A Predictive Mechanism for Enhancing Adaptability of Self-Organised Routing

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Abstract

To tackle problems emerging with rapid growth of information networks in scale and complexity, bio-inspired self-organisation is a promising design principle for future networks. However, self-organising systems fall into local optima or converge slowly under some environmental conditions. This can make self-organising systems slow to adapt to environmental change, despite robustness against environmental change being an important feature expected from self-organisation. To adapt to dynamically changing conditions while retaining its distributed nature, each component predicts the future state of its neighbours from past behaviour, and proceeds according to the predicted states. We take AntNet, an ant-based routing protocol, and add a mechanism to accelerate path convergence with prediction. Simulation results show that introducing our predictive mechanism reduces recovery time by up to 60%.

Keywords

Self-organisation; prediction; routing; bio-inspired networks; ant colony optimisation; ACO; convergence; adaptability

BIOLOGICAL NOTE

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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 changing conditions. There has been active research regarding problems likely to emerge in future networking, including GENI (NSF, 2007) and NSF FIA (NSF, 2010) in the United States, FP7 (European Commission, 2006) in Europe, and the NWGN (New-Generation Network) Project (NICT, 2008) in Japan, in order to establish a novel network architecture and relevant technologies. Future network requirements such as scalability, adaptability, robustness, and sustainability, will require new methods of organising and controlling network systems in a fully distributed and *self-organising manner*. In particular, realisation of network systems that can quickly adapt to changing conditions will require systems that can consider their own future state.

Self-organisation is a natural phenomenon of distributed systems, where components behave individually and autonomously. In a self-organising system, each component follows simple rules using locally available information. Through direct or indirect interactions among components, global behaviour patterns emerge on a macroscopic level without central

control. In a self-organising system, the cost of information management can be considerably reduced, because up-to-date information regarding the entire system or many other components is unnecessary. Moreover, local failures and small environmental change are handled locally and immediately by local components. Therefore, a self-organising system is expected to automatically recover from failures and adapt to environmental change, without involving centralised control. This property is quite important for realising future networks. In particular, biological systems are inherently self-organising, implementing self-organisation models that can be applied to information networking such as routing, synchronisation, and task assignment (Meisel et al., 2010; Feng et al., 2013; Zhang et al., 2013; Zheng and Sicker, 2013; Zhang et al., 2014).

Although self-organisation has various benefits, such control has critical disadvantages that complicate implementation in industrial and business systems (Dressler, 2008). For example, 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. Also, self-organising systems that use only local information can fall into a local optima, while conventional systems using global information can often reach an optimal or semi-optimal solution. These disadvantages can lead to slow adaptation to environmental change in self-organising systems. Therefore, we introduce a predictive mechanism to self-organising systems in order to improve adaptation to environmental change, one challenging problem for implementation of self-organising control. Some bio-groups are known to have the ability of prediction, that is, each component predicts future behaviour of its neighbors from their past behaviour, and adapts movement to conform to the predicted behaviour. Zhang et al., proved that a predictive mechanism incorporated in a model of flocking birds made its convergence speed faster (Zhang et al., 2008). In self-organised flocking with a predictive mechanism, each component achieves faster self-adaptation to environmental changes. It is pointed out that *'historical local information is equivalent to current global information'*, and in this sense, a predictive mechanism can contribute to faster self-adaptation to environmental change with only local information when applied to self-organised behaviour of flocking birds. Montague et al., and Summerfield et al., also provide investigation of self-organisation with prediction in the field of biology (Montague et al., 1995; Summerfield et al., 2006), but the introduction of prediction to self-organised information network systems needs further discussion.

In this paper, we show advantages obtained by introducing a predictive mechanism to self-organizanising network systems through inclusion of a predictive mechanism in AntNet (Di Caro and Dorigo, 1998), which is a self-organising routing mechanism based on ant colony optimisation (ACO) and does not have predictive feature inherently. ACO, a heuristic in the travelling salesman problem, is a mathematical model of foraging behaviour of ants (Dorigo et al., 2006; Abdelaziz et al., 2012; Ahangarikiasari et al., 2013), and many researchers have applied ACO to routing mechanisms in information networks due to similarities between the two systems (Sim and Sun, 2003; Saleem et al., 2011; Saleem and Fisal, 2012). Previous research shows that AntNet (Di Caro and Dorigo, 1998) is superior to conventional mechanisms regarding robustness against failure, control overhead, and communication performance (Dhillon and Van Mieghem, 2007). However, the time required for path establishment to converge depends on the length of the path, defined as the minimum hop count from a source node to a destination node (Carvelli and Sebastiani, 2011). Moreover, the large amount of control messages generated during path establishment depletes network bandwidth, hindering data message transmission (Di Caro and Dorigo, 1998). It is therefore essential to accelerate convergence in self-organising systems. There are various other ACO-based routing mechanisms, but they too have the same inherent problems as AntNet. AntHocNet (Di Caro et al., 2005) is one such example for wireless networks, the target environment in this paper, but we use AntNet because it is one of the most typical ACO-based routing mechanisms, and is designed with simple rules. These features allow easy implementation to other ant-based routing mechanisms (Zhang et al., 2004; Moghanjoughi et al., 2008; Radwan et al., 2011). Of course, ACO and AntNet have tuning parameters for accelerating convergence, but fast convergence via parameters introduces further control overhead necessary for exchanging local information between adjacent nodes to move the entire system to a new stable state. Accordingly, we need another acceleration mechanism that introduces little overhead, one that performs only when it is likely that fast convergence to a new environment is actually necessary. For this purpose, we can easily introduce a predictive mechanism by which each component in a self-organising system behaves according to a future state predicted from past information. Unlike (Zhang et al., 2008), we take an ant-based routing mechanism in a wireless network scenario.

In an ant-based routing mechanism, a shorter path collects more pheromones than do longer paths. The accumulated pheromones attract more ants, which further deposit pheromones on the path, and this positive feedback eventually leads to all ants following a single path; increased pheromone values implicitly indicate 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. Nodes then boost pheromone increases on the predicted path for faster convergence. Self-organising control with a predictive mechanism is thus not only tolerant, but also highly adaptable to environmental change. We show that prediction promotes adaptation to environmental change through simulation experiments on grid and random networks, and that paths established by prediction are more optimal than those formed by the original AntNet. Moreover, we show that the control overhead of predictive ants can be reduced, because prediction reduces the control overhead of forward and

backward ant transmissions.

The remainder of this paper is organised as follows: First, we describe the original AntNet in Section II, and propose and explain a predictive mechanism using increased pheromones for AntNet in Section III. We then evaluate the adaptability of the proposed method through simulation, and give results and a discussion in Section IV. Finally, in Section V we present our conclusions and suggest areas for future work.

II. ANTNET

We consider AntNet as the basis of our investigation of self-organisation with prediction. In this section, we give a brief summary of the AntNet mechanism.

A. Overview

AntNet (Di Caro and Dorigo, 1998) is an adaptive best-effort routing algorithm in packet-switched networks based on the principles of ACO. AntNet introduces two types of control messages called 'ants,' *forward ants* and *backward ants*. A source node proactively launches mobile agents called forward ants at regular intervals. A forward ant stochastically selects a neighbour node to visit according to the amount of *pheromones*, which are laid by ants. On the way to a destination node, a forward ant records its path and the time of arrival at each node to evaluate the quality of the travelled path. When a forward ant arrives at a destination node, it changes into a backward ant. A backward ant returns to the source node on the loop-free reverse path of the forward ant, updating pheromone values along the way. When a path has better quality (smaller delay), a backward ant increases the pheromone value of the neighbour node it came from.

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

B. Path Establishment and Maintenance

In AntNet, each node has a pheromone table $\mathcal{T}^k$ for 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 neighbour node $n \in N_k$ (a set of neighbour nodes of node k) regarding destination node d, $\mathcal{T}_d^k = \{\tau_{nd}^k\}$. 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 neighbour 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.

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

where v_{i-1} is an identifier of the $(i-1)$-th node that the forward ant visited just before arriving at node k at the i-th step. Otherwise, selection is performed based on the pheromone value τ_{nd}:

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

where $V_{s \to k} = \{s, v_1, v_2, \cdots, v_{i-1}\}$ is a list of nodes that the forward ant visited before arriving at node k. l_n is a variable indicating the degree of the congestion for neighbour 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 neighbour node n. $\alpha \in [0,1]$ is a coefficient. From Eq. (1), it is clear that a larger α allows forward ants to select a next hop node according to local traffic conditions. As a consequence, path convergence becomes difficult. In contrast, 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 destination node d, and returns to source node s following the loop-free path it traversed as a forward ant. While doing this, it updates pheromone values at visited nodes. The pheromone value τ_{nd}^k for neighbour node $n \in N_k$ at node k is updated by Eq. (3):

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

where f corresponds to the previous node that the backward ant visited just before arriving at node k, the first node of the path from the node to the destination node. r reflects the goodness of the path, based on the transmission delay from node k to destination node d; the smaller the delay is, the larger r is. (See below for a detailed definition.) Consequently, the shortest path among paths that forward ants have found has the largest amount of pheromones and attracts the most forward ants. In AntNet, as the cycle of this positive feedback mechanism becomes shorter by decreasing the interval of forward ant emissions Δt_f, the speed of convergence becomes faster but the control overhead of forward and backward ants increases, which greatly hinders data transmission. Moreover, further control overhead occurs with increased network size, because the time required for forward ants to wander from sources to destinations rises exponentially, resulting in longer convergence time. We therefore propose in the following section a predictive mechanism that accelerates the convergence speed of established paths while retaining low control overhead.

The parameter r, which determines the amount of pheromone increase, is calculated from the ant's trip time from node k to destination node d, which is defined as $T_{k \to d}$, and the local statistical model $\mathcal{M}^k$, which is given by $\{\mathcal{M}_d^k\} = \{W_k^d, \mu_d^k, \sigma_d^k\}$, where W_k^d is the best travelling time from node k to destination d over the last observation window of size w, and μ_d^k and σ_d^k are respectively the average and dispersion of travelling times over the last observation window w. Specifically, r is given by

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

where I_{sup} and I_{inf} are estimates of the limit of an approximate confidence interval for μ, given by

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

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

where c_1, c_2, and z are coefficients, and (c_1, c_2, z) is set to $(0.7, 0.3, 1.7)$ following (Di Caro and Dorigo, 1998). Moreover, r is squashed by means of a function $s(x)$:

$$s(x) = \left(1 + \exp \left(\frac{a}{x |N_k|} \right) \right), \tag{7}$$

$$r \leftarrow \frac{s(r)}{s(1)}, \tag{8}$$

where a is a coefficient.

In this paper, we use $m \times r$ ($m \in (0, 1]$) as a substitute for r in Eq. (3). For fast convergence of pheromones against environmental change, m may be set to 1.0 as in the original AntNet. However, we found that doing so leads to large path fluctuations. We therefore set m to a rather moderate value of 0.5, which we expect to result in fast convergence without path fluctuations in the proposed predictive mechanism.

A data message is forwarded to a next hop node based on pheromone values, where the selection probability R_{nd}^k that neighbour node n is chosen as the next hop node toward 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 among paths that forward ants found.

III. PREDICTIVE MECHANISM FOR ANTNET

In this section, we propose a predictive mechanism for AntNet. We consider prediction only from pheromone changes (Figure 1) and updates of pheromones independent of the internal control in AntNet.

A. Overview

In the original AntNet, it is difficult for the system to quickly adapt to changing network conditions, because each component uses only current local information. Our approach introduces a predictive mechanism in which components observe their past behaviour, predict the future state of the system, and then control their behaviour according to the predicted future state.

In the proposed method, AntNet is modified as follows. We introduce *predictive ants* alongside the forward and backward ants, and use *increased rates of pheromone values* as an indicator for predictive control. Each node launches predictive ants at regular intervals Δt_p ($< \Delta t_f$). A predictive ant arriving at a neighbour node remembers the increased rate of pheromones in the neighbour node, and returns to its originating node. On its return, the predictive ant boosts pheromone accumulation for the neighbour node for faster path convergence if its increase rates are high. The predictive ants increase control overhead, but in turn the overhead caused by forward and backward ants is reduced because prediction shortens the recovery time,
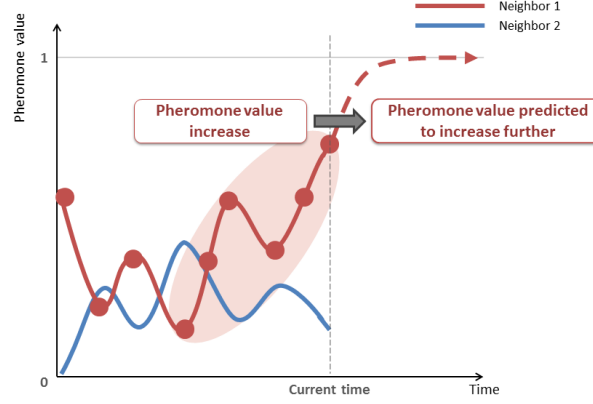
Figure 1. Prediction with increased pheromones rate. A path whose pheromones are increasing obtains a large amount of pheromones.

and predictive ants can furthermore simultaneously collect the increase rate of different destination nodes. Our predictive mechanism therefore accelerates the convergence speed of path establishment with low control overhead.

Each node uses a pheromone table $\mathcal{T}^k$ as routing information, as in the original AntNet. $\mathcal{T}^k = \{\mathcal{T}_d^k\}$, where $\mathcal{T}_d^k$ is a list of pheromone values $\tau_{nd}^k \in [0,1]$ for all neighbour node $n \in N_k$ regarding destination node d, $\mathcal{T}_d^k = \{\tau_{nd}^k\}$. N_k is a set of neighbour nodes of node k. τ_{nd}^k is initialised to $\frac{1}{|N_k|}$. In the proposed method, forward and backward ants behave as in AntNet. Namely, a forward ant stochastically selects a next hop node to visit according to pheromone values by Eq. (1) and Eq. (2), and pheromone values are updated by backward ants by Eq. (3). The pheromone value is used for next-hop selection by ants and data messages.

In the proposed method, each node has an increase rate table $\mathcal{E}^k$ for prediction in addition to the pheromone table $\mathcal{T}^k$. $\mathcal{E}^k = \{\mathcal{E}_d^k\}$, where $\mathcal{E}_d^k$ is a list of increase rates of the pheromone values $e_{nd}^k \in [0,1]$ for all neighbour node $n \in N_k$ regarding destination node d. e_{nd}^k is initialised to zero.

Node k, which receives a backward ant from node $f \in N_k$, updates the increase rate $e_{nd}^k \in [0,1]$ of all its neighbour nodes $n \in N_k$ regarding destination node d by Eq. (9):

$$e_{nd}^k \leftarrow \begin{cases} (1-\beta)e_{nd}^k + \beta, & \text{if } n = f \\ (1-\beta)e_{nd}^k, & \text{otherwise} \end{cases}, \tag{9}$$

where $\beta \in [0,1]$ is a parameter that determines the weight of individual pheromone increments. Eq. (9) slowly changes the increase rate e_{nd}^k, because rapid changes lead to system instability.

B. Pheromone Update by Predictive Ants and Data Transmission

In the proposed method, each node k predicts better paths that will possibly obtain a large amount of pheromones by sending predictive ants to its all neighbour node at regular intervals Δt_p. A predictive ant that arrives at neighbour node $f \in N_k$ remembers node f's increase rate table, $\mathcal{E}^f$, and returns to its originating node k. When the predictive ant returns, the pheromone table of node k is updated. The pheromone value τ_{nd}^k for neighbour node $n \in N_k$ at node k is updated by Eq. (10) if the maximum value in the increase rate table of node f regarding destination node d, $\max e_{n'd}^f$ $(n' \in N_f)$, exceeds θ_e.

$$\tau_{nd}^k \rightarrow \begin{cases} \tau_{nd}^k + p(1 - \tau_{nd}^k), & \text{if } n = f \\ \tau_{nd}^k + p\tau_{nd}^k, & \text{otherwise} \end{cases}. \tag{10}$$

Here, p is a parameter that determines the increasing amount of pheromones. θ_e is a threshold of the value of an pheromone increase rate. A neighbour node whose increase rate exceeds θ_e is considered to collect further pheromones. A lower θ_e allows predictive ants to update pheromone values on the path with a low pheromone increase rate. In consequence, the pheromone values on longer paths may be increased by prediction. On the contrary, it is difficult to adapt to environmental change with higher θ_e. Therefore, θ_e is set to 0.5 in numerical examples. Even if the max value of $e_{n'd}^f$ exceeds θ_e, the pheromone values are not updated when $\mathcal{E}_d^f$ has not been updated, because node f received a predictive ant from node k the last time. Similar to the pheromone increase rate, the pheromone value τ_{nd}^k changes slowly as shown in Eq. (10) to avoid system instability. Moreover, forward and backward ants rarely visit nodes that have a heavy load or are distant from any source or destination node, because the positive feedback through pheromones causes almost all ants to follow a short path
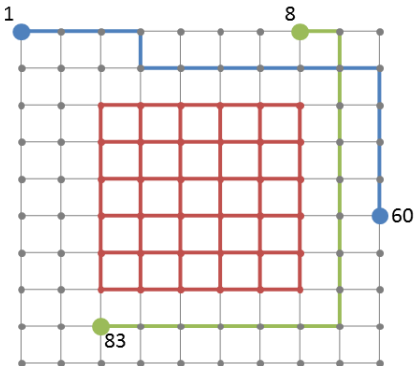
Figure 2. An example grid network with 100 nodes. Blue and green paths are target sessions. Background traffic takes place around the network centre with red nodes and links.

(see Section II). Our predictive mechanism therefore prevents nodes from sending predictive ants when they do not receive backward ants for a fixed period, the interval of forward ants $\Delta t_f \times 10$, to reduce the overhead of predictive ants.

A data message selects a next hop node based on pheromone values as in AntNet: the selection probability R_{nd}^k that neighbour 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 paths among those that forward ants found.

IV. PERFORMANCE EVALUATION

This section presents a detailed description of the adaptability of the proposed method by introducing predictive control. For that purpose, we will mainly focus on two metrics: the path recovery time from various environmental changes, and control overhead caused by our predictive mechanism as compared to the original AntNet. We use two network models (grid and random networks) in an event-driven simulation written in Visual C++. Using those network models, in Subsection IV-B we focus on performance metrics of one designated session, called the *target session* below. For the target session, packets are passed from a source node to a destination node according to our routing method (Eqs. (1) and (2)). We assume that other sessions generate packets at each node according a Poisson distribution. Then, in Subsections IV-B and IV-C, we will consider the case where traffic from other sessions changes. We also test the case where we explicitly have multiple target sessions. See Figure 2 for the grid network in the two target session cases; one is from node 1 to node 60 and the other from node 8 to node 83. In Subsection IV-C, we also focus on reduction of the control overhead (in the number of control packets) using a multiple-sessions scenario. In Subsection IV-D, we consider the case where several nodes fail simultaneously, to show that the proposed method has high adaptability to environmental change other than traffic changes, such as network failures.

A. Simulation Settings

The simulation focuses on one or more *target session(s)*. In the target session, data packets are generated and sent from source nodes to destination nodes with a Poisson process with an intensity of 1 packet per second. Data packets on the target session follow a path established by forward, backward, and predictive ants. We use the following network configuration in experiments for grid and random networks, respectively.

- Grid network:
  100 nodes are distributed on a 10×10 grid with 30 m separation.
- Random network:
  338 nodes are deployed uniform-randomly in a 300×300 m area. The number of nodes is determined so as to compose a connected graph.

In both cases, the communication range of each node is set to 30 m. The bandwidth for each link is 1 Mbps, and the propagation delay is 0.001 s per packet, regardless of the propagation distance. Following (Di Caro and Dorigo, 1998), the size of all types of ant packets is set to $24 + 8 \times |V|$ bytes, where $|V|$ is the number of nodes visited by the ant packet. The ant packet size increases with the number of visited nodes, because ants remember their visited nodes and arrival times at each node to update pheromone values according to the path delay. The data packet size is set to 1,000 bytes.

Table I
PARAMETER SETTINGS IN SIMULATION EVALUATION

Parameter	Value
Δt_f	100ms $\sim$ 1s
Δt_p	100ms
m	0.5
p	0.005 $\sim$ 0.1
β	0.2
θ_e	0.5

Table II
PARAMETER SETTINGS OF ANTNET IN (DI CARO AND DORIGO, 1998)

Parameter	Value
η	0.005
c	0.3
c_1	0.7
c_2	0.3
z	1.7
w	$5 \times (c/\eta)$
a	5
ϵ	1.4

In each of the above simulation settings, we confirmed that each path converges to a stable state where forward ants of each target session repeatedly select the same path within 1,000 s from the simulation start. After 1,000 s have passed from the simulation start, we change the environment, increasing traffic in Subsections IV-B and IV-C, and simulating a node failure in Subsection IV-D. Simulations end at 5,000 s from the simulation start. In the case of traffic changes in Subsections IV-B and IV-C, an increase of traffic from *background traffic sessions* occurs around the network centre at 1,000 s from the simulation start. The background traffic sessions are intended to create a hot spot in the network centre to investigate how the routing protocol detours around heavily loaded areas. Specifically, we set the background traffic session to be a session between two adjacent nodes within the network centre. The packet generation rate is 100 packets per second in each direction. See Figure 2 for the case of two target sessions and a background traffic session in the 100-node grid network. Because the background traffic sessions are one-hop sessions, their paths are deterministic irrespective of pheromone values, which are thus not affected. In the simulation, the background traffic sessions start packet transmission at 1,000 s. The hot spot is 6×6 nodes in the centre of the grid network, and 180×180 m in the centre of the random network. We evaluate the time and the control overhead for paths to recover after hot spot generation, with and without our predictive mechanism. When evaluating node failures (Subsection IV-D), failures occur after 1,000 s from the simulation start. In this experiment, 20 randomly chosen nodes fail in a 6×6 area in the centre of the grid network at 1,000 s.

Regarding performance metrics, we consider the recovery time to be the time from the occurrence of the environmental change until path recovery. However, it is difficult to rigorously define path recovery because our system is constantly changing. We therefore define path recovery in these experiments as 10 consecutive selections of the same path for more than 90% of all target sessions, with the average delay along the paths being less than 150% the average delay of last 10 paths selected by forward ants immediately before the environmental change. This path recovery check is carried out each time a backward ant reaches a source node. The control overhead is the total number of travelled hops of control messages (forward and backward ants in both mechanisms, and additionally predictive ants in the proposed method) of all target sessions from the occurrence of environmental change until path recovery. The recovery time and the control overhead shown in this paper are averaged values over 300 simulation runs for each parameter setting, except for cases where convergence was not achieved by the end of the simulation run. We explicitly note such cases in the results.

In the experiments, the interval of predictive ant emissions Δt_p is set to 100 ms, and we change the interval of forward ant emissions Δt_f from 100 ms to 1 s. The parameter β, which determines the weight of individual pheromone increments in Eq. (9), is set to 0.2. The parameter p, which increases the amount of pheromones in Eq. (10), is changed from 0.005 to 0.1. Table I shows the experimental parameter settings. We set the coefficient α in Eq. (2) to a comparatively small value to obtain path stability. α is set to 0.004 in the grid network and to 0.0004 in the random network. α is an important coefficient that affects the convergence speed of path establishment, but discussion of the relation of α and convergence speed is beyond the scope of this paper; refer to (Park and Kim, 2008) for a detailed discussion of this relation. In (Di Caro and Dorigo, 1998), α is set to 0.2–0.5 to find shorter paths, which leads to many path fluctuations. However, we need to set a to a small value (0.0004–0.004) for fair comparison, because we focus on path convergence in this paper. Moreover, it is difficult to
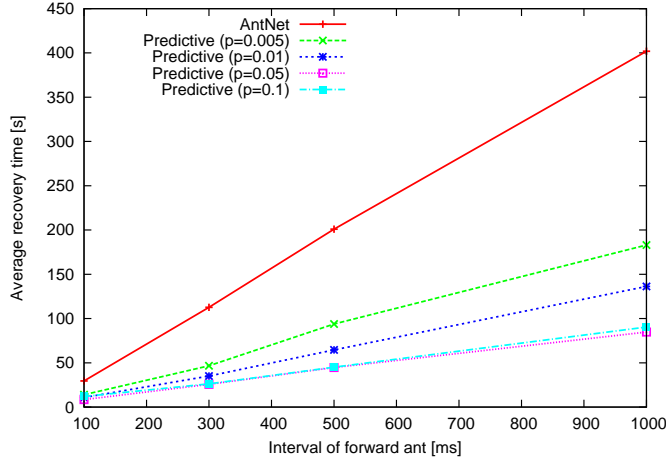
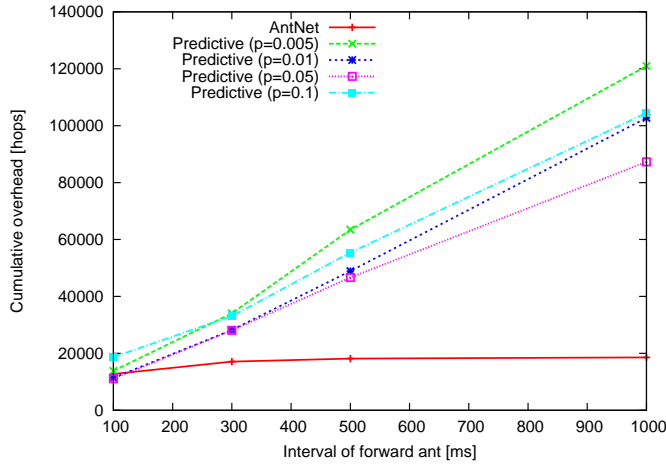Figure 3. Path recovery time (grid network, 1 session)

Figure 4. Cumulative overhead (grid network, 1 session)

compare the original AntNet and the proposed method with the default a setting (Di Caro and Dorigo, 1998), because the value of a depends on the network size. Other parameters of AntNet are set according to their default settings (Di Caro and Dorigo, 1998), shown in Table II.

B. Evaluation with Single Target Session

Here we present the simulation results with one target session to show that our predictive mechanism improves adaptability to environmental change. In each simulation, after traffic changes occur at 1,000 s, a short path that avoids the network centre is re-established by both AntNet and the proposed method.

Figures 3 and 4 show the simulation results with the grid network. We set the node at the top-left corner as the source node, and the one at the bottom-right corner as the destination node for the target session. These figures depict the recovery time and the control overhead for the interval of forward ant emissions. As shown in Figure 3, the recovery time of the proposed method is shorter than that of AntNet. Furthermore, the proposed method is superior to AntNet for any value of p. In the original AntNet, most forward ants go through a path that has more pheromones than others, even if there is a better path, because pheromone updates depend on current pheromone values. It therefore takes a long time to re-establish a shorter path when the quality of an existing path falls due to traffic or other environmental changes. In the proposed method, however, predictive ants update pheromone values at each node while taking into account changes of pheromone values on its neighbour nodes. The proposed method boosts pheromone accumulation on a shorter path whose pheromone values are still low but increasing, so path re-establishment after environmental change is accelerated.
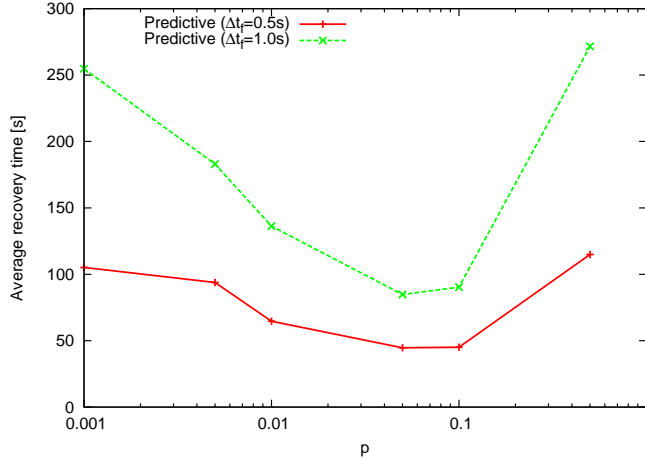
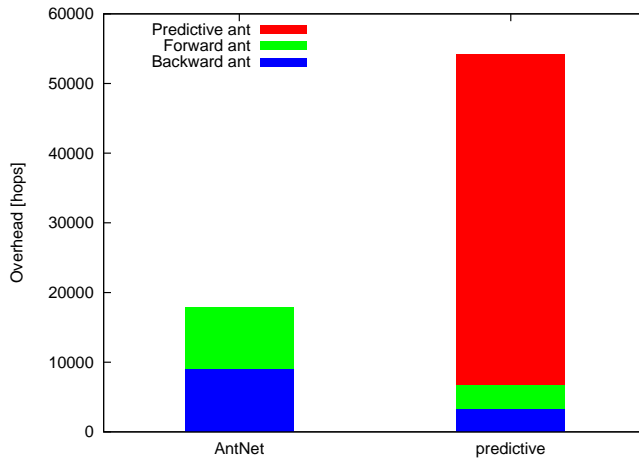Figure 5.   Path recovery time for parameter p (grid network, 1 session)

Figure 6.   Cumulative overhead of ants (grid network, 1 session)

The recovery time is shorter In the proposed method, especially when the parameter p is 0.05 (Figure 3). To reveal the relation between recovery speed and p, we show the recovery time for $p = (0.001, 0.005, 0.01, 0.05, 0.1, 0.5)$ when the interval of forward ant emissions $(= \Delta t_f)$ is 0.5 s and 1.0 s in Figure 5. As shown in this figure, the recovery time is worse when p is too high or too low. If p is too low, the prediction effect is too small to accelerate path reestablishment, making the behaviour of the proposed method similar to the original AntNet with low p. A higher value of p contrastingly leads to heavy pheromone concentration at one neighbour node. This decreases the stochastic nature, thus increasing the deterministic behaviour, of path exploration, despite stochastic features playing an important role for the discovery of shorter paths in an ant-based routing mechanism. In consequence, a loose control with appropriate p leads to a better recovery time.

As shown in Figure 4, the proposed method has much higher control overhead than does AntNet, due to the predictive ants. Each node in the proposed method which receives a backward ant regularly sends predictive ants to each of its neighbour nodes every 0.1 s to obtain neighbour node information. Figure 6 shows a breakdown of the control overhead when the interval of forward ants is 0.3 s and the parameter p is 0.005. Data packets of each background traffic session, whose overhead is not included in this figure, follow a fixed path regardless of pheromone values and thus are not involved in pheromone updates. In other words, pheromone values are updated only by the forward, backward, and predictive ants of target sessions. As shown in Figure 6, the control overhead of forward and backward ants in the proposed method is smaller than that of AntNet, but the total overhead of the proposed method is high due to the predictive ants. This seems to be a serious drawback, but the overhead of predictive ants becomes negligible as the number of sessions increases. We describe the overhead for predictive ants in the multiple session scenario in the following subsection.
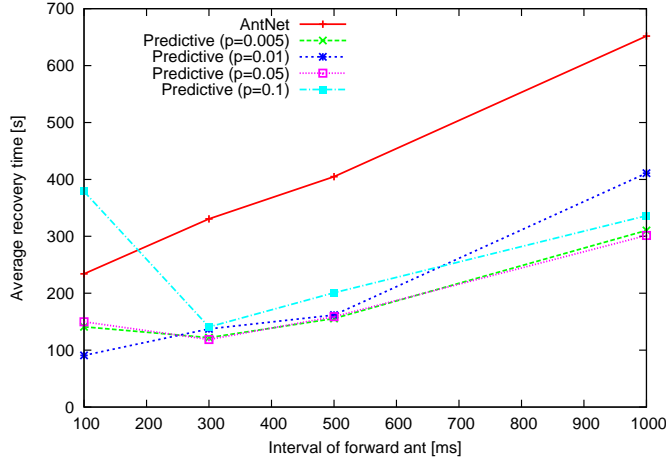
Figure 7. Path recovery time (random network, 1 session)
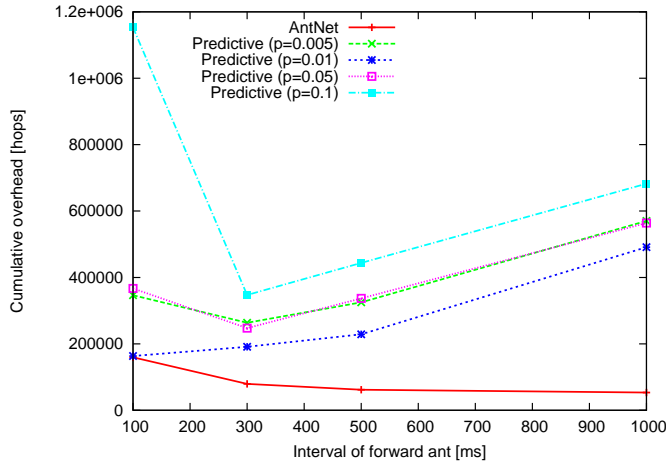

Figure 8. Cumulative overhead (random network, 1 session)

Figures 7 and 8 show the simulation results with the random network. A target session is generated between the two nodes furthest from each other over the diagonal line from the top-left corner to the bottom-right corner in the network. These figures depict the recovery time and the control overhead for the interval of forward ant emissions. As shown in Figure 7, the recovery time of the proposed method is shorter than that of AntNet, but the recovery time is worse when $\Delta t_p = 100$ ms. In the proposed method, increased rates of pheromones, which are indicators for predictive control, are updated simultaneously as backward ants update pheromone values. Therefore, if the interval of predictive ant emissions is too long against that of pheromone updates by backward ants, it is difficult to correctly predict a path that will collect more pheromones, and moreover the control with a predictive mechanism competes against the pheromone updates by backward ants, which results in path fluctuations. These are the reasons why the recovery time of the proposed method is longer than AntNet when Δt_p is small. In consequence, it is important to properly set the interval of forward ant emissions and that of predictive ant emissions to correctly predict paths that will collect more pheromones.

In this experiment, there are cases where path recovery could not be achieved by the end of the simulation, due to path oscillations. Such oscillations are caused by the arrival of many forward ants before a backward ant returns. In AntNet, an intermediate node distant from a destination has to wait a long time for a backward ant. While it is waiting for a backward ant, new forward ants visit it and stochastically choose a next hop node. This results in establishment of multiple paths, and sometimes paths do not converge until the end of the simulation run. The ratio of path recovery within a given simulation time over 300 simulation runs is strongly correlated with the recovery time shown in Figure 7. In other words, the effect of path oscillations is lowered by enhancing the convergence speed.
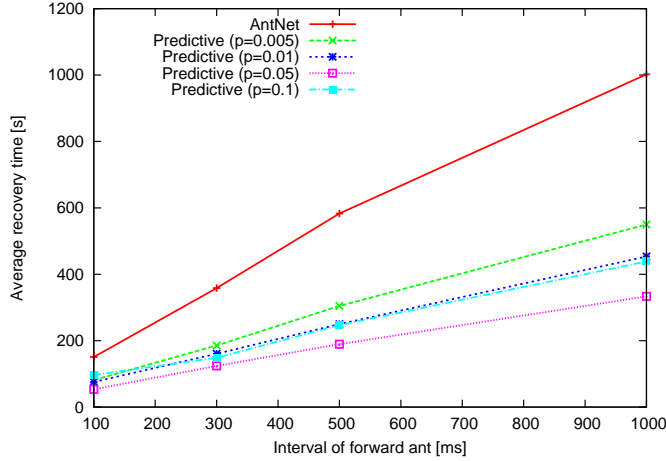
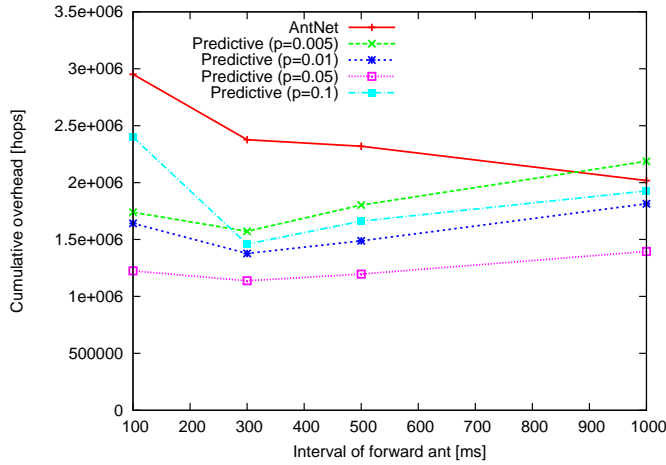Figure 9.   Path recovery time (grid network, 100 session)

Figure 10.   Cumulative overhead (grid network, 100 session)

As shown in Figure 8, the control overhead of the proposed method is much larger than that of the original AntNet. In particular, there are larger differences in control overhead between the original AntNet and the proposed method, as compared to the results in a grid network (Figure 4). These differences are caused by the average degree of nodes, about 9.6 in the random network and 3.6 in the grid network. Therefore, over 2.5 times more predictive ants are transmitted by each node in the random network than in the grid network.

Through simulation evaluation with one target session, we have shown the effect of prediction in AntNet. Our predictive mechanism improves the adaptability against traffic changes not only in the regular network but also the random network. However, the overhead of predictive ants in the proposed method is much larger than that of AntNet in the case of only one target session. This problem is further discussed in the next subsection by considering the case of multiple target sessions.

C. Evaluation with Multiple Target Sessions

In the previous subsection, we presented evaluations for fundamental performance of our predictive mechanism with one target session. In this subsection, we provide further simulation results to show that the overhead for predictive ants becomes negligible in a multiple session scenario. In experiments with multiple target sessions, path recovery is sometimes not achieved due to path oscillations, but the effect of path oscillations is lowered by enhancing the convergence speed (see Subsection IV-B).

Figures 9 and 10 show the simulation results for the grid network. In this evaluation, 100 target sessions start at the beginning of simulation and source nodes and destination nodes are selected at random except for 6×6 nodes in the
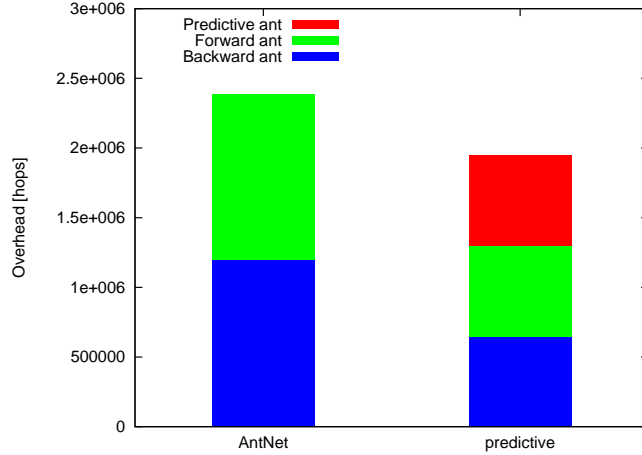
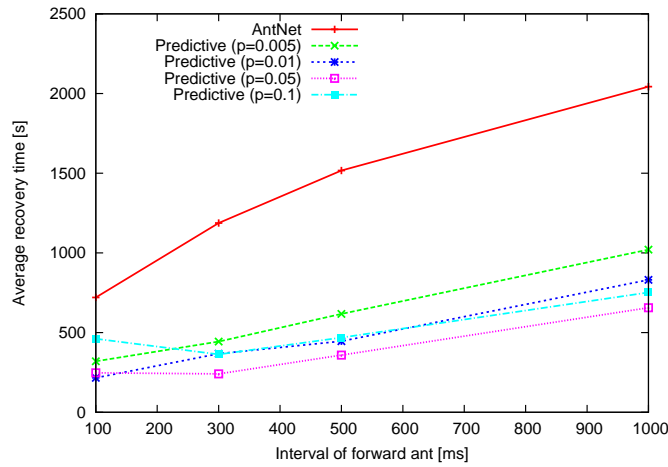Figure 11. Cumulative overhead of ants (grid network, 100 session)

Figure 12. Path recovery time (random network, 100 session)

network centre. These figures depict the recovery time and the control overhead for the interval of forward ant emissions. The recovery time of the proposed method is shorter than that of AntNet (Figure 9). This result is similar to the one session results shown in Figure 3. Figure 10 shows that the control overhead of the proposed method is smaller than or similar to that of AntNet. Figure 11 shows a breakdown of the control overhead when the interval of forward ants is 0.3 s and the parameter p in the proposed method is 0.005. The overhead of predictive ants is large in the proposed method as compared to AntNet, since the latter has no predictive ants. The overhead caused by forward and backward ants in the proposed method is comparatively reduced, however, because the recovery time is shortened with prediction. Moreover, predictive ants can simultaneously collect increase rates for different destination nodes. In consequence, the overhead of predictive ants becomes trivial as the number of sessions increases.

Figures 12 and 13 show the simulation results with the random network. In this evaluation, 100 target sessions start at the beginning of simulation, and a source node and a destination node are selected at random (excluding a 180×180 m area in the network centre). These figures depict the recovery time and the control overhead for the interval of forward ant emissions. As shown in Figures 12 and 13, the recovery time of the proposed method is shorter and the control overhead of the proposed method is lower than that of AntNet. Similar to Figure 8, there are larger differences of the control overhead between the original AntNet and the proposed method, as compared to evaluation with the grid network (Figure 10). However, the control overhead will be further reduced by adding a mechanism where forward and backward ants or data packets collecting past pheromone information substitutes for predictive ants.

In conclusion, adaptability against traffic changes is improved by introducing a predictive mechanism, while control
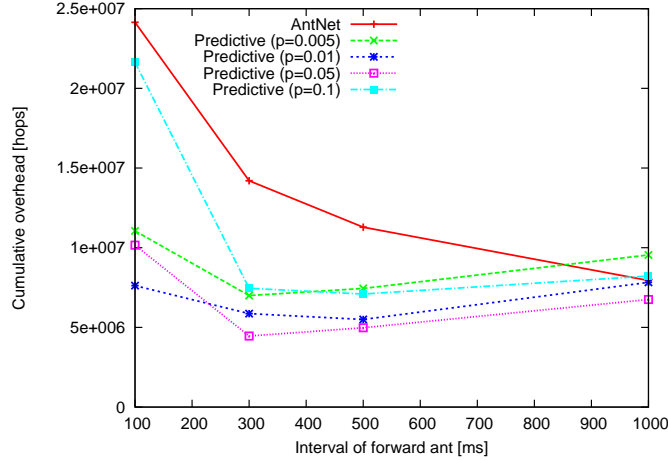
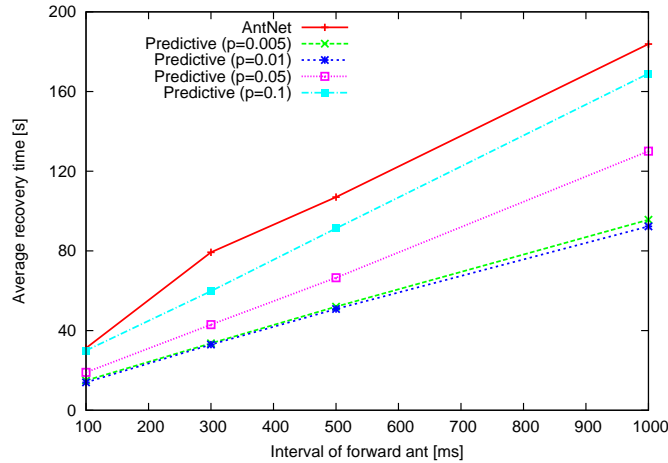Figure 13.   Cumulative overhead (random network, 100 session)

Figure 14.   Path recovery time (node failure)

overhead is reduced in the multiple session scenario. We next show another scenario of environmental change, node failure.

D. Adaptability to Node Failures

Lastly, we provide simulation results in the case where 20 of 100 nodes in the grid network fail, to show that the proposed method has high adaptability to environmental change other than traffic changes. Figures 14 and 15 show simulation results with the grid network. In this evaluation, 100 target sessions start at the beginning of simulation and source nodes and destination nodes are selected at random (excluding 6×6 nodes in the network centre). These figures depict the recovery time and control overhead for the interval of forward ant emissions.

As shown in Figure 14, the proposed method is superior to AntNet in most cases over a broad range of p. Similar to cases where traffic changes occur (Subsections IV-B and IV-C), pheromone updates in accordance not only with current pheromone values but with past pheromone changes play an important role in faster recovery from node failures. The recovery time is reduced at most by about 40% in this evaluation, despite reductions of 60% in the cases where traffic changes occur (Figs 3, 7, 9 and 12). In this evaluation, 20% of all nodes fail at 1,000 s from the simulation start. In other words, the network size gets smaller, which reduces the amount of positive feedback needed for path establishment. Therefore, our predictive mechanism for accelerating positive feedbacks has a smaller effect in cases where node failures occur. The proposed method nonetheless accelerates path recovery, even under such extreme environmental change.

As shown in Figure 15, the control overhead is smaller than or similar to that of AntNet. Similar to the evaluation in Subsections IV-B and IV-C, the control overhead of forward and backward ants is reduced by introducing our predictive
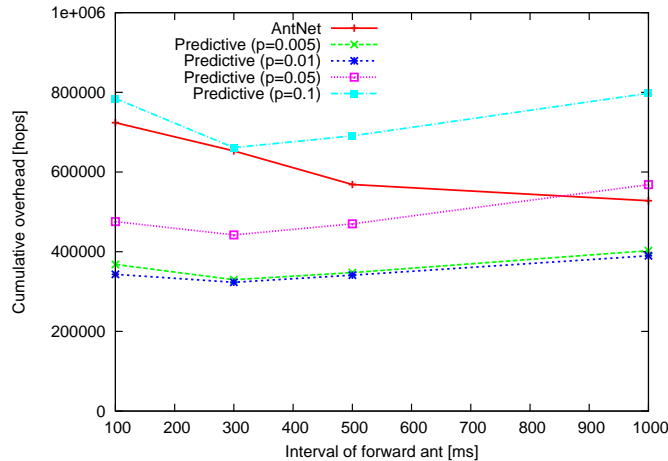
Figure 15. Cumulative overhead (node failure)

mechanism, and predictive ants can simultaneously collect past pheromone information for several destination nodes. The control overhead of predictive ants is therefore also negligible in cases where node failures occur.

In conclusion, the proposed predictive mechanism enhances adaptability for both node failures and traffic changes, while retaining low control overhead.

V. CONCLUSION AND FUTURE WORK

In a self-organising system, each component behaves according to only current local information, which leads to slow adaptation to environmental change. To rapidly adapt to changing conditions, it is therefore necessary that systems be controlled considering the future state of systems as predicted by observing system behaviour. We propose and evaluate a predictive mechanism for AntNet, which is a simple and basic example of ACO-based routing. Simulation results show that the proposed method can facilitate path reestablishment when the network environment changes. Moreover, simulation evaluations showed that the control overhead needed for prediction becomes smaller in multiple session scenarios. Even in a more realistic environment where forward, backward, and predictive ants are lost in a network, ants can quickly re-establish other paths because they explore the network not deterministically but rather stochastically, and the positive feedback through pheromones leads to ants following shorter paths.

In future work, we will consider more general designs of a predictive mechanism for self-organising systems to realise future networks. There are various information network controls besides AntNet based on self-organisation, such as potential-based routing for wireless sensor networks (Kominami et al., 2013) and clock synchronisation inspired by firefly behaviour (Tyrrell and Auer, 2007). Such self-organising systems inherently have the same problems as AntNet, so we will adopt predictive mechanisms to such self-organising systems to enhance their adaptability.

REFERENCES

A.Y. Abdelaziz, R.A. Osama, and S.M. Elkhodary. Application of ant colony optimization and harmony search algorithms to reconfiguration of radial distribution networks with distributed generations. *Journal of Bioinformatics and Intelligent Control*, 1(1):86–94, June 2012.

H. Ahangarikiasari, M.R. Saraji, and M. Torabi. Investigation of code complexity of an innovative algorithm based on aco in weighted graph traversing and compare it to traditional aco and bellman-ford. *Journal of Bioinformatics and Intelligent Control*, 2(1):73–78, March 2013.

L. Carvelli and G. Sebastiani. Some issues of ACO algorithm convergence. In Avi Ostfeld, editor, *Ant Colony Optimization - Method and Application*, chapter 4. InTech, February 2011.

European Commission. *Seventh Framework Programme (FP7)*. http://cordis.europa.eu/fp7/home_en.html [retrieved: October, 2014], 2006.

S.S. Dhillon and P. Van Mieghem. Performance analysis of the AntNet algorithm. *Computer Networks*, 51(8):2104–2125, June 2007.

G. Di Caro and M. Dorigo. AntNet: Distributed stigmergetic control for communications networks. *Journal of Artificial Intelligence Research*, 9:317–365, December 1998.

G. Di Caro, F. Ducatelle, and L.M. Gambardella. AntHocNet: an adaptive nature-inspired algorithm for routing in mobile ad hoc networks. *European Transactions on Telecommunications*, 16(5):443–455, September 2005.

M. Dorigo, M. Birattari, and T. Stutzle. Ant colony optimization. *Computational Intelligence Magazine, IEEE*, 1(4):28–39, November 2006.

F. Dressler. *Self-organization in sensor and actor networks*. Wiley, January 2008.

X. Feng, Y. Liang, and L. Jiao. Bio–inspired optimisation approach for data association in target tracking. *International Journal of Wireless and Mobile Computing*, 6(3):299–304, August 2013.

D. Kominami, M. Sugano, M. Murata, and T. Hatauchi. Controlled and self-organized routing for large-scale wireless sensor networks. *ACM Transactions on Sensor Networks*, 10(1):13:1–13:27, November 2013.

M. Meisel, V. Pappas, and L. Zhang. A taxonomy of biologically inspired research in computer networking. *Computer Networks*, 54(6):901–916, April 2010.

A.A. Moghanjoughi, S. Khatun, B.M. Ali, and R.S.A.R. Abdullah. QoS based fair load-balancing: Paradigm to IANRA routing algorithm for wireless networks (WNs). In *Computer and Information Technology, 2008. ICCIT 2008. 11th International Conference on*, pages 104–109. IEEE, December 2008.

P.R. Montague, P. Dayan, C. Person, T.J. Sejnowski, et al. Bee foraging in uncertain environments using predictive hebbian learning. *Nature*, 377(6551):725–728, October 1995.

National Science Foundation (NSF). *Global environment for network innovations (GENI)*. http://www.geni.net [retrieved: October, 2014], 2007.

National Science Foundation (NSF). *NSF future internet architecture project*. http://www.nets-fia.net/ [retrieved: October, 2014], 2010.

National Institute of Information and Communications Technology (NICT). *New-Generation Network (NWGN) Project*. http://www.nict.go.jp/en/nrh/nwgn/ [retrieved: October, 2014], 2008.

K. Park and Y. Kim. Analysis of AntNet routing scheme by using queueing model. *Computer Communications*, 31(13): 2951–2958, August 2008.

A.A.A. Radwan, T.M. Mahmoud, and E.H. Hussein. AntNet-RSLR: A proposed ant routing protocol for MANETs. In *Electronics, Communications and Photonics Conference (SIECPC), 2011 Saudi International*, pages 1–6. IEEE, April 2011.

K. Saleem and N. Fisal. Enhanced ant colony algorithm for self-optimized data assured routing in wireless sensor networks. In *Networks (ICON), 2012 18th IEEE International Conference on*, pages 422–427. IEEE, December 2012.

M. Saleem, G.A. Di Caro, and M. Farooq. Swarm intelligence based routing protocol for wireless sensor networks: Survey and future directions. *Information Sciences*, 181(20):4597–4624, October 2011.

K.M. Sim and W.H. Sun. Ant colony optimization for routing and load-balancing: survey and new directions. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, 33(5):560–572, September 2003.

C. Summerfield, T. Egner, M. Greene, E. Koechlin, J. Mangels, and J. Hirsch. Predictive codes for forthcoming perception in the frontal cortex. *Science*, 314(5803):1311–1314, November 2006.

A. Tyrrell and G. Auer. Imposing a reference timing onto firefly synchronization in wireless networks. In *65th IEEE Vehicular Technology Conference (VTC2007-Spring)*, pages 222–226. IEEE, April 2007.

G.Y. Zhang, J.C. Zeng, and S.D. Xue. Research on task allocation of multi–target search with swarm robots. *International Journal of Wireless and Mobile Computing*, 7(3):297–304, May 2014.

H.T. Zhang, M.Z. Chen, G.B. Stan, T. Zhou, and J.M. Maciejowski. Collective behavior coordination with predictive mechanisms. *IEEE Circuits and Systems Magazine*, 8(3):67–85, August 2008.

Y. Zhang, L.D. Kuhn, and M.P.J. Fromherz. Improvements on ant routing for sensor networks. In *Ant Colony Optimization and Swarm Intelligence*, volume 3172, pages 154–165. Springer, September 2004.

Z. Zhang, K. Long, J. Wang, and F. Dressler. On swarm intelligence inspired self-organized networking: its bionic mechanisms, designing principles and optimization approaches. *Communications Surveys & Tutorials*, 16:513–537, July 2013.

C. Zheng and D.C. Sicker. A survey on biologically inspired algorithms for computer networking. *IEEE Communications Surveys and Tutorials*, 15(3):1160–1191, January 2013.