SONETOR: a Social Network Traffic Generator

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***Abstract*—The Online Social Networks (OSN) have become an important trend in current networks. Due to the susceptible nature of the private data available in OSN, the acquisition of data sets is not an easy task. In this paper and based on the state of the art of measurement studies, we present SONETOR, a synthetic social network traffic generator, characterized by ease of use and flexibility. SONETOR represents current social network behavior such as user publishing and consuming content, users sharing and commenting on information with their friends. We also proceed to study the impact of OSN in the network traffic with SONETOR. In particular, our social network traffic generator allows capturing the effect of the flash-crowd phenomenon. SONETOR is an open-source and multi-platform tool freely available. The generated traces can be widely distributed without restrictions and they are still privacy compliant.**

I. Introduction

Online Social Networks (OSNs) are currently massively used in the Internet. OSNs allow users to create virtual communities and to share information about their life (pictures, job update, relationships), news or content. As an example, Facebook arose in 2007 and it counts already a billion of users, among which 700 million users connect to the website at least once a day [1] while Twitter or Linkedin are also among the most popular websites in the Internet. Following this trend, every social event defines a communication plan through OSNs. Presidential election uses Twitter to spread information to a larger audience [2]. TV shows encourage audience to participate through OSNs by using specific keywords in Twitter. Most if not all the Internet services improve the users' experience through the addition of social features to rapidly spread interesting content. Companies also invest strongly into OSNs in order to promote new products or attract new customers [3] [4]. The Internet has become a social-oriented network.

The network workload is an essential characteristic to take into account while modeling or simulating new mechanisms or protocols for the Internet [5]. The OSNs have taken an important share of the overall Internet traffic. Indeed, Facebook, Twitter and Linkedin are among the ten most accessed websites in the Internet [6]. It is therefore essential to include social characteristics into network traffic model.

In this paper, we present *SONETOR*, a Social Network Traffic Generator that statistically models users' interaction within social networks. SONETOR extracts parameters from social network measurement studies and allows generating sequences of users' activities within their communities. Our generator is also able to capture traditional effects observed in the Internet such as the massive popularity of content in a short period of time (i.e. flash crowds). The obtained OSN synthetic traces can be directly included into simulations or models and are essential for further evaluation of new mechanisms or protocols. To the best of our knowledge, SONETOR is the first tool, which generates synthetic social network traffic traces that accurately reflects the users' interaction within a social network.

We then use SONETOR to study the effect of social network on content popularity. Indeed, the content popularity on the Internet is traditionally modeled with MZipf distribution function and we show through the use of our generator that the users' interaction within social network has an important impact on the distribution parameters.

The rest of this paper is organized as follows. We review in Section II the related work on network traffic models and users' behavior into social networks. Then, in Section III, we present our new generator SONETOR and its architecture. Section IV introduces the content popularity model and the simulation environment, and then we show the impact of social networks into the popularity model. Finally, in Section V, we sum up our findings, conclude the paper and present future work.

II. Related Work

Numerous studies intend to model different kind of network traffic: web traffic to test web servers and the Internet architecture [5]; e-mail traffic to investigate SPAM [7]; P2P traffic to study and improve P2P protocols [8]. Future Internet architectures are not deployed yet (e.g., CCN), and aim also to be evaluated through simulation experiments with future Internet traffic, which may be an extrapolation of the current Internet traffic [9]. Nevertheless, there does not exist utilities that represent the users' interaction in online social networks.

In the last years and due to its exponential growth, there has been a huge amount of studies and analysis of Online Social Networks. [10] shows evolution on Twitter relationships while [11] studies the first year of Google+; [12] performs an in-deep evaluation of video popularity on Youtube; [13] has a similar purpose but using HTTP requests to consequently model the video popularity; [14] deepens on study of trends in Twitter: evolution in time, participation of users. [15], [16], [17] characterize users' interaction and patterns of usage in OSNs. Although these studies allow understanding social networks, their results are difficult to compare and even more difficult to cross-validate between them. Most of them are

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```
Timestamp 1    User a    Activity(d1, ..., dm)    [opt1, opt2...]
Timestamp 2    User b    Activity(d1, ..., dm)    [opt1, opt2...]
Timestamp 3    User c    Activity(d1, ..., dm)    [opt1, opt2...]
...
```

Fig. 1: Format of Sonetor traces

based on real OSN data set obtained through measurement studies, which are not publicly available. For instance, [15], [16], [17], [13] analyze users' behavior in Orkut, Facebook or Linkedin, collecting the data through private agreements with the OSNs. Otherwise, active measurement with a web crawler is another possible way to collect data from OSNs such as Twitter [18], [10], [14], Youtube [12], Google+ [11].

As we have pointed it out, there is no tool available to model OSN traffic and most of the studies depend on traffic traces that are not publicly available.

III. SONETOR ARCHITECTURE

A. Overview

We propose *SONETOR*, a SOcial NEtwork Traffic generatOR. It aims at offering an open-source tool to generate network traffic workload with OSN characteristics.

SONETOR generates synthetic traces, and a sample is presented in Figure 1. Each line is ordered by a timestamp and describes an activity performed by a user. Each activity can count several dependent parameters. It is noteworthy to mention that there are other options (opt_i) for further extension of our generator tool. Such extensions can take into account mobility of users, or their geographical coordinates for more sophisticated scenarios.

In the rest of the section, we describe in-detail the SONETOR architecture and the three models it relies on: (i) a social network model capturing the social relationships between users, (ii) a users' interaction model capturing the activity schedule for each user, and (iii) a model for each type of activity and its dependent parameters.

B. Social Relationships Model

As we model a social network, it is required to represent the connections between users, which can be described by a social network graph. This social network graph may represent friend relationships as well as professional affiliation depending on the social network (e.g.: Facebook, Linkedin, etc). SONETOR can include several graph models such as *small-world graph* or *random graph*. In addition, SONETOR also includes realistic social network graphs by extracting social relationships from data set publicly available for Facebook [19].

C. Users' Interaction Model

Our interaction model is based on several major research studies on social networks [16], [17]. From these studies we extract four parameters to model the users' interaction: the number of sessions NS, the inter-session time t_{IS_i}, the number of activities per session NA_i and the inter-activity time t_{IAij}.

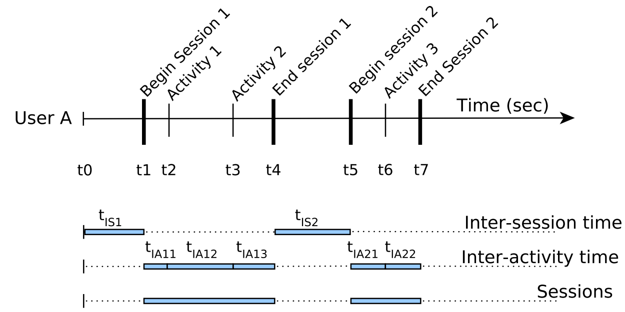


Fig. 2: Users' interaction model. Users can perform several activities within a session

The users' interaction model is depicted in Figure 2 and can be summarized as follows: a user may start NS independent and consecutive sessions. The interval time between each session is calculated with an inter-session time t_{IS_i} from the time origin $t0$ or the previous session ending time. In every session i, the user performs a finite number of activities, NA_i, such as publications or retrievals from friends. These activities are separated by an inter-activity time $t_{IA_{ij}}$. In the Figure 2, we illustrate an example of interactions in-which User A has two sessions ($NS = 2$); the first session starts after the inter-session time t_{IS_1} and contains two activities ($NA_1 = 2$), which are separated by three different inter-activity times $t_{IA_{11}}$, $t_{IA_{12}}$ and $t_{IA_{13}}$. The second session counts only one activity ($NA_2 = 1$) and is separated from the first session by a second inter-session time t_{IS_2}.

D. Activity Model

We presented the social relationship model (Section III B) and the interaction model (Section III C), we now present how to model the different type of activity. From the trace format (figure 1), every user $User_x$ executes an $Activity$ at instant $Timestamp_i$. The parameter $Activity$ corresponds to the type of activity being performed by the user. An activity has also dependent parameters d_i according to the type of activity. For instance, a picture publication (*Activity*) includes necessarily other dependent parameters to the activity such as a text description (d_1), a title (d_2) and the image itself (d_3).

SONETOR includes several Markov Chains that represent distinct users' behavior. For instance some users are more likely to publish pictures than video (or vice versa). Every modeled user has an assigned Markov Chain. The user selects the type of activity to perform. Depending on the type of activity, its dependent parameters are computed.

Our tool SONETOR is freely available [20]. As the traces have been obtained with statistical information, they are compliant with user privacy. The generated traces can also be freely distributed and be replayed by other experiments.

IV. Impact of OSN into Content Popularity Model

In this section, we use SONETOR to generate social network traces. These traces are analytically analyzed throughout this section in order to study the impact of the social networks on the content popularity model.

A. Content Popularity Model

The content popularity model is a function that establishes the popularity of every piece of content: how often every single piece of content is going to be requested. The content popularity is commonly modeled with a probability distribution function. Measurement studies show that users are attracted by only a few web sites, while they give little or no attention to millions of others. This is consistent with the fact that the power law distribution is used in most of content popularity models.

Zipf and its generalization Maldelbrot-Zipf (MZipf) distribution belong to the power law distribution and they are used in most of the models or simulations [21], [9]. There is not consensus about the distribution parameters for the (M)Zipf distribution. In the literature, the Zipf α parameter ranges from 0.6 to 2.5. For instance, the catalog of the PirateBay is modeled with $\alpha = 0.75$, DailyMotion with $\alpha = 0.88$, while the VoD in China exhibits an α parameter ranging from 0.65 to 1.0 [22]. MZipf is commonly used in different simulation environments such as CCNSim, or Content Delivery Networks (CDNs) [23] to model the load of web servers, etc.

Experiments based on MZipf distribution assign probabilities to a fixed catalog of content. Thus, every time a piece of content is demanded, it is selected with a probability value. Depending on the configuration of the α parameter, some pieces of content are more likely to be requested than others.

In the case of social networks, a MZipf function assigns a probability value for a content to be published. The retrieve of content is decided according to a social graph: users have social relationships i.e. acquaintances or friends. In our experiments, users retrieve their friends' content through a timeline composed with the latest publications of friends such as Facebook does. In brief, the users publish pieces of content according to a MZipf distribution but they retrieve content based on their social connections and their latest published content.

B. Simulation Parameters

In this section, we describe the notation and simulation parameters that we use for our experiments. All the simulation parameters are summarized in the Table I.

All along this paper, we contrast results using different content popularity models with and without social networks traffic. From now and so on, the scenarios with content popularity model based on social networks will be called *OSN* traffic while scenarios with popularity model based on a MZipf distribution will be called *regular* traffic. All the experiments are performed with a catalog counting 10,000 pieces of content.

Social Network Activity Traces	
Number of sessions NS	Zipf ($\alpha = 1.792, \beta = 0.0$)
Number of activities NA_i	Zipf ($\alpha = 1.765, \beta = 4.888$)
Inter-session time t_{IS_i} (s)	LogNormal ($\mu = 2.245, \sigma = 1.133$)
Inter-activity time $t_{IA_{ij}}$ (s)	LogNormal ($\mu = 1.789, \sigma = 2.366$)
Catalog Configuration	
Size	10^4 Pieces of Content
MZip Parameters	$\alpha = \{0.65, 1.1\}$
	$\beta = 0.0$
Social Network graph	
#Users	4,039
#Links	88,234
#Avg. Degree	44

TABLE I: Simulation Parameters

```
03.33   UserB   Retrieve(UserA, UserK, UserW)
05.21   UserB   Publish(108, 1024KB)
07.44   UserA   Retrieve(UserB, UserE)
12.35   UserB   Publish(2, 580KB)
```

Fig. 3: A Sample of a SONETOR trace

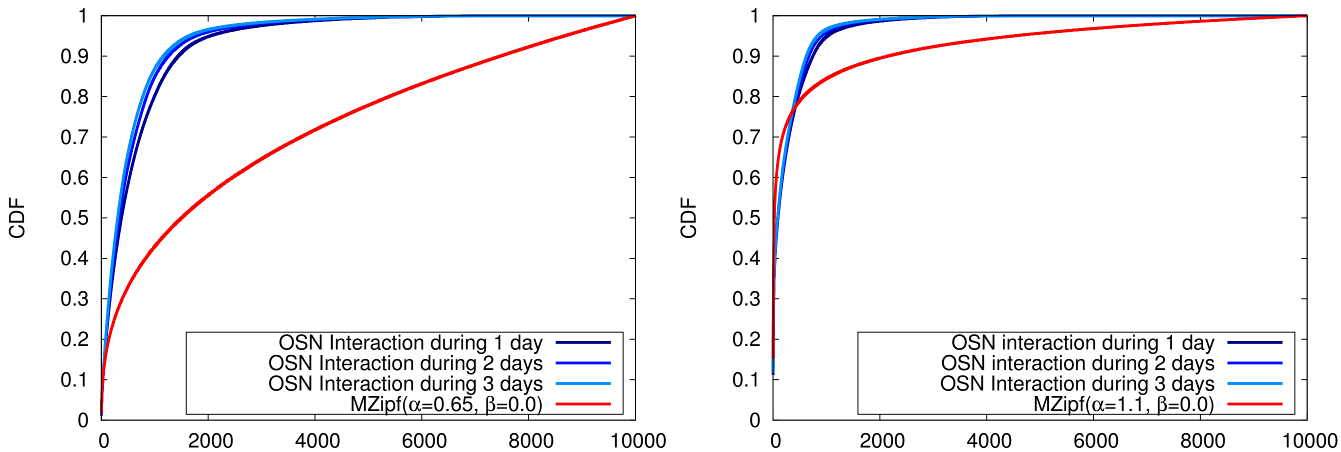
In order to model the social relationships between users, we resort to a Facebook data set publicly available [24]. The data set consists of 4,039 users, 88,234 friend relationships and each user counts in average 44 relationships.

Online Social Networks (OSN) allow users to publish content at their own will and share it with their acquaintances (i.e., *friends*). Friends may always be updated through a timeline. Thus, we model a *social network* by a network where users can publish, retrieve and share information with their communities, according to their personal preferences. In our social model, each user has therefore two functionalities to interact with its community: *Publish* and *Retrieve*, as defined as follows:

- *Publish*: the production of new content. After retrieving a content, users may share it again with their friends (i.e., *re-tweet* a message).
- *Retrieve*: this function allows users to receive the last content issued by all their friends.

As we mentioned in Section III-D, the activities have dependent parameters. In case of a *Publish* activity, the dependent parameters are a content name, which is decided with a popularity model explained in the previous section and its size. In case of a *Retrieve* activity, the dependent parameters are the users whom to retrieve the last updates and it is decided with the social graph. It always selects all their friends. A sample of a SONETOR trace is shown in the Figure 3.

In the following, we analyze the impact of social networks into the content popularity model. First, we investigate the probability distribution found on a stand-alone OSN traffic scenario. Second, we study a mixed scenario where OSN and regular traffic coexist. And last but not least, we show the presence of flash crowds in the stand-alone OSN traffic scenario.



(a) MZipf ($\alpha = 0.65$, $\beta = 0.0$)

(b) MZipf ($\alpha = 1.1$, $\beta = 0.0$)

Fig. 4: Stand-alone Scenario: impact of the OSN on the content popularity model

C. Stand-alone Scenario with OSN Traffic

We aim at discovering the changes on the content popularity model provoked by the interaction of users within social networks. We start the assessment on a stand-alone scenario where all the traffic comes from social networks. In this experiment, we reproduce *SONETOR* traces to analyze the impact of social networks into the content popularity model. We model content popularity with a MZipf distribution ($\alpha = 1.1$; $\beta = 0$). The consumption of content is realized by the users; users receive an update of their friends' publication. The users do not consume all the content from their friends but only a small subset based on influence model [25]. Then, we bound the generated synthetic traces to 1, 2 or 3 days. Once the experiments execute the traces, we build a probability distribution with the consumed content. We proceed to draw the probability distribution obtained and to fit the curve with a new power-law distribution.

In Figures 4b and 4a, we show charts with distinct MZipf configurations. The plotted curves correspond to the Cumulative Distribution Function (CDF) of the content probability distribution. The charts are built with the number of requests for every piece of content. The red line represents the original content popularity model (*input*) while the blue lines stand for the obtained content popularity model (*output*) after 1, 2 or 3 days of social network interaction.

Using a popularity model MZipf ($\alpha = 0.65$; $\beta = 0$), the 90% of most requested content consists of 7,466 pieces of content. While using OSN, the 90% of most requested content get reduced to only 1,165 pieces. It means the subset of most popular content get reduced to 16% of its original number of pieces. It is important to remark as well that in the OSN case, only 6,992 pieces of content were consumed: it means 30% of the content is completely ignored.

Those results are confirmed using the model MZipf($\alpha = 1.1$; $\beta = 0$), the introduction of OSN produces that the 55% of content is ignored and the subset of most popular content is reduced to 29% of its original number of pieces.

From these figures, we observe how the ratio of popular elements got decreased. the viral effect of OSN provokes many users to consume less diverse content and it strengthens the importance of popular elements. As we see in both cases, the subset of most popular contents is reduced in important proportions. The social networks provoke the creation of *super-popular* content. These pieces of content are highly demanded and may have an important impact on the general behavior of the network. In the OSN, there are many pieces of content that are completely ignored and never consumed. This fact reveals that many of the content are irrelevant to most of the users. Even more, in the social network, the number of published content is a subset of all the pieces of content found in the popularity model. In other words, the content found in social networks is subset of all the content found in the Internet.

In the Table II, we present the obtained distribution parameters. We observe that the alpha parameters have grown significantly, which means a few popular content increases its popularity while most of the other stay unpopular.

D. Mixed Scenario with OSN and Regular Traffic

We have already shown the impact of social networks in an environment where all the traffic is produced by social networks. Now, we are interested in mixed scenarios where traffic is composed of two types of traffic: social network and regular traffic. OSN and regular traffic are going to coexist in the near future. We argue that the penetration of social networks into the overall traffic will incur changes in the content popularity model. These changes are analyzed in this section.

To this end, we simulate scenarios with different ratio between *regular* and *OSN* traffic (i.e., 100%-0%; 90%-10%; 80%-20%; 50%-50%; 0%-100%). We then present in Figure 5 the CDF of the content popularity obtained with all the mixed scenarios. We represent the execution of the social network

Original Content Popularity Model (*input*)			Obtained Content Popularity Model (*output*)	
Distrib. Parameters		Period	Distrib. Parameters	
MZipf	$\alpha = 0.65$	1 day	MZipf	$\alpha = 5.27$
	$\beta = 0.0$			$\beta = 2114.89$
MZipf	$\alpha = 0.65$	2 days	MZipf	$\alpha = 5.59$
	$\beta = 0.0$			$\beta = 2009.75$
MZipf	$\alpha = 0.65$	3 days	MZipf	$\alpha = 5.19$
	$\beta = 0.0$			$\beta = 1664.63$
MZipf	$\alpha = 1.1$	1 day	MZipf	$\alpha = 2.43$
	$\beta = 0.0$			$\beta = 181.23$
MZipf	$\alpha = 1.1$	2 days	MZipf	$\alpha = 2.55$
	$\beta = 0.0$			$\beta = 191.67$
MZipf	$\alpha = 1.1$	3 days	MZipf	$\alpha = 2.59$
	$\beta = 0.0$			$\beta = 189.62$

TABLE II: Distribution parameters for the stand-alone scenario

activity traces in a three-days period. For lack of space, we only show the chart for regular traffic with MZipf ($\alpha = 0.65$), still in the Table III the other configurations are shown.

We fit the mixed scenarios with a MZipf function. We summarize the obtained MZipf parameters in the Table III. As seen in Fig. 5, the curves for regular traffic and for the mixed scenario with 10% of OSN traffic seem similar. The mixed scenario with 10% of OSN traffic has an apparently minimal impact in the MZipf obtained MZipf parameter: the α parameter passes from 0.65 to 0.71, which means the 20% of the most popular content passes from 151 pieces of content to 142. If we consider the 90% of all the content, it passes from 7,458 to 7,264 pieces of content: a reduction of 9% and 3% in the most popular contents respectively. The same phenomenon is also observed for the OSN traffic ranging from 20% to 100% but at higher scale. For instance, for the 50% OSN traffic, the α parameter passes from 0.65 to 1.14.

From this experiment, we observe that OSN traffic has an impact on the content popularity model. While we increase the ratio of OSN traffic, we observe the growth of the α parameter (Table III). A higher value for the α parameter implies a smaller subset of *super* popular content (i.e. the shape of the curve tends to the left side). Then with OSN traffic, there is a small subset of *super* popular content that is highly requested while the other content stay unnoticed.

This observation can have a significant impact for the Caches of the Internet. Indeed, with the rise of caching architectures such as Content Delivery Networks (CDN) and Content Centric Networks (CCN), in-network caching has become an important issue for the Internet [26]. By reducing the subset of *super* popular content, it reduces the number of relevant content to be stored into Caches. It then alleviates the load on the Caches, saves the resources (e.g.: memory) and improves their performances.

E. Flash-Crowds Effect

The *Flash-Crowds* phenomenon means that a piece of content is massively requested by a huge number of users on the Internet for a short period of time [27]. In this section, we study *Flash-Crowds* and its correlation with social networks.

Original Content Popularity Model (*input*)	Obtained Content Popularity Model (*output*)		
MZipf0.65 + 10%OSN	MZipf	$\alpha = 0.71$	$\beta = 10.57$
MZipf0.65 + 20%OSN	MZipf	$\alpha = 0.81$	$\beta = 38.90$
MZipf0.65 + 50%OSN	MZipf	$\alpha = 1.14$	$\beta = 123.81$
MZipf0.65 + 100%OSN	MZipf	$\alpha = 5.19$	$\beta = 1664.63$
MZipf1.1 + 10%OSN	MZipf	$\alpha = 1.11$	$\beta = 0.40$
MZipf1.1 + 20%OSN	MZipf	$\alpha = 1.16$	$\beta = 1.78$
MZipf1.1 + 50%OSN	MZipf	$\alpha = 1.38$	$\beta = 16.09$
MZipf1.1 + 100%OSN	MZipf	$\alpha = 2.59$	$\beta = 185.92$

TABLE III: Distribution parameters for the mixed scenario

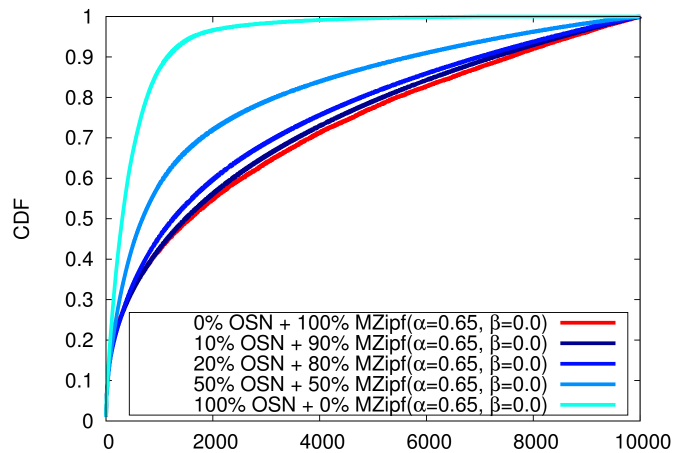


Fig. 5: Mixed Scenario: impact of the OSN on the content popularity model

We study content consumption for a particular piece of content during one-day period. We track all the timestamps in-which the content has been consumed. We then contrast the number of demands between regular traffic and OSN traffic scenarios.

The histogram is shown in Figure 6, the x-axis represents the time in seconds while the y-axis represents the number of requests for a piece of content. For clarity, we zoom in one-hour period (from 2:00 to 3:00). With regular traffic, the requests for content seem to be uniformly distributed and it seems to represent a dense solid line. The OSN traffic shows separated peaks of demand, which are the so-called Flash-crowd effects.

With the regular traffic (in red color), we observe a dense concentration of points and the absence of peaks. This fact points out that the number of requests for certain piece of content is nearly constant with time. With the OSN traffic (in blue color), the histogram shows high peaks and less dispersion, which highlights the presence of multiple *flash-crowds* using social networks. This fact can be observed clearly in the zoom chart (Figure 6).

We believe the correct handling of flash-crowd processes is going to be one of the main issues for the Future Internet. Social networks tend to privilege the distribution of content in a short period of time. This short period of time involves a high number of requests for a piece of content, which becomes the popular content. Once the short period of time has passed,

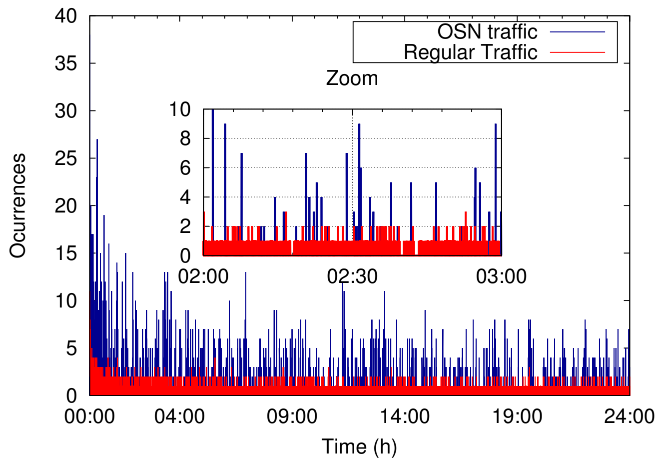


Fig. 6: Flash-crowds observed in the content popularity model

the content stop being popular and it is barely demanded. In typical caching and routing problems, the correct handling of flash crowds involves generating copies and updating routing tables in order to evolve the end-user or overall network performance.

V. Conclusion & Future Work

In this paper, we propose *SONETOR*, an OSN synthetic traffic traces generator. *SONETOR* is based on a social network model capturing the social relationships between users, a users interaction model for the users' activity scheduling, and an activity model to describe distinct type of activities.

We use *SONETOR* and study the impact of social relationships in the content popularity. The social relationships between users enforce that many pieces of content become popular and are spread massively throughout the OSN while many others passed unnoticed. It has a major impact on the content popularity model traditionally used in the Internet. With SONETOR, we showed that OSN privileges a subset of super-popular content. By reducing the number of popular content, network caches can improve their performances with the same storage capabilities. It is an important result as in-network caching is nowadays largely studied with network architectures such as data-centers, Content Distribution Networks or Information-Centric Networks.

As future work, we aim to include other Internet traffic features into SONETOR such as user mobility. SONETOR will also be used to model OSN workload with new network architectures such as CCN.

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