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Ayisat W. Yusuf-Asaju
*Universiti Utara Malaysia*, ayisatwuraola@gmail.com

Zulkhairi Dahalin
*Universiti Utara Malaysia*, zul@uum.edu.my

Azman Ta'a
*Universiti Utara Malaysia*, azman@uum.edu.my

# A Proposed Analytical Customer Satisfaction Prediction Model for Mobile Internet Networks

*Research-in-Progress*

**Ayisat W. Yusuf-Asaju**
School of Computing
Universiti Utara Malaysia
Keddah, Malaysia
ayisatwuraola@gmail.com

**Zulkhairi B. Dahalin**
School of Computing
Universiti Utara Malaysia
Keddah, Malaysia
zul@uum.edu.my

**Azman Ta'a**
School of Computing
Universiti Utara Malaysia
Keddah, Malaysia
azman@uum.edu.my

## Abstract

*Subjective method (such as survey, interview, etc.) has been the most common and reliable method used in analyzing customer satisfaction. However, the subjective method is expensive, time consuming, lacks repeatability in real-time and may not capture the technical aspect of the telecoms network service performance in telecommunication industry. As a result, perceived quality of experience (QoE) has been traditionally used to evaluate the satisfaction of telecommunication services from both Internet service providers and customer's perspective. However, the result of perceived QoE in relation to mean opinion score found not suitable enough to quantify customer satisfaction, and it eliminates the diversity of customer assessment while quantifying satisfaction. Therefore, this paper proposed an analytical customer satisfaction prediction model based on perceived QoE, perceived QoE influence factors, perceived QoE measurements and perceived QoE estimations to overcome the limitations of the subjective measurement. The paper presents how the mean opinion score can be used to quantify customer satisfaction by ensuring the diversity of customer's assessment is not eliminated.*

Keywords: Quality of Experience (QoE), Mean Opinion Score, Internet, Mobile Network Operators (MNOs), QoE measurement, analytics, prediction, Mobile Networks

## Introduction

Telecommunications (Telecoms) industry considered customer satisfaction as a pivotal indicator used to determine the extent at which the Mobile Network Operators (MNOs) are successful in providing mobile internet services to their customers. In most cases, MNOs mainly focused on the monitoring of technical constructs consisting of terminals, network, and service infrastructure to aid the provision of internet services. However, the competitive nature of the telecoms market made MNOs to realize the need not to only consider the technical aspect of the quality provided, but also customer expectations and experiences with the aim of satisfying the customers.

The technical aspect of the network quality provided by the MNOs constitutes quality of service (QoS) parameters of the network services. Among the QoS parameters are throughput, loss, delay, bandwidth and jitter, these parameters are usually measured on network nodes of the MNOs instruments or machines (Andrews et al. 2006). However, customers are more interested in the experiences perceived from the service performance typically in the form of subjective and non technical terms. Overall customer experiences reffered to as quality of experience (QoE), often used to estimate the customer perception of the network level performance. Several studies assumed QoE to be a measure of customer perception in relation to the QoS parameters, context, expectations and other factors, which influence the customer perception to determine the degree of satisfied or dissatisfied customers using a specific service or application (Alreshoodi and Woods 2013; Le Callet et al. 2012). On the other hand, customer expectation is the ideal standards commonly in the form of service level agreement (SLA), which is an agreement between the customers and the MNOs about the service characteristics provided by the MNOs (Gozdecki et al. 2003).

Generally, expectation and other QoE influence factors are used to estimate perceived QoE, which is represented using mean opinion score (MOS) (Alreshoodi and Woods 2013; Demirbilek and Gregoire 2016). MOS is determined through the prediction of the subjective measurement from the objective measurement. However, recent studies argues that MOS is not sufficient enough to quantify the satisfaction of customers, because MOS eliminates the diversity of customer assessment while quantifying customer satisfaction (Hoßfeld et al. 2016). Therefore, this article proposed an analytical customer satisfaction (ACSAT) predition model, which consists of QoE Influence factors, perceived QoE and perceived QoE maximization to determine the diversity of satisfied and dissatisfied customers of internet networks. The remainder of this article discusses perceived QoE, perceived QoE influence factors, perceived QoE measurements, ACSAT prediction model and conclusions.

# Perceived QoE

Qualinet described QoE "*as the degree of delight or annoyance of the user of an application or service. It results from the fulfilment of his or her expectations with respect to the utility and / or enjoyment of the application or service in the light of the user's personality and current state*" (Le Callet et al. 2012). Delight of the user of a service can be influenced by context, network, device application and context of use depending on the application domain. Generally, MNOs need to understand traffic characteristics, most especially the geographical and dynamic nature of the network traffic commonly found in the mobile network. Therefore, to appropriately determine the user perceived QoE, it is important to understand various influence factors of perceived QoE from both users and network perspectives.

### *Perceived QoE influence Factors*

Influence factors is any characteristics consisting of user, system, service application context, whose actual state or settings may have influence on the user perceived QoE (Le Callet et al. 2012). Perceived QoE influence factors can be classified into diiferent dimensions as depicted in table 1. However, the most common dimension is human, context and system influence factors (Barakovic and Skorin-Kapov 2013; Le Callet et al. 2012). Human factors describes the demographic, socio-economic backgroud, physical and users emotional state. System influence factors consititutes the technical properties of application or service used by the user. Context influence factor involves the user's environment in relation to physical, temporal, social economic and techincal charateristics of the service or application used by the user. Basic understanding of all the influence factors would enable a better analysis of the perceived QoE of the users in relation to the specific service used by users.

| **Table 1. Perceived QoE** | **Influence Factors** | |
|---|---|---|
| **Author** | **Dimensions** | **Elements** |
| Baraković et al. (2010) | Technology performance | Application/service, server, network and device. |
| | Usability | Behavioural usability, ease of use, device features, emotions and feelings. |
| | Expectations | Application type, usage history, gender, brand and personality |
| | context | Environment, personal/ social context, technological context and cultural context |
| | subjective evaluation | Service, network and device |
| DeMoor et al. (2010) | QoS parameters | Delay, jitter, loss, throughput and bandwidth. |
| | Context, Prior experiences, Expectations | |
| | User Factors | Personalisation and emotions |
| Stankiewicz and Jajszczyk (2011) | QoS factors, Grade of Service (GoS), Quality of Resilience (QoR) | Terminals, type of content, application specific features, |
| | Customer profiles, environmental, psychological and sociological aspects. | Emotions,occupation, education level and age |
| | Pricing policies | Prepaid or Postpaid. |
| Skorin-Kapov and Varela (2012) | Application | Application configuration-related factors. |
| | Resource space | Delay, jiter, loss, throughput and system-related factors) |
| | Context | customer location, time, and application-related factors |
| | User space | Demographics, customer preferences, requirements, expectations, prior knowledge, behaviour and motivations |

| | | |
|---|---|---|
| Le Callet et al. (2012) | Human factors | Age, education background, emotions, gender and user visual aid |
| | System factors | Bandwidth, delay, loss, throughput, security, display size and resolution |
| | Context factor | Location, movement, time of day, costs, subscription type and privacy |

***Perceived QoE Measurement***

Perceived QoE measurement is classified into subjective and objective measurements (ITU-T Recommendation G.1030 2014). The subjective measurements is based on customer perception of the services delivered to the customers, while objective measurement is the means of estimating subjective quality solely from the measurement obtained from the network traffic (Barakovic and Skorin-Kapov 2013). The subjective method is performed using Mean Opinion Score (MOS). The MOS is an opinion score on five-point category-judgement scales (scores such as Excellent = 5; Good = 4; Fair = 3; Poor = 2; Bad = 1), mostly used in many applications such as audio, video, and web browsing to estimate the perceived QoE. (Demirbilek and Gregoire 2016).

In contrast to the subjective measure that focuses on customer perception through surveys or experiments, the objective measurement is associated with quality estimation models usually in the form of mathematical and/ or comparative methods that generate the quantitative measure of the perceived QoE (Alreshoodi and Woods 2013). Several studies have used objective measurement to estimate MOS (perceived QoE) using machine learning algorithms to interprete customer satisfaction (Alreshoodi and Woods 2013; Anchuen et al. 2016). However, recent studies have argued that, it is necessary to go beyond MOS calculations to allow for better understanding of the customer population experiencing a satisfactory level of perceived QoE, because the MOS eliminates the diversity of customer assessment (Hoßfeld et al. 2016).

In addition, Streijl et al (2016) highlighted that, MOS does not clarified what threshold values should be appointed to identify the problems or acceptability of perceived QoE. Because the MOS measures in most studies measures the amount of perceived QoE satisfaction rather than using the maximization of perceived QoE to determine the satisfactory level of the service in relation to satisfied and dissatisfied users or customers. The authors point out the MNOs might decide to maximize the QoE for different reasons. Thus, maximizing the overall perceived QoE for multiple customers in the network to allocate network resources, maximizing the QoE of a certain individual customers or groups to increase the number of satisfied customers (Barakovic and Skorin-Kapov 2013; Streijl et al. 2016). In this respect, concentrating on the overall MOS alone can lead to unfairness among customers if the MOS is not properly used (Streijl et al. 2016). Therefore, maximization of estimated MOS can be achieved using standard deviation of MOS (SOS hypothesis), distribution and quantiles to determine the satisfied and dissatisfied customers to guarantee certain level of customer fairness.

## Proposed Analytical Customer Satisfaction Prediction Model

In the telecoms industry, customer satisfaction is a yardstick to determine the extent at which the MNOs are successful in providing mobile internet services to their customers. Ideally, if the MNOs could measure customer satisfaction at any point in time and identify the cause of poor QoE, it would be easier for the MNOs to address quality issues promptly before such issues deteriorate into large amount of mobile internet customer dissatisfaction (Diaz-Aviles, et al., 2015). Anderson and Sullivan (1993) developed customer satisfaction model based on assumption of expectancy disconfirmation theory. The customer satisfaction model was improved by Xiao and Boutaba (2007) to an analytical customer satisfaction (CSAT) model used in examining the satisfaction of the mobile internet customers through simulation method. The CSAT model consist of service utility (represents measureable set of services performance such as network QoS, network availability and customer care), expectation and disconfirmation constructs (Xiao and Boutaba 2007). The service utility was used to analysed the objective perceived utility of the customers, while the results of the perceived utility and expectation was used to evaluate disconfirmation in order to determine customer satisfaction. The CSAT model has been confirmed very useful in examining customer satisfaction of the next-generation networks (Djogatovic et al. 2014; Ibarrola et al. 2014). These studies found that overall customer satisfaction is closely linked to other contextual parameters like customers previous experiences. In particular, Djogatovic et al. (2014) modified and improved the CSAT model with service content and security conditions which are among the perceived QoE system influence factors. Based on all the stated evidences, this study proposed an Analytical Customer Satisfaction (ACSAT) prediction model by improving and modifying the CSAT model developed by Xiao and Boutaba (2007) using perceived QoE influence factors, perceived QoE measurements and estimations.

In contrast to the CSAT model, the ACSAT prediction model consist of perceived QoE influence factors that are in relation to system factors (such as the QoS parameters), human factors (like customer demographics) and context factors (such as customer's location). The three QoE influence factors (system, customer and context) was considered in the ACSAT prediction model to enable adequate estimation of the perceived QoE in relation to mobility in relation to time and location (Le Callet et al. 2012). Hence, instead of estimating perceived utilities as used in CSAT model, ACSAT prediction model tends to estimate the overall customer perceived QoE.

In CSAT model, expectation was used to analyze perceived utility. On the contrary, ACSAT prediction model used expectation in two different forms, to estimate the perceived QoE and for expectation update. Expectation as stated in the SLA along with the QoE influence factors would aid the analysis of perceived QoE to identify maximum and minimum expected variable values along with variable weights to determine adequate MOS through the machine learning algorithms (Tsiaras and Stiller 2014). Because, estimation of overall perceived QoE would inform the MNOs about issues causing deterioration in the network performance, this will assist the MNOs to update customer's expectation appropriately.

Customer care support for service utilities in the CSAT model was used along with pricing policies and bandwidth to aid the maximization of perceived to enable the diversity of satisfied and dissatisfied customers (Barakovic and Skorin-Kapov 2013). Customer care support most especially the response time has been confirmed in previous to studies to have a great impact on overall customer experience (Diaz-Aviles, et al., 2015). As a result, customer care support in this study is for the purpose of analyzing the reported cases and challenges experienced by the customer while using the mobile internet services and the response time taken by the customer care support to rectify such issues. In addition the use of pricing policies focused on different types of customer's mobile internet subscriptions that can be used for the maximization of perceived QoE to determine the diversity of satisfied and dissatisfied customers.
Similar to CSAT model is the use of customer satisfaction result for market segmentation, market growth and revenue and profit generation. However, customer satisfaction result can also assist the MNOs in allocating appropriate network resources in location where high dissatisfaction is experienced as depicted in figure 1.

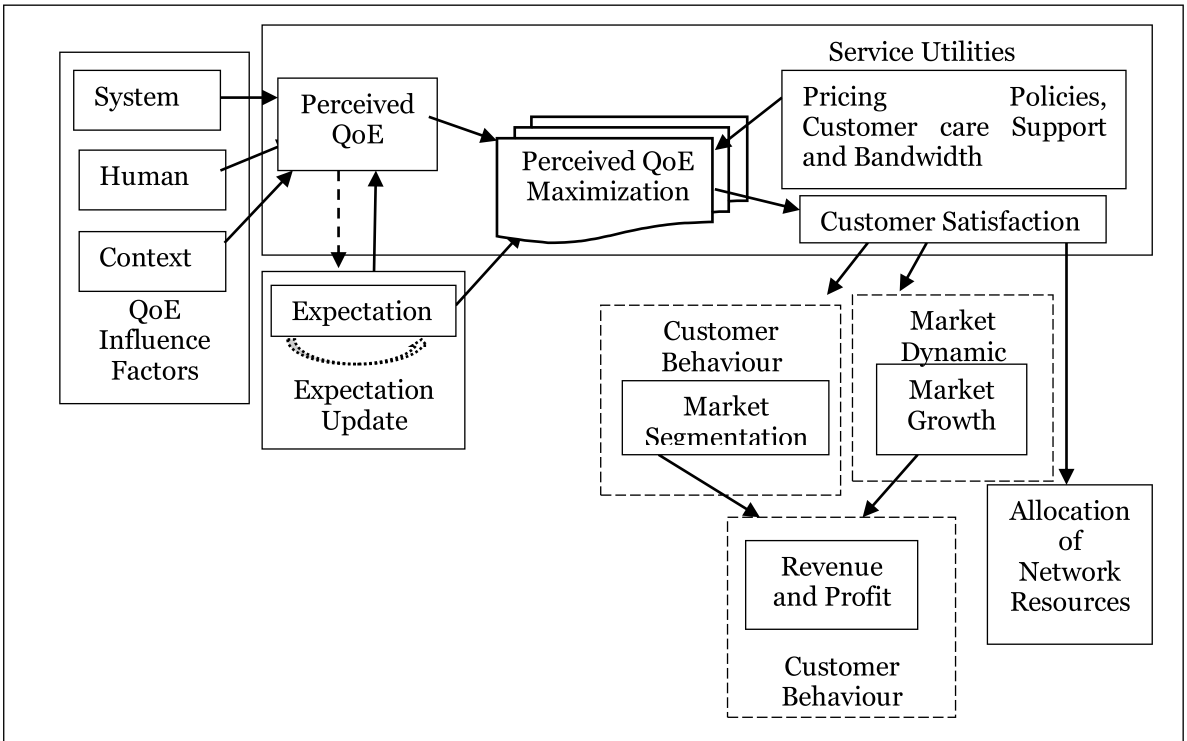

Figure 1. Analytical Customer Satisfaction Prediction Model

## ***Methodological Instances for Implementation of ACSAT Prediction Model***
To implement ACSAT prediction model, this article proposed the use of network data, network billing data, customer care data and expectation data. The network data comprises of user throughput and payload metrics for different users. Network billing data constitutes data bundles and price of the data bundles subscribed by different internet users. Customer care data comprises of the different customer complaints reported to the customer care agents. Expectation data consists of SLA that will be used as a benchmark for the modelling of perceived QoE at the modelling phase.

The experimental design for this article comprises of four different phases (data collection, data preparation, data modelling and maximization of perceived QoE to determine customer satisfaction). The first phase entails the collection of data from the network traffic. Data gathered from the network traffic would aid the extraction of the perceived QoE influence factors (such as system, human and context factors), which can be used for modelling estimated MOS (Perceived QoE).

The second phase is data preparation, which involves different methods such as data exploratory analysis (EDA), data pre-processing, clustering techniques, feature selection and extraction. Generally, EDA aids understanding of the interdependencies among the data attributes to become familiar with the content of the data along with its quality and limitations. Data pre-processing involves data cleaning, data integration and data transformation. Data cleaning is concerned with the process of filling in the missing values, smoothing noisy data, identifying, or removing outlier as well as, resolving inconsistencies and imbalances in the data. Data integration is the process of combining datasets residing in different sources and providing a unified view of the datasets. Data transformation involves transforming the raw data obtained from the data sources into the form that would be appropriate for the analytical modelling stage. Feature selection and extraction process enables the selection and extraction of the perceived QoE influence factors from the dataset obtained from the network traffic. These processes allow better understanding of the underlying process that generate the data to be used for the estimation of perceived QoE, improve the prediction performance of the predictors, provide a fast and cost-effective predictor to be used for the estimation of perceived QoE. Clustering techniques allows the grouping of a set of objects together in such a way the objects in the same group are more similar to each other than those in the other groups. Specifically, use of expectation maximization clustering algorithm (EMCA) that is suitable for continous and categorical variables can aid in grouping the selected and extracted variables into different clusters in relation to Pricing policies, Bandwidth and customer care response. This phase would aid the preparation of the dataset for the perceived QoE modelling phase.

The third phase involves the modelling of the perceived QoE, which is an abstract representation of data and its relationship within the dataset. This phase allows the splitting of dataset into training and testing set usually in the ratio of 70:30. This stage can be carried out by using machine learning algorithms such as decision trees, random forest, support vector machine, K-nearest, and artificial neural network (in case of large data set) or data mining algorithms. The modelling of perceived QoE using machine learning algorithms would map the combination of input parameters to a class value to build an efficient model that classify extracted features with the maximum precision through the perceived QoE function described as QoE:=f (User, Service, Variable) (Tsiaras and Stiller 2014). After, the estimation of the perceived QoE, the next phase is the maximazation of perceived QoE to determine satisfied and dissatisfied customers.

The last phase which is the maximization of perceived QoE to analyze customer satisfaction is concerned with using the identified clusters in the second phase to determine the diversity of satisfied and dissatisfied customers. This can be executed firstly, by predicting expected MOS (mean of the random variable which represents the quality ratings) and SOS as a function of MOS for each cluster. Secondly, by determining quartiles for both discrete and continuous with either probability mass function or probability density function respectively through the q-quantiles for the ratings, estimated as $\alpha' th\ percentiles\ with\ \alpha = 10\ and\ 90$ **(**Hoßfeld et al. 2016**).** Thirdly, analysing acceptability $\theta$, which can be determined in relation to the probability of the MOS above a certain threshold $\theta, P(U \geq \theta)$, where U is the random variable for quality ratings (MOS). This would enable the estimation of acceptance in relation to the quality ratings defined as $U \in \{0, 1\}$. Where 0 and 1 is accepted and not accepted; satisfied or dissatisfied respectively and is analysed through percentage good or bad (%GoB) and percentage poor or worse (%PoW). The estimation for the %GoB is defined as $P_U(U \geq 60)$ while %PoW is defined as $P_U(U \leq 45)$ (Hoßfeld et al. 2016). This phase will enable the estimation of satisfied and dissatisfied customers.

## Conclusion

This study proposed an analytical customer satisfaction prediction model, to predict the customer satisfaction based on the the previous customers experience to assist the MNOs understand the trends of the network traffic, and make intelligent decisions that would enable them to improve their network performance by allocating approriate network resources to enhance their service provisioning. This study contributes to the literature by demonstrating the conceptual view of the ACSAT prediction model by incorporating the perceived QoE influence factors, measurement, and estimations in customer analysis process. The proposed model would assist the MNOs to predict the customer satisfaction ahead before the customer would perceive the rendered services Further research of this study is to employ the use of big data obtained from the telecoms network traffic for the implementaion of the ACSAT prediction model. In addition, the study would design a prototype to enable experimental study through focus group method.

## References


Alreshoodi, M., & Woods, J. 2013. "Survey on QOE\QOS corelation models for multimedia services," *International Journal of Distributed and Parallel Systems (IJDPS) 4:3,* pp. 53-72.

Anchuen, P., Uthansakul, P., and Uthansakul, M. 2016. "QOE Model in Cellular Networks Based on QOS Measurements Using Neural Network Approach," *in proceeding of the 13th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON),* Chiang Mai, pp. 1-5.

Anderson, E. W., and Sullivan, M. W. 1993. "The Antecedents and Consequences of Customer Satisfaction for Firms," *Marketing Science 12:2* , pp. 125-143.

Andrews, M., Cao, J., and McGowan, J. 2006. "Measuring Human Satisfaction in Data Networks," *in Proceedings of the 25th IEEE International conference on Computer Communications* Barcelona, Spain, pp. 1-12.

Barakovic, S., and Skorin-Kapov, L. 2013. "Survey and challeges of QoE management issues in wireless networks," *Journal of conputer networks and communciations*, pp. 1-28.

Baraković, S., Baraković, J., and Bajrić, H. 2010. "QoE Dimensions and QoE Measurement of NGN Services," in *18th Telecommunications forum TELFOR,* Serbia, Belgrade, pp. 15-18.

Demirbilek, E., and Gregoire, J. C. (2016). "Towards Reduced Reference Parametric Models for Estimating Audiovisual Quality in Multimedia Services," in proceeding of IEEE *International Conference on Communications (ICC)*, Kuala Lumpur, pp. 1-5.

DeMoor, K., Ketyko, I., Joseph, W., Deryckere, T., De Marez, L., Martens, L., & Verleye, G. 2010. "Proposed framework for evaluating quality of experience in a mobile testbed- oriented living lab setting," *Mobile Networks and Applications, 15:3,* pp. 378-391.

Diaz-Aviles, E., Pinelli, F., Lynch, K., Nabi, Z., Gkoufas, Y., Bouillet, E., Calabrese, F., Coughlan, E., Holland, P., and Salzwedel, J., 2015. "Towards real-time customer experience prediction for telecommunication operators*," in proceeding of IEEE International Conference on Big Data (Big Data),* pp. 1063–1072.

Djogatovic, V. R., Kostic-Ljubisavljevic, A., Stojanovic, M., and Mikavica, B. 2014. "Quality of experience in telecommunication," *in proceeding of the 8th International Quality Conference,* Kragujevac, pp. 899-904.

Gozdecki, J., Jajszczyk, A., and Stankiewicz, R. 2003. "Quality of service terminology in IP networks," *IEEE Communication Magazine, 41:3,* pp. 153-159.

Hoßfeld, T., Heegaard, P. E., Varela, M., and Moller, S. 2016. "QoE beyond the MOS: an in-depth look at QoE via better metrics and their relation to MOS," *Quality User Experience 1:2* , pp. 1-23.

Ibarrola, E., Saiz, E., Zabala, L., and Cristobo, L. 2014. "A new global qulaity of service model: QoXphere," *IEEE Communications magazine*, *52:1,* pp. 193-199.

ITU-T Recommendation G.1030, 2014. "Estimating end-to-end performance in IP networks for data applications," *in International Telecommunication Union Recommendations*, Switzerland Geneva, pp. 1-22.

Le Callet, P., Möller, S., and Perkis, A. 2012. "Definitions of Quality of Experience (QoE)" in *Qualinet White Output version of the Dagstuhl seminar 12181,* Dagstuhl, pp. 1-22.

Skorin-Kapov, L., and Varela, M. 2012. "A multi-dimensional view of QoE: the ARCU model," *in Proceedings of the 35th International Convention MIPRO*, Opatija, pp. 662-666.

Stankiewicz, R., Cholda, P., & Jajszczyk, A. (2011). QoX: What is it Really? *IEEE Communications Magazine* , 148-158.

Streijl, R. C., Winkler, S., and Hands, D. S. 2016. Mean opinion score (MOS) revisited: methods and applications, limitations and alternatives. *Multimedia System*, *22:2,* pp. 213-227.

Tsiaras, C., and Stiller, B. 2014. "A deterministic QoE formalization of user satisfaction demand (DQX)," in *Proceedings of Annual IEEE conference on local computer networks*, Canada, pp.227-235.

Xiao, J., and Boutaba, R. 2007. "Assessing network service profitability:Modeling from market science perspective," *IEEE/ACM Transactions on networking*, 15:6, pp. 1307-1320.