

# Analytical Model for the Energy Efficiency in Low Power IoT Deployments

Tobias Hoßfeld, Simon Raffeck, Frank Loh, Stefan Geißler

University of Würzburg, Institute of Computer Science, Chair of Communication Networks

Würzburg, Germany

prename.surname@uni-wuerzburg.de

**Abstract**—The recent rise of the Internet of Things (IoT) has given way to numerous challenges and research questions. One of the most critical issues in the area of low powered devices is the question of energy efficiency. Here, technologies like LoRa or Zigbee emerged, promising low power consumption while maintaining adequate performance. However, even when using these tailor made technologies, several configuration aspects need to be taken into account to provide high performance, energy efficient operation. To this end, we propose a generic model to compute the energy efficiency of wireless sensors under the assumption of perfect CSMA/CA channel access. We present numerical results for a typical LoRa device and highlight extensions towards other channel access mechanisms. Finally, we apply Kleinrock’s power metric to obtain ideal system configurations for varying load parameters.

**Index Terms**—IoT random access mechanism, energy efficiency, Kleinrock’s power metric, M/D/1-S queueing system

## I. INTRODUCTION

The Internet of Things (IoT) is one of the hottest topics in this decade. Due to increasing data collection, automation, and communication possibilities that have emerged recently, and will be fostered in the close future, an excessive number of new application areas arise. As a result of this massive increase in visibility and usage, many novel IoT access technologies have been introduced. Besides classical 4G and upcoming 5G communication, alternative radio access techniques like Low Power Wide Area Networks (LPWAN), Bluetooth, or Zigbee gain traction. Although this diversification of access technologies provides many benefits like selected usage tailored for specific use cases, adaptation of transmission rates based on applications, or more energy efficient communication, many additional challenges and research questions arise.

Specifically, channel access mechanisms date back to the last century, starting with different ALOHA based protocols in the seventies and CSMA in the nineties, the adaptation to new IoT environments is still ongoing. While classical cellular networks use CSMA/CA to avoid collisions, the standardized channel access approach for LoRaWAN, for example, is still a random access based pure ALOHA. However, the idea of an improved channel access by alternative access approaches [1]–[3] or other techniques to increase the successful transmission rate [4] and optimize energy efficiency is tackled in research. However, the focus in literature is usually on a single specific IoT access technology, specific transmission scenarios, or on

simulation or measurement of testbeds. Furthermore, many works do not take energy consumption into consideration.

For that reason, we present a general model for the transmission of sensor nodes to an IoT gateway. Modeled an M/D/1-S system where the parameter  $S$  quantifies the queue size and hence the trade-off between success probability for transmission, response time, and energy consumption.

As a baseline in this work we assume a perfect CSMA/CA system where sensors only start a transmission if the channel is not occupied. Here, sensors can either directly start a transmission or need to wait for the channel to be free. As sensors have to wait their energy consumption increases, leading to less efficient transmissions. Therefore, we assume an interaction between IoT gateway and IoT nodes to indicate the current load at the air interface (i.e. the number of packets to be transmitted over the air interface). This allows devices to either wait or abort the transmission attempt due to long waiting times in order to conserve energy. Such a mechanism can feasibly be assumed to exist in, e.g., modern networks and can be realized through software components co-located with the gateway.

Our goal is not to model a specific access schemes in detail, but to highlight the different measures regarding performance (throughput, success probability, response time) as well as energy consumption and efficiency. Furthermore, we show how Kleinrock’s power metric can be utilized to define operational points for the parameter  $S$ . The results obtained in this paper can be easily transferred to specific, commonly used channel access mechanisms (e.g. random access, listen-before-talk).

The contribution of this paper is a generic model for perfect CSMA/CA with restricted accessibility (M/D/1-S) as well as unrestricted access (M/D/1- $\infty$ ). We introduce a general solution and highlight extensions towards more general M/GI/1 models. Finally, we apply Kleinrock’s power metric to identify optimal operational points with respect to the energy efficiency and success probability for the transmission of messages in IoT wireless networks.

The remainder of this paper is structured as follows. Section II provides related work. Section III introduces our IoT system model and key performance and energy measures. Section IV provides numerical results and quantifies the trade-off between performance and energy efficiency. Finally, Section V concludes this work with a brief discussion on remaining issues and future topics.

## II. BACKGROUND AND RELATED WORK

Enhancing the performance and energy efficiency of IoT devices has long been subject of research. Here, we touch on both the technical background in the context of IoT and the general modeling of energy efficiency in wireless networks.

### A. IoT Network Technology

IoT networks can generally be seen as a conglomerate of heterogeneous communication protocols. One of the most prominently used protocols at the time of writing is the LoRa based LoRaWAN protocol that uses pure ALOHA as a channel access method. This in turn means that a large part of the traffic within real world IoT networks is comprised of random access traffic prone to high collision rates. With energy efficiency of sensor networks in mind, this approach proves highly inefficient once deployments reach a certain size. Every lost transmission that has to be repeated will increase the overall energy usage of the network while simultaneously reducing the quality of service. Hence, the research community has put forward various approaches to enhance LoRaWANs performance in regard to collision rates and energy performance, ranging from Slotted ALOHA [3], listen-before-talk [2] over Scheduled MAC [1] to different CSMA/CA adaptations [5]–[7].

### B. Energy Performance and Traffic Modeling

The energy efficiency of different communication protocols has been investigated in various previous works. For LoRaWAN a detailed model of the energy performance and consumption per byte is presented in [8]. Bluetooth Low Energy (BLE), the energy efficient Bluetooth adaptation that is used predominantly in smart-homes and industry is further studied in [9]. Narrow-Band IoTs (NB-IoT) energy consumption is looked into in detail in [10]. The energy performance of IoT devices and protocols has been studied using empirical real-life test-beds in [11]. The focus of these approaches however, rest on one communication protocol at a time, neglecting the heterogeneous nature of IoT networks. It can not be stressed enough however, that LoRaWAN, NB-IoT and BLE are by far not the only IoT protocols used in these environments and an overarching approach to evaluate and enhance the performance and energy efficiency of the network as a whole is paramount.

The modeling and investigation of IoT networks and traffic is subject to various recent studies. General approaches to network models and queuing theory are presented in [12]–[14]. However, while the modeling approaches of these studies do focus on networks characteristics, energy efficiency is not investigated in these works.

## III. MODEL DESCRIPTION

The IoT nodes are independently sending messages over the air interface. The aggregated arrival process is modeled as a Poisson process with rate  $\lambda$ , which is a realistic assumption [15]. The messages are assumed to have constant size which requires time  $b$  on the air interface (time on air, ToA) for the transmission from the IoT node to the IoT gateway.

Note that the time on air depends on the configuration of the channel, e.g. the used modulation scheme, spreading factor, the payload of the message, the preamble length of messages, cyclic redundancy checks for error detection, etc. The time on air  $b$  subsumes the effects in this model. We assume here a maximum packet size for each packet as a worst-case assumption. The model can be easily extended to generally distributed packet sizes corresponding to variable times on air. Then, instead of M/D/1 we have an M/GI/1 system, for which closed formulas can be derived accordingly.

Note that the model for different random access channels is explicitly derived in our open access textbook [16]. In this paper, we recapitulate the performance and energy measures as well as the models for perfect CSMA/CA without and with restricted accessibility. These two mechanisms can be modeled as M/D/1- $\infty$  and M/D/1-S delay systems, respectively. Due to space constraints we omit the detailed derivation of the formulas and only present the resulting model in this paper. The complete derivations of the formulas can be found in [16].

TABLE I  
NOTATION OF VARIABLES.

var.	explanation [unit]
<i>System parameters</i>	
$\lambda$	message or packet arrival rate [ $s^{-1}$ ]
$b$	time on air for single packet [s]
$S$	system parameter for restricted accessibility corresponding to maximum queue size of the M/D/1-S queue [1]
$\gamma_b$	power consumption for sending a single packet [W]
$\gamma_w$	power consumption of a device in idle mode [W]
<i>Performance measures</i>	
$\psi$	success probability for sending a message [1]
$p_B$	blocking probability, $\psi = 1 - p_B$ [1]
$\Theta$	throughput over the air interface [ $s^{-1}$ ]
$W$	waiting time of messages (random variable) [s]
$T$	transmission time or system response time (random variable) [s]
$E[T]$	Mean response time [s]
<i>Energy measures</i>	
$\Omega$	mean energy consumption for single sent message [J]
$\omega$	mean energy consumption per received message [J]
$\eta$	energy efficiency with $0 \leq \eta \leq 1$ [1]

### A. Performance Measures

Depending on the transmission scheme, messages may get lost or have to wait until they are delivered.

- *Success probability*  $\psi$ : probability that an arbitrary message is successfully transmitted to the IoT gateway.
- *Throughput*  $\Theta$ : mean number of successful transmissions per time; it is  $\Theta = \psi\lambda$ .
- *Mean response time*  $E[T]$ : sum of the mean waiting time  $E[W]$  and the processing time  $b$ , i.e.,  $E[T] = E[W] + b$ .

### B. Energy Model and Energy Efficiency

The energy consumption  $\mathcal{E}$  depends on the response time  $T$  for sending a message. To be more precise, the energy consumption is the integral of the power consumption over the time needed to send the message. We may differentiate between the power consumption (1) for sending the message

( $\gamma_b$ ) which takes time  $b$  and (2) for waiting before sending ( $\gamma_w$ ) which takes time  $W$ . Different values  $\gamma_b$  and  $\gamma_w$  for the power use (in Watt) are used. The energy consumption (in Joule = Watt · second) for a single message is then  $\gamma_b b + \gamma_w W$ , which is a linear function  $f$  of the random variable  $W$ . Therefore,

$$\begin{aligned} \text{Mean energy consumption : } E[\mathcal{E}] &= \Omega = \\ E[f(W)] &= f(E[W]) = \gamma_b b + \gamma_w E[W] \end{aligned} \quad (1)$$

However, packets may not be successfully delivered. Therefore, the mean consumed energy per successfully received message is relevant, which is denoted by  $\omega$ . There are  $m$  messages sent in total, from which  $\psi \cdot m$  messages are successfully received. The energy consumption for  $m$  messages is  $m \cdot \Omega$  on average. Then  $\omega$  is the mean energy consumption per successfully received message, i.e.,  $\omega = \frac{\Omega}{\psi}$ .

Energy efficiency can be described as the ratio between the total number of packets received at the destination node (i.e. the IoT gateway) and the total energy consumption spent by the network to deliver these packets (i.e. the sensor nodes), see [17]. In that sense, energy efficiency is equal to how many messages are carried per joule. In this work, we normalize the amount of consumed energy by the energy consumption of a single message. Energy efficiency is then the ratio between ‘How many messages are received?’ and ‘How many messages could have been received regarding the total energy consumption?’. The energy efficiency  $\eta$  takes values in the interval  $[0; 1]$ . Maximum energy efficiency is reached ( $\eta = 1$ ), if all messages are received and require the minimum amount of energy  $\gamma_b b$ . A value  $\eta = 1/2$  may be interpreted in two ways: (a) 50% of the messages are received, but all messages require the minimum energy consumption or (b) all messages are received, but additional energy consumption is required for the successful delivery, e.g. due to waiting times.

$$\text{Energy efficiency : } \eta = \frac{\psi}{\Omega/(\gamma_b b)} = \frac{\gamma_b b}{\omega} \quad (2)$$

In the following, we model perfect CSMA/CA with and without restricted accessibility and apply the performance and energy measures from above. Therefore, we first introduce the energy model used in the analysis. Note, however, that these measures can also be applied to other channel access technologies, e.g. random access in LoRa.

### C. Perfect CSMA/CA: M/D/1- $\infty$

We assume perfect carrier-sense multiple access with collision avoidance. The IoT nodes sense the communication channel and are only sending if the channel is free, i.e., the server is idle. When the channel is occupied by another message transmission, the IoT nodes have to wait until the channel is free again. The nodes are served in a FIFO way, i.e., messages are sent in order over the air interface. There is a single server (the air interface). The customers in the system (the messages from the IoT nodes to the IoT gateways) arrive according to a Poisson process with rate  $\lambda$ . The processing time is the time on air  $b$ . The nodes are waiting until they

are able to transmit which means an unlimited waiting room. Hence, the system is an M/D/1- $\infty$  delay system.

The waiting time distribution and the mean waiting time  $E[W]$  for M/D/1 are explicitly derived in [16]. The stability condition must be fulfilled, i.e.  $\rho = \lambda b < 1$ .

$$E[W] = \frac{\rho b}{2(1 - \rho)} \quad (3)$$

There are no blocked customers. Hence, all messages are eventually transmitted over the air interface and the success probability is  $\psi = 1$ . The throughput is  $\Theta = \lambda$ .

The mean energy consumption of a message directly follows from the mean waiting time. Since all messages are delivered, the mean energy consumption  $\Omega$  per sent message is identical to the energy consumption  $\omega$  per received message. Energy efficiency follows directly.

$$\Omega = \gamma_b b + \gamma_w E[W] = \gamma_b b + \gamma_w \frac{\rho b}{2(1 - \rho)} \quad (4)$$

$$\eta = \frac{\gamma_b b}{\Omega} = \frac{\gamma_b}{\gamma_b + \gamma_w \frac{\rho}{2(1 - \rho)}} \quad (5)$$

Thus, perfect CSMA/CA is modeled as M/D/1- $\infty$  with the performance measures summarized in Table II.

### D. Perfect CSMA/CA with Restricted Accessibility: M/D/1-S

In high load situations, perfect CSMA/CA suffers from large waiting times and thus high energy consumption. To this end, restricted accessibility is introduced which provides a control possibility between blocked messages and energy efficiency. Again, we are investigating a perfect mechanism without modeling the impact of signaling. In practice, the IoT nodes may employ an RTS/CTS (ready to send/clear to send, e.g. wifi) mechanism to inform the gateway about their transmission requests. If there are already  $S$  messages waiting, the IoT gateway rejects the requests and informs the IoT nodes that their request is blocked. If there are less than  $S$  transmission requests waiting at the server, the IoT gateway accepts the request. The requests are served in order. The IoT nodes with accepted requests are waiting until the IoT gateway informs them. Then, the message will be sent over the air interface. There are no message collisions, but messages may be blocked which differs from the previous system. The system can be modeled as a finite capacity queue and is denoted as M/D/1-S in Kendall’s notation.

The random variable  $X$  is the total number of requests in the system, i.e. in the waiting room and currently served. The embedded Markov chain approach is used to derive the steady state probabilities  $x(i)$  for  $i = 0, \dots, S + 1$ . The embedding time is immediately after a service ends. The state probabilities at embedding times are obtained as Eigenvector of  $X\mathcal{P} = X$  or by means of the power method, i.e., iterating  $X_n = X_{n-1}\mathcal{P}$  over the  $n$ -th embedding point until  $X$  converges.

The state transition matrix is  $\mathcal{P} = \{p_{ij}\}$ . The number  $\Gamma$  of arrivals during one service time follows a Poisson distribution with parameter  $\lambda b = \rho$  for M/D/1. Note that for M/GI/1, only

$\Gamma$  is changed and can be derived accordingly as the number of arrivals during a (random) service time with  $\gamma(i) = P(\Gamma = i)$ .

$$P = \begin{pmatrix} \gamma(0) & \gamma(1) & \gamma(2) & \cdots & \gamma(S-1) & 1 - \sum_{i=0}^{S-1} \gamma(i) \\ \gamma(0) & \gamma(1) & \gamma(2) & \cdots & \gamma(S-1) & 1 - \sum_{i=0}^{S-1} \gamma(i) \\ 0 & \gamma(0) & \gamma(1) & \cdots & \gamma(S-2) & 1 - \sum_{i=0}^{S-2} \gamma(i) \\ 0 & 0 & \gamma(0) & \cdots & \gamma(S-3) & 1 - \sum_{i=0}^{S-3} \gamma(i) \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & \gamma(0) & 1 - \gamma(0) \end{pmatrix} \quad (6)$$

The blocking probability  $p_B$  depends on the load  $\rho = \lambda b$  and the probability of an empty system at embedding time:  $P(X = 0) = x(0)$ . It is

$$p_B = \frac{\rho - 1 + x(0)}{\rho + x(0)}. \quad (7)$$

For  $k = 0, \dots, S$ , the steady state probabilities of the queue size  $X^*$  at a random point in time are as follows.

$$x^*(k) = \frac{x(k)}{\rho + x(0)} \quad x^*(S+1) = p_B \quad (8)$$

For more details on the analytical solution of finite capacity M/D/1 queues, see [16].

The success probability is  $\psi = 1 - p_B$ . The throughput of the system is  $\Theta = (1 - p_B)\lambda$ . The mean sojourn time  $E[T]$  in the system follows from Little's theorem. The mean number of customers  $E[X^*]$  is derived numerically.

$$E[X^*] = \sum_{i=0}^{S+1} x^*(i) = (1 - p_B)\lambda E[T] \quad (9)$$

The mean waiting time  $E[W] = E[T] - b$  is used to quantify the mean energy consumption  $\Omega = \gamma_b b + \gamma_w E[W]$  for sent messages. Finally, the energy consumption per received message  $\omega = \Omega/\psi$  and energy efficiency follow. A summary of the performance and energy measures is provided in Table II.

TABLE II  
PERFORMANCE COMPARISON OF MAC PROTOCOLS FOR IOT NODES.

Performance Measure	Perfect CSMA/CA	Restricted Accessibility
Success probability $\psi$	1	$1 - p_B$
Throughput $\Theta$	$\lambda$	$(1 - p_B)\lambda$
Response time $E[T]$	$\frac{b(2-\rho)}{2(1-\rho)}$	$\frac{E[X^*]}{(1-p_B)\lambda}$
Energy consumption $\Omega$	$\gamma_b b + \gamma_w \frac{\rho b}{2(1-\rho)}$	$\gamma_b b + \gamma_w E[W]$
Consump. rcvd msg. $\omega$	$\gamma_b b + \gamma_w \frac{\rho b}{2(1-\rho)}$	$\frac{\Omega}{1-p_B}$
Energy efficiency $\eta$	$\frac{\gamma_b}{\gamma_b + \gamma_w \frac{\rho}{2(1-\rho)}}$	$\frac{\gamma_b(1-p_B)}{\gamma_b + \gamma_w (E[T]/b - 1)}$

## IV. NUMERICAL RESULTS

### A. Definition of Scenario and Parameters

In the numerical results, we focus on a LoRaWAN setting and related parameters. The packet transmission time  $b$ , also known as Time On Air (ToA), is at most 3.2s assuming maximum allowed payload and spreading factor (SF) 12. For

TABLE III  
DEFINITION OF PARAMETERS FOR NUMERICAL RESULTS

par.	value	explanation
$b$	1 s	time for sending a single message
$\gamma_b$	0.092 W	energy required for sending a single message
$\gamma_w$	4.95 $\mu$ W	energy in idle mode, i.e. waiting to send
$\gamma_0$	0.036 W	energy for sensing the channel if it is free
$\alpha$	10 %	ratio of sending time for sensing the channel, i.e. $\alpha \cdot b = 100$ ms
$t_s$	100 ms	sensing interval
$\phi$	0.2 s <sup>-1</sup>	sensing frequency, i.e. once per 5 s
$\gamma'_b$	0.0956 W	adjusted parameter for opt. A (single sensing)
$\gamma'_w$	0.724 95 mW	adjusted parameter for opt. B (periodic sensing)

SF11 and a payload size of 40 B, the packet transmission time is  $b = 1$  s, see [18], which we use in our results. The power required for transmitting a single message with ToA  $b$  is  $\gamma_b$ . For a typical LoRa transceiver like the Semtech SX 1272/73 and a transmission power of 13 dBm, it is  $\gamma_b = 0.092$  W.<sup>1</sup>

For the implementation of our perfect CSMA/CA approach, we consider two different options.

1) *Option A: Single Sensing*: The sensor device listens once if the channel is free. Assuming perfect CSMA/CA, the sensor is informed by the gateway when to send, i.e., how long the sensor has to wait before sending. Then, the device transmits the message. The power required for sensing the channel is  $\gamma_0$ . The sensing time is assumed to be  $\alpha \cdot b$ . In the idle mode, i.e. when the sensor is waiting, the power is  $\gamma_w$ .

Then, the energy  $\mathcal{E}$  to transmit one message with a single listen-before-talk and a waiting time  $W$  in idle mode is:

$$\mathcal{E} = \gamma_b b + \gamma_w W + \gamma_0 \alpha b = \gamma'_b \cdot b + \gamma_w \cdot W \quad (10)$$

2) *Option B: Periodic Sensing*: The sensor device listens periodically if the channel is free. Thus, during the waiting time  $W$ , the devices goes into the listen-before-talk mode with frequency  $\phi$  and the sensing interval is  $t_s$ .

Then, the energy  $\mathcal{E}$  to transmit a single message with periodic listen-before-talk is:

$$\mathcal{E} = \gamma_b b + \gamma_w W + \gamma_0 (W \phi) t_s = \gamma_b \cdot b + \gamma'_w \cdot W \quad (11)$$

Hence, the results for the M/D/1-S queue reflect both options of how CSMA/CA is implemented. Only the coefficients  $\gamma_b, \gamma_w$  of the energy model need to be adapted. Table III summarizes the parameters of our model. In the following, we provide numerical results for option B (periodic sensing), if not mentioned otherwise.

### B. Success Probability

The success probability  $\psi$  of perfect CSMA/CA with periodic sensing is plotted in Figure 1. The offered load  $a = \lambda b$  is given on the x-axis which ranges from low load scenarios ( $a$  close to zero) to high load scenarios ( $a > 1$ ). Note that for  $S = 0$ , messages are blocked if the channel is not free. This is not the same as ALOHA, which would not necessarily

<sup>1</sup>Data sheet: [www.semtech.com/products/wireless-rf/lora-core/sx1272](http://www.semtech.com/products/wireless-rf/lora-core/sx1272)

implement listen-before-talk. For M/D/1-0, the Erlang-B formula can be used to derive the blocking probability  $p_B$  and the success probability  $\psi = 1 - p_B$ , see [16]. Although increasing the number  $S$  of waiting places leads to an increased success probability  $\psi$ , the gain gets smaller and smaller. Therefore, the impact of  $S$  on the energy efficiency may be used to derive practical guidelines for  $S$ .

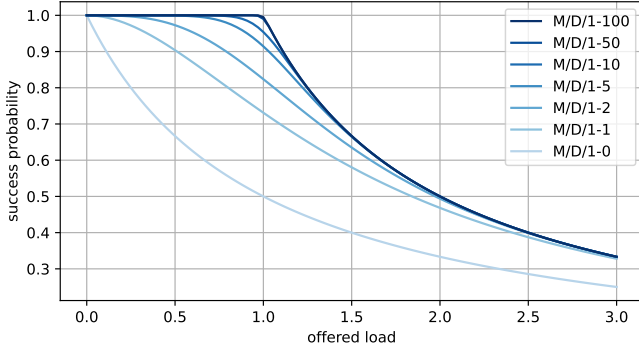


Fig. 1. Success probability  $\psi$  of IoT messages using option B (periodic sensing) for different values of  $S$  of the M/D/1- $S$  queue. Note that the curves for  $S = 50$  and  $S = 100$  are overlapping.

### C. Energy Efficiency

Figure 2 compares the energy efficiency  $\eta$  for varying  $S$  depending on the offered load  $a$ . If the offered load approaches  $a = 1$ , the waiting times are dominating the energy consumption if  $S$  is large. Therefore, we observe a strong decay, e.g. for  $S = 100$ . Hence, there is a trade-off between the success probability and the energy efficiency for M/D/1- $S$ .

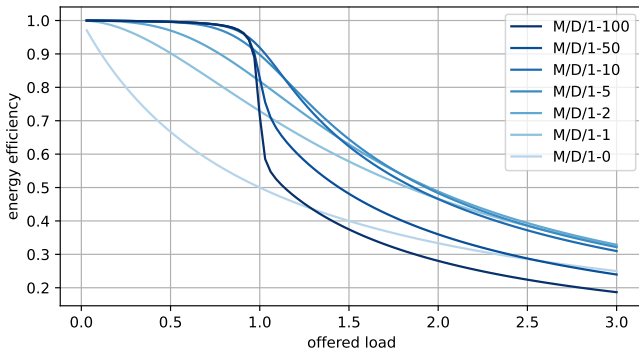


Fig. 2. Energy efficiency for periodic sensing (option B), depending on the system parameter  $S$  and the offered load.

Figure 3 visualizes this trade-off for various loads. Each dot in the figure corresponds to one particular choice of  $S$ . The size of the marker corresponds to the value of  $S$ . The larger  $S$  is the higher the success probability  $\psi$  is. The figure indicates that for low loads ( $a < 0.5$ ), the parameter  $S$  has no significant impact on energy efficiency. However, for  $a = 0.5$ , larger values of  $S$  yield higher success probabilities. For high load situations, e.g.  $a = 2.0$ , an increase in  $S$  results into a strong

decrease of the energy efficiency  $\eta$ . This is due to the fact that the success probability cannot be increased significantly anymore, once a certain threshold of  $S$  is reached. But further increasing of  $S$  negatively affects the energy efficiency due to waiting times. The question is what is a good trade-off value of  $S$ , which we will determine with Kleinrock's power metric in the following.

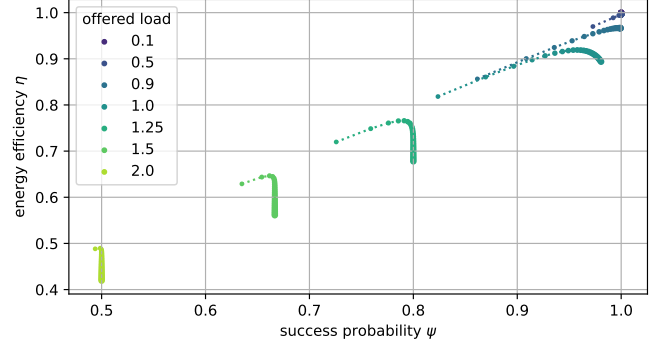


Fig. 3. Trade-off between success probability  $\psi$  and energy efficiency  $\eta$  for perfect CSMA/CA with periodic sensing (option B). The size of the markers indicates the parameter  $S$ .

### D. Kleinrock's Approach for Deriving the Operational Point

For the identification of the operational point, which is the number of waiting places  $S$  for the M/D/1- $S$  queueing system, we follow an approach by Kleinrock [19]. He suggests the *Power* metric in queueing systems as optimization metric to identify the knee of the curve. The power metric is the ratio of 'goodness' divided by 'badness'. Then, the optimization of power leads to a trade-off between maximizing 'goodness' while minimizing 'badness'. For the IoT system and CSMA/CA with restricted accessibility, consider the ratio between energy efficiency  $\eta$  and the counter success probability ( $1 - \psi$ ). The maximum of the ratio  $G/B = \eta/(1 - \psi)$  corresponds to the operational point  $S^*$ . Hence,

$$S^* = \arg \max_S G/B = \arg \max_S \frac{\eta}{1 - \psi} \quad (12)$$

Figure 4 indicates the optimal parameter  $S^*$  depending on the actual load in the network. Thereby, we compare both options for listen-before-talk (A: single sensing, B: periodic sensing). In practice, we may additionally limit the parameter  $S$ , e.g. due to guarantee a maximum response time, i.e. maximum time for waiting and sending a single message. In the results in Figure 4, we limit  $S$  to 25. The plot nicely demonstrates that the optimal number  $S^*$  strongly depends on the offered load in the system. The listen-before-talk options A and B are identical up to an offered load of  $a = 1$ . After that point, periodic sensing suffers more from large values of  $S$  and the required energy consumption. Hence, smaller values of  $S^*$  are obtained for option B. Nevertheless, the shape of the curves are similar.

In practice, adaptive mechanisms are recommended. Depending on the load, the parameter  $S$  in the system may

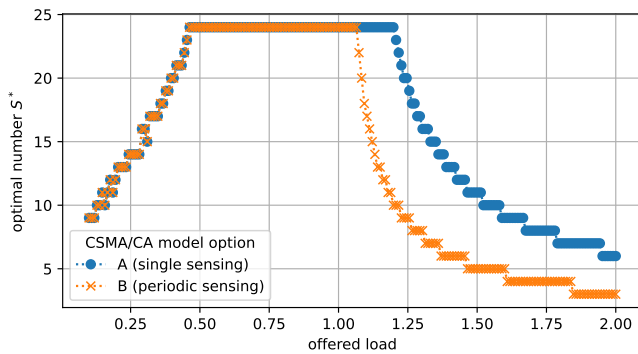


Fig. 4. Trade-off between success probability  $\psi$  and energy efficiency  $\eta$  for perfect CSMA/CA with restricted accessibility (M/D/1-S). Maximum  $S = 25$ .

be adapted. This could be reached via load measurement or estimated at the gateway with simple prediction models, which remains for future work.

## V. CONCLUSIONS AND DISCUSSIONS

The steep growth of use cases in the area of IoT over the last years has simultaneously led to developments of novel technologies to satisfy the need of these many, heterogeneous verticals. Specifically, a range of wireless technologies with the goal of conserving energy have emerged. However, even these specifically developed radio technologies, like LoRa or Zigbee, are supported by legacy approaches to provide e.g. channel access mechanisms. In this paper, we have presented a generic model that describes the energy efficiency of an IoT deployment under perfect CSMA/CA channel access. We have highlighted the calculation rules of the model and provided numerical results for a well-known LoRa device. In our numerical analysis we compare different system configurations against each other and outline the impact of the size of a transmission backlog in CSMA/CA environments. The results show that large backlogs increase energy efficiency for low system loads, but lead to excessive waiting times and hence additional energy consumption under high load scenarios. We finally apply Kleinrock's power metric to identify optimal system configurations for different load levels. The results show that small backlogs are optimal for extremely low as well as extremely high system load, while larger queues are beneficial in medium load scenarios.

The generic model proposed in this work can easily be adapted to more complex or other channel access mechanisms. This as well as an integration into adaptive mechanisms to dynamically reconfigure the system at runtime remains for future work.

## REFERENCES

- [1] F. Loh, N. Mehling, and T. Hoßfeld, "Towards lorawan without data loss: Studying the performance of different channel access approaches," *Sensors*, 2022.
- [2] J. Ortín, M. Cesana, and A. Redondi, "Augmenting lorawan performance with listen before talk," *IEEE Transactions on Wireless Communications*, 2019.
- [3] T. Polonelli, D. Brunelli, A. Marzocchi, and L. Benini, "Slotted aloha on lorawan-design, analysis, and deployment," *Sensors*, 2019.
- [4] F. Loh, S. Raffeck, F. Metzger, and T. Hoßfeld, "Improving lorawan's successful information transmission rate with redundancy," in *2021 17th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*, IEEE, 2021.
- [5] L. Beltramelli, A. Mahmood, P. Österberg, and M. Gidlund, "Lora beyond aloha: An investigation of alternative random access protocols," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 5, 2021.
- [6] C. Pham, "Investigating and experimenting csma channel access mechanisms for lora iot networks," in *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, 2018.
- [7] T.-H. To and A. Duda, "Simulation of lora in ns-3: Improving lora performance with csma," in *2018 IEEE International Conference on Communications (ICC)*, 2018.
- [8] L. Casals, B. Mir, R. Vidal, and C. Gomez, "Modeling the energy performance of lorawan," *Sensors*, 2017.
- [9] J. Tosi, F. Taffoni, M. Santacatterina, R. Sannino, and D. Formica, "Performance evaluation of bluetooth low energy: A systematic review," *Sensors*, vol. 17, no. 12, 2017, ISSN: 1424-8220. [Online]. Available: <https://www.mdpi.com/1424-8220/17/12/2898>.
- [10] M. El Soussi, P. Zand, F. Pasveer, and G. Dolmans, "Evaluating the performance of emtc and nb-iot for smart city applications," in *2018 IEEE International Conference on Communications (ICC)*, 2018.
- [11] R. K. Singh, P. P. Puluckul, R. Berkvens, and M. Weyn, "Energy consumption analysis of lpwan technologies and lifetime estimation for iot application," *Sensors*, vol. 20, no. 17, 2020, ISSN: 1424-8220. [Online]. Available: <https://www.mdpi.com/1424-8220/20/17/4794>.
- [12] A. Strielkina, D. Uzun, and V. Kharchenko, "Modelling of healthcare iot using the queueing theory," in *2017 9th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS)*, vol. 2, 2017.
- [13] G. Bouloukakis, I. Moscholios, N. Georgantas, and V. Issarny, "Performance analysis of internet of things interactions via simulation-based queueing models," *Future Internet*, vol. 13, no. 4, 2021, ISSN: 1999-5903. [Online]. Available: <https://www.mdpi.com/1999-5903/13/4/87>.
- [14] M. Gharbieh, H. ElSawy, A. Bader, and M.-S. Alouini, "Spatiotemporal stochastic modeling of iot enabled cellular networks: Scalability and stability analysis," *IEEE Transactions on Communications*, vol. 65, no. 8, 2017.
- [15] T. Hoßfeld, F. Metzger, and P. E. Heegaard, "Traffic modeling for aggregated periodic iot data," in *2018 21st Conf. on Innovation in Clouds, Internet and Networks and Workshops (ICIN)*, IEEE, 2018.
- [16] P. Tran-Gia and T. Hoßfeld, *Performance Modeling and Analysis of Communication Networks, A Lecture Note*. Würzburg University Press, 2021, ISBN: 978-3-95826-153-2. [Online]. Available: <https://modeling.systems>.
- [17] D. Boyle, R. Kolcun, and E. Yeatman, "Energy-efficient communication in wireless networks," *ICT – Energy Concepts for Energy Efficiency and Sustainability*, 2017.
- [18] F. Adelantado, X. Vilajosana, P. Tuset-Peiro, B. Martinez, J. Melia-Segui, and T. Watteyne, "Understanding the limits of lorawan," *IEEE Communications magazine*, vol. 55, no. 9, 2017.
- [19] L. Kleinrock, "Internet congestion control using the power metric: Keep the pipe just full, but no fuller," *Elsevier Ad hoc networks*, vol. 80, 2018.