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Multi-Fractal Characteristics of Mobile Node's Traffic in Wireless Mesh Network with AODV and DSDV Routing Protocols

Yufeng Chen · Zhengtao Xiang · Yabo Dong · Dongming Lu

Abstract The analysis of traffic characteristics can be used for performance evaluation, design and implementation of routing protocols in WMNs (Wireless Mesh Networks). Higher bursty traffic will cause larger queue size, which means more dropping packets, and thus affects other metrics. Because burstiness can be modeled by multi-fractal characteristics effectively, multi-fractal characteristics of mobile node's traffic in WMNs are analyzed with typical proactive and reactive routing protocols, which are DSDV (Destination Sequenced Distance Vector) and AODV (Ad hoc On-demand Distance Vector), respectively. Three types of traffic models are used to generate traffic at application level, which corresponding to open-loop and closed-loop scenarios. With different configurations, the probability distribution of inter-arrival time and multi-fractal characteristics of traffic at mobile node and gateway are analyzed with DSDV and AODV protocols. Results show that inter-arrival time with AODV and DSDV protocols possesses heavy-tailed property. And traffic with DSDV protocol exhibits more multi-fractal characteristics than that with AODV protocol, which can explain the higher routing performance of AODV.

Keywords Multi-fractal · Mesh network · AODV · DSDV

Y. Chen · Z. Xiang
School of Electrical and Information Engineering, Hubei University of Automotive Technology, 442002 Shiyan, China
e-mail: syxiang2000@163.com

Y. Chen · Y. Dong (✉) · D. Lu
College of Computer Science and Technology, Zhejiang University, 310027 Hangzhou, China
e-mail: dongyb@zju.edu.cn; dongyb2008@163.com

Y. Chen
e-mail: xztcyfnew@zju.edu.cn

D. Lu
e-mail: ldm@zju.edu.cn

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1 Introduction

With the development of wireless communication and network technology, WMN (Wireless Mesh Network) attracts broad attention. As an extension of Ad Hoc network, WMNs can expand a "hot-spot" to a "hot-zone" and connect wireless networks to wired networks. WMNs can be used in many applications, such as digital home, environment monitoring, and secure manufacture.

The large scale deployment of WMNs requires effective routing protocols. The routing protocols in WMNs have the same basic idea as that in Ad Hoc networks. The routing protocols of Ad Hoc networks can be classified into two types, proactive and reactive (on demand) routing protocols [1]. DSDV and AODV are representatives of proactive routing protocols and reactive routing protocols, respectively. DSDV [2] is table-driven. In DSDV protocol, each node maintains a routing table by advertising its routing table to its neighbors. The table can be updated periodically or when some events occur, such as a link break. In AODV protocol [3], the routing procedure is initiated when a node needs to communicate with other nodes. When a link break in an active route occurs, the source node will initiate route discovery again.

The performances of different routing protocols have been evaluated and compared. Boukerche showed that the throughput of AODV is better than that of DSDV [1]. Ren et al. [4] showed that AODV has higher goodput and lower drop rate than DSDV when simulating TCP transmissions. The metrics used for evaluating the performance of routing protocols in wireless networks are usually throughput, drop rate and delay. However, from the aspect of network traffic, higher bursty traffic will cause lower utilization of network resources via queueing theory, which means more dropping packets, and thus affects other metrics [5]. If mobile nodes and gateways in WMNs can balance the traffic burstiness of different paths when making routing decision, the routing performance may be improved.

Burstiness can be modeled by multi-fractal characteristics effectively. For wired networks, multi-fractal methods are used to analyze traffic characteristics. Traffic in LAN [6] and WAN [7] exhibits self-similarity (mono-fractal). TCP traffic [8] and WAN traffic [9] also exhibit multi-fractal characteristics.

For wireless networks, some papers give results related to the multi-fractal characteristics. The incoming traffic of one node collected in Ad Hoc network testbed is analyzed [10,11]. The results show that Ad Hoc network traffic is self-similar. Furthermore, more attention is paid to the characteristics of forwarding traffic [11], which is regarded as the aggregation of some segments of heavy-tailed flows. The traffic characteristics affected by 802.11 MAC protocol are studied in [12]. Simulation results show that traffic of base station possesses multi-fractal characteristics with 802.11 MAC protocol. Pezaros et al. [13] focused on individual IPv6 microflows. The results show that the flows possess heavy-tailed properties and multi-fractal characteristics.

In WMNs, because mobile node's traffic is a combination of traffic generated by itself and forwarding traffic, which is controlled by routing protocols, mobile node's traffic will exhibit complex burstiness behaviors. Thus, the multi-fractal characteristics of mobile node's traffic should be analyzed and can be regarded as an effective metric to evaluate routing performance. However, the effect of routing protocols on multi-fractal characteristics of mobile node's traffic has not been analyzed. We will analyze the fractal characteristics of mobile node's traffic in this paper. Furthermore, the multi-fractal characteristics of gateway's traffic are analyzed because in WMNs, gateways connect wireless networks to wired network, which forward the traffic from mobile nodes in wireless network to the hosts in wired network. The traffic characteristics of gateways are controlled by the routing behaviors of mobile nodes.

To show the influence of different typical routing protocols, DSDV and AODV are selected for analyzing and comparing the multi-fractal characteristics.

The main contributions of this paper are:

(1) Multi-fractal characteristics of traffic of mobile node and gateway in WMNs are analyzed with typical proactive and reactive protocols. The results of multi-fractal analysis will show how different routing protocols bear different traffic models and different traffic volumes.
(2) The multi-fractal characteristics with different scenarios are compared, and the reasons of the differences of multi-fractal characteristics with different routing protocols are discussed.
(3) We propose that the multi-fractal characteristics can be used as an important metric for performance evaluation, and thus will affect the design and implementation of routing protocols in WMNs.

The rest of the paper is organized as follows. The basis of multi-fractal analysis is presented in Sect. 2. Section 3 gives the analysis of multi-fractal characteristics and discusses the differences between different scenarios. Finally, our work is concluded in Sect. 4.

2 Basis of Multi-Fractal Analysis

In this section, we will give the basis of multi-fractal analysis briefly. First, we will show the definition of heavy-tailed distribution. Heavy-tailed distribution depicts the property that a large portion of probability mass can occur in the tail of the distribution, which is much different from exponential distribution. And then the introduction to multi-fractal property is presented. The multi-fractal analysis can satisfy the requirements of describing the burstiness at large time scale and small time scale together. Also, the performance with multi-fractal traffic is presented to show the impact of multi-fractal characteristics on network performance.

2.1 Heavy-Tailed Distribution

If a random variable follows heavy-tailed distribution, the distribution decays slower than exponential. A distribution is defined as heavy-tailed [7] if

$$\bar{F}(x) = 1 - F(x) = P[X > x] \sim x^{-\alpha}, \tag{1}$$

as $x \to \infty$, $0 < \alpha$. The simplest heavy-tailed distribution is Pareto distribution, with Complementary Cumulative Distribution Function (CCDF) as

$$\bar{F}(x) = (k/x)^{\alpha}, \tag{2}$$

where α is shape parameter, denoting the tail thickness. If $\alpha \leq 2$, the distribution has infinite variance. As α decreases, an arbitrarily large portion of the probability mass may be presented in the tail of the distribution. When plotted on log-log axes, the curve of CCDF appears linear.

Another common heavy-tailed distribution is Weibull distribution with CCDF as

$$\bar{F}(x) = e^{-(x/\eta)^{\beta}}. \tag{3}$$

If $\beta < 1$, Weibull distribution belongs to heavy-tailed distribution.

2.2 Multi-Fractal

We will introduce multi-fractal briefly [14]. Consider a probability measure μ on the unit interval [0, 1] and random variables

$$Y_n = \log \mu \left(I_K^{(n)} \right), \tag{4}$$

where $I_K^{(n)}$ denotes one of the 2^n equal subintervals: $I_K^{(n)} := [k2^{-n}, (k+1)2^{-n}]$, and K is a random number from $\{0, \ldots, 2^n - 1\}$ with uniform distribution P_n. If the rate function, also called "partition function" or "free energy"

$$\tau(q) := \lim_{n \to \infty} \frac{-1}{n} \log_2 \sum_{k=0}^{2^n - 1} \mu \left(I_k^{(n)} \right)^q \tag{5}$$

exists and is differentiable on $\Re$, then the double limit

$$f_G(\alpha) := \lim_{\varepsilon \to 0} \lim_{n \to \infty} \frac{1}{n} \log_2 2^n P_n \left[\alpha \left(I_k^{(n)} \right) \in (\alpha - \varepsilon,\ \alpha + \varepsilon) \right] \tag{6}$$

exists. $\alpha \left(I_k^{(n)} \right)$ is the singularity of the subset of probabilities, termed Holder exponent, and defined as

$$\alpha \left(I_k^{(n)} \right) := \frac{-1}{n \log 2} Y_n = \frac{\log \mu \left(I_K^{(n)} \right)}{\log |I_K^{(n)}|}. \tag{7}$$

We can compute the Legendre spectrum f_L with

$$f_G(\alpha) = f_L(\alpha) := \tau^*(\alpha) = \inf_{q \in \Re} (q\alpha - \tau(q)). \tag{8}$$

$f(\alpha)$ is the fractal dimension of the subsets with same α. Due to the robustness and simplicity of f_L, we will analyze the multi-fractal property of our data series through f_L. The dependence of $f(\alpha)$ with α is called multi-fractal spectrum.

We can use the partition sum $S^{(n)}(q)$ to compute $\tau(q)$,

$$\tau(q) := \lim_{n \to \infty} \frac{\log S^{(n)}(q)}{-n \log 2}, \tag{9}$$

where $S^{(n)}(q) := \sum_{k=0}^{2^n - 1} |Y((k+1)2^{-n}) - Y(k2^{-n})|^q$. When we inspect the log-log plots of partition sum against q, if the plot appears linear, the observed process is multi-fractal [14].

The parameter α quantifies the degree of regularity in a point x: the measure of an interval $[x, x + \Delta x]$ behaves as $(\Delta x)^\alpha$. In traffic measurements, $(\Delta x)^\alpha$ can be interpreted as the number of packets or bytes in this interval. For a process, if the range of $\alpha < 1$ in the multi-fractal spectrum is larger, the process possesses more multi-fractal property [15]. $\Delta f = f(\alpha_{\min}) - f(\alpha_{\max})$ gives the difference of the numbers of the maximum probability subset and the minimum one [16].

2.3 Performance with Multi-Fractal Traffic

Traffic modeling is very important for network designing, traffic engineering and QoS (Quality of Service). As we mentioned in Sect. 1, burstiness can be modeled by multi-fractal characteristics effectively. Based on the multi-fractal model of traffic, the queueing performance is analyzed in many papers.

The Multi-fractal Wavelet Model (MWM) [17] is used as a basis to analyze the queueing performance [18]. In [18], the Multi-Scale Queuing (MSQ) formula is proposed to demonstrate the impact of the marginals of traffic at multiple time scales on queuing. With MWM, MSQ shows that larger bursts of traffic at different time scales lead to larger queue sizes. Liu and Baras proposed a new statistical model for scaling and multi-scale traffic [19]. Based on the model, the queueing analysis shows that the packet losses can be divided to two classes, the absolute loss and the opportunistic loss, and the multi-scaling property can contribute to the loss probability in the small and large scales. Ribeiro et al. [20] analyzed the queueing behaviors with MWM model. The results show that tails of marginals of traffic at different time scales have a significant impact on queueing.

The above queueing analyses focus on wired networks. For wireless networks, Teymori and Zhuang investigated the queueing behavior with fractal traffic in wireless network [21]. The results show that the value of queue length is rather large, which implies a very large delay and a large probability of packet loss.

Because the traffic burstiness influences network performance heavily, the performance can be improved by reducing the burstiness at multi-scale. When focusing on the network layer, in [22] and [23], the RED (Random Early Detection) mechanism is used at the gateway, which can reduce the multi-fractal characteristics and the performance is improved.

3 Multi-Fractal Characteristics of Mobile Node's Traffic

In this section, the simulation results using NS-2 (http://www.isi.edu/nsnam/ns) are presented and the heavy-tailed property and multi-fractal characteristics of mobile node's and gateway's traffic are analyzed. The version of NS-2 is 2.33.

We adopted a two-level architecture for mesh network named "wired-cum-wireless network" [24], which can simulate the combination of wireless networks and wired networks. To analyze the traffic with AODV protocol in mesh network, we used AODV+ (http://nsnam.isi.edu/nsnam/index.php/Contributed_Code), which extended AODV in NS-2. We used the same topology configuration as that in [25], which is shown in Fig. 1. The transmission range was set to 250 m.

There are 15 mobile nodes, 2 gateways, 2 routers and 2 hosts in the area. R1 (Router 1), R2 (Router 2), H1 (Host 1) and H2 (Host 2) are wired nodes, while GW1 (Gateway 1) and GW2 (Gateway 2) are hybrid nodes with wired and wireless connections. M6 ∼ M20 are mobile nodes.

As to the nodes mobility, the configuration in [25] was adopted. The mobile nodes move with "random waypoint" mode. The pause time is 5 s and the maximum speed is 10 m/s.

The traffic sources are selected randomly in the 15 mobile nodes and the sinks are selected randomly in the two hosts. We got six source-sink pairs: M8-H2, M9-H1, M12-H2, M13-H2, M14-H1, and M19-H1.

To generate traffic at application level, we selected three types of traffic models. The first two traffic models are EXPOO (Exponential On/Off distribution) traffic and POO (Pareto On/Off distribution) traffic above UDP agents with high and low rates configurations. These are open-loop simulations. The third traffic model is TELNET traffic above TCP agent, which gives a closed-loop simulation. With On/Off distribution, packets are sent at a fixed rate during on periods, and no packets are sent during off periods [24]. The difference between EXPOO and POO models is that the on and off periods are taken from an exponential distribution for

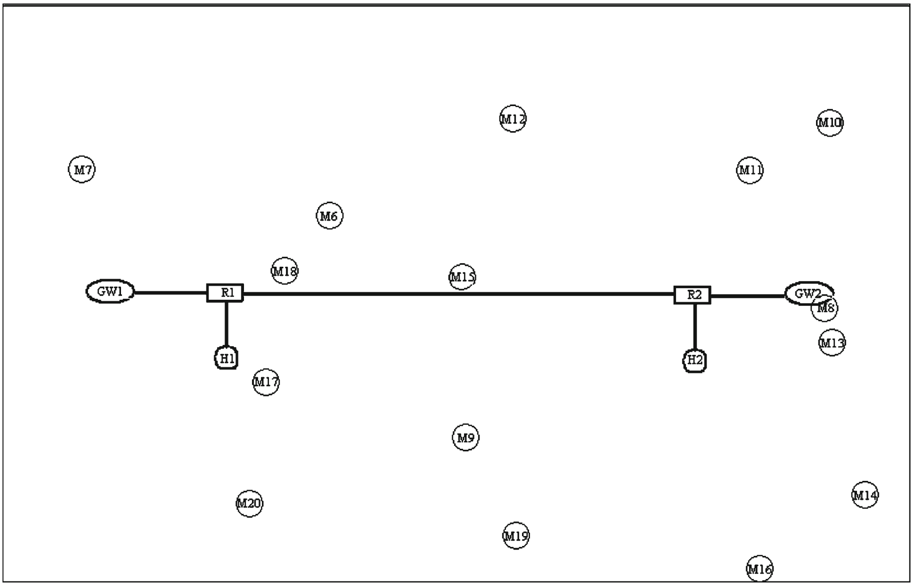

Fig. 1 The initial simulation topology with 800 m length and 500 m width

Table 1 The EXPOO and POO traffic configurations

Traffic generator	Parameter	High-rate	Low-rate
EXPOO	Rate	819200	81920
POO	Rate	819200	81920
	Shape	1.4	1.4

EXPOO model, while for POO model, the on and off periods from a Pareto distribution. Both EXPOO and POO traffic generators can generate traffic with high-variability at application level. The packet size is 512 Bytes. The EXPOO and POO traffic configurations are shown in Table 1. With high rate, the scenario is termed as high-rate scenario, while with low rate, low-rate scenario. For TELNET traffic model, the default configuration in NS-2 is used. With the default configuration of TELNET traffic, the inter-packet times at application level are chosen from an exponential distribution with average equal to 1.0 [24].

All configurations are identical except the routing protocols. To analyze the characteristics of mobile node's traffic, we chose node M9 with the largest amount of traffic including forward traffic for statistical reason. Also, to show the influence of routing protocols, the multi-fractal characteristics of gateways' traffic are analyzed because gateways connect wireless networks to wired networks in WMNs and the traffic characteristics of gateways are controlled by the routing behaviors of mobile nodes. In our experiments, GW2 is chosen to be analyzed because the traffic volume is larger than GW1's. For multi-fractal analysis, the sample time is 100 ms. Each scenario is repeated three times.

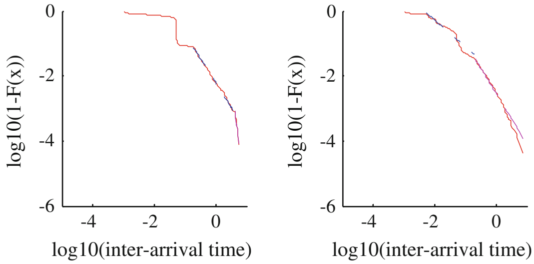

Fig. 2 The heavy-tailed distributions of packets inter-arrival time of M9 with Pareto traffic generator in low-rate scenario with AODV (*left*) and DSDV (*right*) for open-loop case

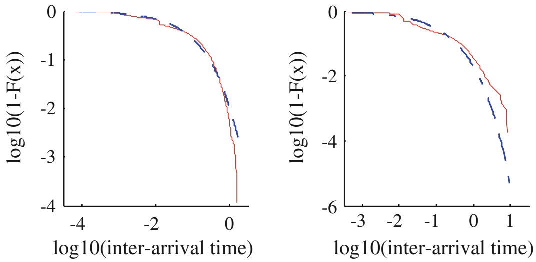

Fig. 3 The heavy-tailed distributions of packets inter-arrival time of GW2 with TELNET traffic generator with AODV (*left*) and DSDV (*right*) for closed-loop case

3.1 Inter-Arrival Time

We will analyze the packets inter-arrival time distribution at M9 and GW2 to show the dynamics of mobile node's and gateway's traffic in this section.

The traffic in one simulation trial of low-rate scenario with Pareto traffic generator is illustrated as an example for open-loop case. The CCDFs of inter-arrival time are computed and plotted in Fig. 2. The Pareto distributions are used to fit, also shown in Fig. 2, which indicates the heavy-tailed property of traffic of M9.

The CCDF with AODV shows a sharp decrease, which means the probabilities of some inter-arrival time are large. Moreover, we can use two Pareto distributions with different parameters to fit the tails of the CCDFs.

For AODV protocol, the values of shape parameter of the two heavy-tailed distributions are 1.5000 and 7.8556, respectively. Both of the two values are higher than that with DSDV protocol, which are 0.8294 and 1.5676, respectively. The less values of shape parameter α mean more heavy-tailed property with DSDV. For the concentration of probability mass of the tails, the values of proportion of the tails with AODV are 0.0762 and 0.0008, respectively, while with DSDV the values are 0.7993 and 0.0359, respectively. The larger values of proportion mean more concentration of probability mass in the tail with DSDV. Thus, For AODV protocol, the less concentration of probability mass in the tail and the higher values of shape parameter α give less probability distribution structure.

Furthermore, the traffic of GW2 in one simulation trial with TELNET traffic generator is illustrated as an example for closed-loop case. The CCDFs of inter-arrival time are computed and plotted in Fig. 3. The Weibull distributions are used to fit, also shown in Fig. 3, which also indicates the heavy-tailed property of traffic of GW2.

Figure 3 shows that although the inter-packet time of TELNET traffic at application level follows exponential distribution, the packets inter-arrival time of network layer traffic at GW2 is heavy-tailed. We used Weibull distribution to fit the CCDFs. The values of β are 0.5409

Table 2 The heavy-tailed property of the traffic of M9 with different configurations in one simulation trial, where α_1 and α_2 are the shape parameters of the two Pareto distributions, respectively, $Prop_1$ and $Prop_2$ are the proportions of the two parts of the tails

Configurations		α_1	$Prop_1$	α_2	$Prop_2$
AODV	EXPOO	1.0447	0.9587	4.9957	0.0008
high-rate	POO	1.0493	0.9606	5.1050	0.0007
AODV	EXPOO	0.5937	0.0704	2.9053	0.0157
low-rate	POO	1.5000	0.0762	7.8556	0.0008
AODV	TELNET	0.4247	0.3199	2.4837	0.0563
DSDV	EXPOO	1.1342	0.9240	2.9319	0.0006
high-rate	POO	1.1235	0.7656	2.3398	0.0010
DSDV	EXPOO	0.9776	0.8157	1.9766	0.0111
low-rate	POO	0.8295	0.7993	1.5676	0.0359
DSDV	TELNET	0.4101	0.3377	1.6539	0.0625

Table 3 The heavy-tailed property of the traffic of GW2 in one simulation trial with different configurations, where α_1 and α_2 are the shape parameters of the two Pareto distributions, respectively, $Prop_1$ and $Prop_2$ are the proportions of the two parts of the tails; β is the shape parameter of Weibull distribution

Configurations		Distribution	α_1 or β	$Prop_1$	α_2	$Prop_2$
AODV	EXPOO	Pareto	1.1383	0.1438	2.1106	0.0021
high-rate	POO	Pareto	1.1734	0.1440	1.0229	0.0001
AODV	EXPOO	Pareto	0.9855	0.0230	3.0864	0.0012
low-rate	POO	Pareto	0.8312	0.9352	1.2475	0.0260
AODV	TELNET	Weibull	0.5409	–	–	–
DSDV	EXPOO	Pareto	1.1602	0.4574	8.9029	0.0003
high-rate	POO	Pareto	1.1161	0.4937	3.7521	0.0005
DSDV	EXPOO	Pareto	1.2571	0.7329	–	–
low-rate	POO	Pareto	0.6836	0.5747	1.2510	0.2169
DSDV	TELNET	Weibull	0.5020	–	–	–

and 0.5020 for AODV and DSDV protocols, respectively. The less value of β for DSDV protocol indicates more heavy-tailed property of traffic at GW2.

Other distributions of traffic inter-arrival time of M9 can also be fitted using Pareto distributions. The results are shown in Table 2.

Also, other distributions of inter-arrival time of the traffic of GW2 can be fitted using Pareto distributions or Weibull distributions. The results are shown in Table 3.

All inter-arrival time distributions of mobile node's traffic and gateway's traffic show heavy-tailed property. With other simulation trials, the traffic of M9 and GW2 show heavy-tailed property, too. However, the values of shape parameter estimated for inter-arrival time can only tell the property that a large portion of the probability mass is present in the tail of the distribution of inter-arrival time. We can use more powerful tools like the multi-fractal analysis to reveal the richer probability distribution structure.

3.2 Multi-Fractal Characteristics of Mobile Node's Traffic

With multi-fractal analysis, we can learn the burstiness at different time scales. We used Fraclab [26] to analyze the multi-fractal characteristics. Figure 4 shows the plots of partition sum $S^{(n)}(q)$ and Legendre spectrum f_L of traffic of M9 in one simulation trial with Pareto traffic generator in low-rate scenario.

From the plots of the partition sum against the scale on log-log scale, we can know that both of the two mobile node's traffic possess multi-fractal characteristics because the two plots show a wide range of scale-invariance. However, the spectrum plots of $f(\alpha)$ show that mobile node's traffic with AODV has less multi-fractal characteristic than that with DSDV. The values of $\alpha < 1$ are 0.2780 and 0.4932, respectively. The less range of $\alpha < 1$ means the distribution of traffic with AODV is less nonuniform, which indicates that the traffic with AODV has less variety. The values of Δf of the two traces are all positive, which means the number of maximum probability subset is higher than that of minimum probability subset.

In addition, the plots of multi-fractal spectrum of traffic of GW2 in one simulation trial with TELNET traffic generator are shown in Fig. 5.

Figure 5 gives similar results for GW2. The values of $\alpha < 1$ are 0.1605 and 0.5677 for AODV and DSDV, respectively. The less range of $\alpha < 1$ for AODV shows less multi-fractal characteristic. Other results in one simulation trial for M9 and GW2 are shown in Table 4 and Fig. 6, and Table 5 and Fig. 7.

Table 4 and Fig. 6, and Table 5 and Fig. 7 show the mobile node's traffic and gateway's traffic possess multi-fractal property with different traffic and routing protocol configurations. Also, we can find that almost all the values of Δf are positive which indicates the number of maximum probability subset is higher than that of minimum probability subset.

Compared with scenarios with AODV protocol, traffic with DSDV protocol exhibits wider ranges of $\alpha < 1$. The observations show that the control of DSDV protocol induces more multi-fractal characteristics. With DSDV, the routing table will be updated periodically, which may not guarantee valid routes when the mobility is high. With high mobility, more invalid routes will occur with DSDV, and the packets will be forwarded along with invalid routes and finally will be discarded due to no route. For intermediate nodes located in the invalid route, the continuous arrival of unnecessary packets will increase traffic burstiness of the nodes at small time scales. In addition, the updating period of routing table is at second-level, which belongs to large time scale. The invalid routes will exist at large time scales, which will induce traffic burstiness at large time scales. Thus, the forwarded packets along with invalid routes will increase the multi-fractal property of the intermediate nodes. On the other hand, for AODV, the routes can be found when needed. This on-demand pattern can provide valid routes although the mobility is high. For intermediate nodes, the number of invalid forwarded packets with AODV is less than that with DSDV, which induces less multi-fractal property with AODV.

When in closed-loop scenarios, the difference of multi-fractal characteristics between AODV and DSDV is more obvious. Although the inter-packet time at application level follows exponential distribution, the traffic possesses multi-fractal property. Furthermore, the ranges of $\alpha < 1$ for M9 and GW2 are 0.3062 and 0.4072 higher with DSDV than that with AODV, respectively. Results of other simulation trials are shown in Table 6, which also indicate the less multi-fractal characteristic for AODV. In closed-loop control, after a packet is dropped due to invalid route, the packet needs to be retransmitted. However, for DSDV, the invalid route still remains in the routing table, which will induce more unnecessary traffic going through the route.

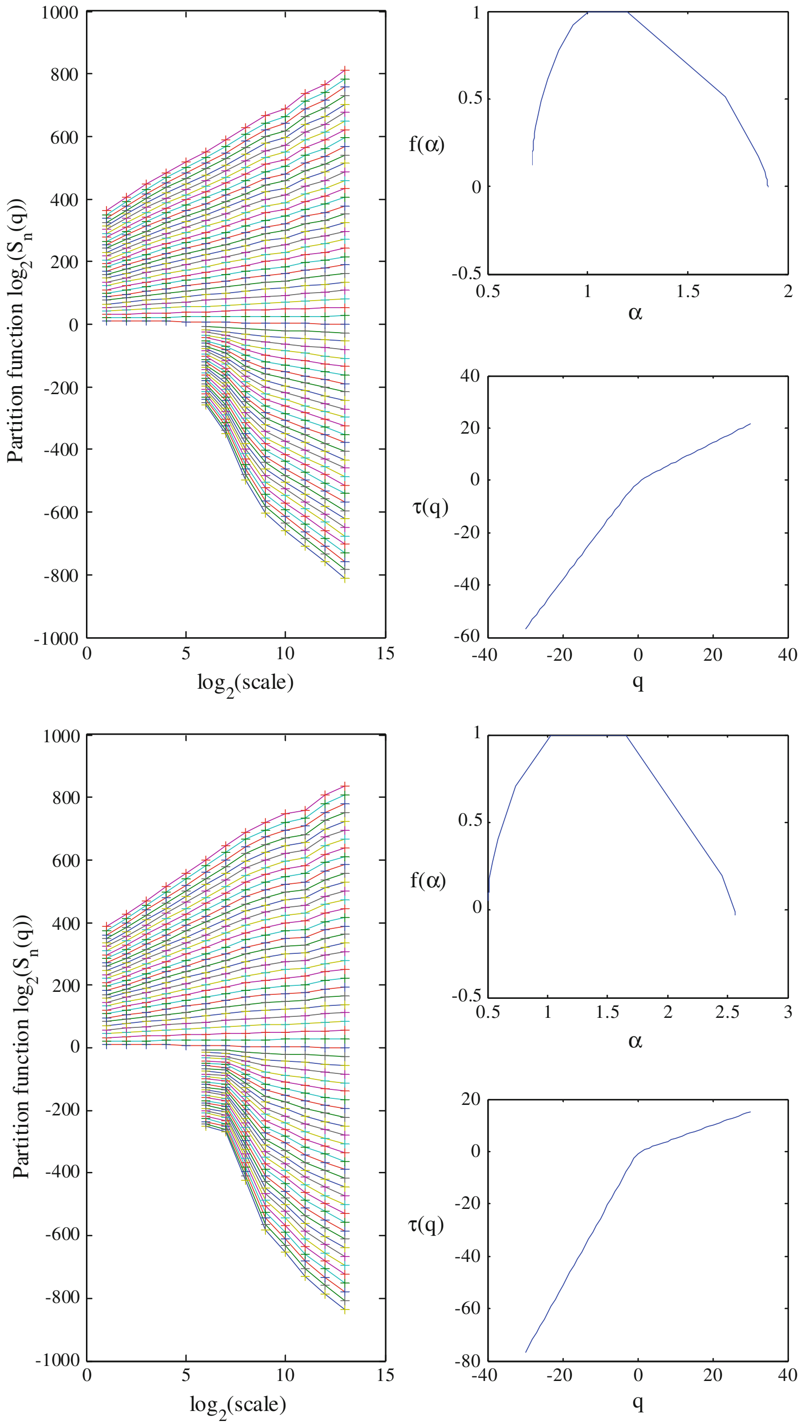

Fig. 4 The multi-fractal spectrum plots of mobile node's traffic in one simulation trial with Pareto traffic generator in low-rate scenario with AODV (*top*) and DSDV (*bottom*)

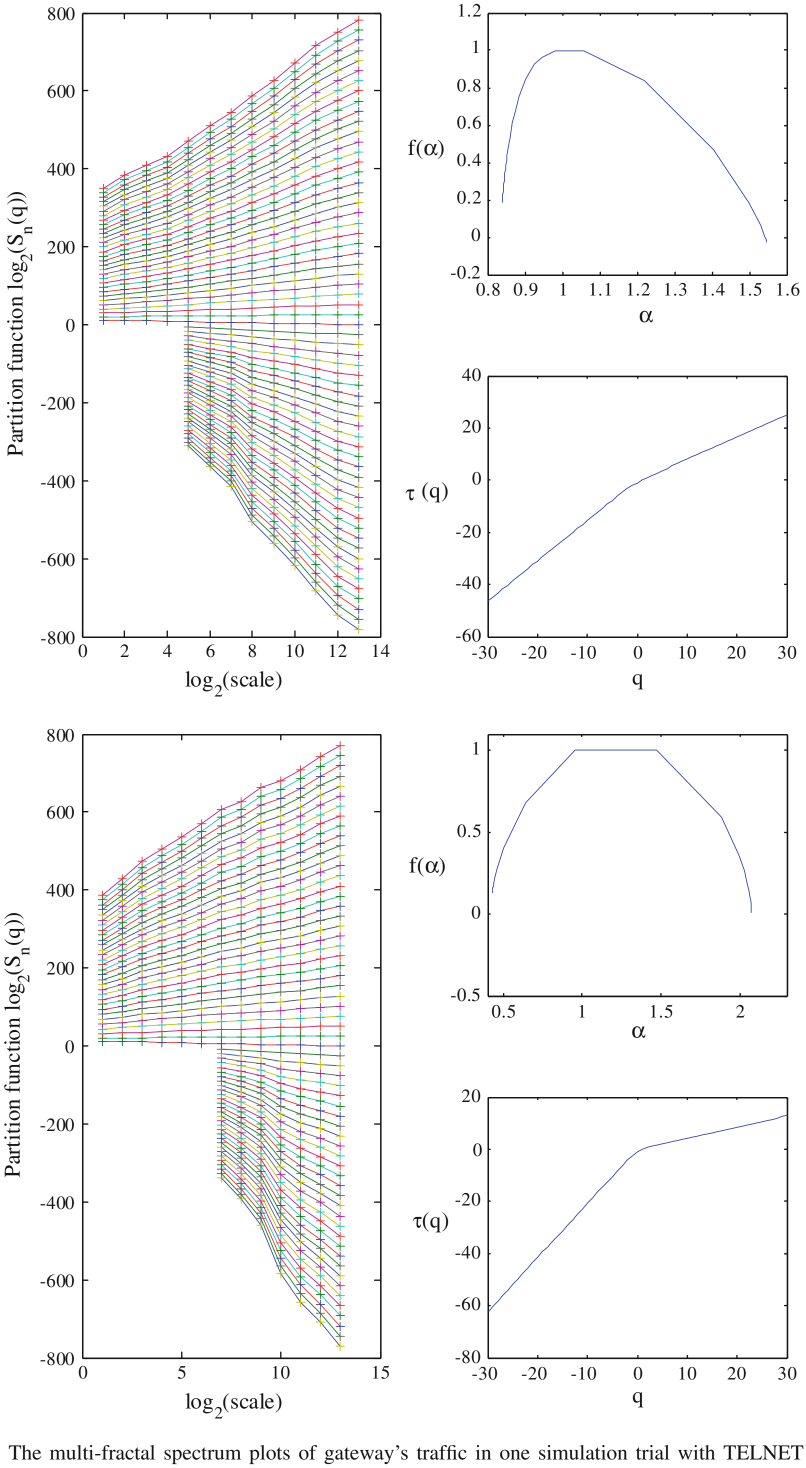

Fig. 5 The multi-fractal spectrum plots of gateway's traffic in one simulation trial with TELNET traffic generator with AODV (*top*) and DSDV (*bottom*)

Table 4 The multi-fractal characteristics of the traffic of M9 in one simulation trial with different configurations

Configurations		$\alpha_{\max}$	$\alpha_{\min}$	$\alpha < 1$	$f(\alpha_{\min})$	$f(\alpha_{\max})$	Δf
AODV	EXPOO	2.5858	0.7436	0.2564	0.0549	0.0855	−0.0306
high-rate	POO	2.7803	0.8424	0.1576	0.3049	0.1357	0.1692
AODV	EXPOO	1.5678	0.6905	0.3095	0.0275	−0.0777	0.1052
low-rate	POO	1.9015	0.7220	0.2780	0.1182	−0.0032	0.1214
AODV	TELNET	1.3357	0.7441	0.2559	0.0633	0.07270	−0.0094
DSDV	EXPOO	2.4417	0.7434	0.2566	0.0382	0.1039	−0.0657
high-rate	POO	2.7043	0.8045	0.1955	0.0433	0.0586	−0.0153
DSDV	EXPOO	2.7807	0.6540	0.3460	0.1478	−0.0612	0.2090
low-rate	POO	2.5650	0.5068	0.4932	0.0541	−0.0280	0.0821
DSDV	TELNET	2.0920	0.4179	0.5821	0.0150	0.0524	−0.0374

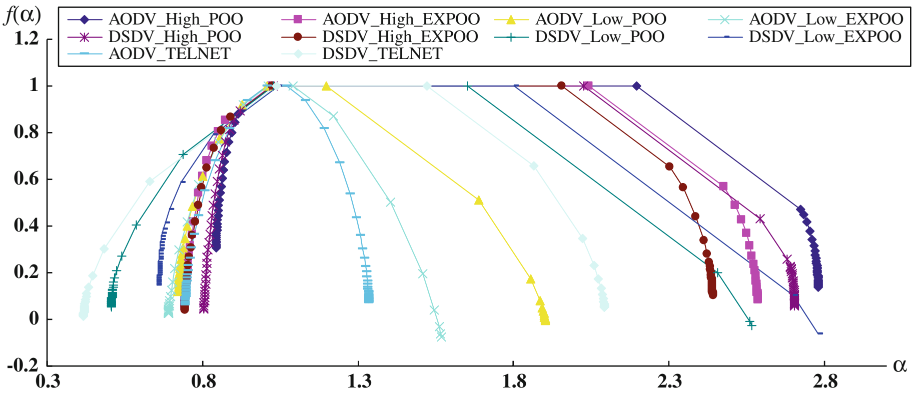

Fig. 6 The multi-fractal spectra of mobile node's traffic in one simulation trial with different traffic models and volumes with AODV and DSDV

Table 5 The multi-fractal characteristics of the traffic of GW2 in one simulation trial with different configurations

Configurations		$\alpha_{\max}$	$\alpha_{\min}$	$\alpha < 1$	$f(\alpha_{\min})$	$f(\alpha_{\max})$	Δf
AODV	EXPOO	1.4789	0.8952	0.1048	0.6449	−0.0429	0.6878
high-rate	POO	2.4038	0.8545	0.1455	0.5705	−0.0602	0.6307
AODV	EXPOO	1.2700	0.8492	0.1508	0.2761	0.1426	0.1335
low-rate	POO	1.3180	0.8217	0.1783	0.0310	0.3182	−0.2872
AODV	TELNET	1.5466	0.8395	0.1605	0.1874	−0.0267	0.2141
DSDV	EXPOO	2.5584	0.7270	0.2730	0.0714	−0.0132	0.0846
high-rate	POO	2.5798	0.5875	0.4125	0.0549	−0.0757	0.1306
DSDV	EXPOO	2.3903	0.7027	0.2973	0.0341	−0.0635	0.0976
low-rate	POO	1.6457	0.6638	0.3362	0.0721	0.0410	0.0311
DSDV	TELNET	2.0771	0.4323	0.5677	0.1267	−0.0007	0.1274

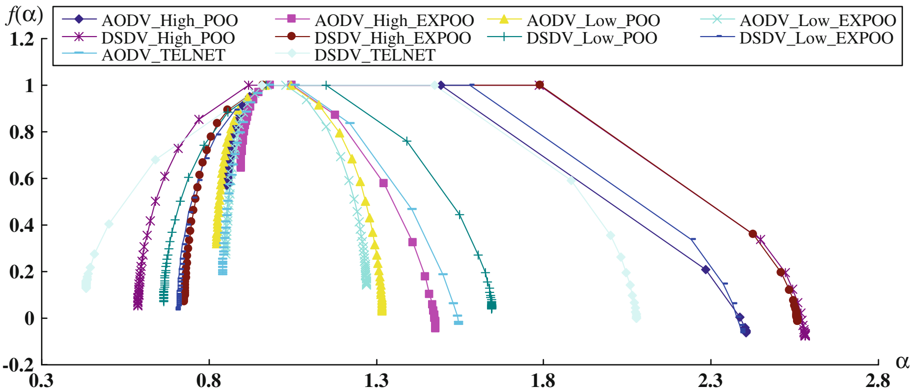

Fig. 7 The multi-fractal spectra of gateway's traffic in one simulation trial with different traffic models and volumes with AODV and DSDV

Table 6 The multi-fractal characteristics of the traffic of M9 and GW2 in other two simulation trials with different configurations

Configurations			High-rate and EXPOO	High-rate and POO	Low-rate and EXPOO	Low-rate and POO	TELNET
AODV Trial 2	M9	$\alpha < 1$	0.2346	0.2653	0.2963	0.2616	0.3230
		Δf	0.1563	0.0649	−0.0649	0.1132	−0.0340
	GW2	$\alpha < 1$	0.1356	0.1549	0.1531	0.1747	0.1550
		Δf	0.2233	0.6396	0.1685	0.2444	0.0754
AODV Trial 3	M9	$\alpha < 1$	0.2722	0.3295	0.3102	0.2368	0.2318
		Δf	−0.0512	−0.0950	−0.0344	−0.0010	0.0841
	GW2	$\alpha < 1$	0.1055	0.1446	0.1899	0.1733	0.1619
		Δf	0.5793	0.5799	0.1267	0.1674	0.2604
DSDV Trial 2	M9	$\alpha < 1$	0.2230	0.3211	0.4389	0.3710	0.5775
		Δf	−0.0913	−0.0435	0.0879	0.1542	−0.1110
	GW2	$\alpha < 1$	0.4469	0.4558	0.3382	0.3311	0.5161
		Δf	−0.0137	−0.0259	0.0541	−0.0788	−0.1647
DSDV Trial 3	M9	$\alpha < 1$	0.2081	0.2231	0.3261	0.3052	0.6856
		Δf	0.0956	0.2527	0.1959	0.1506	−0.0415
	GW2	$\alpha < 1$	0.3529	0.5222	0.3336	0.4570	0.4894
		Δf	0.2773	0.0272	0.1476	−0.0322	−0.0382

We analyzed the routing performance for the three simulation trials. The routing performance of AODV is higher than that of DSDV, as shown in Table 7, which validates the influence of multi-fractal traffic to network performance mentioned in Sect. 2.3. The performance metrics are Packet Delivery Fraction (PDF) and Average End-to-End Delay [27]. PDF is the ratio of the data packets delivered to the destination to those generated by the traffic sources. Average End-to-End Delay includes all possible delays caused by buffering during route discovery, queuing delay at the interface, retransmission delays at the MAC (Media Access Control) layer, propagation and transfer times.

Table 7 Comparison of routing performance of three simulation trials between AODV and DSDV

Configurations		High-rate and EXPOO	High-rate and POO	Low-rate and EXPOO	Low-rate and POO	TELNET
AODV Trial 1	PDF (%)	26.54	26.66	94.84	95.54	98.48
	E-E Delay (ms)	2309	2261	24	28	29
AODV Trial 2	PDF (%)	26.48	26.90	94.55	95.68	98.76
	E-E Delay (ms)	2148	2217	27	238	28
AODV Trial 3	PDF (%)	25.92	24.92	95.34	95.02	98.80
	E-E Delay (ms)	2296	2077	23	24	28
DSDV Trial 1	PDF (%)	18.24	13.24	56.75	46.75	89.26
	E-E Delay (ms)	2299	2496	808	584	163
DSDV Trial 2	PDF (%)	17.83	18.35	53.15	50.43	92.38
	E-E Delay (ms)	2147	2211	555	769	63
DSDV Trial 3	PDF (%)	17.67	15.39	48.92	48.21	89.72
	E-E Delay (ms)	2508	2090	905	727	54

Multi-fractal characteristic describes the traffic burstiness at multiple time scales. At small time scales, if the traffic burstiness increases, the instantaneous packets dropping will occur because of the sudden decease of available buffers. At large time scales, if the traffic burstiness increases, the buffers in routers can not smooth the traffic burstiness, which will induce packets loss, too. The queue sizes will increase as the multi-fractal characteristic of traffic increases [18]. The larger queue size requirement induces higher packet loss rate and larger delay. For DSDV, higher multi-fractal characteristic causes lower PDFs and larger Average End-to-End Delays. The closed-loop simulations can give good examples. With TELNET traffic model, the traffic load is rather low. However, the average PDF of the three trials is 8.34% lower than that of AODV and the average End-to-End Delay of the three trials is 3.24 times higher than that of AODV.

4 Conclusions

In this paper, the multi-fractal characteristics of mobile node's traffic are analyzed in wireless mesh network with typical proactive and reactive protocols, DSDV and AODV, respectively. As a combination of traffic generated by itself and forwarding traffic, the mobile node's traffic needs thorough analysis. With three traffic models and different traffic volumes at application level, the probability distribution of inter-arrival time and multi-fractal characteristics of mobile node's traffic and gateway's traffic are analyzed.

The results of probability distribution show that all inter-arrival time distributions of mobile node's traffic and gateway's traffic with AODV and DSDV protocols show heavy-tailed property. Compared with AODV protocol, traffic with DSDV exhibits more multi-fractal characteristics. Thus we think the reactive protocol, AODV, can make better routing decisions with high mobility, which is also validated by the comparison of routing performance. The routing protocols for mobile nodes should be improved based on reactive protocol in WMNs. In addition, the multi-fractal characteristics can be used as the evaluation metrics because multi-fractal characteristics can illustrate the burstiness at different time scales, which influence network performance.

In the future, as a continuation of this research work, other routing protocols for WMNs, such as DSR, can be analyzed using the multi-fractal methods. In addition, we will investigate how routing behaviors affect the multi-fractal characteristics in detail. Based on the analysis of relationships between routing behaviors and multi-fractal characteristics, we will propose more effective routing protocols for mobile nodes in WMNs.

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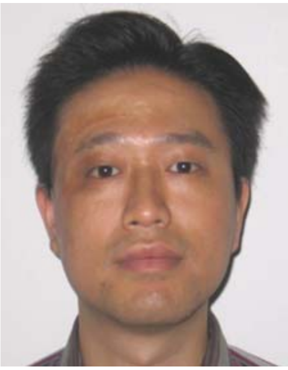
Author Biographies

Yufeng Chen received the B.S. degree in Industrial Electronic Automation from Hubei Automotive Industries Institute (China) in 1996, the Ph.D. degree in Computer Science and Technology from Zhejiang University (China) in 2006. Currently, she works in Zhejiang University as a postdoctor. Her current research interests are in wireless mesh networks, wireless communications and communication protocols.



Zhengtao Xiang received the B.S. degree in Computer Application from Hubei Automotive Industries Institute (China) in 1997, the M.S. degree in Computer Application from Zhejiang University (China) in 2004. Currently, He works in Hubei University of Automotive Technology. His current research interests are in Computer networks and communication protocols.

Yabo Dong received the B.S., M.S. degrees in Control Engineering, and Ph.D. degree in Computer Science from Zhejiang University (China) in 1996, 1999 and 2002, respectively. From 2002, he is working at the College of Computer Science and Technology, Zhejiang University and currently is an associate professor. His current research interests are in wireless mesh networks and embedded systems.

Dongming Lu started his study in Zhejiang University (China) from 1985 and received the B.S., M.S. and Ph.D. degrees in 1989, 1991 and 1994, respectively. He is currently a professor in the College of Computer Science and Technology at Zhejiang University. Prof. Lu is a member of Computer Supported Collaborative Work Professional Committee of China Computer Federation. His research interests are in wireless network, virtual reality and network security.