Proposal and Evaluation of a Predictive Mechanism for Ant-based Routing

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***Abstract*—To tackle problems emerging with rapid growth of information networks in scale and complexity, bio-inspired self-organization is considered one of promising design principles of a new generation network, which is scalable, robust, adaptive, and sustainable. However, self-organizing systems would fall into a local optimum or converge slowly under some environmental conditions. Therefore, it may take a long time for self-organizing systems to adapt to environmental changes. In order to adapt to dynamically changing conditions of information networks, each component needs to predict the future state of its neighbors from their past behaviors and to adapt its movement to conform to the predicted states. There are several investigations into self-organization with prediction in the field of biology, but its application to information network systems and technologies needs more discussion. In this paper, we take AntNet, an ant-based routing protocol, as an example and consider a mechanism to accelerate path convergence with prediction. The proposed mechanism is compared with AntNet from viewpoints of the recovery time, path length, and control overhead. Simulation results show that our predictive mechanism can accelerate path convergence after environmental changes.**

Keywords-self-organization; prediction; routing; Ant Colony Optimization (ACO)

I. Introduction

Due to rapid growth of information networks in scale and complexity, conventional information network systems and technologies, which are based on central control or distributed control with global information, are to face limitations. An information network system adopting conventional control technologies suffers from the considerable overhead in managing up-to-date information to grasp dynamically changing conditions as the scale and mobility increase. Considering the problems that would emerge in future networking, there have been research activities such as GENI [1] and NSF FIA [2] in the USA, FP7 [3] in Europe, and the AKARI Project [4] in Japan to establish a novel network architecture and relevant technologies. Taking into account requirements for new generation networks, i.e., scalability, adaptability, robustness, and sustainability higher than ever before, the paradigm shift is needed to organize and control the whole network system in a fully distributed and self-organizing manner. Moreover, in order to realize information network systems and technologies, which can adapt to dynamically changing conditions in a timely manner, it is necessary that systems should be controlled considering the future state of systems, which is predicted by observing behaviors of systems.

Self-organization is a natural phenomenon of distributed systems, where components behave individually and autonomously. In a self-organizing system, they behave in accordance with simple rules and information locally available to a component. Through direct or indirect interactions among components, a global behavior or pattern emerges on a macroscopic level without central control. In a self-organizing system, the cost of information management can be considerably reduced since none needs up-to-date information of the entire system or many other components. Moreover, local failures and small environmental changes are handled locally and immediately by neighbor components without involving the entire system. Therefore, self-organizing system can recover from failures and adapt environmental changes automatically. In particular, biology is mines of self-organization models that can be applied to information networking such as routing, synchronization, and task assignment since biological systems are inherently self-organizing [5].

However, it is pointed out that self-organizing control has some disadvantages [6]. First, in a large-scale system, it may take a long time for a global pattern to emerge because it appears as a consequence of interaction between autonomous components. Second, self-organization, which uses only local information, would fall into a local optimum while a conventional system using global information can reach an optimal solution in most cases. Furthermore, a self-organizing system is not controllable in general, whereas unnecessity of control is one of the significant aspects of self-organization. These disadvantages lead to the slow adaptation to environmental changes in a self-organizing system. Ant Colony Optimization (ACO), which is a heuristic in the traveling salesman problem, is a mathematical model of foraging behavior of ants [7]. Because of the similarity, it has been adopted as a routing mechanism by many researchers [8], [9], [10]. Previous research shows

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that AntNet is superior to conventional mechanisms in robustness against failure, control overhead, and communication performance [11]. However, the time required for path establishment to converge depends on the length of the path, i.e., the distance between a source node and a destination node [12]. Moreover, a considerable amount of control messages generated in path establishment depletes network bandwidth and hinders data message transmission.

In [13], a predictive mechanism was proposed for faster consensus in flocking birds. In self-organized flocking with a predictive mechanism, each component predicts the future state of its neighbors from their past behaviors and adapts its movement to conform to the predicted states. When applied to self-organized behavior of flocking birds, a predictive mechanism is considered to contribute to faster self-adaptation to environmental changes. There are several investigations into self-organization with prediction in the field of biology [14], [15], but its application to information network systems and technologies needs more discussion. In this paper, we adapt a predictive mechanism to ant-based routing since ant-based routing is a typical self-organizing system and its property and performance have been researched well.

In this paper, we take AntNet [16], which is an ant-based routing, as an example of self-organization based control and propose a predictive mechanism for AntNet. In an ant-based routing mechanism, a shorter path collects more pheromones than longer paths. Then the preferentially accumulated pheromones attract more ants that further deposit pheromones on the path. Such positive feedback eventually leads to all ants' following a single path. Therefore, a increase rate of pheromone values implicitly indicates the goodness of a path. In our mechanism, each node predicts a path that will obtain a large amount of pheromones from historical information about pheromone accumulation. Then, it boosts pheromone accumulation on the predicted path for faster convergence. We show that prediction helps adaptation to environmental changes through simulation experiments.

The reminder of this paper is organized as follows. First, we describe AntNet in Section II. Then we propose and explain a predictive mechanism for AntNet in Section III and give simulation results and discussion of our proposal in Section IV. Finally, in Section V, we provide conclusion and future work.

II. AntNet

We use AntNet as a basis of our investigation of self-organization with prediction. In this section, we give a summary of a mechanism of AntNet.

A. Overview

AntNet [16] is an adaptive best-effort routing algorithm in packet-switched wired networks based on the principles of ACO. AntNet introduces two types of control messages called ants, i.e., *forward ants* and *backward ants*. A source node proactively launches mobile agents called forward ants at regular intervals. A forward ant stochastically selects a neighbor node to visit in accordance with the amount of *pheromones*, which are laid by ants. On a way to a destination node, a forward ant records its path and the time of arrival at each node in order to evaluate the quality of the travelled path.

When a forward ant arrives at the destination node, it changes to a backward ant. A backward ant returns to the source node on the disjoint reverse path of the forward ant, updating pheromone values along the way. When the path has better quality, i.e., smaller delay, a backward ant increases a pheromone value for the neighbor node it came more.

Each data packet is forwarded to a neighbor node as a next hop node according to the pheromone values that backward ants have updated. Since a neighbor node with a larger pheromone value is more likely to be selected, a data packet reaches a destination node following a shorter path.

B. Self-Organization based Path Establishment and Maintenance

In AntNet, each node has a pheromone table $\mathcal{T}^k$ as routing information. $\mathcal{T}^k = \{\mathcal{T}^k_d\}$ where $\mathcal{T}^k_d$ is a list of pheromone values $\tau^k_{nd} \in [0,1]$ for all neighbor node $n \in N_k$ regarding destination node d, i.e., $\mathcal{T}^k_d = \{\tau^k_{nd}\}$. N_k is a set of neighbor nodes of node k. Source node s establishes and maintains a path to destination node d by sending forward ants at regular intervals. A forward ant stochastically selects a next hop node to visit. The probability p_{nd} that neighbor node $n \in N_k$ is selected as a next hop node of node k for destination node d is given as follows.

If there is no pheromone information for destination node d at node k, a next hop node is randomly chosen.

$$p_{nd} = \begin{cases} 1, & \text{if } |N_k| = 1 \\ \frac{1}{|N_k|-1}, & \text{if } |N_k| > 1 \land n \neq v_{i-1} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

Otherwise, selection is performed based on the pheromone value τ_{nd}.

$$p_{nd} = \begin{cases} 1, & \text{if } |N_k| = 1 \\ \frac{1}{|N_k|-1}, & \text{if } |N_k| > 1 \land {}^{\forall}n \in V_{s\to k} \land n \neq v_{i-1} \\ \frac{\tau^k_{nd}+\alpha l_n}{1+\alpha(|N_k|-1)}, & \text{if } |N_k| > 1 \land {}^{\exists}n \notin V_{s\to k} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where $V_{s\to k} = \{s, v_1, v_2, \cdots, v_{i-1}\}$ is a list of nodes that the forward ant has visited before arriving at node k at the i-th step and v_{i-1} is an identifier of the $(i-1)$-th node on the path. l_n is a variable indicating the degree of congestion for neighbor node n at node k, which is given by $1 - \frac{q_n}{\sum_{j\in N_k} q_j}$ and q_n is the number of messages waiting in a sending buffer for neighbor node n. $\alpha \in [0,1]$ is a coefficient. A larger α allows forward ants to select a next hop node in accordance with local traffic condition. As a consequence, path convergence becomes hard to accomplish. On the contrary, with α close to zero, a path traversing congested links would be established. A forward ant whose travelled hop count reaches the predetermined TTL is discarded at a node.

A forward ant changes to a backward ant when it reaches the destination node d and returns to the source node s following the disjoint path that the forward ant traversed while updating pheromone values at visited nodes. The pheromone value τ_{nd}^k for neighbor node $n \in N_k$ at node k is updated by (3).

$$\tau_{nd}^k \leftarrow \begin{cases} \tau_{nd}^k + r(1-\tau_{nd}^k), & \text{if } n = f \\ \tau_{nd}^k - r\tau_{nd}^k, & \text{otherwise} \end{cases} \tag{3}$$

where f corresponds to the previous node that the backward ant visited just before arriving at node k, i.e., the first node of the path from the node to the destination node. r reflects the goodness of the path, on the transmission delay from node k to the destination node d. The smaller the delay is, the larger r is. Consequently, the shortest path among paths that forward ants found has the largest amount of pheromones and attracts most of forward ants.

The parameter r, which determines the increasing amount of pheromones, is evaluated from the trip time $T_{k\to d}$ and the local statistical model $\mathcal{M}^k = \{\mathcal{M}_d^k\}$, where $\mathcal{M}_d^k = \{W_k^d, \mu_d^k, \sigma_d^k\}$.

$$r = c_1\left(\frac{W_k^d}{T_{k\to d}}\right) + c_2\left(\frac{I_{sup} - I_{inf}}{(I_{sup} - I_{inf}) + (T_{k\to d} - I_{inf})}\right) \tag{4}$$

where $T_{k\to d}$ is the ant's trip time from node k to destination node d. W_k^d is the best traveling time of ants from node k to destination node d over the last observation window of size w, and (μ_d^k, σ_d^k) are the average and dispersion of the traveling time of ants over the last observation window. I_{sup} and I_{inf} are estimates of the limit of an approximate confidence interval for μ, which are given by (5) and (6).

$$I_{inf} = W_k^d \tag{5}$$

$$I_{sup} = \mu_d^k + z(\sigma_d^k/\sqrt{w}), \text{ with } z = 1/\sqrt{1-\gamma} \tag{6}$$

where c_1, c_2, and γ are coefficients, and (c_1, c_2, γ) is set to $(0.7, 0.3, 1.7)$ in [16].

C. Transmission of Data Messages

A data message is forwarded to a next hop node based on pheromone values, where the selection probability R_{nd}^k that neighbor node n is chosen as a next hop node for destination node d is given as $\frac{(\tau_{nd}^k)^\epsilon}{\sum_{j\in N_k}(\tau_{jd}^k)^\epsilon}$ $(\epsilon \geq 0)$. Therefore, data messages follow the shortest path established by forward and backward ants.

III. Predictive Mechanism for AntNet

In this section, we propose a predictive mechanism for AntNet. We consider prediction only from pheromone changes and pheromone control with updating it independently of internal control in AntNet.

A. Overview

It is difficult for components to adapt faster to dynamically changing conditions of networks in a self-organizing system because each component uses only local current information. Therefore, we take AntNet as example of self-organization based control and consider a predictive mechanism in which components observe their past behaviors, predict the future state of the system, and then control their behaviors in accordance with the predicted future state.

In our proposal, we introduce *predictive ants* in addition to two types of control messages, i.e., forward ants and backward ants, and *increase rates of pheromone values* are adopted as an indicator for predictive control. Each node launches predictive ants at regular intervals. A predictive ant that arrives at a neighbor node remembers increase rates of pheromones in the neighbor node and returns to its originating node. On its return, the predictive ant boosts pheromone accumulation for the neighbor node for faster path convergence if its increase rates are high.

Each node has a pheromone table $\mathcal{T}^k$ as routing information. $\mathcal{T}^k = \{\mathcal{T}_d^k\}$ where $\mathcal{T}_d^k$ is a list of pheromone values $\tau_{nd}^k \in [0,1]$ for all neighbor node $n \in N_k$ regarding destination node d, i.e., $\mathcal{T}_d^k = \{\tau_{nd}^k\}$. N_k is a set of neighbor nodes of node k. At the beginning, τ_{nd}^k is initialized to $\frac{1}{|N_k|}$. In our proposal, forward ants and backward ants behave similar to AntNet. That is, a forward ant stochastically selects a next hop node to visit in accordance with pheromone values by (1) and (2), and the pheromone value is updated by backward ants by (3). The pheromone value is used for next-hop selection by ants and data messages.

B. Increase Rates of Pheromone Values

In our proposal, each node also has a increase rate table $\mathcal{E}^k$ for prediction. $\mathcal{E}^k = \{\mathcal{E}_d^k\}$ where $\mathcal{E}_d^k$ is a list of increase rates of the pheromone values $e_{nd}^k \in [0,1]$ for all neighbor node $n \in N_k$ regarding destination node d. At the beginning, e_{nd}^k is initialized to zero.

Node k that receives a backward ant from node $f \in N_k$ updates the increase rate $e_{nd}^k \in [0,1]$ of all its neighbor nodes $n \in N_k$ regarding destination node d by (7).

$$e_{nd}^k \leftarrow \begin{cases} (1-\beta)e_{nd}^k + \beta, & \text{if } n = f \\ (1-\beta)e_{nd}^k, & \text{otherwise} \end{cases} \tag{7}$$

where $\beta \in [0,1]$ is a parameter that determines the weight of individual increment of pheromones.

C. Behavior of Predictive Ants

In our proposal, each node k predicts better paths that will obtain a large amount of pheromones from sending predictive ants to its all neighbor node at regular intervals Δt_p. A predictive ant that arrives at neighbor node $f \in N_k$ remembers node f's increase rate table, i.e., $\mathcal{E}^f$, and returns to its originating node k while updating pheromone values at node k. The pheromone value τ_{nd}^k for neighbor node $n \in N_k$ at node k is updated by (8) if the max value in the increase rate table of node f regarding destination node d, i.e., max $e_{n'd}^f$ $(n' \in N_f)$, exceeds 0.5.

$$\tau_{nd}^k \rightarrow \begin{cases} \tau_{nd}^k + p(1-\tau_{nd}^k), & \text{if } n = f \\ \tau_{nd}^k + p\tau_{nd}^k, & \text{otherwise} \end{cases} \tag{8}$$

where p is a parameter that determines the increasing amount of pheromones. Even if the max value of $e_{n'd}^f$ exceeds 0.5, the pheromone values are not updated when $\mathcal{E}_d^f$ has not been updated since node f received a predictive ant from node k at the last time.

Each node starts to send predictive ants when it receives a backward ant, and it stops sending predictive ants when it does not receive backward ants for a fixed period of time.

D. Transmission of Data Messages

A data message selects a next hop node based on pheromone values in the same way as AntNet, where the selection probability R_{nd}^k that neighbor node n is chosen as a next hop node for destination node d is given as $\frac{(\tau_{nd}^k)^\epsilon}{\sum_{j \in N_k} (\tau_{jd}^k)^\epsilon}$ $(\epsilon \geq 0)$. Therefore, data messages follow the shortest path established by forward and backward ants.

IV. Performance Evaluation

In order to evaluate adaptability to environmental changes of our proposal, we evaluate the time to recover from traffic changes.

A. Simulation Settings

We distribute 100 nodes on a 10×10 grid with separation of 30 m. We appoint a node at the top-left corner as a source node and one at the bottom-right corner as a destination node. The communication range is set to 30 m. Therefore, each node can communicate with four neighbors. The coefficient α in (2) is set to 0.004. Other parameters of AntNet are set in accordance with their default settings [16].

In order to establish the path considering the traffic, l_n, which is a variable indicating the degree of congestion for neighbor node n at node k, is given by

$$l_n = 1 - \frac{\lambda_{kn} T_s}{\sum_{j \in N_k} \lambda_{kj} T_s} \tag{9}$$

where λ_{nk} corresponds to the average arrival rate of data packets to the queue for sending to node n at node k, and T_s corresponds to the average processing time per one data packet. The one-hop transmission delay at link (n, k) is given by

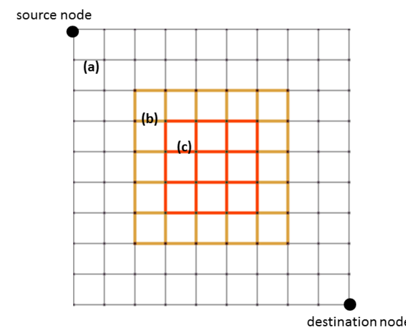

Figure 1. Network and congestion model in simulation where traffic near the center of the network increases after the network converges as shown in Table I.

Table I
TRAFFIC CHANGES IN SIMULATION

	(a)	(b)	(c)
λ (before)	$20 + R$	$10 + R$	$5 + R$
λ (after)	$20 + R$	$40 + R$	$60 + R$

$$cost(n, k) = \frac{|(n, k)|}{15} + \frac{\rho_{nk}}{1 - \rho_{nk}} T_s \text{ [ms]} \tag{10}$$

where ρ_{nk} is the average utilization rate of link (n, k), which is given by $(\lambda_{nk} + \lambda_{kn})T_s$, and $|(n, k)|$ corresponds to the Euclidean distance between node n and node k $(= 30 \text{ m})$. The average processing time T_s is set to 6.5 ms.

In this evaluation, we evaluate the recovery time, control overhead, convergence rate of AntNet with and without prediction. We first have the network converge to a state where ants repeatedly select the same path using original AntNet. Convergence of the network is defined as a state where the same path is selected by forward ants for 10 consecutive times. Convergence check is done everytime a backward ant reaches a source node. After the network converges, we cause traffic changes. At the beginning of the simulation, λ_{nk} of links between 6×6 nodes in the center of the network is set to $10 + R$ packet/s, λ_{nk} of links between 4×4 nodes in the center of the network is set to $5 + R$ packet/s, and λ_{nk} of other links is set to $20 + R$ packet/s (R is a random number in $[-0.5, 0.5]$). Once the network converges, λ_{nk} of links between 6×6 nodes in the center of the network is increased to $40 + R$ packet/s, and λ_{nk} of links between 4×4 nodes in the center of the network is increased to $60 + R$ packet/s as shown in Figure 1 and Table I.

Regarding performance measures, the recovery time is defined as the time from the occurrence of environmental change till path recovery. Path recovery is defined as the time when the network is converged and total delay of a created path from the source node to the destination node is smaller than (the minimum delay) $\times 1.05$. Path recovery

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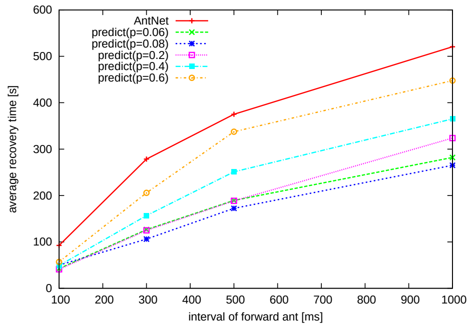

Figure 2. Path recovery time ($\Delta t_p = 100$ ms)

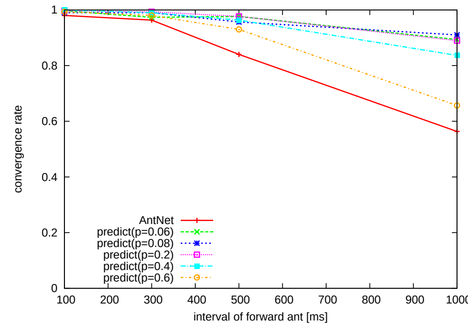

Figure 3. Convergence rate ($\Delta t_p = 100$ ms)

check is done everytime a backward ant reaches a source node. The control overhead corresponds to the total number of travelled hops of control messages until path recovery. The convergence rate is defined as ratio of path recovery within given simulation time, i.e., 1,000 s, to 300 simulation runs.

B. Results and Discussion

In this evaluation, the interval of predictive ant emissions, i.e., Δt_p, is set to 100 ms, and we change the interval of forward ant emissions from 100 ms to 1 s. The parameter β, which determines the weight of individual increment of pheromones in the increase rate of pheromones ((7)), is set to 0.2. The parameter p in (8) is changed from 0.06 to 0.6.

In each simulation, a path that runs through the center of the network is established by AntNet at first because the amount of traffic in the center of the network is small at the beginning of the simulation. Then, another path is reestablished avoiding the center of the network by AntNet or our proposal after traffic changes, i.e., the amount of traffic in the center of the network increases.

We show simulation results in Figures 2, 3 and 4. In these figures, the recovery time, convergence rate, and control overhead for the interval of forward ant emissions are depicted. The recovery time and control overhead in these figures show averaged values over 300 simulation runs for each interval of forward ants except for cases that convergence cannot be achieved by the end of a simulation run, i.e., paths fluctuate.

As shown in Figures 2 and 3, the recovery time of our proposal is shorter and the convergence rate of our proposal is higher than AntNet. Furthermore, our proposal is superior to AntNet regardless of the value of parameter p although we changes p widely. In original AntNet, a forward ant selects a next hop node in accordance with only current pheromone values. Then, most forward ants go through the path that has more pheromones than others even if there are other better paths. Therefore, it takes a long time to reestablish a shorter path when the quality of the existing path falls off because of environmental changes such as traffic changes. On the contrary, a next hop node is selected while taking changes of pheromone values into account in

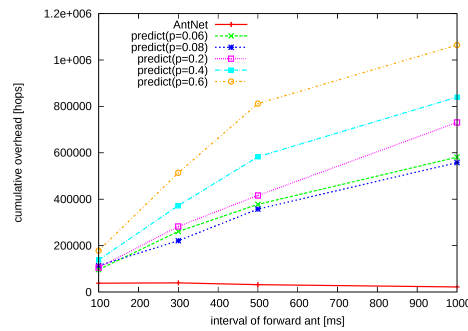

Figure 4. Cumulative overhead ($\Delta t_p = 100$ ms)

our proposal. Our proposal boosts pheromone accumulation on a shorter path whose pheromone values are still low but increasing, and this is the reason why path reestablishment after environmental changes is accelerated.

In our proposal, the recovery time is shorter and the convergence rate is higher especially when the parameter p is low as shown in Figures 2 and 3. In an ant-based routing mechanism, the stochastic path exploration in accordance with pheromone values plays an important role in the discovery of shorter paths. However, a forward ant selects a next hop node in an almost deterministic manner if the increasing amount of pheromones in our proposal is too large, i.e., p is too high. In consequence, a loose control with lower p leads to a better recovery time and a high convergence rate. Moreover, when p ranges between 0.06 and 0.2, there is not much difference in the recovery time and convergence rate in our proposal. In other words, we do not need to take so much care of parameter p setting.

As shown in Figure 4, control overhead of our proposal is much higher than that of AntNet. It is because each node that receives a backward ant regularly sends predictive ants to all its neighbor nodes for a fixed period of time in order to obtain neighbor nodes' information in our proposal. However, overhead of forward and backward ants is reduced because the recovery time is shortened with prediction. Moreover, overhead of predictive ants becomes trivial as the number of sessions becomes larger since predictive ants can collect increase rates for different destination nodes at one

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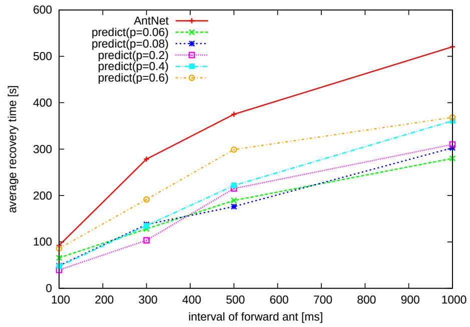

Figure 5. Path recovery time ($\Delta t_p = 1.0$ s)

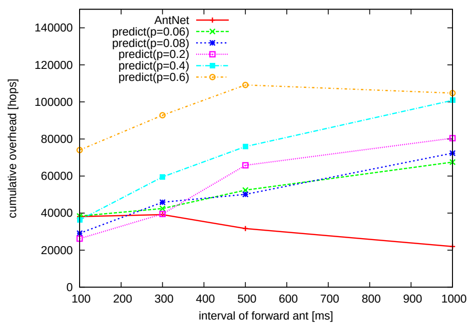

Figure 6. Cumulative overhead ($\Delta t_p = 1.0$ s)

time. It is noteworthy that control overhead can be much reduced with a larger interval ($\Delta t_p = 1.0$ s) of predictive ant emissions while the recovery time is kept shorter as shown in Figures 5 and 6.

In conclusion, the path recover from traffic changes is accelerated with prediction in this simulation settings. However, we need more discussion because the simulation setting is mere one case of network conditions.

V. Conclusion and Future Work

In a self-organizing system, each component behaves in accordance with only local current information, which leads to slow adaptation to environmental changes. Therefore, in order to adapt to dynamically changing conditions in a timely manner, it is necessary that systems should be controlled considering the future state of systems, which is predicted by observing behaviors of systems. In this paper, as an example of a predictive mechanism for self-organizing system, we propose and evaluate a predictive mechanism for AntNet. Simulation results show that our proposal can facilitate path reestablishment when the environment of the network changes. Even in a more realistic environment where ants are lost in the network, ants can reestablish other paths fast because they explore the network not deterministically but stochastically and positive feedback through pheromones leads to ants' following shorter paths.

As future work, we will evaluate our predictive mechanism in more real network environment, such as multiple sessions and a random topology.

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