Routing Optimization in Dynamic Networks based on a New Entropy Metric

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Abstract: A key role in the modern telecommunication networks is played by routing aspects as the great number of works present in literature proves. In particular, in the mobile ad-hoc networks routing is a fundamental aspects because the mobile devices nature and their elevate dynamism. In fact, it is important to have the possibility of finding the minimum overhead for connectivity in the network and, calculate the communication potential through the analysis of different parameters. The focus of this paper is represented by the analysis of the entropy in this type of mobile networks. The entropy gives the possibility of studying and predicting the dynamics of mobile nodes. The knowledge of these aspects can help to optimise some key features of wireless mobile communications, such as nodes stability, channel failures, and routing costs. Many simulation campaigns have been carried out by taking into account the movement of the real nodes, obtaining beneficial results, which confirm the effectiveness of the proposed study.

1 INTRODUCTION

One of the main aspects of any networks, and in particular of decentralized ones, is represented by routing protocols and algorithms which allow the communication among nodes and, considering some parameters, allow to take into account efficiency issues directly correlated with energy consumption, scalability and safety. The main issue in a decentralized and distributed network where no fixed infrastructure regards the elevate dynamism of the network nodes that change their position in the time causing frequent and unpredictable topology, such as shown in (De Rango et al., 2003) and the energy efficiency and saving such as in (De Rango and Fotino, 2009; De Rango and Tropea, 2009). These considerations are still more evident when the number of nodes inside the network increase posing serious problem of scalability. The communication between nodes depends by nodes dynamism and, then the unpredictability of the connection is linked to the number of nodes to be cross for reaching the destination and depends to node mobility that causes frequent network topology changes.

The focus of this paper is to analyse the entropy concept in a mobile ad-hoc networks where nodes are mobile and their position vary in time and space. We propose a entropy concept strongly linked to some different aspects of the network such as Connection Dropping Probability (CDP), fading issues, link disruption phenomena, network instability and other effects on the network conditions (Fazio et al., 2012; Fazio et al., 2014).

So, the paper proposes a detailed analysis of the entropy in a context of a mobile network from a particular point of view: the capability of performing a prediction analysis of the entropy behavior in this network typology. Approaches based on prediction analysis are broadly studied by researchers, and they regard different aspects of a telecommunication network. One of the key aspect of "prediction" is represented by the accuracy, that means the goodness of the approach and how it is able to follow network dynamism (Fazio et al., 2013; Fazio et al., 2016). Integrating, for example, a routing protocol with a predictive approach leads to the enhancement of the overall performance (Masip-Bruin et al., 2010). The concept of entropy related to nodes mobility, is completely suitable to describe mobility predictability, in order to pre-configure the needed resources of the network. In addition, having a model for nodes' entropy, it is possible to choose a proper scenario, that exploits its optimal performance for a given set of protocols.

When dealing with mobile networks, nodes mobility is crucial for the overall performance of the en-

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tire system, especially in Mobile Ad-hoc NETworks (MANETs), where the optimal and stable routes need to be frequently evaluated. There are many works in literature that take into account mobility under a different point of view (as underlined in the next section): so, entropy can be considered as a metric for assigning a weight to each path segment. If we are interested, for example, to MANET routing, and if we are able to define new composite metrics (based also on the entropy concept), it is possible to gauge other aspects of network dynamics, giving the possibility to better develop research testbeds, that can provide more accurate information about the needed resources (best path, channel bandwidth, transmission power, bitrate, etc.) .

The remainder of the paper is organized as follows: Section 3 introduces the entropy concept and the deployment of adaptive filtering for temporal prediction of nodes evolution, while Section 4 provide details about the main obtained results, in terms of entropy values in function of different system parameters and prediction possibilities, discussing the broader aspects of our approach. Section 5 concludes the paper.

2 RELATED WORK

The creation and management of any mobile network is a challenging problem and any metric which can be used to characterize or optimize the network creation is welcome. In the literature, a lot of works proposed by scientific community make use of the entropy information and disparate metrics are used and combined to analyse the mobile behavior in order to enhance and optimize different aspects and routines of mobile networks' protocols.

In the last years, researchers have spent a lot of time and made progress on study about uncertain device location and random propagation conditions in the connectivity among devices. In (Coon et al., 2018) the authors make a study about conditional entropy of wireless networks focus on network entropy with the assumption that pairwise connections between devices are statistically independent. The authors in this contribution present an analytical framework for studying the network entropy conditioned on the node positions in space, providing also a method to calculate a entropy lower bound useful for performing estimation of network entropy.

The channel allocation is another issue object of study by scientific researchers. Normally, the choice of the channel, based on link measurement, fall back on channel with fewest co-channel interference. In (Elujide and Liu, 2020) an entropy-based WLAN channel allocation using channel state information is proposed by authors. The authors present this proposal in order to avoid the known problem of the RSSI technique. The proposal is based on a machine learning approach and, in this way, they try to predict channel spectral entropy from physical layer network. Their results prove the goodness of the proposal able to select a channel with high throughput and low jitter. In (Wang et al., 2020) the concept of entropy is related with a trust reasoning model based on cloud model and fuzzy Petri net (FPN). This approach try to give to nodes a value of credibility. The authors propose a routing algorithm based on trust entropy in order to improve QoS in a MANET. Finally, they present simulation results where they illustrate the better performance of their proposal in terms of packet delivery ratio and average latency. Due to energy issues the authors in (Osamy et al., 2018) a cluster tree routing for wireless networks where a cluster head selection algorithm based on a entropy criteria is proposed.

In (Sun et al., 2006), an entropy-based approach is proposed, emphasising the way ad-hoc nodes move into the considered network. The authors apply the "mobility entropy" concept to optimise routing operations through predictions and guarantee a given level of Quality of Service (QoS). Besides, the concept of information entropy and energy entropy in ad-hoc networks is considered in (Cerasoli and Dimarogonas, 2008). The authors refer to Shannon entropy definition in information theory, considering the "amount of information" which is exchanged through packet signalling. In (Hua and Haas, 2009), the authors propose some in-depth analysis of the way the stability of a point-to-point connection can be predicted, in ad-hoc environments.

3 THE ENTROPY CONCEPT AND THE PREDICTIVE ADAPTIVE FILTERING

In our work, we consider the concept of entropy (proposed by Shannon (Cerasoli and Dimarogonas, 2008) as a way for measuring the uncertainty in a generic statistical model), but from another point of view. Starting from the classical definition, given a finite set of n symbols, any sequence s of those symbols (with duplication allowed) has an associated entropy value, given by the following expression:

$$Et(s) = -\sum_{i=1}^{n} p_i \cdot log_b p_i \tag{1}$$

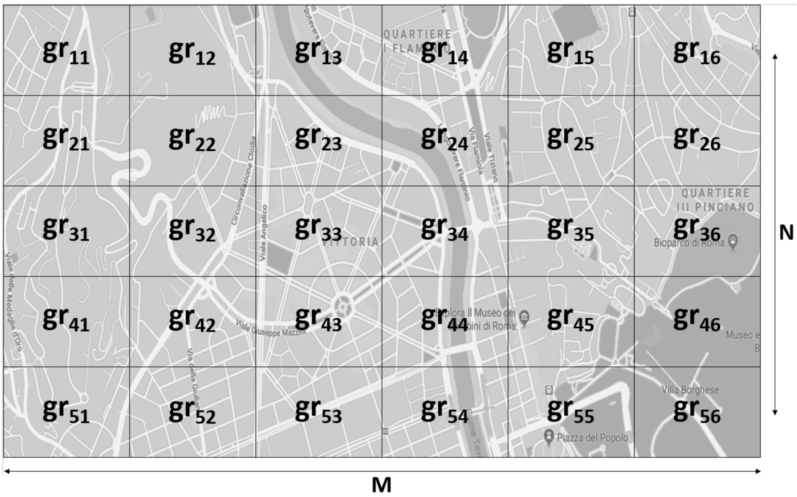


Figure 1: An example of matrix *GR* applied to a geographical *MAP* with N=1.8 km, M=3.5 km, and an area of $M \times N = 6.3\ km^2$; as regards matrix *GR*, we considered n=5 and m=6, so each region gr_{ij} has the dimensions $360m \times 580\ m$.

where p_i is the probability of *i-th* symbol in s and b is the base of the logarithm, that is a positive real value. We base our proposal by starting from eq. 1 and adapting it to extract the needed knowledge from the evolution of a MANET.

3.1 Entropy Evaluation based on Geographic Location/Mobility

In particular, one of the main aims of this work is the association of an entropy value to a node into the network, based on its position and/or the way it has to move among different adjacent areas. Given that we are considering a MANET scenario, a grid *GR* is defined, able to subdivide the considered geographical *MAP* (where mobile nodes are moving) into a finite set of $n \times m$ areas, defined as follows:

$$GR = \begin{bmatrix} gr_{11} & gr_{12} & \dots & gr_{1m} \\ \dots & \dots & \dots & \dots \\ gr_{n1} & gr_{n2} & \dots & gr_{nm} \end{bmatrix} \quad (2)$$

Given that the dimensions of the considered map are $N \times M$, each gr_{ij} belonging to *GR*, with a regular square shape, will have the dimensions (N/n) and (M/m), as depicted in Figure 1.

Entropy can be used to evaluate the activeness of a node in a given observation window *T*, during which mobile nodes are free to move into *MAP*, by changing the area they visit or remaining into the same area for the entire time period. So, if we indicate a mobile with n_k, then the symbol n_k^T represents the set of areas visited by n_k during *T*. So, if $||n_k^T|| = V$ (the number of areas visited by n_k in *T*), then:

$$n_k^T = \{gr_{1j1} \dots gr_{1jV} | gr_{ijl} \in GR, l = 1..V\} \quad (3)$$

The probability of visiting gr_{ij} by n_k in T is:

$$p_k^T(gr_{ij}) = (number\ of\ times\ gr_{ij}\ appears\ in\ n_k^T)/V \quad (4)$$

and it is easy to derive the expression of nodes n_k's entropy Et:

$$Et(n_k^T) = -\sum_{l=1}^{V^*} p_k^T(gr_{ijl}) \cdot ln[p_k^T(a_{ijl})] \quad (5)$$

where V^* is the number of distinct gr_{ij} visited by n_k.

3.2 How to Predict the Entropy Values by the Recursive Least Squares (RLS)

After the definition of the term $Et(n_k^T)$, we would like to describe a way for predicting the future entropy samples. We based our approach on the idea of (Semnani and Cowan, 1994), where an adaptive filter can adapt the coefficients of its impulse response in function of a given optimisation algorithm. We considered the Recursive Least Squares (RLS) (Haykin, 1999), because it optimises the coefficients by minimising a weighted linear least squares cost function. This kind of approach suits our scope perfectly: a MANET topology can be updated periodically so, for each node, entropy can be evaluated step-by-step at each update time. We assume that, the last entropy value depends on the previous K ones, so we can write:

$$\begin{aligned} Et(T) = \beta_1 \cdot Et(T-1) + \beta_2 \cdot Et(T-2) + \dots \\ \dots + \beta_K \cdot Et(T-K) + et \end{aligned} \quad (6)$$

where *et* is the error (generally a white Gaussian process), and $\beta_1, \dots, \beta_K$ are the coefficients that should

Table 1: Parameters used in simulations.

Parameter	Value
Global geographical simulated area (GR)	6.25 km^2
Side lengths (N and M) of the simulated area	2500 m
Mobility scenario	Urban and extra-urban
Average speed of mobile nodes	11.1, 13.9, 19.4 m/s
GR elements side size l	from 50 to 200 meters
Number of GR elements	from 2500 to 156
Simulation Tools	OpenStreetMap and Matlab
Simulation time	3600 s
Mobility model	C4R
Acceleration/Deceleration	-2.4 m/s^2

Figure 2: The simulated geographical area.

be optimised, considering the last K entropy samples. Eq. 6 can be rewritten in a compact form as:

$$Et(T) = [\vec{BETA}] \cdot [Et(\vec{T} - K)]^{tr} + et \tag{7}$$

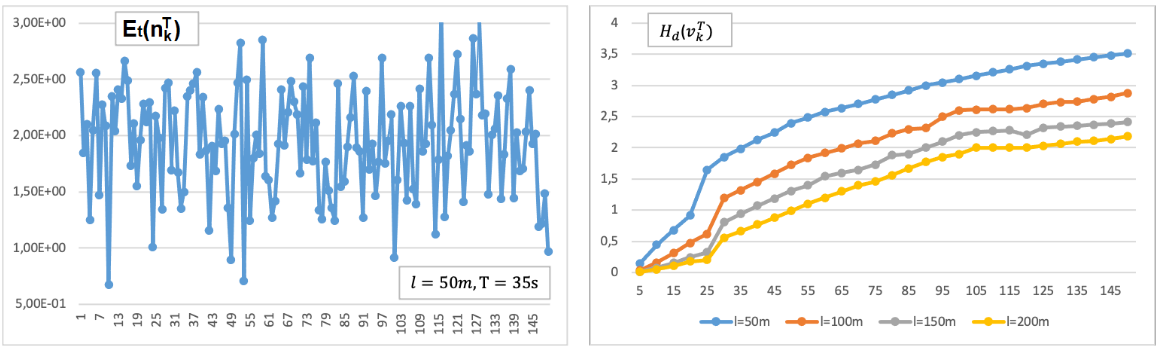
where $\vec{BETA}$ is the vector of coefficients, $Et(\vec{T} - K)$ is the vector of entropy values (samples from $T-1$ to $T-K$, and $[tr]$ is the transpose operator. When the RLS algorithm is applied, the optimal $\vec{BETA}^*$ vector is found (Haykin, 1999). At the end, the algorithm is based on the evaluation of:

$$\begin{aligned} \vec{BETA}(T) = BETA(\vec{T} - 1) \cdot GV(\vec{T}) \cdot [DO(T) + \ldots \\ \ldots - BETA^{\vec{tr}}(T-1) \cdot IN(\vec{T})] \end{aligned} \tag{8}$$

where T is the current observation time window, $IN(\vec{T})$ is the INput vector for the RLS algorithm at T (the set of last K entropy values), $GV(\vec{T})$ is the Kalman Gain Vector (Haykin, 1999) at T, $DO(t)$ is the Desired Output at T (that is $DO(T) = Et(T)$). The initial conditions are $n = 0$ and $BETA(0) = [0]$. There are many other terms that lead to the expression of eq. 8, so for more details please refer to (Haykin, 1999) and to the RLS theory.

4 NUMERICAL RESULTS

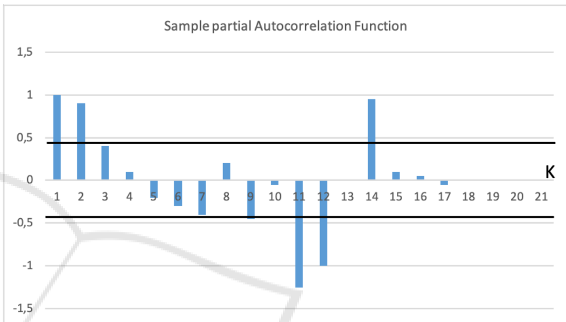
We provide to manage nodes mobility through the OpenStreetMap core (ope, 2019) and C4R (Martinez et al., 2008). A MAP with $N = M = 2500$ meters and an area of about 6.25 km^2 has been considered, ex-



(a) (b)

Figure 3: (a) An example of a typical trend of mobility entropy associated with a mobile node, with an average speed of 13.9 m/s, $l = 60m$ and $T = 25s$; (b) Average entropy associated with mobile nodes for different values of T and l.

	a	b	c	d	p_1	p_2	p_3	p_4
l=50m (a)	3.456	0.0004601	-3.631	-0.02155	4.61E-07	-0.000104	0.000497	3.633
l=100m (b)	3.106	0.0002337	-3.316	-0.0155	-5.12E-10	1.54E-07	-1.87E-05	-1.07E-03
l=150m (c)	2.929	1.04E-05	-3.131	-0.01207	-5.04E-07	0.0001252	-0.00366	-3.698
l=200m (d)	3.271	-0.000594	-3.454	-0.00942	2.46E-09	-1.25E-06	0.000267	-0.03206



(a) (b)

Figure 4: (a) Values for the fitting functions of eq. 9 and eq. 10; (b) PACF for an entropy set of 30 samples, $l = 30m$, $T = 10s$, average speed 13.9 m/s.

tracted from the territory of Cosenza, in the southern of Italy, see Figure 2. Mobility has been configured to be urban and extra-urban, with average speeds of 11.1, 13.9 and 19.4 m/s, while the areas have been considered to be square, with a side size l from 50 m to 200 m. In this way, the number of areas goes from about 2500 to about 156. Mobility traces have been generated and, then, parsed with a Java application, to evaluate entropy samples, according to eq. 5 and the dimensions of *MAP*. Figure 3a shows the typical trend of 135 samples of entropy values (taken every $T = 35$ seconds, while a mobile node n_k is moving). Figure 3b illustrates the average trend of $Et(n_k^T)$ by varying T and l (with a fixed average speed of 11.5 m/s). For larger values of area side l, the entropy value decreases since each mobile node takes more time to move outside the current location gr_{ij}; besides, for larger observation window size T the entropy increases, because each mobile node v_k can visit more locations in T.

After the preliminary analysis, we proceed to fit the obtained curves by using MATLAB and its $cftool$, by which we derived that the trends depicted in Figure 3 can be well approached by a linear combination of exponential functions:

$$Et(T,l) = a(l) \cdot e^{b(l)T} + c(l) \cdot e^{d(l)T} \quad (9)$$

where coefficients a, b, c, d are functions of l which can be expressed as polynomial functions as follows:

$$a(l) = b(l) = c(l) = d(l) = p_1 \cdot l^3 + p_2 \cdot l^2 + p_3 \cdot l + p_4 \quad (10)$$

Figure 4a resumes the obtained values of $p_1, \ldots, p_4$ for each coefficient in eq. 9 and the values of the polynomial fitting of eq. 10. For such combination of parameters, the fitting indicators are Sum of Squares due to Error $(SSE) = 0.1116$, R-square $(R^2) = 0.9926$, Adjusted-R^2 $(AR^2) = 0.9908$ and Root Mean Square Error $(RMSE) = 0.09649$, which describes the appropriate fitting values.

Further, we implemented the RLS filter in MATLAB: given a complete entropy samples data-set of $Et(n_k^T)$ for different values of T, l and average speed, we found the accurate way to predict entropy values with RLS. In particular, this approach can be useful for real-time decisions, such as routing or minimum cost evaluation, given that future entropy trends can be predicted.

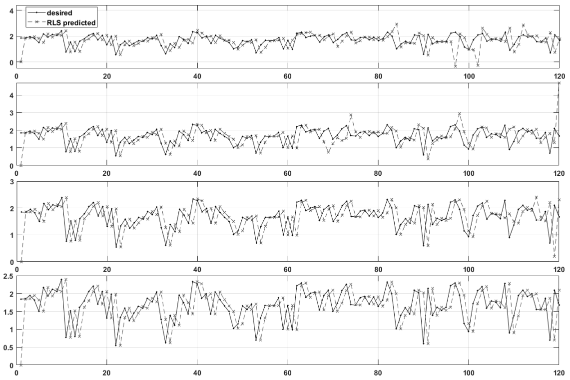


Figure 5: Entropy samples prediction with RLS for K=1, β=0.1, 0.3, 0.5, 0.7 (number of samples on the x-axis and entropy values on the y-axis).

In order to select the proper value of K, we take into account the Partial Auto-Correlation Function (PACF), defined as the autocorrelation between $Et(T)$ and $Et(T-K)$ with the linear dependence of $Et(T)$ on $Et(T-1)$ through $Et(T-K+1)$ removed (Box et al., 2015).

After the analysis of different sets of entropy samples, we can state that the PACF correlogram, like the one depicted in Figure 4b helps to select the best values of K, for which the prediction error is minimised. In our examples, several largest spikes are obtained: that is, for each combination of simulation parameters (T, avg speed, l, mobility model and other) a set $K^* = \{K_1, K_2, ..., K_r\}$ of lag values can be obtained, for which the PACF function has a local maximum. Additional benefit can be seen that regardless of the chosen combination of simulation parameters, each correlogram has a spike for $K = 1$, that is the entropy process can always be considered also as a K=1-order Auto Regressive Process (ARP(1)).

In the next step, we chose $K = 1$ to confirm that the RLS algorithm can predict the entropy trend with an acceptable error. Figure 5 shows the results obtained by considering 120 samples of $Et(n_k^T)$, with $T = 5s$, $l = 30m$, $avg\_speed = 13.9\ m/s$. It can be seen how, in general, the RLS can evaluate future samples with high accuracy.

5 CONCLUSION AND FUTURE WORKS

In this paper, we presented an in-depth analysis of the entropy concept related to mobility in MANETs. In particular, we underlined the key factors that influence its trend during host mobility inside a geographical region. A new way of approaching mobility entropy evaluation has been presented, and a closed form has been obtained for the description of its average values, in function of several system parameters. Also, we provided instructions to predict future entropy values, obtaining beneficial results regarding prediction error. Future works will regard the application of this analysis to forwarding operations in MANETs, such as packet routing, novel metrics definition, system stability analysis and predictive relaying, and considering the possibility of using novel routing approaches based on social networks such as in (Socievole et al., 2013; Socievole et al., 2014).

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