A Simplified Traffic Generating Method for Network Reliability Based on Self-Similar Model

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Abstract—Similar traffic corresponding to the actual usage should be generated when doing the test or simulation for the network reliability. However, in the test or simulation for a large scale network, it is very difficult to generate the realistic network traffic, because it is complex and time-consuming to generate different traffic flows corresponding to businesses in the actual usage of the network. This paper proposes a simplified method of traffic generating based on the ON/OFF self-similar traffic model. We build the ON/OFF traffic model and infer the values of the model parameters. We generate the traffic based on the ON/OFF traffic model with the optimal parameters' values and get the aggregate traffic which is similar to the target traffic. In the simplified traffic generating method, we solve the problem that the network traffic generating is too complex in the test or simulation for the large scale network and we save the time spent on the traffic generating. A case study shows that: the deviation between the aggregate traffic and target traffic is about 0.05, and compared with the actual traffic generating method, the time spent on traffic generating is reduced from 11s to 1s.

Index Terms—complex networks, traffic generating, self-similar, ON/OFF model

I. INTRODUCTION

The correspondence of generated network traffic to actual usage has great impact on the test and simulation for network reliability. The current researches mainly focus on generating realistic distribution of network traffic by constructing a suitable traffic model. Since Will E.Leland found the self-similar feature of the Ethernet traffic in 1994 [1], it has been proved that the traffic of WAN [2], NSFNET [3] and WWW [4] also has the self-similar feature. The self-similar feature not only exists in the internet traffic but also in the ad-hoc network traffic [5] and the satellite network traffic [6]. The self-similar feature has been the most important feature of network traffic [7]-[9]. Hurst parameter is widely used to reflect this feature of network traffic and it has been the metric parameter of network self-similar feature [9]. Some methods to estimate Hurst parameter are given in [10]-[12].

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The basic principle of building models for the network traffic is that: the model should describe the important feature of the network traffic [13]. However the current researches have proved that the traffic generated by traditional traffic models (such as Poisson model, ARMA model, Markov model and so on) couldn't reflect the self-similar feature of the actual traffic [14], so a lot of self-similar traffic models have been proposed: such as heavy-tailed ON/OFF process model [15], α -stable self-similar traffic model [16], HErd-based improved queuing model [17], wavelets model and so on. The difference between the self-similar traffic models and the traditional traffic models is that: the self-similar traffic models are based on the self-similar feature of the network traffic and it could be used to describe the self-similar feature of the network traffic. Among these models, the heavy-tailed ON/OFF models are widely used to generate the self-similar traffic, helping to understand the nature of the self-similar traffic. The traffic generating methods based on the heavy-tailed ON/OFF models regard network similarity process as the result of the superposition of multiple traffic flows generated from different source nodes and explain the causes of self-similarity from the physic's view. However, these methods are limited to the description of superposition process of different traffic flows [18]. In the current test and simulation for the network, the traffic is usually generated in such a method based on modeling each business according to its packets' streams characteristics, such as source, destination, information distribution, task starting time and task ending time, etc. In this paper, this kind of method is called the actual input method. In the test or simulation for a large scale network, it is very complex and time-consuming to generate traffic in the actual input method.

In order to simplify the process of traffic generating and save the time spending on the traffic generating in the current network test and simulation, this paper proposes a simplified input method for a given node's target traffic: we build a heavy-tailed ON/OFF self-similar traffic model and infer the values of the model's parameters theoretically. We generate the similar traffic in this simplified method and simplify the traffic generating process in network test or simulation.

II. THE NETWORK TRAFFIC MODEL

A. Description of the ON/OFF Model

Because the ON/OFF model could provide simple, accurate and realistic description of the sources of network traffic, it is widely used to generate traffic in the network test and simulation. The ON/OFF model assumes that the source alternates between an ON-period and an OFF-period. During an ON-period, packets are sent from the source to the destination at a constant rate, while during an OFF-period, no packets are transmitted. If the duration of ON-periods is well modeled as i.i.d. Pareto, then it is called the Pareto ON/OFF model. Pareto ON/OFF model is one of the most popular heavy-tailed ON/OFF models and widely used to generate self-similar traffic.

In this paper, let $stream_{i,j}$ denote the traffic flow, in which packets are sent from the source node i to the destination node j. The aggregate traffic is the superposition of a lot of different streams sent from different source nodes to their corresponding destination nodes. The aggregate traffic generated by a large of Pareto ON/OFF source nodes appears the self-similar feature over a range of time scales. Ref. [18] explains the self-similar feature of the aggregate traffic generated by a large of Pareto ON/OFF source nodes: let v denote the constant rate that packets sent from the source to the destination during an ON-period. Let T denote the rescaling time factor. Let N_j denote the number of the different streams passed through node j. Then if $N_j \to \infty$ and $T \to \infty$, the aggregate traffic in $[0, Tt]$ could be described as follows:

$$A(Tt) = N_j v \frac{\mu_1}{\mu_1 + \mu_2} Tt + v\sigma_{lim} B_H(Tt)\sqrt{N_j}, \qquad (1)$$

where μ_1 denote the mean time length of the ON-period and μ_2 denote the mean time length of the OFF-period. $B_H(t)$ is a fractional Brownian motion, and $B_H(0) = 0$. σ_{lim} is a finite positive constant. The parameter H is called the Hurst parameter which is widely used to measure the self-similar feature.

Let α_{on} denote the shape parameter of the duration of an ON-period. Let α_{off} denote the shape parameter of the duration of an OFF-period. Then, Yang pointed out that the Hurst parameter could be described as follows [19]:

$$H = \frac{3 - \min(\alpha_{on}, \alpha_{off})}{2} \qquad (2)$$

In this paper, let F_{mean} denote the mean of the traffic. Let F_{var} denote the variance of the traffic. Then the F_{mean} and F_{var} could be described as follows [19]:

$$F_{mean} = Nv\mu_1 / (\mu_1 + \mu_2) \qquad (3)$$

$$F_{var} = Nv^2 \sigma_{lim}^2 \qquad (4)$$

where

$$\sigma_{\lim}^2 = \begin{cases} \dfrac{2\mu_{\max}^2 k^{\alpha_{\min}} \Gamma(2-\alpha_{\min})}{(\alpha_{\min}-1)(\mu_1+\mu_2)^3 \Gamma(4-\alpha_{\min})}, \alpha_{on} \neq \alpha_{off} \\ \dfrac{4\mu_1^2 k^{\alpha_{on}} \Gamma(2-\alpha_{on})}{(\alpha_{on}-1)(\mu_1+\mu_2)^3 \Gamma(4-\alpha_{on})}, \alpha_{on} = \alpha_{off} \end{cases} \qquad (5)$$

Equation (2) describes the self-similar feature of the aggregate traffic. Equation (3) describes the mean of the aggregate traffic. Equation (4) describes the variance of the aggregate traffic. We could point out that the smaller the $\min(\alpha_{on}, \alpha_{off})$ is, the bigger the H is, where $1 < \alpha_{on}, \alpha_{off} < 2$.

B. The Traffic Model

There are always many edge nodes in the test and simulation for a large-scale network. These edge nodes in the network topology always correspond to the terminal users in the use of the actual network. So we assume the edge nodes as the source nodes. For the source nodes, we choose the other nodes as the destination nodes randomly. We also assume that the packets are sent from their source nodes to their destination nodes in the shortest paths.

We build a Pareto ON/OFF traffic model: the duration of an ON-period (or OFF-period) is independent to the duration of an OFF-period (or ON-period). And the duration of an ON-period (OFF-period) is modeled as i.i.d Pareto. During an ON-period, packets are sent at a constant rate, while during an OFF-period, no packets are transmitted.

Let M_j denote the number of different streams passed through the node j. Let T denote the rescaling time factor. Then for the large $M_j \to \infty$ and $T \to \infty$, the traffic in node j is similar to the superposition of the M_j different *stream* passed through the node j and we still holds (1), (2), (3) ,(4), (5). Let μ_1 denote the mean length of the time of an ON-period and μ_2 denote the mean length of the time of an OFF-period. Then we find out that:

$$\begin{cases} k_{on} = k_{off} = k \\ \alpha_{on} = \alpha_{off} = \alpha \\ \mu_1 = \mu_2 = k\alpha / (\alpha - 1) \end{cases} \qquad (6)$$

Hurst parameter could be described as follows according to (2):

$$H = \frac{3 - \min(\alpha_{on}, \alpha_{off})}{2} = \frac{3 - \alpha}{2} \qquad (7)$$

Let v denote the constant rate during an ON-period. According to (3), the mean of the network traffic passed through node j could be described as follows:

$$F_{mean} = M_j v \mu_1 / (\mu_1 + \mu_2) = M_j v / 2 \qquad (8)$$

According to (4) the variance of the network traffic passed through node j could be described as follows:

$$F_{var} = M_j v^2 \sigma_{lim}^2 \quad (9)$$

where

$$\sigma_{lim}^2 = \begin{cases} \dfrac{2\mu_{max}^2 k^{\alpha_{min}} \Gamma(2-\alpha_{min})}{(\alpha_{min}-1)(\mu_1+\mu_2)^3 \Gamma(4-\alpha_{min})}, if\ \alpha_{on} \neq \alpha_{off} \\ \dfrac{4\mu_1^2 k^{\alpha_{on}} \Gamma(2-\alpha_{on})}{(\alpha_{on}-1)(\mu_1+\mu_2)^3 \Gamma(4-\alpha_{on})}, else\ \alpha_{on} = \alpha_{off} \end{cases} \quad (10)$$

We replace k_{on}, k_{off}, μ_1, μ_2 in (10) with the k_{on}, k_{off}, μ_1, μ_2 in (6), it follows that:

$$F_{var} = \frac{M_j v^2 (\alpha-1) k^{\alpha-1}}{2\alpha(3-\alpha)(2-\alpha)} \quad (11)$$

where

$$\sigma_{lim}^2 = \frac{(\alpha-1) k^{\alpha-1}}{2\alpha(3-\alpha)(2-\alpha)} \quad (12)$$

III. The Simplified Input Method

In the network test or simulation, there are two important reasons leading to the complexity and time-consuming problem of generating traffic in the actual input method. First, the problem is mainly due to the modeling process for each traffic flow corresponding to the businesses in the actual use of the network. When you generate traffic in the actual input method, you need to build the traffic model for each business in the actual use of the network. When you build the model for a business, you need to consider the business's characteristics such as: source node, destination node, the start of the task and the end of the task. Second, in the preceding paragraphs we assume that the source nodes correspond to the terminal users in the actual use of the network, so before the traffic generated, the traffic model should be chosen for each source node with the purpose of corresponding the terminal users' business.

To solve the problem of traffic generating in the large scale network test or simulation, we proposed a simplified input method based on the ON/OFF traffic model in this paper.

We generate the aggregate network traffic in the simplified method as follows, shown in Fig. 1:

Step 1: we input the adjacency matrix of the network topology A, the mean of the target traffic (F_{mean}), the variance of the target traffic (F_{var}), the Hurst parameter of the target traffic (H);

Step 2: we initialize the source-destinations' set OD. We generate the corresponding shortest paths' set P in the dijiskta method and calculate M_j for the given node j;

Step 3: we infer the initial value of the model's parameter v according to (7) and the initial value of the model's parameter α according to (8). We set the initial values of the parameters v and α as: $v = 2F_{mean}/M_j$, $\alpha = 3-2H$. We replace the v, α, M_j in (11) by their corresponding initial values and get the initial value of the model's parameter k theoretically;

Step 4: we generate the aggregate traffic using the Pareto ON/OFF model;

Step 5: we calculate the traffic features of the aggregate traffic. If the traffic features of the aggregate traffic is close to the traffic features of the target traffic, we go to the step 7. If not, we go to the step 6;

Step 6: we tune the values of the model's parameters according to (11) and go to the step 4;

Step 7: we output the optimal values of the model's parameters and generate the aggregate traffic using the Pareto ON/OFF model with the optimal parameters (M_j, v, k, α).

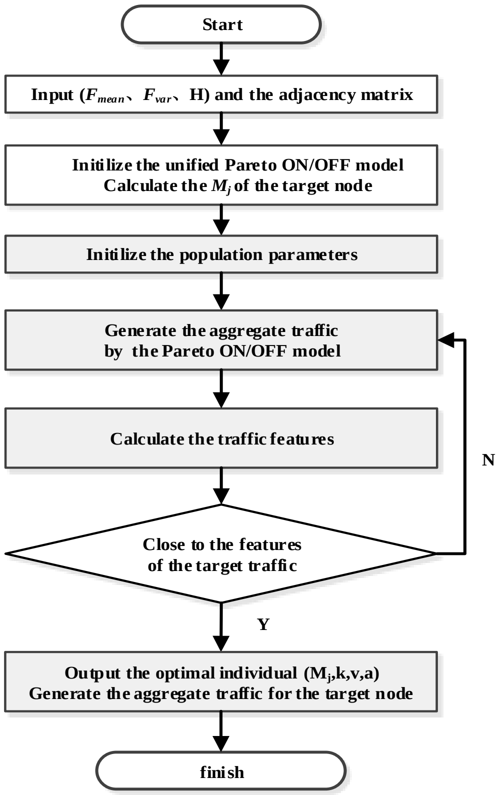

Figure 1. The simplified input method

We find out the initial values of the Pareto ON/OFF model's parameters according to (7), (8) and (11) respectively. Assumed that the M_j and T is large enough, we derived (7), (8) and (11) in the preceding paragraphs. However, the assumption is not always strictly true in the test and simulation for the network. So there is a deviation between the aggregate traffic and the target traffic. In order to reduce the deviation between the aggregate traffic and the target traffic, we need to tune the Pareto ON/OFF model's parameters in the step 6.

IV. Case Study

In this paper, we use the BA scale-free [20]-[21] network as our simulation subjects, adopting two different input methods: the actual input method and the simplified input method. Firstly, we generate the target traffic in the actual input method. Then, we generate the aggregate traffic in the simplified input method and the traffic features of the aggregate traffic are close to the features of the target traffic.

A. Case Description

We generate the network in the BA method and conduct the simulation using the network topology shown in Fig. 2.

In this case, there are 1000 nodes in the network: 656 edge nodes and 344 interior nodes. The edge nodes in the network topology correspond to the terminal users in the actual use of the network. We set the node with the largest M_j as the given node and renamed it the key-node.

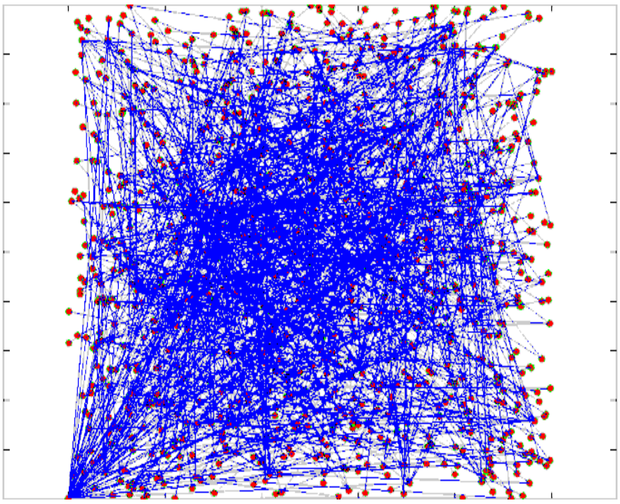

Figure 2. Network topology

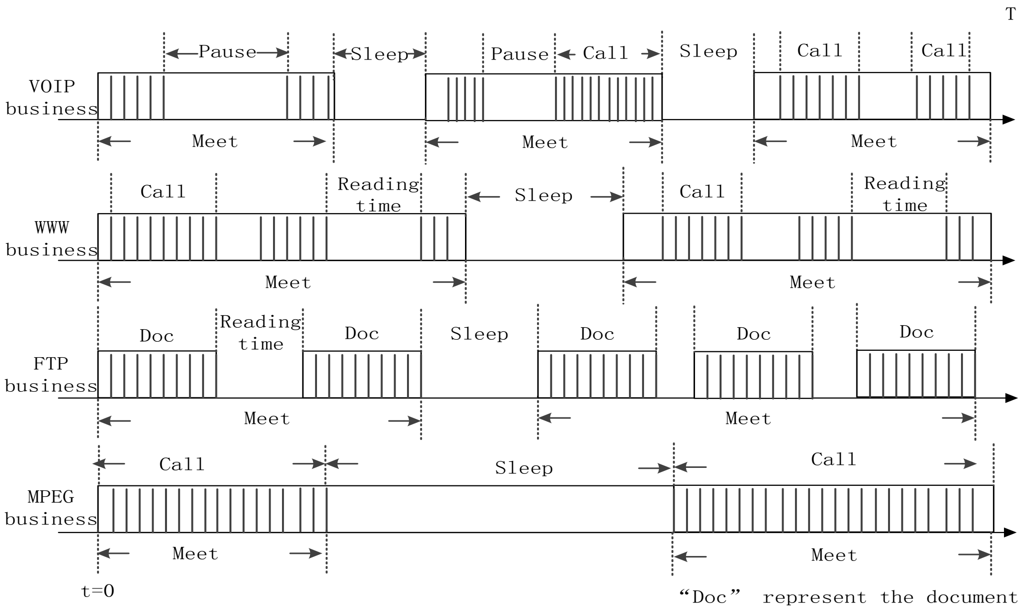

Figure 3. Four kinds of traffic model.

We assume that there are four different kinds of streams in the use of the actual network: the VoIP stream, the WWW stream, the FTP stream and the MPEG stream. We model these four different kinds of businesses' traffic [22] in this case. The businesses' traffic models are shown in Fig. 3.

1) VoIP traffic model

For the VoIP business, the model alternates between a Meet-period and a Sleep-period. During a Meet-period, calls are made. During a call, packets are sent from the source nodes to the destination nodes at a constant rate. The parameters are shown in Table I. The source node whose corresponding user is running the VoIP business in the actual network is defined as the VoIP source node. We use the simulation time units as the time units in Table I~Table IV.

2) WWW traffic model

For the WWW business, the model alternates between a Meet-period and a Sleep-period. During a Meet-period, several calls are made, while during a Sleep-period time no calls are made. The number of the calls during a call is modeled as i.i.d Geometric. During a call packets are sent from their source nodes to their destination nodes at a constant rate. One call corresponds to downloading a document. We define the time between two continuous calls as the reading time. The parameters are shown in Table II. The source node whose corresponding user is running the WWW business in the actual network is defined as the WWW source node.

3) FTP traffic model

For the FTP business, the model alternates between a Meet-period and a Sleep-period. During a Meet-period, we download the FTP documents. In this case, we assume that we download only one FTP document during a Meet-period. So the downloading time is proportional to the document size during a Meet-period. The size of the document downloaded in a meet-period is modeled as i.i.d Lognormal. We define the time between downloading two continuous documents as the reading time. The parameters are shown in Table III. The source node whose corresponding user is running the FTP business in the actual network is defined as the FTP source node.

4) MPEG traffic model

For the MPEG business, the model alternates between a Meet-period and a Sleep-period. During a Meet-period, several calls were sent from their source nodes to their destination nodes. One call corresponds to downloading a stream of data. The parameters are shown in Table IV. The source node whose corresponding user is running the MPEG business in the actual network is defined as the MPEG source node.

TABLE I: VOIP TRAFFIC MODEL

Model parameters	Distribution (parameter value)
Duration of a meet	Exponential(1200)
Duration of a call	Exponential(30)
Duration of a pause	Exponential(30)
The sent rate of packets during a call	Fixed value(5)
Duration of a sleep	Pareto($k=10$, $\alpha=1.1$)

TABLE II WWW TRAFFIC MODEL

Model parameters	Distribution (parameter value)
Duration of a call	Exponential(1200)
The sent rate of packets during a call	Fixed value(1)
The number of calls during a meet	Geometric (5)
Reading time	Exponential(125)
Duration of a sleep	Pareto($k=10$, $\alpha=1.1$)

TABLE III FTP TRAFFIC MODEL

Model parameters	Distribution (parameter value)
The size of a document	Lognormal ($u=8.5$, $\delta^2=3.7$)
The sent rate of packets during a call	Fixed value(10)
Duration of a sleep	Pareto($k=10$, $\alpha=1.1$)

TABLE IV MPEG TRAFFIC MODEL

Model parameters	Distribution (parameter value)
Duration of a call	Pareto($k=815$, $\alpha=1.1$)
The sent rate of packets during a call	Fixed value(10)
The number of calls during a meet	Fixed value(1)
Reading time	Fixed value(0)
Duration of a sleep	Pareto($k=10$, $\alpha=1.1$)

B. Traffic Generating

In this case, we assume that there are 164 users for each kind of the businesses in the actual use of the network. It means that in this network there are 164 VoIP source nodes, 164 WWW source nodes, 164 FTP source nodes and 164 MPEG source nodes. For each source node, we randomly choose the other node as its destination. Let O_1D_1 denote the source-destination pairs' set. For each source-destination pair, the packets are sent in the corresponding shortest path. Let P_1 denote the shortest paths' set in this case.

We generate the target traffic flow in the actual input method using the corresponding traffic models shown in Table I~Table IV. We get the mean and variance of the target traffic and estimate H parameter in the R/S method [12]. The traffic features of the target traffic are shown in Table V.

TABLE V THE TRAFFIC FEATURES OF THE KEY NODE GENERATED IN THE ACTUAL INPUT METHOD

M_j	F_{mean}	F_{var}	H
503	1884.3	8953.8	0.9467

We get the traffic features of the target traffic in the proceeding paragraphs. In this part, we generate the aggregate network traffic in the simplified input method. The specific steps are shown as follows:

Step 1: we use the network topology shown in Fig.2. The O_1D_1 is the source-destination pairs' set and the P_1 is the corresponding shortest paths' set. The traffic features (F_{mean} , F_{var} , H) of the target traffic are shown in Table V.

Step 2: we infer the model's parameter $M_j=503$ according to the set P_1 ;

Step 3: we set the model's parameter $v=7.4922$ according to (7). Then we set the model's parameter $\alpha=1.1066$ according to (8). Finally, according to (11) and the initial values of the model's parameters v and α , we set the $k=7.08$;

Step 4: we generate the aggregate network traffic based on the Pareto ON/OFF traffic model with the initial values of the parameters. Then we calculate the traffic features of the aggregate traffic. The traffic features of the aggregate traffic are shown in Table VI;

TABLE VI THE TRAFFIC FEATURES OF THE KEY NODE GENERATED IN THE SIMPLIFIED METHOD WITH THE INITIAL VALUES OF THE PARAMETERS

M_j	F_{mean}	F_{var}	H
503	1889.8	6526.3	0.8849

Step 5: according to the Table VI and Table V, we find out that the mean of the aggregate traffic is very close to the mean of the target traffic. The variance of the

aggregate traffic is lower than the variance of the target traffic. The H of the aggregate traffic is lower than the H of the target traffic. So we need to tune the models' parameters in order to make the variance and Hurst of the aggregate traffic get close to the features of the target traffic. According to (7), (8) and (11), we find out that the mean and variance of traffic will obviously change if parameter M_j or v changed. So we tune the model's parameter α and set $\alpha = 1.0066$;

Step 6: we update the values of the model's parameter α and generate the aggregate traffic based on the Pareto ON/OFF model. The traffic features of the aggregate traffic are shown in Table VII;

TABLE VII THE TRAFFIC FEATURES OF THE KEY NODE GENERATED IN THE SIMPLIFIED METHOD WITH THE INITIAL VALUES OF THE PARAMETERS (2)

M_j	F_{mean}	F_{var}	H
503	1913.9	7182.5	0.9523

Step 7: according to the Table VII and Table V, the mean of the aggregate traffic is very close to the mean of the target traffic. And the H of the aggregate traffic is very close to the H of the target traffic. So we tune the model's parameter k. We update the values of the model's parameters and generate the aggregate traffic. When the parameters of the Pareto ON/OFF models are set as Table VIII, the traffic features of the aggregate traffic are close to the target traffic.

TABLE VIII THE VALUES OF THE TRAFFIC MODEL'S PARAMETERS

M_j	v	k	α
503	7.4922	95	1.0066

TABLE IX TRAFFIC FEATURES

Traffic feature	Target traffic	Aggregate traffic
F_{mean}	1884.3	1885.8
F_{var}	8953.8	8843.6
H	0.9467	0.9301

We compare the aggregate traffic's features with the target traffic's shown in Table IX:

In this case, let sd denote the deviation between the aggregate traffic and the target traffic, then:

$$\begin{aligned} sd = & |(H_{sim} - H_{tar})/H_{tar}| + \\ & |(mean(F_{sim}) - mean(F_{tar}))/mean(F_{tar})| + \\ & |(var(F_{sim}) - var(F_{tar}))/var(F_{tar})| \end{aligned} \quad (17)$$

where the H_{sim} is the Hurst parameter of the aggregate traffic. The $mean(F_{sim})$ is the mean of the aggregate traffic. The $var(F_{sim})$ is the variance of the aggregate traffic. The H_{tar} is the Hurst parameter of the target traffic. The $mean(F_{tar})$ is the mean of the target traffic. The $var(F_{tar})$ is the variance of the target traffic.

The deviation between the aggregate traffic and the target traffic is shown in Table X.

TABLE X THE DEVIATION BETWEEN THE AGGREGATE TRAFFIC AND THE TARGET TRAFFIC

M_j	k	v	α	sd
503	7.08	7.4922	1.1066	0.34
503	7.08	7.4922	1.0066	0.22
503	95	7.4922	1.0066	0.03

In this case, the time which is spent on generating network traffic is recorded by the Matlab program and shown in Table XI.

TABLE XI DURATION OF GENERATING TRAFFIC IN TWO METHODS RESPECTIVELY

Input method	Traffic generating	time
Actual input method	We build the traffic model for each business in the actual use of the network. We generate the traffic in the actual input method based on the traffic model with the parameters shown in the Table I-Table IV	11.7618s
Simplified input method	We build the Pareto ON/OFF traffic model and find out the parameters. We build the Pareto ON/OFF model and configure its parameters according to Table VIII.	1.3801s

We show the network traffic in Fig.4. The red curve denotes the target network traffic, while the blue curve denotes the aggregate network traffic. According to the Fig.4, we could find out that there is a big deviation between the aggregate traffic and the target traffic in the beginning of the simulation, however after a period of simulation the deviation becomes smaller and the blue curve is closer to the red curve.

According to the Table IX, we find out that the features of aggregate traffic are close to the features of the target traffic. According to the Table X , the deviation between the aggregate traffic and the target traffic is below than 0.05. According to the Table XI, we could find out that: 1. we build a Pareto ON/OFF traffic model to generate the aggregate traffic in the simplified method, while we build four kinds of traffic model corresponding to the terminal users' businesses to generate the target traffic in the actual input method; 2. it takes about 1 second to generate the aggregate network traffic in the simplified method, while it spends more than 11 seconds on generating the target network traffic in the actual input method. So generating network traffic in the simplified input method proposed in this paper could simplify the process of the traffic generating and save the time to generate traffic.

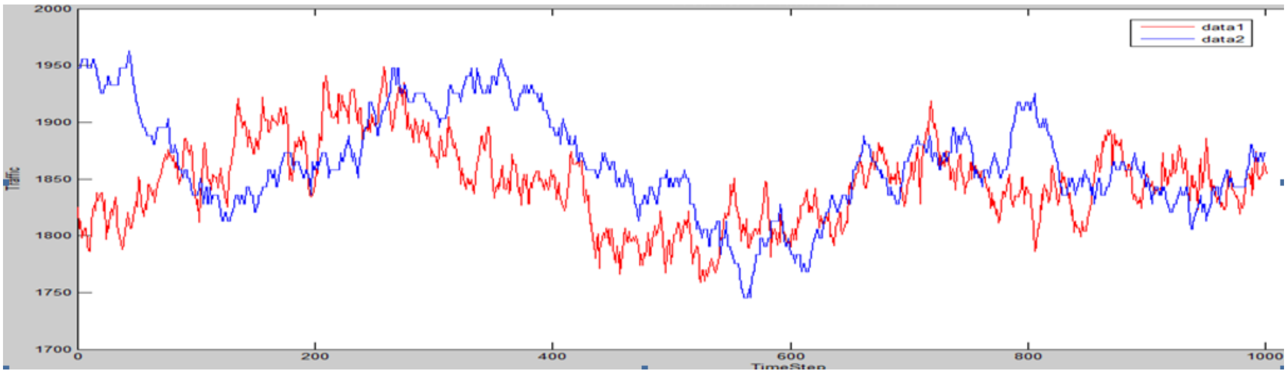

Figure 4. Comparison between target traffic flow and aggregate traffic flow

V. Conclusion and Discussions

In this paper, we have proposed a method to generate aggregate network traffic. The simplified input method relies on the self-similar traffic model. We build the Pareto ON/OFF model and infer the values of the model's parameters theoretically. The aggregate traffic generated in the simplified method is similar to the target traffic and has the similar traffic features (F_{mean} , F_{var} , H) with the target traffic.

In the simulation case, we use the BA-free model to generate the network topology and validate that the traffic generating process was simplified and the time of traffic generating was saved in the simplified method. Indeed this method is not directly related with the network topology and equally applicable in other network topology.

In this paper, we concentrated on the estimation of deviation between the aggregate traffic and target traffic. We assumed that the target traffic feature is known. However, mostly in the test and simulation for network we just know the actual input method actually. How to get the traffic features from the actual input method is needed in future.

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