Chapter 2
Incentives for Repair in Self-Repair Networks

Abstract This chapter discusses when selfish agents begin to cooperate instead of defect, focusing on a specific task of self-maintenance. To consider the incentive for repair in a game theoretic framework, the Prisoner's Dilemma is introduced in a two-nodes model for the network cleaning problem where a collection of agents capable of repairing other agents by modifying their contents can clean the collection. With this problem, cooperation corresponds to repairing other agents and defect to not repairing. Although both agents defecting is a Nash equilibrium—no agent is willing to repair others when only the repair cost is involved in the payoff —agents may cooperate with each other when system reliability is also incorporated in the payoff and with certain conditions satisfied. The incentive for cooperation will be stronger when a system-wide criterion such as availability is incorporated in the payoff.

Keywords Reliability engineering · Game theory · Mechanism design · Nash equilibrium · Prisoner's dilemma · Hamilton's rule · Kin selection · Multi-agent systems · Mutual repair · Autonomous distributed systems

2.1 Introduction

If von Neumann had worked on introducing active elements (assuming repairing capability) in his research on biological robustness (e.g., probabilistic logic), reliability theory would be more tailored for recent artificial systems involving networked machines. But he left a fundamental framework for active agents, namely game theory. The first step toward a self-repair network is assumed to be a

Most of the results of this chapter are presented in Ishida (2007).

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capability of repair other than classical assumptions for each agent subject to failure and hence passive elements of being repaired. Thus, the fundamental difference from the conventional reliability theory is the assumption of the active aspect in addition to the passive aspect in the nodes. This can be captured as an extension of reliability theory and at the same time as a specialization (for networked computer systems) of the theory. This is made possible by modeling self-involvement of the self-action models (Chap. 1) as follows:

- Self-involvement;
- Autonomous and distributed systems with selfish agents;
- Asymmetry of existence and non-existence.

The model in this chapter is related to asymmetry of existence and non-existence, for it deals with availability and reliability, which are concepts reflected from the real existence space to the functional space. Indeed, the concept of availability is a matter of survival not only for each machine but also for a cooperative collective of machines. In order to consider selfish agents, we need to confirm incentives for the selfish agents to seek. We use the word "agent" when we need to note that the entity is autonomous and hence capable of actions such as repairing and capable of becoming selfish. We also use the word "node" when we need to consider the network structure.

For the self-repair networks, the first question is: even if a framework of self-repair is available, are there any nodes (computers) which would repair other nodes by sacrificing their own resources? Thus, the problem of this chapter is:

> Are there any incentives for a node of the self-repair network to repair other nodes by sacrificing their own resources?

This chapter explores possible incentives by extending the interest of the self-node in space and time. A hint can be gained from the theory of altruism found in social insects (Hamilton 1963). Hamilton noted: "The theory of kin selection defines how an individual values the reproduction of a relative compared with its own reproduction (Hamilton 1964)." With regard to self-repair networks, the remark can be interpreted as: how each node values the assignment of its resources to related nodes compared with its own use. This may be a matter of "exchange rate" as acutely pointed out in an economic theoretical grounding of social evolution by Frank (Frank 1998). We will revisit an evolutionary framework in Chap. 4 involving strategies but this chapter concentrates on incentives for repairing.

Technically, we intend to extend measures of reliability and availability in reliability engineering [e.g., (Shooman 1968; Barlow and Proschan 1975; Anderson and Randell 1979)] so that those of mutually cooperative (repair and being repaired) machines may be measured.

Unexpected growth of large-scale information systems such as the Internet suggests that an open and evolutionary environment for selfish agents will lead to collective phenomena. The Internet is undoubtedly one of the most complex and large-scale artifacts that humans have ever invented. An examination on how the Internet has been built and grown suggests that systems of this complexity may be built not by a usual design but by its own growing logic that not even the designer foresaw before its maturation: a synthetic view that a self-repair network could be embedded in the field.

Since the Internet has formed itself as a field that allows many selfish activities, several utilities and protocols have converged on what may be called the "Nash equilibrium" from which no players want to deviate (Nash 1951, 1953; Nash 1950a, b). In Papadimitriou (2001), a problem for the network protocol is explained, which will lead to economic models that allow the current Internet to exist as an equilibrium point because of its simplicity in permitting distributed and free joining to the network. These studies shed new light on computational intelligence. That is, rather than implementing an intelligent program, design a field in the Internet that allows intelligent systems to emerge as the Nash equilibrium of the Internet field.

Further, the game theoretic approaches to the Internet reveal that obtaining some Nash equilibrium is computationally hard. This fact, looked at from the opposite side, would indicate that a computationally difficult task may be solved by selfish agents. Resource allocation, for example, which is computationally tough, may be solved by a market mechanism in which many selfish agents participate. Mechanism Design, a subfield of economics, has been studied (Hurwicz and Reiter 2006; Maskin 2008; Myerson 1988, 2008) and has been extended to Algorithmic Mechanism Design (Hershberger and Suri 2001; Nisan and Ronen 1999) and to Distributed Algorithmic Mechanism Design (Feigenbaum et al. 2001; Feigenbaum and Shenker 2002; Feigenbaum et al. 2002).

This chapter makes an initial attempt at embedding a computational intelligence in the Internet field by selfish agents; that is, whether selfish agents can ever cooperate and even converge on some tasks. Selfish routing and task allocation have been studied extensively in the computational game community, but can agents ever take care of themselves in the first place? We first pose the problem of self-maintenance in an agent population, and then a game theoretic approach will be tested to determine whether or not cooperation would occur or under what conditions cooperation would occur.

While this chapter amounts to a microscopic analysis focusing on conditions when two interacting agents have an incentive to cooperate (i.e. mutually repair), Chap. 4 amounts to a macroscopic study on a network with many interacting agents.

Section 2.2 discusses the motivations and a paradigm of the present research, and describes the problem of cleaning a self-repair network. Section 2.3 discusses the incentives for selfish agents to cooperate based on system reliability and availability of mutually repairing agents that do not have recognition capability. Section 2.4 discusses when and how the selfish agents will cooperate based on the result of Sect. 2.3.

2.2 Economic Theory for Selfish Agents

The game theoretic approach has demonstrated its power in the field of economics and biology. The Internet has already reached a level of complexity comparable to economic systems and biological systems. Moreover, an agent approach permits a structural similarity where selfish individuals (in the economic system of the free market) and selfish genes (in biological systems) cooperate or defect in an open network where many things have been left undetermined before the convergence.

Economic approaches have been actively studied in the distributed artificial intelligence community [e.g. (Boutilier et al. 1997; Walsh and Wellman 1998)], and their application to auction may be a successful domain [e.g. (Parkes and Ungar 2000)]. Economic approaches, and a game theoretic approach in particular, have been extensively studied in the algorithm and computation community and are having an impact on network applications. Rigorous arguments with the equilibrium concepts, the Nash equilibrium among others, are building a basic theory for economic aspects of the Internet. The cost of selfish routing has been estimated by using the extent to which the selfish routing might be degraded at the equilibrium (Nash equilibrium from which no one wants to deviate) relative to the optimal solution, as imagined from the traffic congestion caused by most cars want to use the one shortest path. Protocols such as TCP (Akella et al. 2002), Aloha, CDMA and CSMA/CA have been studied. Packet forwarding strategies in wireless Ad Hoc Networks can also be recast in the framework. Network intrusion detection has also been investigated (Kodialam and Lakshman 2003) in the framework of a two-players game: Intruder and Defender.

What has been computed by a market mechanism or more generally by a collection of selfish agents turned out to be hard to obtain by computation (as a typical example: prices of commodities as an index for resource allocation). This fact indicates that the market economy, or more generally free and hence selfish agents properly networked, has the potential for computing something that could be hard when approached otherwise. Also, the fact that the eradication of the planned economy by the market economy and that the market economy remains in spite of perturbations suggests that the market economy may be "evolutionarily stable" (Maynard Smith 1982) within these economic systems.

This fact further indicates that a problem-solving framework by properly networked selfish agents may have some advantage over other usual problem-solving frameworks such as those organized by a central authority. Also, solutions can be obtained almost for free or as a byproduct of the problem solving mechanism, or solutions are almost inseparably embedded in the solving mechanism. The above two observations encourage the recasting of problems which have been known to be computationally hard or problems difficult to even define properly and approach, such as attaining self-repair systems.

Studies with agents usually assume that agents can be autonomous, hence allowing different rules of interactions: heterogeneous agents. We further assume that agents are selfish in the sense that they will try to maximize the payoff for the agent itself. Thus, agents can be broader than the program or software and they involve users that are committed to the agents. Agents may include not only programs but also humans (end-point users and providers running autonomous systems for the Internet) behind the programs. Mutually supporting collectives may emerge as a result of the interplay among agents. Spam mail, computer viruses and worms may be called (malicious) agents, but they are not mutually supporting collectives; they are rather parasitic lone wolves. However, DDoS (Distributed Denial of Service) attacks and some distributed viruses and worms, however, can be considered collectives.

The idea developed here can apply not only to the Internet but also to other information networks such as sensor networks, as long as they can be placed in the model.

The models presented in this chapter have the following components:

M1. States: Agents have two states (0 for normal; 1 for abnormal). The state will be determined by the action and state of interacting agents.
M2. Actions: Agents have two actions (C for cooperation; D for defection).
M3. Network: Agents (nodes) are networked and agents can act only on the connected (and directed by arcs) agents (neighbor nodes).

Actions may be controlled uniformly or may be determined by the acting agent itself in a selfish agent framework so that the payoff assigned to each agent will be maximized. The network may be defined (and visualized as well) explicitly with a graph or implicitly by specifying the neighbor agents (e.g., the lattice structure as in cellular automata and the dynamical network as in scale-free networks).

The network cleaning problem considered here assumes a self-repair network composed of nodes capable of repairing other nodes by modifying the state of the target node (such as resetting, overwriting memory content or even the possibility of re-programming as long as it can be done through the network). Since agents throughout this book are assumed not to have recognition capability, source nodes (repairing agents) can be abnormal and target nodes (agents being repaired) can be normal. Hence mutual repairing without recognition could cause spreading rather than eradication of abnormal states.

Since we focus on the self-maintenance task by mutual repair, cooperation and defection correspond to repairing and not repairing, respectively.

In the agent based approach, we place the following restrictions similar to immunity-based systems (Ishida 2004):

- Local information: For each immune cell mounting a receptor or a receptor itself (antibody), only matching or not (some quantitative information on degree of matching is allowed) can be provided as information.
- No a priori labeling: For an immune cell or antibody, an antigen is labeled neither as "antigen" nor as "nonself."

Because of these two restrictions, we face the "double-edged sword" in this chapter (and throughout the book), since the effectors part (repairing by copying) could harm rather than cure based on local information. This double-edged sword problem (Ishida 2005) (Chap. 3) may be more significant than that the self-recognition model of immunity-based systems because we do not assume recognition capability (that could avoid adverse effects) here as assumed in immunity-based systems. Actions of agents are motivated by selfishness (payoff) rather than the state of the target.

In the following sections, we use a Markov model used for reliability theory as a microscopic model that incorporates M1, M2 and M3 above. The microscopic model focuses on the incentive for cooperation while keeping the network simple with only two interacting agents.

2.3 A Microscopic Model: Negotiation Between Agents

The microscopic model of self-repair networks is based on the concepts of reliability theory such as fault probability, reliability, system reliability and availability. The model also uses a game theoretical framework to consider the network cleaning problem raised in Chap. 1. The model assumptions are as follows:

- Fault: Each node becomes abnormal independently and randomly at a constant rate in a unit time.
- Repair: Each node will repair other nodes at a constant rate in a unit time. Repairing involves consumption of resources of the repairing node. Only normal nodes can repair successfully. Abnormal nodes can also repair successfully but at a constant rate smaller than one.

We need the following game theoretic concepts before defining the microscopic model (two-nodes model).

2.3.1 *Prisoner's Dilemma*

In solving the problem of cleaning the contaminated network by mutual copying, another problem (other than the double-edged sword) is that each autonomous (and hence selfish) node may not repair others and thus fall into a deadlock waiting for other nodes to repair. This situation is similar to that of the Prisoner's Dilemma that has been well studied in game theory and has been applied to many fields.

The Prisoner's Dilemma (PD) is a game played just once by two agents with two actions (cooperation, C, or defect, D). Each agent receives a payoff R, T, S, P (Table 2.1) where $T > R > P > S$ and $2R > T + S$. Because of the inequality $T > R > P > S$, each player will take action D no matter what action the adversary takes, for the player will get the higher payoff. Since the situation is symmetrical for

Table 2.1 The payoff matrix of the Prisoner's Dilemma (R, S, T, P are payoffs to agent 1)

Agent 1	Agent 2	
	C	D
C	R (Reward)	S (Sucker)
D	T (Temptation)	P (Punishment)

both players, they will take action D, resulting in payoff P which is lower than payoff R when both players cooperate. The inequality $2R > T + S$ prevents one player and another from taking actions C and D respectively (and dividing the payoff equally afterward) whose averaging payoff is (T + S)/2.

In the Iterated Prisoner's Dilemma (IPD) (Axelrod 1987, 1984), each iterated action is evaluated many times. In the spatial Prisoner's Dilemma (SPD) (Nowak and May 1992) (Chap. 4), each site in a two-dimensional lattice corresponding to an agent plays PD with its neighbors, and changes its action depending on the total score it received.

When the above inequalities are satisfied, the case where both players take action D is a Nash equilibrium from which neither player wants to deviate. In our model, no agent wants to repair other agents. When trapped in this Nash equilibrium, all agents remain silent, and hence all the agents will eventually enter the abnormal state. With this state of all agents abnormal, there will be no hope of recovering. Incorporation of a system theoretic framework will reveal not only the Nash equilibrium with all agents taking D actions, but also the absorbing state with all agents abnormal from which no recovery can happen.

Other than the prisoner's dilemma with the structure of a payoff matrix satisfying $T > R > P > S$ and $2R > T + S$, other structures such as the Hawk-Dove game (Smith and Price 1973) have been discussed. We mainly focused on PD, for it often applies to society and even to information systems where selfish agents mainly seek their own interest. However, adopting other game structures such as Hawk-Dove and the public goods game (agents not willing to repair other agents may be called free-riders) will be interesting challenges.

2.3.2 *Models of System Reliability by Birth-Death Process*

Models of system reliability consider how the component reliability and the system structure affect the system reliability. Reliability is an essential probabilistic concept (which is complementary to fault probability) in reliability theory. Reliability of the system can be defined as the probability of being normal (not being faulty or abnormal) at a snapshot, or as the rate of being fault-free during a unit time as a probabilistic process. For a repairable system, yet another probabilistic concept of availability is important, which is related not only with the fault rate but also with the repair rate. Probability (probabilistic measure) is not directly related to time and is meant to indicate the tendency of an event to occur relative to other events (hence, it has no dimension). Rate in a probabilistic process (a Markov process, the birth-death process in particular), on the other hand, is related to time, and is meant to indicate a tendency of occurrence during a unit of time. Although the probability is normalized as values ranging from 0 to 1, the rate can be larger than 1.

Here we face the intrinsic problem of mapping probability to time again. In reliability engineering, the mapping is carried out based on an experimental knowledge of statistical data such as how often a component of interest failed during a specific time interval. In this chapter, we mainly use the rate instead of the probability.

Using conventional notations in reliability theory, λ and μ indicate the failure rate (rate of becoming abnormal) and the repair rate respectively. For example, if the system has only one component which fails with the rate λ, the transition rate from normal state to abnormal state during time Δt is $\lambda\ \Delta t$ (*death*). Likewise, the state transition rate from abnormal state to normal state is $\mu\ \Delta t$ (*birth*). Thus, this simplest model with one component being abnormal as well as being normal (repaired) has the following state transition matrix and state transition diagram (Fig. 2.1).

$$\begin{pmatrix} 1-\lambda\Delta t & \lambda\Delta t \\ \mu\Delta t & 1-\mu\Delta t \end{pmatrix}$$

Let us consider a Markov model with the continuous time variable. Letting $p_i(t)$ be a probability of being a state i (i = 0 for normal and 1 abnormal) at a continuous time t, the following equations describe the state transition:

$$\begin{aligned} p_0(t+\Delta t) &= (1-\lambda\Delta t)p_0(t)+\mu\Delta t\, p_1(t)+\mathrm{O}(\Delta t) \\ p_1(t+\Delta t) &= \lambda\Delta t p_0(t)+(1-\mu\Delta t)p_1(t)+\mathrm{O}(\Delta t) \end{aligned}$$

where $\mathrm{O}(\Delta t)$ denotes all the terms with second order or higher of Δt.

In the limit of Δt converging on 0 (denoted by $\Delta t \rightarrow 0$), the above equations may be written as a differential (Kolmogorov) equation:

$$\boldsymbol{dP}(\mathrm{t})/\mathrm{dt} \ = \boldsymbol{P}(\mathrm{t})\boldsymbol{M}^t$$

where the time dependent vector variable

$$\boldsymbol{P}(\mathrm{t}) = (p_0(t), p_1(t)),$$

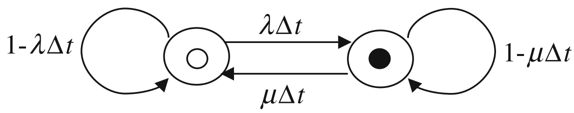

Fig. 2.1 State-transition diagram for one component to be abnormal (faulty) and to be normal (repaired). The white circle indicates a normal node and the black one an abnormal node

and $\boldsymbol{M}^t$ is the transpose of the following matrix $\boldsymbol{M}$:

$$\boldsymbol{M} = \begin{pmatrix} -\lambda & \mu \\ \lambda & -\mu \end{pmatrix}.$$

Stationary distribution $\boldsymbol{P}(\infty) = (p_0(\infty), p_1(\infty))$ can be obtained by making $\boldsymbol{dP}(\mathrm{t})/\mathrm{dt} = 0$, hence solving the linear equation $\boldsymbol{P}(\infty)\,\boldsymbol{M}^t = 0$. In this simplest example of the birth-death process, $\boldsymbol{P}(\infty) = (\mu/(\lambda + \mu), \lambda/(\lambda + \mu))$, however the stationary distribution itself simply follows from the symmetry of the model (death and birth is just a matter of labeling the different symbols λ and μ, and the exchange symmetry holds).

2.3.2.1 Mutual Repairing with Selfish Agents

Consider a model with only two agents i ($i = 1, 2$) that are capable of repairing the other agent. Using conventional notations again in reliability theory, λ and μ indicate the failure rate (rate of becoming abnormal) and the repair rate respectively. In considering two agents, a repair action must be considered as an interaction from the repairing agent to the agent being repaired, while the failure event (of normal agents becoming abnormal) occurs within an agent. The double-edged sword framework allows agents that are capable of repairing other agents, but when the repairing agents are themselves abnormal they will cause the target agents to be abnormal (spread contamination) rather than repairing. Thus the state-transition diagram as a Markov model is as shown in Fig. 2.2. Let μ_i denote the repair rate done by agent i, and let α (<1) indicate the repair success rate when repair is done by an abnormal agent. This repair success rate is in fact a probability, for it switches the successful repairs with the rate $\alpha\,\mu_i$ and the failed repair with the rate $(1-\alpha)\mu_i$. Repairs by normal agents are assumed to be always successful. For simplicity, both a failure event and a repair action do not occur simultaneously. The corresponding Kolmogorov equation is:

$$\frac{d\mathbf{P}(t)}{dt} = \mathbf{MP}(t)$$

where the time dependent vector variable

$$\mathbf{P}(t) = (p_{00}(t), p_{01}(t), p_{10}(t), p_{11}(t))^T$$

comprises a component $p_{s_1 s_2}(t)$ denoting a probability of agent 1 being S_1 and agent 2 being S_2 at time t where $S_1, S_2 \in \{0, 1\}$ (0: normal; 1: abnormal). $\mathbf{M}$ is a transition matrix corresponding to the state-transition diagram shown in Fig. 2.2.

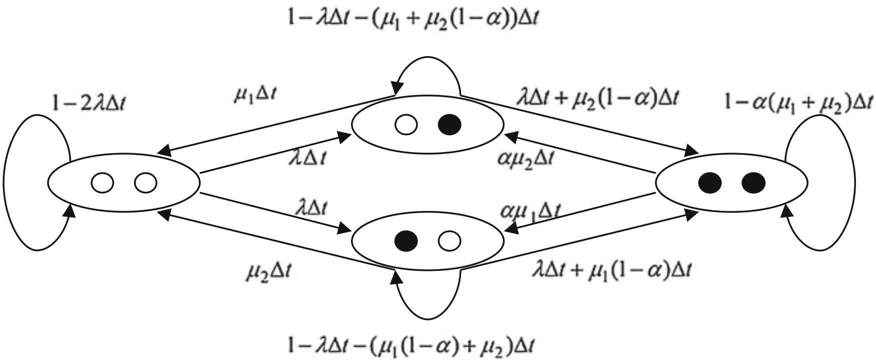

Fig. 2.2 State-transition diagram for the mutual repairing two agents system. White circles indicate normal nodes and black ones abnormal nodes

$$\boldsymbol{M}=\begin{pmatrix} -2\lambda & \mu_1 & \mu_2 & 0 \\ \lambda & -\lambda-(\mu_1+(1-\alpha)\mu_2) & 0 & \alpha\mu_2 \\ \lambda & 0 & -\lambda-((1-\alpha)\mu_1+\mu_2) & \alpha\mu_1 \\ 0 & \lambda+(1-\alpha)\mu_2 & \lambda+(1-\alpha)\mu_1 & -\alpha(\mu_1+\mu_2) \end{pmatrix}$$

For a game theoretic argument, it is further assumed that an agent must decide whether it will repair others or not, corresponding to cooperation and defection in the Prisoner's Dilemma. For agent i, C_i = 1 if it repairs another agent, and 0 otherwise. Let P_i (C_1, C_2) denote a probability of agent i being normal when agent i's action is C_i. A simple calculation yields the steady-state probability of P_i (C_1, C_2) as listed in Table 2.2.

When abnormal agents are assumed to do nothing and remain silent as in the case of mechanical systems, then both agents in the abnormal state is the absorbing state, and hence the steady-state probabilities of P_i (C_1, C_2) are all 0. In this model, all agents will be abnormal eventually no matter whether cooperation takes place or not. Thus, we assume that even abnormal agents may repair when they take action C. When one agent repairs another agent, the repairing rate is assumed to be the same one: μ. That is, if both agents cooperate (repair), then $\mu_1 = \mu_2 = \mu$. If agent 1 cooperates, but agent 2 does not, then $\mu_1 = \mu$ but $\mu_2 = 0$.

Table 2.2 Steady-state reliability of each agent when mutual repairing is involved $\rho = \frac{\lambda}{\mu}$

	$C_2 = 1$	$C_2 = 0$
$C_1 = 1$	$P_1(1, 1) = \frac{\alpha}{\rho+\alpha}$	$P_1(1, 0) = 0$
	$P_2(1, 1) = P_1(1, 1)$	$P_2(1, 0) = P_1(0, 1)$
$C_1 = 0$	$P_1(0, 1) = \frac{\alpha}{\rho+1}$	$P_1(0, 0) = P_2(0, 0) = 0$
	$P_2(0, 1) = P_1(1, 0)$	

Table 2.2 can be regarded as a payoff matrix of the two-players game. If we simply regard P_i (C_1, C_2) as agent i's payoff when actions C_1, C_2 are taken, mutual repairing may happen because of the inequalities:

$$P_1(1,1) > P_1(0,1) > P_1(1,0) = P_1(0,0),$$
$$P_2(1,1) > P_2(1,0) > P_2(0,1) = P_2(0,0).$$

While the action does not make any difference (e.g. for the agent 1, $P_1(1, 0) = P_1(0, 0)$) when another agent does not cooperate, the agent should certainly cooperate when another agent cooperates (e.g. for agent 1, $P_1(1, 1) > P_1(0, 1)$). This is because by raising the reliability of others, the repairing by them to the self becomes more effective, a circular effect.

Let us take the cost of repairing into consideration. Although both D is a Nash equilibrium when there is a positive repair cost, the agents do not have an incentive to remain in the both D when the repair cost is negligible.

Let us focus on the payoff. Then agent 1, for example, will choose its action C_1 to maximize:

$$P_1(C_1, C_2) - c \cdot C_1,$$

where c is a cost of repairing relative to the benefit measured by the reliability of itself. Incorporating a cost for cooperation would naturally bias the situation toward more defect-benefiting. When the adversary agent defects, an agent simply loses the cost for cooperation if it cooperates. However, there is still a chance for mutual cooperation when the opponent cooperates: $P_1(1, 1) - c > P_1(0, 1)$ holds when the cost relative to benefit satisfies:

$$\frac{\alpha(1-\alpha)}{(\rho+1)(\rho+\alpha)} > C.$$

Selfishness of an agent is reflected on the objective function that the agent will maximize, and the reflection is not a trivial task. The above agents are shortsighted in implementing the selfishness. Foresighted agents would consider the event of another agent's failure as losing the chance of being repaired by the agent, and the extinction of all normal agents as a fatal event that should be avoided by paying a high cost. If the repairing by abnormal agents does not happen, extinction of normal agents is an absorbing state from which no other normal state will arise when the repair success rate by abnormal agents α is close to 0 (repairs by abnormal agents do not virtually succeed).

Figure 2.3 plots the difference $P_1(1, 1) - P_1(0, 1)$ when the repair success rate by abnormal agent α changes from 0 to 1 and $\lambda = 10^{-4}$, $\mu = 10^2\ \lambda$ are fixed. There is a strong incentive for agent 1 to cooperate when the success rate α is about 0.1. The incentive decreases almost linearly when the rate exceeds 0.2 in this case, which indicates that reliable repairs by abnormal agents would not promote cooperation.

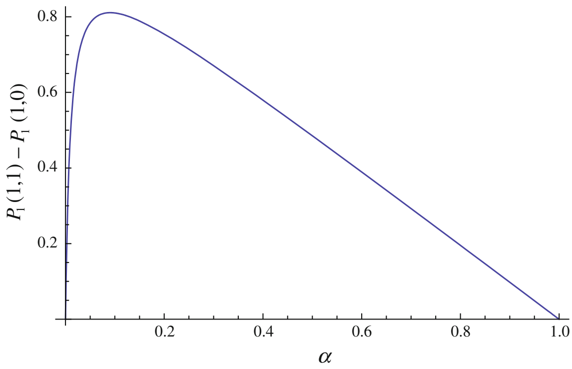

Fig. 2.3 Plot of the difference when the repair success rate by abnormal agents α changes from 0 to 1 and $\lambda = 10^{-4}$, $\mu = 10^2\ \lambda$ are fixed

Table 2.3 Steady-state availability AV where availability is a probability that at least one agent is normal

	$C_2 = 1$	$C_2 = 0$
$C_1 = 1$	$AV(1,\ 1) = \frac{\alpha(2\rho+1)}{(\rho+1)(\rho+\alpha)}$	$AV(1,\ 0) = \frac{\alpha}{\rho+1}$
$C_1 = 0$	$AV(0,\ 1) = \frac{\alpha}{\rho+1}$	$AV(0,\ 0) = 0$

Let us consider the availability (the probability that the system is available at the time, hence in our model, the probability that at least one agent remains normal). Let $AV(C_1,\ C_2)$ denote the availability when agent i's action is C_i. Technically, we use *limiting average availability* (e.g., (Barlow and Proschan 1975)) as a payoff for each agent, then there will be a stronger incentive to cooperate when the other agents cooperate, since the difference $AV(1,\ 1) - AV(0,\ 1)$ is larger than the difference $P_1(1,\ 1) - P_1(0,\ 1)$ as shown in Table 2.3.

This indicates that even selfish agents will be more likely to cooperate if they take a systemic payoff that evaluates cost and benefit in a more system-wide fashion and a longer-term basis: the beginning of self-organization of mutually supporting collectives.

2.4 Discussion

2.4.1 Nash Equilibrium

The worst-case analysis (Koutsoupias and Papadimitriou 1999) uses a Nash equilibrium as a solution when tasks are left to selfish agents. The cost for the Nash equilibrium relative to the optimized solution has been proposed to measure the cost of “anarchy” (Koutsoupias and Papadimitriou 1999). This chapter rather focused on the self-maintenance task, self-repairs by mutual copying in particular, and discussed when selfish agents begin to cooperate. Further discussions are needed on when these selfish agents organize themselves into mutually supporting collectives.

The present research has two significances: one engineering and another theoretical. For engineering, computing paradigms such as distributed computing systems (Farber and Larson 1970), grid computing (Foster and Kesselman 2001; Foster and Kesselman 2003; Foster et al. 1998) and parasitic computing (Barabási et al. 2001) provide a background. When grid computing becomes dominant for large-scale computing, what we call agents (autonomous programs that can move from nodes to nodes) will become like processes in the Unix operating system. One important difference is that agents may be selfish, and will not be organized with a central authority as is done in conventional operating systems. Then, the organization of selfish agents will become an organization with a weakest central authority, or even with a distributed authority as seen in the free market economy. Naturally, information processing with selfish agents will be imperative, thus making the game theoretic approach and economic approach such as selfish task allocation and routing important.

Another significance is that it will provide an organizational approach to artificial life (a life-like form which has some identity hence boundary). Self-organization of selfish agents will be more than a mere collection of independent agents, but rather a cluster of cooperative agents. This would reveal an intrinsic logic and process that selfish agents form multi-agent organisms, similarly to multi-cellular organisms. The game theoretic approach will provide a threshold and a mechanism for selfish agents to develop into cooperative agents when payoffs are recast in a broader context of time and space.

2.4.2 Hamilton Rule as a Condition for Altruism

In evolutionary biology, many theories have been proposed that explain the altruistic behaviors of individuals. One of them is kin selection where altruistic behaviors among relatives can be explained by extending fitness to inclusive fitness with relatedness. Hamilton's rule (Hamilton 1964) is formulated as follows:

$$rB > C$$

where the relatedness r (the kin selection coefficient of relatedness between altruistic agent and recipient agent) can be measured by genetic distance. B is the reproductive benefit to the recipient by the altruistic behavior and C is the cost for the altruistic behavior. Frank (Frank 1998) has applied Hamilton's rule to social evolution by extending this relatedness r to a measure generalized from the genetic distance. The rule can explain the extraordinary sex ratio observed in social insects such as honey bees (Hamilton 1963).

From a cost-benefit point of view, Hamilton's rule can be a simple condition for an action of an agent where the action will be carried out when the benefit exceeds the cost. Let us borrow Frank's understanding of relatedness in the framework of economic optimization through *exchange rate* (Frank 1998). One notable point is that the benefit is not directly oriented toward the self but indirectly received, hence the benefit must be discounted by multiplying by a discount rate r. Thus, the relatedness can be regarded as a spatial version of discount rate (usually discount rate is related to time; the value at a future time is discounted compared to the value at the present time). In the model of this chapter, the indirect benefit (discounted by relatedness r) from the interacting agent is measured by the difference of reliability: $P_1(1, C_2) - P_1\ (0, C_2)$ or the difference of availability: $AV_1(1, C_2) - AV_1\ (0, C_2)$. One challenge would be to compare the benefit by actions toward itself and actions toward a neighbor, rather than comparing the benefit by actions toward the neighbor with that of doing nothing.

The model proposed in this chapter recast a possible mechanism to promote altruistic behavior among nodes in a network based on Hamilton's rule where the relatedness r can be measured by a distance in the network, that is, how close the nodes are in the network (how direct the exchange of resources can be). In the cost-benefit analysis of the previous Sect. 2.3, the relatedness $r = 1$ of Hamilton's rule when the node is in the neighbor (directed by an arc) and $r = 0$ otherwise. The condition for mutual repair is also the cost-benefit condition for the action of repairing the neighbor nodes where the benefit is measured by the increase of the reliability (or availability) discounting the fact that the repairing effect is not directly to the self but indirectly through the neighbors. Since the self-repair network uses a network to express the structure, the benefit of being repaired is discounted if the repaired node is far from the repairing node. But why would the repairing node (the self-node) not use the entire resource for repairing itself (the self-node)? We suppose the following rationale for the diversification of the risk specific to the self-repair network: when the node repairs itself there are only two cases in the repair pattern, i.e. a normal node repairs the normal node; or an abnormal node repairs the abnormal node. When the node repairs the neighbor nodes, even though the benefit is indirect (and hence discounted), there are two other cases in the repair pattern, i.e., a normal node repairs an abnormal node; or an abnormal node repairs a normal node. The former is an *edge* (advantage) for a custom repair of the double-edged sword and the latter is another *edge* (disadvantage) that is inevitably associated with mutual repair in the self-repair network without recognition. We will compare mutual repair and self-repair in the self-repair network in Chap. 9.

Hamilton's rule (the condition for altruism) may be viewed from another way, that is, the self can be extended to a system connected by the mutual repair: *quasi-self*. We will consider re-modification of the payoff called *systemic payoff* in Chap. 5, which amounts to considering the *availability* (as a system) rather than the *reliability* (of a node) in the theory of reliability.

Although this chapter focused on the incentive for a node to repair other nodes, the mechanism of spreading the repairing *trait* will be considered in Chap. 4 (direct mechanism where repairing is inevitably associated with copying of the repairing strategy) and in Chap. 5 (indirect mechanism where the node copies the strategy of the neighbor node who earned the largest payoff).

2.5 Conclusion

For large-scale information systems, a game theoretic approach is important, since it will give results concerning what would happen when selfish agents are involved. However, what is "selfish" depends on the context and the environment. This research assumes that selfish agents try to maximize their payoff. Then the next problem is to set the payoff function reflecting the context and the environment. We discussed the cases when only a repair cost, the system reliability, and a more systemic evaluation such as the availability (*limiting average availability*) are incorporated. Incentives to cooperation increase when a more systemic evaluation is involved in the payoff. Specifically, if an agent sticks to a short-sighted payoff such as the repair cost, the agent will lose the partner that would repair the agent when it becomes abnormal, or even worse, all the agents will eventually become abnormal and will forever lose the chance of being repaired.

The current research should be further developed through studies on how and when mutually supporting collectives emerge in large-scale information systems such as the Internet.

It is important to note that the models not only in this chapter but throughout this book have limitations in directly applying them to real situations due to the fact that they sacrifice reality for simplicity in order to focus on the problem in question. For example, the model parameters are expressed as constant values, however, they could change or adapt to the environment, or they may even be difficult to be expressed as parameters. For the model in this chapter, the key parameter of repair success rate and other parameters such as repair rate, could change over time. But the essence of the self-repair network as a model resides in the asymmetry (of existence and non-existence) that the repair success rate by abnormal agents is less than that by normal agents.

While this chapter views the self-repair network from the nodes within it and attributes incentives for cooperation (repair) to the relatedness of nodes reminiscent of Hamilton's theory of altruism, one can also view the self-repair network from outside and attribute incentives for cooperation to the fact that the network is so integrated that cooperation is the selfish act of helping the network itself.

Although we have shown that there is an incentive for a node of the self-repair network to cooperate (repair other nodes) in terms of reliability engineering, whether mutual repair can be realized or not is another story. We will further study game theoretically with the spatial prisoner's dilemma, and examine how and when the strategy with cooperation remains or should remain, in Chap. 4. Before that, we will investigate the network cleaning problem with mutual and non-strategic repair (meaning uniform repairing carried out independently from neighbors' actions) in the following Chap. 3.

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