Bio-inspired Link Quality Estimation for Wireless Mesh Networks

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***Abstract*—In this paper, the problem of estimating the link quality in mesh networks has been considered. Such a process is a major task to develop an efficient network layer, since it allows routing protocols to efficiently use neighbors as relays for multi-hop communications. In the last years, a number of link-quality aware routing metrics have been proposed and analyzed. However, such metrics usually adopt simple link-quality estimators based on moving average filters, which lead to poor performances due to their static nature. In this paper, we propose to improve the estimation of the link quality resorting to a bio-inspired estimator based on the neural network paradigm. The effectiveness of the proposal has been proved by means of a numerical performance comparison between the proposed estimator and the traditional ones under several environmental conditions.**

I. Introduction

Wireless mesh networks have attracted tremendous attention due to their properties of self-organization and inexpensive deployment in presence of any or limited pre-existing infrastructure. However, their application in the real world requires the development of a network layer able to assure satisfactory throughput performances [1].

The selection of reliably connected neighbors plays a significant role to successfully and efficiently support data transfers. In fact, experimental results clearly show that the estimation of neighbors' link qualities has a substantiative impact on the network throughput in traditional ad-hoc forwarding [2], [3], as well as in opportunistic forwarding [4], [5] and network coding [6] techniques.

In the last years, the problem of designing quality aware routing metrics has received great attention and several metrics have been proposed and evaluated [7]–[13]. Despite these efforts, all the cited metrics assess the link quality by evaluating the loss rates of probe packets with very simple estimators, usually the Simple Moving Average (SMA) or the Exponentially Weighted Moving Average (EWMA). Recently, more efficient estimators have been proposed by combining the average and the standard deviation of observed channel loss rates [14], [15] or by resorting to supervised learning algorithms [16]. However, such proposals introduces excessive computational and memory requirements, due to the need of recording probe packets at the bit level or storing large amount of data sets.

In this paper, we propose a bio-inspired estimator based on the neural network paradigm since it assures the ability to learn from the environments in unsupervised mode. A neural network is essentially an interconnected assembly of simple processing elements, namely unit or *neurons*, in which the processing ability is reached by means of inter-unit connection strengths, or *weights*, which are set by a process of adaptation, or *learning*.

The proposed solution has the suitable properties of having computational and memory requirements comparable with those of the moving average estimators, allowing so its implementation in low-power devices. At the same time, the proposal, thanks to its adaptive nature, will perform well in different environmental conditions.

To test the effectiveness of the proposed solution, we have compared its performances with those of SMA and EWMA filters in terms of network throughput and hop count. Each estimator has been used to assess the widely adopted Expected Transmission Count (ETX) metric [8] for a proactive multi-path routing protocol, namely the Augmented Tree-based Routing (ATR) protocol [17], across a wide range of environmental conditions and both for mesh and ad hoc topologies. It is worthwhile to underline that the proposed solution can be slightly modified to operate with different quality aware routing metrics and, moreover, it does not require any change in both the data-link and the network layers.

The outline of the paper is the following: Section II presents the design and implementation details of the proposed estimator, whereas in Section III the performance evaluation is illustrated. Finally, in the last section conclusions and open problems are drawn.

II. System design

The Expected Transmission Count (ETX) [8] is a quality aware routing metric which aims to minimize the expected total number of layer-2 transmissions (including retransmis-

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sions) required to successfully deliver a packet towards its final destination.
The ETX of a link $l_{i,j}$ between node i and j at time n is defined as:

$$ETX_{i,j}(n) = \frac{1}{d_{i,j}(n)d_{j,i}(n)} \quad (1)$$

where $d_{i,j}(n)$ is the delivery ratio of the packets sent by node i experienced by node j at time n.
Consequently, the ETX of the path $P_{s,d}$ between source s and destination d at time n is defined as:

$$ETX_{s,d}(n) = \sum_{l_{i,j} \in P_{s,d}} ETX_{i,j}(n) \quad (2)$$

To estimate the delivery ratios, each node broadcasts probe packets with an average period τ. Thus, we can model the probe reception events as binary independent random variable $x(n) \in \{0,1\}$ and, since the channel is time-variant, the probability that the node j receives a probe from the node i depends on the time, namely $P(x_{i,j}(n) = 1) = p_{i,j}(n)$.
Our proposal estimates the delivery ratio by predicting at time $n-1$ the next probe reception event for link $l_{i,j}$ by means of the M previous reception events and the bias coefficient θ, according to the technique depicted in Fig. 1.
More specifically, the predicted value $\tilde{x}_{i,j}(n)$ is the sum of the M past values, weighted by the coefficients $w_i(n); 1 \leq i \leq M$, plus bias θ, weighted by the coefficient $w_\theta(n)$:

$$d_{i,j} = \tilde{x}_{i,j}(n) = \sum_{k=1}^{M} w_k(n)x_{i,j}(n-k) + w_\theta(n)\theta \quad (3)$$

Consequently the prediction error at time n for the link $l_{i,j}$is given by:

$$e_{i,j}(n) = x_{i,j}(n) - \tilde{x}_{i,j}(n) = \quad (4)$$

$$= x_{i,j}(n) - \sum_{k=1}^{M} w_k(n)x_{i,j}(n-k) - w_\theta(n)\theta \quad (5)$$

To assess the weights $\mathbf{w}(n) = [w_1(n), ..., w_m(n), w_\theta(n)]$ at time n we adopt an unsupervised algorithm that at each time adapts the weights' values in order to minimize the prediction error.
As minimization criteria, we chose the least square error (LSE) criterion, and the process of estimating the weights' values $\mathbf{w}(n)$, namely the *learning process*, is based on the *delta rule* [18]:

$$\Delta\mathbf{w}(n) = 2\eta e_{i,j}(n)\mathbf{x}_{i,j}(n) + \alpha\Delta\mathbf{w}(n) \quad (6)$$

$$\mathbf{w}(n) = \mathbf{w}(n-1) + \Delta\mathbf{w}(n) \quad (7)$$

where $\mathbf{x}_{i,j}(n) = [x_{i,j}(n-1), ..., x_{i,j}(n-M)]$, η is the learning rate and α is the momentum term which increases the speed of convergence.

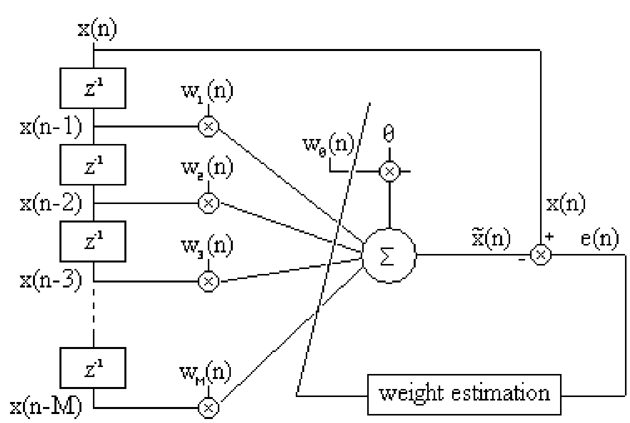

Fig. 1. Bio-inspired link-quality estimator

III. Performance evaluation

To evaluate the effectiveness of the proposed estimator from a networking point of view, we consider as performance metric the widely adopted network throughput one and we state out a performance comparison with two representative traditional estimators, namely the SMA and the EWMA.
More in detail, we have implemented the considered estimators on the widely adopted network simulator ns-2 [19] version 2.33 to assess the delivery ratios, which have been utilized by the routing protocol to estimate the ETX metric according to (1).
As regard to Simple Moving Average (SMA) filtering, each node has to remember the packets received by its neighbors during the last $M\tau$ seconds and the delivery ratios are estimated as:

$$d_{i,j}(n) = \sum_{m=0}^{M-1} b_m x_{i,j}(n-m) \quad (8)$$

where b(m) is the weighting factor.
With reference to Exponential Weighted Moving Average (EWMA) filter, the delivery ratios are estimated according to:

$$d_{i,j}(n) = \alpha x(n) + (1-\alpha)d_{i,j}(n-1) \quad (9)$$

where $\alpha \in [0,1]$ is the smoothing factor.
While the SMA is an un-weighted mean of the previous M data points, the EWMA is an weighted average which applies to data points weighting factors which decrease exponentially, and the degree of weighing decrease is expressed by α. In other words, the EWMA gives much more importance to recent observations without discarding the older observations entirely.

A. Experimental setup

Usually, performance analyses adopt a deterministic radio propagation model which is clearly unrealistic. Therefore, we consider a propagation model, namely the Shadowing, which accounts for the long-term fading effects by means of a zero-mean Gaussian variable $N(0,\sigma)$. According to it, the received mean power $P_{dB}(d)$ at distance d is:

$$P_{dB}(d) = P_{dB}(d_0) - log\beta\frac{d}{d_0} + N(0,\sigma) \quad (10)$$

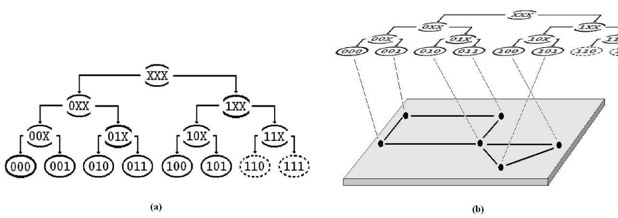

Fig. 2. ATR overlay network

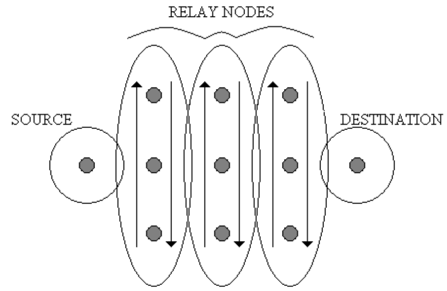

Fig. 4. Simple topology

where $P_{dB}(d_0)$ is the received mean power at the first meter, β is the path-loss exponent and σ is the shadow deviation, both empirically determined for a certain environment.
In our performance analysis, we set β to 3.8 to model a shadowed urban area, and we vary σ from 1.0 to 12.0dB in order to assess the behavior of the analyzed protocols under a wide range of variability levels of the propagation conditions. Moreover, we set the values of the parameters of the data link layer to simulate an IEEE 802.11b Orinoco network interface [20] with long preamble, CCK11 modulation and two-handshake mechanism, resulting in a transmission range of roughly 35 meters.
For each experiment we made 100 trials, and the duration of each trial is 1500 seconds. After the initial 500 seconds which are used to assure that the routing protocol reaches a steady state, the nodes involved in the traffic generation start to generate CBR data traffic over UDP transport protocol. Each traffic source sends packets of 1000 bytes, deferring the subsequent transmissions of 1 second.

B. Routing Protocol

It is worthwhile to note that the comparison among the considered estimators must be carried out for any fixed arbitrary routing protocol, provided that it adopts the ETX as routing metric. Therefore, we have adopted as routing protocol the Augmented Tree-based Routing (ATR), a proactive routing protocol based on a Distributed Hash Table (DHT), for convenient reasons since we have more familiarity with it. In the following we give only a brief overview of ATR, since further details can be found in [5], [17], [21], [22] .
Upon the network topology, the ATR builds an overlay network (Fig. 2-b) by assigning location-dependent network addresses, namely strings of l bits, to nodes by means of a distribute procedure and of locally broadcasted probe packets. Thus, the address space can be represented as a complete binary tree of $l+1$ levels, that is a binary tree in which every vertex has zero or two children and all leaves are at the same level (Fig. 2-a).

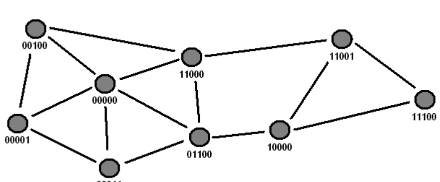

Fig. 3. Physical network topology

ATR performs the whole routing process resorting to an iterative procedure which explores the topological meaning of the network addresses with a hierarchical form of multi-path proactive distance-vector routing.
Each node stores a routing table with l sections, one for each bit, and the k-th section stores the routes towards destinations whose network addresses share the same prefix of $l-k$ bits with the node's address.
With reference to the topology depicted in Fig. 3 where $l=5$, we suppose that the node with address 10000 has to communicate with the node with address 11000. Since 10000 and 11000 share a 1-bit prefix, the source will forward a packet along the route stored in the 4-th section which has the lowest ETX value.

C. Numerical Results

The performance comparison considers two different scenarios: a simple mesh topology and a more complex random one. The metrics are the network throughput and the hop count, and we evaluate both the average value and the standard deviation as a function of the shadow deviation (we note that in some cases the standard deviation values are too small to be depicted).
In the first scenario, we deploy a topology, illustrated by Fig. 4, which allows us to evaluate the effect of the link quality estimation over multiple hops. In fact, the source and the destination nodes are static and they are connected through nine intermediate nodes, which move in accordance with the arrows with a speed value taken uniformly in the range $[0.1; 1.0]$ m/s without generating data traffic[1]. The distances among the nodes are chosen to allow the data packets to reach the destination in about four hops in absence of intermediate node mobility as well as link dynamic.

[1]We ran different sets of experiments to explore the impact of node mobility on the performances, but here we present only a subset of such experiments for sake of brevity.

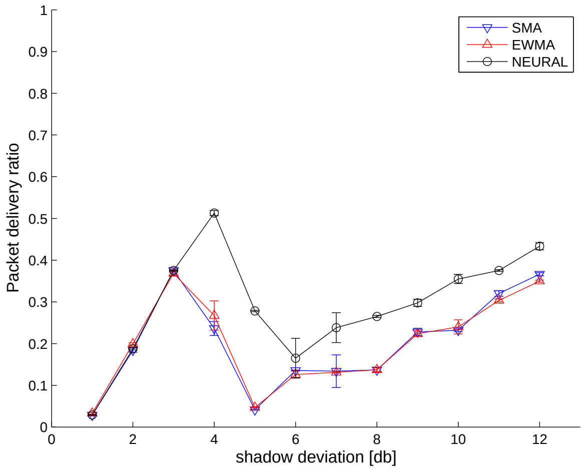

Fig. 5. Network throughput vs. shadow deviation for simple topology

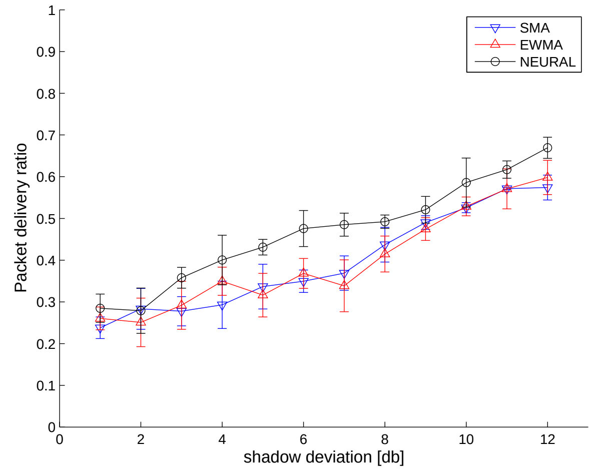

Fig. 7. Network throughput vs. shadow deviation for random topology

Fig. 5 reports the network throughput as a function of the shadow deviation. The results shows that the performances of all the estimators are strongly affected by the shadow deviation. Moreover, the proposed neural-based estimator outperforms the traditional ones for each value of σ.

More in detail, the network throughput exhibits a maximum in correspondence of a deviation equal to $3-4$ (depending on the particular estimator) and a minimum for $\sigma = 6$. For values of σ lower than $3-4$ and higher than 6 the network throughput grows with the shadow deviation, while for values of deviation in the range $(4, 6)$ the ratios decrease.

It is worthwhile to note that this surprising behavior is reasonable, also if unintuitive. It is well known that the overall system throughput grows for increasing shadow deviation [23] in random medium access control (MAC) techniques due to the capture effect. However, when σ exceed the value of $3-4$, the capture effect allows the nodes to route the packets along shorter but less reliable paths due to the peculiar topology, as confirmed by the results which account for the average hop number (Fig. 6). In particular, the average hop number decreases from about four hops for $\sigma = 3$ to about three hops for $\sigma = 6$.

In the second scenario, we deploy a random topology in which 30 nodes move according to the *random way-point* model [24] with no pause time and at a steady speed over a square area, sizes to avoid the presence of isolated nodes. Each node generates data traffic toward a destination randomly selected according to a uniform distribution.

Fig. 7 shows the network throughput vs. the shadow deviation for such a scenario. The results are in accordance with those of Fig. 5, and the increasing of the overall throughput with the shadow deviation is particularly evident. The neural

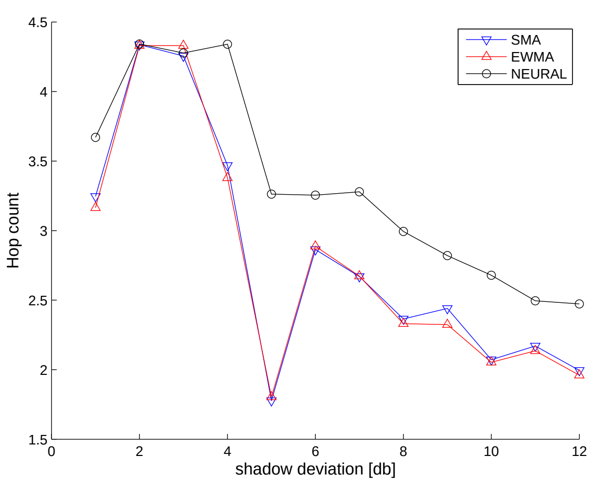

Fig. 6. Hop count vs. shadow deviation for simple topology

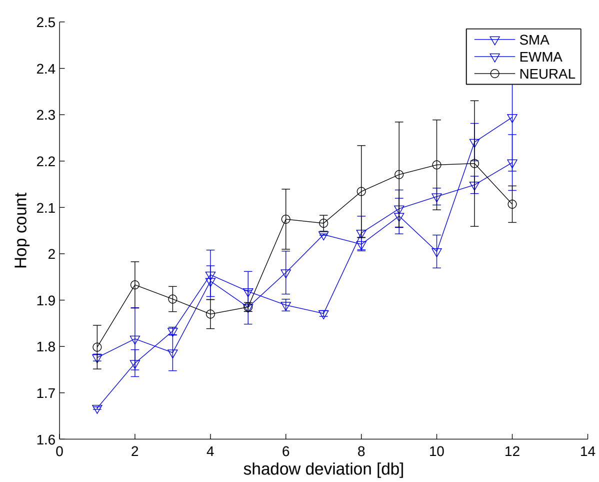

Fig. 8. Hop count vs. shadow deviation for random topology

estimator, thanks to its adaptive nature, is able to outperform the other ones for each value of $sigma$. Moreover, we note that performance gain is more significant for $\sigma = 6$, which accounts for indoor propagation.

Finally, Fig. 8 accounts for the last results, the hop count vs. the shadow deviation, for the 30 nodes topology. The results are intuitive: the more considerable are shadowing effects become the longer become the routes.

IV. Conclusion

The paper proposes a bio-inspired link quality estimator based on the neural network paradigm. Numerical performance comparison with two representative traditional estimators substantiate the effectiveness of the proposed estimator for both mesh and ad hoc scenarios. Currently, we are working on applying the proposed estimator to the opportunistic routing paradigm.

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