Thermodynamics-based Entropy Adjustment for Robust Self-organized Network Controls

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***Abstract*—As key technologies for future information networks, many researchers have focused on self-organized network controls. In the process of their ordering, their robustness against environmental changes decreases while their performance increases. Therefore, their behavior in dynamic environment should retain appropriate amount of disorder. In this paper, we conduct simulation experiments and show that higher entropy leads to higher robustness against node failures.**

Keywords*—self-organized network control; robustness; performance; thermodynamics

I. Introduction

For a communication network to serve as an indispensable infrastructure for secure, dependable, and comfortable societies, future information networks must be more scalable, adaptive, and robust against ever-increasing size, dynamics, and complexity [1]. As one of key ideas, many researchers have focused on self-organization [2] in natural systems. Then, they adopt its mathematical models to various types of network controls [3]. In self-organized network (SON) controls, network elements' behavior gradually becomes ordered through direct or indirect interactions among them. In the process of their ordering, they produce their own structures adaptively to the current environment while decreasing robustness which reflects the ability to maintain the network performance against environmental changes. This is because robustness is derived from disorder in SON controls. Thus, in this paper, we show that SON controls in dynamic environment should retain appropriate amount of disorder in their behavior.

As an idea to adjust the degree of disorder in SON controls' behavior, we focus on a substance's thermodynamic equilibrium, where the balance between its ordering behavior and its disordering behavior is well kept depending on its temperature T. In thermodynamics, we know that a substance's state changes while satisfying this condition $\Delta E - T \times \Delta S \leq 0$, where variables E and S are *internal energy* which captures the total energy due to motion of molecules and *entropy* which captures the degree of disorder in the substance's state, respectively. Then, this condition means that T determines E and S in the thermodynamic equilibrium. For example, higher T leads to the thermodynamic equilibrium with higher E and S. From the perspective of SON controls, we interpret internal energy E into the goodness of the emerging structure at the macroscopic level, and we do entropy S into the degree of disorder of their behavior in the structure. We think that appropriate temperature T can bring in a SON control with better robustness and performance in dynamic environment.

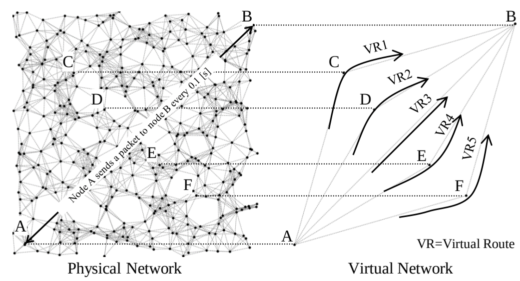

Fig. 1. Overview of Simulation Setting

II. Entropy Adjustment of SON Controls

We take the attractor selection model-based overlay multipath routing [4] as an example of SON controls. In this example, there is a pair of a source node and a destination node, and K virtual routes are organized in advance. Virtual route $i \in \{1 \dots K\}$ has state value m_i, and the source node selects the virtual route with the highest state value among K virtual routes. The dynamics of state value m_i is defined by

$$m_i(t+\Delta)=m(t)+\left(\frac{\beta\times\alpha^{\gamma}(t)+\frac{1}{\sqrt{2}}}{1+\max_{1\leq j\leq K} m_j^2(t)-m_i^2(t)}-m_i(t)\right)\times\alpha(t)+\eta_i. \quad (1)$$

Here, symbol Δ is the control interval where this equation is evaluated. Coefficients β (> 0) and γ (> 0) affect the increasing rate of state values. Variable η_i is a normal random number with average 0 and variance 1. Variable α $(0 \leq \alpha \leq 1)$ represents the goodness of the current condition of the network control. In Eq. (1), the third term of the right side affects the probabilistic behavior. The second term of the right side affects the deterministic behavior, where the highest state value becomes higher and the other state values become lower. Using the deterministic or probabilistic behavior properly, this SON control approaches the optimum state, that is, internal energy E spontaneously decreases. As coefficient β is smaller, the relative influence of the noise term increases, that is, entropy S increases. As a larger number of virtual routes exist, there are more diverse choices, that is, entropy S also increases. High entropy S makes it difficult that the network control stays at the optimum state, and this leads to high internal energy E.

III. Simulation Experiment

A. Simulation Setting

We uniformly arrange 394 physical nodes in region of $100\text{m} \times 100\text{m}$ as illustrated in Fig. 1. Additionally, we arrange 6 physical nodes at coordinates $(5\text{m}, 5\text{m})$, $(95\text{m}, 95\text{m})$, $(25\text{m}, 75\text{m})$, $(41.6\text{m}, 57.2\text{m})$, $(57.2\text{m}, 41.6\text{m})$, and $(75\text{m}, 25\text{m})$, respectively. These physical nodes are identified by node A, B, C, D, E, and F, respectively. A physical node can communicate with physical nodes within its proximity of 12m. Link delay is set at 0.01 seconds. 5 virtual routes, which correspond to physical routes from node A to node B via node C, D, E, and F, respectively, are constructed in advance. These virtual routes are identified by virtual route 1, 2, 3, 4, and 5, respectively. Node A sends a data packet to node B. When node B receives a packet, node B sends an ack packet back to node A. We call node A *source node*. We call node B *destination node*. A data packet is sent every $\Delta = 0.1$ seconds via a virtual route, which is selected by the model. Activity α is defined by equation $\alpha(t+\Delta) = \alpha(t)+0.01\times(d_m/d_l-\alpha(t))$, where d_l and d_m are the last delay and the minimum delay for the past 10 seconds, respectively. For simplicity of simulation experiments, we assume that all physical nodes compute the shortest paths to other physical nodes every 50 seconds using global information. One of physical nodes on a randomly selected virtual route dies every 40 seconds. We call this physical node *failure node*. We assume that a packet loss occurs only if a packet is transmitted to a failure node. One of failure nodes recovers every 100 seconds. We call this physical node *recovery node*. A recovery node begins to forward packets again.

B. Influence of parameter β on robustness against failures

We assume that the network control has virtual routes 1, 3, and 5 ($K = 3$). The goodness of a virtual route depends on the hop length of the corresponding physical route. In this simulation setting, virtual route 3 is the best, and virtual routes 1 and 5 are equally good. The coefficients $(\beta_1, \beta_3, \beta_5)$ are set at $(3, 3, 3)$, $(5, 5, 5)$, or $(7, 7, 7)$. In a simulation run of 500 seconds, we derive the average delay of packets that the destination node receives and the ratio of packets that the destination node receives over packets the source node sends. We conduct 500 simulation runs with the same node placement and draw the cumulative distributions in Figs. 2 and 3.

We compare simulation results when $(\beta_1, \beta_3, \beta_5)$ are set at $(3, 3, 3)$, $(5, 5, 5)$, or $(7, 7, 7)$. Figure 2 shows that the ratio of received packets is higher as β is smaller. This shows that the network control becomes more robust against node failures as entropy S becomes higher. This is because a selected virtual route more quickly changes to another after the occurrence of node failures. Additionally, Figure 3 shows that the average delay is within narrower range between 0.31 seconds and 0.33 seconds when $(\beta_1, \beta_3, \beta_5)$ are set at $(3, 3, 3)$. This is because the network control with quite high entropy S uniformly selects a virtual route in a simulation run. As a result, the average delay is nearly equal among all simulation runs. On the contrary, the network control with quite large β stably selects a specific virtual route in a simulation run. As a result, the average delay disperses within wider range between 0.27 seconds and 0.36 seconds when $(\beta_1, \beta_3, \beta_5)$ are set at $(5, 5, 5)$ or $(7, 7, 7)$.

C. Influence of parameter K on robustness against failures

Figure 4 shows that the received ratio becomes higher as parameter K is higher. This shows that the robustness against

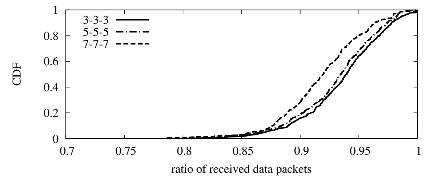

Fig. 2. Influence of parameter β on ratio of received data packets

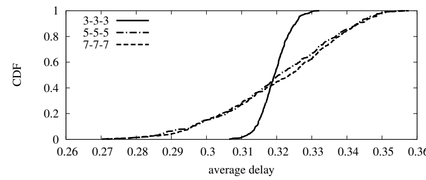

Fig. 3. Influence of parameter β on average delay

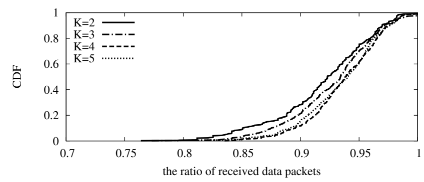

Fig. 4. Influence of parameter K on ratio of received data packets

node failures becomes higher as entropy S becomes higher. This is because the selected virtual route is less likely to be disconnected as more virtual routes exist. This figure also shows that the increase in the number of received packets is less remarkable as more virtual routes exist. From this result, we can expect that appropriate parameter K exists depending on the frequency of node failures.

IV. Conclusion and Future Work

In this paper, we focus on thermodynamics to realize robust SON controls. Through simulation experiments, we analyze the influence of the parameters, which affect entropy S, on the robustness against node failures. The results show that the network control with higher entropy can achieve higher robustness against node failures. As our future work, we will organize the quantitative design methodology, which can determine the appropriate parameter setting.

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