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# A Novel Method of Routing for MANETs with Considering the Energy by Learning Automata

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**Abstract:** Abstract_Recent advances in wireless technology have enabled the rapid development of wireless manet networks. This paper proposes a novel on-demand routing protocol for mobile ad hoc networks based on best route selection with learning automata. Our proposed protocol is capable of operating efficiently in the route with considerationenergy restriction.We applied our method in an optimized version of an ad hoc on-demand distance vector (AODV) routing algorithm, namely Learning Automata AODV Routing (AAODV). In this protocol, a learning automata agent keeps running on every node and this agent routes the packets in a best path (most of the time shortest path), which in turn saves the energy. We have discussed simulation results by comparing with AODV and DSDV protocols.

**Key words:** Mobile ad hoc network · AODV Routing · Learning Automata · AODV-based Routing

## INTRODUCTION

Mobile Ad hoc Networks (MANETs) consist of a collection of wireless mobile hosts (called nodes), recently have received increasing attention. Independence from central network administration, ability for being self configured, self-healing through continuous reconfiguration, scalability and flexibility are the distinguished reasons to deploy such networks [1]. MANETs require no fixed infrastructure or central administration. Mobile nodes in an ad hoc network work not only as hosts but also as routers and communicate with each other via packet radios.

Topology of a mobile ad hoc network will often change rapidly; this behavior needs some management and solving problem of this type of networks. If source and destination nodes are not within the transmission range of each other, intermediate nodes are needed to serve as intermediate routers for the communication between the two nodes [2]. Moreover, mobile platform moves autonomously and communicate via dynamically changing network. Thus, frequent change of network topology is a main challenge for many important topics, such as routing protocol robustness and performance degradation [3].

In this paper we first consider the ad hoc On-demand Distance Vector Routing Protocol (AODV) and optimized version ofthis algorithm namely Learning Automata AODV Routing (AAODV). For designing our algorithm, we used learning automata for selection best route between available routes. For path discovery, route with shortest and highest energy is selected in path.

The remainder of the paper is organized as follows. Introduction to learning automata is presented in section 2. Section 3 discusses the proposed protocol. Simulation results are explained in section 4 and section 5 presents the survey of related work. Section 6 concludes with an outlook on future directions.

**Learning Automata (Concepts):** In a learning automata system, when a specific action is performed, the random environment provides either a favorable or an unfavorable feedback. The objective in the design of the learning automaton is to determine how the previous actions and responses should affect the choice of the current action to be taken. Figure 1 shows learning operating in a random environment. Automaton learns from the feedback provided by the random environment and it takes decisions based on the knowledge provided by the random environment. At any stage, the choice of action could be either deterministic or stochastic.

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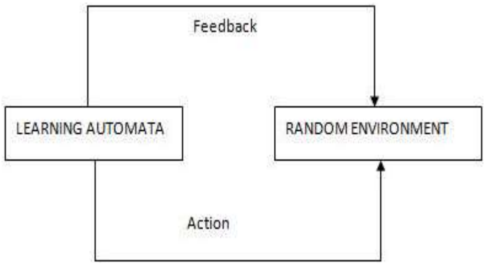


Fig. 1: Automation

A learning automaton [4]can be formally and precisely described in terms of the following:

- State of the automaton at any instant, denoted by $\phi(n)$, is an element of the finite set

$$\phi = \{\phi_1, \phi_2, ..., \phi_s\}$$

- Output or action of an automaton at the instant n, denoted by $\alpha(n)$, is an element of the finite set

$$\alpha = \{\alpha_1, \alpha_2, ..., \alpha_s\}$$

- Input of an automaton at the instant n, denoted by $\beta(n)$, is an element of the finite or in finite set

$$\beta = \{\beta_1, \beta_2, ..., \beta_s\}$$

- Transition function F (.) determines the state at the instant (n+1) in terms of the state and input at the instant n and could be either deterministic or stochastic $\phi(n+1) = F[\phi(n), \beta(n)]$
- Output function G (.) determines the output of the automaton at any instant n in terms of the state at that instant and could be either deterministic or stochastic $\alpha(n) = G[\phi(n), \beta(n)]$

In the latter case, probabilities are maintained for each possible action to be taken which are updated when the feedback is received from random environment.

Designing an updating algorithm is a crucial one in learning schemes. The updating algorithm can be either linear or non-linear. Several linear reinforcement schemes are such as the linear Reward-Penalty (LR-P) scheme and the linear Reward-Inaction (LR-I) scheme and the linear Reward-ε-Penalty scheme (LR- εP).

The updating algorithm (function) is used to enable the automaton to learn the state of the random environment based on the feedback obtained and choose the best possible action at any point off time.

Basic idea behind the LR scheme is as follows. When a positive response is obtained for an action, its probability is increased and the probabilities of all other actions are decreased. If a negative feedback is received for an action, the probability of that action is decreased and that of others is increased. Mathematically, for a two action system, it can be written as follows: When a positive feedback is obtained for action 1,

$$p_1(n+1) = p_1(n) + a(1 - p_1(n))$$
$$p_2(n+1) = p_2(n)(1 - a)$$

When a negative feedback is obtained for action 1,

$$p_1(n+1) = p_1(n)(1 - b)$$

$$p_2(n+1) = p_2(n) + b(1 - p_2(n))$$

And similarly for action 2, where a and b are the reward and penalty parameters, respectively and $0 < a < 1$, $0 \leq b < 1$. These parameters a and b, determine the rate of learning. For a multi-action system with S states, the updating algorithm can be written as follows:
When a positive feedback is obtained for action i,

$$p_j(n+1) = p_j(n)\ (1 - a), j \neq i$$

$$p_j(n+1) = p_j(n) + a(1 - p_i(n))$$

When a negative feedback is obtained for action i,

$$p_j(n+1) = p_j(n)\ (1 - b)$$

$$p_j(n+1) = \frac{b}{s-1} + (1-b)\, p_j(n), j \neq i$$

And similarly for all i = 1... S, where $0 < a < 1$, $0 \leq b < 1$. An outline of the proof of convergence of the LR-P scheme is provided in [4]. In all our simulations, we assume $a = b$ and we refer to this as learning parameter.

**Related Works:** Many service discovery approaches have been proposed in the literature, with the most efficient in terms of energy consumption being cross layer approaches, which try to embed service discovery functionality into routing protocols [5, 12]. These cross layer approaches aim to minimize energy consumption by combining service and routing information into routing packets. This way, redundant transmissions of service discovery packets at the application layer are avoided and a lot of energy is saved. However, besides the basic service discovery process another process that can be modified in order to take into account (and possibly save) energy is service selection. Service selection can be categorized to automatic and user assisted [7]. User assisted service selection requires the active participation of the user in the selection process. In such case the user has to run through a list of discovered services and select the best service that satisfies his/her needs. However, pervasive devices (e.g. PDAs) forming MANETs impose many limitations in such a process. On the one hand such devices have limited capabilities (i.e: small screen size, limited Graphical User Interfaces) and on the other hand it is hard for users on the move to concentrate (and also loose time) on reviewing service lists for selecting the most appropriate one. In a fast changing environment, where services appear and disappear in an unexpected way, it is crucial to employ a fast and efficient service selection process, which will also not distract the user.

This has lead researchers to investigate automatic service selection mechanisms, mainly based on service ranking systems with the ranking function requiring only an initial parameterization by the user. This parameterization regards assigning weights to various desirable service characteristics, so that user preferences can be reflected by a ranking function. A representative example of such a mechanism is found in [5], in which authors propose that users customize their selection algorithm and embed it in a mobile agent. Agents are then transferred to the service providers and compute a rank based on the specified metrics. They then send back to the requestor these ranks and based on a local user policy the desired service is selected.

In general a service selection strategy is based on certain criteria or metrics. These metrics can be either route (e.g. hop-count, bandwidth, delay) or service (e.g. server mobility, load, remaining energy and capacity) specific. In the discovery protocols proposed in [6] and [7] authors employ the lowest hop-count metric for selecting the service that is the closest to the requesting node. In [9] the discovery protocol proposed (based on proactive server advertisements) selects a service instance based on two metrics, the hop-count between service requestor and service provider and also the capacity of service (CoS), which expresses the nominal capacity of a service instance.

In this paper our contribution is to investigate how a service selection strategy based on a route specific metric (hop-count) and a service selection strategy based on a service specific metric (remaining energy) affect the discovery process in a MANET by using an AODV-based service discovery protocol. We select the hop count metric since it is the most representative of route specific metrics and also commonly used by service selection mechanisms [7, 9, 11, 12]. For the second service selection strategy, the remaining energy is selected, among other candidate service specific metrics, since energy preservation is of major importance in energy-constrained environments like MANETs.

**Proposed Method:** One of the prime and evergreen research areas in wireless networks is the enhancement of network's lifetime. Before describing the proposed protocol, we give some definitions. The neighbors of a node are the nodes which are directly connected to that node and the number of such nodes is called the degree of the node. The objective of our approach can be compared to the earlier ones. In brief, the nodes in this protocol continuously obtain pertinent information, or in other words learn about the most preferred neighbors for routing, by considering the hop count to the destination and the remaining energy.

Stability method in this paper for route selection and increasing performance is introduced. A good design of the ad hoc routing protocol is needed to overcome the problem. AAODV algorithm solved this problem with selection the route with minimum length and remaining energy in available set of route that found.

The protocol has different phases, which are described as follows:

**Flood Phase:** The node which wishes to transmit data initiates this phase by flooding the network to reach the destination.

This is a source initiated flooding wherein, the source node upon detection of an event generates a RREQ PACKET and forwards it to its neighbors. The packet carries the destination ID with it. The nodes en-route to the destination, upon receiving the packet checks if the ID on the packet and its node ID match. If it does, then it initiates the LT phase or else it will just forward the packet to its neighbors.

**Learning and Construction Route Table:** During this phase the intermediate nodes receive initial feedback from their immediate neighbors and construct their local forwarding table.

Following the flooding phase, the destination node creates a packet RREP (FEEDBACK packet) with two fields namely node ID, The node ID field contains the ID of the node from which the packet has been received, hop count. The hop count fields contain the number of hops to the destination from.

The probability of the selecting ith neighbor node is referred as preference. The initial preference for that node is calculated equally.

**Learning Phase and Routing:** The packets are routed in consultation with the forwarding tables and the nodes continuously learn through this process. Routing Phase: Routing from the source nodes to the destination is realized with the help of the routing table constructed during the LT phase and the entries in the table are continuously updated based on the system state (parameters such as hop count and energy).

To route, each node scans its forwarding table and picks the node with the highest preference and forwards the DATA packet(which is different from FLOODING packet) to this node. This process is repeated until the destination node is reached.

**Learning Algorithm:** The periodic feedbacks received from the nodes during the routing phase aid the system in learning about the best routes available. When a node routes a packet to another node, the node at the receiving side, sends a feedback which has the node's residual energy on it.

If the node energy is between 50 and 75 percent of average energy nodes in the network, it will get a positive feedback then the node's performance will be increased by the formula (1):

$$P_{new}(j) = \partial(P_{prev})(j) + \alpha) \qquad (1)$$

Where:

$a$ = *revard function* & $\partial$ = *cons* tan *t number*

If the node energy is between 75 and 100 percent of average energy nodes in the network, it will get a positive feedback then the node's performance will be increased by the formula (2):

$$P_{new}(j) = \partial(P_{prev})(j) + 3\alpha)$$

Where:

$\alpha$ = *reward function*

Else

$$P_{new}(j) = \partial(P_{prev})(j) - \beta)$$

Where:

$\beta$ = *penatly function* & $\partial$ = *cons* tan *t number*

And

$$\alpha = \psi_1 * \frac{\gamma * energy_i + (\max hop - hop_i)}{\gamma * avgenergy + \max hop}$$

$$\beta = \psi_2 * \frac{\gamma * (avgenergy - energy) + hop_i}{\gamma * avgenergy + \max hop}$$

Where:
*Energy$_i$: energy level of node i.*
*Hopi$_:$ hop count of node i.*
*Avgenergy: average energy of network nodes.*
*Maxhop: maximum hop between two nodes.*

Evaluation for evaluating the new algorithm we used Network Simulator (ns2). It should be mentioned that different scenarios are used for simulation considering the type of experiment. In this section, we compared proposed algorithm with DSDV and AODV. It should be mentioned that our analysis is based on packet delay, drop and remaining energy.

**Simulation:** Evaluation for evaluating the new algorithm we used Network Simulator (ns2). It should be mentioned that different scenarios are used for simulation considering the type of experiment. In this section, we compared proposed algorithm with DSDV and AODV. It should be mentioned that our analysis is based on packet delay, drop and remaining energy.

In Figure 2, the protocols have been compared on the base of delay. As you see, because we have chosen a route with many hops, AAODV delay is greater than AODV delay. And it occurs when the energy of the route with less hops is decreasing. This measure, is defect for this approach.

As you see in the Fig 3, the dropping of AAODV is the least because the energy consuming in the network is in balance. This makes their paths are less corrupt therefore send action for transmit packet not be done again.

Figure 4 show the sum of all dropping packet in simulation time and so AAODV is less than other protocol.

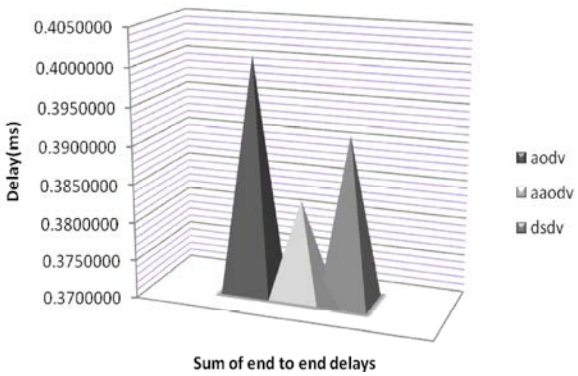


Fig. 2: latency

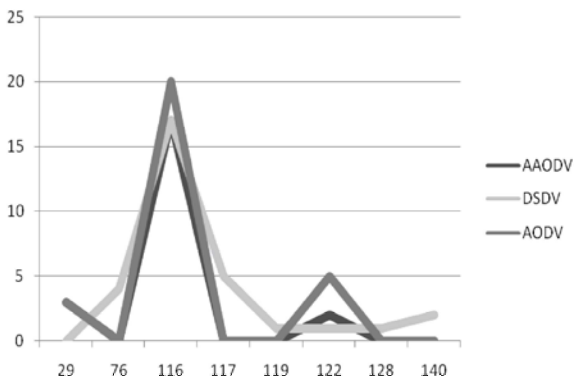


Fig. 3: Dropping in different time.

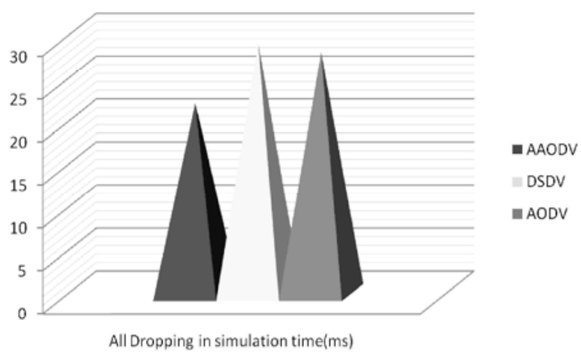


Fig. 4: Sum of all Dropping in simulation time

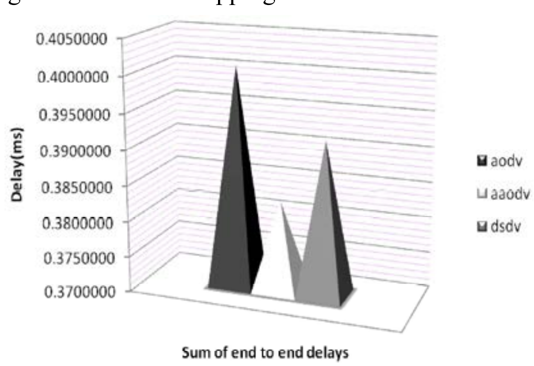


Fig. 5: Energy Consuming

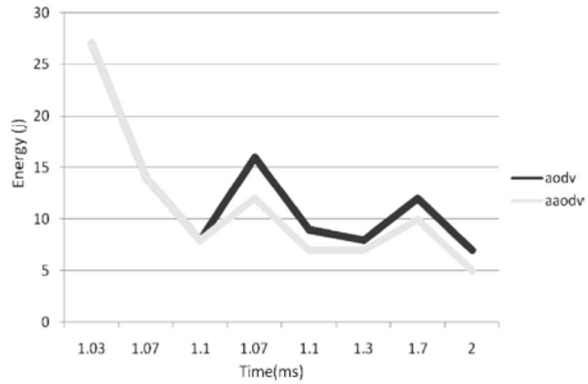


Fig. 6: Consuming Energy for one node.

From Figures 5 it can be understood that energy consuming of AAODV method less than AODV protocol in the entire network because AAODV approach is less dropping packet than AODV where this issue of preventing resending packets.

Figure 6 show Energy Consuming for one nod between AODV and AAODV, Where this node between other nodes is closest to the destination. The purpose of this experience is show energy balance in the network. From the figure 6 is clear that AAODV approach choose the different paths with more hop counts and routes with high remaining energy. This makes its energy consumption to be balanced.

## CONCLUSION

We have presented an AAODV protocol, in which a approach was adopted to increase the network lifetime. In this protocol, a learning automata agent keeps running on every node and this agent dynamically learns the best path. The protocol consist of three phases in which the node learns the best route to the destination. We have discussed the simulation results by comparing with AODV and DSDV protocols.

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