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EAAC: Energy-Aware Admission Control Scheme for Ad Hoc Networks

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Abstract—The decisions made by admission control algorithms are based on the availability of network resources viz. bandwidth, energy, memory buffers, etc., without degrading the Quality-of-Service (QoS) requirement of applications that are admitted. In this paper, we present an energy-aware admission control (EAAC) scheme which provides admission control for flows in an ad hoc network based on the knowledge of the present and future residual energy of the intermediate nodes along the routing path. The aim of EAAC is to quantify the energy that the new flow will consume so that it can be decided whether the future residual energy of the nodes along the routing path can satisfy the energy requirement. In other words, this energy-aware routing admits a new flow iff any node in the routing path does not run out of its energy during the transmission of packets. The future residual energy of a node is predicted using the Multi-layer Neural Network (MNN) model. Simulation results shows that the proposed scheme increases the network lifetime. Also the performance of the MNN model is presented.

Keywords—Ad hoc networks, admission control, energy-aware routing, Quality-of-Service, future residual energy, neural network.

I. Introduction

IN the recent literature, ad hoc networks (AHN) have gained much attention, due to the convenience of building mobile wireless networks without any need for pre-existing infrastructure. The nodes in an ad hoc network cooperatively maintain network connectivity. Each node acts as a router and forwards packets to the next hop in order to reach the final destination via multiple hops. The AHN environment is typically characterized by energy-constrained nodes, variable-capacity, bandwidth-constrained wireless links and dynamic topology, leading to frequent and unpredictable connectivity changes. Multimedia applications that use these type of networks require QoS support for effective communication. Therefore, the QoS has to provide applications with guarantee in terms of bandwidth, energy, delay, etc [3].

Many dynamic routing protocols for AHNs have been proposed and evaluated. The on-demand source routing protocols such as DSR[1] and AODV[2] are energy-unaware. Routing is done based on number of hops or end-to-end delay at the time when route is established and they do not proactively modify the routes until they break. If nodes are energy-constrained, such metrics may have adverse effect on the network lifetime leading to performance degradation. Several works has been done on energy-aware routing in mobile ad hoc networks since the nodes are characterized by their limited battery power [8], [9], [12], [15], [16], [17], [18]. Motivated by the increasing importance of real time and multimedia applications with different QoS requirements e.g., VoIP and video conferencing, several QoS-constrained algorithms for multimedia communications in wired/wireless networks have been proposed in the literature [4], [5], [6], [12]. Because of the provision of high speed wireless Internet services, QoS-guaranteed applications are crucial to new generation wireless multimedia communication systems. To meet the QoS requirements of the applications, routing protocols are required to construct routes, with the QoS being guaranteed. The goal of any QoS support is to provide applications with guarantee in terms of bandwidth, energy, etc. To provide such guarantee in a networked environment, the MAC layer is responsible for resource allocation at individual nodes, while the network layer must consider resources along the entire route of communication.

Energy-aware communication is a challenging issue in AHNs due to the energy constraint of battery in each node, which are responsible for relaying data packets for neighbor nodes. Therefore, considerable research has been devoted to the research on energy-aware routing. Care has been taken not only to reduce the overall energy consumption but also balance individual battery usage, since unbalanced energy consumption will result in earlier node failure for overloaded nodes, leading to network partition and reduced network lifetime. In this paper, we present an energy-aware admission control (EAAC) scheme for AHNs based on the knowledge of the present and future residual energy of each node along the routing path. Only nodes with sufficient residual energy to complete the transmission of data by the application will take part in forwarding packets. Therefore, it can be avoided that any node in the routing path does not run out of its energy during the transmission of packets. The future residual energy of a node is calculated using MNN model.

Rest of the paper is organized as follows. In Section II, some previous energy-aware routing protocols relevant to AHNs are reviewed. Some key characteristics of wireless mobile ad hoc communication are discussed in Section III. Section IV discusses the challenges and solutions for providing admission control based on energy in ad hoc networks. The MNN model and its training procedure for residual energy predictions are described in Section V. In Section VI, we present the design of EAAC protocol in detail. Simulations are carried out to demonstrate the effectiveness of the proposed work and is presented in Section VII. In Section VIII, this paper concludes with some remarks.

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II. Related Works

The early literature on ad hoc networking primarily addressed the design of efficient routing algorithms but without the consideration of energy of mobile nodes. After the work of Singh et. al. [9], there has been a growing literature on energy-aware routing in wireless ad hoc networks. Many energy-aware routing protocols have been proposed from a variety of perspectives and some of the related works are briefly described below.

Two main representative energy-aware routing protocols are minimum total transmission power routing (MTPR) [8] and min-max battery cost routing (MMBCR) [9]. MTPR was initially developed to minimize the total transmission consumption of nodes in the acquired route. This routing mechanism prefer routes with more hops having short transmission ranges to those with fewer hops but having long transmission ranges and increases end-to-end delay. MMBCR considers the residual power of nodes as metric for acquiring routes to prolong the lifetime of each node.

A conditional max-min battery capacity routing (CMM-BCR) protocol arbitrate between MTPR and MMBCR is presented in [10]. It considers both the total transmission energy consumption of routes and the remaining energy of nodes. When all nodes in some possible routes have sufficient remaining battery capacity (i.e., above some pre-specified threshold), a route with minimum total transmission energy is chosen among these routes.

In [11], an energy preserving mechanism is proposed which considers total energy consumption and residual energy of nodes as routing metrics. The energy cost calculation is based on the prediction of node energy consumption in the future using ARIMA model. The OLSR protocol is extended using this mechanism.

In [14], two routing mechanisms for mobile AHNs, minimum drain rate (MDR) and conditional minimum drain rate (CMDR) based on the energy drain rate is proposed. In MDR, each node computes the energy drain rate (DR) every T seconds. This DR metric is used to predict the lifetime of nodes according to the current traffic conditions. Combined with the value of residual energy, this metric is used to establish whether or not a node can be part of an active route. The CMDR mechanism is based on choosing a path with minimum total transmission energy consumed among all the possible paths constituted by nodes with a lifetime higher than a given threshold as in MTPR approach. In case no routes verifies this condition, CMDR switches to the basic MDR mechanism.

In [15], routing algorithms for traffic-dependent and energy-based time delay for improving the energy efficiency in AHNs were proposed. Two algorithms energy-based time delay routing (EBTDR) and highest energy routing (HER) try to increase the operational life time of the network by implementing a few modifications to the basic DSR protocol and making it energy efficient in routing packets. In EBTDR, the modification is enabled by introducing a delay in forwarding the packets by nodes, which is inversely proportional to the remaining energy level of the node. In HER, the route selection is based on the energy drain rate information that constitutes the route. The drain rate is used to predict the lifetime of nodes, according to the current traffic conditions similar to [14].

Based on the above related works and literature [16], [17], [18], [19] in the area of energy-aware routing in AHNs, the observations made are as follows.

- Since MTPR [8] does not consider the remaining energy of nodes, it may not succeed in extending the lifetime of each node.
- MMBCR [9] extends the lifetime of nodes, but it does not guarantee that the total transmission energy is minimized over a given route.
- However, the CMM-BCR protocol [10] does not guarantee that the nodes with high residual energy will survive without energy breakage even when heavy traffic is passing through the node.
- Routing mechanisms based on the current residual energy cannot be used to establish the best path between source and destination nodes. If a node accepts all route requests only because it has enough residual energy, much traffic load will be injected through that node. This results with the sharp reduction of energy, causing the node to halt soon.
- The mechanisms in [14], [15] calculates the drain rate based only on two values, i.e., previous and newly calculated DR values. Therefore, these values used to predict the lifetime of a node based on the current traffic conditions is not (nearly) accurate.
- When a node that lies on several routes forwarding packets generated from different source applications, could not determine when it completely drains out its energy.
- Less attention is paid to the issues related to the energy-based QoS requirement of a route, i.e., to provide guaranteed battery power for the transmission of packets along the path from a source node to the destination such that any node in the path does not run out of its power during the transmission of packets.

To mitigate these problems, we predict the future residual energy of a node based on the history of nodes' energy and admit a new flow only if the future residual energy can meet the energy requirement of the new flow while maintaining the energy levels of the already admitted applications.

III. Characteristics of Energy-aware Routing in AHNs

To enable services such as streaming real-time multimedia and voice data in multi-hop wireless networks, it is necessary to develop algorithms that guarantee QoS. Energy and bandwidth are both limited and precious resources in wireless mobile ad hoc networks. Investigating the utilization of energy in mobile nodes while routing is necessary in energy-constrained ad hoc environments. In the following, we highlight some of the important characteristics energy-aware routing in ad hoc networks.

A. Battery Problems

Battery power is a precious resource in AHNs since it is *nonrenewable*: a mobile node has a finite, monotonically decreasing energy store [20]. Mobile node batteries has unique characteristics of drain rate (energy dissipation rate) that depends on the make, model, property, capacity, etc. The drain rate of some batteries are higher/lower as compared to other batteries. These characteristics have made designing an efficient and reliable QoS routing based on energy a challenging problem.

B. Mobility

The features of mobility affects mobile communications on all the components, including devices, networks, services and also the protocol stack. Mobility consumes more energy because of the network connection and packets transaction overhead. It may be possible to follow a strict QoS in wired networks, but the same cannot be guaranteed in an AHN where mobility is present. Because mobility can break routes frequently and is unpredictable. Therefore, the QoS requirements in these type of networks should be realized to allow a better-than-best-effort service.

C. Admission control

Admission control is a fundamental mechanism used for QoS provisioning in a network. It restricts the access to the network based on resource availability in order to prevent network congestion, service degradation, connection failures, etc. for already supported users. A new request is accepted only if there are enough amount of resources to meet the QoS requirements without violating the QoS of already accepted requests.

D. QoS Routing

QoS routing protocols search for routes with sufficient resources in order to satisfy the QoS requirements of a flow. Depending on the applications involved, the QoS constraints could be bandwidth, cost, end-to-end delay, jitter, energy, probability of packet loss, and so on [3]. The energy metric is concave (i.e., a certain amount of energy must be available on each node along the path). The energy considered for making a routing decision is the residual energy available for the new traffic flow. The energy of a path is defined as the minimum of the residual energy of all nodes on the path or the bottleneck energy.

This work addresses the above challenges with the goal of providing an effective admission control scheme for AHNs so that end-to-end connections with QoS requirements (i.e., energy-satisfied route) can be established.

IV. Energy-Aware Admission Control (EAAC) Scheme

The aim of EAAC is to determine whether the available resource (i.e., energy in our case) can meet the requirements of a new flow while maintaining energy levels for the existing flows. So, the source node admits a new flow to the network only if any node along the path to the destination do not run out of its energy during the transmission of packets. Due to the fact that each node's energy dissipation rate depends on the number of transmission (T_x), reception (R_x) and overhearing (O_h) activities, it is required to calculate the energy consumption when single/multiple flows are considered, predicting the residual energy (RE) in the future and quantifying the energy that a new flow will consume, so that it can be decided whether the RE can satisfy the requirements of the flow without disrupting the completion of the entire flow. In the following, we discuss these challenges and their solutions.

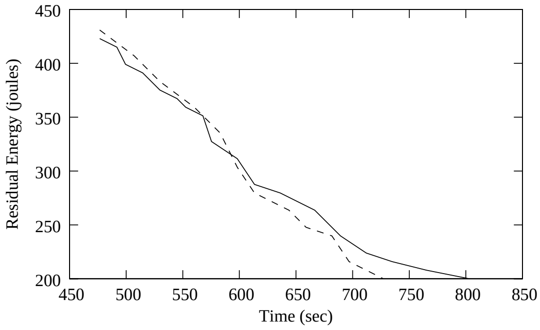

Fig. 1. Residual energy values of two selected nodes recorded over a period of time.

A. A Simple Scenario

In this section, we demonstrate a simple simulation scenario of the energy dissipation of nodes in an ad hoc network environment when multiple flows are considered using *ns-2*[30]. In this scenario, 50 nodes move within a 800x800 area. The node speed is varied between 0 to 20m/sec. Each node has a fixed transmission range of 250 meters. The simulation had a duration of 800 seconds. Ten CBR connections were generated producing 4 packets/sec with a packet size of 512 bytes in different times. All nodes have different initial energy values. The DSR protocol is used as the underlying routing protocol. Fig. 1 shows the dissipation of energy of two randomly selected nodes. The residual energy values are recorded between 470-800 seconds duration. From the graph, it is observed that as the simulation time increases, the remaining energy of the two nodes in consideration decreases. The recorded residual energy data over a period of time is a non-linear monotonically decreasing data.

B. Calculation of RE in a single flow

Each node in the network monitors its energy consumption caused by the transmission and reception activities and calculates the RE every Δ seconds. In general, let E_{ckt} be the energy dissipated to run the transmitter or receiver by the node's circuit. Assuming d^2 energy loss, where d is the distance between nodes, a node further consumes E_{eloss} for transmitting packets[1]. Thus, to transmit a packet of size l units to a distance d, the energy consumed is:

$$E^s_{T_x}(l,d) = E_{ckt} \times l + E_{eloss} \times l \times d^2 \qquad (1)$$

[1] E_{cir} and E_{eloss} is measured in $nJoule/bit$ and $nJoule/bit/m^2$ units respectively.

and to receive a packet of size l units, the energy consumed is:

$$E^s_{R_x}(l) = E_{ckt} \times l \tag{2}$$

Hence, the total energy consumption to relay a packet is given by:

$$E^s_{tot} = E^s_{T_x} + E^s_{R_x} + E^s_{O_x} \tag{3}$$

where $E^s_{O_x}$ is the energy consumed in overhearing activities. The newly calculated RE after receiving and transmitting a packet of l units is:

$$RE^s_{new} = RE_{old} - E^s_{tot} \tag{4}$$

where RE_{old} is the residual energy calculated up to the previous interval.

C. Calculation of RE with multiple flows

To calculate the RE of a node v, when multiple flows are considered, depends on the number of upstream nodes (nu) transmitting packets to node v and the number of downstream nodes (nd) receiving packets from v. Thus the energy required by node v to transmit packets of l units to its downstream nodes which are at a distance d is given by:

$$E^m_{T_x} = \sum_{i=1}^{nd} E_{T_{x_i}}(l, d_i) \tag{5}$$

and the energy required by node x to receive packets of l units from its upstream nodes is given by:

$$E^m_{R_x} = \sum_{i=1}^{nu} E_{R_{x_i}}(l) \tag{6}$$

The total energy consumed when multiple flows are considered is given by:

$$E^m_{tot} = E^m_{T_x} + E^m_{R_x} + E^m_{O_x} \tag{7}$$

where $E^m_{O_x}$ is the energy consumed in overhearing activities. Thus, the newly calculated residual energy when multiple flows are considered is calculated as:

$$RE^m_{new} = RE_{old} - E^m_{tot} \tag{8}$$

D. Predicting the RE in future

Each node in the network is able to calculate its current RE independently and continuously in regular time intervals according to Eqn. 8. For efficiency purpose, such calculation interval may be set to the generating Topology Control (TC) messages interval. Every time the calculation is made, the most recent amounts of measured residual energy are used to predict the residual energy in future intervals. If the RE are recorded at regular time intervals, generally it shows some pattern according to the energy consumption behavior. Since the nodes' energy tends to dissipate all the time based on the flows passing through it, the dissipate curve is a monotonically decreasing one. This constitutes a time series data obtained at determined time interval. The time series consists of measurements of the previous outcomes that are made sequentially over time. If these consecutive observations are dependent on each other, then it is possible to attempt a prediction. In addition, as highlighted in section III, the energy dissipation rate of a mobile node may be different from another mobile node depending on the make, model, property, capacity, etc. Any node which acts as a router in reception (transmission) of packets from (to) the neighboring nodes with the current traffic flow, consume its energy depending on the number of downstream nodes (1-hop receivers), number of upstream nodes (1-hop transmitters), packet arrival rate, etc. If the RE after such activities are recorded for several times as RE pattern and investigated, then some periodicity in the pattern is exhibited. Therefore, this periodicity is a key in predicting the future RE of a mobile node. Section V describes the future RE prediction of a node using Multi-layer Neural Network. This method predicts the future RE of a mobile node based on the data obtained from the history of the node's RE, which is recorded at regular time intervals. The MNN is trained with respect to the history of RE pattern for making the predictions.

Why MNN?: As demonstrated in section IV. A, the energy consumption of mobile nodes recorded over a period of time in an AHN environment is a non-linear data. Several techniques has been developed to predict the future behavior of a particular series of events from the knowledge of its present and past data. The most well known and widely used methods are the ARMA and ARIMA models for non-stationary time series. However, these models attain results with great deal of difficulty and has limited applicability [26]. Among non-linear methods, neural network techniques have been widely used for time series prediction problems (for ex. [27], [28]) than other models which are known for its convenience, dynamic capability, high prediction veracity, etc.

E. Energy Consumption of the new flow

It is essential to quantify the energy consumed by the new flow so that it can be decided whether the available energy can satisfy the requirements of the new flow. The energy consumed by a node when single and multiple flows are considered are given in Eqns. 3 and 7 respectively. If P is the maximum number of packets generated by the application in the source node, the energy requirement is:

$$E_{req} = E^s_{tot} \times P \tag{9}$$

To summarize, the energy consumed by a node when single and multiple flows are considered can be calculated by using Eqns. 3 and 7, residual energy pattern are recorded at regular intervals of time to predict the future RE and the energy requirement for the new flow can be calculated based on amount of packets generated by the application and energy consumed for each packet.

V. Multi-layer Neural Network Design

In this section, we discuss the construction and design of the multi-layer neural network. The MNN is constructed for prediction which uses back propagation learning algorithm[24], [25]. The role of this MNN is to capture the unknown relation between the past and the future values of the RE pattern.

TABLE I
TRAINING PATTERNS DERIVED FROM THE RE PATTERN OF A MOBILE NODE.

Training Pattern	I_1	I_2	I_3	I_4	*Expected Output(O)*
T_1	r_1	r_2	r_3	r_4	r_5
T_2	r_2	r_3	r_4	r_5	r_6
T_3	r_3	r_4	r_5	r_6	r_7
T_4	r_4	r_5	r_6	r_7	r_8
T_5	r_5	r_6	r_7	r_8	r_9
T_6	r_6	r_7	r_8	r_9	r_{10}

A. Preliminaries

Prior to the discussion of the proposed MNN model, we present some of the definitions below.

Definition 1: ***Residual energy pattern*** **(*R_n*):** It is the history of the node's RE recorded for a period of time δ_n, where n is the number of regular time intervals at which the node's RE are recorded. The RE pattern R_n can be represented by a series of residual energy, $R_n = r_1, r_2, ..., r_n$ at regular time intervals $t_1, t_2, ..., t_n$ respectively, where r_i indicates the RE of a node during the time interval t_i.

Definition 2: ***Training pattern*** **(*T*):** Training patterns are derived from the RE pattern. Suppose we have the RE pattern R_n with RE recorded for n time intervals, then we have $n - m$ training sub-patterns, where m is a predicting order and $m << n$. The first training sub-pattern T_1 is composed of the RE pattern with $r_1, r_2, ..., r_m$ as input and r_{m+1} as the expected output. The second training sub-pattern T_2 is composed of the RE pattern with $r_2, r_3, ..., r_{m+1}$ as input and r_{m+2} as the expected output. Finally, the last training sub-pattern T_{n-m} is composed of $r_{n-m}, r_{n-m+1}, ..., r_{n-1}$ as input and r_n as the expected output. The prediction order m determines the input of the training pattern for training the neural network[2].

An Example: For $n = 10$ and $m = 4$, the derived training patterns are shown in Table I.

B. Selection of neurons for MNN model

The MNN model is constructed with three layers namely, the input layer, hidden layer and output layer. The number of hidden layers are restricted to one since the complexity of the problem is moderate. For easy analysis and from the universal approximation theorem a single hidden layer is sufficient for achieving good generalization [23]. The number of neurons in the input layer is an important parameter since it corresponds to the length of the sub-pattern used to discover the underlying features in the given RE data. Too few or too many input neurons can have significant impact on the learning and prediction ability of the neural network[22]. In practice, the number of neurons is often chosen through experimentation or by trial-and-error to have more generalization capability for the MNN model.

[2]value of m has to be varied to get the best prediction accuracy.

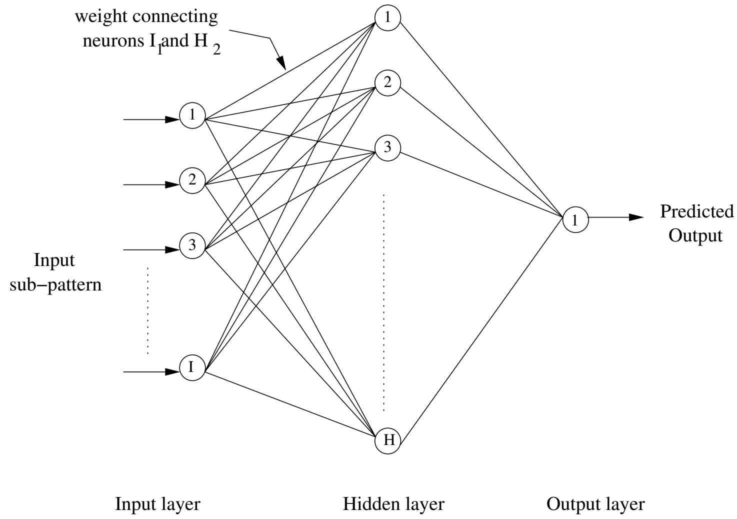

Fig. 2. Multi-layer neural network architecture.

For the training set data given in Table 1, with $m = 4$, requires four neurons in the input layer. The number of hidden layer neurons depends on the length of the sub-pattern, and the number of sub-patterns provided for training[23], [25]. In this work, we consider twice the number of input layer neurons as the number of hidden layer neurons. The number of neurons in the output layer depends on the expected output of the training pattern. For the training pattern given in Table 1 requires one output neuron.

C. Training procedure

The training procedure uses back propagation learning algorithm. There are three layers in the proposed MNN architecture as shown in the Fig. 2. The input layer, hidden layer and output layer consists of I, H and 1 number of neurons respectively. The output of the 1^{st} layer is fed as input to the 2^{nd} layer and the output of the 2^{nd} layer is fed as input to the 3^{rd} layer. The neurons in the i^{th} layer are connected to neurons in the $(i+1)^{th}$ layer with an adaptive weight. The output of each neuron is determined by applying a transfer function $f(.)$ to the neurons' input. We use the sigmoid function:

$$f(x) = (1 + e^{-x})^{-1} \tag{10}$$

The training is done by using back propagation in two passes, *forward* and *reverse*. The forward pass is used to evaluate the output of the neural network for a given input in the existing weights. In the reverse pass, the difference in the actual output and the desired output is compared and is fed back to the MNN as an error to change the weights of the neural network. The neural network training model for future RE prediction is given in Fig. 3. The actual (computed) output r'_{i+m} is compared with the desired (expected) output of the training pattern r_{i+m} and the error values are used to calculate new weights of connections between neurons of all input, hidden and output layers, thereby reducing the error in the output.

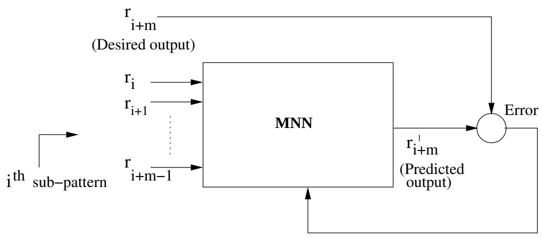

Fig. 3. Neural Network training model for future RE prediction.

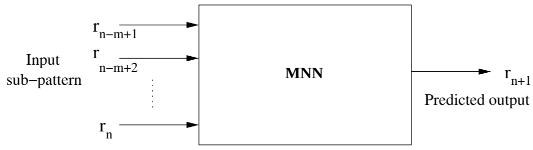

Fig. 4. MNN model for immediate next RE prediction.

This training procedure is iterated over all the entries in the training data set for several times until the mean square error reaches some specified threshold (for ex., the threshold value may be between 0.001 to 0.005 for better accuracy).

D. MNN model for future RE prediction

The RE prediction is to find the future RE of a node from the MNN model trained with respect to the training data set. To predict the future RE of a node, we can either predict the immediate next RE (i.e., next interval) or the RE after $n+s$ (i.e., multiple) time intervals as follows.

1) Immediate next RE prediction: In this case, we predict the RE of a node in the t_{n+1} time interval, i.e., r_{n+1} for the given residual pattern R_n. To obtain the immediate next RE prediction, the sub-pattern $\{r_{n-m+1}, r_{n-m+2}, ..., r_n\}$ is fed as input to the trained MNN which gives the output r_{n+1}. Fig. 4 illustrates the immediate next RE prediction model.

2) Prediction of RE after $n+s$ time intervals: It is the prediction of the RE of a node after $n+s$ time intervals, i.e., r_{n+s} which is done recursively, first predicting r_{n+1}, then predicting r_{n+2}, and finally predicting r_{n+s}, where $s > 1$. Fig. 5 illustrates the MNN model for RE prediction after $n+s$ time intervals. The RE pattern of a node over a period of time $[0, T_n)$ is recorded and is processed to construct the MNN model for future RE prediction. If the RE of a node is to be known at time T_k, for $T_k > T_n$, the algorithm calculates the time difference between T_n and T_k to find the number of time intervals ahead the prediction is to be carried out, i.e., $|s| = \frac{(T_k - T_n)}{\Delta t}$ time intervals, where $\Delta t = t_i - t_{i-1}$. If $s = 1$, then a immediate RE prediction is carried out, else if $s > 1$, then a multiple RE prediction.

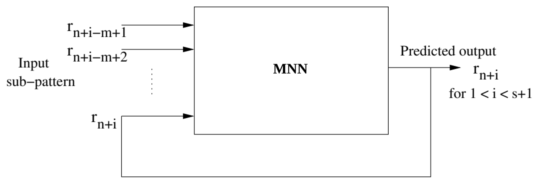

Fig. 5. MNN model for RE prediction after $n+s$ time intervals.

Based on the method of predicting the future RE, the RE patterns of a node can be further classified into *uniform*, *regular* and *random* changes. Uniform changes are the ones in which the changes in residual energy of nodes will be same over a period of time considered. However, in realistic ad hoc network conditions, the uniformity in the RE pattern is rare. Therefore, by recording the RE pattern over a long period of time could yield better accuracy. Regular changes in the RE pattern is periodic and deterministic in nature. However, random changes are stochastic in nature.

VI. Basic Protocol Design

In this section, we describe the EAAC protocol. EAAC combines both energy-aware routing and admission control. EAAC consists of three parts: route discovery, admission control, and mobility management.

A. Route Discovery

The aim of the route discovery is to find a route between the source and destination with the condition that all intermediate nodes along the routing path have enough energy for the flow to complete the transmission. EAAC uses on-demand route discovery with source routing, similar to DSR [1]. The source-routing approach is used because it allows EAAC to specify directly which route the flow will use so that the packets for the flow are ensured to only go through the specified route that has been admitted by the admission control and has enough energy for the flow. It can also provide a provision for easy traffic splitting at the source node so that different flows with the same destination can follow different route to avoid congestion in the network.

To reduce the message overhead, EAAC performs admission control during the route discovery process to preliminarily eliminate routes without enough energy. When a source node has data to send, to know the route to the destination, it broadcasts a route request (RREQ) packet to its neighbors. The RREQ contains *source-ID*, *destination-ID*, the energy requirement for the new flow calculated using Eqn. 9, and a record of the sequence of hops taken by the RREQ as it is propagated through the ad hoc network. Each node that receives a RREQ performs the admission control to determine if the node has enough energy for the flow along the partial route. If not, or the route so for determined contains loops, the RREQ is dropped. Otherwise, the node adds its own ID to the partial route and rebroadcasts the route request.

When the intended destination node receives the RREQ, the partial route in the RREQ becomes the *full route* which contains the sequence of hops through which the request traveled to reach the destination. The destination then reverses the full route contained in the RREQ, and use this route to send the route reply (RREP) packet back to the source along that route. Suppose if the destination receives multiple such RREQs carrying different routes, the destination only sends the RREP along one route based on a selection criteria (minimum number of hops, first RREQ or may adopt the HER mechanism from [15]). However, other routes are cached for a short period of time as backup in case the RREP does not reach the source due to link breakage, mobility, node expiration or admission failure.

Suppose, if the energy dissipation rate of the mobile nodes are different from one another as highlighted in section III, then the RREQ may contain an extra field that defines the maximum number of packets to be transmitted by the source application (i.e. P). In this case, each node calculates the energy requirement for the flow so that it can be decided that whether the node has enough energy to accommodate the flow and participate in route discovery process.

B. Distributed Admission Control Algorithm

Route discovery finds the possible route(s) to reach a destination. Admission control is used to determine which of these routes can admit the new flow. At each node on the route, admission decisions is based on the expected energy consumption of the flow as well as the present and future residual energy at the node. When a node receives a RREQ packet, partial admission control is performed by comparing the future residual energy with energy requirement of the flow. If the future residual energy is not satisfied with energy requirement of the new flow, admission control fails. Otherwise, admission control succeeds and the route request can be forwarded to the next hop.

In the route reply phase, when a node receives a route reply, it performs full admission control. The energy requirement of the flow is compared with the nodes' future residual energy. Since the route reply carries the full route, the admission control is accurate. If the full admission control succeeds at the node, soft reservation of energy can be set up in the node and a RREP is forwarded to the next hop. Otherwise, an admission failure message is sent to the destination. In this case, the soft reservation of energy along the route need to be explicitly torn down when nodes along the route receive the admission failure message. When the destination node receives the admission failure message, it selects another cached route and sends a RREP along it. When the RREP successfully arrives at the source, enough end-to-end energy has been reserved for the flow.

Routing protocols usually integrate route discovery and route maintenance by continuously sending periodic routing updates. It is possible that once a route is computed, it may remain active for a long period of time. In such cases, it might happen that the future residual energy of one or more nodes on the route may fall below a given threshold (explained below) as they deplete their energy in forwarding or overhearing packets. If this continues for a long time then nodes may die leading to network partition. During such conditions, the node sends a route warning ($RWAR$) packet back to the source(s). The $RWAR$ is propagated much like the $RERR$ [1] packet, except that the route is not erased. Thus the flow of data packets is not interrupted. A new route discovery process can be initiated or an alternate route may be used (if available in the cache) at the source on the receipt of $RWAR$.

C. Residual Energy Threshold Mechanism

In the EAAC scheme presented above, it is stated that the threshold for the RE of a node is incorporated. Each node is categorized by two states: *normal* state and *warning* state. Nodes are in normal state if their current RE is greater than 20% of its initial energy (i.e., above the threshold). This signifies that these nodes have ample energy to take part in routing process. Nodes are in warning state, if their current energy is less than 20% of its initial energy (i.e., below the threshold). This signifies that the nodes are running low on energy and the protocol should avoid the use of these nodes (if possible).

D. QoS Violations and Mobility Management

Strict QoS cannot be guaranteed in ad hoc networks since the nodes in an AHN are inherently subjected to mobility that is beyond any protocol's ability to predict and control. Therefore, it is likely that QoS violations can be quite frequent in AHNs. In such dynamic situations, each node shall monitor the where abouts of its neighbors and future RE prediction of the next hop node along the route. If the node notices that one of its one-hop next neighbor along the route does not get enough energy or running out of energy in the near future due to newly added flows, increased congestion, or if the next hop of the flow moves out of the range of the node, a notification message is sent to the source of the flow indicating changes in the route. The source can either search for a new route (select an alternate route already available in its route cache or perform a fresh route discovery process) or reduce its QoS requirement to accommodate the degraded or broken route. Of course, this reestablishment of a QoS commitment may take a long time and cost extra message overhead, it is desirable to reduce the frequency of QoS violations.

An alternate approach is for all source nodes periodically perform route discovery in order to find a new energy-aware route that take into account the continuously changing energy states of nodes even when there is no route breakage or QoS violations.

VII. Simulation Study

In this section, we evaluate EAAC by simulations in *ns-2* simulator [30] and construct the MNN model using C++ programming language. The MNN model is used offline to determine the future residual energy of a node. In the experiments, 50 nodes move within a $1km \times 1km$ area. The node speed is varied between 0 to 25m/sec. Each node has a fixed transmission range of 250 meters. We assume all nodes are equipped with 2Mbps IEEE802.11 network interface cards. Each traffic source is made to start at different times at the beginning and stay active throughout. Each simulation was executed for 900 seconds duration. Constant bit rate (CBR) flows are used that generates 4 pkts/sec with packet size of 512 bytes.

The initial energy values of nodes is varied between 400 to 1200 Joules with assigning more values for source and destination nodes, so that the combined network wide initial energy value equals 40,000 Joules. The intermediate nodes forwarding packets which have low energy levels (entering warning state) sends a warning packet to the source node(s) to find an alternate route. Figures in 6 and 7 shows the number

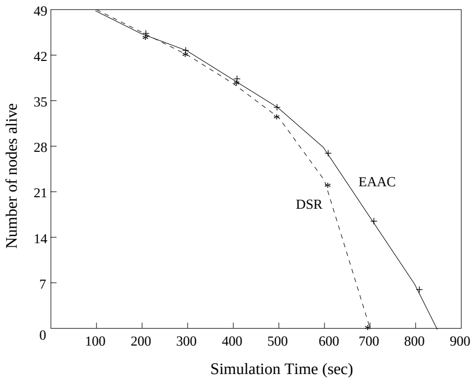

Fig. 6. Number of nodes alive against simulation time (10 sources)

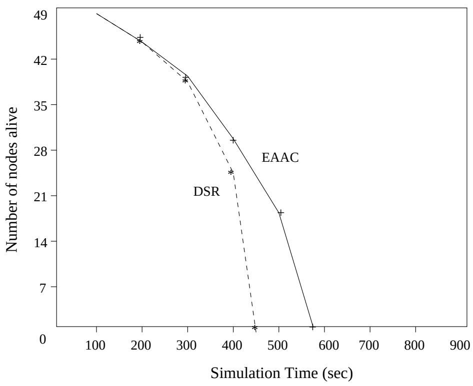

Fig. 7. Number of nodes alive against simulation time (20 sources)

of nodes that are alive during different simulation times for 10 and 20 traffic sources respectively. It is observed that more number of nodes using EAAC remains alive than the regular DSR leading to increase in network lifetime.

A. MNN prediction for uniform, regular and random changes

The MNN model is devised with m neurons in the input layer, where m is made to vary depending on the RE pattern for better prediction accuracy. It is observed that too few or too many input neurons can have significant impact on the learning and prediction ability of the neural network. For simulation purpose, we used 4, 6, and 8 input neurons for uniform, regular and random changes respectively. The number of hidden layer neurons taken is twice the number of input neurons, whereas the number of output neurons is one. All training data are normalized into real values between 0.0 and 0.1. The learning rate parameter $\alpha = 0.2$. For a mobile node, we have considered a desired RE pattern recorded over the time intervals of 100 to 200. The training of MNN is performed by using first 60% of the desired RE pattern as training data set and remaining part of the RE pattern as a test data set for predictions. Also the training is performed by picking a portion of the RE pattern in random as training data set and the prediction test is carried out over the remaining portion of the RE pattern. An example of the pattern with training and test data set are shown in Fig. 8. The results are taken for both immediate next and future predictions. The

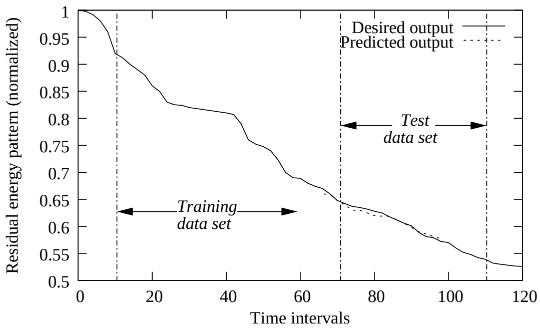

Fig. 8. Comparison of desired and predicted RE pattern

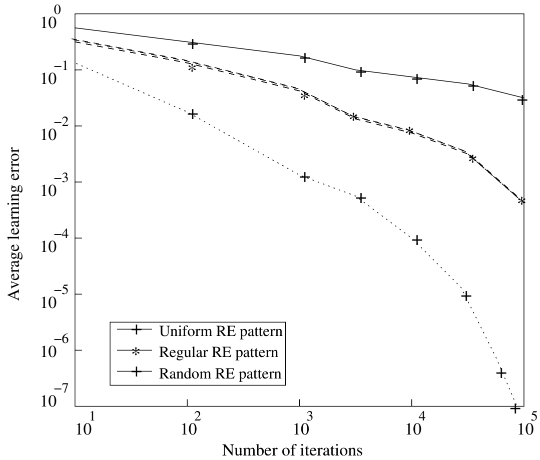

Fig. 9. Learning error w.r.t number of iterations

average learning error (ALE) and prediction accuracy (PA) measures are defined as follows:

$$ALE = \frac{1}{100-m}\sum_{i=m}^{100}(o_i - o_i^{'})^2$$

where o_i and $o_i^{'}$ denotes the desired output and actual output at the i^{th} interval respectively and m is the prediction order and,

$$PA = \frac{N_{correct}}{N_{total}}$$

where $N_{correct}$ is the number of times the correct prediction of RE of a node and N_{total} is the total number of times the prediction of RE of a node. Results are taken by considering different sets for each RE pattern to find the average prediction accuracy. The graph shown in Fig. 9 is plotted for learning error with respect to the number of iterations used during training of MNN. From the graph plotted, it is observed that the number of iterations used for training required for uniform and regular are much less than the random patterns, for a given learning threshold value. The results shows the time required for training the MNN for a given RE pattern of a node. In Fig. 10, the graph is depicted for the average prediction accuracy of MNN against the number of prediction intervals. It is observed that the average prediction accuracy for uniform RE patterns is 90%, for regular RE patterns is $45\% - 70\%$ and for random RE patterns is $1\% - 30\%$ which

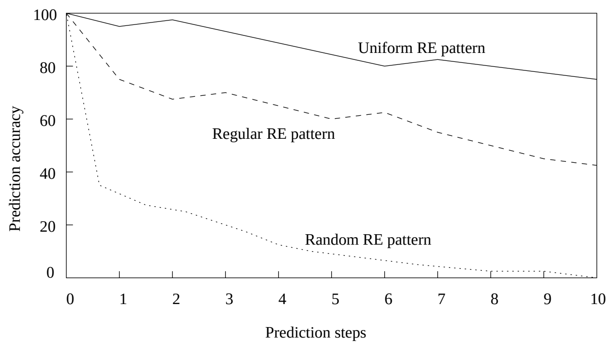

Fig. 10. Average prediction accuracy of MNN

decreases drastically with respect to the time ahead intervals. Thus, as the prediction intervals increases, prediction accuracy decreases, especially for random RE patterns it decreases drastically.

VIII. Conclusion

This paper presents an energy-aware admission control scheme for ad hoc networks based on the knowledge of present and future residual energy of each node along the routing path. This scheme admits a new flow only if any node along the routing path do not run out of its energy during the transmission of packets. Such distributed mechanisms in each individual node participating in routing of packets is desirable to increase the network lifetime. Simulation results show that EAAC satisfies the energy requirement and found that it performs better than DSR in terms of increasing the network lifetime.

In addition, this scheme uses a Multi-layer neural network model to predict the future residual energy of a node based on the history of energy usage pattern. The performance has been verified for prediction accuracy by considering different such patterns and learning accuracy. Simulation results used for predicting future residual energy shows that the average prediction accuracy was achieved upto 90%, 60% and 20% for uniform, regular and random patterns respectively.

EAAC can be used in any of the existing AHN's source-initiated routing protocols during the route discovery and maintenance phases and can be applied to other energy-constrained routing in mobile networks.

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