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# Understanding the Traffic Nature of Mobile Instantaneous Messaging in Cellular Networks: A Revisiting to $\alpha$-Stable Models

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**ABSTRACT** Mobile instantaneous messaging (MIM) services significantly facilitate personal and business communications, inevitably consume substantial network resources, and potentially affect the network stability. In this paper, we aim to understand the traffic nature of MIM in cellular networks. Specifically, in order to reach credible conclusions, our research takes account of practical measurement records of MIM services from China Mobile at two different levels. First, a data set of individual message level (IML) traffic is exploited and reveals power-law distributed message length and lognormal distributed interarrival time, the heavy-tailness of which completely diverts from the geometric model and the exponential model recommended by the 3rd generation partnership project (3GPP). Second, another data set considers the statistical pattern of aggregated traffic within one whole base station, and demonstrates the accuracy of $\alpha$-stable models for the aggregated traffic. Furthermore, it verifies that the $\alpha$-stable models are suitable for characterizing the traffic in both the conventional fixed core networks and the cellular access networks. At last, with the aid of the generalized central limit theorem, we build up a theoretical relation between the distributions of IML traffic and aggregated traffic.

**INDEX TERMS** Mobile instantaneous messaging, Wechat/Weixin, cellular networks, traffic distribution, heavy-tailed distributions, $\alpha$-stable models.

## I. INTRODUCTION

Instantaneous messaging (IM) services, longly running on PC platforms for personal and business communications, has recently flourished in mobile devices and quickly generated significant amount of traffic loads within cellular networks. However, compared with traditional voice and messaging services within cellular networks, these newly emerging mobile IM (MIM) services distinguish themselves with the inborn packet-switching nature and its accompanied keep-alive (KA) mechanisms, which imply to consume only small amount of core network bandwidth but considerable radio resources of mobile access networks. Moreover, due to the KA mechanism to keep mobile users in touch with servers, MIM services fundamentally affect the stabilization and reliability of cellular networks [1], [2], and could become a huge burden on the network operators [3]. Therefore, it is meaningful to carefully examine the traffic nature of MIM services, so as to design MIM service-oriented protocols to overcome their induced negative influence to cellular networks. In this paper, we take account of a widely booming MIM service "WeChat/Weixin", which allows over 6 hundred million mobile users to exchange text messages and multimedia files like voices, pictures and videos with each other via smartphones [4], in China as well as around the world.

Indeed, due to its apparent importance to the protocol design and performance evaluation of telecommunications networks, there have already existed some former works towards modeling the traffic in various networks. In fixed broadband networks, researchers showed that aggregate traffic traces demonstrate strong burstiness and could be modeled with $\alpha$-stable models[1] [5], [6]. On the other hand,

[1]In this paper, the term "$\alpha$-stable models" is interchangeable with $\alpha$-stable distributions.

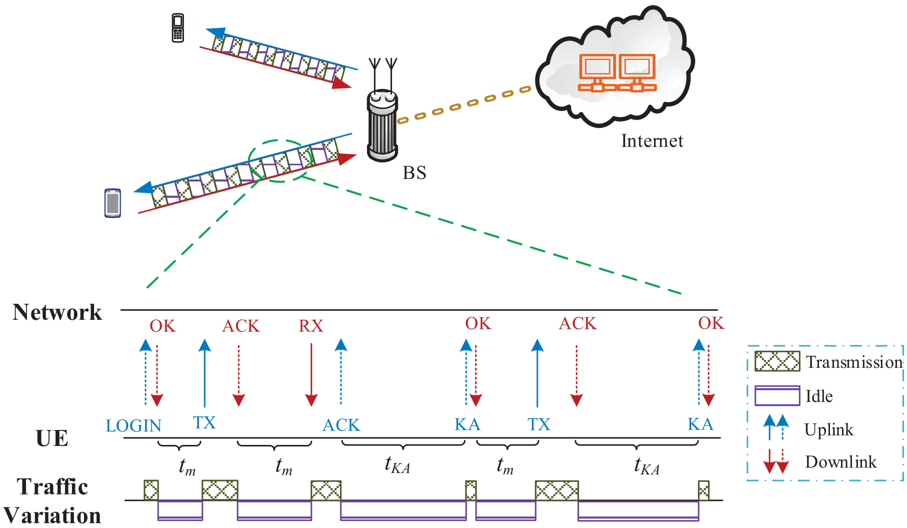


**FIGURE 1.** An illustration of mobile instantaneous messaging activities.

the investigation over traffic characteristics of IM in wired Internet revealed heavy-tailed distribution phenomena in services like AIM (AOL Instant Messenger) and Windows Live Messenger [7], [8]. Therefore, it is natural to raise a question, namely which one of the aforementioned models is more suitable for MIM traffic? Meanwhile, it remains doubtful whether cellular networks with distinct characteristics from fixed networks (e.g., more stringent constraints on radio resources, relatively expensive billing polices and different user behaviors due to mobility) [9] need a totally different traffic model?

In this paper, following our previous work [3], we make an intensive study on the fundamental traffic nature of MIM service through large amount of "Wechat/Weixin" traffic observations from operating cellular networks. Based on these practical measurements, we aim to find the precise model for the traffic of MIM services, and try to explain the reasons behind the somewhat conflicting results in previous studies. Interestingly, our measurements reveal that the distribution of individual message's length and inter-arrival time could be better fitted using a power-law distribution and a lognormal distribution, which are completely different from the recommended models in 3GPP [10]. Instead, the aggregated traffic of these individual messages in a specific base station (BS) of cellular access networks obeys $\alpha$-stable models, which usually characterize the statistical patterns of the summation of lots of independently identically distributed random variables [11]. Besides, we build up a theoretical explanation to the evolution from power-law distributed individual message length to aggregated traffic within one BS. In a word, this paper contributes to the comprehensive understanding of traffic nature of MIM services, by analyzing practical traffic records of MIM services and further building models for traffic characteristics. Consequently, the related research results are able to benefit the MIM services-related traffic prediction and network protocol design.

The remainder of the paper is organized as follows. In Section II, we firstly present some necessary background of MIM services, describe the details of utilized practical datasets, and introduce the fundamentals of $\alpha$-stable models. In Section III, we provide fitting results for individual message's length, inter-arrival time, and aggregated traffic within one BS, and give our theoretical explanation between them. Finally, we conclude this paper with a summary and future research direction in Section IV.

## II. BACKGROUND

### A. MIM WORKING MECHANISMS AND DATASET DESCRIPTION

MIM services, which solely rely on mobile Internet to exchange information, have quite distinct working mechanisms from traditional short messaging services. One of the prominent differences is that born with standard protocols [12], traditional short messaging services could conveniently fulfill timely information delivery and provision "always-online" service. However, for mobile Internet in packet switching domain, a TCP connection would release itself if exceeding a TCP inactivity timer. Therefore, as depicted in Fig. 1, besides transmitting (TX) and receiving (RX) normal packets after logging onto a server, MIM services commonly take advantage of keep-alive mechanisms to send packets containing little information periodically and maintain a long-lived TCP connection. Hereinafter, *message* refers to a series of packets transmitted between the user equipment (UE) and the servers of service provider on application layer. Therefore, the messages delivered on every TCP connection constitute the fundamental elements of MIM services, and are named as *individual message-level (IML) traffic* in this paper. Comparatively, when the messages are transmitted through one BS, they become accumulated and could be regarded as the *aggregated traffic* from a slightly more macroscopical perspective.

 

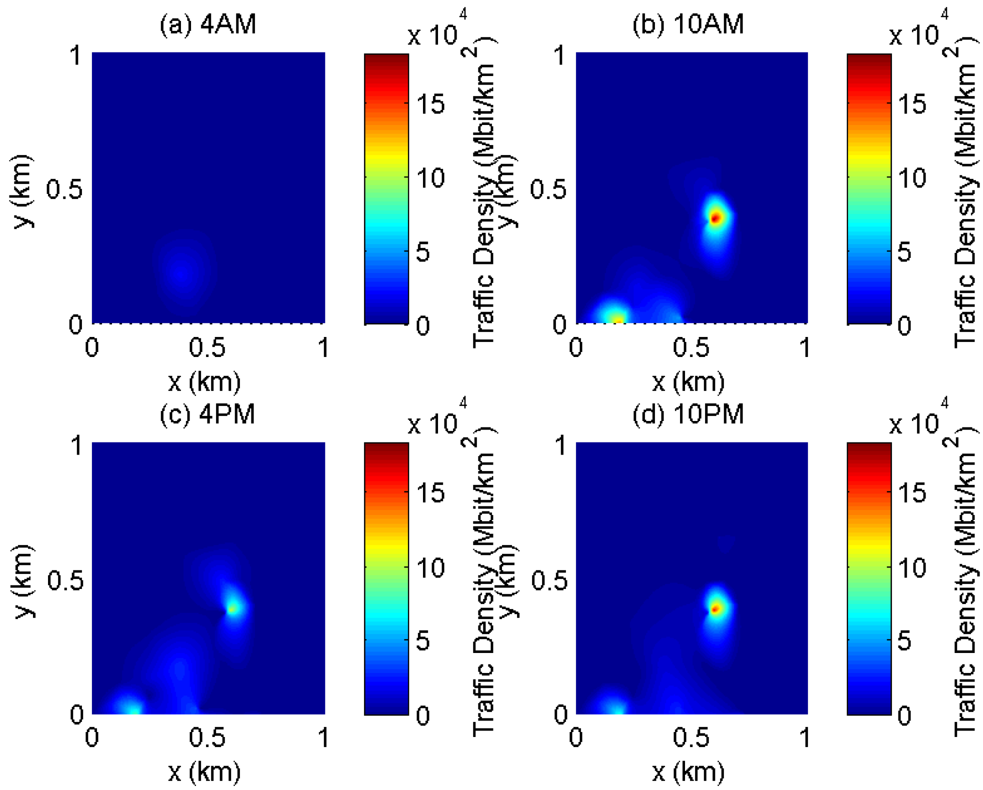


**FIGURE 2.** The snapshots of aggregated traffic at three different moments in a region containing 23 base stations.

In order to build primary models, we collect measurements of the MIM traffic from the on-operating cellular networks. Our datasets collected from the Gb and Gn interfaces [3], covering about 15000 GSM and UMTS BSs of China Mobile in an eastern provincial capital within a region of 3000 km$^2$, could be classified as two categories in terms of the corresponding resolutions (i.e., IML traffic and aggregated traffic). The 1-month measurement records of IML traffic are collected from 7 million subscribers, and contain timestamps, cell IDs, anonymous subscriber IDs, message lengths, and message types. Generally, messages are usually transmitted via a TCP connection on both uplink and downlink data channel (as depicted in Fig. 1). However, for ease of analyses, we do not distinguish the directions of messages hereafter. In contrast, the measurement records of aggregated traffic possess coarser resolution than those of IML traffic, and merely specify per 5-minute traffic volume of roughly 6000 BSs in the same city on September 9th, 2014. Fig. 2 plots the snapshots of aggregated traffic at three different moments in a region.

### *B. MATHEMATICAL BACKGROUND*

Following the generalized central limit theorem, $\alpha$-Stable models manifest themselves in the capability to approximate the distribution of normalized sums of a relatively large number of independently identically distributed random variables [11]. Besides, $\alpha$-stable models produce strong bursty results with properties of heavy-tailed distributions and long range dependence. Therefore, they arose in a natural way to characterize the traffic in fixed broadband networks [5], [6] and have been exploited in resource management analyses [13], [14].

$\alpha$-Stable models, with few exceptions, lack a closed-form expression of the PDF, and are generally specified by their characteristic functions.

*Definition 1:* A random variable $X$ is said to obey $\alpha$-stable models if there are parameters $0 < \alpha \le 2$, $\sigma \ge 0$, $-1 \le \beta \le 1$, and $\mu \in \mathcal{R}$ such that its characteristic function is of the following form:

$$\begin{aligned}\Phi(\omega) &= E(\exp j\omega X)\\ &= \begin{cases}\exp\left\{-\sigma^{\alpha}|\omega|^{\alpha}\left(1 - j\beta(\mathrm{sgn}(\omega))\tan\dfrac{\pi\alpha}{2}\right) + j\mu\omega\right\}, & \alpha \neq 1;\\ \exp\left\{-\sigma|\omega|\left(1 + j\dfrac{2\beta}{\pi}(\mathrm{sgn}(\omega))\ln|\omega|\right) + j\mu\omega\right\}, & \alpha = 1.\end{cases}\end{aligned} \tag{1}$$

Here, the function $E(\cdot)$ represents the expectation operation with respect to a random variable. $\alpha$ is called the characteristic exponent and indicates the index of stability, while $\beta$ is identified as the skewness parameter. $\alpha$ and $\beta$ together determine the shape of the models. Moreover, $\sigma$ and $\mu$ are called scale and shift parameters, respectively. Specifically, if $\alpha = 2$, $\alpha$-stable models reduce to Gaussian distributions.

Furthermore, for an $\alpha$-stable modeled random variable $X$, there exists a linear relationship between the parameter $\alpha$ and the function $\Psi(\omega) = \ln\{-\mathrm{Re}[\ln(\Phi(\omega))]\}$ as

$$\Psi(\omega) = \ln\{-\mathrm{Re}[\ln(\Phi(\omega))]\} = \alpha\ln(\omega) + \alpha\ln(\sigma), \qquad (2)$$

where the function $\mathrm{Re}(\cdot)$ calculates the real part of the input variable.

Usually, it is challenging to prove whether a dataset follows a specific distribution, especially for $\alpha$-stable models without a closed-form expression for their PDF. Therefore, when a dataset is said to satisfy $\alpha$-stable models, it usually means the dataset is consistent with the hypothetical distribution and the corresponding properties. In other words, the validation needs to firstly estimate parameters of $\alpha$-stable models from the given dataset, and then compare the real distribution of the dataset with the estimated $\alpha$-stable model [6]. Specifically, the corresponding parameters in $\alpha$-stable models can be determined by quantile methods, or sample characteristic function methods [5], [6].

## III. THE STATISTICAL PATTERN AND INHERITED METHODOLOGY OF MIM SERVICES

### A. IML TRAFFIC

In order to understand the IML traffic nature of MIM services, we firstly calculate the probability density functions (PDF) of message length, and then fitting them to common heavy-tailed distributions listed in Table 1. Specifically, during the fitting procedures, we obtain the unknown parameters in candidate distribution functions (except $\alpha$-stable models) using maximum likelihood estimation (MLE) methodology. For $\alpha$-stable models, we estimate the relevant parameters using quantile methods [15], correspondingly build the models to generate some random variable, and finally compare its induced PDF with the exact (empirical) one.

**TABLE 1. The accuracy measured by RMSE after fitting empirical data to candidate distributions.**

| Distribution | PDF | $W_{v_i}$ | $W_t$ | $W_{v_a}$ |
|---|---|---|---|---|
| Power-law | $ax^{-b}$ | 9.76e-5 | 9.25e-5 | 0.0357 |
| Geometric | $(1-a)^x a$ | 607e-5 | 48.0e-5 | 0.0258 |
| Exponential | $ae^{-bx}$ | 56.0e-5 | 22.9e-5 | 0.0899 |
| Weibull | $abx^{b-1}e^{-ax^b}$ | 65.8e-5 | 8.08e-5 | 0.0470 |
| Lognormal | $\frac{1}{\sqrt{2\pi}bx}e^{-\frac{(\ln x-a)^2}{2b^2}}$ | 34.0e-5 | 7.44e-5 | 0.0491 |
| $\alpha$-Stable | – | 790e-5 | 170e-5 | 0.0144 |

In Fig. 3, we provide the corresponding results after fitting candidate distribution functions to the empirical PDF of message length $v_i$. Recalling the statements in Section II-B, if the simulated dataset generated by one distribution has the same or approximately same PDF as the real one, the distribution of empirical dataset could be coarsely determined. Interestingly, Fig. 3 demonstrates that instead of geometric distribution function recommended by 3GPP [10], power-law distribution (i.e., $0.347x^{-2.407}$) could most accurately approximate the empirical PDF of message length. Furthermore, a root mean

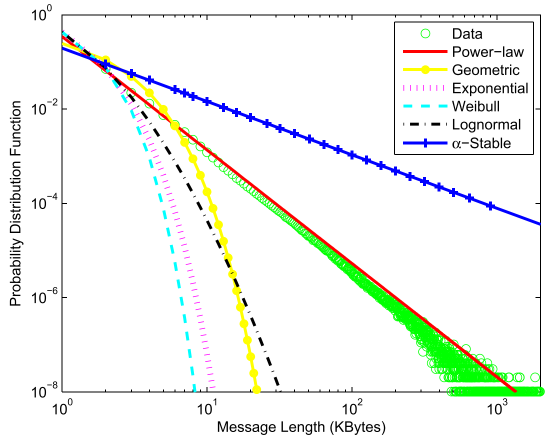


**FIGURE 3. The fitting results of MIM activities' message length by candidate distribution functions.**

square error (RMSE),[2] a larger one of which reflects a lower degree of fitting preciseness, is also applied to quantitatively find the fittest distribution function. The RMSE results in column $W_{v_i}$ of Table 1 also show that the PDF of message length is most appropriately to be modeled by power-law distribution function.

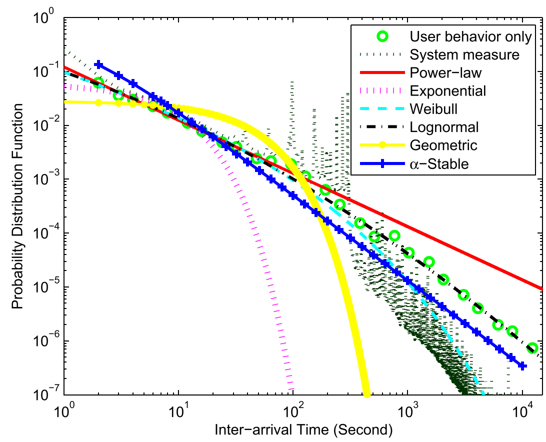


**FIGURE 4. The PDF of inter-arrival time of MIM messages and other distribution functions with MLE parameters estimation.**

On the other hand, according to the timestamps of messages, we calculate inter-arrival time $t$ between consecutive messages in order of second, and examine the fitting preciseness of MLE estimated candidate distribution functions to the corresponding PDF. Fig. 4 depicts the related fitting results compared to the empirical data (see legend: User behavior only) with the inter-arrival time from

[2]Our previous study in [3] provides a similar fitting preciseness result after performing an Akaike information criterion (AIC) test [16]. However, AIC test is not applicable for $\alpha$-stable models. Besides, a Kolmogorov-Smirnov (K-S) test [17] is employed to check for goodness-of-fit of the empirical data. However, all candidate distributions are rejected according to the K-S test at a 95% confidence level, probably due to the scattering tail of individual message length in Fig. 3 and the sudden probability increase of aggregated traffic in Fig. 5. Therefore, in this paper, in consideration of its simplicity, RMSE is exploited as the uniform criterion for gauging the fitting preciseness.

2nd to 3000th second. Similarly, column $W_t$ in Table 1 shows the results in terms of RMSE. Compared with the exponential distribution function recommended in [10], Fig. 4 and Table 1 shows lognormal distribution function (i.e., $\frac{1}{\sqrt{2\pi}\times 2.975x}e^{-\frac{(\ln x-2.36)^2}{2\times 2.975^2}}$) exhibits superior fitting preciseness for the inter-arrival time of MIM messages. Notably, Fig. 4 shows consecutive packets arrive with very small inter-arrival time, the probability for which larger than 20s is smaller than 1%. Meanwhile, the peaks in Fig. 2 with the legend: System measure are incurred by KA messages from various UE's operating systems and diverse MIM versions. Usually, KA cycles are quite different but usually appear at multiples of 30 seconds. Moreover, the PDF of the inter-arrival time decreases sharply when $t_m$ is larger than the maximal KA (300s) and the percentage of messages with inter-arrival time larger than the maximal KA period accounts only 2%, implying that MIM has to send the KA messages if it has been out of touch with the servers for KA period unless the connection to the network is abnormal.

*Remark 1: Compared with the geometric and exponential distribution functions recommended by 3GPP [10], power-law and lognormal distribution functions are more suitable to model the statistical pattern of message lengths and inter-arrival time of consecutive messages, respectively.*

### B. AGGREGATED TRAFFIC

In this section, from the perspective of one whole BS, we examine the fitting results of aggregated traffic within one BS to candidate distributions. Fig. 5 presents the corresponding PDF comparison between the simulated results and the real aggregated traffic in one randomly selected BS. By taking advantage of a similar methodology to that in Section III-A, Fig. 5 implies the traffic records in these selected areas could be better simulated by $\alpha$-stable models. Similarly, column $W_{v_a}$ in Table 1 shows $\alpha$-stable models lead to better fitting accuracy in terms of RMSE.

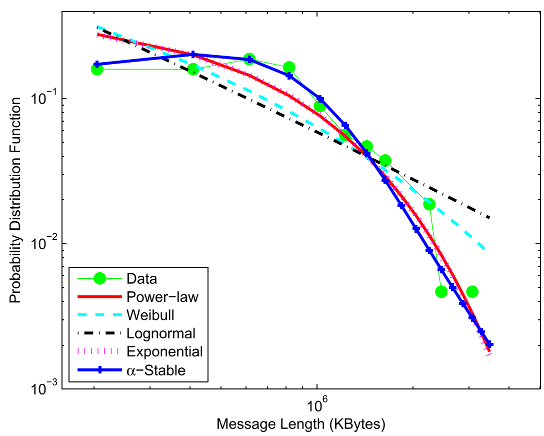


**FIGURE 5.** Fitting results of candidate distributions to empirical aggregated traffic in one randomly selected BS.

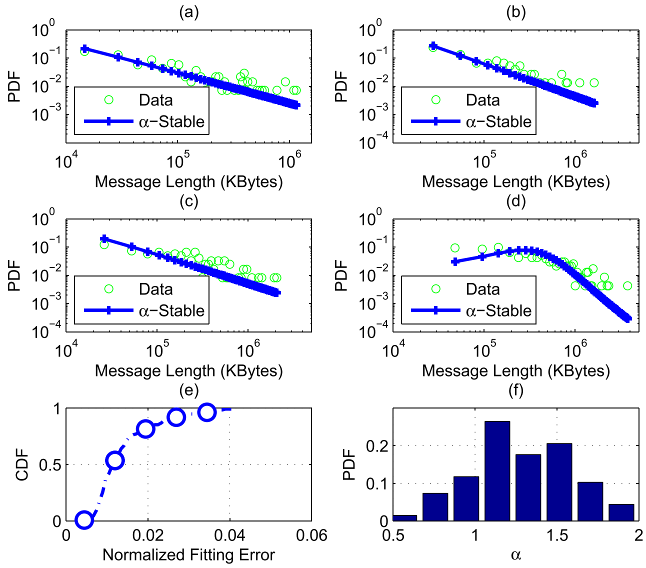


**FIGURE 6.** (a)∼(d): Fitting results of $\alpha$-stable models to empirical aggregated traffic in another two randomly selected BSs; (e): The preciseness error CDF for all the cells after fitting $\Psi(\omega)$ with respect to $\ln(\omega)$ to a linear function; (f): The PDF of $\alpha$ estimated for aggregated traffic in different cells.

Furthermore, Fig. 6(a)∼(d) verify the fitting preciseness of empirical data to $\alpha$-stable models in another four randomly selected BSs. Fig. 6(e) shows the cumulative distribution function (CDF) of preciseness error for all the cells after fitting $\Psi(\omega)$ with respect to $\ln(\omega)$ to a linear function, and demonstrates there merely exists minor fitting errors. In other words, according to the statements in Section II-B, Fig. 6(e) implies that the aggregated traffic possesses the property of $\alpha$-stable models. Given the previous results, it safely comes to the following remark.

*Remark 2: Due to their generality, $\alpha$-stable models are most suitable to characterize the aggregated traffic in cellular networks. Together with previous findings in fixed broadband networks [5], [6], $\alpha$-stable models are proven to accurately model the aggregated traffic from cellular access networks to core networks.*

On one hand, the universal existence of $\alpha$-stable models implies and contributes to understanding the intrinsic self-similarity feature in MIM traffic [18]. On the other hand, the reasons that MIM traffic universally obeys $\alpha$-stable models can be explained as follows. Section III-A unveils that the length of one individual MIM message follows a power-law distribution. Meanwhile, the distribution of aggregated traffic within one BS can be regarded as the accumulation of lots of IM messages from diverse UEs. Moreover, the analysis results of inter-arrival time imply frequent packet transmission. Therefore, according to the generalized central limit theorem, the sum of a number of random variables with power-law distributions decreasing as $|x|^{-\alpha-1}$ where $0 < \alpha < 2$ (and therefore having infinite variance) will tend to be an $\alpha$-stable model as the number of summands grows. Interestingly, Fig. 6(f) shows that the PDF of $\alpha$ obtained by fitting aggregated traffic in different cells to $\alpha$-stable models, and reflects the fitting values of $\alpha$ mostly fall between 1.136 to 1.515, while the slope of power-law distribution for IML traffic is 2.407. These fitting results prove to be consistent with the theory from the generalized central limit theorem [19].

*Remark 3: The aggregated traffic within one BS, following $\alpha$-stable models, can be explained as the accumulation of a number of power-law distributed messages.*

## IV. CONCLUSION AND FUTURE WORKS

In this paper, we investigated the traffic characteristics of MIM services from two different viewpoints. For IML traffic, we showed that message length and inter-arrival time better follow power-law distribution and lognormal distribution, which are quite different from the recommendation by 3GPP. For aggregated traffic within one BS, we revealed the accuracy of applying $\alpha$-stable models to characterize this statistical pattern, and extended the suitability of $\alpha$-stable models for traffic in both fixed core networks and cellular access networks. Besides, following the generalized central limit theorem, we built up the theoretical relationship between distributions of IML and aggregated traffic. These heavy-tailed traffic models of MIM service could contribute to the design of more efficient algorithms for resource allocation and network management in cellular networks.

In this paper, we characterized the preciseness of modeling IML traffic and aggregated traffic by power-law distribution and $\alpha$-stable models respectively, depending on extensive traffic records-based fitting processes. However, it is still worthwhile to mathematically verify these remarks, and try to establish the mathematical relationship more rigorously.

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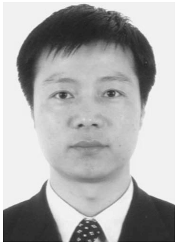

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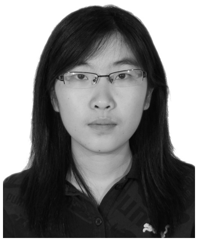

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