Paper

ACO-Inspired Energy-Aware Routing Algorithm for Wireless Sensor Networks

Ryo Yamamoto[1,4], Seira Nishibu[2], Taku Yamazaki[3,4], Yasushi Okamura[1], and Yoshiaki Tanaka[2,4]

[1] Graduate School of Informatics and Engineering, University of Electro-Communications, Chofu-Shi Tokyo, Japan
[2] Department of Communications and Computer Engineering, Waseda University, Tokyo, Japan
[3] College of Systems Engineering and Science, Shibaura Institute of Technology, Saitama, Japan
[4] Global Information and Telecommunication Institute, Waseda University, Tokyo, Japan

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Abstract—Multi-hop networks, such as WSNs, become an object of increasing attention as an emerging technology which plays an important role for practical IoT applications. These multi-hop networks generally consist of mobile and small terminals with limited resources, which makes them vulnerable to various network status changes. Moreover, the limited nature of terminal resources available, especially in terms of battery capacity, is one of the most important issues to be addressed in order to prolong their operating time. In order to ensure efficient communications in such networks, much research has already been conducted, especially in the field of routing and transmission technologies. However, conventional approaches adopted in the routing field still suffer from the so-called energy hole problem, usually caused by unbalanced communication loads existing due to difficulties in adaptive route management. To address this issue, the present paper proposes a novel routing algorithm that utilizes ACO-inspired routing based on residual energy of terminals. Operational evaluation reveals its potential to ensure balanced energy consumption and to boost network performance.

Keywords*—*ant colony optimization, load balancing, routing algorithm, sensor networks.

1. Introduction

A wireless sensor network (WSN) generally consists of a number of terminals which have the capability of sensing and communicating. WSN terminals transmit the information collected to a sink, responsible for collecting and processing information, by direct or multi-hop transmission. WSN is thought to be a promising technology for wide-range observation and requires a bunch of sensors to acquire and relay data. WSN terminals are powered by batteries with limited capacity, and powering the network's nodes in a continuous manner is nearly impossible. Moreover, WSNs are intended to operate in the long-term, and smaller batteries are preferred due to manufacturing and deployment costs. In addition, the cost of replacing the batteries significantly increases when terminals are deployed in an environment that cannot be easily accessed by operators, such as deep forests or underwater installations. Therefore, prolonging the lifetime of WSN with limited battery capacity an important issue that needs to be tackled in order extend the network's operating time as much as possible. Therefore, efficient routing and communication technologies are imperative for the achievement of that objective.

A number of routing methods relying on various approaches have been studied with the view of prolonging the lifetime of WSN, such as [1]–[3]. Although all proposals improve efficiency to a certain degree, there is a drawback in the scalability required to increase the physical coverage of the network, because it requires central management for information processing and terminals with specific capability. To address the drawback, autonomous and distributed mechanisms inspired by the behaviors of living organisms, such as insects, are proposed [5]–[8]. They allow to solve various problems with autonomous and distributed optimization procedures, by imitating the behavior of the living organisms. In this paper, we adopt the concept of ant colony optimization (ACO) [5]–[7] to achieve an energy-aware routing mechanism. In the proposed scheme, ACO is utilized not in order to optimize the route, but to dynamically select routes according to the level of the terminals' residual energy, with the transition statuses relied upon for ACO optimization process.

2. Related Work

2.1. Energy-Aware Routing Protocols for WSN

Paper [1] introduces an asymmetric communication approach enabling to save energy. It utilizes the fact that sinks are generally operated by external power supplies. Thus, sinks are capable of conducting longer-range transmissions, compared with terminals powered by batteries. Therefore, terminals with energy constraints adopt the multi-hop communication model, with shorter range communication, to send information to the sink. Then, the sink, as a mains powered device, provides long range communication with the host. In other words, battery operated terminals require less energy compared with the sink. However, it is the placement of the sink that greatly affects its energy saving ability, because energy consumption is determined by the sum of path lengths from the terminals to the sinks.

The routing method introduced in paper [2] utilizes several topologies, depending on network characteristics, to reduce energy consumption. The method adaptively utilizes star-shaped, tree-shaped, chain-shaped and cluster-shaped topologies. In the star-shaped topology, sinks become the center of the star and other terminals use direct transmission to the sinks for reducing the energy required to receive, process and aggregate the data sensed. The tree-shaped topology will be applied to suppress the energy required for transmission by using the multi-hop method. In the chain-shaped topology, the method establishes a single route that reaches every terminal once, and minimizes the route length to improve reliability. In the cluster-shaped topology, the method divides networks into clusters that have 2-hop neighbors at the most, just as conventional clustering in WNS does. Then, the cluster head aggregates the received information and sends it to sinks to suppress the total amount of send and receive data and the transmission distance. However, environment-related changes caused by joining and leaving of terminals or by other factors forces the method to recalculate the optimal topology and the cost increment that is proportional to the network's size becomes an inevitable issue.

Optimized LEACH-C [3] also adopts cluster-based routing that estimates required energy consumption based on the terminals' location and the number of cluster members of a sink. Optimized LEACH-C utilizes the estimated energy consumption to generate an initial solution and uses the simulated annealing to generate heuristic solutions. Then, the solution is notified to each terminal and clusters will be assigned to terminals entirely. However, in optimized LEACH-C, sinks must play the role of collecting information, performing clustering calculations and notifying the results, which increases the operational costs.

2.2. Ant Colony Optimization

The issues described in Subsection 2.1 may be solved by network-wide optimization which is accomplished by autonomous and distributed state prehension and a decision made by an individual terminal, i.e. by the so-called divide-and-conquer method. The swarm intelligence strategy may serve as an example of such an approach, as it is inspired by the group behavior of insects. Their simple individual behaviors optimize objectives entirely. There are methods that apply the optimization mechanism to manage the behavior of terminals acting as elements of swarms, such as [4].

Ant colony optimization (ACO), inspired by the feeding behaviors of ants, is proposed as one particular application [5]–[7]. ACO generally utilizes agents, called "ants", that secrete "pheromone" to the traveled route, serving as an evaluation value of the route, for adaptive and continuous route updating. Therefore, application of ACO in such an environment as WSN, where the communications conditions change over short periods of time and mutual state prehension by the terminals is difficult, allows to achieve effective performance.

ACO has an ability to discover the shortest route without an effort of centralized management by utilizing the behaviors of ants and the secretion of pheromones, as described previously. Thus, ACO is applied in various combinatorial issues, such as the traveling salesman problem (TSP). A feeding ant detects pheromones on the ground, follows them towards the food source and then returns to the nest with the food, secreting pheromones. As the secreted pheromones volatilize at a constant pace, more pheromones are present along shorter, rather than longer routes. A route with more pheromones attracts more ants and pheromone secretion in regions adjacent to the shortest route becomes active, i.e. ants tend to select the shortest route, as the time passes, as shown in Fig. 1.

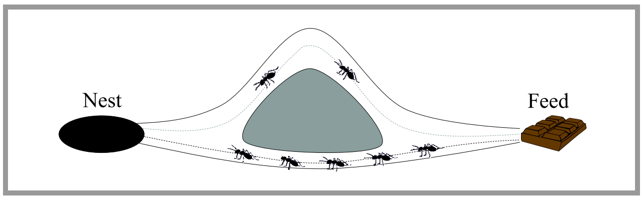

Fig. 1. The principle of ACO routing.

Papers [6], [7] proposed a basic ACO model, called the ant system (AS). Here, we will explain AS with TSP, which is applied, in particular, to combinatorial problems. In the specific application, each ant is treated as m agents and placed in n cities, and creates a route based on the rule that each agent visits each city only once and decides the next city to be visited based on the pheromone level. Equation (1) calculates the probability that agent k in city i on cycle t travels to city j in the next cycle:

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum\limits_{s \in J_k(i)} [\tau_{is}(t)]^\alpha [\eta_{is}]^\beta} & j \in J_k(i) \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where $\tau_{ij}(t)$ represents the pheromone level between city i and j on cycle t, η_{ij} represents the invert of route length between city i and j, $J_k(i)$ represents the set of visiting cities of agent k in city i, and α, β are the constant.

After the agent finishes the trip upon visiting each city and after the route has been created, AS calculates the pheromone level to be secreted along the traveled route with the following Eq. (2):

$$\Delta\tau_{ij}^k = \begin{cases} \dfrac{1}{C_k} & (i,j) \in T_k \\ 0 & \text{otherwise} \end{cases}, \quad (2)$$

where τ_{ij}^k represents the pheromone level to be secreted between city i and j and C_k represents the length of route T_k between city i and city j that agent k created. Then, AS applies the calculated pheromone level to the route and update the residual pheromone level using Eq. (3):

$$\tau_{ij}(t+1) = \rho\,\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \,, \tag{3}$$

where ρ represents the volatile coefficient, i.e. AS volatilizes a certain pheromone level from the remaining pheromones and adds the pheromones secreted by agents. AS continuously repeats this procedure until it discovers the optimal solution.

AS enables ACO-based routing, by relying on simple procedures performed by individual terminals, to find the optimal route without using centralized network management. In addition, as the data travels along the optimal route, reliability improves and energy consumption per packet becomes lower. Although the mechanism identifies and utilizes a route that is most efficient in terms of network performance, concentration of traffic along specific routes may cause an early drop out of terminals due to the exhaustion of batteries.

3. ACO-Inspired Energy-Aware Routing

Here we propose an ACO-inspired energy-aware routing algorithm, named AERO, based on the residual energy of terminals and relied upon for adaptive and dynamic routing. The significant characteristic of AERO is that the agent ant behavior tries not to find the optimal solution, but strives to identify semi-optimal solutions. This prevents the routes with a sufficient pheromone level from being utilized on a continuous manner, until the terminals along the route exhaust their batteries, that is until AERO positively utilizes the transient state of ACO to improve route diversity.

AERO introduces three types of ant imitating control packets to apply ACO while routing, namely forward ant (F-ANT), backward ant (B-ANT) and data ant (D-ANT). In addition, AERO does not secrete pheromones into links between terminals, as the conventional ACO does, but into terminals. The secreted and residual pheromone levels are notified to neighboring terminals with periodical hello message exchanges, just as in the case of conventional routing. A brief description of the routing procedure is presented below.

In AERO, a source terminal first sends F-ANTs towards the desired destination in the same way as conventional routing protocols do, as shown in Fig. 2. The F-ANTs sent by the source terminal travel along various routes and F-ANTs store the terminal ID and the residual energy of each intermediate terminal during the travel. The destination terminal that receives the F-ANTs waits for other F-ANTs, for a predetermined period of time, to collect information about multiple routes.

After the predetermined waiting time elapses, the destination terminal that received multiple F-ANTs evaluates each route using the information stored in the F-ANTs. It needs to be noted that the detailed evaluation procedure will be explained later. The destination terminal generates B-ANTs that contain information about the route and its evaluation value after the evaluation procedure is completed. Then, B-ANTs start their travel by tracing back along the route that F-ANTs traveled, and B-ANTs secrete pheromones to the intermediate terminals along the route during the travel (Fig. 3). This is recursively performed until the B-ANTs reach the source terminal. Note that the source terminal also waits for other B-ANTs, over a predetermined period of time, to receive multiple B-ANTs, just as it was the case with F-ANTs.

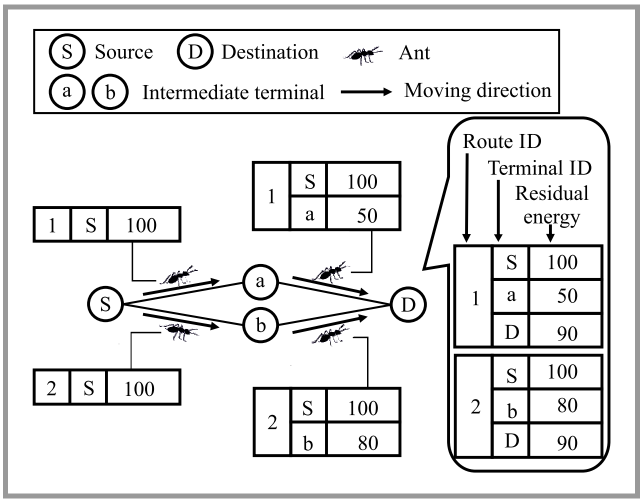

Fig. 2. Forward ant.

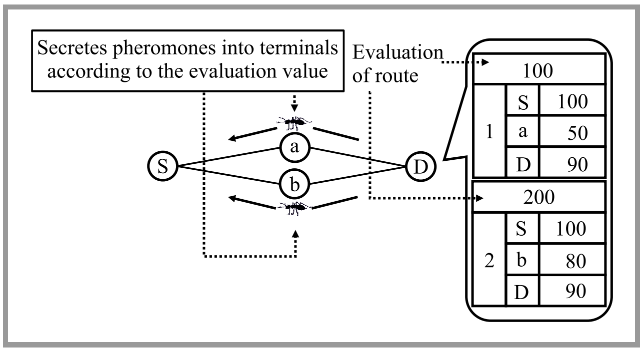

Fig. 3. Backward ant.

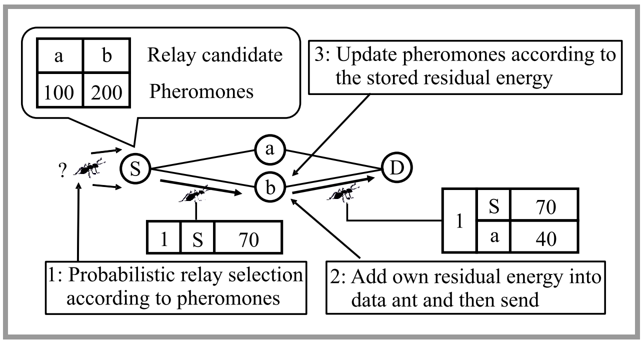

Fig. 4. Data ant scheme.

After the arrival of B-ANTs at the source terminal, it starts the forwarding procedure for data encapsulated by D-ANT (Fig. 4). Senders of D-ANT, namely source and intermediate terminals, select the next hop terminal probabilistically, according to the pheromone level at the candidate receivers. Once the sender determines the receiver, it records its own residual energy to the D-ANT, and the D-ANT travels to the receiver. The receiver selection procedure will be explained in detailed later in this section. The receiver that the D-ANT reaches then updates own pheromones according to the information stored in the D-ANT. By repeating the above scheme recursively, AERO updates the pheromone levels on intermediate terminals and the data encapsulated by the D-ANTs reaches the destination node.

3.1. Route Evaluation and Pheromone Update

The pheromone level on each terminal is calculated at the destination terminal by means of two evaluation values, with the use of the collected route information and the terminal information stored in D-ANT.
We will describe the evaluation values as $H_{A,i}$ and $H_{B,i}$. It needs to be noted that the pheromone level in AERO will always be positive, and that AERO assigns upper and lower limits to that value.

Evaluations at destination terminals. The destination terminals calculate the evaluation values for each route using the information obtained by F-ANTs. In this procedure, AERO first calculates the average residual energy $E_{sd,i}$ of each terminal along route i whose source and destination terminals are s and d, by:

$$E_{sd,i} = \frac{\sum\limits_{j \in n_{sd,i}} e_{ij}}{\left|n_{sd,i}\right|} \ , \tag{4}$$

where e_{ij} represents the residual energy of terminal j along route i, $n_{sd,i}$ represents the set of terminals along route i. Then, the destination terminal calculates the average residual energy of complete routes using the result of Eq. (4) and:

$$E_{sd} = \frac{\sum\limits_{i \in r_{sd}} E_{sd,i}}{\left|r_{sd}\right|} \ , \tag{5}$$

where r_{sd} represents the route set obtained by F-ANTs. Next, the destination terminal calculates the evaluation value $H_{A,i}$ as:

$$H_{A,i} = (1-\beta)\,\frac{E_{sd,i}}{E_{sd,\max}} + \beta\left(\frac{\sum\limits_{j \in n_{sd}, e_{ij} \leq E_{sd}} (e_{ij} - E_{sd})}{\left|e_{i,\mathrm{low}}\right| E_{sd}} + 1\right), \tag{6}$$

where $E_{sd,\max}$ represents the maximum average residual energy along the route set r_{sd}, $e_{i,\mathrm{low}}$ represents the number of terminals along route i whose residual energy is lower than E_{sd}, and β is a constant.

The first member of Eq. (6) becomes closer to 1 when the residual energy of terminals composing route i is high. The second member of Eq. (6) gets closer to 1 when the variance between the residual energy levels of terminals along route i is low. The evaluation value $H_{A,i}$ will be stored in B-ANTs, and the intermediate terminals that the B-ANTs travel along update their pheromones by adding the evaluation value to the current pheromone level.
In addition to the above, AERO takes hop counts into account to calculate the overall evaluation H_i. AERO evaluates the hop count of each route and calculates $H_{B,i}$ as:

$$H_{B,i} = \frac{h_i - (1+\alpha)h_{sd}}{(1+\alpha)h_{sd}}, \tag{7}$$

where h_i represents the hop-count of route i, h_{sd} represents the average hop-count of all routes from source s to destination d, and α represents the acceptable route length increment ratio. With $H_{A,i}$ and $H_{B,i}$, AERO calculates the overall evaluation using the weight parameter γ as:

$$H_i = (1-\gamma)H_{A,i} + \gamma H_{B,i} \ . \tag{8}$$

Pheromone update with data ant. D-ANTs record the residual energy of the terminals along the route and intermediate terminals update their pheromones using the evaluation value calculated with the use of the information stored. The evaluation value for D-ANTs $H_{C,j}$ for intermediate terminal j will be calculated by:

$$H_{C,j} = \frac{e_j - E_{sj}}{E_{sj}} \ , \tag{9}$$

where E_{sj} represents the average residual energy of intermediate terminals after the source terminal s, and e_j represents the residual energy of terminal j at which the D-ANT is currently staying. The evaluation value $H_{C,j}$ becomes positive when the residual energy of the current terminals is higher than the average residual energy, and becomes negative when the latter value is lower. Afterward, the terminal adds $H_{C,j}$ to its own pheromone level, in order to increase or decrease the pheromone level:

$$P_i(t+\Delta t) = (1-\rho)P_i + H_{C,j} \ , \tag{10}$$

$$\rho = \theta \Delta t \ , \tag{11}$$

where Δt represents the time gap between the current time and the last update time, ρ represents volatilization rate, and θ represents a fixed parameter to determine the rate ρ.

3.2. Route Selection

In AERO, route selection is done by the probabilistic way based on the pheromone level of each terminal. Each terminal first confirms the set of candidate intermediate terminals for sending data towards the destination, before D-ANTs travel to other nodes. If there is only one candidate in the set, D-ANTs just start their travel towards the terminal. If there are multiple candidates, sender m calculates the probability of D-ANTs' travel towards the next intermediate terminal n:

$$Q_{mn} = \frac{P_n}{\sum_{i \in N_m^d} p_i}, \tag{12}$$

where Q_{mn} represents the probability that terminal m selects terminal n as the next hop, P_n represents the pheromone level in n, and N_m^d represents the set of candidate intermediate terminals for F-ANTs, leading towards destination d from m. By relying on the probabilistic intermediate terminal selection procedure described above, AERO assigns a higher priority to the node with a higher pheromone level and data encapsulated by D-ANTs travel towards the destination terminal.

4. Performance Evaluation

4.1. Simulation Setup

Computer simulations have been conducted to evaluate the effectiveness of AERO compared to conventional routings, using the QualNet [9] network simulator. In the simulations, we adopted AODV [10], optimized LEACH-C [3], and AS [6], [7] for the routing to be compared. Two scenarios were used to evaluate the performance from the viewpoint of communication qualities and network lifetime. The first evaluates network performance by changing terminal densities that greatly affect the routing results. The second evaluates network lifetime by observing the number of active terminals over time. The common parameters for the simulations are shown in Table 1.

Table 1
Simulation parameters

Parameter	Value
Routing methods	AODV, optimized LEACH-C, AS
Simulation duration	1000 s
Simulation area	1000 × 1000 m
The number of terminals	100–400
The number of sinks	2–10
Wireless medium	IEEE 802.11b
Bandwidth	11 Mbps
Communication radius	150 m
Terminal placement	Random
The number of sessions	50 sessions
Source terminals	Randomly chosen
Packet generation interval	100 ms
Packet size	1000 bytes
Battery capacity	18,000 mAs
Power consumption for sending	840 mAs
Power consumption for receiving	800 mAs

In the simulations, terminals are randomly placed in the square area of 1000×1000 m, and communicate with each other using IEEE 802.11b with the radius of 150 m at the most. Source terminals and the number of packets to be transmitted are randomly chosen, and every packet with the size of 1000 bytes is transmitted every 100 ms. In this paper, we have conducted two simulations by changing terminal density and sink density. The number of terminals is changed from 100 to 400 and the number of sinks from 2 to 10 with 400 nodes.

4.2. Network Performance Evaluation

We evaluate the impact that terminal or sink density has on communication performance by relying on successful delivery rate and end-to-end delay. The successful delivery rate is calculated by dividing the number of received packets by the number of packets generated in terminals. The end-to-end delay indicates the time gap between the initiation time of packet transmission and the time that the destination sink receives the packet.

4.3. Network Lifetime Evaluation

In this simulation, we evaluate the number of active terminals every 25 s to show the efficiency of each routing method. We defined the active terminal as the terminal with the battery level of 40% of the initial capacity. We firstly conducted simulations with 100 and 200 terminals to evaluate the performance in an environment that is tough for the routing methods since the available route diversity is limited to a certain degree. In addition to the aforementioned simulations, we conducted simulations using 6 or 10 sinks with 400 terminals. It is obvious that with the higher number of singles, the path diversity increases and balances traffic load and energy use. However, the improvement in traffic load performance and energy consumption, generally derives from how the routing protocols select or manage routes. Therefore, the simulations reveal the balancing performance from a different point of view.

4.4. Simulation Results

Figures 5–8 show the impact of terminal density on communication performance. In the results, we exclude abnormal outcomes caused by unclosed sessions. Moreover, the values of top and bottom 5%, such as the outlier in the calculation of end-to-end delay, were excluded as well.

Figures 5–7 show the successful delivery rate results. The result indicates that the proposed method could achieve a successful delivery rate of nearly 90%, regardless of terminal and sink density. This is due mainly to the adaptive and dynamic route management of AERO, which effectively suppresses unnecessary route reestablishment by avoiding energy exhaustion of terminals caused by the exhaustion of batteries. The conventional AODV decreases its

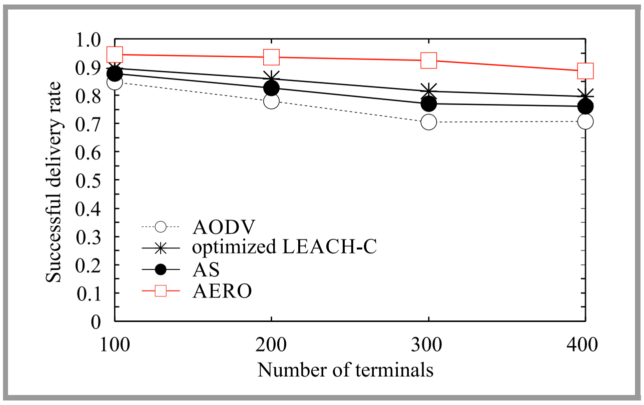

Fig. 5. Simulation of successful delivery rate versus number of terminals.

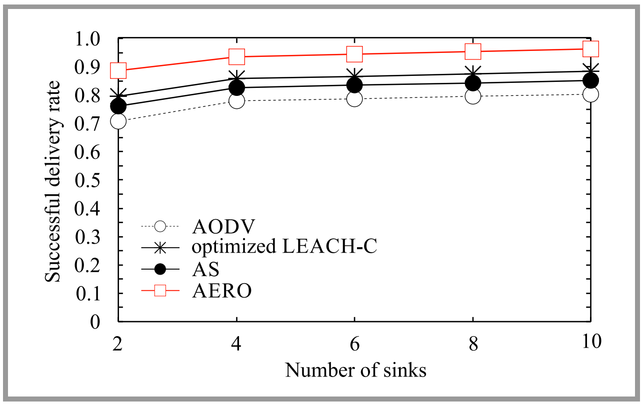

Fig. 7. Simulation of successful delivery rate as a function of number of sinks.

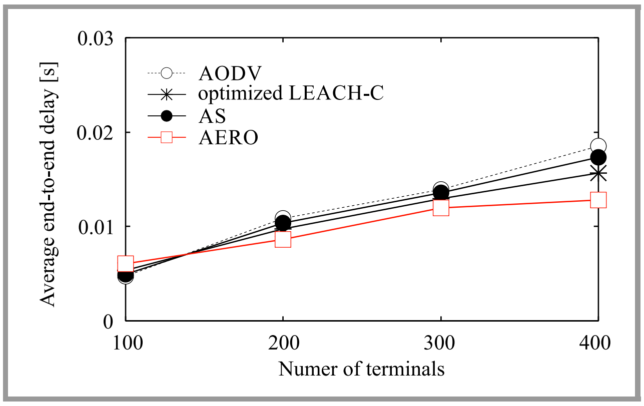

Fig. 6. Average end-to-end delay versus number of terminals.

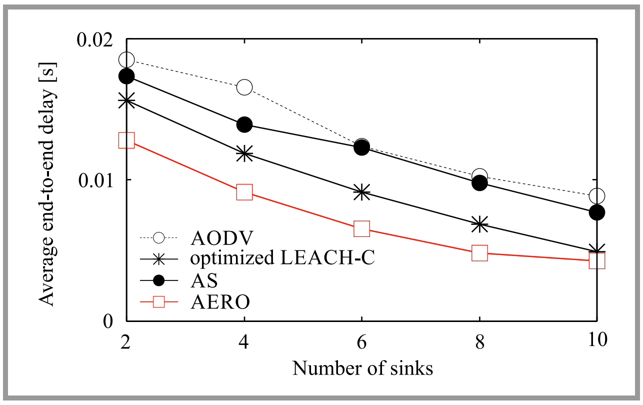

Fig. 8. Average end-to-end delay as a function of number of sinks.

reliability since the routing procedure is basically aimed to establish a single end-to-end route from a source terminal to the destination terminal based on a route length. Moreover, the route length only takes hop-counts into a consideration, and other parameters such as residual energy and reliability are not the metrics for evaluating route quality. Thus, the route established by AODV could not achieve better route quality except for route length. Optimized LEACH-C could achieve better routing performance due to its complex and centralized comprehensive route management, since it can comprehend the states of the entire network and is capable of deriving entirely optimal solutions. Pure AS could achieve a certain degree of improvement compared to AODV, since AS can take other metrics into account, such as pheromone level. However, improvement is limited because pure AS ceases optimization once the optimal solutions are found, and further optimization will be suspended until another route request comes in.

In addition, a common feature could be observed. Namely, the success rate of routing protocols gradually improves as the number of sinks increases. The reason of this is obvious: routes established within the network were autonomously distributed, since the overlapping link usage is autonomously eliminated to a certain degree. However, AERO could achieve a higher rate since the aforementioned characteristics were capable of increasing the base performance of AERO to the higher degree than in the remaining cases.

Figures 6 and 8 show the results of end-to-end delay for each of the routing methods. The results show that each protocol gradually increases the delay as the terminal density increases, whereas the delay is decreased as the sink density grows. The reason for the delay increase mainly derives from the increase in overall traffic within the networks, which will be a cause of a higher queuing delay and interference in transmission to other terminals. Although the delay increase is inevitable, AERO could suppress this type of degradation by means of its adaptive route management and could decrease the delay compared to the other methods. In other words, the probabilistic intermediate terminal selection by D-ANTs could efficiently select the intermediate terminals with less traffic load. On the other hand, other single route-based routing methods degrade the performance compared with AERO, since their routing procedures only show an advantage in terms of route establishment. The decrease of delay, observed as the sink density increases, can also be explained with the same characteristic as described in the explanation of the success rate. In other words, the increase in sink density autonomously balances traffic load without a systematic procedure. In addition to that, we could observe that the base performance is also affected as the density increases.

4.5. Network Lifetime Evaluation

Figures 9–12 show the transition of the active terminal ratio versus elapsed time. The result shows that AERO could reasonably reduce the number of inactive terminals compared with other routing methods. Moreover, the decrease observed in AERO seems to be linear, whereas the decrease typical of other methods seems to be an inversely proportional or exponential. The main reason for the difference can be explained by the routing strategy, as AERO relies on the principle of dynamic and adaptive intermediate selection, whereas other approaches adopt the one-time optimization principle. Another characteristic trend may be identified as the simulation time elapses, namely the rate at which the number decreases is more gentle in the case of conventional routing methods. This can be explained by the manner in which intermediate terminals are selected by the individual methods, since they attempt to utilize the optimal terminals for end-to-end routes and such devices must transmit more packets than others. Thus, the optimal terminals exhaust their batteries and become inactive sooner than other non-optimal nodes. After the rapid exhaustion phase, the methods must select the rest of the terminals as intermediate devices and the selection procedure may autonomously balance traffic loads.

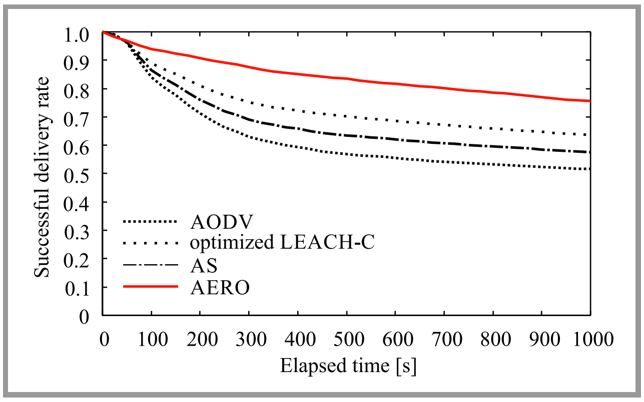

Fig. 9. Active terminal ratio (100 terminals) vs. time.

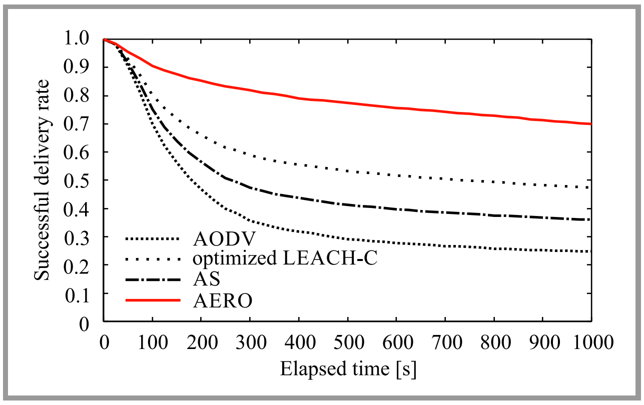

Fig. 10. Simulation results on active terminal ratio (200 terminals) vs. time.

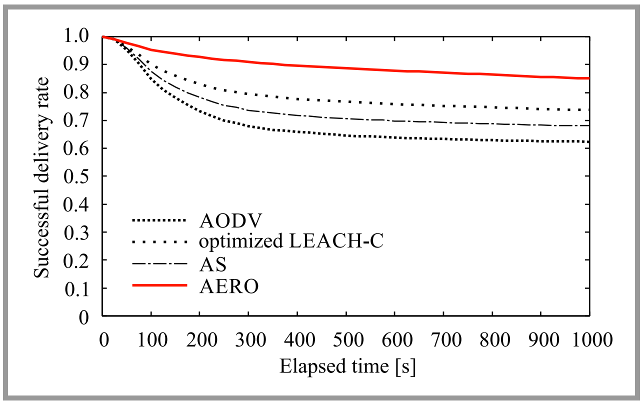

Fig. 11. Active terminal ratio value (6 sinks) vs. simulation time.

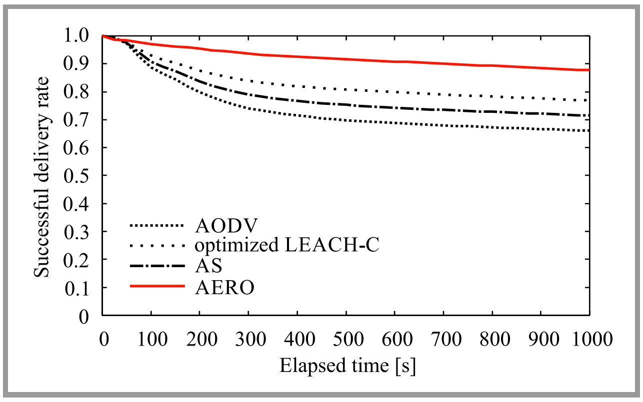

Fig. 12. Results on active terminal ratio (10 sinks) vs. simulation time.

4.6. Summary of the Simulations

Through the simulations conducted above, we confirmed that the proposed AERO approach may extend the lifetime of a network while maintaining its reasonable performance. The major contribution of the proposed solution derived primarily from its adaptive and dynamic route and intermediate terminal selection principle, which utilizes the transient state of ant-colony optimization. Moreover, the unique characteristic consisting in the fact that AERO secretes pheromones not to links, but to terminals, enables adaptive and dynamic intermediate terminal selection.

5. Conclusions

This paper proposes an ACO-inspired routing strategy, known as AERO, for WSNs, enabling to balance traffic loads by utilizing transient behaviors for optimization. Performance evaluation reveals that the AERO approach proposed may achieve improved routing efficiency compared with other existing routing methods. In other words, AERO requires less transmission effort to send the same amount of data and improves energy efficiency.

Although the improvement achieved by AERO contributes to prolonging the lifetime of WSNs, there is still room for further improvement, since AERO currently does not take into account terminal statuses, such as their awake and sleep modes. Moreover, such issues as refining the procedure relied upon to calculate the evaluation values, as well as assessment of performance with the use of realistic models may also be addressed in the future.

Acknowledgments

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Ryo Yamamoto received his B.Eng. and M.Eng. degrees in Electronic Information Systems from Shibaura Institute of Technology, Tokyo, Japan, in 2007 and 2009. He received D.Sc. in global telecommunication studies from Waseda University, Tokyo, Japan, in 2013. He was a research associate at Graduate School of Global Information and Telecommunication Studies, Waseda University, from 2010 to 2014, and has been engaged in researching in wireless communication networks. He is presently an Assistant Professor at Graduate School of Informatics and Engineering, The University of Electro-Communications. He received the IEICE young researcher's award in 2010, the IEICE Network System Research Award in 2014, the CANDAR/ASON Best Paper Award in 2014, IEICE Communications Society Distinguished Contributions Award in 2017, IEICE Information and Communication Management Distinguished Contributions Award in 2014 and 2017. His current research interests are ad hoc networks, sensor networks, IoT/M2M networks, and network protocols for the networks. He is a member of IEICE and IEEE.

E-mail: ryo-yamamoto@uec.ac.jp
Graduate School of Informatics and Engineering
The University of Electro-Communications
1-5-1 Chofugaoka
Chofu-Shi Tokyo, 182-8585 Japan

Global Information and Telecommunication Institute
Waseda University
3-4-1 Okubo
Shinjuku-ku, Tokyo, 169-8555 Japan

Seira Nishibu received the B.Eng. degree in Communication and Computer Engineering from Waseda University, Tokyo, Japan, in 2018. She is presently an employee of The Kansai Electric Power Co., Japan.

Department of Communications and Computer Engineering
Waseda University
3-4-1 Okubo
Shinjuku-ku, Tokyo, 169-8555 Japan

Taku Yamazaki received the B.E. and M.Sc. degrees in Electronic Information Systems from Shibaura Institute of Technology, Tokyo, Japan, in 2012 and 2014, respectively. He received the D.E. degree in Computer Science and Communications Engineering from Waseda University, Tokyo, Japan, in 2017. He was a research associate at Department of Communications and Computer Engineering, Waseda University, from 2015 to 2018. He is presently an Assistant Professor at Department of Electronic Information Systems, Shibaura Institute of Technology, Saitama, Japan. He is also presently an Adjunct Researcher at Global Information and Telecommunication Institute, Waseda University, Tokyo, Japan. His research in-

terests are ad hoc networks, sensor networks, and Internet of Things.
E-mail: taku@shibaura-it.ac.jp
College of Systems Engineering and Science
Shibaura Institute of Technology
307 Fukasaku, Minuma-ku
Saitama-shi, Saitama, Japan

Global Information and Telecommunication Institute
Waseda University
3-4-1 Okubo
Shinjuku-ku, Tokyo, 169-8555 Japan

Yasushi Okamura received the B.Eng. degree in Informatics and Engineering from The University of Electro-Communications, Tokyo, Japan, in 2018. He is presently a master course student at Graduate School of Informatics and Engineering, the University of Electro-Communications. His research interests are ad hoc networks, sensor networks, and Internet of Things.
E-mail: okamura@net.lab.uec.ac.jp
Graduate School of Informatics and Engineering
The University of Electro-Communications
1-5-1 Chofugaoka
Chofu-Shi Tokyo, 182-8585 Japan

Yoshiaki Tanaka received the B.Eng., M.Eng., and D.E. degrees in Electrical Engineering from the University of Tokyo, Tokyo, Japan, in 1974, 1976, and 1979, respectively. He became a staff at Department of Electrical Engineering, the University of Tokyo, in 1979, and has been engaged in teaching and researching in the fields of telecommunication networks, switching systems, and network security. He is presently a professor at Department of Communications and Computer Engineering, Waseda University. He received the IEICE Achievement Awards in 1980, the Okawa Publication Prize in 1994, the Commendation by Minister for Internal Affairs and Communications in 2009, the IEICE Distinguished Achievement and Contributions Awards in 2013. He is an Honorary Member of IEICE.
E-mail: ytanaka@waseda.jp
Department of Communications and Computer Engineering
Waseda University
3-4-1 Okubo Shinjuku-ku, Tokyo, 169-8555 Japan

Global Information and Telecommunication Institute
Waseda University
3-4-1 Okubo
Shinjuku-ku, Tokyo, 169-8555 Japan