Modeling and parameter analysis of IEEE 802.15.4-based networks and the metering application

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Abstract
As the support of wireless sensor networks expands to various application scenarios, the communication environments and the performance requirements of different application scenarios vary a lot. To cope with different communication environments and performance requirements, both data transmission ability and medium access ability are equivalently important. In this article, a joint analytical model is proposed to fully and precisely estimate networks’ communication performance, energy efficiency, and scalability. In the proposed model, both the physical layer’s and medium access control layer’s key parameters are taken into consideration. By comparing with OPNET-based simulation model, the rationality of the proposed analytical model is first validated under a wide range of network scenarios. Then, a series of simulations under general network scenarios and metering network scenarios are conducted. With these simulations, the performance of adjusting both layers’ parameters in improving communication performance and energy efficiency was proved superior to single-layer’s parameter optimizations. Finally, by comparing the available range of different key parameters’ optimal value under different network scenarios, the maximum backoff numbers and the minimum backoff exponent are considered to be the most effective parameters for metering network optimization.

Keywords
IEEE 802.15.4, CSMA/CA, transmission power control, data packet size, periodic traffic, metering networks

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Introduction
Wireless sensor networks (WSNs) have penetrated many kinds of applications, from habitat monitoring to industrial control, for its advantages of low deployment costs, easier to installation, maintenance and reconfiguration, as well as inherent intelligent-processing capability over traditional wired devices.¹ For example, as one of the emerging applications of WSNs, new smart meters have superseded the traditional counterpart—wired electricity, water, and gas meters.² While, as the support of WSNs expands to various applications, the network configurations and performance requirements diverse a lot. In general IEEE 802.15.4-based metering networks, the scale of network usually ranges from tens to thousands of meters.³ And the data acquisition interval ranges from milliseconds to days.¹ Salam and Khan⁴ list some critical issues that can degrade overall network efficiency for WSNs, which include energy efficiency, reliability, latency, climate, dynamic network, and security. Since sensor nodes are battery-powered while WSNs are generally designed to support applications in long-term

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deployments, the object of high energy efficiency usually
contradicts with high reliable and real-time communica-
tion. These contradictions become more outstanding in
metering networks. In metering network, maintaining
high reliability and low latency communication is indis-
ensible. However, the performance of communication in
WSNs usually fluctuates over time and space. And
the harsh environment that metering networks exist
makes communication links even more unreliable. For
example, the multipath effect, frequency selective fading,
and data delay often occur in the underwater acoustic
communication due to the low transmission rate (gener-
ally ≤ 100 kbps).\textsuperscript{5} Besides, the metering network may
have to accommodate more and more devices, which
demands the network with good scalability. To deal with
these challenges, single-layer’s analysis is not sufficient
anymore. Hence, this article takes the key parameters of
the physical layer and medium access control (MAC)
layer into consideration and constructs an overall analy-
tical model to investigate the joint impact of these para-
eters on networks’ reliability, time efficiency, energy
efficiency, and scalability.

The contributions of this article are as follows:

1. Without directly assuming the distribution of
network traffic as previous works do, in this
article, the network traffic on each channel is
mathematically approximated as a Poisson’s
process by characterizing the generation process
of network traffic with a series of transforma-
tions among different stochastic processes.

2. An accurate and comprehensive analytical
model for the analysis of IEEE 802.15.4 is pro-
posed. The characteristic of sensor nodes is
based on the TelosB mote Module.\textsuperscript{6} On the
physical layer, we take both modulation way
and handshake mechanisms into consideration.
On the MAC layer, by leveraging the properties
of Poisson’s process, a simple but accurate for-
mula of calculating the probability of successful
channel access is obtained.

3. The effect of adjusting different layer’s para-
meters on improving networks’ communication
performance and energy efficiency is simulated
and analyzed in both general networks and
metering networks.

4. According to the optimal value of key para-
meters under different network scenarios, we
find out that the maximum backoff numbers
and the minimum backoff exponent are the
most effective parameters for metering network
optimization.

The remainder of the article is organized as follows:
related work is given in section “Related works.”
Section “System model” presents the WSN network
traffic analysis, the analytical model, and critical issues.
In section “Critical issues,” three critical issues concern-
ing data transport performance and energy efficiency
are proposed and analytically characterized. In section
“Simulation and analysis,” rational analysis and per-
formance evaluation of the proposed analytical model
and critical issue optimizations are presented. Section
“Conclusion” provides our concluding remarks and
discussions of the results.

Related works

IEEE 802.15.4 has been thoroughly investigated and
many models together with optimization approaches
have been proposed in the literature.\textsuperscript{7–27} Most of
the proposed analytical models focus on either the physical
layer or on the MAC layer. While in fact, the perfor-
mance of communication is affected by both layers.

On the physical layer, in the quest for more accurate
wireless channel characteristics, most analytical models
adopt empirical data-based channel models.\textsuperscript{8–19} While
the assumption of transmission features and corre-
sponding energy dissipation characteristics differs a lot.
The models in the literature\textsuperscript{8,9} assume the transmission
power to be fixed. The models in the literature\textsuperscript{10–12}
assume the transmission power can be adjusted con-
tinuously within a predefined range. While in the litera-
ture,\textsuperscript{13,14} they adopt discrete transmission power levels
which are based on the characteristics of real sensor
motes, such as Mica2 motes. Besides, within these stud-
ies, few of them consider the two-way handshaking
mechanism completely. Although the model in the liter-
ature\textsuperscript{15} considers the energy dissipation of both data
packet and ACK packet transmission, it ignores the
failure probability of ACK transmission. Inspired by
Kurt et al.,\textsuperscript{16} many analytical models of physical layer
start to take both successful probability and energy dis-
sipation of two-way handshaking mechanism into con-
sideration.\textsuperscript{17–19} Similarly, in this article, we model the
physical layer according to the characteristics of the
MICAz mote and take both modulation way and hand-
shake mechanism into consideration.

Inspired by Bianchi’s\textsuperscript{20} work, many models of the
IEEE 802.15.4 MAC layer have been proposed in the
literature.\textsuperscript{7,21–27} The majority of them are the Markov
chain based.\textsuperscript{21–27} Park et al.\textsuperscript{21} propose a general
Markov chain model for the analysis of the IEEE
802.15.4 MAC layer. They took the retransmission
limit and handshaking mechanism into consideration.
However, the model in Park et al.\textsuperscript{21} assumed a satu-
rated traffic input which is not suitable for the majority
appliances where the network does not always have
packets to send. Jung et al.\textsuperscript{22} propose an analytical
Markov chain model under unsaturated traffic condi-
tions. In their proposed model, they considered
superframe structure, retransmission limit, and handshaking operation, which is better reflected the characteristics of the IEEE 802.15.4 MAC layer. However, since the Markov chain model adopts states to characterize the status and behaviors of wireless sensor nodes, a large number of states will be defined for a precise model. In some applications like industrial metering, the network may envisage a relatively large node population. The adoption of Markov chain model would render the whole model more complicated. Besides, another detail of Jung et al.22 that needs to be reconsidered is the assumption of each node’s data frame arrival rate. For many metering networks, nodes usually generate data periodically. Hence, successive data packets from the same node are almost strongly correlated with each other, which is inadequate to model as a Poisson’s process.

To avoid the high computational complexity that the Markov chain model brings about in dense WSNs, the model in Elshabrawy et al.7 assumes the traffic of a WSN with thousands of devices follows the Poisson’s distribution. And the arrival rate of clear channel assessment (CCA) attempts is analytically derived as a Poisson’s process. The report success probability is finally evaluated according to the aggregate CCA attempts rate. However, the relationship between aggregate CCA arrival rate and the report success probability in Elshabrawy et al.7 cannot be formulated, which will definitely take additional calculations in simulations. Inspired by Elshabrawy et al.7 and Kurt et al.16 we propose a more comprehensive and scalable analytical model for the analysis of IEEE 802.15.4. Instead of directly assuming the distribution of network traffic as Elshabrawy et al.7 and Jung et al.22 do, we provide a series of rigorous deductions on it. The MAC layer model in this article furtherly uses the properties of Poisson’s process and obtains a more detailed analytical model but with lower computation complexity than the model in Elshabrawy et al.7 Besides, in addition to evaluating the throughput and energy consumption issue, this article explicitly analyzes and formulates three critical issues for WSNs, that is, reliability, time efficiency, and energy efficiency. Finally, a typical metering network is analyzed objectively and comprehensively under different network scales and traffic loads.

System model

Overview

We consider a WSN working in the beacon-enabled mode with star topology. One base station at the center and multiple sensor nodes are uniformly deployed around the base station within carrier sensing range. On the physical layer, we assume the transmission of a data packet is confirmed with handshaking mechanism (i.e. each successful transmission is replied with an ACK packet by the receiver). The characteristics of sensor nodes in this research take the TelosB mote Module as a reference, to simulate the actual situation as possible. On the MAC layer, we only consider the contention access period (CAP) in the active period. Beacon period and contention-free period (CFP) in the active period, as well as the inactive period, are beyond the consideration.

Network traffic analysis

Each sensor node is assumed to send a data packet to the base station in every T seconds, which consists of $n_T$ sequential time slots. For one sensor node, the probability that there exists a data packet needs to be reported is $1/n_T$. For one channel shared by $N_C$ devices, the probability that there exists a data packet needed to be transmitted from this channel at each single time slot is

$$p_C = 1 - \left(1 - \frac{1}{n_T}\right)^{N_C} \quad (1)$$

For each sensor node, its successive data packets usually have a very strong correlation since each node usually reports to the base station periodically. However, for one channel shared by several sensor nodes, the correlation between its two successive data packets is much weaker. Since successive data packets that arriving at one channel always come from different sensor nodes, which may be completely irrelevant no matter in terms of external surroundings or application objects. Hence, it is more adequate to approximate the case that $k$ data packets are transmitted through one channel within $n_T$ time slots as a Binomial process. And the corresponding probability is

$$P_C^{k,n_T} = \frac{k}{n_T} p_C (1 - p_C)^{n_T-k} \quad (2)$$

According to equation (1), for a given report period $T$, as the duration of each time slot decreases, the value of $n_T$ increases while the value of $p_C$ decreases. Hence, we can get the limit of $P_C^{k,n_T}$

$$\lim_{n_T \rightarrow \infty, p_C \rightarrow 0} P_C^{k,n_T} = \lim_{n_T \rightarrow \infty, p_C \rightarrow 0} \frac{(n_T p_C)^k}{k!} \frac{(1-p_C)^{n_T-k}}{(1-p_C)^k} = e^{-p_C} \left(\frac{n_T p_C}{e}\right)$$

As $n_T$ increases and $p_C$ approximates to 0, $(1 - p_C)^{-1/p_C}$ approximates to $e$ and $1/(1-p_C)^k$ approximates to 0. The limit of $P_C^{k,n_T}$ can be furtherly expressed as
\[
\lim_{n_T \to \infty, p_C \to 0} p_C^{k,n_T} = \lim_{n_T \to \infty, p_C \to 0} \frac{(n_Tp_C)^k}{k!} e^{-(n_Tp_C)} \quad (4)
\]

Let the product of \(n_T\) and \(p_C\) as \(\lambda\), according to equation (4) we can get the limit of \(p_C^{k,n_T}\) approximates to Poisson’s distribution

\[
\lim_{n_T \to \infty, p_C \to 0} p_C^{k,n_T} = \lim_{n_T \to \infty, p_C \to 0} \frac{\lambda^k}{k!} e^{-\lambda} \quad (5)
\]

In the slotted CSMA/CA algorithm, the duration of one unit backoff slot is 320 \(\mu\)s. While for a sensor node in the network, the time interval between its two successive data packets is always counted by seconds. The value of \(n_T\) is at the level of hundreds to thousands accordingly. Hence, the data packet transmission on one channel is reasonable to be approximated as a Poisson’s process with the arrival rate \(\lambda\) as \(n_Tp_C\).

**Device mode analysis**

A wireless sensor node is always composed of several modules, including sensors, radio module, antenna, microcontroller unit (MCU), and so on. Radio module, antenna, and MCU are three main components in charge of data transmission. In the following analyses, we only consider the operation modes and energy consumption of the radio module and MCU, since these two modules are major modules in terms of both device function and energy consumption. TelosB mote takes the Chipcon CC2420\(^{28}\) as its radio module and adopts the TI-MSP430 microprocessor\(^{29}\) as its MCU module. The Chipcon CC2420 radio module has four operation modes: transmit, receive, idle, and sleep. Different operation modes correspond to different power consumptions. The TI-MSP430 microprocessor has six operation modes: one active mode and five low-power modes, that is, from LPM0 to LPM4.\(^{29}\)

According to the IEEE 802.15.4 standard, a node can be in one of the following four states: transmit, receive, idle, and sleep. A sensor node enters in transmit state as long as it is sending data packet. When in transmit state, the radio module stays in transmit mode and the MCU module stays in active mode for the procession of data packet. A node stays in the receive state as long as it is receiving a packet or performing CCA. And then, its radio module turns to receive mode and the MCU module stays in active mode to process received data or to identify whether the channel is clear or not. If there is no packet to be transmitted while the node is in the active period or it stays at the backoff period, the node is in idle state. And then, the radio module is in receive mode and the MCU module is assumed to be in LPM3. Because in LPM3, the main clock source and the timer oscillator should be enabled in the MCU module to support for scheduled wake-ups. When a node is in the inactive period, it stays in sleep state with its radio module in sleep mode and its MCU module is assumed to be in LPM4, that is, the deepest sleep mode. Hence, the power consumption of the mentioned modes is shown in Table 1.

### Analytical model

The occurrence of a successful packet reception can be attributed to a series of layers. The proposed model is targeted to theoretically analyze the impact of physical layer and MAC layer on successful communication. For the physical layer and the MAC layer, packets are successfully received due to two reasons: successful channel access and successful packet transmission. In this analytical model, the key parameters of both the physical layer and the MAC layer that concerning the channel access operations and packet transmission are taken into consideration, as is shown in Figure 1. It should be noticed that the proposed model does not take the correlation and interaction between two layers into consideration. Since the impact of each layer on communication is independent. With the successful handshaking probability and the successful CCA probability, network performance metrics including network reliability, time efficiency, and energy efficiency can be estimated easily.

According to the datasheet of the Chipcon CC2420 radio module, the radio module provides eight transmission power levels, which is listed in Table 2 together with corresponding output power and power consumption.

| Devices | Modes         | Energy consumption (mW) |
|---------|---------------|-------------------------|
| TI-MSP430 | Active mode  | 1.5                     |
|         | Idle mode    | 0.006                   |
|         | Power down mode | 0.0006              |
| CC2420  | Receive mode | 59.1                    |
|         | Idle mode    | 0.06                    |
|         | Sleep mode   | 0.003                   |

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Considering a data packet is transmitted at power level \(l\), the received signal power with a distance of \(d(m)\) away from the transmitter can be expressed as

\[
P_T(l)(dBm) = P_S(l)(dBm) - PL(d)(dB) \quad (6)
\]

where \(PL(d)(dB)\) is the path loss. In this research, the lognormal path loss model is taken as the reference since it can capture the random variations of path loss more accurately than either the two-ray model or the
The log-normal path loss model can be expressed as

$$PL_{ij}(dB) = PL(d_0)(dB) + 10\eta \log \left(\frac{d}{d_0}\right) + \chi$$ \hspace{1cm} (7)

where $d$ is the distance between transmitter and receiver, $d_0$ is the reference distance, $PL(d_0)(dB)$ is the path loss at the reference distance, $\eta$ is the path loss exponent and $\chi$ is a zero-mean Gaussian random variable with the standard deviation $\chi(dB)$ to model large-scale fading effects. It should be noticed that the log-normal path loss model can be applied to general monitoring scenarios, such as industrial process monitoring and advanced metering infrastructures in the smart grid. While for wireless body area networks, additional losses should be added. Therefore, the signal to noise ratio (SNR) that due to the transmission power at level $l$ and the propagation distance of $d(m)$ can be expressed as

$$\psi(l, d)(dB) = P_{tx}(l)(dBm) - LF(d)(dB) - P_n(dBm)$$ \hspace{1cm} (8)

To cope with bit errors caused by noise, in digital communication, signals are always been modulated before transmission. To present the effect of modulation in improving the reliability of communication, we tried to transmit a signal in two different ways: one is to transmit it with offset-quadrature phase-shift keying (O-QPSK) modulation and the other way is to transmit it directly without any modulation. In Figure 2, it can be found that the transmitted signal with modulation can always obtain lower bit error rate (BER) than without modulation, especially when the SNR is high.

The BER of binary phase-shift keying (BPSK) modulation can be simply expressed with $Q$-function as

$$ber(l, d) = Q\left(\sqrt{2\psi(l, d)}\right)$$ \hspace{1cm} (9)
where the $Q$-function is defined as

$$ Q(x) = \frac{1}{\sqrt{2\pi}} \int_{x}^{\infty} e^{-\frac{1}{2}t^2} dt $$  \hspace{1cm} (10) $$

For the O-QPSK modulation scheme, it consists of two BPSK modulations on in-phase and quadrature components of the signal. Hence, its BER can also be expressed as

$$ \text{ber}(l, d) = Q\left(\sqrt{2\psi(l, d) \cdot G_p}\right) $$  \hspace{1cm} (11) $$

where $G_p$ is the process gain and equal to 8 for CC2420 radios.

Hence, the probability of a successful handshake can be expressed as

$$ p_{\text{S}}^{\text{HS}}(l, k, b_{\text{ack}}, d) = p_{\text{S}}^{\text{tx}}(l, b, d) \cdot p_{\text{S}}^{\text{tx}}(k, b_{\text{ack}}, d) $$  \hspace{1cm} (14) $$

And the probability of a failed handshake should be

$$ p_{\text{F}}^{\text{HS}}(l, k, b_{\text{ack}}, d) = 1 - p_{\text{S}}^{\text{HS}}(l, k, b_{\text{ack}}, d) $$  \hspace{1cm} (15) $$

On the MAC layer, sensor nodes start to perform CCA attempt as a new data packet arrives. Let $p_{\text{CCA}}^{\text{S}}$ depicts the probability of successfully passing CCA. Every time sensor nodes fail to access to the channel, a new CCA process starts. Considering all chances until the maximum number of backoffs $N_{B}^{(\text{max})}$ is reached, the aggregate arrival rate of CCA attempts for one channel $\lambda_{\text{CCA}}$ can be represented in terms of $\lambda$

$$ \lambda_{\text{CCA}} = \lambda \cdot \sum_{k=0}^{N_{B}^{(\text{max})}} (1 - p_{\text{CCA}}^{\text{S}})^k $$  \hspace{1cm} (16) $$

Since the packet arrival rate at one channel is assumed to follow a Poisson’s distribution, the CCA attempt rate of a channel $\lambda_{\text{CCA}}$ also follows a Poisson’s distribution with fixed $N_{B}^{(\text{max})}$ and $p_{\text{CCA}}^{\text{S}}$. According to the slotted CSMA/CA algorithm, sensor nodes should perform the CCA process to check whether a channel is idle or not before transmission. If the channel is busy, it will wait for a random period of time and check again. The backoff period is a random number of unit backoff slots from 0 to $2^{BE} - 1$. With the assistance of backoff, nodes can avoid the failure of CCA to some extent. Larger $N_{B}^{(\text{max})}$ offers more chances of performing CCA. Larger backoff exponent $BE$ offers nodes more backoff delay options, which will enlarge the disparity in backoff duration among nodes to decrease the probability of CCA failure. IEEE 802.15.4
slotted CSMA/CA algorithm bounds the value of back-off exponent between minimum backoff exponent value $BE_{\text{min}}$ to maximum backoff exponent value $BE_{\text{max}}$. It is to be noted that the maximum value allowed for minimum $BE$ by the IEEE 802.15.4 standard is equal to 8. Hence, the probability of successfully passing CCA $p_{\text{CCA}}^S$ is affected by $N^{(\text{max})}_B$ and $BE_{\text{min}}$.

As is shown in Figure 3, according to whether the time interval between two successive CCAs on one channel is larger than one complete handshaking duration or not, the probability of successful CCA can be classified into two cases. According to case 1, if the time interval between the current CCA attempt and previous CCA attempt on one channel is larger than one complete handshaking duration, the current CCA will succeed for the length of time interval is enough for handshaking. In this notation, the backoff period is included in the time interval for the first CCA of a new data packet. According to the theory of Poisson's distribution, the distribution of time interval between two consecutive CCA attempts follows the exponential distribution. Therefore, the probability of case 1 can be expressed as

$$p_{\text{CCA}}^{\text{CI}} = e^{-\lambda_{\text{CCA}}} T_{\text{HS}}^S$$

(17)

A complete operation of handshaking includes the time of transmitting data packet, the time of waiting for ACK packet, and the time of receiving ACK packet. Accordingly, the time of one complete handshaking operation $T_{\text{HS}}^S$ is

$$T_{\text{HS}}^S = T_{\text{pkt}} + T_{\text{ack}} + T_{\text{wait}}$$

(18)

where $T_{\text{pkt}}$ and $T_{\text{ack}}$ are the transmission time of data packet and ACK packet, respectively. Term $T_{\text{wait}}$ is the time interval between the end of data packet transmission and the beginning of ACK packet reception.

As is shown by case 2 in Figure 3, if the time interval between current CCA attempt and previous CCA attempt on this channel is no larger than one complete handshaking duration, the sensor node of performing current CCA attempt can take its previous backoff period as a reference to do the primary evaluation. Supposing that all nodes are staying at the same back-off stage $S$, one node's CCA attempt can be successful only if no CCA attempts succeed within the previous $T_{\text{HS}}^S$, which can be expressed as

$$p_{\text{CCA}}^{\text{BE}} = 1 - \left(1 - \left(1 - \frac{1}{2^B - 1}\right)^{N_{\text{BE}}-1}\right) \cdot p_{\text{CCA}}^{\text{BE}} \cdot \frac{T_{\text{HS}}^S}{T_{\text{bk,unit}}}$$

(19)

where $T_{\text{bk,unit}}$ is the time duration of unit backoff slot. Hence, the probability of successfully passing CCA can be expressed as

$$p_{\text{CCA}}^S = 1 - \prod_{i=0}^{N_{\text{BE}}^{(\text{max})}} \left( p_{\text{CCA}}^{\text{CI}} + (1 - p_{\text{CCA}}^{\text{CI}}) \cdot p_{\text{CCA}}^{\text{BE}}(i) \right)$$

(20)

Critical issues

Reliability

Reliability is denoted as the probability of successful packet reception $p_S^R$. According to previous analyses on the physical layer and the MAC layer, packets are unsuccessfully received due to two reasons: channel access failure and packet collision. Channel access failure happens when a packet fails to access the channel within $N_{BE}^{(\text{max})}$ times of CCAs. And a packet is discarded if it cannot be received within $n$ times of retry. Hence, the probability of successful packet reception can be expressed with the probability of successfully passing CCA $p_{\text{CCA}}^S$ and the probability of a successful handshake $p_{\text{HS}}^S$.
\[ p^S = \sum_{j=1}^{n} p^S_{CCA} \cdot (1 - p^S_{HS})^{j-1} \cdot p^S_{HS} \]  

**Time efficiency**

Time efficiency is denoted as the excepted time interval for a successfully received packet from ready to be transmitted, until the transmission is successful and the ACK is received, that is, expected transmission latency \( T^E_{DL} \). The delay mainly comes from two operations: backoff operations on the MAC layer and handshaking operations on the physical layer. Based on the analytical model proposed earlier, the expected duration of the delay caused by backoff operation can be expressed as

\[
T^E_{BF} = \sum_{k=0}^{N_{min}} \sum_{i=0}^{k} \left( E\left( 2^{\text{min}(BE + i, \text{BEmax})} - 1 \right) T_{blk} + 2T_{CCA} \right) \cdot P^S_{CCA}(p^F_{CCA})^k
\]

(22)

The expected delay caused by successful handshaking is given in equation (18). The expected delay caused by failed handshaking includes two parts, that is, the transmission time of data packet \( T_{pkt} \) and the maximum duration of waiting for acknowledgment \( T^\text{max}_{wait} \)

\[ T^E_{HS} = T_{pkt} + T_{wait}^\text{max} \]

(23)

where the maximum duration of waiting for acknowledgment \( T_{wait}^\text{max} \) is 864 \( \mu \text{s} \).

Hence, the expected transmission latency with the retransmission times as \( n \) can be expressed as

\[
T^E_{DL} = \sum_{j=0}^{n} (T^E_{BF}(j + 1) + T^E_{HS} + T^S_{HS} \cdot P^S_{HS}(p^F_{HS})^j) + \left( T^E_{BF} + T^E_{HS}(j + 1) \cdot (p^F_{HS})^j \right) + 1
\]

(24)

**Energy efficiency**

The operation of transmitting a packet is composed of performing CCA, backoff, data packet transmission, and ACK packet reception, which have been carried out earlier in the node’s behavior analysis. And the energy consumption of each operation can be estimated as the product of its duration and its power. With the expected latency of successful handshaking and failed handshaking, the expected energy consumption of handshaking operations can be derived similarly

\[
E^S_{HS} = P^{tx} \cdot T^\text{pkt}_{tx} + P^{idle} \cdot T_{ack} + P^{rx} \cdot T^\text{ack}_{rx}
\]

(25)

\[
E^F_{HS} = P^{tx} \cdot T^\text{pkt}_{tx} + P^{rx} \cdot T^\text{wait}_{max}
\]

(26)

The expected energy consumption caused by backoff operations can be expressed as

\[
E^E_{BF} = \sum_{k=0}^{N_{success}} \sum_{i=0}^{k} \left( E\left( 2^{\text{min}(BE + i, \text{BEmax})} - 1 \right) T_{blk} + 2T_{CCA} \right) \cdot P^S_{CCA}(p^F_{CCA})^k
\]

(27)

Hence, the expected energy consumption of successful transmitting a packet is

\[
E^E = \sum_{j=0}^{n} (E^E_{BF}(j + 1) + E^S_{HS} + E^F_{HS}) \cdot p^S_{HS}(p^F_{HS})^j + \left( E^E_{BF} + E^S_{HS}(j + 1) \cdot (p^F_{HS})^j \right) + 1
\]

(28)

In the following section, the energy efficiency is measured by energy per megabits (EPMs), the energy consumed by sending 1 MB of data with the unit as mJ

\[
E^E_{MB} = \frac{1 \text{MB}}{b \cdot p^x}.
\]

(29)

**Simulation and analysis**

**Simulation setup**

In the following simulations, WSN devices are uniformly distributed within an area of 100 m \( \times \) 100 m and operate in the 2.4-GHz industrial, scientific and medical (ISM) radio band with 16 workable channels. We borrow one of the path loss models from Kilic and Gungor\textsuperscript{34} as \( \eta = 1.64, \chi = 3.29 \text{dB}, d_0 = 1 \text{m}, \) and \( PL(d_0)(\text{dB}) = 71.84 \text{dB}, \) which is derived from real smart grid environment measurements. The noise power \( P_n \) at the receiver can be evaluated as 100 dBm according to Pöttner et al.\textsuperscript{35} The power consumptions of a device in different modes are according to Table 1. Key parameters are assumed to follow the IEEE 802.15.4 standard\textsuperscript{32} and TelosB mote Module,\textsuperscript{6} and they are listed in Table 3 together with parameters of simulation scenarios.

The value of the time interval between the end of data packet transmission and the beginning of acknowledgment packet reception \( T_{wait} \) is assumed as 360 \( \mu \text{s} \), according to the measurement result of Pöttner et al.\textsuperscript{35} In the following simulations, parameters are equal to the default value unless specified. And all the optimal values of key parameters are obtained through exhaust algorithms, which is reliable to search for the global optimum solution.

**Rational validation**

To validate whether the proposed analytical model is rational or not, a simulation model based on the
OPNET simulator is taken as a reference.\textsuperscript{36} The validation is carried out from two perspectives: different network scales and different traffic loads.

Figure 4(a)–(c) presents the result of validation from the traffic load perspective. From this perspective, 100 nodes are deployed within the square area with each node’s packet arrival rate $\lambda$ increases from 0.1 packets per second to two packets per second. Figure 4(d)–(f) presents the validation from different network scales, where from one node up to 225 nodes are deployed within the square area with a constant packet arrival rate of 0.5 packets per second.

As is shown in Figure 4(a) and (d), the reliability decreases slowly at first and then sharply as the number of devices increases and the packet arrival rate gets higher. Similarly, Figure 4(b) and (e) shows network with a larger scale and higher packet arrival rate will have a higher value of average delay. Figure 4(c) and (f) further compares the performance of two models in terms of power consumption. This could be explained in conjunction with the behavior of the physical layer and the MAC layer. A large number of nodes in dense networks will experience more serious fading on the link due to heavier interference and longer average

| Parameter | Range | Default |
|-----------|-------|---------|
| $T_{bk}$ | –     | 320 $\mu$s |
| $T_{wait, max}$ | –     | 864 $\mu$s |
| $T_{cca}$ | –     | 128 $\mu$s |
| $N_{c}^{(\text{max})}$ | 0–5   | 4       |
| $B_{E_{\text{min}}}$ | 3–8   | 5       |
| $B_{E_{\text{max}}}$ | –     | 8       |
| $P_{\text{tx}}(l)$ | [0, $-1$, $-3$, $-5$, $-7$, $-10$, $-15$, $-25$] dBm | 0 dBm |
| $P_{\text{rx}}(l)$ | –     | $-100$ dBm |
| $\lambda$ | 0.1–2 (packets per second) | 0.5 (packets per second) |
| $N_{c}$ | 1–225 | 100 |
| $b$ (with 8-byte header) | 28–128 (bytes) | 60 (bytes) |
| $b_{\text{back}}$ | –     | 12 (bytes) |

Figure 4. Performance comparisons between analytical models and simulated model under different traffic loads and different network scales.
transmission distance. A higher arrival rate of data packet brings a higher network load, which promotes more intensive CCA attempts and longer backoff duration, which then aggregate the competition of channel access and finally lead to substantial transmission failure.

As is shown in Figure 4, the proposed analytical model fits the simulation model well in terms of reliability, transmission latency, and EPM with small network scale and low packet arrival rate. Even though significant gaps appear as the number of nodes and the packet arrival rate increases, the analytical model always behaves as an upper bound of the simulation model in reliability and as a lower bound in transmission latency and EPM. From equation (1), we can find out large network scale and frequent data packet arrival bring each channel with higher value of $N_C$ and $n_T$, which increases the value of $p_C$. According to equation (3), smaller value of $p_C$ leads the value of $(1 - p_C)^{-1/p_C}$ more close to $e$, which makes the traffic on one channel approximates to a Poisson’s process.

**Numerical analysis**

The following simulation is performed under a typical scenario of 100 nodes deployed in the $100 \times 100$ m area. To test the performance of both layer’s parameter optimization, default parameter setting according to IEEE 802.15.4, physical layer–focused parameter optimization and MAC layer–focused parameter optimization are also presented.

**General network.** In this part of analyses, the default parameter settings are taken as a baseline setting to compare with. And the comparison is elaborated from two perspectives, that is, communication performance and energy effectiveness. In communication performance comparison, we take the energy efficiency of default parameter settings as the upper bound $EE_{MB, max}$. Three optimization methods present their best communication performance with their EPM no more than $EE_{MB, max}$. Figure 5(a)–(c) presents the comparisons among different parameter settings given fixed 100 nodes but with $\lambda$ ranges from 0.1 to 2. As is shown in Figure 5(a), no significant gaps present among four sets of parameters in terms of successful packet reception probability when $\lambda$ is lower than 0.5. While gaps present as the arrival of data packet getting intense. So does transmission comparisons shown in Figure 5(b), the differences getting obvious as $\lambda$ is larger than 0.5. While the EPM curve of default parameters always behaves as an upper bound regardless of the variation of data packet arrival rate. Similarly, the performances of four different parameter settings are very close with the network scale of less than 30. While as the network scale increases, the differences getting more obvious in terms of both successful packet reception probability and expected transmission latency. However, the EPMs of three optimized parameter settings are always lower than the default setting. From Figure 5, we observe that optimization considering both layers outperforms the rest optimizations and default setting in terms of both...
network reliability and time efficiency under various kinds of network scales and traffic loads.

In energy effectiveness comparison, we present the best energy effectiveness of three optimization methods with their communication performance no worse than default parameter settings. As is shown in Figure 6, three optimized parameter sets are all managed to meet the data transport performance constraints defined by default setting with higher energy efficiency. It should be noticed that the advantage of optimization considering both layers is more obvious in networks with more than 100 nodes and packet arrival rate more than 1.8. Hence, the optimization considering both layers outperforms the rest optimizations in terms of both data transport performance and energy efficiency under different network scales and traffic loads, especially in large-scale networks with heavy traffic loads.

Figure 7 gives a comparison between different optimization methods. With the requirements of successful packet reception probability no less than 90% and transmission latency no more than 500 ms, adequate results are presented in Figure 7 with corresponding energy consumption. By comparing Figure 7(d) with Figure 7(a)–(c), we can find out that with the assistance of joint layer parameter optimization, sensor nodes can meet the requirements of data transport performance but with lower energy consumption than other optimizations. Besides, joint layer parameter optimization enables the best network scalability than other optimizations since it guarantees sensor nodes working in denser networks with heavier traffic loads while still meets the network performance constraints, which is impossible with the assistance of other optimizations.

The optimal parameter settings derived by joint layer parameter optimization is shown in Figure 8. Nodes in small-scale networks with low traffic load can send larger packets with lower transmission power, more backoff times, and small backoff exponent. While as the network scale and traffic load increase, nodes should send smaller packets with higher transmission power, fewer backoff times, and large backoff exponent. It should be noticed that although Figure 8(a) indicates the size of data packet can be adjusted widely, it will be affected by the requirement of metering applications, such as the precision of sampling. From Figure 8(c), we can find that the available range of

**Figure 6.** Energy effectiveness comparisons among different optimization methods under different traffic loads and different network scales.

**Figure 7.** Comparison between different optimization methods under different network scales and traffic loads.

**Figure 8.** Optimal parameter settings derived by joint layer parameter optimization.
transmission power’s optimal value is limited. However, Figure 8(b) and (d) indicates that both the maximum number of backoffs and minimum backoff exponent can be adjusted within a large range. Therefore, the maximum number of backoffs and the minimum backoff exponent should be adjusted prior to other parameters in metering network optimizations.

Besides, in Figure 8(d), the optimal value of minimum backoff exponent changes with network scale and traffic load, which is different from the result shown in Elshabrawy et al. In networks with the traffic approximates to Poisson’s distribution, prolonging the duration of backoff has a limited contribution to successful packet reception probability. Since one of the basic properties of Poisson’s process is each event is statistically independent of all the other events in the process. On the contrary, larger value of backoff exponent brings higher average end-to-end delay, which will increase the probability of exceeding the transmission latency constraint $T_{DL, max}$.
Conclusion
To cope with different application characteristics, both communication link states, which may subject to path loss and interference, as well as the competition for medium access, which becomes inevitable with a large number of devices, should be equally considered. In this article, a joint analytical model considering both the physical layer and the MAC layer was proposed at first. On the physical layer, the model referred to the actual working modes of the TelosB mote Module and formulated the relationship among transmission power level, transmission distance, data packet size, modulation way, and successful handshaking probability. On the MAC layer, based on the approximation of Poisson’s distributed traffic on each channel, a formula to calculate the probability of successful channel access was obtained. Simulation results suggested that the proposed analytical model can precisely estimate networks’ communication performance and energy efficiency of different network scales as well as traffic loads. Then, we compared the effect of adjusting different layer’s parameters on improving networks’ communication performance and energy efficiency. The results showed that adjusting both layers’ parameters can provide better reliability, time efficiency, and energy efficiency than only focusing on a single layer’s parameters. Finally, to fulfill the communication requirement of metering applications, key parameters’ optimal value under different network scales and traffic loads were presented. By comparing the available range of different key parameters’ optimal value, the maximum number of backoffs and the minimum backoff exponent are considered to be more suitable for the optimization of the metering network.

In the following research, several aspects of the proposed model will be improved. First and foremost, the proposed model should be compatible with more kinds of modulation schemes. Based on the improvement, the impact of different modulation schemes on improving the performance of communication should be tested. Second, the key parameters and key features of network layer should be considered. More than physical layer and MAC layer, the impact of routing on the network layer will also be analyzed. Finally, more WSN-based network applications should be analyzed. The analytical model can be modified according to the network scales, traffic patterns, and communication performance requirements of different application scenarios, so as to comprehensively and accurately estimate the communication performance, energy efficiency, and scalability of the network.

Author contributions
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