This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2016.2573679, IEEE Internet of Things Journal

Distributed Timely-Throughput Optimal Scheduling for the Internet of Nano-Things

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***Abstract*—Nanotechnology is enabling the development of miniature devices able to perform simple tasks at the nanoscale. The interconnection of such nano-devices with traditional wireless networks and ultimately the Internet enables a new networking paradigm known as the Internet of Nano-Things (IoNT). Despite their promising applications, nano-devices have constrained power, energy and computation capabilities along with very limited memory on board, which may only be able to hold one packet at once and, thus, requires packets to be delivered before certain hard deadlines. Towards this goal, a fully-distributed computation-light provably-correct scheduling/MAC protocol is introduced for bufferless nano-devices, which can maximize the network throughput, while achieving perpetual operation. More specifically, the proposed scheduling algorithm allows every nano-device to make optimal transmission decisions locally based on its incoming traffic rate, virtual debts, and channel sensing results. It is proven that the proposed algorithm is timely-throughput optimal in the sense that it can guarantee reliable data delivery before deadlines as long as the incoming traffic rates are within the derived maximum network capacity region. This feature not only can lead to high network throughput for the IoNT, but also guarantees that the memory of each device is empty before the next packet arrives, thus addressing the fundamental challenge imposed by the extremely limited memory of nano-devices. In addition, the optimal deadline is derived, which guarantees that all the nano-devices can achieve perpetual communications by jointly considering the energy consumption of communications over the THz channel and energy harvesting based on piezoelectric nano-generators.**

***Index Terms*—Internet of Nano-Things, Nanonetworks, Scheduling, Terahertz Band**

This project was funded by the National Plan for Science, Technology and Innovation (MAARIFAH)-King Abdulaziz City for Science and Technology-the Kingdom of Saudi Arabia- award number 12-NAN-2730-03. The authors also acknowledge with thanks the Science and Technology Unit, King Abdulaziz University for technical support.

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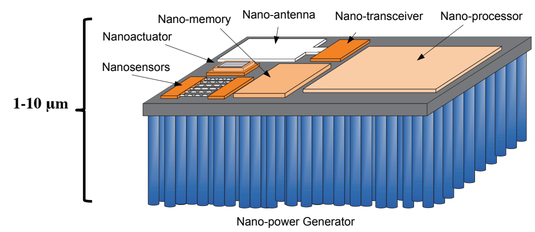

Fig. 1. System Overview of Nano-devices [2]

I. Introduction

Nanotechnology is providing a new set of tools to the engineering community to create nanoscale components with very specific functionalities, such as computing, data storing, sensing and actuation. As shown in Fig. 1, advanced nano-devices can be created by integrating several of these nano-components in a single entity, which leads to promising applications in diverse fields. For example, nanosensors exploit the unique properties of novel nanomaterials to detect physical, chemical and biological events at the nanoscale [1]. The size of individual nanosensors is in the order of a few cubic micrometers, which enables non-invasive deployments but, at the same time, requires very large node densities, in the order of a few nanosensors per cubic millimeter. The interconnection of such nano-devices with traditional wireless communication networks and, ultimately, the Internet, defines a new networking paradigm known as the Internet of Nano-Things (IoNT) [2]. The IoNT enhances the existing applications of the Internet of Things (IoT) and brings in many new applications, such as intra-body health monitoring and drug delivery systems, agriculture plague and air pollution control [3], and surveillance systems against new types of biological and chemical attacks.

The peculiarities of nano-things introduce many challenges in the realization of the IoNT. On the one hand, the miniaturization of classical antennas to meet the size requirements of nano-devices would impose the use of very high operating frequencies (hundreds of Terahertz), which would limit the feasibility of the IoNT. To overcome this limitation, graphene-based nano-transceivers and nano-antennas have been recently proposed [4], [5], [6], [7]. These allow nano-devices to communicate in the Terahertz (THz) band (0.1-10 THz). The THz band suffers from a very high propagation loss, while providing a very large bandwidth, which can be used to develop simple but yet efficient medium sharing schemes.

On the other hand, the very limited amount of memory

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equipped on the nano-devices may only allow one packet to be temporarily queued before being transmitted [2]. This means that if the current packet is not delivered before the next packet arrives, the current packet has to be dropped. Consequently, the protocols designed for nanonetworks, i.e., networks of nano-devices, not only need to guarantee high throughput, but also need to ensure that the packet is delivered before certain deadlines. Besides memory size, nano-batteries can only hold very limited amount of energy and it is infeasible to manually recharge or replace them. To counter such challenge, nanoscale energy harvesting systems [8], [9], [10] have been developed. Power nano-generators convert vibrational, fluidic, electromagnetic or acoustic energy into electrical energy. By using energy harvesting systems wireless nano-devices can achieve perpetual operation if the energy consumption process and the energy harvesting process are jointly optimized.

Wireless scheduling, as one of the most critical networking operations, aims to coordinate the communications of network devices so that network resources can be efficiently allocated among those devices for the desired network performance. However, classical MAC protocols cannot directly be used in the IoNT because they do not capture (i) the small-capacity memory of nano-devices, which may only hold one packet; (ii) the limited processing capabilities of nano-devices, which requires the development of ultra-low-complexity protocols [1]; (iii) the peculiarities of the THz band [11], i.e., the very high path-loss and the very large distant-dependent bandwidth; and, (iv) the temporal energy fluctuations of nano-devices due to the behavior of power nano-generators [12]. Therefore, there is a need to revisit the traditional MAC design and propose new solutions tailored to this paradigm.

In this paper, we address the above mentioned challenges by developing a fully-distributed computation-light provably-correct scheduling/MAC protocol for bufferless nano-things, which can maximize the network throughput, while achieving perpetual operations. More specifically, we design a distributed timely-throughput optimal scheduling algorithm, which distributively determines the optimal transmission times for nano-devices so that the largest set of traffic rates can be supported, while ensuring timely data delivery within deadlines. Towards this, we first derive the optimal deadline, which guarantees that all the nano-devices can achieve perpetual communications by jointly considering the energy consumption of THz communications and energy charging with piezoelectric nano-generators. Then, we reveal the maximum network capacity region that timely-throughput optimal scheduling algorithms can achieve. Next, we develop a fully distributed scheduling algorithm by exploiting the principles of CSMA Markovian chain and Lyapunov optimization in such a way that every user can make optimal transmission decision locally based on its incoming traffic rate, and virtual debt queue length. Moreover, we also extend the proposed algorithm to incorporate the transmission priorities for difference sensors. Finally, we prove that the proposed scheduling algorithms are timely-throughput optimal in the sense that it can guarantee the timely data delivery before the deadline, e.g., the time when the next packet arrives, as long as the incoming traffic rates are within the maximum network capacity region.

The contributions of this paper are summarized as follows

- We rigorously formulate the timely-throughput optimal scheduling problem for IoNT, which addresses the fundamental challenges of achieving high throughput under the inherent energy and memory limits of nano-sensors.
- We derive the optimal transmission deadline for nano-sensors, which reveals the inherent relationship between the energy consumption process of Terahertz bands and the energy harvesting process from nano-generators.
- We propose two fully-distributed scheduling algorithms for bufferless nano-devices, which aim to maximize the network throughput with transmission deadlines, while achieving perpetual operations in the IoNT.
- We rigorously reveal the maximum network capacity region and prove the timely-throughput optimality of the proposed scheduling algorithms.
- we carry on simulation studies to verify the optimality of the proposed solutions.

The rest of the paper is organized as follows. In Sec. III, we introduce the system model and formally define the timely-throughput optimal scheduling problem. We propose our distributed scheduling algorithms, which are provable timely-throughput optimal, in Sec. IV. In Sec. V, we present the simulation results, and we conclude the paper in Sec. VI.

II. Related work

There are not many MAC solutions for IoNT for the time being. In [13], we proposed the PHLAME, the first MAC protocol for ad hoc nanonetworks. In this protocol, nano-devices such as nanosensors are able to dynamically choose different physical layer parameters based on the channel conditions and the energy of the nano-devices. These parameters were agreed between the transmitter nano-device and the receiver nano-device by means of a handshaking process. However, there are two limitations in the PHLAME. On the one hand, as shown in the paper, the use of a handshake process can limit the real potential of the THz band. On the other hand, nano-devices might not have enough computational resources to dynamically find the optimal communication parameters.

More recently, we have proposed an energy and spectrum-aware MAC protocol for nanonetworks in the THz band [14]. Such MAC protocol aims to achieve fair, throughput and lifetime optimal channel access by jointly optimizing the energy harvesting and consumption processes, while taking into account the unique features of THz channels and the piezoelectric power nano-generator. Despite its promising feature, it has two fundamental limitations which impede its practical application. First, its design does not take into account the limited memory of nano-devices by assuming there is sufficiently large memory on board. Therefore, data packets do not need to be delivered before hard deadlines. Second, it is inherently a centralized algorithm, which has limited scalability. In [15], a receiver-initiated MAC protocol for nanosensor networks was proposed, which implements the TDMA algorithm in a distributed manner, thus leading to scalable networking performance. However, this protocol did not take into account the limited memory capacity of the nano-devices and cannot maximize the network throughput.

In the past few years, there have been increased interests in designing optimal wireless scheduling algorithms with hard deadlines, which, however, generally focus on the centralized

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implementation and thus is not suitable for distributed networks [16], [17]. What is more important, these algorithms did not take into account the unique properties of THz channel and the energy harvesting features of nano-generators. On the other hand, recent advance in distributed scheduling algorithms mainly focuses on designing CSMA-type protocols to achieve maximum network throughput in a fully distributive manner [18], [19]. However, it is inherently difficult for distributed scheduling algorithms to promise high throughput while maintaining low average delay [20]. Moreover, even if low average delay can be achieved, it is still not sufficient to allow data to be delivered within hard deadlines before being dropped at the time the next packet arrives.

III. System Model

A. Nano-device Model

The capabilities of nano-devices introduce major constraints in the design of protocols for the IoNT, including

- **Very limited computational capabilities**: Onboard nano-processors are being enabled by the development of smaller transistors [21]. The smallest transistor that has been experimentally tested to date is based on a thin graphene strip, which is made of just 10 by 1 carbon atoms [22]. These transistors are not only smaller, but also able to operate at much higher frequencies (up to a few THz). However, the complexity of the operations that a nano-processor will be able to handle depends on the number of transistors in the chip, thus, on its total size. We capture this peculiarity by designing a low-complexity and fully distributed MAC protocol, which is explained in detail in section IV-B and IV-C.
- **Very limited memory space:** Nanomaterials and new manufacturing processes are enabling the development of much denser memories, in which the storage of one bit of information might eventually require just a few atoms [23], [24]. For example, in a magnetic memory [25], atoms are placed over a surface by means of magnetic forces. Ultimately, however, the total amount of information storable in a nano-memory will ultimately depend on its dimensions. By taking into account that the total size of a nano-device is in the order of a few cubic micrometers at most, it is unlikely for a nano-thing to be able to store more than one data packet at a time.
- **Continuous energy harvesting for normal operation:** Despite major developments in the field of nano-batteries [26], the amount of energy that can be stored in the nano-device battery is extremely low. As a result, nano-devices can only complete a very few tasks with a single battery charge. Due to the impossibility to manually recharge or replace the batteries of the nano-devices, novel energy harvesting nano-systems have been developed [8], [9], [10]. In contrast to the classical battery-powered devices, the energy of the self-powered devices does not just decrease until the battery is empty, but it has both positive and negative fluctuations. As a result, the lifetime of energy harvesting networks can tend to infinity provided that the energy harvesting and the energy consumption processes are jointly designed. We capture this peculiarity in our protocol by designing the energy-aware deadline for nano-things, which jointly considers the energy consumption process due to communication in the THz band and the energy harvesting process by means of a piezoelectric nano-generator, as we explain in Sec. IV-A

By addressing above three challenges, this paper will develop a fully-distributed computation-light provably-correct scheduling/MAC protocol for bufferless nano-devices, which can maximize the network throughput, while achieving perpetual operations in the IoNT.

B. Network Model

Consider a fully-connected network with N nano-devices sharing a single wireless channel. The memory of each nano-device is limited and can only temporally store one packet. Time is slotted with size of T. Due to the energy constraints of nano-sensors, T should be large enough to allow nano-sensor to recharge itself and have sufficient energy to transmit one packet. The optimal value of T is determined by the Terahertz channel capacity and the recharging rate of nano-generator, which is derived in Section IV.A. At the beginning of each slot, each nano-device i generates one packet with probability λ_i. We denote such packet arrival process by $N_i(t)$. The packets from all users need to be delivered within a delay bound of T. In other words, packets that are generated at the beginning of a slot interval are only useful if they are delivered no later than the end of the interval. If a packet is not delivered with the time interval, the packet is dropped. By this way, it is guaranteed that the delay of every delivered packet is at most T. This also ensures that the memory is empty before next packet arrives. Since wireless channel is inherently lossy, each user i has a packet error rate $1 - m_i$, which means with probability m_i, a packet is delivered without errors. m_i can be different from user to user because of the channel diversity.

Based on the above network model, we formally define the time-throughput optimal scheduling problem as follows.

Definition 1 *(**Timely-delivery Ratio**) To enforce the QoS, each user can demand a timely-delivery ratio a_i, which means that at least a percentage a_i of packets from user i have to be delivered without errors before the deadline.*

Definition 2 *(**Viable Schedule**) A scheduling algorithm is viable if it can yield a transmission order for the network users in such a way that all network users can meet their respective timely-delivery ratio.*

Definition 3 *(**Maximum Achievable Capacity Region**) The maximum network capacity region is the closure of the set of all arrival rate vectors under which there exists an viable scheduling algorithm.*

Definition 4 *(**Timely-throughput Optimal Scheduling**) A scheduling policy is timely-throughput optimal if it is viable for any arrival rates within the maximum network capacity region.*

To develop the time-throughput optimal scheduling algorithms, we construct the following queueing system with virtual debt queues. Assign an virtual debt queue (i.e., a counter) D_i to each nano-device i. Let $D_i(t)$ denote the length of the queue D_i by the end of time interval t. Let $A_i(t) = a_i$ denote

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the debt arrival process of queue D_i, where a_i is the actually required timely-delivery ratio of sensor i defined in Definition 1. Specifically, $A_i(t) = a_i$ means that at the beginning of each slot i, a new debt of size a_i arrives at queue D_i. Define $H_i(t)$ as the scheduling decision of sensor i during the time slot t, where $H_i(t)$ characterizes the transmission time of sensor i during time slot t and $H_i(t) \leq 1$. Let $M_i(t) \in \{0, 1\}$ denote the successful packet deliver rate over lossy wireless channel. Let m_i denote the packet loss rate of sensor i, we have

$$P(M_i(t) = 1) = 1 - m_i \tag{1}$$

Then, the queueing system with virtual debt queues can be represented by

$$D_i(t+1) = D_i(t) - H_i(t)R_i(t) + A_i(t), \tag{2}$$

where $R_i(t) = N_i(t)M_i(t)$ denote how much debts can be paid off after time slot t. $R_i(t)$ indicates one debt can be removed if the sensor has one packet in its memory (i.e., $N_i(t) = 1$) and this packet is successfully delivered without errors $M_i(t) = 1$.

By defining $S_i(t)$ as the total amount of debts which are released from queue i at time interval k under a certain scheduling policy, the queueing dynamics in (2) can be rewritten by

$$D_i(t+1) = D_i(t) - S_i(t) + A_i(t). \tag{3}$$

where $S_i(t) = R_i(t)H_i(t)$.

Let D_i denote the steady-state queue length of $D_i(k)$. Based on the queueing dynamics of (3), we have the following lemma.

Lemma 1 *A scheduling algorithm is viable if and only if it can strongly stabilize the virtual debt queueing system so that* $E[D_i] \leq \infty, \forall 1 \leq i \leq N$.

Proof: Recall that $N_i(t)$ is the number of packet that user i generates at the beginning of time interval T, and need to be delivered before the deadline T, and $1 - m_i$ is the packet error rate of user i. It follows by (3) that $S_i(t) = H_i(t)N_i(t)M_i(t)$ is actually the number of packets transmitted by user i before the deadline T without errors. Therefore, on one hand, it follows by definition 2 that if a scheduling algorithm is viable, it has to guarantee that $E[S_i(t)] \geq E[A_i(t)] = a_i, \forall 1 \leq i \leq N$, which means the virtual debt queueing system is strongly stable, i.e., $E[D_i] < \infty, \forall 1 \leq i \leq N$. On the other hand, if the virtual debt queueing system is strongly stable, this necessarily implies that $E[S_i(t)] = E[A_i(t)] = a_i, \forall 1 \leq i \leq N$. ■

IV. Distributed Maximum Debt Scheduling

In this section, we first derive the optimal time slot T in such a way that all the nano-devices in the network can achieve perpetual operations by balancing the energy consumption for transmissions and energy harvesting through nano generators. Then, we propose the distributed maximum debt scheduling algorithm, develop its achievable network capacity region, and prove that DMDS is timely-throughput optimal.

A. Energy-aware Deadline Design

The energy limitations of nano-devices impose strict constraints in the achievable throughput. In particular, to guarantee that nano-nodes can harvest enough energy before attempting to transmit a packet, a minimum slot time needs to be defined. In this section, we compute the minimal slot time needed to guarantee that a nano-node can harvest the energy needed to transmit one packet in the next time slot.

For this, our starting point is the energy model introduced in [12], which can accurately reproduce experimental measurements. We are interested in the energy harvesting rate, i.e., the speed at which the battery is replenished, λ_{harv}. The energy in the battery E_{batt} can be written as

$$E_{batt} = \frac{1}{2} V_g^2 C_{cap} \left(1 - \exp\left(-\frac{\Delta Q}{V_g C_{cap}} n_{cycle}\right)\right), \tag{4}$$

where V_g is the generator voltage, C_{cap} refers to the ultra-nano-capacitor capacitance, and ΔQ is the electric charge harvested per cycle. From this, the energy harvesting rate is obtained as:

$$\begin{aligned} \lambda_{harv} &= \frac{\partial E_{batt}}{\partial n_{cycle}} \lambda_{cycle} \\ &= \frac{1}{2} C_{cap} V_g^2 \left(2 \frac{\Delta Q}{V_g C_{cap}} \exp\left(-\frac{\Delta Q}{V_g C_{cap}} n_{cycle}\right)\right. \\ &\quad \left. -2 \frac{\Delta Q}{V_g C_{cap}} \exp\left(-2 \frac{\Delta Q}{V_g C_{cap}} n_{cycle}\right)\right) \lambda_{cycle}, \end{aligned} \tag{5}$$

where λ_{cycle} is the vibration frequency or compression-release rate of the ZnO nanowires, and the rest of parameters have already been defined.

From [14], the average energy per bit consumption E_{bit} as a function of the transmission distance d can be obtained as

$$E_{bit}(d) = \frac{SNR \int_{B_{3dB}(d)} A(d, f) S_{N_0}(d, f) \, df}{B_{3dB}(d) \log_2(1 + SNR)}, \tag{6}$$

where SNR stands for the signal-to-noise ratio required for achieving the target packet loss rate m given in (1) [27], A is the path-loss of the THz-band channel, S_{N0} is the noise power spectral density, f stands for frequency and B_{3dB} refers for the 3-dB bandwidth at a distance d of the transmitter. A, S_{N0} and B_{3dB} are computed as in [14], and their derivation is skipped for brevity.

For a target maximum transmission distance d_{max} m and SNR, the maximum energy per bit consumption is fixed. Considering that l-bit-long packets are transmitted, the lower bound on the slot time can be then obtained as

$$T = \frac{l E_{bit}(d_{max})}{\lambda_{harv}}, \tag{7}$$

where all the parameters have already been defined. In Figure 2, the minimum slot time is shown as a function of the transmitted distance, when transmitting packets with $l = 1024$ bits, SNR=10 dB, and C_{cap}=9 nF, V_g=0.42 V, λ_{cycle} =50 cycles/s, and $\Delta Q = 6$ pC.

B. Distributed Maximum Debt Scheduling Algorithm

Definition 5 ***(DMDS Algorithm)***

Step I*: at the beginning of each time slot t, each sensor i determines the length of its channel sensing period τ_i by*

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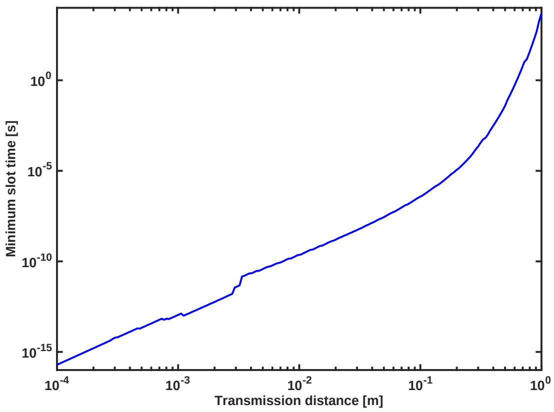

Fig. 2. Minimum slot time (7) as a function of the transmission distance.

independently generating an exponentially distributed random variable with the mean $\exp(-w_i(t))$*, i.e.,*

$$P(\tau_i > x) = \exp\Big(-\exp(w_i(t)x\Big) \tag{8}$$

and

$$w_i(t) = \min\left(D_i(t)R_i(t), w^*\right), \tag{9}$$

where w^* *is the predefined maximum value of* $w_i(t)$*.*

Step II*: during this sensing period* τ_i*, if no transmissions from other users are detected, the sensor* i *transmits its packets until the end of the time slot.*

It can be shown by CSMA Markovian chain [28] that the average service rate provided to the sensor i during time slot t is given by

$$E[H_i(t)] = \frac{\exp(w_i)}{Z}\left(1 - \frac{1}{Z}\right), \tag{10}$$

where $Z = \sum_{i=1}^{N}\exp(w_i)$, $\exp(w_i)/Z$ is the probability that sensor i grabs the channel during t, and $1 - \frac{1}{Z}$ is the average transmission time sensor i can have during the time slot t.

Remark 1 By step 1 and 2, it is easy to see that DMDS algorithm is fully distributive with very low complexity, where each sensor can make transmission decision only based on its local information, including its debt value, the channel sensing result, and channel reliability condition.

Next, we first derive the network capacity region of DMDS so that as long as the incoming traffic vector is within such region, the network is stable.

Theorem 1 *If a scheduling policy is viable, then we have*

$$\sum_{i\in\mathbf{V}}\frac{a_i}{m_i} \le \left(1 - \prod_{i\in\mathbf{V}}(1-\lambda_i)\right)\left(\frac{|\mathbf{V}|\exp(w^*)-1}{|\mathbf{V}|\exp(w^*)}\right), \quad \forall \mathbf{V} \subset \{1,...,N\}. \tag{11}$$

Remark 2 It can be shown that as the w^* becomes large enough, the stability region of DMDS approaches the largest possible one, i.e., $\sum_{i\in\mathbf{V}}\frac{a_i}{m_i} \le \left(1-\prod_{i\in\mathbf{V}}(1-\lambda_i)\right)$, as $w^* \to \infty$. By above theorem and the similar techniques of proving the following theorem 2, it is easy to show that the DMDS is timely-throughput optimal if the incoming traffic arrivals from all sensors are within the network capacity region. Moreover, the DMDS is very suitable for fast fading environment because of its negligible hitting time of the underlying CSMA Markov chain [28]. It is worth to note that to derive the capacity region, we assume the time slot T should be large enough to allow the nanosensor to recharge itself and have sufficient energy to send one packet. In other words, T follows equation (7).

Proof: See appendix for detailed proof. ■

C. Distributed Maximum Debt-α Scheduling

In this section, we develop a generalized version of DMDS algorithm, namely, the distributed Maximum Debt-α Scheduling (DMDS-α) algorithm and prove that DMDS-α is also timely-throughput optimal. Compared with DMDS algorithm, DMDS-α allows us to assign different priority to different sensors by using different α parameters.

Definition 6 ***(DMDS-α Algorithm)***

Step I*: at the beginning of each time slot* t*, each sensor* i *determines the length of its channel sensing period* τ_i *by independently generating an exponentially distributed random variable with the mean* $\exp(-w_i(t))$*, i.e.,*

$$P(\tau_i > x) = \exp\Big(-\exp(w_i(t)x\Big) \tag{12}$$

and

$$w_i(t) = \min(D_i(t)^{\alpha_i}R_i(t), w^*), \tag{13}$$

where the sensors with higher priority will be assigned with larger value of α*.*

Step II*: during this sensing period* τ_i*, if no transmissions are detected, the sensor* i *transmits its packets until the end of the time slot.*

Remark 3 Based on the Step 1 of DMDS-α, it is easy to see that the sensors assigned with larger α have higher probability to use small sensing period. This by Step 2 increases the chance of the sensor to win the competitions with other nodes, thus leading to higher priority to transmit.

Theorem 2 *Under DMDS-α algorithm, the network is strongly stable if*

$$\sum_{i\le N}\frac{a_i}{m_i} < \left(1 - \frac{N}{\exp(w^*)}\right)\left(1 - \frac{1}{\exp(w^*)}\right)\left(1 - \prod_{i\le N}(1-\lambda_i)\right). \tag{14}$$

Remark 4 Combining with lemma 1, the above theorem indicates DMDS-α algorithm is timely-throughput optimal as w^* approaches infinity. In other words, the stability region of DMDS-α approaches the largest possible one, i.e., $\sum_{i\in\mathbf{V}}\frac{a_i}{m_i} \le \left(1-\prod_{i\in\mathbf{V}}(1-\lambda_i)\right)$, as $w^* \to \infty$. Moreover, if we assign $\alpha = 1$, DMDS-α algorithm becomes DMDS algorithm. Thus, DMDS algorithm is also timely-throughput optimal.

Proof: Let $\mathcal{D}(t) = (D_1(t),...,D_N(t))$ denote a vector process of queue lengths of N sensors. We define the Lyapunov function:

$$L(\mathcal{D}(t)) = \sum_{i=1}^{N} L(D_i(t)), \tag{15}$$

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where

$$L(D_i(t)) = \frac{m_i^{-1} D_i(t)^{\alpha_i+1}}{\alpha_i+1}. \quad (16)$$

We next evaluate each term $L(D_i(t))$ under two cases:$1 \leq \alpha_i < \infty$ and $0 < \alpha_i < 1$. For the first case, using queueing dynamics and Taylor's expansions, we have

$$\begin{aligned} & L(D_i(t+1)) \\ & = \frac{m_i^{-1}}{\alpha_i+1}(D_i(t)+A_i(t)-S_i(t))^{\alpha_i+1} \\ & = m_i^{-1}(\frac{D_i(t)^{\alpha_i+1}}{\alpha_i+1} + \Delta_i(t)D_i(t)^{\alpha_i} + \alpha_i\frac{\Delta_i(t)^2}{2}\delta^{\alpha_i-1}), \end{aligned} \quad (17)$$

where $\Delta_i(t) = A_i(t) - H_i(t)$ and $\delta = [D_i(t)-1, D_i(t)+A_i(t)]$. Therefore, by the fact that $\Delta_i(t)^2 \leq A_i(t)^2+1$ and $(D_i(t)+A_i(t))^{\alpha_i-1} < 2^{\alpha_i-1}(D_i(t)^{\alpha_i-1}+A_i(t)^{\alpha_i-1})$, for any positive constant θ, we have

$$\begin{aligned} & E[L_i(D_i(t+1)) - L_i(D(t))|\mathcal{D}(t)] \\ & = m_i^{-1}(D_i(t)^{\alpha_i}E[\Delta_i(t)|\mathcal{D}(t)] + \frac{\alpha_i}{2}E[\Delta_i(t)^2\delta^{\alpha_i-1}|\mathcal{D}(t)]) \\ & \leq m_i^{-1}(E[(A_i(t)-S_i(t)+\theta)D_i(t)^{\alpha_i}|\mathcal{D}(t)] + W_i(\theta)), \end{aligned} \quad (18)$$

where

$$\begin{aligned} W_i(\theta) \quad = \quad & \left(\theta^{-1}2^{\alpha_i-2}\alpha_i E[A_i(t)^2+1]\right)^{\alpha_i-1} \\ & +2^{\alpha_i-2}\alpha_i E[A_i(t)^{\alpha_i+1}+A_i(t)^{\alpha_i-1}]. \end{aligned} \quad (19)$$

The last inequality in (18) holds because $1 < \alpha_i < \infty$, which implies that $E[A_i(t)^2]$, $E[A_i(t)^{\alpha_i+1}]$, and $E[A_i(t)^{\alpha_i-1}]$ are finite.

For the second case $0 < \alpha_i < 1$, by the similar arguments, we obtain

$$\begin{aligned} & E[L_i(D_i(t+1)) - L_i(Q(t))|\mathcal{D}(t)] \\ & \leq m_i^{-1}(E[(A_i(t)-S_i(t)+\theta)D_i(t)^{\alpha_i}|\mathcal{D}(t)] + W_i(\theta)), \end{aligned} \quad (20)$$

where

$$W_i(\theta) = \theta + 1 + E[A_i(t)^{\alpha_i+1}]. \quad (21)$$

By (15), (18), and (20), the conditional Lyapunov drift is upper bounded by

$$\begin{aligned} & E[L(\mathcal{D}(t+1)) - L(\mathcal{D}(t))|\mathcal{D}(t)] \\ \leq \quad & \sum_{i=1}^{N}\frac{a_i}{m_i}D_i(t)^{\alpha_i} + \sum_{i=1}^{N}\left(\frac{\theta D_i(t)^{\alpha_i}+W_i(\theta)}{m_i}\right) \\ & -E\left[\sum_{i=1}^{N}m_i^{-1}S_i(t)D_i(t)^{\alpha_i}|\mathcal{D}(t)\right]. \\ = \quad & T_I + T_{II} + T_{III} \end{aligned} \quad (22)$$

We now evaluate the term T_I and T_{III}. Towards this, we first define the following notations. At each time slot t, we arrange the queues in a decreasing order of the weight $w_i(t) = D_i(t)^{\alpha_i}R_i(t)$, i.e., $w_1(t), w_2(t), ..., w_N(t)$ with $w_i(t) \geq w_{i+1}(t)$, where ties are broken randomly.

We can rewrite T_I as follows

$$\begin{aligned} T_I = & \sum_{i=1}^{N-1}(D_i(t)^{\alpha_i} - D_{i+1}(t)^{\alpha_{i+1}})\sum_{n=1}^{i}\frac{a_n}{m_n} \\ & + D_N(t)^{\alpha_N}\sum_{n=1}^{N}\frac{a_n}{m_n}. \end{aligned} \quad (23)$$

By equation (10), we now evaluate T_{III} as follows

$$\begin{aligned} T_{III} = & \sum_{i=1}^{N-1}(D_i(t)^{\alpha_i} - D_{i+1}(t)^{\alpha_{i+1}})\sum_{n=1}^{i}\frac{E[S_n(t)]}{m_n} \\ & + D_N(t)^{\alpha_N}\sum_{n=1}^{N}\frac{E[S_n(t)]}{m_n} \end{aligned} \quad (24)$$

Let $X(t)$ denote the set containing all the sensors which have packets to send at time t. Then, it follows by (10) that

$$\begin{aligned} & \sum_{n=1}^{i}\frac{E[S_n(t)]}{m_n} \quad (25) \\ & = \sum_{n\leq i}\left(\sum_{j\leq n}E[H_j(t)]\right)P(|X(t)|=n) \\ & = \sum_{n=1}^{i}\left(\sum_{j\leq n}\frac{\exp(w_j(t))}{Z}\right)P(|X(t)|=n)\left(1-\frac{1}{Z}\right) \\ & \geq \left(\frac{\exp(w_1(t))}{Z}\right)\left(\sum_{n=1}^{i}P(|X(t)|=n)\right)\left(1-\frac{1}{\exp(w_1(t))}\right) \\ & \geq \left(\frac{\exp(w_1(t))}{Z}\right)\left(1-\prod_{j\leq i}(1-\lambda_j)\right)\left(1-\frac{1}{\exp(w_1(t))}\right) \\ & \geq \left(1-\sum_{1<j\leq i}\frac{\exp(w_1(t))}{Z}\right)\left(1-\prod_{j\leq i}(1-\lambda_i)\right) \\ & \qquad \left(1-\frac{1}{\exp(w_1(t))}\right) \\ & \geq \left(1-\sum_{1<j\leq i}\frac{\exp((1-\eta)w_1(t))}{\exp(w_1(t))}\right)\left(1-\prod_{j\leq i}(1-\lambda_i)\right) \\ & \qquad \left(1-\frac{1}{\exp(w_1(t))}\right) \\ & \geq \left(1-\frac{N}{\exp(\eta w_1(t))}\right)\left(1-\prod_{j\leq i}(1-\lambda_i)\right) \\ & \qquad \left(1-\frac{1}{\exp(w_1(t))}\right). \end{aligned}$$

This, combining with (24), leads to

$$\begin{aligned} T_{III} = & \sum_{i=1}^{N-1}(D_i(t)^{\alpha_i} - D_{i+1}(t)^{\alpha_{i+1}})\mu_i(w_1(t)) \\ & + D_N(t)^{\alpha_N}\mu_N(w_1(t)), \end{aligned} \quad (26)$$

where

$$\mu_i(w_1(t)) = \left(1 - \frac{N}{\exp(\eta w_1(t))}\right)\left(1 - \prod_{j \le i}(1-\lambda_i)\right) \left(1 - \frac{1}{\exp(w_1(t))}\right)$$

and $\eta < 1$ is a constant such that $w_2 = (1-\eta)w_1$.

Combining (22), (23), and (26) then, we obtain

$$\begin{aligned} & E[L(\mathcal{D}(t+1)) - L(\mathcal{D}(t))|\mathcal{D}(t)] \\ & \le \sum_{i=1}^{N-1}\left(\left(D_i(t)^{\alpha_i} - D_{i+1}(t)^{\alpha_{i+1}}\right)\left(\sum_{n=1}^{i}\frac{a_i}{m_i} - \mu_i(w_1(t))\right)\right) \\ & + \sum_{i=1}^{N}\frac{\theta}{m_i}D_i(t)^{\alpha_i} + \sum_{i=1}^{N}\frac{W_i(\theta)}{m_i} \\ & + D_N(t)^{\alpha_i}\left(\sum_{i=1}^{N}\frac{a_i}{m_i} - \mu_i(w_1(t))\right). \end{aligned}$$

By defining

$$d = \max_{D \subset \{1,\dots,N\}}\left\{\sum_{i \in D}\frac{a_i}{m_i} - \mu_i(w^*(t))\right\},$$

which is a negative constant, we can rewrite (27) as

$$\begin{aligned} & E[L(\mathcal{D}(t+1)) - L(\mathcal{D}(t))|\mathcal{D}(t)] \\ & \le (d + \frac{\theta}{r_{min}})\sum_{i=1}^{N}D_i(t)^{\alpha_i} + \sum_{i=1}^{N}\frac{W_i(\theta)}{m_i}, \end{aligned}$$

where $r_{min} = \min_{i \le N} m_i$ Letting $\theta = -\frac{d}{2}r_{min}$, the Lyapunov drift can be bounded by

$$\begin{aligned} & E[L(\mathcal{D}(t+1)) - L(\mathcal{D}(t))|\mathcal{D}(t)] \\ & \le \frac{d}{2}\sum_{i=1}^{N}D_i(t)^{\alpha_i}\left(I(w_1(t) > w^*) + I(w_1(t) \le w^*)\right) \\ & + \sum_{i=1}^{N}W_i(-\frac{d}{2}r_{min}). \end{aligned}$$

By Foster's criterion for ergodic Markov chain, the queueing length process converges in distribution. Using iterated mean and telescoping sums, we have

$$\sum_{i=1}^{N}E[D_i(t)^{\alpha_i}] \le (-\frac{2}{d})\sum_{i=1}^{N}W_i(-\frac{d}{2}r_{min}),$$

where $W_i()$ is defined in (19) and (21), respectively. This completes the proof. ■

V. Simulation Results

In this section, we use simulations to illustrate our theoretical results. More specifically, we first demonstrate the timely-throughput optimality of the proposed distributed maximum debt scheduling algorithm. More specifically, we consider the sensor nodes have the packet loss rate smaller than 0.1, which indicates that $m_i = 0.9$. The target timely-delivery ratio, i.e., the average number of packet transmitted with the deadline without errors, is $a_i = 0.1$. The packet arrival rate or sensing rate of the sensors is $\lambda_i = 0.8$. Under above network settings, according to theorem 1, the maximum number N of sensors any scheduling algorithm can support should be less than 9. This means any timely-throughput optimal scheduling algorithm should at least support 8 sensors, while ensuring that each sensor can achieve the target timely-delivery ratio $a_i = 0.1$. As shown in Figure 3, by applying DMDS, all sensor nodes have the timely-delivery ratio larger than 0.1. This verifies that DMDS is timely-throughput optimal. Moreover, Figure 4 shows the evolution of the time-delivery ratio of node 1 as time proceeds. This indicates that DMDS is a fast convergent algorithm in the sense that under DMDS, the sensor quickly achieves the targeted timely-delivery ratio. In addition, as proven in Theorem 1 and 2, the timely-throughput optimality implies the boundedness of the debt queue. Therefore, as shown in Figure 5, the debt queue of node 1 fluctuates within finite lower and upper bounds. Next, we increase the number of nodes to 10. In this case, as indicated by Theorem 1, no scheduling algorithm can lead to the target timely-delivery ratio. It is shown in Figure 6 and 7 that as the number of nodes increases to 10, the timely-delivery ratio of every sensor is less than the targeted value 0.1. In this case, according to lemma 1, the debt queue will grow unboundedly, which is verified in Figure 8.

Next, we will investigate the performance of DMDS-α algorithm. More specifically, we will show that DMDS-α allows us to assign different priority to different sensors by using different α parameters. Towards this, we assume that all the sensors have the packet loss rate smaller than 0.1, which indicates that $m_i = 0.9$. The target timely-delivery ratio, i.e., the average number of packet transmitted with the deadline without errors, is $a_i = 0.25$. The packet arrival rate or sensing rate of the sensors is $\lambda_i = 0.8$. According to theorem 1, the maximum number $N = 3$ of sensors can be supported by any scheduling algorithm. First, we let all the sensors have the same $alpha_i = 1$. In this case, DMDS-α algorithm becomes DMDS algorithm. As shown in Figure 9, all the sensors achieve the similar timely-delivery ratio, which is larger than the target one 0.25. This is because DMDS treats every sensor equally. Then, we set the different α values for the three sensors. More specifically, we let $\alpha_1 = 1$ for node 1, $\alpha_2 = 2$ for node 2, and $\alpha_3 =$ for node 3. It can be seen in Figure 10 that the sensors achieve the different timely-delivery ratios, all of which are larger than the target one. More specifically, The sensor 3 with the largest α achieve the highest timely-delivery ratio, while the node 1 assigned with the smallest α obtains the lowest time-delivery ratio. The above observations implies that DMDS-α algorithm is not only timely-throughput optimal, but also can lead to differentiated treatment by setting up different priority levels through α values.

VI. Conclusion

In this paper, we propose the timely-throughput optimal algorithm, which distributively determines the optimal transmission times for nano-devices so that the largest set of traffic rates of nano-devices can be supported, while ensuring timely data delivery within hard deadlines. More specifically, the maximum network capacity region that timely-throughput optimal scheduling algorithms can achieve is first derived, which characterizes the closure of the set of all arrival rate

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2016.2573679, IEEE Internet of Things Journal

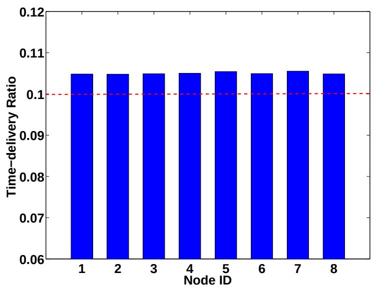

Fig. 3. Timely-delivery ratio of DMDS algorithm. Network size is 8 nodes.

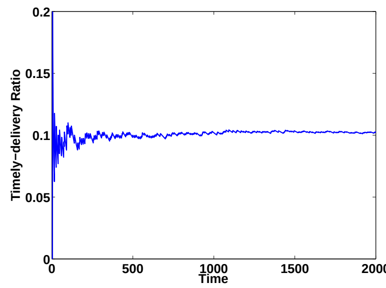

Fig. 4. Convergence speed of DMDS algorithm on node 1. Network size is 8 nodes.

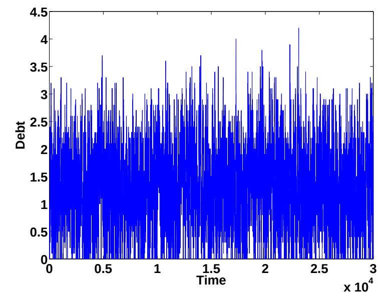

Fig. 5. Debt queue dynamics of node 1 under DMDS algorithm. Network size is 8 nodes.

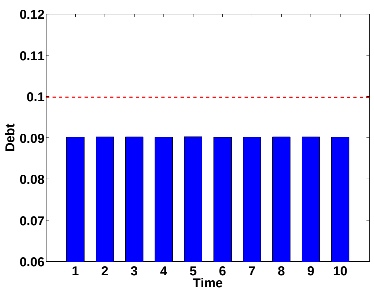

Fig. 6. Timely-delivery ratio of DMDS algorithm with 10 nodes.

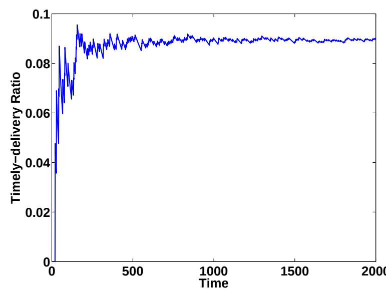

Fig. 7. Convergence speed of DMDS algorithm on node 1. Network size is 10 nodes.

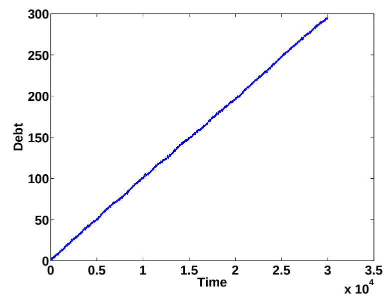

Fig. 8. Debt queue dynamics of node 1 under DMDS algorithm. Network size is 10 nodes.

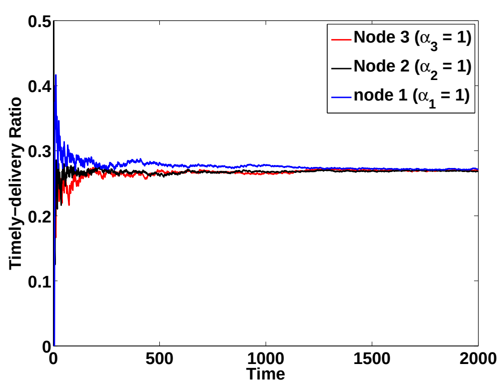

Fig. 9. Timely-delivery ratio of DMDS algorithm.

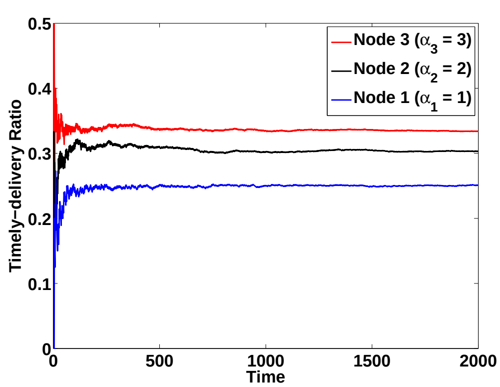

Fig. 10. Timely-delivery ratio of DMDS-α scheduling algorithm.

vectors under which there exists an viable scheduling algorithm to guarantee that all network sensors can meet the delay deadlines. Then, a distributed scheduling algorithm, namely distributed maximum debt scheduling (DMDS), is proposed, which allows every sensor to make optimal transmission decision locally based on its incoming traffic rate, virtual debts, and channel sensing results. It is proven that DMDS algorithm is timely-throughput optimal in the sense that it can guarantee reliable data delivery before deadlines as long as the incoming traffic rates are within the derived maximum network capacity region. Moreover, we further generalize DMDS algorithm by proposing DMDS-α algorithm. This algorithm is not only timely-throughput optimal but also allows to set up different priories for different sensor nodes. Finally, the performance of the proposed algorithms is verified through simulations.

VII. Appendix

proof of Theorem 1: Firstly, we define the Lyapunov Function as $L(t) := \sum_{i\in\mathbf{V}} D_i(t)m_i^{-1}$. We will show that if $L(t) \geq |\mathbf{V}|w^*$, we have a negative Lyapunov drift, i.e.,

$$E[L(t+1) - L(t)|\mathcal{D}(t)] \leq -\epsilon, \tag{27}$$

where $\mathcal{D}(t) = (D_1(t), ..., D_{|\mathbf{V}|}(t))$ is a vector process of queue lengths of $|\mathbf{V}|$ sensors.

Based on the queue dynamics (3), we obtain

$$L(t+1) = L(t) - \sum_{i\in\mathbf{V}} \frac{S_i(t)}{m_i} + \sum_{i\in\mathbf{V}} \frac{A_i(t)}{m_i},$$

which leads to

$$E[L(t+1)|\mathcal{Q}] = E[L(t)|\mathcal{Q}] + \sum_{i\in\mathbf{V}} \frac{a_i}{m_i} - \sum_{i\in\mathbf{V}} E[C_i(t)], \tag{28}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2016.2573679, IEEE Internet of Things Journal

where $C_t = H_i(t)N_i(t)$. Define $X(t)$ as the number of sensors in set $\mathbf{V}$, which have packets to send at the beginning of time interval t, i.e., $X(t) = |\{i|N_i(t) \neq 0, i \in \mathbf{V}\}|$. Since $P(N_i(t) = 1) = \lambda_i$, this implies that $X(t)$ follows Poisson binomial distribution. Then, we have

$$\sum_{i\in\mathbf{V}} E[C_i(t)] = E\left[E\left[\sum_{i\in\mathbf{V}} C_i(t)|X(t), D_i(t-1), i \in \mathbf{V}\right]\right] \tag{29}$$

The event $e = \{X(k), D_i(k-1), i \in D\}$ can be partitioned into three disjoint sets

$$\begin{aligned} e_1 &= \{X(t) = 0\} \\ e_2 &= \{X(t) = 0\}^c \wedge \{D_i(t-1) = 0, i \in D\} \\ e_3 &= \{X(t) = 0\}^c \wedge \{D_i(t-1) = 0, i \in D\}^c. \end{aligned} \tag{30}$$

It is easy to verify that

$$E\left[\sum_{i\in\mathbf{V}} C_i(t)|e_i\right] = 0, \quad i = 1, 2. \tag{31}$$

As for event e_3, we have

$$\begin{aligned} E\left[\sum_{i\in\mathbf{V}} C_i(t)1_{e_3}\right] &= \sum_{i\in\mathbf{V}} E[C_i(t)|u_j]P(u_j) \\ &\leq \left(\sum_{i\in\mathbf{V}} E[H_i(t)]\right) P\left(\{X(t) \neq 0\}\right. \\ &\qquad \left. \wedge \{D_i(t-1) = 0, i \in \mathbf{V}\ \}^c\right) \\ &\leq \left(\sum_{i\in\mathbf{V}} E[H_i(t)]\right)\left(1 - \prod_{i\in\mathbf{V}}(1-\lambda_i)\right). \end{aligned}$$

It follows by (10) that

$$E[H_i(t)] = \frac{\exp(w_i)}{Z}(1 - \frac{1}{Z}).$$

Assume that $Q_i(t) \geq \frac{w^*}{R_i(t)}, \forall i \in \mathbf{V}$, which by (9) indicates $L(t) \geq |\mathbf{V}|w^*$ and $w_i(t) = w^*$. As a consequence, we have

$$\sum_{i\in\mathbf{V}} E[H_i(t)] = \frac{|\mathbf{V}|\exp(w^*) - 1}{|\mathbf{V}|\exp(w^*)},$$

which, along with (3) and (28), indicates (27) holds, i.e., the Lyapunov function has a negative drift when the queue lengths are large enough. By the Foster's criterion, the network is steady-state stable and the queue length process converges in distribution. ■

REFERENCE

[1] I. F. Akyildiz and J. M. Jornet, "Electromagnetic wireless nanosensor networks," *Nano Communication Networks (Elsevier) Journal*, vol. 1, no. 1, pp. 3–19, Mar. 2010.

[2] ——, "The internet of nano-things," *IEEE Wireless Communications Magazine*, vol. 17, no. 6, pp. 58–63, Dec. 2010.

[3] A. Afsharinejad, A. Davy, B. Jennings, and C. Brennan, "Performance analysis of plant monitoring nanosensor networks at thz frequencies," *IEEE Internet of Things Journal*, vol. PP, no. 99, pp. 1–1, 2015.

[4] J. M. Jornet and I. F. Akyildiz, "Graphene-based plasmonic nano-antenna for terahertz band communication in nanonetworks," *IEEE JSAC, Special Issue on Emerging Technologies for Communications*, vol. 12, no. 12, pp. 685–694, Dec. 2013.

[5] M. Tamagnone, J. Gomez-Diaz, J. Mosig, and J. Perruisseau-Carrier, "Analysis and design of terahertz antennas based on plasmonic resonant graphene sheets," *Journal of Applied Physics*, vol. 112, no. 11, p. 114915, 2012.

[6] J. M. Jornet and I. F. Akyildiz, "Graphene-based plasmonic nano-transceiver for terahertz band communication," in *Proc. of European Conference on Antennas and Propagation (EuCAP)*, 2014.

[7] L. Vicarelli, M. S. Vitiello, D. Coquillat, A. Lombardo, A. C. Ferrari, W. Knap, M. Polini, V. Pellegrini, and A. Tredicucci, "Graphene field-effect transistors as room-temperature terahertz detectors," *Nature Materials*, vol. 11, pp. 865–871, Oct. 2012.

[8] Z. L. Wang, "Towards self-powered nanosystems: from nanogenerators to nanopiezotronics," *Advanced Functional Materials*, vol. 18, no. 22, pp. 3553–3567, 2008.

[9] L. Gammaitoni, I. Neri, and H. Vocca, "Nonlinear oscillators for vibration energy harvesting," *Appl. Physical Letters*, vol. 94, Apr. 2009.

[10] F. Cottone, H. Vocca, and L. Gammaitoni, "Nonlinear energy harvesting," *Physical Review Letters*, vol. 102, no. 8, Feb. 2009.

[11] J. M. Jornet and I. F. Akyildiz, "Channel modeling and capacity analysis of electromagnetic wireless nanonetworks in the terahertz band," *IEEE Transactions on Wireless Communications*, vol. 10, no. 10, pp. 3211–3221, Oct. 2011.

[12] ——, "Joint energy harvesting and communication analysis for perpetual wireless nanosensor networks in the terahertz band," *IEEE Transactions on Nanotechnology*, vol. 11, no. 3, pp. 570–580, 2012.

[13] J. M. Jornet, J. Capdevila-Pujol, and J. Sole-Pareta, "Phlame: A physical layer aware mac protocol for electromagnetic nanonetworks in the terahertz band," *Nano Communication Networks (Elsevier) Journal*, vol. 3, no. 1, pp. 74 – 81, 2012.

[14] P. Wang, J. M. Jornet, M. Abbas Malik, N. Akkari, and I. F. Akyildiz, "Energy and spectrum-aware mac protocol for perpetual wireless nanosensor networks in the terahertz band," *Ad Hoc Networks (Elsevier) Journal*, vol. 11, no. 8, pp. 2541–2555, 2013.

[15] S. Mohrehkesh and M. C. Weigle, "Rih-mac: receiver-initiated harvesting-aware mac for nanonetworks," in *Proceedings of ACM The First Annual International Conference on Nanoscale Computing and Communication*, 2014, pp. 1–9.

[16] I.-H. Hou, V. Borkar, and P. Kumar, "A theory of qos for wireless," in *Proceeding of INFOCOM 2009*, 2009, pp. 486–494.

[17] M. Moore, A. Enomoto, T. Nakano, Y. Okaie, and T. Suda, "Non-preemptive fixed priority scheduling of hard real-time periodic tasks," in *Proc. of the 7th International Conference on Computational Science*, May 2007, pp. 881 – 888.

[18] J. Ni, B. Tan, and R. Srikant, "Q-csma: Queue-length-based csma/ca algorithms for achieving maximum throughput and low delay in wireless networks," *IEEE/ACM Transactions on Networking*, vol. 20, no. 3, pp. 825–836, 2012.

[19] L. Jiang and J. Walrand, "A distributed csma algorithm for throughput and utility maximization in wireless networkss," *IEEE/ACM Transactions on Networking*, vol. 18, no. 3, pp. 960–972, 2010.

[20] D. Shah, D. Tse, and J. Tsitsiklis, "Hardness of low delay network scheduling," *IEEE Transactions on Information Theory*, vol. 57, no. 12, pp. 7810–7817, 2011.

[21] H. Yan, H. S. Choe, S. Nam, Y. Hu, S. Das, J. F. Klemic, J. C. Ellenbogen, and C. M. Lieber, "Programmable nanowire circuits for nanoprocessors," *Nature*, vol. 470, no. 7333, pp. 240–244, 2011.

[22] L. A. Ponomarenko, F. Schedin, M. I. Katsnelson, R. Yang, E. W. Hill, K. S. Novoselov, and A. K. Geim, "Chaotic Dirac billiard in graphene quantum dots," *Science*, vol. 320, no. 5874, pp. 356–358, Apr. 2008.

[23] A. Demming, "Nanomemory: information and ingenuity," *Nanotechnology*, vol. 24, no. 13, p. 130201, 2013.

[24] R. Bennewitz, J. N. Crain, A. Kirakosian, J.-L. Lin, J. L. McChesney, D. Y. Petrovykh, and F. J. Himpsel, "Atomic scale memory at a silicon surface," *Nanotechnology*, vol. 13, no. 4, pp. 499–502, 2002.

[25] S. S. P. Parkin, M. Hayashi, and L. Thomas, "Magnetic domain-wall racetrack memory," *Science*, vol. 320, no. 5873, pp. 190–194, 2008.

[26] D. Pech, M. Brunet, H. Durou, P. Huang, V. Mochalin, Y. Gogotsi, P. Taberna, and P. Simon, "Ultrahigh-power micrometre-sized supercapacitors based on onion-like carbon," *Nature nanotechnology*, vol. 5, no. 9, pp. 651–655, Sep. 2010.

[27] N. Akkari, J. Jornet, P. Wang, E. Fadel, L. Elrefaei, M. Malik, S. Almasri, and I. Akyildiz, "Joint physical and link layer error control analysis for nanonetworks in the terahertz band," *Wireless Networks*, pp. 1–13, 2015.

[28] B. Li and A. Eryilmaz, "Optimal distributed scheduling under time-varying conditions: A fast-csma algorithm with applications," *IEEE Transactions on Wireless Communications*, vol. 7, no. 12, pp. 3278 – 3288, 2013.