Autonomous and Adaptive Wireless Networking with Bio-Inspired Algorithms

Naoki Wakamiya and Masayuki Murata
Graduate School of Information Science and Technology, Osaka University
1-5 Yamadaoka, Suita, Osaka 565-0871, Japan
Email: {wakamiya,murata}@ist.osaka-u.ac.jp

***Abstract*—A new generation network is expected to keep operating and providing users and applications with means of communication while being exposed to dynamic and substantial change in the operational environment such as network topology, traffic, and QoS requirement. To establish a highly adaptive and reliable network, we take an approach to be inspired by biological systems, which adapt themselves to dynamically changing and even unexpected environment. In this paper we show examples of application of bio-inspired models, more specifically the attractor selection/composition models built on adaptive behavior of biological systems, to autonomous and adaptive networking in wireless communication systems. The first application is MANET routing, where a path connecting a source-destination pair must be maintained under dynamically changing environment. The second application is resource allocation among nodes and applications competing for wireless networks with heterogeneous characteristics. We further discuss future direction of bio-inspired adaptive networking.**

I. Introduction

In the forthcoming future, our daily life will be surrounded by a considerable number of intelligent devices communicating through broadband wired/wireless access networks. Whereas they provide us with safe, secure, and comfortable environment, they cause the considerable increase or even explosion in the following dimensions and bring new challenges to a new generation network [1].

Scale: The number of nodes connected to a network, the physical and logical area of a network, the number of applications running on a network, the number of sessions and flows going through a network, and the amount of traffic transmitted over a network affect network performance. As the scale of network increases, Centralized control technology becomes infeasible and impossible for maintenance overhead of up-to-date global information and govern the whole system. Therefore, a new generation network must employ fully distributed and autonomous control technologies to achieve the higher scalability than before.

Heterogeneity: All devices are not the same from viewpoints of implemented protocols, communication performance, processing capability, and embedded functions. A new generation network must be flexible to accommodate a variety of nodes with different performance and reliability, while conventional protocols mostly assume that nodes are homogeneous or their diversity is within a certain range. In addition, different applications have different traffic characteristics and different QoS requirements. A new generation network needs to satisfy their requirements by efficient and effective use of limited network resources.

Dynamism: Network topology, traffic pattern, and QoS requirements of applications dynamically and drastically change in a course of operation of a network. Only if the degree of change is predictable and it remains within the assumed range, pre-optimization of control parameters, mechanisms, and algorithms is useful and a network can provide the optimal performance. However, an optimized network is fragile and it will easily collapse once assumptions break. The high level of adaptability is one of indispensable features of a new generation network to keep providing a reliable and dependable communication vehicle under unexpected operational condition. Robustness is also highly required since all devices are not reliable and they often fail without notice.

In recent years, to address substantial need for scalable, flexible, adaptive, and robust new generation networks, interdisciplinary researches have become an active area. Researchers cross boundaries of academic disciplines and integrate knowledge, theories, models, and methods of other disciplines to solve problems faced in information networking. Among disciplines such as mathematics, physics, chemistry, economics, and sociology, biology is a main source of inspiration because of the high level of survivability, adaptability, scalability of biological systems [3]–[5]. Furthermore, biological systems are self-organizing, where the globally organized pattern emerges from collective behavior of mutually interacting individuals. Each individual acts based on simple rules which use locally available information. Typical examples of self-organizing behavior of biological systems can be found in the so-called swarm intelligence [6], such as an ant trail.

In this paper, we introduce our bio-inspired research activities for highly adaptive and reliable wireless networking. As biological algorithms, we adopt nonlinear mathematical models, i.e. the attractor selection model and the attractor composition model. We focus on wireless networking, since the above non-trivial issues are more critical in an access network, especially which is wireless, than a core network. Except for the scale, heterogeneity and dynamism can be mitigated or averaged to some extent at a core network for statistical multiplexing and the law of large numbers. On the other hand, a wireless network suffers from unpredictability and instability of communication which result in frequent changes in a network topology and quality of communication.

We first describe biological adaptation and the attractor selection and composition models in Section II. Next in Section III, we show two examples of application of the biological algorithms to wireless networking, more specifically, MANET (mobile ad-hoc network) routing and wireless resource allocation. Then we discuss future direction of bio-inspired adaptive networking in Section and conclude the paper in Section IV.

II. Biological Adaptation

Biological systems are known to exhibit highly adaptive behavior against the dynamically changing environment. At the longer timescale, all species on earth have evolved their genetic structures, physical structures, organic activities, and social relationship to fit to their surroundings in order to live, grow, and reproduce. At the same time, biological systems always adapt themselves to perturbations in the environment, such as change in temperature, brightness, pressure, and humidity, as well as physical and mental conditions.

There are two types of adaptation mechanisms in a biological system, i.e. rule based and non-rule based. Although there are different levels of adaptation from gene expression to social behavior, now consider adaptation in a cell, more specifically, in a gene regulatory network. The heat-shock response is a well conserved mechanism of an adaptive reaction of a cell to protect itself from the heat shock, i.e. sudden elevation of temperature. The mechanism is implemented as a series of chemical reactions, i.e. signal transduction network, and it is modeled by multiple feedforward and feedback modules [7]. A heat shock denatures proteins from folded to unfolded and damages them. Although there are HSPs (Heat Shock Proteins) which repair damaged proteins, their concentrations in a usual cell are not high enough to refold too many unfolded proteins. By being exposed to the heat shock, synthesis of heat-shock transcription factor σ^{32}, which governs the heat-shock response, is activated in a cell. Synthesized σ^{32} reduces the concentration of RNA polymerase, which inhibits synthesis of HSPs. As a result, the concentration of HSPs increases and the number of unfolded proteins decreases. Consequently, a cell recovers from the heat shock.

On the contrary to the heat-shock response, where a series of chemical reactions are pre-programmed in a cell, there exists a non-rule based adaptation mechanism. A mutant *E. coli* cell has a metabolic network consisting of two mutually inhibitory operons. Each of operons corresponds to synthesis of different nutrient and synthesizing one nutrient suppresses synthesis of the other. When a cell is in the neutral environment where both nutrients are sufficient, mRNA expression levels are similar with each other among the operons in a cell. It means that a cell can live and grow in the environment independently of nutrient it synthesizes. Once one of the nutrients becomes insufficient in the environment, the level of gene expression of an operon corresponding to the missing nutrient eventually increases. As a result, a cell can compensate the missing nutrient and survive. So, there is no embedded adaptation rule or a signal transduction network, such that the insufficient nutrient concentration in the environment triggers synthesis of the missing nutrient in a cell. The attractor selection model imitates the adaptive metabolic synthesis of bacteria to dynamically changing nutrient condition in the environment [8]. The behavior of cell is formulated as a nonlinear dynamic system and an attractor is a stable state where a nonlinear dynamic system reaches after an arbitrary initial state.

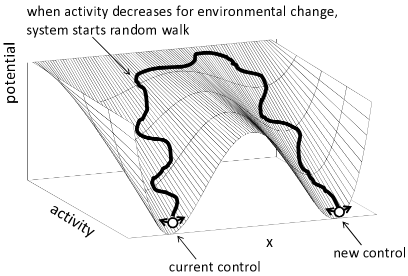

Fig. 1. Behavior of attractor selection model

A. Attractor Selection Model

In the attractor selection model, mRNA concentrations m_1 and m_2 for synthesis of nutrient 1 and 2 dynamically change based on equations below, respectively.

$$\frac{dm_1}{dt} = \frac{S(\alpha)}{1+m_2^2} - D(\alpha)m_1 + \eta_1 \quad (1)$$

$$\frac{dm_2}{dt} = \frac{S(\alpha)}{1+m_1^2} - D(\alpha)m_2 + \eta_2 \quad (2)$$

α is the cellular activity such as growth rate and it expresses the goodness of the current behavior, i.e. the state of gene expression and nutrient synthesis. Functions $S(\alpha)$ and $D(\alpha)$ are rate coefficients of mRNA synthesis and decomposition, respectively. In [8], $S(\alpha) = \frac{6\alpha}{2+\alpha}$ and $D(\alpha) = \alpha$ are used. From a viewpoint of nonlinear dynamics, the first two terms of the right side define the potential of attractors. η_i $(i = 1, 2)$ corresponds to inherent noise or fluctuation in gene expression.

The activity α is determined by the following equation.

$$\frac{d\alpha}{dt} = \frac{p}{\{(\frac{N\_thr_1}{m_1+N_1})^{n_1}+1\}\{(\frac{N\_thr_2}{m_2+N_2})^{n_2}+1\}} - c\alpha \quad (3)$$

N_1 and N_2 are nutrient concentrations in the environment. N_thr_1 and N_thr_B are thresholds and n_1 and n_2 are coefficients of sensitivity. p and c are constants. If a cell can compensate the insufficient nutrient having small N_i $(i = 1, 2)$, the activity α becomes high.

When the activity α is high, the nonlinear system formulated by the above equations has one attractor where $m_1 = m_2 = m$. Here, m is a constant and larger than one. It means that a cell stays at the attractor and generates either of two nutrient when there are sufficient nutrients and the growth rate is high. When the concentration of either of nutrients becomes insufficient, the activity decreases and there appear two attractors, i.e. $m_1 = m$ and $m_2 = 1/m$ or $m_1 = 1/m$ and $m_2 = m$. Since the first two terms of the right side of Eqs. (1) and (2) are multiplied by the activity α, potential of attractors becomes shallow and the dynamics becomes driven by the noise terms as shown in Fig. 1. Consequently, m_1 and m_2 change at random. When the mRNA concentration, i.e. m_1 or m_2, of the missing nutrient occasionally becomes large, the activity α slightly increases as a cell can live better. The increase in the activity makes the potential of attractor deeper and their force of entrainment stronger. Then, the state of cell begins to move toward the attractor. Consequently the activity further increases and the influence of noise becomes smaller. Eventually the state of a cell reaches an appropriate attractor and remains there stably.

The attractor selection model is a metaheuristic to find a solution under some criteria, which change during optimization processes. The solution space is defined by temporal differential equations and attractors are possible solutions. The objective to maximize is expressed as an activity, which is a function of the state of a dynamic system. In the biological case, the state of bacteria is expressed by two mRNA concentrations and bacteria adaptively choose one of solutions, i.e. synthesis of either of two nutrients, so that it can increase the growth rate given the environmental nutrient condition.

From a view point of control algorithm, the attractor selection model is a combination of deterministic control expressed by a potential function and random control realized by a noise term. It balances those two control mechanisms with mediation of the activity term, which introduces a feedback loop to a system. When we apply the attractor selection model to adaptive and autonomous network control, parameters defining the state of a dynamic system, e.g. m_1 and m_2 in the biological model, correspond to control parameters or control policies. The activity is a scalar metric reflecting the goodness of control such as throughput or delay, which cannot be explicitly formulated in most cases and should be obtained by observation. When the current control is appropriate for the current operational environment, deterministic control dominates the system behavior. Once the environmental condition changes and control becomes inappropriate, the system looks for new appropriate state, i.e. a good attractor, by being driven by random and stochastic control. Eventually the system approaches a new appropriate attractor by reinforcing the current control.

B. *Emergence of Symbiosis*

The attractor selection model describes adaptive behavior of a single entity. However, there are multiple entities, i.e. bacteria, in the same shared environment, i.e. the culture in a reactor, in an actual situation. Although there is no mechanism of direct communication among cells, they indirectly affect each other through the environment. Nutrients generated in a cell permeate the cell membrane and change the nutrient condition of the reactor. The change in the environment affects the activity of other cells and further causes their adaptive reaction. Such interaction through environmental changes is called *Stigmergy* [6]. Based on adaptive nutrient synthesis and indirect mutual interaction, the system eventually reaches the good symbiotic condition as a whole, where all cells live comfortably. However, local optimization of a single entity does not necessarily lead to the global optimization. There are two alternatives to extend the attractor selection model for better global optimization.

The first extension is to explicitly formulate cellular interaction mediated by the environment. For example, dynamic change of concentration of nutrient 1 in the environment can be formulated as,

$$\frac{dN_1}{dt} = k(F_1 - N_1) + \sum_i v_i(m_{i,1} - u\alpha_i) \qquad (4)$$

k is the dilution rate and F_1 is the nutrient concentration of the fresh culture fed into the reactor, i.e. turbidostat experiment. v_i and α_i are the volume and the activity of cell i, respectively. $m_{i,1}$ is the concentration of nutrient 1 in cell i. u is the consumption rate. As the equation indicates, the nutrient concentration in a reactor dynamically changes through membrane permeation. Other equations for dynamics of volume and population of bacteria are not shown for space limitation. The model can express a variety of symbiosis, such as mutualism where bacteria help each other and commensalism where nutrients flow in only one direction. However, in applying this model to network control, there is difficulty in formulating the dynamics of environment as Eq. (4).

The other extension is called the attractor composition model, where entities share the same activity. In the generalized form of the attractor selection model, each of two entities i and j, for example, uses different activity α_i and α_j.

$$\frac{d\vec{m}_i}{dt} = f_i(\vec{m}_i)\alpha_i + \vec{\eta}_i, \frac{d\vec{m}_j}{dt} = f_j(\vec{m}_j)\alpha_j + \vec{\eta}_j \qquad (5)$$

where $\vec{m}_i = (m_{i,1}, \ldots)$ and $\vec{m}_j = (m_{j,1}, \ldots)$ are vectors of entities i and j, respectively. $f_i(\vec{m}_i)$ and $f_j(\vec{m}_j)$ are potential functions and $\vec{\eta}_i$ and $\vec{\eta}_j$ are noise terms. In the attractor selection model, each of entities i and j tries to maximize its activity α_i or α_j while directly or indirectly interact with each other. As a consequence of mutual interaction, the whole system reaches the stable condition where both of α_i and α_j are sufficiently large. In the attractor composition model, on the other hand, their dynamics are formulated as,

$$\frac{d\vec{m}_i}{dt} = f_i(\vec{m}_i)\alpha + \vec{\eta}_i, \frac{d\vec{m}_j}{dt} = f_j(\vec{m}_j)\alpha + \vec{\eta}_j \qquad (6)$$

Here, entities i and j share the same activity α as the objective of maximization. With such coupling, entities can cooperatively optimize the system, but at the same time, behavior of an entity directly affects others and the system can be driven to the unstable condition.

III. Applications of Bio-Inspired Algorithms to Autonomous and Adaptive Wireless Networking

In this section, we show applications of the attractor selection model to MANET routing and the attractor composition model to resource allocation in vehicular networking.

A. *MANET routing*

MANET is a field of networking which most suffers from dynamic and frequent change in the operational environment. A network consists of mobile nodes which can freely join

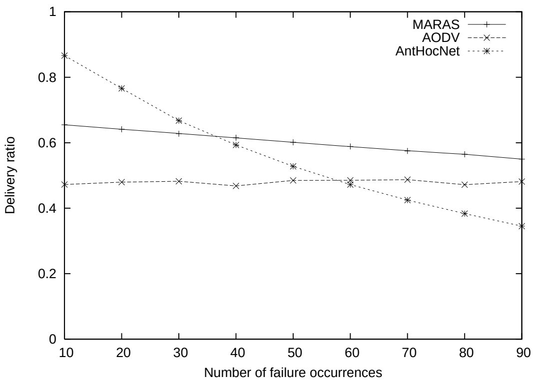

Fig. 2. Delivery ratio against failures

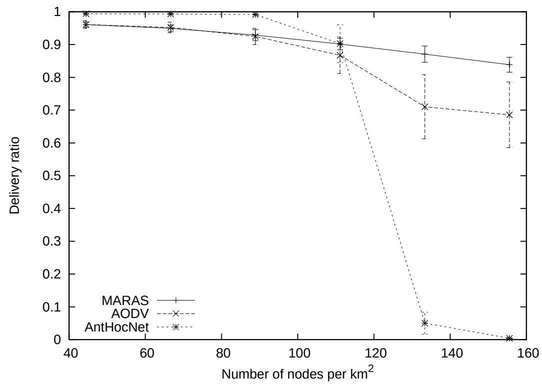

Fig. 3. Delivery ratio against density

and leave. A pair of nodes is connected by a wireless and bidirectional link in general, if they are within the range of radio signals. Since communication is wireless, a link is unreliable and unstable. Therefore, it is a challenging task to establish and maintain a path from a source to a destination to achieve high delivery ratio and low delay in packet transmission. As such, routing in MANET has been an active research area and many protocols have been proposed [9].

In applying the attractor selection model to MANET routing, a cell corresponds to a node and selection is to choose one of neighbor nodes as a next hop node. Each node maintains a routing vector of m_i, called state value, for a certain destination. On receiving a packet for the destination, a node chooses a next hop node stochastically according to state values. For this purpose, the model first needs to be extended to be multidimensional as [10],

$$\frac{dm_i}{dt} = \frac{s(\alpha)}{1 + m_{max}^2 - m_i^2} - d(\alpha)m_i + \eta_i, \tag{7}$$

where i is an identifier of a neighbor node $(1 \leq i \leq M)$. M is the dimension and equal to the number of neighbors of a node. $m_{max} = \max_{j=1,\ldots,M} m_j$, $s(\alpha) = \alpha(\beta\alpha^\gamma + \phi^*)$, $d(\alpha) = \alpha$, and $\phi^* = 1/\sqrt{2}$. The equation has M attractors at the equilibrium, where one m_i has a high value and the other $M-1$ m_js $(j \neq i)$ have low values, indicating the goodness of nodes for a next hop to a destination. Neighbor node i is chosen as a next-hop with probability $m_i / \sum_{1 \leq j \leq M} m_j$.

When a packet arrives at a destination, a feedback packet is generated. While it is transferred to the source, the number of hops that it traveled is counted. On receiving a feedback packet, an intermediate node first calculates the activity by using the following equation.

$$\alpha(t_0) = \frac{\min_{t_0 - T < t \leq t_0} w(t)}{w(t_0)}, \tag{8}$$

where t_0 is time when it received the feedback packet and T is a constant. $w(t)$ is the number of hops to the destination of a feedback packet received at t. When the number of hops becomes larger, it implies that the current path is getting worse for dynamic change in the topology and a better path should be found. Therefore, by Eq. (8) the activity decreases. Consequently, the noise term in Eq. (7) begins to affect the next-hop selection probability and a random walk is induced. When there is no feedback from a destination, it implies that the current path is no longer useful or it is under instantaneous congestion. To avoid using the old and non-updated information, the activity automatically decays at regular intervals, e.g. 1.0 s, regardless of feedback packet arrival. For further details of the attractor selection-based MANET routing, which we call MARAS, please refer to [11].

We compare MARAS with AODV [12] and AntHocNet [13] by using QualNet 4.0. AODV is a well-known reactive routing protocol and it uses local route repair and intermediate node reply features. AntHocNet is used as an example of adaptive routing protocol which is also bio-inspired. It is based on ACO (Ant Colony Optimization) and combines reactive route establishment and recovery with proactive route maintenance. We distributed 256 nodes in the area of $1500 times 1500$ m^2. Each node can communicate with a node within the distance of 510 m (free-space model without fading) at the data rate of 2 Mbps by using IEEE 802.11b. We placed two source nodes at the lower left corner and two destination nodes at the upper right corner to set up two diagonal sessions. Each of source nodes sends out 10 packets per second at the rate of 8 kbps.

Figure 2 shows results of simulation experiments. On the x-axis, the number of failure occurrence is shown. During each of intervals given by dividing the simulation time of 1000 seconds by the number of failure occurrence, randomly chosen 25% of nodes stop operating. Therefore, a larger number of failure occurrence implies that the topology changes more frequently. As shown in the figure, MARAS achieves higher delivery ratio, defined as the ratio of successfully delivered packets to the total packets sent from sources, than AODV for all cases. AntHocNet provides even higher delivery ratio under less dynamic conditions, but the performance drastically decreases as the number of failure occurrence increases. It is because that AntHocNet introduces excessive overhead in route maintenance and it cannot promptly update routing information to adapt to changes. Figure 3 also supports the superiority of MARAS to AODV and AntHocNet, where the node density is changed. Error bars show the confidence intervals of 99.95%. Although MARAS provides a slightly lower delivery ratio than AntHocNet in the sparse environment, the performance remains high against the increased node density.

B. Vehicular networking

Nowadays, various means of wireless communication are available to mobile users and applications to support our daily life everywhere. Wireless networks, such as cellular, Wi-Fi, and WiMAX have heterogeneous characteristics in terms of, e.g. availability, capacity, delay, connectivity, and cost. Furthermore, most characteristics dynamically change due to instability of wireless communication and competition among users and applications for wireless network resources. Therefore, it is necessary for a node to choose a wireless network resource dynamically to use for each of applications taking into account the condition of wireless networks and QoS requirements of applications.

Such resource allocation can be formulated as an optimization problem to maximize the degree of satisfaction per node and per application, once information about the current condition of available wireless networks and QoS requirements of all applications is given. However, such optimization requires for a central node, e.g. an access point, to maintain the up-to-date information by frequent and aggressive message exchanges with nodes in the area. Even if the task of derivation of optimal resource allocation is distributed among nodes, nodes need to frequently exchange messages with other nodes to obtain latest information about the current status of applications running on the other nodes. From a viewpoint of dynamic features of wireless networks and cost, e.g. bandwidth and energy, spent in message exchanges, such mechanisms are not feasible at all in the new generation network environment, where various wireless networks are available to a large number of networked applications.

Therefore, in this section, we show adaptive and autonomous resource allocation in vehicular networking as an example of application scenarios of the attractor composition model, although details are not shown for space limitation. A car, whose control is now fully governed by information technology, is one of dominant mobile users of ubiquitous wireless networks. With a help of sufficient energy resource and significant capacity of computing, a variety of applications such as road navigation, automobile condition reporting, video streaming, VoIP, e-mail, and web browsing are operating and they have different QoS requirements. In the scenario, cars compete for wireless networks available in the region to satisfy QoS requirements of applications.

In applying the attractor composition model to resource allocation among cars and among applications, there are two alternatives different in interpretation of the global activity α shared among entities. When we define the activity α as the goodness of resource allocation in a certain region where multiple cars exist, entity i corresponds to a car. Such a mechanism requires all cars or a central node of the region to know the degree of satisfaction of all cars to derive the activity. It apparently is bandwidth expensive and not feasible.

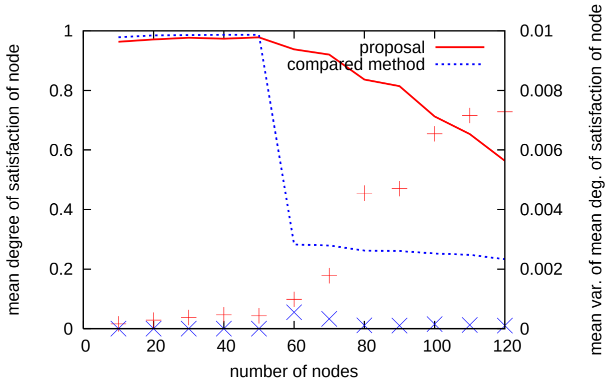

Fig. 4. Mean and variance of degree of satisfaction of node against number of nodes

On the other hand, to define the activity α per car is more practical. In this case, entities competing for resources correspond to applications. Application i running on a car autonomously decides a wireless network to use by using Eq. (6), where the size of $\vec{m}_i$ is equal to the number of available wireless networks. Since the activity α shared among applications is derived from the degree of satisfaction of all applications running on a car, applications behave in a cooperative manner to maximize the degree of satisfaction of the car. Cars further behave in a cooperative manner through indirect interaction among cars by sharing network resources.

At regular control intervals, empirically set at 1 s, each application running on a node, i.e. a car, declares its QoS requirements in terms of the required bandwidth, tolerable delay jitter, and affordable transmission cost, for example, to a node. At the same time, a node obtains the information about available wireless networks, e.g. the available bandwidth, delay jitter, and transmission cost by using a cognitive radio technology. Next the node evaluates the degree that QoS requirements of each application are satisfied with an allocated network. Then, from the degree of satisfaction of all applications, the degree of satisfaction of node is calculated, from which the activity of node is further derived. Based on the activity, a vector of state value of each application is updated by Eq. (6). Finally, to each of applications, a wireless network with the largest state value is allocated. If the current allocation can satisfy QoS requirements of applications, the activity is high and resource allocation does not change. Otherwise, the noise term drives resource allocation to find better allocation.

We consider the torus region of 300 m $\times$ 300 m large with two roads crossing at the center. One road has four lanes and cars move at the speed of 40 km/s and the other has two lanes with the speed of 20 km/h. DSRC, Wi-Fi, WiMAX, and cellular networks are available and they have different characteristics in terms of the capacity, delay jitter, and cost. Each of DSRC, WiMAX, and cellular networks covers the whole region, while the access area of Wi-Fi network is limited within the radius 100 m from the center of the region. For simplicity, the distance between a node and a base station or an access point does not affect the communication speed. Therefore, dynamic change is mainly caused by a car moving across a Wi-Fi access area and resource allocation. We consider Web, VoIP, and Video applications which have different QoS requirements. All nodes use Web. One-tenth of nodes additionally use either of VoIP or Video and one-twentieth of nodes use all of three applications.

For a purpose of comparison, we consider another method where each node adopts the optimal allocation using the locally available information, i.e. characteristics of wireless networks. At regular intervals identical to the proposal, a node obtains the information about the remaining bandwidth, delay jitter, and cost of networks available to the node. Then, the node decides resource allocation by solving the optimization problem to maximize the degree of satisfaction of node under given conditions of wireless networks.

We change the number of nodes from 10 to 120. If there are more than more than 99 nodes, there is no resource allocation which satisfies all nodes for the shortage of network resources. Figure 4 shows the mean degree of satisfaction of node and its mean variance. When the mean degree of satisfaction of node is 1.0, all applications on all nodes in the region are fully satisfied with resource allocation. As shown in the figure, the compared method achieves the mean degree of satisfaction of node higher than 0.9 when the number of nodes is small. However, once the number of nodes exceeds 60, the performance considerably and suddenly deteriorates to about 0.28. On the other hand, our proposal can sustain the mean degree of satisfaction of node at the moderate level even when there are 120 nodes in the region. Since our proposal takes a probabilistic approach in finding a good solution as biological systems do, an application is occasionally allocated the second best network. Such allocation results in the sub-optimal resource allocation as indicated by the lower mean degree of satisfaction of node for the small number of nodes. However, it enables nodes to find the moderate solution at the sacrifice of the degree of satisfaction of applications to some extent in the environment where the optimal solution to satisfy all applications does not exist. It is also a reason why the mean variance of degree of satisfaction of node increases as the number of nodes increases with our proposal.

IV. Discussion and Conclusion

Intuitively speaking, biological organisms are scalable, adaptive, flexible, and robust systems. By being based on fundamental principles behind those characteristics of biological systems, we can build a new generation network with the higher scalability, adaptability, flexibility, and robustness than ever before. Thanks to development of various fields of biology, such as mathematical biology and molecular biology, we can utilize biological mathematical models in the form of stochastic differential equation to design a networking technology which is not a mere imitation of biological systems.

Such an approach makes it possible for us to understand the source of adaptability and theoretically discuss advantages and disadvantages of a bio-inspired method. However, there are some limitations in bio-inspired methods. First, bio-inspired methods are often slower in reaction and adaptation than conventional control methods. The high level of adaptability comes from the stochastic nature of biological systems. Their adaptation is often driven by fluctuations and not deterministically directed to a certain goal. Second, because of self-organization, the optimality of control is not guaranteed. In a sense, the optimality is exchanged for the other *-ties.

Therefore, it is of great importance to thoroughly understand both of characteristics of biological algorithm and requirements of networking problem before application. We are now trying to establish the taxonomy which answer such questions: what kind of bio-inspired algorithms are applicable to network control, what kind of networking problems can be solved by bio-inspired algorithms, and how a bio-inspired algorithm can be applied to a networking problem.

Acknowledgment

This work is supported by "Early-concept Grants for Exploratory Research on New-generation Network" of National Institute of Information and Communications Technology, Japan and Grant-in-Aid for Scientific Research (B) 22300023 of the Ministry of Education, Science, Sports and Culture, Japan.

References

[1] AKARI project, "New generation network architecture AKARI conceptual design," Report of National Institute of Information and Communications Technology, October 2007.

[2] K. L. Mills, "A brief survey of self-organization in wireless sensor networks," *Wireless Communications and Mobile Computing*, vol. 7, pp. 823–834, May 2007.

[3] K. Leibnitz, N. Wakamiya, and M. Murata, *Cognitive Networks: Towards Self-Aware Networks*. Wiley-Interscience, August 2007, ch. Biologically Inspired Networking.

[4] M. Meisel, V. Pappas, and L. Zhang, "A taxonomy of biologically inspired research in computer networking," *Computer Networks*, vol. 54, no. 6, pp. 901–916, April 2010.

[5] F. Dressler and O. B. Akan, "A survey of bio-inspired networking," *Computer Networks*, vol. 54, no. 6, pp. 881–900, April 2010.

[6] E. Bonabeau, M. Dorigo, and G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press, 1999.

[7] H. Kurata, H. El-Samad, R. Iwasaki, H. Ohtake, J. C. Doyle, I. Grigorova, C. A. Gross, and M. Khammash, "Module-based analysis of robustness tradeoffs in the heat shock response system," *PLoS Computational Biology*, vol. 2, no. 7, pp. 663–675, July 2006.

[8] A. Kashiwagi, I. Urabe, K. Kaneko, and T. Yomo, "Adaptive response of a gene network to environmental changes by fitness-induced attractor selection," *PLoS ONE*, vol. 1, no. 1, December 2006.

[9] N. Meghanathan, "Survey and taxonomy of unicast routing protocols for mobile ad hoc networks," *International Journal on Applications of Graph Theory in Wireless Ad hoc Networks and Sensor Networks*, vol. 1, no. 1, December 2009.

[10] K. Leibnitz, N. Wakamiya, and M. Murata, "A bio-inspired robust routing protocol for mobile ad hoc networks," in *Proceedings of 16th International Conference on Computer Communications and Networks (ICCCN 2007)*, August 2007, pp. 321–326.

[11] N. Asvarujanon, K. Leibnitz, N. Wakamiya, and M. Murata, "Robust and adaptive mobile ad hoc routing with attractor selection," in *Proceedings of 4th International workshop on Adaptive and Dependable Mobile Ubiquitous Systems (ADAMUS 2010)*, July 2010.

[12] C. Perkins, E. Belding-Royer, and S. Das, "Ad hoc on-demand distance vector (AODV) routing," RFC 3561, July 2003.

[13] G. D. Caro, F. Ducatelle, and L. M. Gambardella, "Anthocnet: An adaptive nature-inspired algorithm for routing in mobile ad hoc networks," *European Transactions on Telecommunications (Special Issue on Self-Organization in Mobile Networking)*, vol. 16, no. 5, pp. 443–455, September/October 2005.