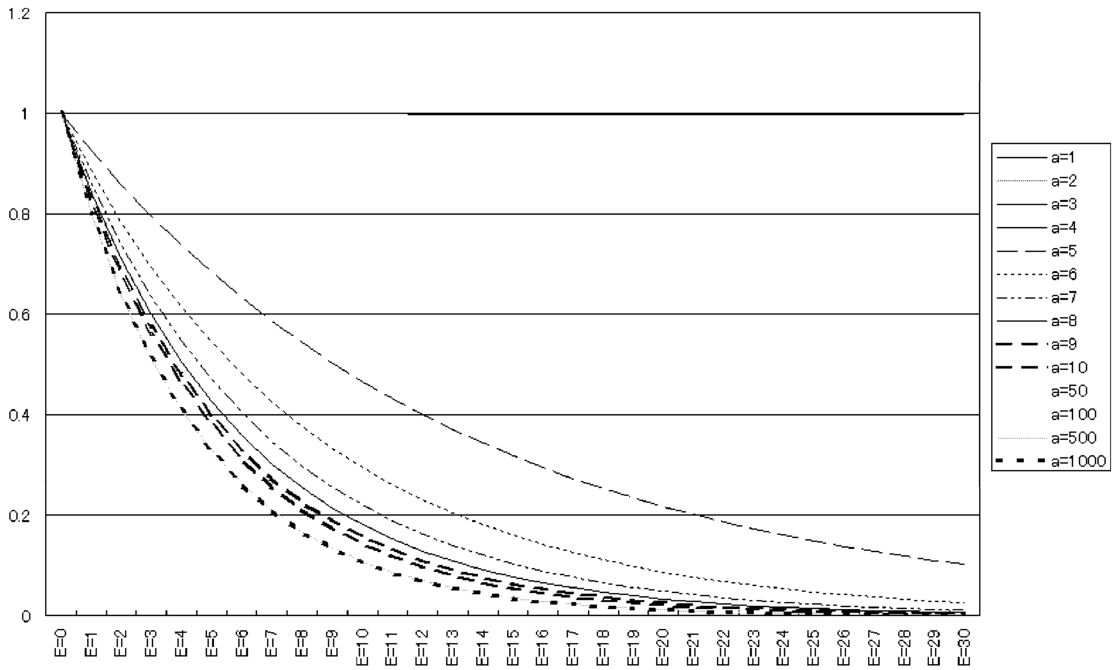

Figure 5: Death rate as a function of the initial energy ($q = 30$).

The death rate remains 1, or decreases exponentially with the initial energy z.

4.3 The Mean Number of Steps to Death

We calculate the mean number of steps D_z until death, which we described in section 3.3. The experimental condition is the same as in section 4.1. The threshold N is set to be 2000 in this part.

The death rate is almost 1 in the range we consider about the probability q. We draw the graph of the range in which the death rate is small since we find out that we cannot neglect the effect of the above threshold. The vertical axis shows the mean number of steps until death and the horizontal axis shows the initial energy.

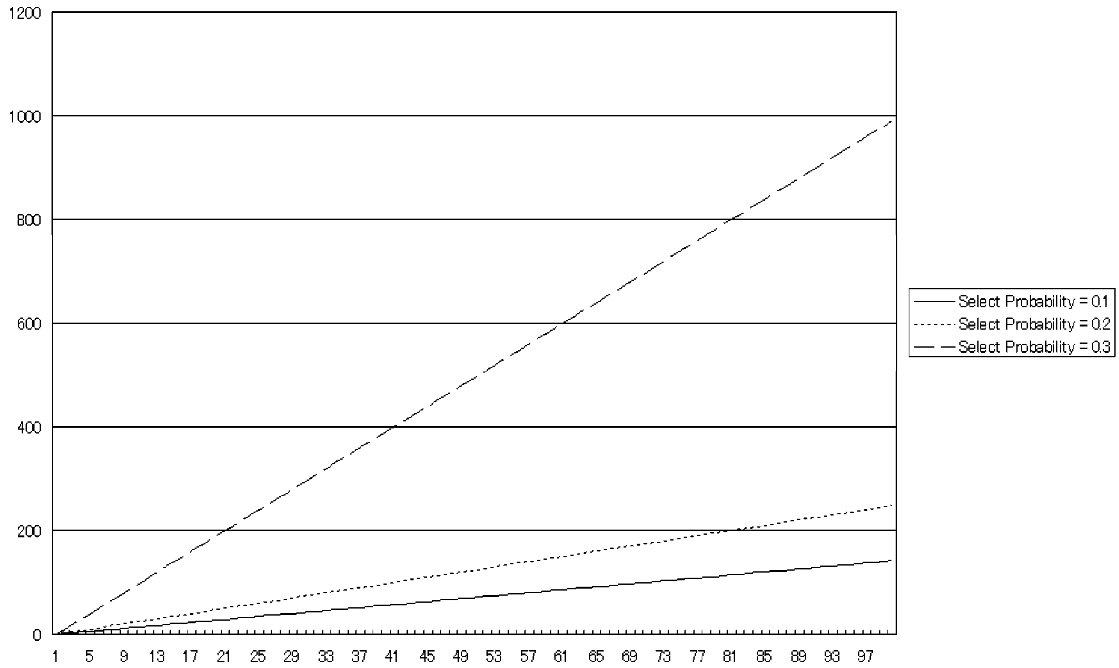

Figure 6: The mean number of steps to death ($a = 2$).

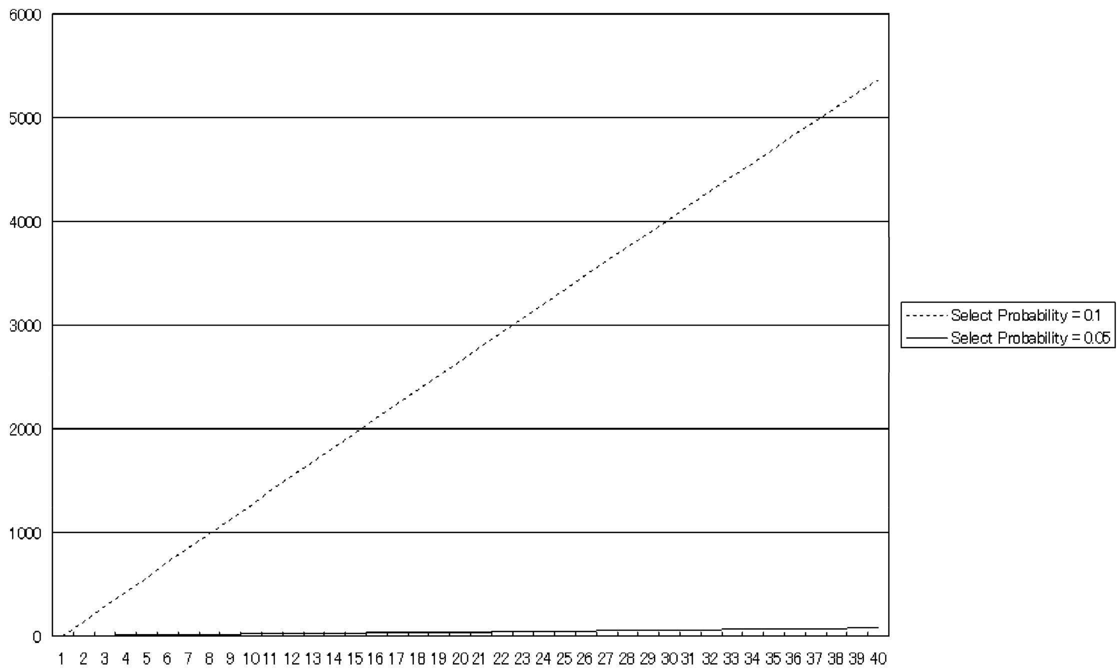

Figure 7: The mean number of steps to death ($a = 9$).

If the death rate remains 1, the mean number of steps is different. When the select probability is larger, the mean number of steps is also larger.

4.4 Migration

We consider the effect of migration. We draw the probability mass function of the amount of energy. The first line is before migration. The second is the case CE does not migrate. The third is after CE migrates In this part, we start the initial energy 50. CEs exchange energy for 50-time steps, and we compare the case CE does not migrate and the case after a CE migrates.

First, we show the case of the CE's access rate is R/n. We prepare three platforms, and the numbers of CEs are 2, 3 and 4. The probabilities we define to these platforms, R, are $0.5, 0.9, 0.9$ respectively. The numbers of A we define to the platform are $6, 15, 60$ respectively. Threshold N is set to be 256. The judgment CE is on the platform that has two CEs at the first time. The horizontal axis shows the amount of energy and the vertical axis shows the probability of the energy.

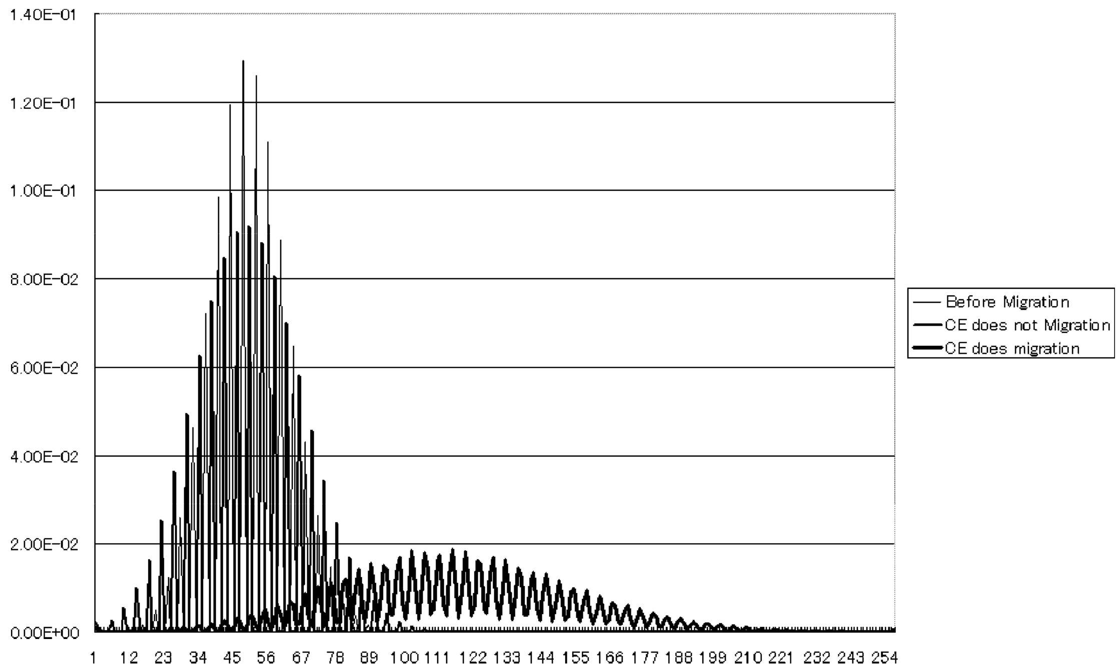

Figure 8: Migration (the case of the equally divided access rate).

Second we show the case of the constant access rate, and its access rate does not change even when the CE migrates.

We prepare three platforms, and the numbers of CEs are 2, 3 and 4. The probabilities we define to the each CE, r, are $0.25, 0.3, 0.225$ respectively. The rest parameter is the same as before. We assign the same probability to the CEs on the same platform before migration judgment. The numbers of A we define to platforms are $6, 15, 60$ respectively. Threshold N is

256. The judgment CE is on the platform that has two CEs at the first time. The horizontal axis also shows the amount of energy and the vertical axis shows the probability of the energy.

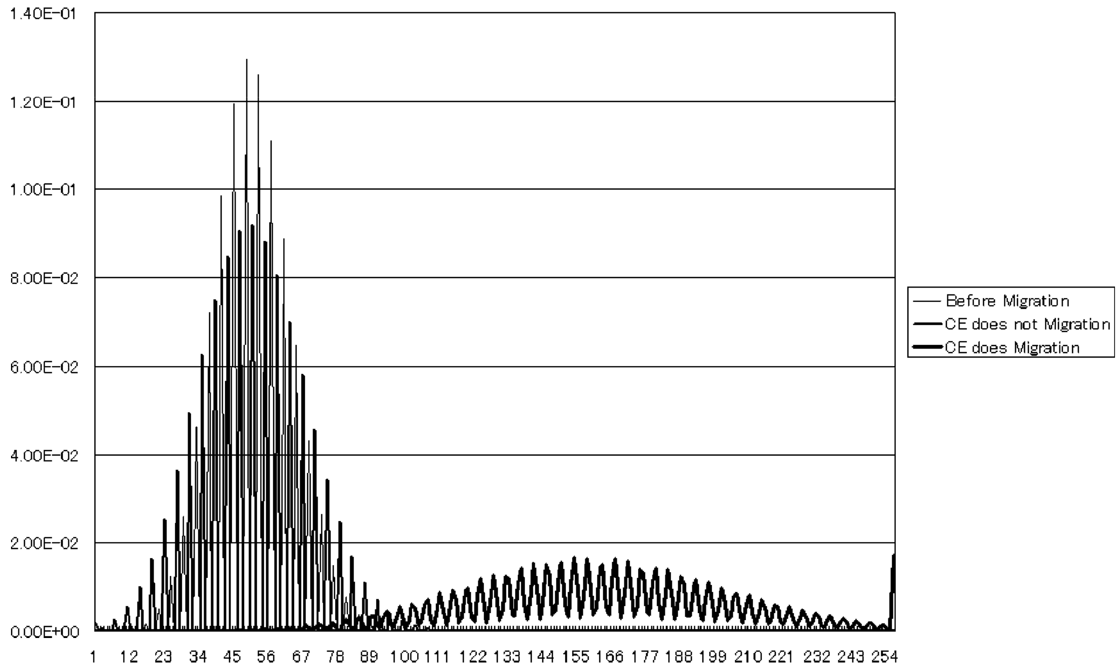

Figure 9: Migration (the case of the constant access rate).

Since the peak of graph moves toward the energy increase, we can check the proper situation: CE can receive more energy than before migration if the CE moves to the platform on which the death rate decreases.

4.5 Replication

We consider the effect of replication. We consider the situation that CEs can replicate and migrate. Under the condition we describe in section 3.4, we compute the death rates.

We prepare three platforms, where the numbers of CEs are 2, 3 and 4 respectively. The probabilities we define to these platforms, R, are $0.2, 0.9, 0.8$ respectively. The number of A we define to these platforms are $30, 60, 60$ respectively. The threshold N is set to be 1000. and the replication cost is set to be 50. We consider the behavior of a CE on the first platform. Figure 10 shows the living rate as a function of the initial energy.

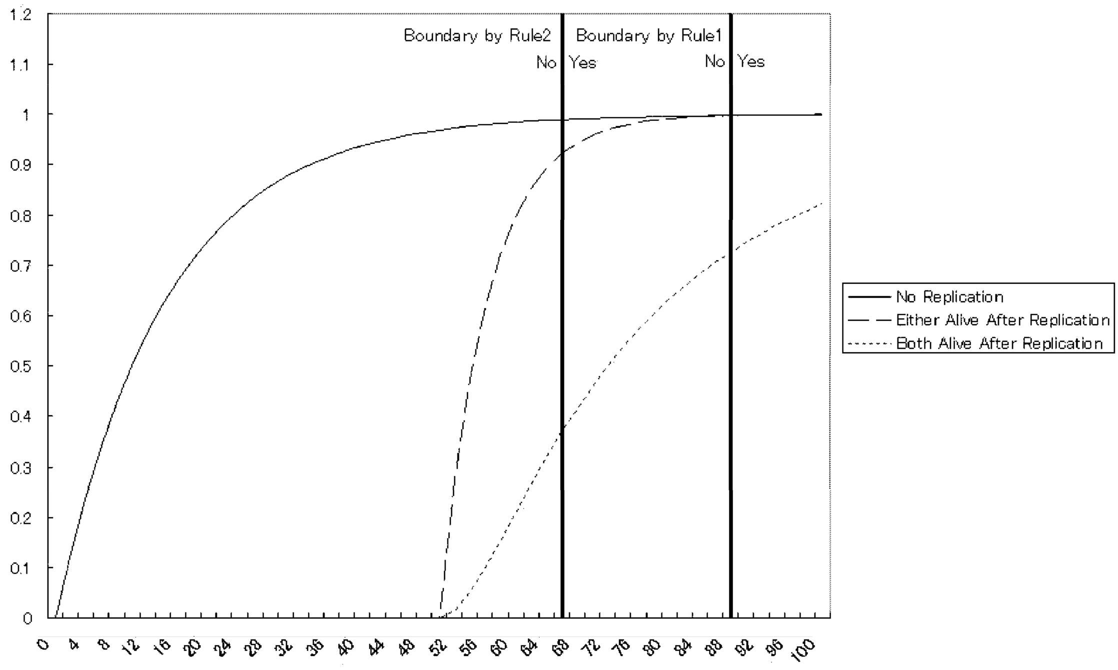

Figure 10: Living rate.

From the boundaries, we find that when CE has much initial energy, the replication occurs.

5 Conclusion

We introduced a method to calculate the death rate in the energy system. By setting parameters well, we can adjust the death rate irrelevant to the select probability. Therefore, the platform can control the survival of CEs according to its preference. About migration and replication we proposed the behavior rule based on the death rate estimation.

As a future works, we will estimate the amount of CE energy to use statistics, such as a moving-average model. We estimate the future amount of input energy according to the average of the past data. We could also use a regression analysis. We estimate the best function from the data and we use the function to estimate the energy change. From simulation we get the data of input energy and output energy of the focus CE on every unit time. To use the data, we do the statistical work and make a transition probability matrix. And we run the matrix analysis and estimate the future death rate of the CE.

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A Appendix

A.1 Derivation of (6)

We solve the recurrence formula (6) under the initial condition $g_0(a,q) = 1$, and $g_{N+a+1}(a,q) = \cdots = g_{N+2a}(a,q) = 0$.

$$
\begin{aligned}
g_1(a,q) &= (1-q) + q g_{a+1}(a,q), && (18)\\
&\dots \\
g_z(a,q) &= (1-q) g_{z-1}(a,q) + q g_{z+a}(a,q), && (19)\\
&\dots \\
g_{N-1}(a,q) &= (1-q) g_{N-2}(a,q) + q g_{N+a-1}(a,q), && (20)\\
g_N(a,q) &= (1-q) g_{N-1}(a,q) + q g_{N+a}(a,q), && (21)\\
g_{N+1}(a,q) &= (1-q) g_N(a,q) + q g_{N+a+1}(a,q) = (1-q) g_N(a,q), && (22)\\
&\dots \\
g_{N+a}(a,q) &= (1-q) g_{N+a-1}(a,q). && (23)
\end{aligned}
$$

From (22) and (23), we have

$$g_{N+a}(a,q) = (1-q)^a g_N(a,q).$$

Also, from (21),

$$g_N(a,q) = (1-q) g_{N-1}(a,q) + q(1-q)^a g_N(a,q),$$

$$g_N(a,q) = \frac{1-q}{1-q(1-q)^a} g_{N-1}(a,q). \tag{24}$$

We describe this as $g_N(a,q) = b_{N-1} g_{N-1}(a,q)$. That is,

$$b_{N-1} = \frac{1-q}{1-q(1-q)^a}.$$

Next we evaluate g_{N-1}. Using (22) and (23), we obtain

$$
\begin{aligned}
g_{N-1}(a,q) &= (1-q) g_{N-2}(a,q) + q g_{N+a-1}(a,q), && (25)\\
&= (1-q) g_{N-2}(a,q) + q(1-q)^{a-1} g_N(a,q), && (26)\\
&= (1-q) g_{N-2}(a,q) + q(1-q)^{a-1} b_{N-1} g_{N-1}(a,q). && (27)
\end{aligned}
$$

Therefore,

$$g_{N-1}(a,q) = \frac{1-q}{1-q(1-q)^{a-1} b_{N-1}} g_{N-2}(a,q).$$

We describe this as $g_{N-1}(a,q) = b_{N-2} g_{N-2}(a,q)$. That is,

$$b_{N-2} = \frac{1-q}{1-q(1-q)^{a-1} b_{N-1}}.$$

We repeat the above procedure and then we have

$$b_{N-3} = \frac{1-q}{1-q(1-q)^{a-2}b_{N-1}b_{N-2}}, \tag{28}$$

$$b_{N-a-1} = \frac{1-q}{1-qb_{N-1}b_{N-2}\dots b_{N-a}}, \tag{29}$$

$$b_1 = \frac{1-q}{1-qb_{a+1}\dots b_2}. \tag{30}$$

Now $g_1(a,q) = (1-q) + qg_{a+1}(a,q)$, so $g_1(a,q) = (1-q) + qb_a \dots b_1 g_1(a,q)$.
Therefore

$$g_1(a,q) = \frac{1-q}{1-qb_a\dots b_1},$$

which completes the proof.

A.2 Derivation of (9)

The current energy amount is z $(0 < z < N+a)$. $u_{z,n}$ is the probability of the CE death after n time steps.

After one time step, the amount of energy becomes $z+a$ or $z-1$. For $1 < z < N+a$ and $n \geq 1$, we have

$$u_{z,n+1} = (1-q)u_{z-1,n} + qu_{z+a,n}.$$

This is the boundary values similar to (6), but depends on two variables z and n, so we want to define that boundary values $u_{0,n}$,$u_{N+a+1,n}\dots u_{N+2a,n}$ and $u_{z,0}$ are hold for $z=1, z=N, n=0$. Therefore, we put

$$u_{0,n} = 0, u_{N+a+1,n} = \dots = u_{N+2a,n} = 0 \qquad n \geq 1, \tag{31}$$

$$u_{0,0} = 1, u_{z,0} = 0 \qquad z > 0. \tag{32}$$

Then boundary values are hold for all z $(1 < z < N+a)$ and for all $n \geq 0$.

We introduce the generating function

$$U_z(s) = \sum_{n=0}^{\infty} u_{z,n}s^n.$$

Multiplying s^{n+1} by this and summing up for $n = 0, 1, 2, \dots$, we obtain

$$U_z(s) = qsU_{z+a}(s) + (1-q)sU_{z-1}(s).$$

The condition about boundary values is

$$U_0(s) = 1, U_{N+a+1}(s) = \dots = U_{N+2a}(s) = 0.$$

This is a similar boundary condition to (6). It is different that the coefficient and unknown variable $U_z(s)$ are related to variable s, but in the view point of difference equations, s is merely the optional constant. We use the same way as in section A.1, so we completes the proof.

A.3 Derivation of (12)

We solve (12) under the initial condition $D_0 = 0$ and $D_{N+a+1} = \cdots = D_{N+2a} = 0$.

$$\begin{aligned}
D_1 &= qD_{a+1} + 1, && (33)\\
&\dots \\
D_z &= (1-q)D_{z-1} + qD_{z+a} + 1, && (34)\\
&\dots \\
D_{N-1} &= (1-q)D_{N-2} + qD_{N+a-1} + 1, && (35)\\
D_N &= (1-q)D_{N-1} + qD_{N+a} + 1, && (36)\\
D_{N+1} &= (1-q)D_N + qD_{N+a+1} + 1 = (1-q)D_N + 1, && (37)\\
&\dots \\
D_{N+a} &= (1-q)D_{N+a-1} + 1. && (38)
\end{aligned}$$

Therefore, from (37) and (38)

$$D_{N+a} = p^a D_N + (p^{a-1} + \cdots + 1).$$

Also, from (36)

$$D_N = pD_{N-1} + qp^a D_N + q(p^{a-1} + \cdots + 1) + 1,$$

$$D_N = \frac{p}{1-qp^a} D_{N-1} + \frac{q(p^{a-1} + \cdots + 1) + 1}{1-qp^a}. \quad (39)$$

We describe this as $D_N = b_{N-1}D_{N-1} + c_{N-1}$, i.e.,

$$\begin{aligned}
b_{N-1} &= \frac{1-q}{1-qp^a}, && (40)\\
c_{N-1} &= \frac{q((1-q)^{a-1} + \cdots + 1) + 1}{1-q(1-q)^a}. && (41)
\end{aligned}$$

Next we ask for P_{N-1}. Using (37) and (38), we have

$$\begin{aligned}
D_{N-1} &= (1-q)D_{N-2} + qD_{N+a-1} + 1,\\
&= (1-q)D_{N-2} + q(1-q)^{a-1}D_N\\
&\quad +q((1-q)^{a-2} + \cdots + 1) + 1,\\
&= (1-q)D_{N-2} + q(1-q)^{a-1}b_{N-1}D_{N-1} + q(1-q)^{a-1}c_{N-1} + q((1-q)^{a-2} + \cdots + 1) + 1.
\end{aligned}$$

Therefore,

$$D_{N-1} = \frac{1-q}{1-q(1-q)^{a-1}b_{N-1}} D_{N-2} + \frac{q((1-q)^{a-1}c_{N-1} + (1-q)^{a-2} + \cdots + 1) + 1}{1-q(1-q)^{a-1}b_{N-1}}.$$

We describe $D_{N-1} = b_{N-2}D_{N-2}$. That is,

$$b_{N-2} = \frac{1-q}{1-q(1-q)^{a-1}b_{N-1}}, \tag{42}$$

$$c_{N-2} = \frac{q((1-q)^{a-1}c_{N-1} + (1-q)^{a-2} + \cdots + 1) + 1}{1-q(1-q)^{a-1}b_{N-1}}. \tag{43}$$

We repeat the above procedure and obtain

$$\begin{aligned} b_{N-3} &= \frac{1-q}{1-q(1-q)^{a-2}b_{N-1}b_{N-2}}, \\ b_{N-a-1} &= \frac{1-q}{1-qb_{N-1}b_{N-2}\ldots b_{N-a}}, \\ b_1 &= \frac{1-q}{1-qb_{a+1}\ldots b_2}, \end{aligned}$$

$$\begin{aligned} c_{N-3} &= \frac{q((1-q)^{a-2}b_{N-1}c_{N-2} + (1-q)^{a-2}c_{N-1} + (1-q)^{a-3} + \cdots + 1) + 1}{1-q(1-q)^{a-2}b_{N-1}b_{N-2}}, \\ c_{N-a-1} &= \frac{q(b_{N-1}\ldots b_{N-a+1}c_{N-a} + b_{N-1}\ldots b_{N-a+2}c_{N-a+1} + \cdots + b_{N-1}c_{N-2} + c_{N-1}) + 1}{1-qb_{N-1}b_{N-2}\ldots b_{N-a}}, \\ c_n &= \frac{q(b_{n+a}\ldots b_{n+2}c_{n+1} + b_{n+a}\ldots b_{n+3}c_{n+2} + \cdots + b_{n+a}c_{n+a-1} + c_{n+a}) + 1}{1-qb_{n+a}b_{n+a-1}\ldots b_{n+1}}, \\ c_1 &= \frac{q(b_{a+1}\ldots b_3c_2 + b_{a+1}\ldots b_4c_3 + \cdots + b_{a+1}c_a + c_{a+1}) + 1}{1-qb_{a+1}\ldots b_2}. \end{aligned}$$

On the other hand, from $D_1 = qD_{a+1} + 1$, we have

$$D_1 = qb_a\ldots b_1D_1 + q(b_a\ldots b_2c_1 + b_a\ldots b_3c_2 + \cdots + b_ac_{a-1} + c_a) + 1.$$

Therefore,

$$\begin{aligned} D_1 &= \frac{q(b_a\ldots b_2c_1 + b_a\ldots b_3c_2 + \cdots + b_ac_{a-1} + c_a) + 1}{1-qb_a\ldots b_1}, \\ &= c_0. \end{aligned}$$

We can rewrite the recurrence formula:

$$D_2 = b_1D_1 + c_1, \tag{44}$$

$$D_3 = b_2D_2 + c_2, \tag{45}$$

$$\ldots$$

$$D_k = b_{k-1}D_{k-1} + c_{k-1}, \tag{46}$$

$$\ldots.$$

or equivalently

$$D_i = b_1 b_2 \dots b_{i-1} c_0 + b_2 b_3 \dots b_{i-1} c_1 + \cdots + b_{i-1} c_{i-2} + c_{i-1},$$

$$D_i = \sum_{l=1}^{i-1} \prod_{k=1}^{i-1} b_k c_{l-1} + c_{i-1},$$

which completes the proof.