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Analysis of Cross-Layer Design of Quality-of-Service Forward Geographic Wireless Sensor Network Routing Strategies in Green Internet of Things

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ABSTRACT Wireless sensor networks suffer from some limitations such as energy constraints and the cooperative demands essential to perform multi-hop geographic routing for Internet of things (IoT) applications. Quality of Service (QoS) depends to a great extent on offering participating nodes an incentive for collaborating. This paper presents a mathematical model for a new-generation of forwarding QoS routing determination that enables allocation of optimal path to satisfy QoS parameters to support a wide range of communication-intensive IoT's applications. The model is used to investigate the effects of multi-hop communication on a traffic system model designed with a Markov discrete-time $M/M/1$ queuing model, applicable to green deployment of duty-cycle sensor nodes. We present analytical formulation for the bit-error-rate, and a critical path-loss model is defined to the specified level of trust among the most frequently used nodes. Additionally, we address the degree of irregularity parameter for promoting adaptation to geographic switching with respect to two categories of transmission in distributed systems: hop-by-hop and end-to-end retransmission schemes. The simulations identified results for the average packet delay transmission, the energy consumption for transmission, and the throughput. The simulations offer insights into the impact of radio irregularity on the neighbor-discovery routing technique of both schemes. Based on the simulation results, the messages en-coded with non-return-to-zero have more green efficiency over multi-hop IoT (without loss of connectivity between nodes) than those encoded with the Manchester operation. The findings presented in this paper are of great help to designers of IoT.

INDEX TERMS Wireless sensor networks, quality of Service, Internet of Things, geographical routing, euclidean distance, network topology.

I. INTRODUCTION

Internet of Things (IoT) has been envisioned as one of promised collaborative distributed networks that consisting of numerous smart devices assembled for the purpose of monitoring real environments [1]. These devices may be scattered throughout an area of interest to observe a physical phenomenon [2], [3]. For example, sensor nodes that are deployed in hostile environments can track moving vehicles on high-ways, monitor climate changes, and provide early warnings for radiation hazards or an earthquake [4]. Moreover, the sensor nodes integrate with IoT as three sub-systems: sensing, processing, and communicating [5]. In most IoT's applications, they are placed above the floor or within a liquid medium using an antenna that is a few centimeters above the ground [1].

Several studies have demonstrated the communication component of sensor nodes; however, the operation of inefficient design of the antenna exhausts most of the battery-life of the sensor nodes, which might adversely affect the wireless channel and lead to error-prone links and inefficient routing [6]. In another hand, traffic control access to the media from the distributed sensor nodes should be strictly controlled to avoid or reduce redundancy and collisions, which have a dramatic impact on the lifetime of theses devices [7].

Hence, certain routing protocols in Wireless Sensor Networks (WSNs), such as geographic routing, require information (for example, a self-configuring localization mechanism or a-priori mechanism) that is adapted to the location of the sensor nodes for the purpose of information delivery [8]. Thus, geographic routing protocols are considered more efficient in IoT, since they minimize the size of sensor node storage by storing only the information on direct neighbors for forwarding the packet [9]. In this case, geographic routing is usually considered to be a smart forwarding mechanism whereby every node makes a decision to route the packet to the closest neighbors or to the nodes that are closest to the sink. Furthermore, such geographic routing protocols may be efficient, low-over-head methods that have sufficient network density, accurate localization, and significant link reliability in the sensor networks [10]. However, unfortunately they conserve more energy and bandwidth because the discovery floods and state propagation are not required beyond a single hop. Such energy conservation may generate unreliable links for forwarding; these situation are referred to as weakest link problems [11].

Unreliable links increase the rate of packet drops, delays, and energy consumption because of continuous retransmission. Certain sensor nodes may decide which path to forward the packets to based on the distance and number of hops and on the loss characteristics [12]. However, sensor nodes in IoT in most applications are distributed in an ad hoc fashion broadly use two transmission techniques to communicate among themselves or to send data to a sink: single-hop communication (SHC) and multi-hop communication (MHC), as shown in Fig. 1.

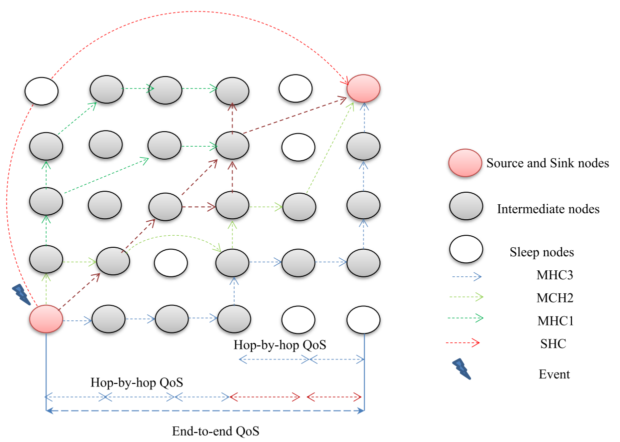

FIGURE 1. Single communication hop (SHC) and multi-hop communication (MHC) routing algorithm in wireless sensor networks.

In single-hop communication, the sensor nodes can cover the entire network and thus consume energy according to the longest transmission range [8]. Therefore, because of this fixed transmission range, extra energy is wasted even when the sensor nodes are close to one another because of retransmission caused by the unreliable links.

Meanwhile in MHC, the energy consumed for end-to-end increases as a nonlinear function of both the number of relaying nodes and the energy consumption for each individual hop; the sensor nodes attempt to maximize the per-hop reliability by forwarding to the nearest node with highly reliable links. This results in increased energy expenditure because of the increase in the number of hops until the final destination is reached. Regardless of weakest link problems, the hop distance is mainly determined by the transmission range. Moreover, the energy consumed in each individual hop increases with the transmission range set by the distance in relation to the attenuation factor of the signal propagation. As a result, differences between the number of hops and the transmission range occur. For example, if the hop number is small and the transmission range is large, the energy consumed for one transmission increases nonlinearly. Alternatively, if the hop distance is small for the same overall end-to-end transmission range, the energy consumption is dominated by the energy consumption of the transceivers; therefore, the total energy increases in an almost linear manner as a function of the hop number (in other word, with an increasing number of hops).

Apparently, there is a trade-off between the hop number, transmission range, and link status of each hop in MHC to achieve optimal green energy efficiency. More precisely, the network designer must consider these three parameters that govern energy consumption model in what is referred to as the distance-hop-energy trade-off [13].

Increasingly, a large number of IoT's applications require a real-time approach combined with queuing theory to provide a stochastic green model to guarantee the QoS parameters. This green model and several other solutions proposed for multimedia communications on the Internet and the wireless environment cannot be directly applied to IoT because of the influence of the wireless channel and the duty-cycle of the sensor nodes on various design characteristics, in addition to the resource allocation constraints of IoT applications [14]. Furthermore, the random nature of the wireless channel prohibits guaranteeing deterministic QoS parameters in MHC sensor networks. Consequently, an analysis of the stochastic green model of QoS metrics is necessary to address the QoS requirements in IoT's applications [15].

In this paper, an analytical green model is presented for a new-generation of forward QoS geographically routing determination that enables the allocation of the optimal path to satisfy the required QoS parameters. This green model is an extension the work reported [16] which intended to support a wide range of communication-intensive real-time multimedia for wireless sensor applications. Thus, the approach usually involves all of the structural layers in the communication protocol and the physical (PHY) and Media Access Control (MAC) layers of the IoT as depicts in Fig. 2.

The proposed model investigates the effects of MHC when deriving the equation for the bit-error-rate (BER). A critical path-loss model of the adaptive switching for two categories of transmission schemes is designed when the topology of the IoT matches the topology of the physical surroundings

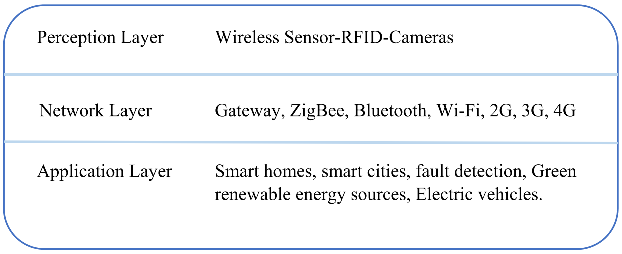

FIGURE 2. The three layers of IoT.

to govern the performance of energy consumption and QoS parameters. This adaptive switching occurs in accordance with the criterion embedded in the path-loss model parameter called the degree of irregularity (DOI) which is a function of the distance between two sensor nodes; this criterion is used in deciding which path from the source node to the next hop will be selected in forwarding the packet. Thus, effective path-loss predication is considered significant green scheme in the traffic system model, which is designed with a Markov discrete-time $M/M/1$ queuing model and applied to duty-cycled for each sensor nodes.

We describe the behavior of two categories of transmission schemes to achieve a green model with applying the stationary distribution of the probability of the packet transmission for both schemes for the purpose of investigating the performance of the duty-cycle of the MAC layer in IoT. The analysis of the energy consumption, delay, and throughput of the this green model can be used to optimize the protocol parameters essential to enable achieving the desired network performance.

The main contribution of this paper is the development of a framework for analyzing the optimal forwarding choices with respect to QoS parameters, with the intention of quantifying the impact of the relay of radio irregularity on MAC and routing layers of two categories of transmission schemes in IoT. We show that minimizing the energy consumption per information along a selected path can be obtained by deriving the end-to-end BER for more practical transmission schemes. In summary, the contributions paper is summarizes as:

1) a mathematical green model to analyze the optimal forwarding choice as a trade-off between distance-per hop and overall hop counts for two categories of transmission schemes;
2) a radio model to simulate these two categories of transmission schemes under various channel conditions in order to investigate the impact of the radio channel on MAC and routing layers in IoT;
3) a mathematical model of channel access mechanism based on discrete $M/M/1$ queuing modeling to describe the behavior of duty-cycled MAC protocol in order to analyze handling real-time traffic of a detected event with acceptable transmission range under the impact of radio irregularity.

The remainder of this paper is organized as follows. In section II, an overview of previous analyses of MHC schemes in WSNs is provided. The analysis and traffic-system model are introduced in sections III and IV, respectively. In section V, a simulation of the proposed traffic system model is provided, and the results for each site are presented. Finally, the conclusions are summarized in section VI.

II. RELATED WORK

Many research groups are exploring issues related to the design of lower-complexity nodes for deployment scheme for green IoT as sensor hardware components [8]. There are several projects such as smart cities, structural health and smart lighting that have sought or are seeking ways to integrate three functions: sensing, processing, and communicating, into a single integrated circuit for various IoT's applications with limited energy consumption [5]. Furthermore, studies focusing on new techniques, such as cooperative multilayer communication among nodes and network coding for wireless communication using particle-sized sensor nodes that are distributed for wide-area sensing [17]. However, the increasing interest in IoT's applications in multimedia sensor networks have lead these studies to focus on increasing the network performance by relying on an accurate link estimation in order to ensure efficient use of energy resources of the node [3], [18]. Cross-layer awareness is considered as a potential solution to various issues and a means of improving the performance in IoT because of the possibility of involving both the PHY and MAC layers as shown in Fig. 2 to provide functions other than routing, such as the power efficiency [19].

In [20] an investigation of the trade-off between two schemes, Forward Error Correction (FEC) and Automatic Repeat Request (ARQ), were proposed in terms of the energy consumption, delay, and end-to-end BER. The authors explored the improvement of the channel capacity by reducing the interference with the intention of transmitting power through a channel-aware cross-layer design. FEC codes and ARQ are considered as candidates for delay-sensitive traffic in WSNs. Our approach and the system model proposed in this paper depends on the analysis for cross-layer green IoT through the derivation of the equation for the BER by defining a critical path-loss model of adaptive switching for the QoS-sensitive traffic in the WSNs. Consequently, the effect of BER on the QoS parameters of both hop-by-hop and end-to-end retransmission schemes is studied. Furthermore, the derivation of the equation for the BER has never been considered in the context of traffic system model in IoT before.

The technique referred to as the hop-length extension assesses the performance of two routing protocol schemes. An analysis of the hop-and-packet reception ratio (PRR) forwarding strategies to maximize the lifetime and minimize the energy consumption cost of sensor networks was performed in [21] by introducing two new forwarding schemes, i.e. the single-link energy efficient forwarding schemes (SEEF) and multi-link energy-efficient forwarding (MEEF), based on a realistic link loss model. The selected path for forwarding was based on an energy efficiency metric, defined as the ratio between the end-to-end delivery packet rate and the energy required for the transmission of the packets to reach the sink. Therefore, our two proposed green schemes focused on the trade-offs involved in minimizing the expected number of retransmissions or the endeavor to increase the end-to-end BER. However, this forwarding strategy does not maximize the lifetime in terms of minimizing the energy cost. Because those nodes are not addressed in the packet header as the destination, they temporarily turn their radio unit to sleep mode to save energy and achieve green model. As long as some sensor nodes in this stochastic green model stay awake to overhear the incoming packets, it might be more efficient to prevent retransmission of the entire packet even if retransmission requires more energy.

A new technique called cooperative communication has been applied to Wireless Multimedia Sensor Networks (WMSNs) to improve network performance, and the results are primarily classified in the literature as either cooperative ARQ protocols or transformation from single-hop to multi-hop transmission. The Network-Coding-based Cooperative ARQ MAC protocol for WSN (NCCARQ) proposed in [22] focused on a centralized WSN topology to coordinate the retransmission of channel access among a set of relay nodes that operate in a promiscuous mode and provide bidirectional connections between any pairs of sensor nodes. Each sensor node stores a copy of the received data packet until a positive acknowledgment from the sink is received; otherwise, the error mechanism performs an error control operation on the received messages. The protocol based on *CSMA*, therefore, is compatible with the *IEEE*802.15.4 standard. This compatibility enables the NCCARQ to use the same structure in the control packets and follows the same principles as the standard with certain modifications to improve the efficiency of the proposed protocol. It is similar to the model proposed in this paper, which uses less control packets than ARQ-based protocols and delivers increased energy efficiency while satisfying QoS parameters.

A typical ad-hoc network operates according to a cooperative multi-hop transmission approach, which achieves greater power efficiency because it operates at a low signal-to-noise-ratio (SNR) which is needed to cover the transmission range. In [23], Feng and Cimini, Jr., adopted the linear multi-hop transmission approach by considering quasi-static fading without spatial reuse. This adaptation simplified the linear multi-hop transmission approach by including Hybrid Automatic Repeat Request (HARQ) retransmission protocols. The authors focused on a design that provides the optimal number of hops with a maximum delay along a linear multi-hop network that achieves maximum end-to-end throughput. This analytical framework allows the parameters to be set as an optimization problem, which is solved using numerical methods. Likewise, Sikora *et al.* [24] considered an uncooperative linear approach for multi-hop and single-hop network transmission (in which the nodes do not cooperate and attempt to access the channel simultaneously) to investigate the performance of the distributed channel access capacity at the MAC layer and the power channel at the PHY layer, especially in delay and bandwidth-constrained scenarios. The analytical framework provides the optimum number of hops under the delay constraint using a sphere-packing bound. The authors indicated that choosing the optimum number of hops using Time Division Multi Access (TDMA) multi-hop transmission resulted in asymptotic per-link spectral efficiency.

Our research in this paper is similar to previous studies [6] and [25] as far as fundamental construction of network topologies is concerned but differs in the forwarding strategy, in which each sensor node can be placed arbitrarily between the source and the sink along a selected path. Additionally, with respect to the energy consumption, our green model incorporates all transmission operations with all of the circuit processing energy consumption.

Many researchers have focused on a single-layer design in centralized WSN topology to tackle energy dissipation problems [4], [6], and [8]. The cross-layer design typically focuses on multi-layers, such as MAC, routing, and transport, but does not consider the PHY layer. The consideration of the PHY layer was of paramount importance in the cross-layer design in [26] to minimize energy consumption. The proposed cross-layer works as follows. First, an estimation of the channel gains between every node and the sink is performed. Second, the MAC layer cooperates with this information to design the time-slot lengths in a comfortable, energy-efficient manner. Finally, the calculated time slot lengths and BER determine the suitable modulation level for the PHY layer.

In [27] the physical layer was specifically considered, and parameters such as the hop distance, transmission power, and modulation schemes were regarded as open parameters for the network designer. The authors proposed an approach for minimizing the energy consumption and maximizing the network lifetime by finding the optimal transmission distance while controlling the transmit power for a given modulation scheme and a given channel model. In the process, the authors derived a new metric called energy per successfully received bit, in which the probability of error was defined as a function of a basic modulation scheme and depends on two parameters, the received signal energy and the noise level of the channel.

Differently from existing approaches, our contributions in this paper are based on real-time queuing theory [28] which uses a simple stochastic $M/M/1$ queuing model to investigate the performance of the duty-cycle MAC layer and to simultaneously analyze its QoS parameters in terms of average delivery delay, throughput, and energy consumption. It should be noted that this paper does not focus on the scheduling problem in real-time systems; instead, it is aimed at providing an analytical tool to help designers to develop new geographic routing communication solutions for green IoT. For ease of understanding, we present an overview of some existing SHC and MHC approaches in Table 1.

III. ANALYTICAL FORMULATION

The proposed framework is reviewed in this section by considering a certain number of sensor nodes that create a direct,

TABLE 1. Some existing SHC and MCH approaches.

Protocol	Scheme approach	Trade-off between	Minimum energy consumption	Minimum delay
Cross-layer analysis of error control [20]	SHC and MHC	FEC and ARQ schemes	Yes	Yes
Energy-efficient forwarding [21]	SHC and MHC	SEEF and MEEF schemes	Yes	Yes
NCCARQ [22]	SHC and MHC	retransmission of channel access and providing bidirectional connectivity among nodes	Yes	Yes
Linear multihop [23]	SHC and MHC	optimal number of hops and maximum end-to-end throughput using cooperative multi-hop transmission approach	Yes	Yes
Linear multihop [24]	SHC and MHC	optimal number of hops and maximum end-to-end throughput using uncooperative multihop transmission approach	Yes	Yes
multipath routing protocol using partitioning approach [25]	SHC and MHC	optimal number of hops and minimum end-to-end power and delay using partitioning approach	Yes	Yes
Cross-layer design [26]	MHC	channel estimation, time-slot length and determine better BER for suitable modulation	Yes	No
Green modulation [27]	SHC and MHC	optimal transmission distance and transmit power	Yes	No

fully connected network topology. This topology consists of sensor nodes distributed according to a 2-D matrix Poisson distribution with a given density over a short interval. Thus, the nodes making up a small density in an area are selected as intermediate relays to construct the multi-hop network topology and obtain a closed-form expression for the number of hops, which can be used to estimate the network performance [29].

A framework is composed of two main components; a channel access mechanism and a wireless link channel access modeling.

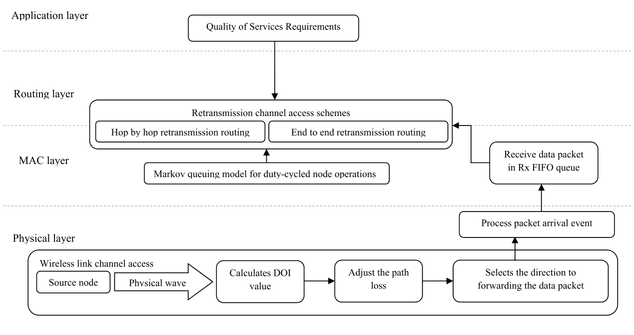

FIGURE 3. The framework of the flow of packet forwarding mechanism.

To understand the impact of radio model on the QoS requirements for multimedia data traffic, we take a close look into the work flow on a *MICA*2 sensor device that a sensor node forwards a packet towards the sink. As depicted in Fig. 3, the flow begins with first stage at the physical (PHY) (i.e. the wireless modeling) with a node perceiving the physical wave that carries the packet from the source node. This perceiving of node depends on the calculation of corresponding DOI values that inform the variances of SNR with incremental changes in directions. Each node's DOI value is calculated, and then we adjust the value of path loss models based on a K coefficient in order to forward direction from next hop to the nearest neighbor. This stage will end when the node successfully receives ACK message from next-hop intermediate node at the MAC (i.e. the channel access mechanism). A packet is not accepted as long as any bit of the packet is received with error. Finally, at the network layer, the node is likely to cause mismatch between the path estimation and the real forwarding in order to indicate a reliable wireless channel from an unreliable one for the data transmission.

A. CHANNEL ACCESS AND DUTY-CYCLE NODE MECHANISM

The channel access mechanism is composed of two sub-protocols: retransmission channel access and duty-cycle node operations. The two sub-protocols are described below.

1) ANALYSIS OF RETRANSMISSION CHANNEL ACCESS SCHEMES

The proposed framework enables a comprehensive comparison of two routing schemes in which medium access to the channel is achieved through a request to send/clear to send/data/acknowledgment RTS/CTS/DATA/ACK handshaking to guarantee successful end-to-end retransmission or multi-hop transmission, as illustrated in Fig. 4. The transmission schemes in distributed systems are categories as:-

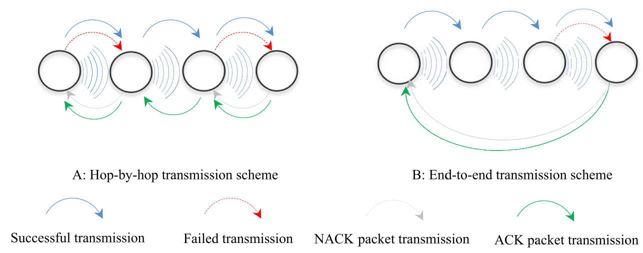

FIGURE 4. Two categories of transmission in distributed systems.

1) Hop-by-hop retransmission routing scheme: in this scheme at every next-hop, the intermediate node checks the correctness of the data packet and requests for retransmission with NACK packet until a correct data packet arrives. After that, an ACK packet is transmitted to the sender node indicating a successful transmission [30]. Figure 5 depicts the mechanism of retransmission, whereas the first data packet for example fails between the nodes 2 and 3. Then node 3 sends an NACK data packet asking node 2 for retransmission. After that, node 2 retransmits the data packet, node 3 transmit an ACK data packet after successfully receiving the data packet.
2) End-to-end retransmission routing scheme: the intermediate nodes simply forward received data packets to

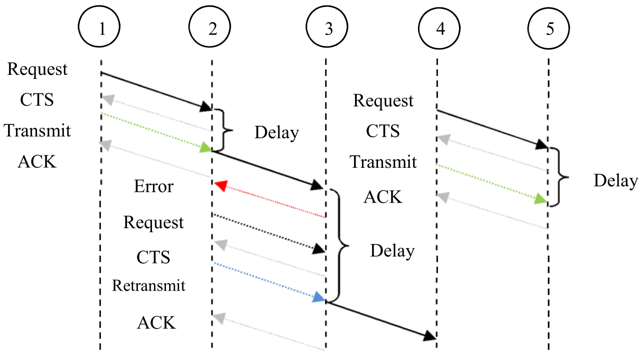

FIGURE 5. **Hop-by-hop retransmission routing strategy.**

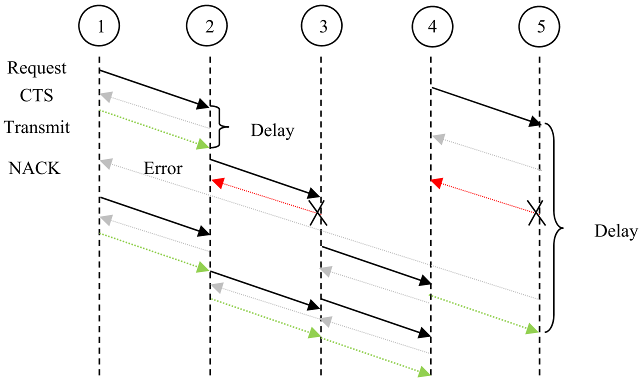

FIGURE 6. **End-to-end retransmission routing strategy.**

the next hop and do not check the correctness of the data packets until they arrive at the sink. Figure 6 depicts the mechanism of retransmission routing scheme, whereas the received data packets forwarded to the next hop do not check the correctness of the data packets until they arrive at the sink. Moreover, the sink checks the correctness of the data packets and retransmits with an NACK packet to the source if the data packets are incorrect [30].

2) MODELING DUTY-CYCLE NODE OPERATIONS

Each node has a finite queue size with heterogeneous initial energy and communication capabilities determined by the transmission range. Moreover, a duty-cycle operation is deployed in green IoT such that the sensor nodes enter the sleep state when there is no ongoing transmission and enter the wake-up state when transmission is required. The Scheduling-Driven Sensing Traffic (SDST) application is part of a very active field namely distributed tracking for vehicles within smart cities or on high-ways with low sensor rates but a higher reliability of messages transmission.

The tracking scenario raises a number of fundamental information processing problems in distributed information representation, discovery, storage and communication in collaborative processing, networking routing and aggregation, data abstraction and query optimization, human-computer interface interaction and finally in the software services [31]. Therefore, we focuses in this paper on how the information processing aspect of the tracking problems such as how routing the collected information from the environment under resources QoS constraints of IoT which may require specified multi-hop geographic routing which considerably differs from other routing protocols.

Consequently, the research community has been searching for appropriate IoT stack-layers that can provide suitable abstractions networking and the limitation of hardware resources. While defining a unifying architecture that involves all the structure layers in the communication protocol, PHY and MAC layers of the sensor network are still active areas [31]. Moreover, the event-driven model for traffic analysis and QoS constraints are considered the most challenging among other models because it is continuous, observer-initialized, and hybrid; thus, the occurrence of events is completely unpredictable, resulting in arbitrary traffic patterns [32]. We believe that an approximate solution of defining a unifying architecture is the principled interaction or cooperation between IoT and sensor network stack-layers.

To evaluate the performance of SDST application, we consider a realistic channel model for dense distributed networked sensors. This realistic channel model can improve perceived SNR by decreasing average hop-distances to improve a traffic-system queuing model for routing determination that enables the allocation of the path for reporting events from the source to the sink in IoT.

Most recent empirical studies have based their assumptions on the proposed mathematical model for a channel-aware system derived from [33]; several studies have proposed new link models, but these suffer from significant shortcomings [16]. Our channel-aware routing algorithm serves as a method to evaluate QoS parameters by considering the relationship between realistic hop-distance, number of hops, and link quality of the path. More precisely, the determination of the next hop for each node to transmit independently is based on the probability of link quality at a distance from the sink. The expected hop-distance is found by deriving the equation of BER and defining the critical path-loss model parameters as a function of the distance between two nodes to decide which path from the source node to the next hop will be selected to forward the packet.

IV. A MARKOV QUEUING MODEL FOR DUTY-CYCLED NODE OPERATIONS

In order to satisfy the QoS requirements for IoT's applications, a Markov discrete-time stochastic process $M/M/1$ queuing model for green model is proposed under a realistic assumption of a finite queue size that can hold-up to m packets for duty-cycling with schedule-driven operation for sensor nodes. The arrival and departure of the data packets are regulated under a realistic assumption of a finite queue size. Therefore, the proposed model makes the following assumptions:

1. Event/packet arrivals denote a stochastic process $\{A(\tau)|\tau \geq 0\}$ that represents the total number of arrivals that have occurred from time 0 to time τ; this procedure creates an independent Poisson process at each node, and the number of packet arrivals in any time slot is distributed with a Poisson process with parameter $\lambda.\tau$, for time of arrival τ $\tau \geq 0$.
2. Let $\pi_\imath(\tau)$ denote the steady state of power for the node at time τ; the inter-arrival $\delta \geq 0$ times (that is, the distribution of time at state $\imath$ before marking the transition) are independent and exponentially distributed with the λ, where $o(\delta)$ is defined as a function of δ such that $\lim_{\delta \longrightarrow 0} \frac{o(\delta)}{\delta}$.
3. The queueing discipline of data packets is First-Come, First-Served (FCFS).
4. The queueing system assumes equilibrium under the condition that the probability of arrival is less than the independent probability of transmitting the information packet, or $\lambda < \beta$.
5. The processing and radio-transmission times are independent and identical ($i.i.d.$) with an arbitrary distribution.
6. Retransmission is supported.
7. When an event is sensed, the node processes it and sends the information packet with a probability of transmission per node per cycle, and every sensor node in the network has an independent probability of transmitting information packet β in the duty-cycle.

These assumptions are made based on [34] and [35] and are similar to [36] and [37], which have been verified as valid approximations of realistic scenarios. The proposed Markov model shows that the power transition of each sensor node in the network may be modeled by a discrete-time $M/M/1$ Markov chain, which represents a different predefined status for a node for an event at the wake-up/sleep mode of the duty cycle. Table 2 lists all the notations used in the model.

TABLE 2. Notations of the proposed model.

Symbol	Quantity
$A(\tau)$	the total number of packets arrival
$\imath, \jmath$	the state of node
$\pi_\imath$	the steady state of power for the node of state $\imath$
$P_{\imath,\jmath}$	the probability of transition from state $\imath$ to state $\jmath$ for the node
λ	expected DATA packet arrival rate at the MAC layer
β	the independent probability of transmitting DATA packet
δ	the time of inter-arrival of packet arrival
m	the number of packets in the queue
M	The capacity of queue for DATA packets in units

A node may exchange its status slot by slot, which corresponds to the transition from one state to another in the Markov chain. Figure 7 shows that the proposed Markov model has limited queuing capacity with finite state slots from left to right, which corresponds to 0 state for processing packets in the queue and so on to m packets in the queue (full queue). Specifically, if a packet arrives and the queue is full, then the packet is simply dropped; nevertheless, the packets are removed from the queue when they are successfully transmitted.

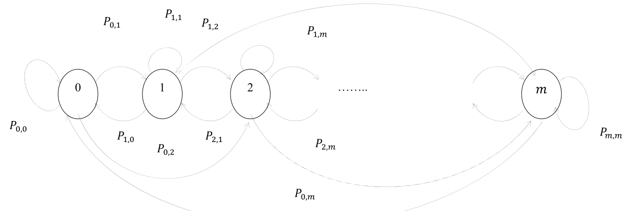

FIGURE 7. Discrete-time Markov chain for $M/M/1$ modeling of a traffic queuing behavior system.

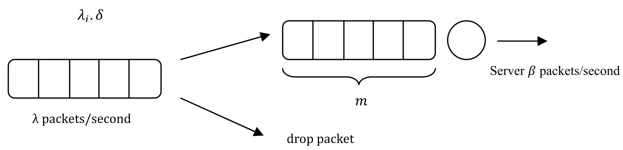

FIGURE 8. Splitting of a Poisson process.

By contrast, when the queue is neither full nor empty, then a node may obtain access to the channel to transmit packets with an independent probability, as depicted in Fig. 8. The analysis of the Markov discrete-time $M/M/1$ queuing model offers insights into the traffic behavior of IoT in general and points to an idea for a control algorithm. The steady state probability and the transition probabilities of moving from one state to another can be described as follows:-

$$
\begin{aligned}
P_{0,\imath} &= \lambda_\imath \delta, \quad \imath = 0, \ldots, M, & (1)\\
P_{0,M} &= \lambda_{\geq M}, & (2)\\
P &= \beta\lambda_0\delta, \quad \imath = 0, \ldots, M, & (3)\\
P_{\imath,\imath-1} &= \beta\delta\lambda_{\jmath-\imath+1}\delta \\
&\quad + (1-\beta\delta)\lambda_{\jmath-\imath}\delta, \quad \imath = 1, \ldots, M-1, & (4)\\
P_{\imath,M} &= \beta\delta\lambda_{\geq M-\imath+1}\delta \\
&\quad + (1-\beta\delta)\lambda_{\geq M-\imath}\delta, \quad \imath = 1, \ldots, M, & (5)\\
P_{\imath,\jmath} &= 0, \quad \imath = 2, \ldots, M, \ \jmath = 0, \ldots, \imath-2, & (6)
\end{aligned}
$$

If the event of interest is detected during the specified operations, then Equations 1 and 2 describe all transitions from an empty-queue status to a non-empty status according to the Poisson process probability of new packet arrival λ. The typical schedule-driven node operates with two timers: one for the wake-up mode and another for sleep mode, for each node in the network [30]. Therefore, if an abnormal event is detected by a sensor node and needs to be transmitted to another node or to the sink, the node stops the sleep-mode timer, turns on its radio, and starts processing the event; otherwise, the node remains in sleep mode. Equations 3 and 6 describe the transition probability of the schedule-driven duty-cycle node operation, including the processing and transmission of information packets. Equations 4 and 5 also describe the non-transition probability state (i.e., the probability of having a non-decreasing queue), which can be obtained from two terms depending on the oldest information packets still in the queue and winning the contention to access the channel (first term) or otherwise (second term) [28], [31].

The proposed Markov model with a finite set of power mode transition states for each is node defined in space $S = 0, 1, \ldots, M$ and transitional probabilities $\pi_m(\tau)$ in matrix P of being in state m (the system has m packets), as illustrated in Figure 7. The steady state equations for each schedule-driven duty-cycle node operation are described as follows:

$$\pi_0(\tau) = \pi_0(1-\lambda\delta) + \pi_1\beta\delta + o(\delta) \tag{7}$$

$$\pi_M(\tau) = \pi_{M-1}(\tau)\beta\delta + \pi_M(\tau)(1-\beta\delta) + o(\delta) \tag{8}$$

$$\begin{aligned}\pi_m(\tau) = {} & \pi_{m-1}(\tau)\beta\delta + \pi_m(\tau) \\ & \times (1-\lambda\delta-\beta\delta) + \pi_{m+1}(\tau) \\ & \times \beta\delta + o(\delta), \quad \forall m \neq 0, m\end{aligned} \tag{9}$$

The proposed model is considered to be an irreducible, periodic, and recurrent non-null Markov chain; therefore, the model possesses the unique stationary probability $\Pi_m(\tau) = (\Pi_0(\tau), \ldots, \Pi_M(\tau))$, where $\Sigma_m^M \Pi_m(\tau) = 1, \Pi_m(\tau)P = \Pi_m(\tau)$ which strictly provides that the mean rate of arrivals per state λ is less than the mean rate at which packets are obtained by the server per state β. Moreover, the queue length process will become stable, and the number of packets in the queue will be finite under this balanced assumption. Thus, both the packet arrival information λ and the probability of successful transmission β for a specified schedule-driven duty-cycle node operation in multi-hop communication become variables in the transition matrix P. Previously, $\Pi_m(\tau)$ was considered to be a unique stationary probability; hence, $\Pi_m(\tau)$ can represent a function of both the packet arrival information λ and the probability of successful transmission β.

Specifically, Equation 9 is defined as a function that describes the relationship among the steady state for a specified schedule-driven duty-cycle node operation, the packet arrival information λ, and the probability of successful transmission β, to assess the node in the network in varying to access the media. The model depends on the mechanism of protocol-specific channel access rules to obtain β for each node in the duty-cycle to win access to the channel, which is obtained by the knowledge of the initial stationary steady state matrix of the power mode for the node and the channel access rules of the protocol. By solving the steady state equations, the stationary probabilities of the power mode and β can be obtained. These values enable an analysis of the traffic behavior of IoT in delay, throughput, and energy consumption of the QoS parameters.

The model is used to investigate the behavior of two routing categories, hop-by-hop and end-to-end transmission schemes, shown in Figs. 5 and 6 to show how to optimize protocol parameters to achieve the desired network performance. The power transition mode of the node, described as the wake-up period of the cycle, has a fixed length that is determined by the MAC layer contention window size, whereas the sleep period might be shorter or longer depending on the predefined duty-cycle, which is the ratio of the wake-up period length to cycle length. Because there are different protocols with different media access rules, the our model uses RTS/CTS/DATA/ACK handshaking in addition to ACK and message retransmission to guarantee successful unicast multi-hop transmission.

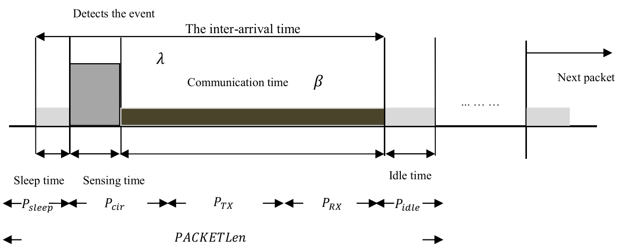

FIGURE 9. The power profile of simplified sensor node model.

A. ENERGY CONSUMPTION MODELING

The proposed Markov chain evaluates the energy consumption for multi-hop network communication by defining a critical path-loss for considering the randomness of the hop-distance between connected nodes. The main concepts in terms of delay and throughput will be described below. The proposed chain model assumes that every sensor node in the network has the following four main power transition states as depicted in Fig.9: transmit, receive, idle, and sleep, which are denoted as P_{TX},P_{RX}, P_{idle}, and P_{sleep}, respectively. Furthermore, $P_{total}(n)$ is defined as the total power consumption for these four power states during the transmission period via n hops from the source to the sink along the selected route. Thus,

$$\begin{aligned}P(n) = 2P_{startup} + \frac{PACKETLen}{R}((n-1)P_{RX} \\ + nP_{TX} + 2P_{cir} + P_{idle} + P_{amp} + P_{sleep})\end{aligned} \tag{10}$$

where $2P_{startup}$ represents the power for the start-up radio frequency (RF). The power amplifier is denoted as $P_{amp} = \frac{c\gamma(\frac{D_{max}}{n})^{\alpha}}{\eta}$, where η is the performance of the RF power amplifier (which is widely cited by the WSN community to support a more realistic characterization of power consumption [37]), γ is defined as a sufficient SNR at the received node, R denotes the transmission rate, c is a constant value defined as proportional to the packet length, channel attenuation, and non-linear effects of the power amplifier, and D_{max} is the total distance between the source and the sink [39], [40].

Therefore, to transmit one DATA packet from the source to the sink via n, it is necessary to provide to n units of transitional power. This operation sequentially occupies n duty cycles; in each duty-cycle period, the total time spent at each power state of the sensor node may be approximated as

$$\lim_{TimePeriod \to \infty} TimePeriod = TimePeriod\,\Pi_m(\tau) \quad (11)$$

The total energy consumption during the duty-cycle period varies because the sensor node plays several roles. On one hand, the node might be transmitting a DATA packet with a successful transmission probability according to the steady state of the Markov chain model. Meanwhile, the node might be in receive mode, receiving a DATA packet successfully with a different successful transmission probability because each node selects its neighbors through the embedded criteria in the path-loss model as opposed to random selection. Because of a queue overflow, the node may fail to receive a DATA packet; therefore, it goes into idle mode until it enters sleep mode. The determination of the steady state probabilities of the power mode depends on the regulation of protocol for media access. Thus, the total energy consumed at each node in the four power states is the sum of the energy consumption of each power mode multiplied by the corresponding steady state probability,

$$E(\Pi_m(\tau)) = TimePeriod\,\Pi_m(\tau) \times (P_{RX} + P_{TX} + P_{idle} + P_{amp} + P_{sleep}) \quad (12)$$

Furthermore, energy consumption for a multi-hop communication network is expressed as

$$\begin{aligned} E(\Pi_m(\tau)) = &(n-1)TimePeriod\,\Pi_m(\tau)P_{RX} \\ &+ nTimePeriod\,\Pi_m(\tau)P_{TX} \\ &+ TimePeriod\,\Pi_m(\tau)(P_{idle} + P_{sleep} + P_{amp}) \end{aligned} \quad (13)$$

The cost of the energy transition between these four states may be obtained by multiplying the total cost of a single transition by the average number of transitions. However, the total energy consumption at each power state and the energy cost of transitioning from one state to another should not exceed the total energy resource [41]. The energy consumption of a successful hop-by-hop transmission from the source to the sink with a four-way RTS-CTS-DATA-ACK handshake or a three- way RTS-CTS-DATA handshake, is given as

$$Energy_{hbh} = \Sigma_{(\iota=1)}^{n} \frac{1}{(1 - PER_\iota)} E(\Pi_m(\tau)) \quad (14)$$

Where PER defines the packet error rate at hop ι of selected path in specified direction as depicted in Fig. 5. Usually, the definition model of PER assumes independence of packet errors in different directions. This is called a poor wireless link channel with respect to the function of distance between two sensor nodes. However, the probability of a packet error in any direction at hop ι is PER and no packet error is $1-PER$. From the assumed independence of the errors, that is for good wireless link channel, the probability for no error in the n-hops from detect event toward the sink is $(1 - PER)^n$ [16].

In the end-to-end retransmission scheme as depicted in Fig. 6, the source node waits to receive either ACK or NACK packets, which are sent only to the sink node; the intermediate nodes simply forward the DATA packets, and the total expected number of transmissions may be evaluated by $\frac{1}{P_{st}}$, where $P_{st} = \prod_{(\iota=1)}^{n}(1 - PER_\iota)$. Therefore, the total expected energy consumption of transmitting a packet from the source to the sink can obtained as

$$Energy_{e2e} = \frac{1}{P_{st}}[\sum_{\iota=1}^{n} E(\Pi_m(\tau))] \quad (15)$$

B. DELAY MODELING

As a DATA packet travels from one node to a subsequent node along the route toward the sink, it suffers from various types of delays at each node along the selected path [42]. The most important of these are the nodal processing, queuing, transmission, contention, propagation, and switching delays.

The proposed model calculates the total delay by considering different delays types separately. Let d_{prco}, d_{queue}, d_{trans}, d_{cont}, d_prop, and d_{swit} denote the processing, queuing, transmission, contention, propagation, and switching delay, respectively. The processing node delay depends on the network data processing algorithm, but it can also include other factors, such as the time needed to check for bit-level errors in the packet that might have occurred in the process of transmitting the packet bits from the upstream source node to a neighboring node.

The queuing delay is defined as the time the DATA packet spends in the queue as it waits for all the DATA packets ahead of it to obtain access to the media. According to the stationary probability distribution $\Pi_m(t)$ of the proposed Markov model, the mean queue delay of the DATA packet can be calculated directly from Little's result as [34].

$$d_{queue} = \frac{\Sigma_{m=0}^{\infty} m\Pi_m(\tau)}{\lambda\delta} \quad (16)$$

As previously mentioned in the model assumptions, the queuing discipline of the data packets is first-come, first-served (FCFS); moreover, a packet may be transmitted only after all the packets that have arrived before they have been transmitted. Thus, the transmission delay, which is also called the store-and-forward delay, is defined as the amount of time required to transmit the packets into the link, which is given as

$$d_{trans} = \frac{S}{(transmissionrateoflink)} \quad (17)$$

Most studies dismiss the contention delay in the calculation of the total delay and even of the queuing delay. The contention delay is defined as the interval from the time the DATA packet reaches to the first queue slot to being successfully transmitted and dropped from the queue. Moreover, for any DATA packet newly joined the first queue slot, the discipline will be to set a period in which it should start contending for media access. The calculation of contention delay is thus based on the probability of successful and/or unsuccessful transmission of the DATA packets during the cycle length,

$$d_{cont} = T\sum_{\iota=0}^{\infty}(\iota+1)\beta(1-\beta)^{\iota} \tag{18}$$

The propagation delay depends on two factors: the propagation speed of the physical medium of the link and the distance between the two connecting nodes. Finally, the switching delay is defined as the switching time between duty-cycle node operations. Therefore, the total nodal delay is given by

$$D_{total} = d_{prco}+d_{trans}+d_{queue}+d_{trans}+d_{cont}+d_{prop}+d_{swit} \tag{19}$$

The nodal delay is given as

$$D_{\iota} = \Sigma_{\iota=1}^{n} d_{\iota_{prco}}+d_{\iota_{trans}}+d_{\iota_{queue}}+d_{\iota_{trans}}+d_{\iota_{c}ont}+d_{\iota_{prop}}+d_{\iota_{swit}} \tag{20}$$

For hop-by-hop transmission, the expected number of transmissions may be evaluated by $P_{\iota} = \frac{1}{1-PER_{\iota}}$; therefore, the expected hop-by-hop delay in transmitting a DATA packet from the source to the sink can evaluated by

$$Delay_{hbh} = \sum_{\iota=1}^{n} D_{\iota}P_{\iota} \tag{21}$$

In the end-to-end retransmission scheme, the expected delay may be calculated as

$$Delay_{e2e} = \frac{1}{P_{st}}D_{\iota}, \tag{22}$$

C. THROUGHPUT MODELING

Throughput is defined as the amount of information successfully delivered within a specified unit of time [37]. The throughput is calculated during the duty-cycle of the node operation on information packets within a given cycle time. Successful transmission of information is described as the probability of sending out information between two or more connected nodes k that are competing for media access in the network which is a function of the current steady state of the power transition mode of the nodes:

$$P_k(\Pi_m(\tau)) = \binom{N-1}{k}(1-\Pi_m(\tau))^k\Pi_m(\tau)^{N-1-k} \tag{23}$$

In case of the use of RTS/CTS/DATA/ACK handshaking between k nodes that are competing for media access, the probability of winning the contention and successfully sending the RTS can obtained as follows:

$$p_k = \Sigma_{\iota=1}^{Win}\frac{1}{win}.(\frac{win-\iota+1}{win})^k, k=0,\ldots,N-1, \tag{24}$$

The probability of successfully sending DATA packets is calculated as

$$p_k = \Sigma_{\iota=1}^{Win}\frac{1}{win}.(\frac{win-\iota}{win})^k, k=0,\ldots,N-1, \tag{25}$$

where win is the contention window size; therefore,

$$p_s = \sum_{k=0}^{N-1} P_k(\Pi_m(\tau))p_{sk} \tag{26}$$

and, finally, the throughput is given by a fraction of the length of the node cycle time; that is,

$$Th = \Sigma_{m=1}^{\infty}\Pi_m(\tau) = 1-\Pi_0(\tau). \tag{27}$$

For multi-hop, communication, the number of nodes in the network is N, the MAC layer DATA packets size is S, the length of the cycle is T, and $\Pi_m(\tau)$ is known; furthermore, the only variable is the probability of successful DATA packet transmission, which can be obtained according to the media access protocol. Thus, the throughput of the network can be determined as

$$Th_{MHC} = N(1-\Pi_m(\tau))p_s\frac{S}{T} \tag{28}$$

D. WIRELESS LINK CHANNEL MODELING

Because of the limited functionality of the sensors, power consumption and reliability pose the greatest challenges in IoT's applications, such as how sensor nodes may be deployed in varied locations with different deadlines using more flexible and low-cost wireless links [43]. Different sets of models, such as the link quality model, energy-transmission model, and interference model, initially focused on both designing and analyzing real-time routing protocols for WSNs [44].

Several studies of wireless link channels partition the area into the following three main regions: connected, transitional, and disconnected regions. The transitional region is regarded as the main region because: (1) it is quite significant in size and generally characterized by asymmetric connectivity and high-variance in reception packets rates [33], and (2) it has contributed to the understanding of the realistic link layer model for WSNs.

The definition of the transitional region results in dense and random deployment of sensor devices for IoT to monitor, sense, and control the environment, to perform local processing, and to communicate the results with a base station. It is important to understand how the channel can be analyzed to determine the width of the transitional region and how altering both can affect the extension of the transitional region [45], which prospectively influences the traffic behavior of MHC. Hence, the proposed green model for IoT requires an abstraction to illustrate the log-normal path loss channel and to present an approximate expression of the variance in PER with respect to the function of distance; with the Radio Irregularity Model (RIM), this abstraction also provides the packet received ratio (PRR) as a function of the SNR in MHC, as described in the subsequent sections.

E. THE LOG-NORMAL PATH-LOSS MODEL

Propagation phenomena are diverse and complex because of the separation of the receiver and the transmitter, in addition

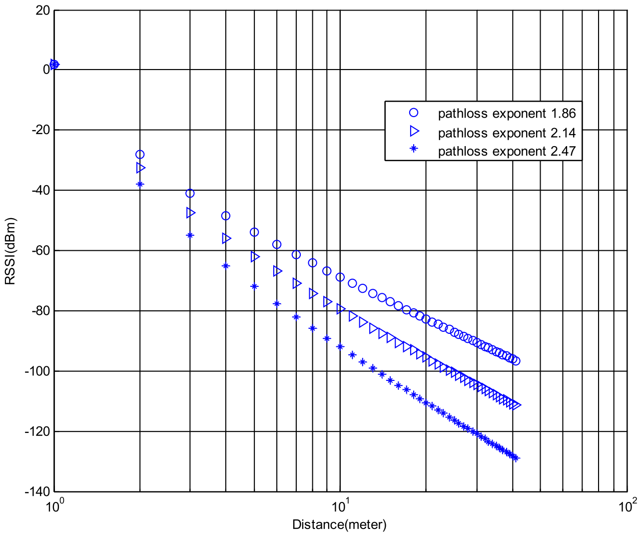

FIGURE 10. The average RSSI reading as a function of the distance (on logarithmic scale).

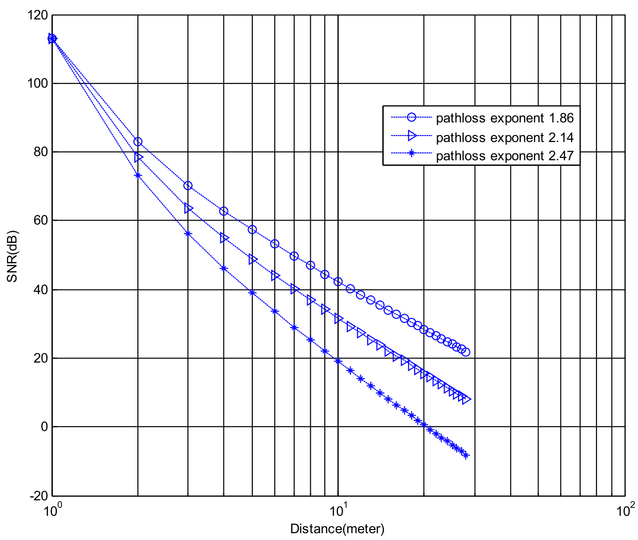

FIGURE 11. The SNR reading as a function of the distance (on logarithmic scale) for MHC.

to having a random variation in power due to path shadowing, which causes the signal strength to decay exponentially with respect to the separation. Radio signal strength attenuates as a function of distance as shown in Fig. 10. Basically, the graph is composed of 1942 average received signal strength indication (RSSI)-log distance which is expressed in meter between sending and receiving sensor nodes. However, RSSI is not only affected by the distance but also there are a few other factors that affect the radio signal propagation and hence the RSSI value that is perceived by a sensor node at an equal distance [46]. Figure 11 shows the SNR as a function of distance between all sending and receiving sensor nodes. The measured SNR does not decrease monotonously with distance, a SNR of 17dB is measured and at the shorter distance about of 18 meter. Let there be two links, both of them affected by channel fading, and the measured SNR is 17dB for one link and 25dB for the other. Thus, it could happen that when the channel fading is affects both links in the same way, the SNR of the former link falls to 5dB whereas the latter still enjoys an SNR of 17dB, which is a more efficient link quality than the former. Therefore, to compare the two links, it is useful to account for their estimated SNR values, which are considered to be very helpful in refining the link quality judgment [16]. Furthermore, at the distance of 20 meter the expected value of a RSSI is -95dBm. The measured signal is much too strong, even at small distance. This effect occurs in all experimental studies in industrial indoor environments and cannot be explained by many theories [1], [47].

There are various propagation models for path loss, which can be categorized into the following three types: (1) empirical models, (2) deterministic models, and (3) stochastic models. For the free space model a path loss proportional to the square of the distance, for example the IEEE802.15.4 standard recalculates this path loss for MHC as

$$PL(d_\iota) = PL(d_0) + 20\xi \log_{10}(d_\iota)$$
$$\text{for} \quad d_\iota < 8meter, \quad \iota = 1, 2, \ldots, n \tag{29}$$
$$PL(d_\iota) = PL(d_0) + 33\xi \log_{10}(\frac{d_\iota}{8})$$
$$\text{for} \quad d_\iota > 8meter, \quad \iota = 1, 2, \ldots, n \tag{30}$$

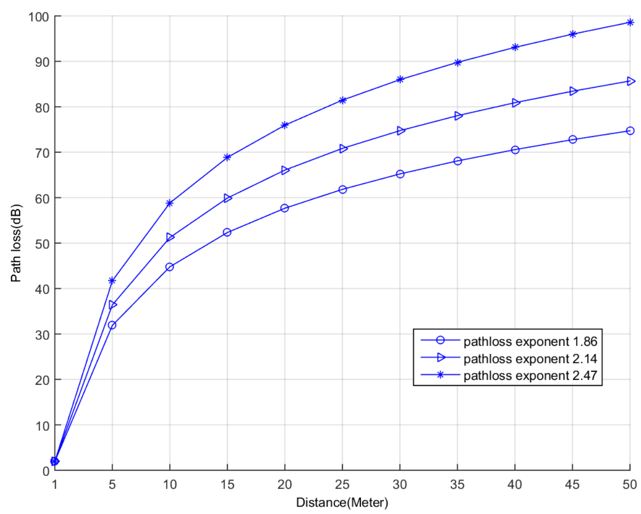

FIGURE 12. The path-loss versus the log-distance for MHC.

where $PL(d_0)$ is the path loss at a reference distance d_0 in meter. Existing techniques either consider the path-loss is known apriori by assuming the WSN environment is free space, or obtain the path-loss through extensive channel measurement and modeling by measuring both SNR and distances in the same environment of WSN prior to system deployment [48]. However, an accurate knowledge of the path-loss is required in order to obtain an accurate estimate of the inter-sensor distance from the corresponding SNR measurement. Figure 12 shows the path-loss versus the log-distance for MHC approximated by linear regression [49]. Whenever the path-loss exponent ξ is increased, the node consumed energy with the increased node distance and becomes more incomparable with the energy received because of the exponential increasing. Meanwhile, we defined the mean path loss as a function of the hop-distance in relation to the power of the path-loss exponent ξ as $PL(d_\iota) \propto (\frac{d_\iota}{d_0})^\xi$. Therefore, our model assumes that there are multi-hop nodes between the source and the sink; thus, the relationship between the path-loss and the multi-hop-distance may be obtained by

$$PL(d_\iota) = PL(d_0) + 20\xi \log_{10}(\frac{d_\iota}{d_0}) + \varepsilon(0, \sigma), \quad \iota = 1, 2, \ldots, n \tag{31}$$

Therefore, the received power P_{RX} in dB is given by

$$P_{RX} = P_{TX}(d_\iota - PL_{d\iota}) \tag{32}$$

where $P_{TX}(d_\iota)$ is defined as the output power, $PL(d_\iota)$ is the power decay at a reference distance close to the transmitter, $d_0 \leq TR$ can be 1 millimeter to 20 meters, ξ is the path-exponent, and $\varepsilon(0, \sigma)$ is defined as a zero-means Gaussian distribution with standard deviation σ. Consequently, the MHC path-loss derived by linear regression is given as [1] and [49]

$$\Theta(n, \xi_\iota) = \Sigma_{\iota=1}^{n}(PL(d_\iota) - PL(d_n) - 10\xi_\iota \log_{10}(\frac{d_\iota}{d_0}))^2, \quad \iota = 1, \ldots, n \tag{33}$$

The number of hops n and the values of the path exponent for each hop may be obtained through a linear regression algorithm. The algorithm begins with the calculation $\Theta(n, \xi_\iota)$ and is repeated with an increasing number of hops. Finally, the number of hops and the values of the path-exponent can be obtained. We assume that the criterion of hop-distance depends on the maximum power level of a specific output power P_{TX}, i.e., $0 \leq P_{TX} \leq P_{max}$, therefore the transmission range (TR) of any single-hop-distance is given as

$$TR = \sqrt[\xi]{\frac{(P_{RX} + P_{TX})\eta}{(1 - 2^{1-\xi})}}, \tag{34}$$

This indicates that there is a relationship between the log-normal path-loss and transmission range, in which the hop-distance can be attributed to the influence of the path-loss because of the various propagation environments [1]. Figure 12 shows the exponential impact of the path loss on the distance between the transmitter and the receiver.

With this knowledge of $P_{TX}(d_\iota)$, the path-loss, and the receiver sensitivity S_r, the P_{RX} and SNR values can be estimated to redefine the PER expression, which is derived from equation (36) and corresponds to the Non-Coherent-Frequency-Shift-Keying (NC-FSK) modulation used in early WSN platforms, such as *MICAZ* [50]. Thus, SNR is given as

$$SNR = P_{TX} - PL(d_0) - 10\xi \log_{10}(\frac{d_\iota}{d_0}) + \varepsilon(0, \sigma) - S_r, \\ = P_{TX} - PL(d_\iota) - S_r, \iota = 1, \ldots, n \tag{35}$$

Certain companies supply the PER value for developers. For example, the Zigbee implementation on the $MC13213$ chip produced by FreeScale Semiconductor Inc. [51] has a basic function called MLME Link Quality that developers can use to obtain the current PER. The link quality of a hop from the source to the sink is represented by the PER so the value of the transmission of packets on each hop from the source to the sink may be defined as an independent event that circumvents the complexities of retransmission and requires no coding; thus, the single BER leads to packet error. Therefore, the successful delivery probability for one packet may be closely approximated for MHC as [52].

$$PRR = (1 - PER)^n \tag{36}$$

where

$$PER = (1 - \frac{1}{2}exp^{(\frac{-SNR}{2}\frac{1}{0.64})})^{\rho.8.f.n} \tag{37}$$

For each correctly received packet, f data frame length is received over the time period $\frac{f}{bitrate}$, where $bitrate = numberofbitspersymbol.symbolrate$, and ρ is the encoding ratio that used NRZ and Manchester encoding operations.

F. NON-ISOTROPIC TRANSMISSION MODELING

In addition to line-of-sight, signal propagates by the means such as diffraction, reflection, scattering, etc., which exhibit radio irregularity patterns that might influence the communication performance of WSNs in most environments. Radio irregularity is considered to be a common and non-negligible propagation phenomenon that arises because of several factors and results in irregularity in TR and diversity in packet reception in various antenna directions; such irregularity has significant direct or indirect influences on MAC because of asymmetric radio collision or interference and on many aspects of the upper layer performance because of asymmetric paths [53], [54].

In generally, there are two factors that cause radio irregularity: the device properties and the propagation media. The device properties includes antenna characteristics, such as antenna gains, radiation patterns, polarization, etc., the effects of which Hasan *et al.* [1] investigated under three different scenarios of antenna operations for path-loss prediction, which has become a key issue in system design.

Unlike existing models, our model proposes that the radio propagation model approximates the anisotropic property to present the effects of irregularity on the localization technique for correct MAC in case of asymmetric radio collision between two nodes, which occurs when a node is unable to reserve the wireless channel, and on the routing performance through paths asymmetrical to the traffic behavior in the two transmission schemes.

Our model is defined as geo-directional-cast forwarding that consists of a set of mathematical expressions that represent the non-isotropic log-normal path-loss with differences in transmit power levels of 0dB,−3dB,−5dB,−7dB, −10dB,and −25dB as well as $IEEE802.15.4$ respectively

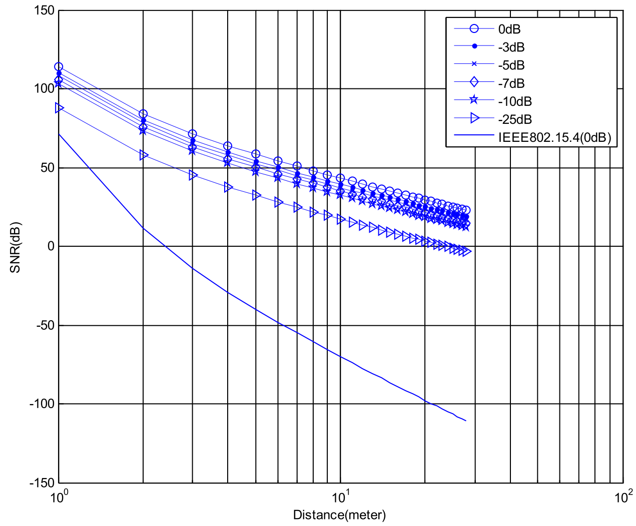

FIGURE 13. **SNR multipath fading for MHC at different power levels.**

according to Equations 29 and 30 as shown in Fig. 13. The SNR in function of distance on a semi-logarithmic scale on multi-hop sensor nodes varies according to the propagation direction from the node to its neighbor. Figure 13 was constructed with the average of decreasing SNR values of packets sent at different power levels from sensor nodes to the sinks. Figure 14 shows an example of a geo-directional-cast mechanism where the source node forwards DATA packets to only one-neighbor to reduce packet flooding and minimize collision. Therefore, SNR is given as

$$SNR = P_{TX} - PL(d_\imath) + fading, \imath = 1, \ldots, n \tag{38}$$

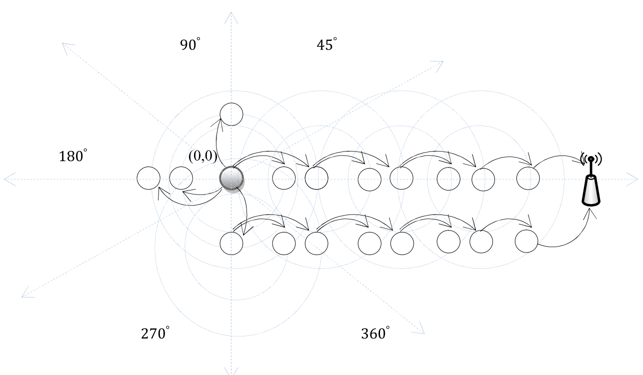

FIGURE 14. **Geo-directional-cast forwarding for network topology.**

The DOI is introduced to denote the irregularity of the radio pattern. The DOI is based on the distance over which one node can hear its neighbor. It is defined as "the maximum path loss percentage variation per unit degree change in the direction of radio propagation" [53]. Figure 15 depicts the radio irregularity pattern at various degrees. It can be observed that when the DOI is zero, the transmission range is considered as a perfect sphere, whereas any continued increase in the DOI value causes the transmission range to

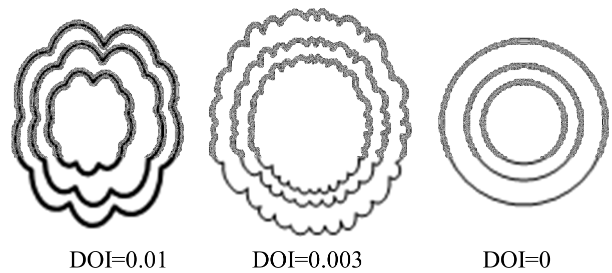

FIGURE 15. **Degree of irregularity.**

have an increasingly irregular radio pattern. To establish a radio irregularity model, our propagation model relies on real-data values (which have been repeatedly used in many experiments on *MICAZ* sensor nodes in vehicle tracking systems) to approximate the radio irregularity by calculating the corresponding DOI values [54]. To reflect the path-loss for a specified angle toward an optimal forward direction from the next hop to the nearest neighbor, a new coefficient K is defined; directional forwarding is used to adapt the bounds of the DOI model value between an upper and a lower signal propagation for the two categories of retransmission schemes by adjusting the path-loss for forwarding to the next nodes that have the best progress toward the sink in the specified direction.

Beyond the upper bound, all neighbors are outside TR; within the lower bound, all neighbors are guaranteed to be within the inner TR, and the signal is strong enough to be received correctly. Therefore, it becomes more critical to carefully select the sensor nodes that participate in sensor transmission range forwarding the information against its resource consumption. Thus, the DOI modeling results are given as

$$SNR = P_{TX} - DOIAdjustedPL(d_\imath) + fading, \tag{39}$$

where $DOIAdjustedPL(d_\imath) = PL(d_\imath).K_\imath$ Specifically, $K_\jmath$ is defined as the adjustable $\jmath^{th}$ coefficient used to adjust the path-loss value according to a specified direction, which is calculated as

$$K_\jmath = \begin{cases} 1 & \text{if} \quad \jmath = 0 \\ K_{\jmath-1} \pm Rand.DOI & \text{if} \quad 0 < \jmath < 360 \wedge \jmath \in N \end{cases} \tag{40}$$

where $|K_0 - K_{359}| \leq DOI$.

Thus, minimizing the amount of energy consumption and adjusting the transmission range as much as possible through observed DOI value can significantly prolong the lifetime of sensor network.

V. THE SENSOR NETWORK SCENARIO AND SIMULATION RESULTS

This section analyzes the QoS parameters obtained from the analysis of the effects of radio irregularity on a multi-hop network routing protocol with the focus on realistic scenarios at low densities considering effects that might have a significant influence on the performance of geographic routing in IoT.

In the following subsection, the average packet delay transmission, the energy consumption for transmission, and the throughput are analyzed in view of the impact of radio irregularity on the neighbor-discovery routing technique of both the hop-by-hop and end-to-end retransmission schemes. The parameters used in proposed model are presented in Table 3 MATLAB was used to construct a network topology consisting of *MICAZ* sensor nodes in uniform Poisson distribution over a short interval and implemented according to non-coherent-frequency shift keying modulation with NRZ and Manchester encoding.

TABLE 3. Experiments parameters.

Parameter	Value
P_{TX}	59.1mW
P_{RX}	52.2mW
P_{idle}	55.0mW
P_{cir}	12.0mW
$P_{startup}$	1.0mW
$Preamblelength$	4 bytes
$Framelength$	8 bytes
$thewavelength$	0.1224489796 bytes
Path-loss exponent	$1 \sim 6$
Noise floor	-115.0dBm
Modulation	Non
Coding	NRZ & $Manchester$
Link capacity	19.2kbps

A. THE SENSOR NETWORK SCENARIO

Generally, there are two core issues for automated surveillance : (1) object detection, and (2) tracking. Object detection is an important capability for senor networks. Several events that smart surveillance system in IoT has to detect in real-time such as abandoned object alert, motion, object removal, and observation of any other abnormal behavior. Supporting a smart surveillance system has several additional characteristics, challenges and factors which influence the design of distributed smart devices in IoT. These characteristics, challenges and factors are depend on the real-time multimedia traffic data flow from surveillance cameras. Moreover, the quality of the video depends on the lightning conditions.

Additionally, any suspicious activity or behavior should be detected at the time of occurrence. Therefore, object detection must be performed in real-time. But the strongly challenging problem for detection in IoT is the optimization allocation of sensing and communication resources to multiple competing detection tasks spawned by emerging stimuli which is more computationally complex and resource demanding.

This study provides a dynamic mean to define and form a group of sensor nodes based on task requirements of resources in response to external events and dynamic resource allocation availability. The *MICA*2 sensor characteristics and network topology scenario were defined with the following assumptions under the SDST application behavior:

1) From a sensing and information processing, a vehicle physical process model need to be designed which correspondence to some real processes such as spatial correlation of information, and variability over time. The basic model is defined for each sensor node in wireless network as a tuple $S_n = \nu, E, P_\upsilon, P_E$ where ν and E specify a network topology with its sensor nodes ν and link connectivity $E \subseteq \nu$. P_υ is a set of functions which characterizes the properties as a static values of each sensor node in ν, including the sensor location, computational capabilities, sensor output type, and sensing modality.
P_E specifies the properties of each link such as the quality of link. All sensor nodes have a common transmission range TR, and are deployed with a uniform distribution. The average number of nodes within an area of TR conforms to a Poisson distribution with parameter λ where $\lambda = \Pi.TR^2 density$. Thus, the probability that ν nodes cover an arbitrary geometric point is $\frac{\lambda^n}{\nu!}\exp^\lambda, \nu = 1, 2, \ldots$. Furthermore, any pair of sensor nodes in the network topology, for example, $(u, \upsilon) \in \nu$, can obtain connectivity with another pair if they are within TR from each other. The model assumes that when a sensor node discovers a neighboring node, a wireless link E is established between them, and the sensor can set the level of transmission power to be used over that link. Furthermore, the model assumes that the sensors can adjust their transmission range toward a neighbor over time.

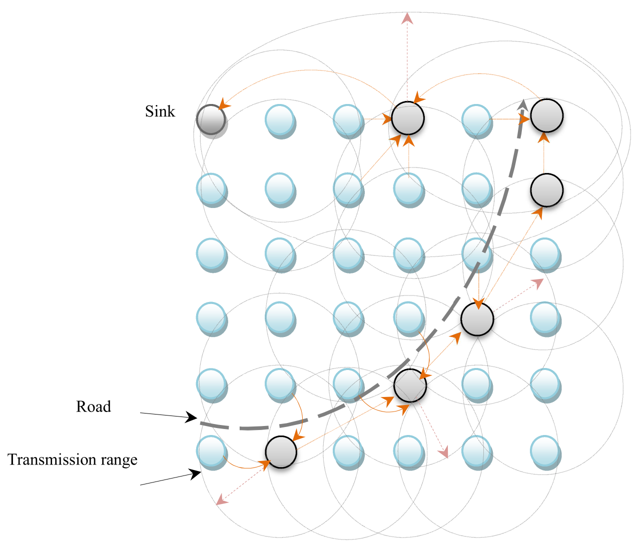

FIGURE 16. An object detection scenario showing moving vehicle *s* in field of sensors.

2) The construction of the network topology as shown in Fig. 16 depends on the location management, which determines the localized information of uniformly deployed sensor nodes. It assumes that all *MICAZ* sensor nodes are in a fixed position and that the sink is at the origin (0,0).
For multi-hop communication, there is at least a single path connecting the source to the sink through

intermediate sensor nodes, issuing network commands such as "sleep," "idle," and "wake-up;" changing the level of transmit power; and synchronizing the transmission time. The object detection used to bring out key of SDST application. As vehicles move along the road with specific velocity, the information is stored at a sensor node called leader node which are numbered as 1,2,3,4,and 5.
These leader sensor nodes collect information from their neighbor's relevant intermediate sensor nodes and forwarded toward direction of next hop of the nearest leader sensor node. As the vehicle moves or environmental conditions vary, the leaderships may change hands among sensor nodes. Therefore, the movement of leader between the sensor nodes may lead to design localized communication, reducing overall communication and increasing the lifetime of the network. Figure 17 shows with the average SNR values of the leader sensor nodes that sent packets at different power levels and the distance between the sensor nodes are known.

3) Vehicles are simulated as sources of abstract sensor readings that can be detected in sensing range of the sensor node. Each reading is dispersed in the simulation over at a certain point and at a certain time as

$$Y(p,t) = \sum_{allvehicles_{\iota}} \frac{(Y_{\iota}(\tau))}{(Kd_{\iota}(\tau)+1)^{a}} \tag{41}$$

where $Y(p,\tau)$ denotes the position of the vehicle physical process at a certain point p and at a certain time τ, $Y_{\iota}(\tau)$ denotes the position of ι^{th} vehicle at time τ and called snapshot of vehicle which help to defined the maximum possible number of pickup of snapshots for all vehicle s, $d_{\iota}(\tau)$ denotes the distance of the ι^{th} vehicle from the sensor node at time τ in the sensing range.
The parameters K and a define multiplicative constant and attenuation constant parameters that are set to 0.1 and 1 respectively and are used to determine the value from a diffused vehicle. The road itself is specified in the simulation space by two points given by their x and y coordinates. These points are set by the following four parameters of a vehicle physical process model. Each time a vehicle needs to enter in a highway, it follows a Poisson Arrival process with a specific velocity along a straight or non-straight route as shown in Fig.16. Each sensor generates DATA packets of a constant size at a given rate when the sensor node senses an anomalous event; the first DATA packets are buffered while awaiting their transmission to another node. As previously mentioned, the queuing discipline of DATA packets is stable and modeled as FCFS.

4) Each node tries to access the channel through a handshaking technique, which is designed to resolve hidden and exposed terminal problems. However, when the source node generates DATA packets for transmission, it sends a RTS message to its neighbor, which responds with a CTS message. If the DATA packet transmission is successful, then the source node receives ACK from its neighbor in the hop-by-hop transmission scheme, or an ACK message from the sink in the end-to-end transmission scheme.

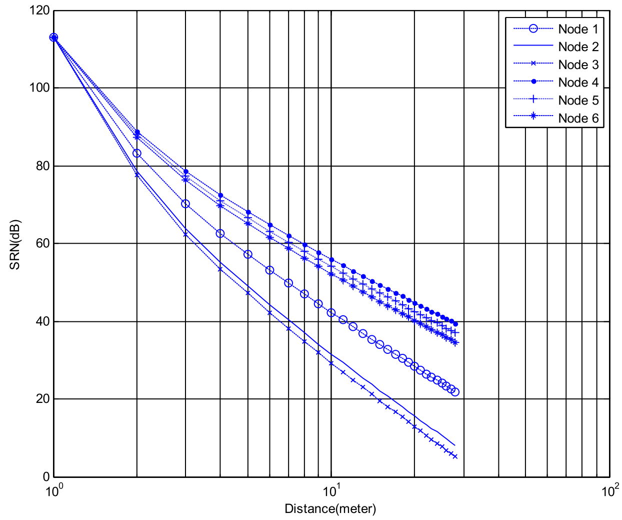

FIGURE 17. SNR versus logarithmic distance for MHC at different power levels.

5) The proposed model depends on Lee's model calculation [55] to estimate the path-loss since it is the most commonly used in urban areas

The expected hop-distance can be attributed to the influence of the path-loss due to the various propagation directions, which is a function of SNR for different power values P_{TX}, as shown in equation (38). It can be observed from Fig. 13 that for small values of SNR, the average hop-distance value increases because nodes with a high-quality channel may be chosen as the next hop in the specified direction, and other nodes may become the next hop. Therefore, for the perfect route, the smallest number of hops to a sink decreases for smaller SNR values.

B. THE IMPACT OF RADIO IRREGULARITY ON ENERGY CONSUMPTION IN THE MULTI-HOP ROUTING PROTOCOL

Generally, in most single-hop and multi-hop communication scenarios, when $TR \leq D_{max}$ the single-hop strategy is considered more energy efficient within the range of the radio. Particularly, given the low-path-loss exponents because the distance for one hop is close to the perfect value of SNR, and the start-up power overhead makes the multi-hop strategy inefficient for hop-distances of less than D_{max}. Consequently, increasing the amount of energy exhaustion of nodes that is closer to the sink [56].

The supposed reduction in energy consumption is considered a central issue and should be analyzed in terms of reducing the power overhead through a new strategy for multi-hop communication when $TR > D_{max}$; thus, multi-hop communication would become more attractive when the number of hops is denoted as the upper integer or ceiling of $\frac{TR}{D_{max}}$ [16].

Consequently, the power overhead in retransmission schemes must be properly analyzed. Figure 17 presents the amount of energy consumed when the power overhead is reduced for each individual node using a discrete $M/M/1$ Markov queuing model that synchronizes the power overhead in sending and receiving control messages within a sensor network. Results are shown for the hop-distances between nodes for the two retransmission schemes with various PER.

The model is useful for most real-time IoT's applications, particularly when the traffic load is heavy and changes over time. When the PER is very low, the energy consumption increases because the power amplifier must consume more energy to guarantee a smaller PER as seen in equation (10). The average energy consumption in the hop-by-hop retransmission scheme shows more energy efficiency than the end-to-end retransmission scheme because the Markov chain results in a more efficient synchronization overhead in sending and receiving control messages in the hop-by-hop retransmission scheme than in the end-to-end retransmission scheme; it actually introduces more delay in the former than in the latter scheme. Suppose a sensor camera detects an abnormal event. Heavy traffic would be generated, and some sensor nodes might have little or no chance to transit to the sleep mode. In contrast, the sensor node has more sleep time when there is little traffic. Therefore, increasing the traffic sensor nodes results in fewer chances to go into sleep mode and thus consumes more energy, whether in the hop-by-hop or end-to-end scheme.

The effects of coding and channel access control on energy consumption in various retransmission schemes are also compared. The average energy consumption in the hop-by-hop retransmission scheme is approximately 35.8%, whereas in the end-to-end retransmission scheme, the value is approximately 65.9% because the DATA packet errors are not thrown out until the packets are received by the sink in end-to-end retransmission, which leads to higher energy wastage; such wastage is avoided in hop-by-hop retransmission. Figure 18 depicts the energy efficiency of both retransmission schemes, indicating that non-return-to-zero (NRZ) encoding is more efficient than the Manchester encoding operation because the word error probability in encoding DATA packets with the Manchester coding operation is larger when the number of hops is increased by virtue of duplication of the DATA packets.

C. THE IMPACT OF RADIO IRREGULARITY ON AVERAGE ENERGY CONSUMPTION IN THE MULTI-HOP ROUTING PROTOCOL

Figure 19 shows the average delay versus the hop-distance from the source to the sink with various PER for the two retransmission schemes. The results indicate that the delay first hover near zero and then increases as the hop-distance increases; the maximum delay in hop-by-hop transmission with NRZ coding is larger than that in end-to-end

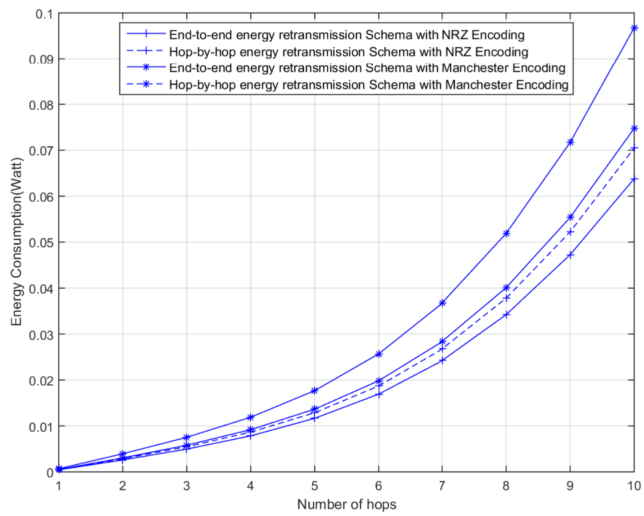

FIGURE 18. The energy consumption of both retransmission schemes.

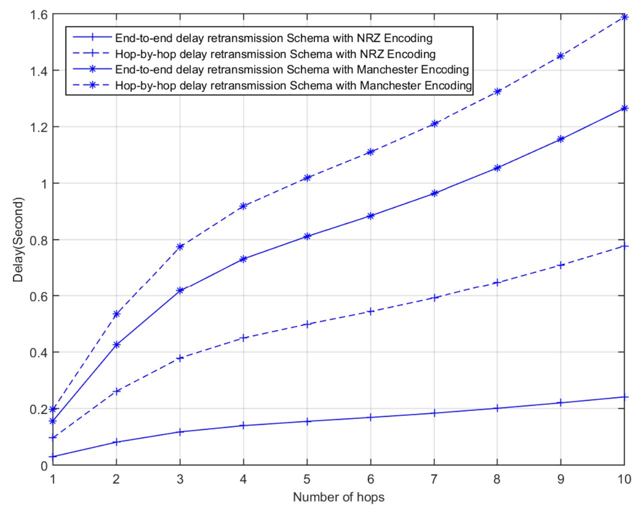

FIGURE 19. The average delay in retransmission schemes.

retransmission with the same coding operation. When the number of hops increases to more than two, the average maximum delay in the end-to-end retransmission scheme becomes approximately 31.9% which is less than that in hop-by-hop retransmission. Whenever the number of hops is increased, the maximum delay in end-to-end retransmission improves to approximately 41.8% (compared to approximately 47.9% in hop-by-hop retransmission) because every intermediate node must transmit ACK/NACK packets in hop-by-hop retransmission, which leads to more traffic pattern transmissions and the increased delay compared to the end-to-end retransmission scheme. Compared to NRZ encoding, Manchester encoding causes a larger increase in delay in both retransmission schemes because the packet length is double-decoded in the operation; therefore, the reliability of the Manchester-coded packet length m is given as $(1 - PER)^m$ [57]. The $M/M/1$ queuing model can deliver incoming DATA packets as soon as they arrive at the network; thus, only a few DATA packets are accumulated in the queue for sending in every duty cycle (as illustrated in Fig. 7), and the DATA packet delay begins with a small value. Therefore, when transmitting DATA packets with specific probability β and with stationary distribution Π_m, increasing the number of hops might cause an increase in the contention delay for each sensor node in the network before the associated RTS message is sent. Consequently, the average queue length, which cannot be longer than the queue capacity m, increases in response to the dropping of DATA packets from the queue; otherwise, the retransmission is defined indefinitely as ∞. Therefore, the average delay increases according to equation (18) as the number of hops increases because β and Π_m are more sensitive to an increase in the number of hops; this can be attributed to the influence of the path-loss as a result of the various propagation directions.

D. THE IMPACT OF RADIO IRREGULARITY ON THROUGHPUT IN THE MULTI-HOP ROUTING PROTOCOL

Figure 20 depicts the amount of DATA throughput versus the hop-distance from the source to the sink with various PER for the two retransmission schemes. The results illustrate the changes in the throughput trend, where the hop-distance between the source and the sink increases with larger SNR, and the data rate becomes limited by the number of hops; the throughput bounds for each retransmission scheme decrease.

In turn, the MAC delivers all DATA packets as soon as they arrive at the network; therefore, the throughput starts with an increasing trend. When the MAC reaches its delivery limit and can no longer deliver more incoming DATA packets from other nodes in the network, the DATA packets become backlogged in the queue, which may eventually overflow, as shown in Fig. 8. This consequently causes β to decreases with the increasing number of hops toward the sink, and more packets are ultimately dropped because of queue overflow or collision during retransmission.

The DATA packets sent over the multi-hop network are encoded with Manchester operation. The throughput is approximately 63.3kbps in end-to-end retransmission and 41.3kbps in hop-by-hop retransmission, which represents a larger decrease compared to that of the NRZ encoding operation (approximately 163kbps in end-to-end retransmission and 139.6kbps in simple hop-by-hop retransmission). This results because the duplication of DATA packets might have a significant effect on the efficiency of the system and the specified network capacity.

As previously mentioned, the proposed model uses the probability of successful transmission; therefore, the duplication of DATA packet lengths decreases the probability of successfully receiving DATA packets and increases the probability of error rates. Thus, the transmission power varies for each link between connecting nodes, $(1 - PER)^n$, where the value of PER depends on the SNR and on the modulation and encoding method used [56]. However, this is only true if the

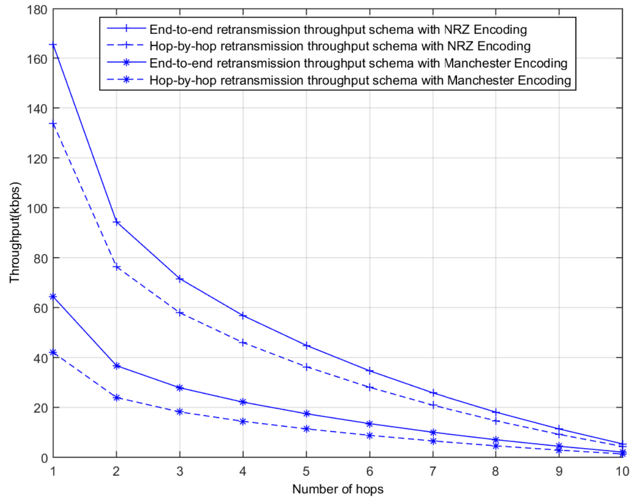

FIGURE 20. The average throughput in both retransmission schemes.

packet overhead is not taken into consideration; otherwise, the throughput of the system approaches zero per hop. Thus, the optimal packet length must be considered to obtain the highest energy efficiency and network capacity. However, if TR were to decrease too much, network connectivity would be compromised, and the average per-node throughput would drop considerably, as shown in Fig. 20. Therefore, setting the common power transmission level to the minimum value to achieve full network connectivity is the optimal choice for increasing network throughput.

VI. CONCLUSIONS

In order to eliminate the impact of the single-hop routing strategy in IoT with uniform sensor nodes distribution. A fundamental question raised is whether it is advantageous to route over many short hops or over a smaller number of longer hops? Multi-hop geographic routing green schemes propose that transmit as far as possible and outperform nearest-neighbor routing models. Clearly, the benefits of short-hop routing include the SNR gain to choose the furthest neighbor that can be reached with sufficient reliability. Therefore, this paper provides a comprehensive study for the hypothesis that the effective anisotropic radio properties inside the deployment scheme for green IoT that have an influence on the components of energy consumption and on the traffic system model.

A traffic system model is developed with a Markov discrete-time $M/M/1$ queuing model for duty-cycle nodes to describe the green behavior of two categories of transmission schemes and to derive the stationary distribution of the probability of packet transmission for both schemes to investigate the performance of the duty cycle of the MAC layer in analyzing the delay, throughput, and energy consumption simultaneously.

The results are compared with hop-by-hop and end-to-end retransmission with NRZ and Manchester encoding operations. Based on the results, the messages encoded with NRZ have more efficiency over multi-hop networks (without loss of connectivity between nodes) than those encoded with the Manchester operation. The findings presented in this work are of great help to designers of WSNs. The implications of this study for future works are as follows:

- It is important to match the optimal modulation scheme and encoding operation with the expected hop- distance and channel-noise model to guarantee the efficient usage of limited sensor residual energy and to achieve a long network lifetime. This match should be obtained using heuristic algorithms, which are considered to be very promising and effective in designing multi-hop geographic routing schemes.
- The use of heuristic algorithms is recommended to find the optimal angle for the nodes chosen around the optimum distance with some probability; the optimum transmit energy would likely change according to the geographic routing schemes chosen for the relay sensor nodes to meet QoS requirements. The proposed model should also be applied to actual hardware devices and implemented in realistic scenarios (such as Motes, *MICAZ*, or *Libelium waspmote*) and the results should be evaluated.

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