Packet Arrival Analysis in Wireless Sensor Networks

Krishna Doddapaneni*, Purav Shah* Enver Ever† Ali Tasiran*, Fredrick A Omondi*,
Leonardo Mostarda‡ and Orhan Gemikonakli *
*School of Science and Technology, Middlesex University, London, UK
Email: K.doddapaneni@mdx.ac.uk
†Computer Engineering Program, Middle East Technical University
Northern Cyprus Campus, Turkey
‡School of Science and Technology, University of Camerino, Camreino, Italy

***Abstract*—Wireless Sensor Networks have seen a tremendous growth in various application areas including health care, environmental monitoring, security, and military purposes despite prominent performance and availability challenges. In such applications, clustering plays an important role in enhancement of the life span and scalability of the network. Although researchers continue to address these challenges, the type of distributions for arrivals at the cluster head and intermediary routing nodes is still an interesting area of investigation. The general practice in published works is to compare an empirical exponential arrival distribution of wireless sensor networks with a theoretical exponential distribution in a Q-Q plot diagram. In this paper, we show that such comparisons based on simple eye checks are not sufficient since, in many cases, such plots may lead to incorrect conclusions. After estimating the Maximum Likelihood parameters of empirical distributions, we generate theoretical distributions based on the estimated parameters. By conducting Kolmogorov-Smirnov Test Statistics for each generated inter-arrival time distributions, we find out, if it is possible to represent the traffic into the cluster head by using theoretical distribution. Statistical analysis concluded that the general assumption of Empirical exponential arrival distribution in wireless sensor networks holds only for a few cases. There are both theoretically known such as Gamma, Log-normal and Mixed Log-Normal of arrival distributions and theoretically unknown such as non-Exponential and Mixed cases of arrival in wireless sensor networks. The work is further extended to understand the effect of delay on inter-arrival time distributions based on the type of medium access control used in wireless sensor networks.**

I. INTRODUCTION

Sensor networks offer a powerful combination of distributed sensing, computing and communication. Self-configuring Wireless Sensor Networks (WSNs) can be invaluable in many civil and military applications for collecting, processing, and disseminating wide ranges of complex environmental data, hence they have attracted considerable research attention in the last few year. Recent work [1] illustrated tools and methodologies for the modelling, simulation and script generations for simulation tools for various WSN applications and performance evaluation by employing physical environment as well. Depending on the area of application, information monitoring and reporting may further be classified as continuous, periodic, or event-based (driven) [2], [3]. In all these cases, data arrival delay is clearly determined by the nature of application and the chosen monitoring scheme. Quality of Service (QoS) provision in relation to the end to end delay of transmitted packets remains a serious concern along with the commonly accepted challenges such as energy consumption, network connectivity, data aggregation, computation power [4]. Characterization of the end-to-end delay distribution is fundamental for real-time communication applications with probabilistic QoS guarantees. The general practice in published works is thus to compare empirical exponential arrival distributions of wireless sensor networks with theoretical exponential distributions in QQ plot diagrams [5]. In [3], cross layer analysis of the end to end delay distribution in WSNs was studied and the results show that inter-arrival time mostly follow exponential distribution except for low periodic traffic. There are many studies which consider exponential arrivals to sensor nodes [5]–[9]. However, in other quarters there has been mixed opinions on the appropriate distribution for modelling inter arrival delay of WSN data packets [3], [10], [11]. In other works, there has been mixed opinions on the appropriate distribution for modelling inter-arrival time of WSN data packets [10]. This strongly indicates the the need for a study to identify acceptable types of distributions for inter-arrival times used in modelling WSNs. In this paper, an investigation is carried out to establish the most appropriate distribution for the inter-arrival times at Cluster Heads (CH) and relay nodes. The process is started by identifying and characterizing various applications and determining suitable data delivery models depending on application requirements. Simulation results are presented and analysed in detail to characterize end to end delay between arriving data packets. Regardless of the medium access scheme employed, energy efficiency is of utmost importance in WSNs. A MAC protocol must certainly support the operation of power saving modes for the sensor node. The main motivation must to minimize the medium access delay that may occur due to high traffic rate. In this paper, the average end-to-end delay for various application rates is also presented, whilst various MAC protocols are considered to save energy.

II. LITERATURE SURVEY

Performance modelling and analysis continues to be of great importance in supporting research as well as in the design, development and optimization of WSN and their applications. The current trend towards the use of WSNs for sensing and control now has the potential for significant advances, not only in science and engineering, but also, on a broad range of applications. This brings the need for performance modelling for the optimization of deployment of WSNs. However, the special design, characteristics of sensors and their applications separate them from the traditional networks. These characteristics pose great challenges for the architecture, protocol design, performance modelling and their implementation. It is essential to consider energy efficiency of WSNs because of their limited energy sources (most of the times batteries). In order to minimise the energy consumption, one of the effective techniques is to place sensors in sleep mode during the idle period [12]. In [13]–[15], a wake-up scheduling scheme at the MAC layer is proposed, which wakes up the sleeping nodes when there is a need to transmit or receive, thus avoiding a degradation in network connectivity or quality of service provisioning.

Characterising delay in distributed systems has been considered in various contexts. However, it can be observed that accurately characterizing end-to-end delay at the CH is still an open problem. Considerable amount of research on sensor networks reported recently has been ranging from network capacity and signal processing techniques, to topology management, algorithms for traffic routing and channel access control. The model presented in [10] is used to investigate system performance in terms of energy consumption, network capacity, delay in data delivery along with the trade-off's that exist between performance metrics and sensor dynamics in active/sleep modes. A Markov model is presented for WSNs, where the nodes may enter into sleep mode. Through standard Markovian techniques, a system model representing the behaviour of a single sensor has been constructed along with the dynamics of the entire network, and the channel contention among interfering sensors. The proposed solution of the system model is then obtained by means of a Fixed Point Approximation (FPA) procedure, and the model has been validated via simulation.

Due to hardware constraints for energy efficiency, optimizing node packet buffer and maximizing the performance is necessary to improve the Quality of Service(QoS) for transmission in WSNs. In [16], a packet buffer evaluation method using queuing network models is proposed where, the blocking probabilities and system performance indicators of each node are calculated using an approximate iterative algorithm. The model considered focuses on a single server model in WSNs and the method used to calculate packet buffer capacity for nodes also indicate that the sink node requires higher performance, when compared to the other nodes in the network. The Markov model of the sensor sleep/active dynamics is presented in [17], that predicts the sensor energy consumption by acquiring this information for each sensor, while a central controller constructs the network energy map representing the energy reserves available in various parts of the system. Only a single node is represented by a Markov chain, while the network energy status is derived with the help of simulation studies.

With regard to analytical studies, results on the capacity of large stationary ad-hoc networks are presented in [18]. Two network scenarios were considered; one including arbitrarily located nodes and traffic patterns, while the other one with randomly located nodes and traffic patterns. An analytical approach on network coverage and connectivity of sensor grids is presented in [19]. The sensors are considered unreliable and fail with a certain probability leading to random grid networks. Results on coverage and connectivity are derived as functions of key parameters such as the number of nodes and their transmission radius.

Several approaches based on simulations and experiments, have been proposed for performance evaluation of IEEE 802.15.4 networks [20]. In [21], an analytical framework based on a Markov chain characterization of the MAC protocol is proposed for IEEE 802.11 networks in saturation conditions. Based on this pioneering work, several approaches have been proposed for the characterization of the MAC performance in IEEE 802.15.4 networks with a star topology. In this work, a scenario with acknowledgement (ACK) messages is considered and an evaulation of the network performance in both saturation and non-saturation regimes is presented, while trying to characterize the conditions under which the network enters the saturation region [22]. A simple Markov chain theoretical model to characterize the sensors as well as the channel status is proposed in [23]. The models shows good agreement with ns-2 based simulations. This model allows to investigate throughput and energy consumption metrics within WSNs. In [24], an extended framework of the one proposed by [23] is presented for a 2-hop network scenario, i.e., networks where sensors communicate with the coordinator through an intermediate relay node, which forwards data packets from the sources (the sensors) towards the destination (the coordinator). Similar works have been presented in [25], [26], emphasising the use of a relay for interconnecting two different clusters in IEEE 802.15.4 networks and analysing the performance through a queueing theoretical analysis. However, the proposed scenario models the (simpler) cases where the relay does not content the medium access to the sensors. Hence, it is observed that accurately characterizing arrivals at the cluster head in WSNs is still an open problem. Although it is quite difficult to analyse each possible application in WSNs, it is sufficient to analyse each class of application classified by data delivery models, as most of these applications in each class have common requirements on the network [27]. A well established simulation tool Castalia which provides realistic node behaviour, wireless channel and radio models, and enables to mimic and analyse the real life scenarios for various types of applications is employed in this study.

III. SYSTEM COMMUNICATION PARADIGM

A system of Wireless Sensor Network with identical sensor nodes deployed in a cluster tree topology is considered. The sensor nodes used are assumed to self-configure during initial deployment and remain stationary thereafter. All the nodes in a cluster and adjacent CHs are considered directly connected to the CH. The primary focus is to study the inter-arrival distribution of packets at the CH. The total arriving data packets at the CH at any given time is therefore equal to the sum of all the independent arrivals from the cluster nodes and arrivals from adjacent CHs forwarding their data to the sink. For this case continuous monitoring of event driven systems are considered.

In this set up all nodes are considered to be equipped with an omnidirectional antenna and they also have a common maximum radio range r within which they are able sense event occurrences and also transmit information to the CH based on the 802.15.4/Zigbee standards. The topology of interest is shown in Figure 1. For simplicity, all sensor nodes are shown connected directly to the CH0 in Figure 1. CH0 can forward data to the sink either through CH1 or CH4, whereas CH2 and CH3 forwards their packets to the sink passing through CH0.

It is also shown that nodes N1 to N8 are directly connected to the CH0.

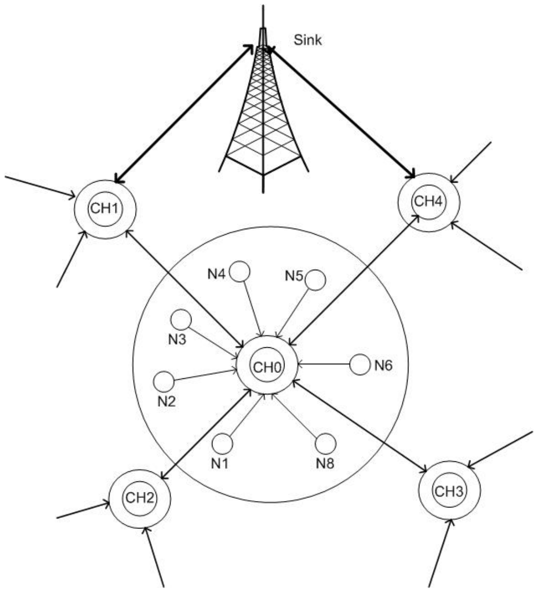

Figure 1: Network topology of the reference scenario

Each sensor node is able to independently monitor its habitat and organise the information sensed into fixed data units storable at the sensor buffer before finally forwarding to the CH. The buffers, both at the sensor nodes and at the CH are assumed to have infinite capacity and are follows First in First out (FIFO) queuing discipline. The Cluster Head is only able to receive or transmit at one go within the assigned time slots of unit duration. Once Information sensed and aggregated at the nodes are forwarded to the CH, it finalizes cluster aggregation and transmits all the information to the sink either directly or through other intermediary CHs. It is assumed that at least one path always exists towards the sink [10].

In this study continuous monitoring applications where the nodes periodically (deterministic) sense and transmit information are considered for various MAC protocols, in order to see the effects of MAC protocols on the distribution of arrival process for the CHs. Castalia simulation environment is employed in order to analyse the inter-arrival distribution at the CH. For each experiment, packet arrival rate and number of nodes is set at desired values. Desired MAC properties; TMAC, CSMA, and no MAC are then considered for each experiment. The generated inter-arrival distribution time results are then further analysed using statistical tools to identify the actual distribution pattern.

IV. NUMERICAL RESULTS AND DISCUSSIONS

In table V below, we report the results of finding theoretical distributions to the empirical arrival distributions of simulated data series at the CH and the intermediary routing nodes. The first column presents the number of observations in the simulated series. The second column displays estimated Maximum Likelihood parameters of empirical distributions [1].

The well-known theoretical distributions corresponding properly to the empirical distributions of the simulated data series are Exponential, Gamma, Log-Normal and Mixed Log-Normal distributions. Columns three and four report the K-S Test Statistics and their P-Values. Although we display Q-Q plots to compare empirical distribution to theoretical distributions whether these two population distributions are exactly the same, we also conduct a statistical test to prove it. Checking by eye, the quantiles for the first distribution versus the quantiles for the second distribution will fall on the 0 – 1 line of the Q-Q plots can be insufficient. It can be both difficult and subjective to decide how differences between distributions will yield various kinds of deviations from a straight line. Appendix B presents details about the probability plots or Q-Q plots.

K-S Test Statistics belong to the goodness of fit tests which indicate whether or not it is reasonable to assume that a random sample comes from a specific distribution. It is used to decide if a sample comes from a population with a specific distribution. It can be applied both for discrete (count) data and continuous binned and both for continuous variables. It is based on a comparison between the empirical distribution function (ECDF) and the theoretical one that is the upper extreme among absolute value differences between ECDF and the theoretical CDF. The hypothesis regarding the distributional form is rejected if the K-S Test Statistic, $KSTS$, is greater than the critical value obtained from a table, or, which is the same, if the P-value is lower than the significance level.

For example in Table I for 10 nodes and employing CSMA as the MAC protocol, the K-S Test Statistic, $KSTS = 0.04$, P-value = 0.45 alternative hypothesis is two sided. Also, wta represents the waiting time of arrivals, while wtf represents waiting time of first part of arrivals and wts represent waiting time of the second part of arrivals. These values are obtained as means of $KSTS$ values and P-values of 141 runs starting from the Lower Confidence Level(LCL) value of the estimated rate parameter of Exponential distribution to the Upper Confidence Values(UCL). It means that we cannot reject null hypothesis that the data follow an Exponential distribution because the P-value is enough higher than significance levels usually referred in statistical literature. Tables[2] II and III present detailed statistical analysis used for estimating the arrival time distributions. Since the wireless channel is essentially a broadcast medium, only a single transmission is allowed in a transmission area by the MAC protocol. As a result, simultaneous transfers are not possible. Moreover, the MAC

---

[1] When the joint density for a set of variables is viewed as a function of the parameters alone, that function is called a *Likelihood function*. Hence the Likelihood function, $L(\theta)$, is defined as $L(\theta) = f_\theta(x)$. Here $\log f_\theta(x)$ is a scalar function of a k-dimensional variable θ and $x = (x_1, x_2, \ldots, x_n)$. A value of the parameter θ that maximizes $L(\theta)$ is called a maximum likelihood estimator (MLE), and is denoted by θ_{ML}. It is often easier to maximize the log-likelihood function, $\log L(\theta)$, and since the (natural) logarithmic function is monotonically increasing in θ, the same value of θ_{ML} maximizes both $L(\theta)$ and $\log L(\theta)$. Under quite general conditions, MLEs have a number of favourable properties. Consistency: Under mild conditions, MLEs converge to the true parameter value as the sample size increases. Asymptotic Normality: As the sample size increases, the distribution of the MLE approaches that of a (potentially) Multivariate Normal variables.

[2] Please note that only few tables and corresponding figures are presented.

Table I: Distribution of Inter-Arrival times, for 10 nodes with CSMA, sending 1 packet/10 minutes; corresponding Figures 2, 3, 4, 5

Number of observation in the simulated series	ML Estimates of the parameters of empirical distribution	Kolmogorov-Smirnov Test statistics	P-values	Corresponding theoretical distribution for the empirical one
All:255 Used:255	Exponential Rate = 20.86 LCL = 18.38 UCL = 23.50	Average of 141 runs :0.04	Average of 141 runs :0.45	Exponential

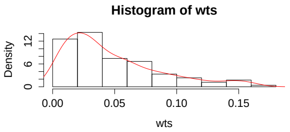

Figure 2: Histogram of inter-arrival times

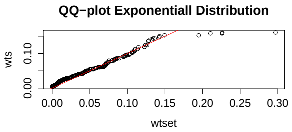

Figure 3: QQ-plot for Exponential Distribution

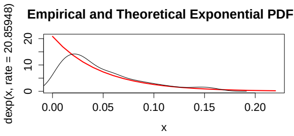

Figure 4: Empirical and Theoretical Exponential PDF

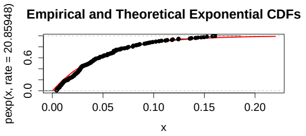

Figure 5: Empirical and Theoretical Exponential CDF

Table II: Distribution of Inter-Arrival times, 20 nodes without MAC, sending 1 packet every 5 minutes; corresponding Figures 6, 7, 8, 9

Number of observation in the simulated series	ML Estimates of the parameters of empirical distribution	Kolmogorov-Smirnov Test statistics	P-values	Corresponding theoretical distribution for the empirical one
All:443 Used:411	Gamma shape = 1.49 scale = 0.03	Average of 100 runs :0.08	Average of 100 runs :0.24	Gamma

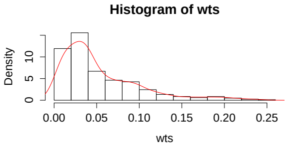

Figure 6: Histogram of inter-arrival times

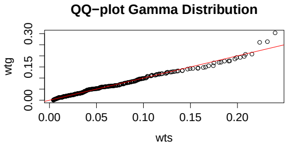

Figure 7: QQ-plot for Gamma Distribution

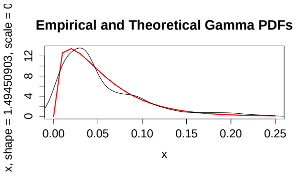

Figure 8: Empirical and Theoretical Gamma PDF

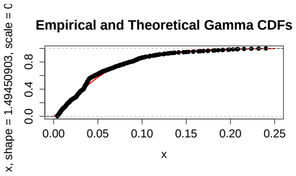

Figure 9: Empirical and Theoretical Gamma CDF

Table III: Distribution of Inter-Arrival times for 35 nodes, with TMAC, sending 1 packet every 5 minutes; corresponding Figures 10, 11, 12, 13, 14, 15, 16

Number of observation in the simulated series	ML Estimates of the parameters of empirical distribution	Kolmogorov-Smirnov Test statistics	P-values	Corresponding theoretical distribution for the empirical one
All:990 Used:958 First part: 914 Second part: 44	Mixed Log-Normal Meanlog1 = -5.23 Sdlog1 = 0.23 Meanlog2 = -0.62 Sdlog2 = 0.09 Mixing proportion: 0.05	Average of 100 runs :0.19	Average of 100 runs : $3.18 * e^{-14}$	An unknown Mixed distribution

Table IV: Average end-to-end delay for various application rates and MAC protocols applied

	1 packet every 5 min			1 packet every 5 sec			5 packet every sec		
Nodes	No MAC	TMAC	CSMA	No MAC	TMAC	CSMA	No MAC	TMAC	CSMA
10	0.03685413	0.03812471	0.03710934	0.036910934	0.0401187	0.039160543	0.040109	0.05791289	0.050281007
20	0.043585577	0.046399014	0.044012909	0.043902188	0.04895094	0.0462243	0.048610932	0.068023776	0.060010211
35	0.053775437	0.057112543	0.05489443	0.0539886	0.0600218	0.058330089	0.059124145	0.081778643	0.070666612
40	0.060177122	0.066062393	0.06276331	0.060289387	0.069779437	0.065319035	0.068324234	0.090668109	0.081224243

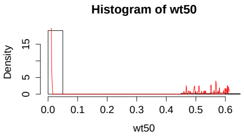

Figure 10: Histogram of Inter arrival times

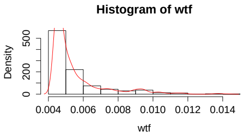

Figure 11: Histogram of Inter arrival times first part

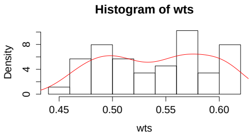

Figure 12: Histogram of Inter arrival times second part

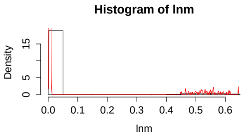

Figure 13: Histogram of log-normal distribution

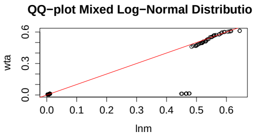

Figure 14: QQ-plot of Mixed Log-Normal Distribution

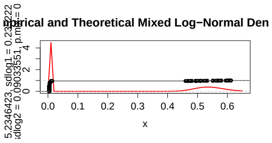

Figure 15: Empirical and Theoretical Mixed Log-Normal Densities

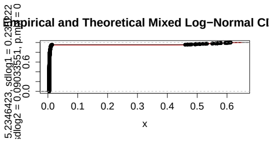

Figure 16: Empirical and Theoretical Mixed Log-Normal CDF

Table V: Summary for Inter arrival time distributions for various application categories

S.No	Application Type	Packet Rate (1packet/time)	Inter arrival time distribution		
			No MAC	TMAC	CSMA
1	Environment monitoring, Smart agriculture [28], [29]	5 - 10 min	Exponential for 10-15 nodes	Mixed-Log normal for 10-15 nodes	Exponential for 10-15 nodes
2	Traffic monitoring, Vehicle tracking [30], [31]	5 - 10 sec	Gamma for 20-30 nodes	Unknown Mixed distribution	Unknown mixed distribution
3	Military applications, BANs [32], [33]	1 sec or higher	Constant	Unknown mixed distribution	Unknown non-Exponential

layer introduces a non-deterministic delay for channel access because of the activities of other nodes. If a neighbor of a node is transmitting a packet, the MAC protocol delays the transmission for a random amount of time to prevent collisions with the ongoing transmission as well as other neighbours that are trying to access the channel. This may significantly impact the performance of the network. The delay incurred due to various MAC protocols for different application rates is presented in Table IV.

V. CONCLUSION

To the best of our knowledge, this is the first work that provides statistical proof for finding theoretical distributions of arrivals at the CH and relay nodes in WSNs. A clustered model is considered characterised by its sending rate, inter-arrival distribution and the service process. The empirical distributions of inter-arrival times of the packets considering such physical events that do not occur frequently are generally assumed by Poisson processes, and the inter-arrival times by exponential distributions. The general practice in published works is thus to compare empirical exponential arrival distributions of wireless sensor networks with theoretical exponential distributions in Q-Q plot diagrams. In this paper, we show that such comparisons based on simple eye checks are not sufficient since in many cases incorrect conclusions may be drawn from such plots. After estimating Maximum Likelihood parameters of empirical distributions, we generate theoretical distributions based on the estimated parameters. By conducting Kolmogorov-Smirnov Test Statistics for each generated data series, we find out, if it is possible, a corresponding theoretical distribution. Empirical exponential arrival distribution assumption of wireless sensor networks holds only for a few cases. There are both theoretically known such as Gamma, Log-normal and Mixed Log-Normal of arrival distributions and theoretically unknown such as non-Exponential and Mixed arrival distributions in wireless sensor networks. The effects caused by MAC properties are also analysed by experimenting with well known MAC protocols and the summary of the inter arrival time distributions after extensive tests are presented for various application categories in V. Therefore, these results confirm that the assumption of exponential inter-arrival distributions does not hold in all the cases. Exponential arrival distribution assumption of wireless sensor networks holds only when a fewer nodes (10-15), sending packet every 5-10 minutes with no MAC properties, as-well as when CSMA properties are considered.

ACKNOWLEDGMENT

The authors would like to thank the members of **SENSOLAB** for their valuable feedback.

REFERENCES

[1] K. Doddapaneni, E. Ever, O. Gemikonakli, I. Malavolta, L. Mostarda, and H. Muccini, "A model-driven engineering framework for architecting and analysing wireless sensor networks," in *Software Engineering for Sensor Network Applications (SESENA), 2012 Third International Workshop on*, pp. 1–7, 2012.

[2] N. Bouabdallah, M. E. Rivero-Angeles, and B. Sericola, "Continuous monitoring using event-driven reporting for cluster-based wireless sensor networks," *IEEE Transactions on Vehicular Technology*, vol. 58, no. 7, pp. 3460–3479, 2009.

[3] Y. Wang, M. C. Vuran, and S. Goddard, "Cross-layer analysis of the end-to-end delay distribution in wireless sensor networks," *IEEE/ACM Transactions on Networking (TON)*, vol. 20, no. 1, pp. 305–318, 2012.

[4] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer networks*, vol. 38, no. 4, pp. 393–422, 2002.

[5] K. Doddapaneni, F. A. Omondi, E. Ever, P. Shah, O. Gemikonakli, and R. Gagliardi, “Deployment challenges and developments in wireless sensor networks clustering,” in *2014 28th International Conference on Advanced Information Networking and Applications(AINA)*, pp. 227–232, May 2014.

[6] I. Dbibih, O. Zytoune, and D. Aboutajdine, “On/off markov model based energy-delay aware mac protocol for wireless sensor network,” *Wireless Personal Communications*, vol. 78, no. 2, pp. 1143–1155, 2014.

[7] F. Omondi, E. Ever, P. Shah, and O. Gemikonakli, “Modelling wireless sensor networks for performability evaluation,” in *Ad-hoc, Mobile, and Wireless Network* (J. CichoÅĎ, M. GÈl’bala, and M. Klonowski, eds.), vol. 7960 of *Lecture Notes in Computer Science*, Springer Berlin Heidelberg, 2013.

[8] Y. Zhang and W. W. Li, “Modeling and energy consumption evaluation of a stochastic wireless sensor network.,” *EURASIP J. Wireless Comm. and Networking*, p. 282, 2012.

[9] Y. Zhang and W. Li, “An energy-based stochastic model for wireless sensor networks.,” *Wireless Sensor Network*, vol. 3, no. 9, pp. 322–328, 2011.

[10] C. Chiasserini and M. Garetto, “Modeling the performance of wireless sensor networks,” in *INFOCOM, Twenty-third AnnualJoint Conference of the IEEE Computer and Communications Societies*, vol. 1, pp. 4 vol. (xxxv+2866), march 2004.

[11] C. Chiasserini and M. Garetto, “An analytical model for wireless sensor networks with sleeping nodes,” *IEEE Transactions on Mobile Computing*, vol. 5, pp. 1706–1718, Dec 2006.

[12] S. Singh and C. S. Raghavendra, “Pamas—power aware multi-access protocol with signalling for ad hoc networks,” *SIGCOMM Comput. Commun. Rev.*, vol. 28, pp. 5–26, July 1998.

[13] W. Ye, J. Heidemann, and D. Estrin, “An energy-efficient mac protocol for wireless sensor networks,” in *Proceedings of the IEEE Infocom*, (New York, NY, USA), pp. 1567–1576, IEEE, June 2002.

[14] C. Schurgers, V. Tsiatsis, S. Ganeriwal, and M. Srivastava, “Topology management for sensor networks: Exploiting latency and density,” in *Proceedings of the 3rd ACM International Symposium on Mobile Ad Hoc Networking &Amp; Computing*, MobiHoc ’02, (New York, NY, USA), pp. 135–145, ACM, 2002.

[15] R. Zheng, J. C. Hou, and L. Sha, “Asynchronous wakeup for ad hoc networks,” in *Proceedings of the 4th ACM International Symposium on Mobile Ad Hoc Networking and Computing*, MobiHoc ’03, (New York, NY, USA), pp. 35–45, ACM, 2003.

[16] T. Qiu, L. Feng, F. Xia, G. Wu, and Y. Zhou, “A packet buffer evaluation method exploiting queueing theory for wireless sensor networks.,” *Comput. Sci. Inf. Syst.*, vol. 8, no. 4, pp. 1028–1049, 2011.

[17] A. F. Mini, B. Nath, and A. A. F. Loureiro, “A probabilistic approach to predict the energy consumption in wireless sensor networks,” pp. 23–25, 2002.

[18] P. Gupta and P. Kumar, “The capacity of wireless networks,” *IEEE Transactions on Information Theory*, vol. 46, no. 2, pp. 388–404, 2000.

[19] S. Shakkottai, R. Srikant, and N. Shroff, “Unreliable sensor grids: coverage, connectivity and diameter,” vol. 2, pp. 1073–1083 vol.2, 2003.

[20] G. Ferrari, P. Medagliani, S. D. Piazza, and M. Martalò, “Wireless sensor networks: performance analysis in indoor scenarios,” *EURASIP J. Wirel. Commun. Netw.*, no. 1, pp. 41–41, 2007.

[21] G. Bianchi, “Performance analysis of the ieee 802.11 distributed coordination function,” *IEEE J.Sel. A. Commun.*, vol. 18, pp. 535–547, Sept. 2006.

[22] J. Misic, S. Shafi, and V. Misic, “Performance of a beacon enabled ieee 802.15.4 cluster with downlink and uplink traffic,” *IEEE Transactions on Parallel and Distributed Systems*, vol. 17, no. 4, pp. 361–376, 2006.

[23] I. Ramachandran, A. K. Das, and S. Roy, “Analysis of the contention access period of IEEE 802.15.4 MAC,” *ACM Trans. Sen. Netw.*, vol. 3, no. 1, p. 4, 2007.

[24] M. Martalò, S. Busanelli, and G. Ferrari, “Markov chain-based performance analysis of multihop ieee 802.15.4 wireless networks,” vol. 66, no. 12, pp. 722–741.

[25] J. Misic, J. Fung, and V. Misic, “Interconnecting 802.15.4 clusters in master-slave mode: queueing theoretic analysis,” in *ISPAN 2005. Proceedings. 8th International Symposium on Parallel Architectures,Algorithms and Networks,.*, pp. 8 pp.–, 2005.

[26] J. Misic and R. Udayshankar, “Slave-slave bridging in 802.15.4 beacon enabled networks,” in *Wireless Communications and Networking Conference, 2007.WCNC 2007. IEEE*, pp. 3890–3895.

[27] I. Emary and S. Ramakrishnan, *Wireless Sensor Networks: From Theory to Applications*. Telecommunications books, Taylor & Francis, 2013.

[28] A. Mainwaring, D. Culler, J. Polastre, R. Szewczyk, and J. Anderson, “Wireless sensor networks for habitat monitoring,” in *Proceedings of the 1st ACM international workshop on Wireless sensor networks and applications*, WSNA ’02, (New York, NY, USA), pp. 88–97, ACM, 2002.

[29] A. Boulis, C.-C. Han, and M. B. Srivastava, “Design and implementation of a framework for efficient and programmable sensor networks,” in *Proceedings of the 1st International Conference on Mobile Systems, Applications and Services*, MobiSys ’03, (New York, NY, USA), pp. 187–200, ACM, 2003.

[30] W. Heinzelman, A. Murphy, H. Carvalho, and M. Perillo, “Middleware to support sensor network applications,” *Network, IEEE*, vol. 18, pp. 6–14, Jan 2004.

[31] K. RÃűmer, “Tracking real-world phenomena with smart dust,” in *In EWSN 2004*, pp. 28–43, Springer-Verlag, 2004.

[32] L. Schwiebert, S. K. Gupta, and J. Weinmann, “Research challenges in wireless networks of biomedical sensors,” in *Proceedings of the 7th Annual International Conference on Mobile Computing and Networking*, MobiCom ’01, (New York, NY, USA), pp. 151–165, ACM, 2001.

[33] M. Storey, G. Blair, and A. Friday, “Mare: Resource discovery and configuration in ad hoc networks,” *Mob. Netw. Appl.*, vol. 7, pp. 377–387, Oct. 2002.