Enhancing Convergence with Optimal Feedback for Controlled Self-Organizing Networks

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***Abstract*—To tackle with problems emerging with rapid growth of information networks in scale and complexity, self-organization is one of promising design principles for future networks. Convergence of self-organizing controls, however, is pointed out to be comparatively slow in some practical applications. Therefore, it is important to reveal and enhance convergence of self-organizing controls. In controlled self-organization, which introduces an external observer/controller into self-organizing systems, systems are controlled in order to guide them to the desired state. Although previous controlled self-organization schemes could achieve this feature, convergence speed for reaching an optimal or a semi-optimal solution is still a challenging task. In this paper, we take potential-based self-organizing routing and provide an optimal feedback for faster convergence using the future state of the system. Simulation results show that the convergence time of potentials is reduced by 86% with a proposed mechanism.**

***Keywords*-Self-organization; prediction; potential-based routing; convergence.**

I. Introduction

Rapidly increasing network scale and complexity pose significant limitations for conventional network systems and technologies based on central or distributed control. As scale and complexity increase, information network systems adopting conventional control technologies in particular suffer from considerable overhead in managing up-to-date information to grasp and respond changing conditions. Then, future network requirements such as scalability, adaptability, robustness, and sustainability, necessitate new methods of organizing and controlling network systems in a fully distributed and *self-organizing manner* [1], [2], [3]. In spite of this, it is a challenging issue to reveal the optimality of self-organization based controls and improving the convergence speed for reaching an optimal or semi-optimal solution.

Self-organization is a natural phenomenon of distributed systems, where components behave individually and autonomously and a variety of self-organization based models have been applied to information networking such as routing, synchronization, and task assignment [4]. In a self-organizing system, each component follows simple rules using locally available information. Through direct or indirect interactions among components, a global behavior or pattern emerges on a macroscopic level without a central control entity. In a self-organizing system, up-to-date information regarding the entire system or many other components is unnecessary, which reduces considerable computation costs and management costs for global information. This localized control enables to immediately handle local failures and small environmental changes by local components, and therefore, self-organizing systems are expected to automatically recover from failures and adapt to environmental changes, without involving centralized control.

Although self-organization has various benefits, such control has critical disadvantages that complicate implementation in industrial and business systems [5]. It may take a long time for global patterns to emerge in large-scale systems because they appear as a consequence of interactions between autonomous components. This property also leads to slow adaptation to environmental changes in self-organizing systems. Also, self-organizing systems that use only local information can fall into a local optima while conventional systems using global information can often reach an optimal solution.

Complaints about these disadvantages from engineers brought an idea of controlled (or guided, managed) self-organization where a self-organizing system is controlled through added some kinds of constraints [6], [7]. The authors of [8], [9] introduce a concept of controlled self-organization proposed in [6], where an external observer/controller controls a self-organizing system through a feedback mechanism in order to guide it to the desired state. They can allow self-organizing systems to own an adaptable property, however, enhancing the convergence speed for reaching a optimal or semi-optimal solution is still a residual task.

In this paper, we show an upper limit of convergence by an external control in a self-organizing network whose dynamics is extremely linear. To this end, we investigate potential-based routing *guided by an external controller*, which can observe and also manipulate some prespecified nodes, in a wireless sensor network scenario. We show how the controller estimates unobservable state of the system and provides an optimal feedback for fast and robust convergence of potential-based routing [10]. We first assume an ideal situation where a controller can collect all nodes' states correctly and immediately without any cost, and present the optimal convergence of the system in that situation. Since it is impracticable to monitor and control the overall system in actual networks, therefore secondly, we add several constraints to the system that the controller can observe the network state via these monitored nodes with communication delay. Moreover, communication overhead occurs for the controller's collecting information of nodes within limited hops from the monitored nodes.

The reminder of this paper is organized as follows. First, we describe potential-based routing in Section II, propose and explain potential-based routing with an optimal feedback in Section III. We then evaluate the adaptability of the proposed method through simulation, and give simulation results and a discussion of our proposal in Section IV. Finally, in Section V, we present our conclusions and suggest areas for future work.

II. Potential-based Routing

Potential-based routing is a self-organizing routing mechanism. In potential-based routing, each node has a scalar value called *potential* and a data packet is forwarded to a neighbor whose potential is smaller than forwarder's. Basically, the smaller the number of hops from the sink node is, the lower potential value assigned to the node is. Therefore, a simple forwarding rule, "forwards data to its neighbor node with lower potential," can carry out data packets collection toward sink nodes (Fig. 1). Potential-based routing has high scalability because each node uses only local information for calculating potentials and a local rule for forwarding data. Furthermore, it can acquire various properties by calculating potential using some sort of information, such as flow rates, queue length, or remaining energy [11].

In [12], the authors focused on the convergence of potential-based routing and achieved the enhancement of it. They proposed potential calculation is based not only on current potentials but also on last potentials in order to accelerate potential convergence. Node n's potential at time t, $\theta_n(t)$, is calculated by (1).

$$\theta_n(t+1) = (\alpha+1)\theta_n(t) - \alpha\theta_n(t-1) + \beta\sigma_n\left(\sum_{k\in N_b(n)}\{\theta_k(t)-\theta_n(t)\} + f_n(t)\right), \quad (1)$$

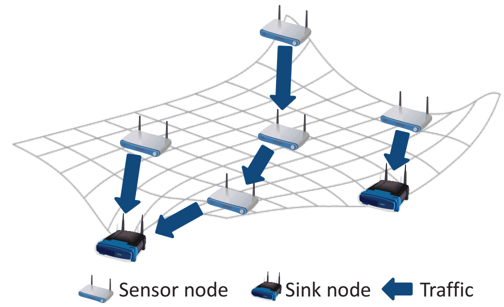


Figure 1. Potential-based routing

where $N_b(i)$ is a set of node i's neighbors. α is a parameter that determines weights of current and last potential values when calculating the next potential. Larger α means that the weight of the last potential value is larger and then system is less subject to current noise, whereas the convergence speed is slower. β is a parameter that determines the influence amount of neighbor nodes' potentials. σ_n is defined as $1/|N_b(n)|$ and $f_n(t)$ corresponds to flow injection rate of node n at time t.

The convergence speed based on (1) is faster than the simple Jacobi iterations, but it still takes a long time to converge due to its calculation based only on local information. In this paper, we introduce an external controller into potential-based routing which observes states of the network, predicts the future state of it, and regulates potentials of a part of nodes for faster convergence.

III. Potential-based Routing with an Optimal Feedback

In this section, we describe network dynamics and explain our optimal control scheme illustrated in Fig. 2. A 'controller' monitors network states, such as the network topology, potential values, and flow-injection rate of nodes. Then, the controller estimates the potential value of unobservable nodes using the model that describes the behavior of the system, and send suitable control input to some nodes for faster convergence of the potential distribution.

A. Network Dynamics

Let the dynamics of potentials be given by a deterministic discrete-time model. In our proposal, node n updates its potential by

$$\theta_n(t+1) = (\alpha+1)\theta_n(t) - \alpha\theta_n(t-1) + \beta\sigma_n\left(\sum_{k\in N_b(n)}\{\theta_k(t)-\theta_n(t)\} + f_n(t)\right) + \eta_n(t) + d_n(t), \quad (2)$$

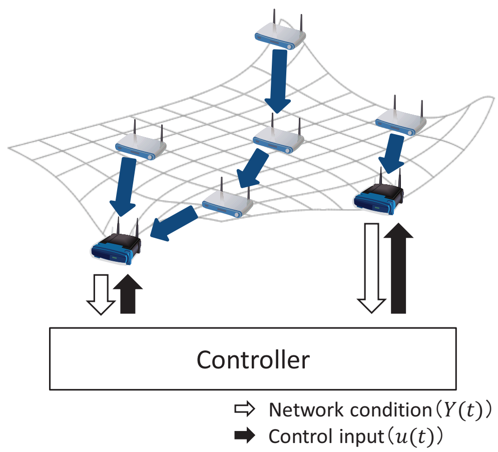


Figure 2. Potential-baser routing with a contoller's feedback

where η_n (resp. d_n) represents a feedback input received from the controller (resp. disturbance or noise). If node n is uncontrollable, $\eta_n(t) = 0$. In [12], σ_n is set to $1/|N_b(n)|$, but this value may lead to oscillation of potentials in some situations. Therefore, we set σ_n to the constant value σ ($0 < \sigma < 1$) for all n ($n \in \{1, 2, \cdots, N\}$) in this paper. We define a matrix $\boldsymbol{\Theta}(t)$ that shows potential values for all nodes as

$$\boldsymbol{\Theta}(t) := [\boldsymbol{\theta}_1(t)\ \boldsymbol{\theta}_2(t)\ \cdots\ \boldsymbol{\theta}_N(t)]^T,$$

where $\boldsymbol{\theta}_i(t)$ is defined as $[\theta_i(t)\ \theta_i(t+1)]^T$. Under this dynamics, the stationary value of the states is given by the solution of $(I_{N\times N} - A)\boldsymbol{\Theta}(\infty) = [f_1(\infty)\ \cdots\ f_N(\infty)]^T$, where Γ is the graph Laplacian, $\boldsymbol{I}_{N\times N}$ is the identity matrix of $N \times N$, and

$$\boldsymbol{A} = \boldsymbol{I}_{N\times N} \otimes \boldsymbol{A}_1 - \boldsymbol{\Gamma} \otimes \boldsymbol{A}_0,$$

$$\boldsymbol{A}_1 = \begin{bmatrix} 0 & 1 \\ -\alpha & \alpha+1 \end{bmatrix}, \boldsymbol{A}_0 = \begin{bmatrix} 0 & 0 \\ 0 & \beta\sigma_i \end{bmatrix}.$$

Then, the dynamics of the regulation error $\boldsymbol{X}(t) := \boldsymbol{\Theta}(\infty) - \boldsymbol{\Theta}(t)$ can be rewritten as

$$\boldsymbol{X}(t+1) = \boldsymbol{A}\boldsymbol{X}(t) + \boldsymbol{B}_1\boldsymbol{d}(t) + \boldsymbol{B}\boldsymbol{u}(t), \tag{3}$$
$$\boldsymbol{B}_1 = \boldsymbol{I}_{N\times N} \otimes [0\ 1]^T, \boldsymbol{B} = \boldsymbol{E} \otimes [0\ 1]^T, \tag{4}$$

where the N_{ctrl}-dim vector $\boldsymbol{u}$ (resp. N-dim vector $\boldsymbol{d}$) concatenates $\eta_n(t)$ for controllable nodes (resp. d_n), and N_{ctrl} denotes the number of nodes that receive the feedback from the controller. Note that $(N \times N_{ctrl})$-matrix $\boldsymbol{E}$ specifies the controllable node, that is, the element $e_{ij} \in \{0, 1\}$ of $\boldsymbol{E}$ is 1 if and only if node i receives the j-th element of $\boldsymbol{u}(t)$ as the control input $\eta_i(t)$.

B. Optimal Feedback Gain

Next, we explain the controller dynamics. We consider the case where the controller can observe

$$\boldsymbol{Y}(t) = (\boldsymbol{H}^T \otimes \boldsymbol{I}_{2\times 2})\boldsymbol{X}(t) + (\boldsymbol{I}_{N\times N} \otimes [0\ 1]^T)\boldsymbol{d}(t) \tag{5}$$

where $(N \times N)$-matrix $\boldsymbol{H}$ determines directly monitorable nodes. Then, the control input is calculated according to

$$\tilde{\boldsymbol{X}}(t+1) = \boldsymbol{A}_c\tilde{\boldsymbol{X}}(t) + \boldsymbol{B}_c\boldsymbol{Y}(t), \tag{6}$$
$$\boldsymbol{u}(t) = \boldsymbol{C}_c\tilde{\boldsymbol{X}}(t) + \boldsymbol{D}_c\boldsymbol{Y}(t). \tag{7}$$

Here, $\tilde{X}$ is the controller's state and $\boldsymbol{A}_c, \boldsymbol{B}_c, \boldsymbol{C}_c, \boldsymbol{D}_c$ are design parameters.

Concerning the performance criteria, let us define

$$\phi(k) = \boldsymbol{X}(k)^T\boldsymbol{X}(k) + r\boldsymbol{u}(k)^T\boldsymbol{u}(k),$$

which is the stage cost where r specifies the trade-off between the convergence speed and input energy. With a larger r, control inputs become smaller and then, the stability of the system is enhanced. Namely, potentials changes more gently, whereas the convergence speed of potentials become slower. Then, our design objective is to minimize the worst case error

$$\sup_{\boldsymbol{d}} \frac{\sum_k \phi(k)}{\sum_k \boldsymbol{d}(k)^T\boldsymbol{d}(k)}.$$

This min-max type problem is called H^∞ optimization [10]. It is known that the optimal $\boldsymbol{A}_c, \boldsymbol{B}_c, \boldsymbol{C}_c, \boldsymbol{D}_c$ can be obtained based on semi-definite programming; see also the next section.

IV. Performance Evaluation

Our purpose is to investigate the upper limit of convergence speed of self-organizing linear systems with an external controller. We conduct computer simulation and evaluate the convergence speed comparing our proposal and the non-predictive scheme proposed in [12]. Subsection IV-B presents simulation evaluation in an ideal environment where the future converged potentials of all nodes can be correctly predicted. Next, Subsection IV-C shows evaluation considering the specific wireless sensor network constraints. We use an event-driven packet-level simulator written in Visual C++ as a network simulator, which calls MATLAB procedures to calculate control inputs $\boldsymbol{u}(t)$. This calculation is done with *dhinflmi* function and the detail is not explained in this paper.

A. Simulation Settings

We evaluate and show the convergence speed of potentials and traffic after traffic changes. The network model with 54 nodes for evaluation is shown in Fig. 3. Sink nodes are illustrated with squares and sensor nodes with dots in this figure and only sink nodes can be controlled directly by the controller. The controller provides the feedback to each sink node at intervals T_f. Each node calculates its next potential at intervals T_p and forwards data packets in accordance with potential values of itself and its neighbors. When receiving a data packet, a sensor node stochastically selects a neighbor node that is assigned a lower potential value than itself and forwards the data packet to the selected node. A next hop node is selected proportionally with potential values and the probability $p_{i\to n}(t)$ that sensor node i selects a neighbor node n as a next hop node of a data packet at time t is given by

$$p_{i\to n}(t) = \begin{cases} \frac{\theta_i(t)-\theta_n(t)}{\sum_{j\in N_l(i)}\{\theta_i(t)-\theta_j(t)\}}, & \text{if } n \in N_l(i) \\ 0, & \text{otherwise} \end{cases},$$

where $N_l(i)$ shows a set of node i's neighbor nodes that are assigned lower potential values than node i. If node i has no neighbor node with lower potential, i.e., $|N_l(i)| = 0$, the data packet is not sent to any nodes and drops.

At the beginning of the simulation, potential values of all nodes are initialized to 0. After $1,000$ s from the beginning of the simulation, data packets begin to be generated at sensor nodes. The potential field is constructed so that all sink nodes can receive approximately the same number of data packets every second. At $10,000$ s from the start of the simulation, data packet generation rates of sensor nodes changes, and the potential field is reconstructed so that all sink nodes can receive data packets equally. We evaluate the convergence speed of potentials and traffic after traffic changes. In order to measure the convergence speed of potentials, we define the degree of the potential convergence $D_c(t)$ (≥ 0) as the maximum value of the regulation errors at sink nodes. In other words, $D_c(t)$ is given by

$$D_c(t) = \max_{i\in N_s} |\theta_i(t) - \theta_i(\infty)|,$$

where N_s is a set of sink nodes. $D_c(t)$ that shows the convergence degree of sink nodes indicates the convergence degree of the entire network because the controller provides an optimal feedback to sink nodes for faster convergence of the entire network. The smaller $D_c(t)$ implies that potentials are close to convergence, and the potential convergence is achieved at sink nodes when $D_c(t)$ becomes 0. At first, data packet generation rates are 0.025 packet/s at the left half of sensor nodes in Fig. 3 and 0.075 packet/s at the right half of sensor nodes. After traffic changes, data packet generation rates are 0.075 packet/s at the left half of sensor nodes and 0.025 packet/s at the right half of sensor nodes. In this paper, the average data generation rate of a node is 0.05 packet/s corresponds $f_n(t) = 1$, and therefore, before traffic changes ($t < 10,000$ s), the flow rate matrix $\boldsymbol{F}(t) := [f_1(t) \ \cdots \ f_N(t)]^T$ is given by

$$\boldsymbol{F}^t = [0.5 \ \cdots \ 0.5 \ 1.5 \ \cdots \ 1.5 \ –12.5 \cdots –12.5]^T.$$

After traffic changes $(10,000 \text{ s} \leq t)$, $\boldsymbol{F}(t)$ is given by

$$\boldsymbol{F}^t = [1.5 \ \cdots \ 1.5 \ 0.5 \ \cdots \ 0.5 \ –12.5 \cdots –12.5]^T.$$

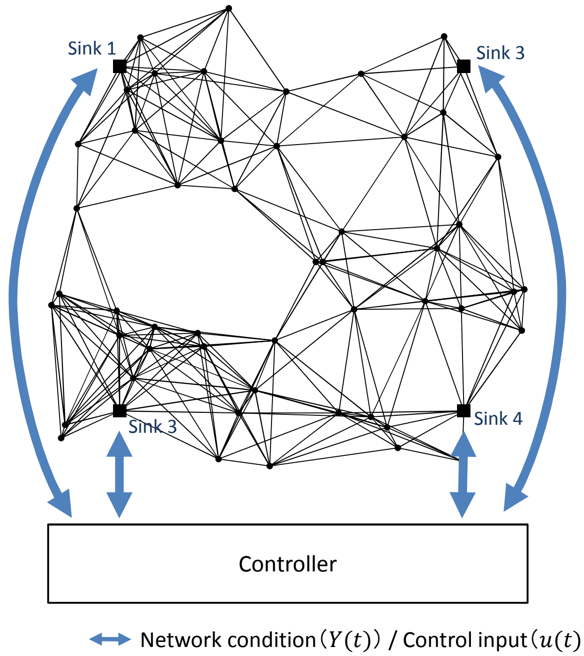


Figure 3. The network topology

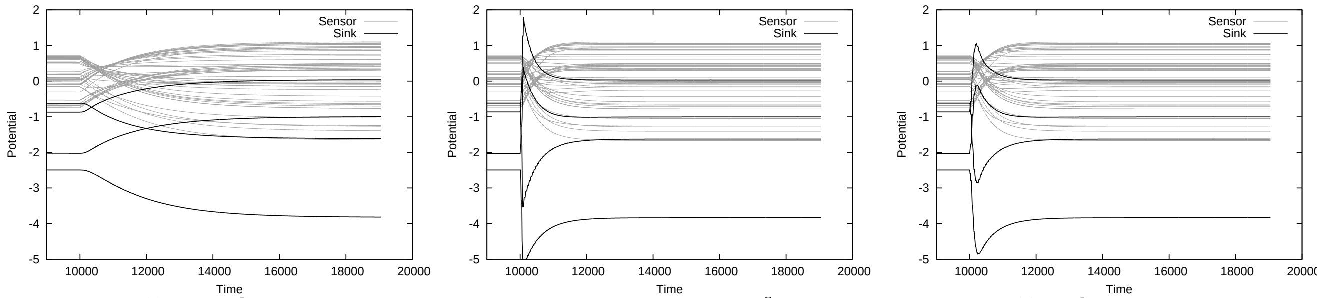
Table I
PARAMETER SETTINGS

parameter	value
α	0.4
β	0.2
σ	0.1
r	10^{-5}, 10
T_f	50 s
T_p	50 s

Parameters are set as shown in Table I. All results presented afterwards are averaged over 10 simulation runs for each parameter setting.

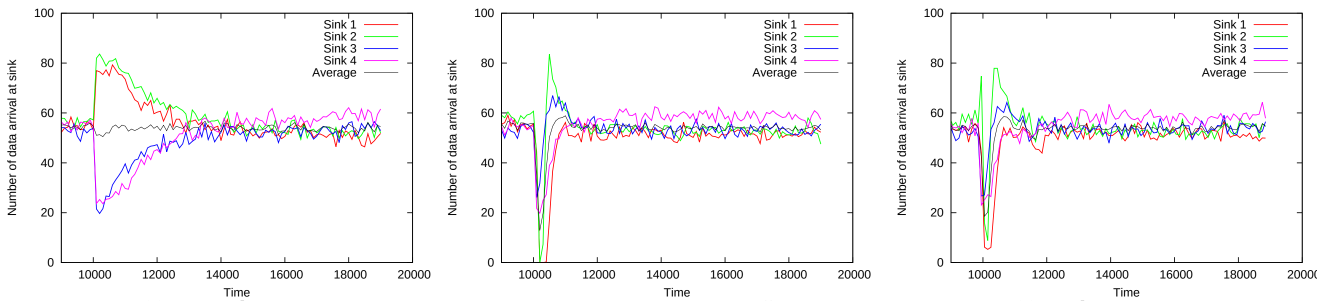
B. Upper Limit of the Convergence

Here, we evaluate the convergence in an ideal environment. The controller can monitor the latest conditions of all nodes without any communication delay or control overhead, and predict correctly the future states. Figures 4(a)∼4(c) show potential changes of our proposal and the non-predictive scheme. Even after $9,000$ s from traffic changes, potentials do not converge in the non-predictive scheme, and $D_c(19,000 \text{ s})$ is 1.7881. On the other hand, in our proposal, $D_c(t)$ becomes smaller than 1.7881 at $1,220$ s from traffic changes with $r = 10^{-5}$ and at $1,240$ s from traffic changes with $r = 10$. As a result, the convergence speed of potentials is improved by about 86% with an optimal feedback. In our proposal, when r is lower, the convergence speed is high. With a lower r, $r\boldsymbol{u}(k)^T\boldsymbol{u}(k)$ of $\phi(k)$ shown in Subsection III-B becomes smaller so that



(a) No prediction (b) Prediction, $r = 10^{-5}$ (c) Prediction, $r = 10$

Figure 4. Potential change of each node (no cost)



(a) No prediction (b) Prediction, $r = 10^{-5}$ (c) Prediction, $r = 10$

Figure 5. Data arrivals at each sink node (no cost)

the controller is allowed to change potentials largely at one time and therefore, the potential convergence is accelerated.

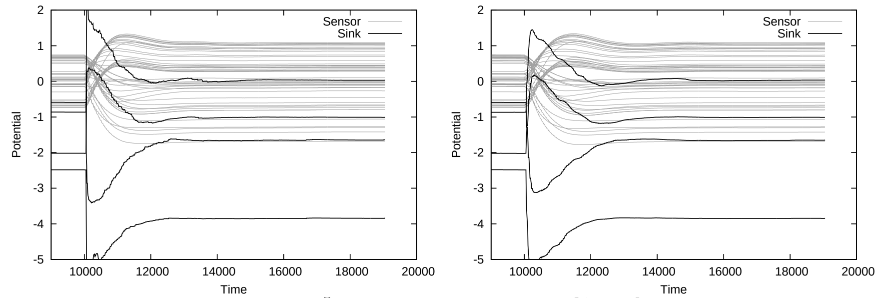
Figures 5(a)$\sim$5(c) show the number of data packet arrivals every 100 s at each sink node and the averaged number of them. The traffic convergence is also accelerated with an optimal feedback, but our proposal reduces the average number of data packet arrivals at each sink node just after traffic changes. It is because some sink nodes temporarily get highest potentials within their communication ranges due to control inputs and, therefore, data packets cannot arrive at sink nodes. However, the number of data packet drops reduces immediately and the traffic finally converges faster than the non-predictive scheme because of the faster potential convergence. Therefore, data packets can be retransmitted instantly but, in this paper, we evaluate only cases where data packets are never retransmitted because our main purpose is to reveal the upper limit of convergence speed of self-organizing systems. Moreover, Figs. 5(b) and 5(c) are the worst cases because the controller changes potentials of sink nodes, that is, the destinations of data packets, and almost all data packets are affected by the rapid changes of potentials at sink nodes. If the controller provides an optimal feedback to several sensor nodes where only a part of data packets arrive, the number of data packet drops will be smaller. With a lower r, sink nodes are more likely to be assigned higher potential value because the controller can change potentials largely, whereas the recovery speed of data packet arrivals becomes faster.

In this subsection, we show that the convergence speed of potentials is improved by 86% with an optimal feedback. However, in this experiments, we do not consider restrictions of actual networks. In particular, communication delay affects considerably the optimality of the feedback. In next subsection, we show that the convergence is improved with an optimal feedback even in the case where communication delay is considered.

C. The Convergence with Restrictions in Wireless Sensor Networks

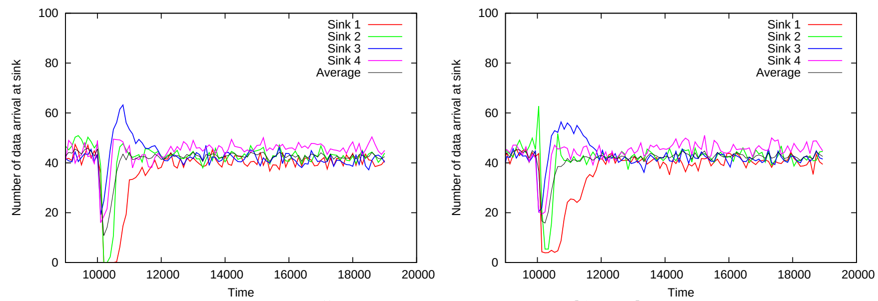
Here, we evaluate the convergence considering restrictions of wireless sensor networks. The controller broadcasts potential request packets via the sink nodes at intervals of Δt to collect potentials of sensor nodes. Potential request packets are broadcasted within p hops from the sink nodes, and then, return to the sink nodes collecting potential values of visited nodes. The interval of potential request packet emission Δt is set to 50 s. Each node can be arrived within 2 hops from a sink node in the network of Fig. 3 and, therefore, p is set to 2. In other words, the controller collects information of all nodes and $\boldsymbol{H}$ is set to $\boldsymbol{I}_{N\times N}$.

Figures 6(a) and 6(b) show potential changes of our proposal. In case, the monitored information is not always the latest. In our proposal, $D_c(t)$ becomes smaller than



(a) Prediction, $r = 10^{-5}$ (b) Prediction, $r = 10$

Figure 6. Potential change of each node (communication cost)



(a) Prediction, $r = 10^{-5}$ (b) Prediction, $r = 10$

Figure 7. Data arrivals at each sink node (communication cost)

1.7881 at $2,000$ s from traffic changes with $r = 10^{-5}$ and at $2,190$ s from traffic changes with $r = 10$. As a result, even with constraints such as communication delay, the potential convergence is accelerated by 77% due to an optimal feedback. Figures 7(a) and 7(b) show the number of data packet arrivals every 100 s at each sink node and the averaged number of them. As shown in these figures, the average number of data packet arrivals in our proposal is lower than that in the non-predictive mechanism. It is because the congestion of traffic occurs around sink nodes due to under layer protocols. That is not a critical problem in our proposal.

In this subsection, we show that our proposal enhances the convergence speed of potentials even with restrictions of wireless sensor networks. Moreover, the latest potentials can be estimated by past potentials because the dynamics of potentials is described as the linear model, i.e., (2). Therefore, the convergence speed will be improved still more if the controller estimates the latest potentials with the past potentials that are collected by the controller and calculates control inputs using the estimated potentials.

V. Conclusion and Future Work

In self-organizing systems, each component behaves according to only local information, which leads to slow convergence. We propose and evaluate potential-based routing with an optimal feedback, where a controller predicts the future state of the system and provide an optimal feedback to the system for the fastest convergence. Simulation results show that our proposal can facilitate the convergence of potentials. Moreover, this accelerated potential convergence can be achieved even if the controller can monitor nodes only within one hop from sink nodes and the monitored states are not always the latest ones.

Concerning the computation burden to solve the optimal control problem, we are currently investigating model reduction based implementation [13]. Furthermore, we are now trying a distributed predictive mechanism where each component predicts the future state of the entire system using its and its neighbor nodes' historical information. In a predictive mechanism consisting of an observer and a controller, considerable control overhead is needed for collecting network-state information when the network size is large. With a distributed predictive mechanism, control overhead can be reduced because it is not necessary to collect network information.

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