Traffic Models for Machine Type Communications

Markus Laner*, Philipp Svoboda*, Navid Nikaein† and Markus Rupp*
*Vienna University of Technology, Austria, Email: firstname.name@nt.tuwien.ac.at
†EURECOM, France, Email: firstname.name@eurecom.fr

***Abstract*—Machine-to-machine (M2M) or Machine-type Communication (MTC) is expected to significantly increase in future wireless networks. It exhibits considerably different traffic patterns than human-type communication, thus, claims for new traffic models and simulation scenarios. The challenge in designing such models is not only to accurately capture the behavior of single MTC devices but also to handle their enormous amount (e.g., up to 30 000 devices per cell) and their coordinated behavior. Source traffic models (i.e., each device is modeled as autonomous entity) are generally desirable for their precision and flexibility. However, their complexity is in general growing quadratically with the number of devices. Aggregated traffic models (i.e., all device are summarized to one stream) are far less precise but their complexity is mainly independent of the number of devices. In this work we propose an approach which is combining the advantages of both modeling paradigms, namely, the Coupled Markov Modulated Poisson Processes (CMMPP) framework. It demonstrates the feasibility of source traffic modeling for MTC, being enabled by only linearly growing complexity. Compared to aggregated MTC traffic models, such as proposed by 3GPP TR 37.868, CMMPP allows for enhanced accuracy and flexibility at the cost of moderate computational complexity.**

I. Introduction

In contrast to traditional Human-type Communication (HTC) which 3G wireless networks are currently designed for, Machine-type Communication (MTC) or Machine-to-Machine Communication (M2M) is regarded as a form of data communication that does not require human interaction [1]. MTC promises huge market growth with expected 50 billion connected devices by 2020 [2]. The support for such a massive number of MTC devices has deep implications on the end-to-end network architecture. Lowering both the power consumption and the deployment cost are among the primary requirements. This calls for a migration from high data rate networks to MTC-optimized low cost networks.

A. Why do we need M2M Traffic Models?

To prepare mobile networks for future requirements, standardization organizations currently investigate shortcomings of present networks by simulation of future scenarios. First studies on MTC services shine a light on such scenarios [3], the amount of deployed devices however is still far below the expected numbers, cf. [4]. Hence, a faithful definition of traffic models and reference scenarios is required, in order to validate application scenarios on current and future networks.

Conventional traffic (i.e., HTC) and MTC traffic have two major differences: (i) HTC traffic is heterogeneous whereas MTC traffic is highly homogeneous (all machines running the same application behave similar) and, further, (ii) HTC is uncoordinated on small timescales (up to minutes), while MTC may be coordinated, namely, many machines react on global events in a synchronized fashion. Thus, well known traffic models designed for HTC require adaptations for their application to MTC.

A fundamental question is whether it is feasible to model the traffic of a large amount of autonomous machines simultaneously. This approach is called *source traffic modeling*. It is in general more accurate than its counterpart, *aggregated traffic modeling* (i.e., treating the accumulated data from all MTC devices as single stream). Comparing both approaches in the context of MTC is an open issue.

B. Contributions of this Work

We give an overview of the M2M traffic models and deployment scenarios developed in literature. The divergence between different approaches is highlighted, which yields certain results incomparable. We review the 3GPP model in detail, since it is the model most commonly used at present. It models MTC as aggregated traffic.

Furthermore, we propose Coupled Markov Modulated Poisson Processes (CMMPP) as a candidate to accurately model MTC traffic sources on a per-device basis. To capture the fact that many devices behave in a synchronized fashion we incorporate couplings to the well known MMPP framework, yielding convergence between the 3GPP and CMMPP approaches. A complexity evaluation shows that the emulation of hundreds of thousands of machines on device level is feasible. However, the complexity is significantly higher compared to the 3GPP approach.

C. State of the Art MTC Traffic Models

Traffic modeling means to design stochastic processes such that they match the behavior of physical quantities of measured data traffic, cf. [5]. Traffic models are classified as *source traffic* models (e.g., video, data, voice) and *aggregated traffic* models (e.g., backbone networks, Internet, high-speed links). MTC traffic fits into the second class, since the typical use case includes numerous simple machines assigned to one server or medium. This can be modeled as simple Poisson process, however, due to coordination (synchronizations) in MTC traffic, the respective arrival rate λ may be changing over time, $\lambda(t)$ (i.e., temporal modulation, [6, 7]). The more complex the single MTC devices behave (e.g., video surveillance), the more questionable becomes the approach of modeling them as aggregated traffic. The global data stream may exhibit high-order statistical properties which are difficult to capture [8]. We further expect this effect to be enhanced by the synchronization of sources. In such a case, traffic modeling in terms of source traffic is preferable. Source traffic models which can capture the coordinated nature of MTC traffic are available, cf. [9]. However, they are designed for a low amount of sources, thus, are too complex for MTC traffic (e.g., for N devices a $N \times N$ matrix-vector multiplication is required in each time slot).

Mobile networks have to adopt certain key features in order to allow MTC devices to access the air interface [10]. For example, (i) mass device transmission, (ii) uplink-only data traffic and (iii) small burst transmissions. Future networks shall support up to 30 000 MTC devices in one cell, which is orders of magnitude more than today's requirements [11]. Nowadays networks suffer serious Quality of Service (QoS) degradation if confronted with (i) simultaneous access attempts from many devices [4] or (ii) continuous serving of multiple devices with very low transmission duty cycle [12]. Those topics are the main focus of the research [7, 13, 14] at present.

For multiple access and capacity evaluations, aggregated traffic models such as homogeneous [13, 14] or inhomogeneous [7] Poisson processes, are a satisfactory description of reality and therefore largely deployed. Respective setups are defined in by 3GPP [4] and further discussed in Sec. II. For the simulation of strongly scalable multiple access schemes in future networks (e.g., priority access, delay tolerant devices, QoS demands), mixed source traffic models have been adopted [15–17]. In those studies the case of synchronized MTC devices has not been considered [15, 16] or only for a limited number of MTC devices [17].

Concluding, we observe a divergence between traffic models deployed within different studies. On the one hand higher accuracy requires source traffic models, on the other hand reduced complexity claims for aggregated traffic models. This motivates the search for refined traffic models which combine the benefits of both worlds, in order to guarantee comparability of future studies by the deployment of common models.

II. The 3GPP Model

Because of its popularity and its relation to the approach presented in Sec. III, we first provide an overview of the 3GPP model developed in [4].

The 3GPP model consists of two scenarios called *Model 1* and *Model 2*. The first one treats uncoordinated traffic and the second one synchronous traffic. Both scenarios are defined by a distribution of packet arrivals (or, equivalently, access trials) over a given time period T, cf. Tab. I. This is shown in Fig. 1 (left), where the Probability Density Functions (PDFs) of both distributions are depicted, being equivalent to the expected number of arrivals. The distributions $f(t)$ are both defined on the interval $[0, 1]$, which has to be rescaled to the time interval $[0, T]$ to yield $f_T(t)$. In order to simulate arrivals, it is sufficient to draw N samples from the given distribution and order them in time, where N is the expected number of MTC devices, cf. Tab. I. This number may reach up to 30 000, which is the maximum amount of smart meter devices expected to be served by one cell in a densely populated urban area [4].

TABLE I
3GPP MTC traffic model: Different scenarios

Characteristic	Model 1	Model 2
Number of devices N	1 000, 3 000, 5 000, 10 000, 30 000	
Distribution $f(t)$ over $[0, 1]$	uniform	beta(3,4)
Period T	60 s	10 s

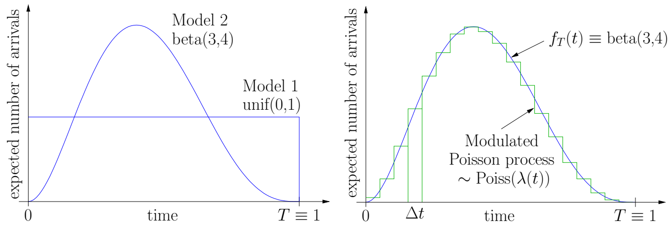


Fig. 1. 3GPP MTC traffic model. Left: expected arrival rate over time. Right: interpretation as modulated Poisson process (sequential approach).

In general it is undesired for simulations to generate the full traffic pattern for T beforehand. In the present case this may not be an issue, however, basic problems such as undefined run length T or large amounts of generated data, may require a sequential drawing of samples. This issue is discussed in [7], where it is pointed out that the 3GPP model is equivalent to a modulated Poisson process. Thereby, the modulation is achieved by the (deterministic) PDF of the arrival distribution $f_T(t)$. This is depicted in Fig. 1 (right), where the mean arrival rate $\lambda(t)$ of a Poisson process is modulated in each time bin Δt by a beta distribution. For infinitesimal Δt both curves coincide. Consequently, sequential sampling is performed by the generation of a Poisson distributed number of arrivals in each time bin Δt with mean arrival rate $\lambda(t)$. In order to obtain an expected outcome of N samples within the period T (i.e., one sample per machine), the arrival rate has to be normalized according to $\lambda(t) = f_T(t) \cdot \frac{\Delta t}{T} \cdot N$. The two different sampling strategies are summarized in Fig. 3 (a–b).

The 3GPP model reaches its limits for further requirements such as: (i) the amount of machines becomes lower, so that a data source has to be associated with a fixed location, (ii) multiple packets (bursts) shall come from the same machine, (iii) the synchronous traffic (Model 2) influences the regular traffic (Model 1) and (iv) the network has an influence on the traffic patterns (e.g., the devices are forced to suppress delay tolerant traffic).

III. The CMMPP Source Modeling Approach

In order to circumvent the limitations of the 3GPP model, we have to adopt a source modeling approach. This means that each MTC device is represented by a separate entity. Thereby, we have to find a trade-off between mutual couplings among data sources (synchronization) and a tolerable complexity for large amounts of devices. Generic traffic models introduce couplings by bidirectional links between devices (cf. Sec. I-C)

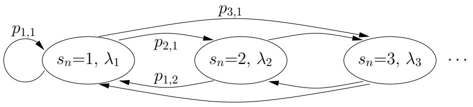
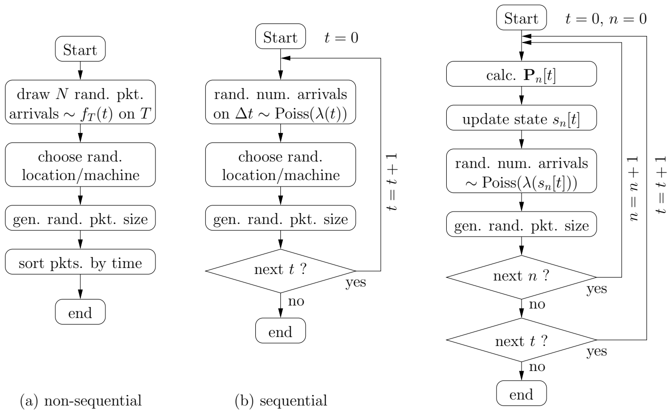


Fig. 2. The MMPP model: each MTC device n is represented by a Markov chain with states s_n, which inherit the parameter λ_i. This is the mean arrival rate, modulating the respective Poisson process.



(a) non-sequential 3GPP model
(b) sequential 3GPP model
(c) CMMPP model

Fig. 3. Flow diagrams for traffic generation by the three different models presented in this work, ordered by computational complexity.

which would be too complex for the present purpose. Instead, we propose one background process acting as *master* which modulates all MTC device entities.

In the following Markov Modulated Poisson Process (MMPP) are presented as models for single MTC devices. Due to their simplicity the operation of large amounts of device models in parallel is computationally feasible. Further, the coupling to a master process with low complexity is possible.

A. MMPP Basics

Markov models and Markov modulated Poisson processes are common in traffic modeling and queueing theory, since they allow for analytically tractable results for a broad spectrum of use cases [6, 18]. MMPP models consist of a Poisson process modulated by the rate $\lambda_i[t]$, which is determined by the state of a Markov chain $s_n[t]$. This principle is depicted in Fig. 2, where $p_{i,j}$ are the transition probabilities between the states of the chain. In the present source modeling approach each MTC device n out of N is represented by a Markov chain and a corresponding Poisson process. The state transition probabilities are condensed into the state transition matrix $\mathbf{P}$ and the state probabilities π_i into the state probability vector $\boldsymbol{\pi}$ according to

$$\mathbf{P} = \begin{pmatrix} p_{1,1} & p_{1,2} & \cdots \\ p_{2,1} & p_{2,2} & \\ \vdots & & \ddots \end{pmatrix} \qquad \boldsymbol{\pi} = \begin{pmatrix} \pi_1 \\ \pi_2 \\ \vdots \end{pmatrix}. \tag{1}$$

In the stationary case both are related by the balance equation $\boldsymbol{\pi} = \boldsymbol{\pi}\mathbf{P}$, which yields $\boldsymbol{\pi}$ an eigenvector of $\mathbf{P}$ to the eigenvalue of 1. Further, the global rate of the MMPP calculates to $\lambda_g = \sum_{i=1}^{I} \lambda_i \pi_i$, where I is the total number of states. A basic example for an MTC device modeled by a MMPP would be a two state MMPP with the first state representing *regular* operation, the second *alarm*. This is analogous to the 3GPP model presented in Sec. II.

B. Coupling Multiple MMPP

It remains to determine the state transition matrix $\mathbf{P}$, such that each device model resides a dedicated amount of time in the regular and alarm states. From the perspective of a single device this may be an easy task; however, from the global perspective, the devices in the 3GPP model do the transition from the regular to the alarm state in a strongly correlated manner, both in time and space. To achieve the same for multiple MMPP models they must be coupled.

Coupled Markov chains, as introduced in the context of pattern recognition [19, 20], are multiple chains which mutually influence their transition probability matrices $\mathbf{P}_n[t]$. The matrices are influenced by the respective multiplication of weighting factors $\gamma_{n=i|m=j}[t|t-1]$, which depend on the past states $s_m[t-1]$ of other chains m.

For the present purpose we only consider unidirectional influences from a background process (*master*) Θ to the MTC device MMPP models. We name this approach Coupled Markov Modulated Poisson Processes (CMMPP). To avoid the separate tuning of each of the parameters $\gamma_{n=i|\Theta=j}[t|t-1]$ for each machine, we set them into the following framework: Let there be two transition matrices $\mathbf{P}_C$ and $\mathbf{P}_U$ globally valid for all N MMPP models and a background process Θ producing samples $\theta[t]$ within the interval $[0, 1]$. Further, a parameter $\delta_n \in [0, 1]$, constant over time, is associated to each MTC device n yielding

$$\theta_n[t] = \delta_n \cdot \theta[t]. \tag{2}$$

Then the state transition matrix $\mathbf{P}_n[t]$ shall be calculated for machine n at time t according to

$$\mathbf{P}_n[t] = \theta_n[t] \cdot \mathbf{P}_C + (1-\theta_n[t]) \cdot \mathbf{P}_U. \tag{3}$$

This form is a convex combination of both transition matrices, yielding itself a valid transition matrix. The advantage is that instead of tuning an enormous amount of parameters $\gamma_{n=i|\Theta=j}[t|t-1]$, only one global parameter $\theta[t]$ has to be generated and can be applied for all device models n. The matrices $\mathbf{P}_C$ and $\mathbf{P}_U$ can be interpreted as transition matrices for the case of perfectly coordinated devices and uncoordinated devices, respectively. The parameter δ_n can be interpreted as closeness (distance) to the epicenter. The closer $\theta_n[t]$ to zero, the more uncoordinated the respective machine behaves; the closer $\theta_n[t]$ approaches one, the stronger the coordination. Further, Θ may have an infinite amount of states, yielding $\theta[t]$ a continuous process. The global arrival rate λ_g equals

$$\lambda_g = \sum_{t=0}^{T} \sum_{n=1}^{N} \sum_{i=1}^{I} \lambda_i \pi_{n,i}[t], \tag{4}$$

however, the calculation of this expression is rather involved, since $\boldsymbol{\pi}_n[t]$ changes for each time instant t and device n. Un-

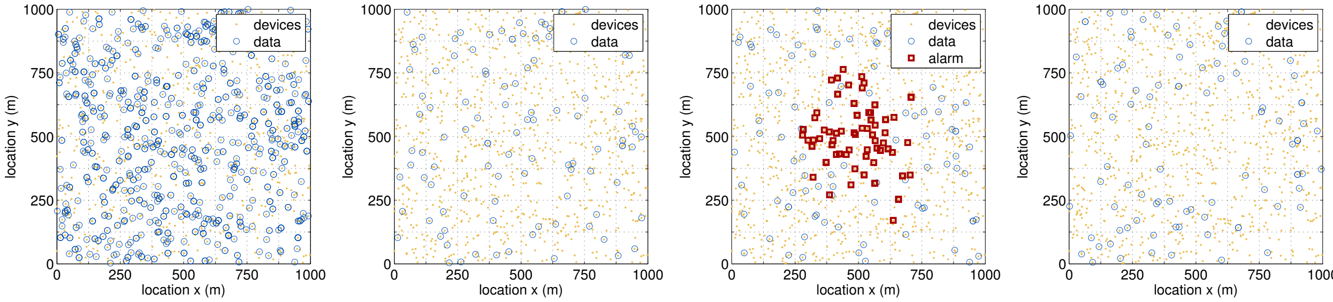


Fig. 4. Deployment of the 3GPP model with basic extensions: 1 000 MTC devices, 60 s runtime, regular operation with 17 pkt/s/km^2, four different states: *startup*, *regular*, *alarm*, *silent*. Left: startup phase, second 0–7. Center left: regular operation phase, second 16–23. Center right: alarm phase, second 26–33. Right: silent phase, second 40–47, note the low activity in the center, since all devices which issued an alarm are silent at this phase.

like the transition probability matrix $\mathbf{P}_n[t]$ the state probability vector is not a convex combination of $\boldsymbol{\pi}_C$ and $\boldsymbol{\pi}_U$, but a rational function in $\theta_n[t]$ with degree $I-1$.

The generation of arrivals according to the CMMPP model is outlined in Fig. 3 (c). Two iteration loops are required, both for the devices n and time instances t, respectively. In each iteration the transition matrix $\mathbf{P}_n[t]$ is calculated anew according to Eq. (3). This may appear expensive, however, since it is a convex combination it can be computed efficiently. Then the random state update from $s_n[t-1]$ to $s_n[t]$ is performed. Afterwards, a number of arrivals and packet sizes are generated appropriate to the actual state $s_n[t]$.

C. Deployment Example

To emphasize the convergence between the 3GPP model and the CMMPP model, we assume a two-state model, with State 1 representing *regular* operation and State 2 *alarm* operation. Thereby, $\lambda_1{=}0.0005$ pkt/s/device and $\lambda_2{=}\frac{1}{\Delta t}$ pkt/s/device. The global transition matrices were defined to

$$\mathbf{P}_U = \begin{pmatrix} 1 & 1 \\ 0 & 0 \end{pmatrix} \qquad \mathbf{P}_C = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix}, \tag{5}$$

where the focus for the uncoordinated case is to never trigger an alarm and for the coordinated case to trigger one alarm in one time slot and then to return to regular operation. The function $\theta[t]$ was fixed to $\theta[t]{=}f_T(t)\cdot\frac{\Delta t}{T}$, namely, the PDF of the beta distribution of Model 2 of the 3GPP model, scaled by the number of time slots.This is convenient since for a high amount of short intervals ($\Delta t{\ll}T$) the function $\theta[t]$ becomes small (close to zero). Consequently, the state probability vector $\boldsymbol{\pi}[t]$ can be approximated as linearly dependent on $\theta[t]$, instead of considering a rational polynomial function, cf. Sec. III-B. The probability of residing in the alarm state estimates to $\pi_2[t] \approx \kappa\cdot\theta[t]$. By scaling the value λ_2 (or $\theta[t]$ itself) according to κ, it is easily achieved to trigger approximately one alarm per machine during the whole simulation/emulation run. Finally, the closeness function δ_n was fixed to the values of Gaussian PDFs, scaled to one at the epicenter. The results of a respective traffic emulation closely resembles the 3GPP model, however, with superimposed uncoordinated traffic (Model 1) and synchronous traffic (Model 2).

In a further example, we augment the CMMPP model for two states, namely, State 3, representing the *startup* phase, and State 4, representing an extended *silent* phase of the MTC device after having issued an alarm. In this simulation setup the strengths of the CMMPP modeling approach become explicit. Namely, multiple devices are able to pass state sequences in a spatially/temporally coordinated fashion. For illustration, snapshots at different time instances of a simulation run are depicted in Fig. 4. Four different phases corresponding to the four state of the CMMPP are clearly distinguishable: (i) during the *startup* phase each device tries to transmit information, (ii) in the *regular* phase sparse uncoordinated traffic is generated, (iii) the *alarm* phase triggers affected devices to change their state, whereas the others stay in regular operation, and (iv) during the *silence* phase all devices which issued an alarm do not transmit. This last phase can be distinguished from the *regular* phase by the low activity in the central region of the rightmost figure, compared to the activity in the respective area of the center left figure. Such correlations between spatial and temporal activities are far beyond the capabilities of the 3GPP model.

IV. Model Comparison

Most advantages and drawbacks for both the 3GPP (non-sequential and sequential) and the coupled MMPP models have already been discussed in Sec. II and Sec. III, respectively. For completeness a summary and comparison of the models is given in Tab. II.

For comparing the computational complexity of both models, the basic example from Sec. III-C has been considered, which is similar to the plain 3GPP model. The simulated time was 60 s with a resolution of 10 ms. The three models have been implemented in *Matlab* (available [21]) and the respective simulation durations on a commodity desktop workstation were recorded. The resulting absolute numbers for the emulation of 30 000 devices are: 0.02 s, 1.1 s and 36 s for the *3GPP*, *3GPP seq.* and *CMMPP* model, respectively. The result for CMMPP positively answers the general question of the feasibility of source modeling approaches for large numbers of sources. A comparable simulation with conventional source traffic models (cf. Sec. I-C) would be unfeasible, since it requires roughly 20 h for 30 000 devices. A visual comparison

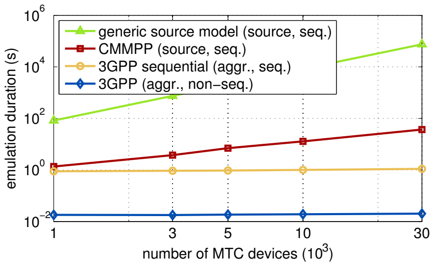


Fig. 5. Comparison of the simulation/emulation duration (Matlab) of the two 3GPP models, the CMMPP model and a conventional source traffic model (estimate). The first two are aggregated models, the second two source traffic models. The simulated time is 60 s with a resolution of 10 ms.

is provided in Fig. 5. In general the sequential approaches perform slower than the non-sequential. Both 3GPP models show a negligible raise in complexity with increasing number of MTC devices, which is expected for accumulated traffic models. The CMMPP approach exhibits a linear growing complexity with the number of devices, since each device is internally represented by a separate MMPP model. Conventional source traffic models experience a quadratic grow.

V. Conclusion

Existing traffic models for MTC or M2M communications are mostly *aggregated* traffic models, defining MTC traffic as one stream from multiple devices (e.g., see 3GPP [4]). For a more accurate traffic description, *source* models are required, which model each MTC device on its own. Yet, M2M traffic bears two fundamental problems to source modeling: (i) the massive amount of devices to be modeled in parallel and (ii) the strong spatial and temporal correlation between the devices.

We proposed CMMPP models for MTC traffic to overcome those problems. The generation of multiple MMPPs exhibits low computational cost, such that their massive parallel deployment is feasible. The coupling to a background process is done by a convex combination of multiple state transition matrices. This solution is inexpensive and allows for involved correlation structures, exceeding the capabilities of the 3GPP modeling approach. A complexity evaluation of the proposed model emphasized its usefulness as it demonstrates the parallel deployment of 30 000 machines with reasonable effort. We finally concluded that source traffic modeling is feasible for MTC traffic. In elaborate scenarios and for a low or medium number of devices CMMPP are preferable over aggregated traffic models for the higher achievable accuracy.

TABLE II
Comparison of the four models.

Model Type	3GPP aggreg.	3GPP seq. aggreg.	CMMPP source	Generic source
Complexity	low	medium	high	unfeas.
Temporal coord.	yes	yes	yes	yes
Spatial coordination	yes	yes	yes	yes
Temp./Spatial coord.	/	/	yes	yes
QoS possible	yes	yes	yes	yes
Determ. sample path	yes	yes	yes	yes
Random sample path	/	yes	yes	yes
Random run time	/	yes	yes	yes
Fixed device location	/	/	yes	yes
Coupling traffic states	/	/	yes	yes
Reciprocal dev. coupl.	/	/	/	yes

Acknowledgment

The research was partially funded by the LOLA EU–FP7 project and the DARWIN 4 FFG–Comet project.

References

[1] 3GPP. Service Requirements for Machine-Type Communications. Technical report, TR 22.368, 2012.
[2] Y. Morioka. LTE for Mobile Consumer Devices. In *ETSI Workshop on Machine to Machine Standardization*, 2011.
[3] M. Z. Shafiq et al. A First Look at Cellular Machine-to-Machine Trafffic – Large Scale Measurements and Characterization. In *SIGMETRICS/Performance'12, London, UK*, 2012.
[4] 3GPP. Study on RAN Improvements for Machine-type communications. Technical report, TR 37.868, 2012.
[5] A. Adas. Traffic Models in Broadband Networks. *IEEE Commun. Mag.*, 35(7):82–89, 1997.
[6] H. Heffes and D. M. Lucatoni. A Markov Modulated Characterization of Packetized Voice and Data Traffic and Related Statistical Multiplexer Performance. *IEEE J. Sel. Areas Commun.*, 4(6):856–868, 1986.
[7] R. C. D. Paiva, R. D. Vieira, and M. Säily. Random access capacity evaluation with synchronized MTC users over wireless networks. In *VTC Spring '11, Brasilia, Brazil*, 2011.
[8] G. Casale, E. Z. Zhang, and E. Smirni. Trace data characterization and fitting for Markov modeling. *Elsevier Perform. Eval.*, 67(2):61–79, 2010.
[9] M. Laner, P. Svoboda, and M. Rupp. Modeling Randomness in Network Traffic. In *SIGMETRICS'12, London, UK*, 2012.
[10] G. Wu et al. M2M: From Mobile to Embedded Internet. *IEEE Commun. Mag.*, 49(4):36–43, 2011.
[11] M. Laner et al. Users in Cells: a Data Traffic Analysis. In *WCNC'12, Paris, France*, 2012.
[12] D. Drajic et al. Impact of online games and M2M applications traffic on performance of HSPA radio access networks. In *esIoT'12, Palermo, Italy*, 2012.
[13] K. Zhou et al. Contention Based Access for Machine-Type Communications over LTE. In *VTC Spring '12, Yokohama, Japan*, 2012.
[14] R. Ratasuk, J. Tan, and A. Ghosh. Coverage and Capacity Analysis for Machine Type Communications in LTE. In *VTC Spring '12, Yokohama, Japan*, 2012.
[15] S. Lien, K. Chen, and Y. Lin. Toward Ubiquitous Massive Accesses in 3GPP Machine-to-Machine Communications. *IEEE Commun. Mag.*, 49(4):66–74, 2011.
[16] Y. Jou et al. M2M over CDMA2000 1x Case Studies. In *WCNC'11, Cancun, Mexico*, 2011.
[17] Y. Zhang et al. Home M2M Networks: Architectures, Standards, and QoS Improvements. *IEEE Commun. Mag.*, 49(4):44–52, 2011.
[18] R. Nelson. *Probability, Stochastic Processes, and Queueing Theory*. Springer, 1995.
[19] M. Brand, N. Oliver, and A. Pentland. Coupled hidden Markov models for complex action recognition. In *CVPR'97, San Juan, PR*, 1997.
[20] M. Brand. Coupled hidden Markov models for modeling interacting processes. Technical report, MIT Media Lab, 1997.
[21] Institute of Telecommunications, TU Vienna. [Online]. Available: www.nt.tuwien.ac.at/about-us/staff/markus-laner/.