Performance Analysis Models of BLE Neighbor Discovery: A Survey

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***Abstract*—As Internet-of-Things (IoT) applications today utilize many diverse devices to collect information, Bluetooth low energy (BLE), featuring low power and low cost, is one of the most promising wireless solutions. To meet the requirements of diverse IoT applications, the neighbor discovery process (NDP) in BLE networks requires low cost and low latency, which is one of the most challenging tasks in supporting such a large number of BLE devices. Since the choice of BLE parameters is essential for achieving the required performance of BLE NDP, many performance analysis models have been proposed, aiming to provide guidance for the parameter configuration in IoT applications. This article reviews and studies the BLE NDP models and BLE performance analysis models proposed over the period 2012–2020, considering the advantages and constraints in utilizing these models in IoT. The performance analysis models are divided into two categories: 1) probabilistic models and 2) Chinese reminder theory-based models. The model design, performance metrics, deployment constraints, analysis results, and use cases are discussed for research, development, and applications.**

***Index Terms*—Bluetooth low energy (BLE), neighbor discovery, parameter optimizing, performance analysis.**

I. Introduction

BLUETOOTH low energy (BLE) is designed to provide wireless low-cost and short-distance communications by the Bluetooth Special Interest Group (Bluetooth SIG) [1]. Different from Bluetooth Classic, the specification of Bluetooth 5.0 [2] is designed to be an energy-efficient technology suitable for power-constrained IoT applications, such as beacons, security, fitness, and home entertainment industries. The latest specification of Bluetooth 5.2 was announced in 2020, featuring an upgraded version of the original attribute protocol, LE power control, and isochronous channels. These new features provide benefits for lots of the latency-sensitive and power-sensitive IoT applications [3].

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BLE provides two communications modes: 1) connected communications and 2) broadcast communications (also marked as beacons) [1]. The devices in the broadcast communication mode are based on passive scanning, which is designed to receive nonconnectable packets of data frequently on advertising channels. Advertisers can discover a large number of devices nearby in a short period of time through broadcasting passive advertisement messages. BLE broadcast communications is widely used in IoT applications with a large number of devices, such as indoor tracking, fitness, smart homes, and security. Although broadcasting with no interaction is simple and effective to discover neighbors, it is not sufficient for BLE-connected communications. Neighbor discovery based on active scanning is aiming to discover devices nearby and establish a connection with each other. The active advertisement messages are received and acknowledged by the scanners during the neighbor discovery process (NDP). Then, the devices create a connection and transmit packets of data in the connected communication mode.

To achieve low-cost communications, neighbor discovery of BLE is desired to be fast, energy efficient, and reliable. The BLE core specification provides a wide range of parameter options to support neighbor discovery, which allows us to adjust them to achieve an acceptable performance requirement. However, despite the fact that the flexible BLE parameter options can be set in an acceptable range to support various IoT applications, it is not easy to balance the two most important performance metrics: 1) energy consumption and 2) discovery latency [4]. Since BLE unifies the advantages of unmanned power-constrained IoT applications and Bluetooth-enabled smart devices, it increasingly attracts the interests of both industry and academia. To provide guidance for various IoT applications, many analysis models have been proposed for evaluating BLE performance.

To provide an overview on the state-of-the-art performance analysis models of the BLE NDP, this article presents the different features of these models, including their model designs, application conditions, complexity, feasibility, and reliability for IoT solutions. The main highlights of this article are summarized as follows.

1) An overview of BLE NDP, the related key parameters, and the challenges of the performance analysis.
2) A survey of the state-of-the-art research on the analysis models of BLE NDP.
3) A review of the conditions or constraints of these models and the applications for IoT system configuration.

TABLE I
LIST OF ABBREVIATIONS IN ALPHABETICAL ORDER

Acronym	Explanation
ADV_PDU	Advertising Protocol Data Unit
ADV_IND	Advertising Indications
BLE	Bluetooth Low Energy
Bluetooth SIG	Bluetooth Special Interest Group
CRT	Chinese Reminder Theory
NDP	Neighbor Discovery Process
IoT	Internet of Things

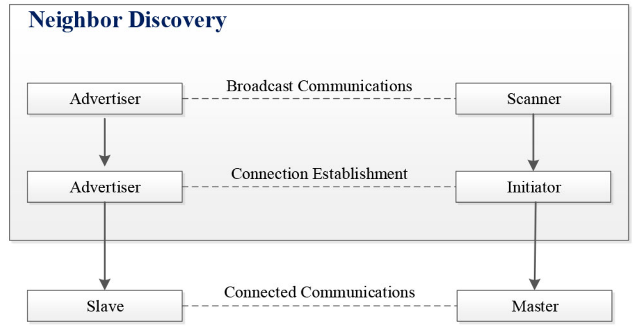

Fig. 1. BLE communication modes and node status.

This article presents a holistic overview of BLE NDP analysis models, which are divided into two categories: 1) probabilistic models and 2) Chinese reminder theory (CRT)-based models. We discuss their main advantages and drawbacks to provide a comprehensive survey for both research and application designs in the industry.

The remainder of this article is structured as follows. Section II provides an overview of the BLE NDP and discusses the challenges of the performance analysis issue; followed by an introduction of the BLE NDP models and a review of the possibilistic models and the CRT-based models in Section III. Finally, this article concludes with Section IV.[1]

II. BLE Neighbor Discovery

This section briefly introduces the significant characteristics of BLE and BLE NDP, the challenging issues of BLE NDP performance analysis, and a classification for the performance analysis models.

A. Bluetooth Low Energy

BLE was defined for the first time in 2010 by the Bluetooth SIG as part of the Bluetooth 4.0 specification [1]. Since then, the following subsequent Bluetooth revisions have been published, Bluetooth 4.1, Bluetooth 4.2, Bluetooth 5.0, Bluetooth 5.1, and Bluetooth 5.2. As a successor to the previous Bluetooth Classic, whose primary goal was to provide an effective high data rate for audio and data streaming applications, BLE essentially offers low-power consumption in sensor devices and transfers small bit data between devices. Since it operates in the sleep mode and is woken up only when a connection requirement is initiated, a BLE device can be powered by a coin cell for 1–5 years [5]. This feature makes the BLE technology an ideal choice for applications that do not require continuous connection but depend on long battery life.

Similar to Bluetooth Classic, BLE operates in the same 2.4-GHz ISM band on 40 RF channels. Three of these channels (channels 37–39) are reserved for the nonconnected communication mode and the others are for the connected communication mode. Bluetooth 5 allows the payload of an advertising packet to be transmitted on the secondary channels (CH0-CH36), and only header data is transmitted on channels 37–39, known as the primary channels in the context of Bluetooth 5 advertising. Meanwhile, the advertisers have to start advertising events in primary channels with strict order (37-38-39) [2]. To improve packet collision avoidance, advertisers can randomly select channel index sequences in Bluetooth 5.1 [6] and Bluetooth 5.2 [3].

There are three modes and five statuses in the BLE network as shown in Fig. 1. In the broadcast communication mode, BLE data transfer is essentially a one-way communication. A BLE peripheral device transmits the same packet on the primary channels. To discover devices nearby, a central device scanning for devices or beacons will listen to those channels for the advertising packets. Once the scanner receives the advertising packets from the advertiser, it turns into the connection establishment mode. In this mode, the scanner changes to be an initiator and exchanges handshaking packets with the advertiser to establish a connection. Then, the devices transfer to the connected communication mode, in which the master and slave exchange data in every connection interval.

Accordingly, the broadcast communication mode and the connection establishment mode are the essential parts of neighbor discovery, which is also a significant former process for the connected communication mode. The application of the two kinds of mode will be discussed in detail in the next section.

B. BLE Neighbor Discovery Performance Analysis and IoT Applications

BLE technology plays a significant role in IoT applications; for example, BLE beacon-based services are more and more common in real life. BLE beacon is another term of the broadcast communication mode, which has been adopted frequently by many big industrial companies, such as Google, Apple, and Line [5]. The typical applications of BLE beacons include indoor localization, proximity detection-based tour, and navigation, push promotion in malls, and activity sensing. Such applications will deploy hundreds and thousands of BLE devices, the collision caused by all the messages broadcasting simultaneously in a limited area can lead to energy waste and short network lifetime. It is essential to understand the impact of the increasing density of BLE devices on the performance of NDP. Besides these, some IoT applications are relying on the connected communication mode of BLE, such as smart tags, behavior tracking, smart lighting, in-vehicle systems, and home automation systems. All the applications

[1]We list the abbreviations used throughout this article in Table I.

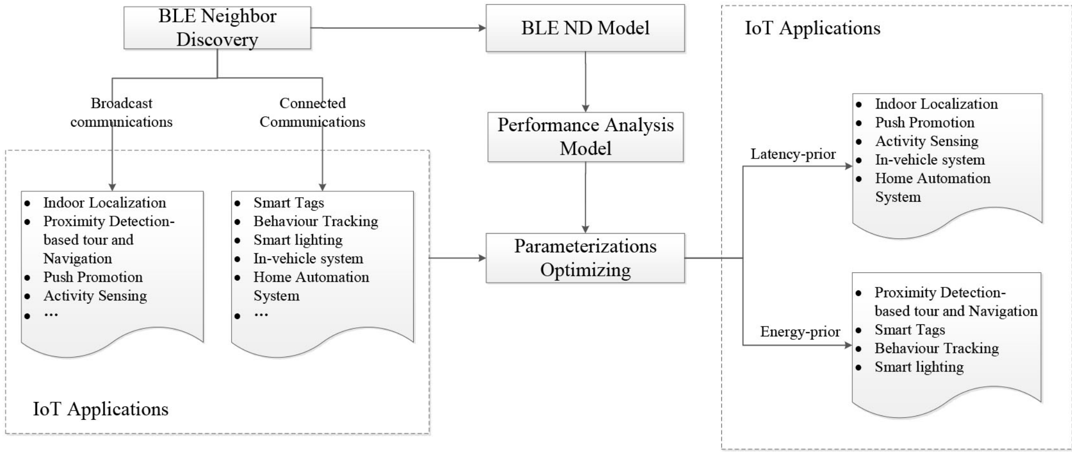

Fig. 2. BLE ND and IoT applications.

are intended to achieve the lowest energy consumption and the acceptable latency. However, in the absence of a bound, the performance evaluations of the BLE ND protocol often rely on the parametrization and the assumed setup [7]. Furthermore, it has been shown that the parameter settings recommended by the specification profiles lead to performance far from the optimum [8].

Although it is hard to balance the energy consumption and the discovery latency, the requirements of different application scenarios may focus on different performance metrics. For instance, the push promotion in the retail stores is a typical BLE beacon-based proximity system. When the users walk pass through the region of the beacon, a notification can be received if the users' devices finish the discovery within a maximum acceptable latency. Therefore, comparing with the energy consumption, discovery latency has a higher priority for consideration in this use case. As shown in Fig. 2, the IoT applications can be considered in terms of two categories: 1) latency prior and 2) energy prior. The study of performance analysis of the BLE ND protocol is to explore the theoretically lowest possible discovery latency for a given energy budget or *vice versa*. Meanwhile, the investigation of the simulation results of the BLE ND protocol in different IoT application scenarios can provide guidance for parameter optimization.

C. BLE Neighbor Discovery Process and Key Parameters

BLE NDP has two main events: 1) an advertising event and 2) a scanning event. One device sends advertising packets periodically in the advertising event, which is known as the advertiser; the other device scans during the scanning event, which is called the scanner. Figs. 3(a) and (b) and 4(a) and (b) show the two events in Bluetooth 4.2 and Bluetooth 5.0. The advertising event occurs at every advertise interval on the channel with a predefined order 37-38-39. The advertise interval is called AdvInterval T_{adv} and includes a fixed interval ω_{AI} and a pseudorandom delay μ. In the advertising event, the advertiser broadcasts advertising packets Adv_PDUs and listens for responses from scanners on the primary channels. τ_{wa} denotes the time that it takes in broadcasting and listening in each channel [4]. A scanner periodically listens to advertising information from advertisers in scanning events with the same predefined channel order [4]. The interval time between the start of two scanning events is called ScanInterval T_{sin}, and a fixed duration of length ω_{SW} is the scanning time, called ScanWindow [4].

Accordingly, the broadcast process of the NDP is similar with the broadcast communication mode. However, it is worth noting that the advertising performed in the broadcast communication mode is nonconnectable and advertising packets Adv_PDUs are discoverable. To distinguish them, there are two types of scanning: 1) passive and 2) active. In the broadcast communication mode, the passive scanning is used to simply listen for advertising packets. In BLE NDP, the active scanning is used to acknowledge and respond when the advertising packets Adv_PDUs are received.

In Bluetooth 4.2, once the scanner receives the advertising packets from the advertiser, it will send the connection request to the advertiser in waiting time d_{IFS}, which is called the interframe space in the same channel. After the advertiser receives the response from the scanner, the connection has been established. This process is called the connection establishment, as shown in Fig. 3(c). In Bluetooth 5.0, the secondary channels (CH0-CH36) are utilized for the connection establishment process. As shown in Fig. 4(c), in addition to the packet ADV_EXT_IND, AuxPTR contains CHx and the Offset option for the AUX_ADV_IND packet transmission. CHx is defined as the channel index (one of the secondary channels) that may be used, and the Offset is used to tell the nodes when AUX_ADV_IND would be sent. Different from Bluetooth 4.2, the extended advertising packet AUX_ADV_IND can be transmitted in any secondary channel, which reduces the signal collision probability and has a significant influence on the performance of neighbor discovery [9].

Table II shows the list of significant timing parameters and their value range standardized for advertising and scanning events in Bluetooth 4.2 and Bluetooth 5.0. These parameters can be configured in the recommended range for devices. However, the specification provides such a large range for these parameters; therefore, it is not easy to make a choice to meet the performance requirement of applications.

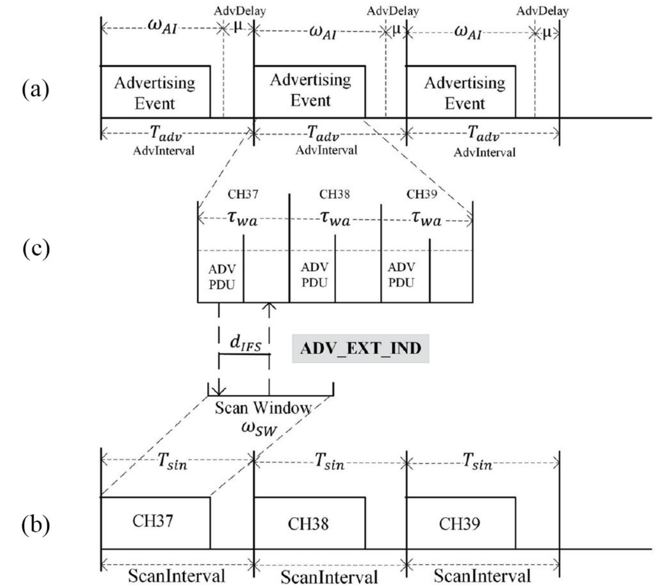

Fig. 3. BLE NDP for Bluetooth 4.2 [10]. (a) Advertiser. (b) Scanner. (c) Connection establishment.

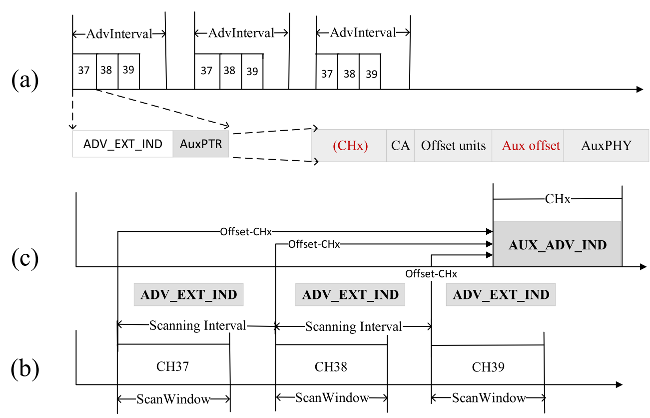

Fig. 4. BLE NDP for Bluetooth 5.0. (a) Advertiser. (b) Scanner. (c) Secondary channel.

TABLE II
BLE KEY PARAMETERS AND RECOMMENDED VALUES IN SPECIFICATION 4.2 AND 5.0 [9], [11]

Item	Notation	Value in Bluetooth 4.2	Value in Bluetooth 5.0
Fixed Interval	ω_{AI}	$20\ ms \leq \omega_{AI} \leq 10.24\ s$	$20\ ms \leq \omega_{AI} \leq 10{,}485.759375 s$
AdvDelay	μ	$0 \leq \mu \leq \mu_{MAX} \leq 10\ ms$	$0 \leq \mu \leq \mu_{MAX} \leq 10\ ms$
AdvInterval	T_{adv}	$\omega_{AI} + \mu$	$\omega_{AI} + \mu$
Advertising period per channel	τ_{wa}	$0 \leq \tau_{wa} \leq 10\ ms$	$0 \leq \tau_{wa} \leq 10\ ms$
ScanWindow	ω_{SW}	$0 \leq \omega_{SW} \leq T_{sin}$	$0 \leq \omega_{SW} \leq T_{sin}$
ScanInterval	T_{sin}	$0 \leq T_{sin} \leq 10.24\ s$	$0 \leq T_{sin} \leq 40.96\ s$
Interframe-space	d_{IFS}	$150\ \mu s$	$150\ \mu s$

D. Challenges for BLE NDP Performance Analysis

Since it is important to understand the impact of the parameter configuration, many researchers attempt to analyze the relationship between parameter settings and the performance. However, even though massive BLE devices have applied the neighbor discovery protocol, their behaviors have not been fully analyzed due to the asynchronous and periodic interval feature of NDP [12]. Here, we summarize several main challenges as follows.

First, some researchers attempted to observe the energy consumption and discovery latency through measurement [13], [14]. However, due to the large range of the parameters, it is almost impossible to perform the experiments with the whole range of parameters, much less the combination of different parameters. Therefore, measuring involves significant work when analyzing the impact of the parameter options on the performance.

Some papers have developed simulators targeted the BLE NDP analysis. Compared with the experimental analysis, it is more effective for applications with a large number of devices such as dense IoT. Due to the increasing density of the devices, the signal collision results in long latency and wasted energy. However, it is easy to provide the results of the impact of the number of devices on the NDP performance under a fixed parameter setting in the simulation; to explore the impact of parameter settings on the signal collision, simulations are computationally very complex. The discovery process needs to be simulated repeatedly for a large number of initial parameter settings in order to assess the mean discovery latency and energy consumption.

Thus, many researchers focus on modeling the BLE NDP to analyze the performance. However, the BLE neighbor discovery problem poses one challenge for these models, the impact of different parameter settings cannot be studied in a systematical manner for slotless, periodic interval-based protocols. As the clocks of these devices are completely unsynchronized, the point in time when two devices meet for the first time is random [12].

However, parameter optimization is extremely important, since unfavorable parameter settings may result in a hyperbolic peak and therefore cause long mean latency and high energy consumption for the nonconnected communication mode and connection setup in a BLE network.

E. Category of Performance Analysis Models

Recognizing the importance of parameter settings for BLE NDP, many performance analysis models have been proposed to address the problems. The key issue is that most of the BLE devices are supposed to operate their radios at low duty cycles to maximize lifetime, yet be actively vigilant to detect or be discovered [4]. These two performance metrics (low power and fast discovery) are a type of tradeoff with each other. Most of the models tried to derive the discovery latency for BLE NDP [9], [10], [12], [15]–[23], and some of them focused on the energy consumption [4], [24]–[27], while other models considered both metrics [28]–[30].

Our surveyed theoretical models can be roughly divided into two categories: 1) probabilistic models and 2) CRT-based models. The first category addresses the neighbor discovery problem as the slotless protocol, deriving the performance through calculating the possibility of the first meet for advertisers and scanners based on the main parameter settings. While periodic interval-based protocols are considered to be

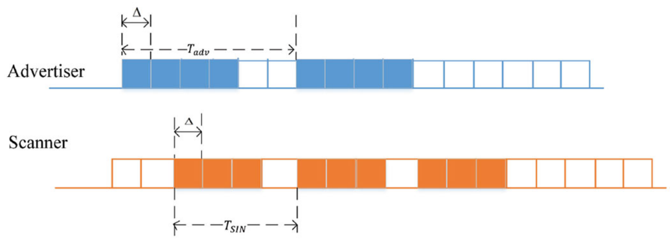

Fig. 5. Slotted BLE NDP model.

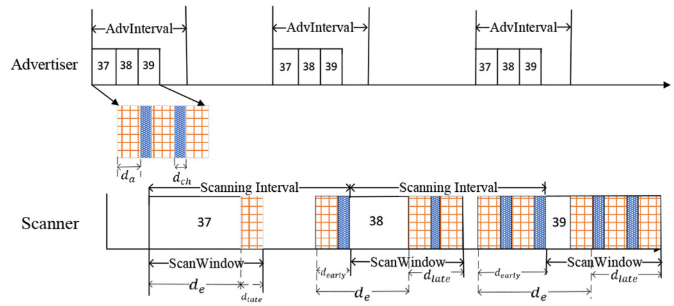

Fig. 6. Effective ScanWindow-based BLE NDP model.

nondeterministic under the slotless situation, the possibility calculation should be made under some assumption. Therefore, there are some solutions that configure the BLE NDP as the slotted protocol, such that the parameter values fulfill the CRT. Then, the performance can be derived from the CRT solutions. These models will be summarized in the second category.

III. BLE NDP Models and Performance Theoretical Analysis Models

In the last few years, there have been various proposals to analyze the performance of neighbor discovery in BLE networks. Currently, performance optimization without the constraint of assumptions remains open for future research. We have classified the proposed models into two main categories: 1) probabilistic solutions and 2) CRT-based solutions. Among them, the key issue is how to model the NDP. Different BLE NDP models lead to diverse analysis models. The detailed NDP models will be introduced in the following section. Table III summarizes the main characteristics of the analysis models for BLE NDP described in this article.

A. BLE NDP Models

To analyze the performance of BLE NDP, many proposals modeled the NDP to quantify the parameters. Slotted and slotless solutions are two typical approaches for neighbor discovery research. This section summarizes the proposed BLE NDP models, which fall into one of the following categories.

1) Slotted BLE NDP Model: As a slotless, periodic interval-based protocol, BLE NDP can have an infinite number of different parameter settings that are associated with the latency. Since the slotted protocol makes the infinite parameter settings be finite, modeling the process as a slotted protocol can simplify the complexity of the analysis. Fig. 5 shows the slotted BLE NDP model, which is used in [4], [16], [28], [29], and [31].

In this model, time is subdivided into small fixed slots Δ for both advertisers and scanners. In each slot, the state of the node can be active or sleep. For advertisers, the slots within the advertising event are active for sending advertising packets; then, the event repeats in the T_{adv} interval. For scanners, the slots within the scanning event are active for scanning the channel and switching the channel every T_{sin} interval. In this case, the parameter values in the continuous-time domain are transformed into the corresponding discrete values [28]. Therefore, the analysis of the performance is related to the discrete parameter values. In addition, if the slot value Δ is small enough, the discrete value can approximate the continuous time value effectively. However, the BLE NDP operates in an unsynchronized manner, which leads to the occurrence of the slot alignment issue for advertisers and scanners in this model.

2) Slotless BLE NDP Model: Instead of using the slotted protocol model, adaptations of the slotless scheme described in this section are also widely used. One of the most popular models is the effective ScanWindow-based model, as shown in Fig. 6.

In this model, three new parameters are defined for the performance analysis. According to the discovery protocol, there is a duration time before the start time of the scanning event during which the advertiser starts advertising called d_{early}. If the advertising event begins during d_{early}, it guarantees success for the discovery. Meanwhile, there is a duration time before the end of the scanning event that is called d_{late}. It is impossible for the discovery to be successful if the advertiser starts during d_{late}. Therefore, according to this model, the effective ScanWindow d_e can be expressed as $d_e = \omega_{\text{SW}} + d_{\text{early}} - d_{\text{late}}$. In addition, as shown in Fig. 4, the values of d_{early} and d_{late} are different for different channels. The value details are shown in Table IV, where d_a denotes the duration time for translating the advertising packets, and d_{ch} denotes the duration time for changing the channel.

This model is designed for solving the infinite solution problem, while it is as restrictive as the slotted solution. Moreover, this model only works when it satisfies these two conditions

$$\begin{aligned} \omega_{\text{SW}} &\geq \omega_{\text{AI}} \\ T_{\text{sin}} - \omega_{\text{SW}} &> \frac{2}{3}\omega_{\text{AI}}. \end{aligned} \tag{1}$$

Therefore, it is easy to see that the effective ScanWindow-based model only holds when $T_{\text{sin}} > T_{\text{adv}}$ is satisfied. This model was first presented in [10]. The effective ScanWindow-based model guaranteed the discovery when the starting time of advertising fell into the effective scanWindow. The discovery latency is defined as the duration between the starting time of the first advertising event and the acknowledging time of the scanner. In slotless BLE NDP models, the average discovery latency can be analyzed using statistical methods based on the effective scanWindow-based model [21]–[24], [27], [28]. Different from slotless BLE NDP models, the effective scanWindow-based model can be used to determine the beginning slots in slotted BLE NDP. The discovery latency can

TABLE III
MAIN FEATURES OF SURVEYED DISCOVERY AND ANALYSIS MODELS

BLE NDP Model	Performance Analysis Model	Key Ideas	Adjustable Parameter	Performance Metrics	Proposal
Slotless Model	Probabilistic	Effective ScanWindow-based	AdvInterval ScanInterval ScanWindow	Mean energy	[24]
				Mean latency and energy	[27]
				Mean latency	[23]
			Duty ratio	Mean latency	[10]
			AdvInterval	Expected latency	[21]
				Bound latency	[22]
		Residual Time	AdvInterval ScanInterval ScanWindow	Mean latency	[18]
				Mean latency and energy	[25]
		State Transition	N\A	Mean latency	[20]
		Real Chipsets	AdvInterval	Upper bound discovery capacity	[17]
		Temporal Distances	AdvInterval ScanInterval	Bound latency	[12]
Slotted Model	CRT-based	N\A	Duty ratio	Bound latency	[16]
		Effective ScanWindow-based	AdvInterval ScanInterval ScanWindow	Mean latency	[28]
		Effective ScanWindow-based model in Bluetooth 5.0		Discovery delay energy consumption	[31]
		Distributed Channel		Mean latency	[29]
				Mean energy	[4]

be analyzed by calculating the acknowledging slots in slotted BLE NDP models.

In addition to the effective ScanWindow-based model, Cho *et al.* [18], [25] proposed an analysis model based on residual time, which is the time between the start of the scanner receiving the advertising packet and the end of the scanning event. Yang and Tseng [20] analyzed the performance of NDP by using the state transition diagram. In addition, some real scanning gaps were found according to the experimental results, and these nonideal cases in real chipsets were considered in [17]. Instead of considering the corresponding absolute points, Kindt *et al.* [12] put forward a model by tracking the change in the temporal distance, which is the distance between neighboring advertising packets and scan windows over time. All the above approaches will be further discussed with their analysis models in the next section.

B. Probabilistic Analysis Models

In this section, we provide the detailed review of the existing models for neighbor discovery of BLE networks. As already mentioned, the models are divided into two categories, and the probabilistic analysis method is very popular.

The first known model using the probabilistic method to derive the performance of BLE NDP was presented in [10]. Meanwhile, it was also the first one to present the effective ScanWindow-based BLE NDP model, which has been widely used in subsequent research. In [10], based on the BLE NDP model, the possibility of the discovery latency that the advertising begins within the effective ScanWindow was expressed as $P = ((\omega_{\mathrm{SW}} - d_a)/3T_{\mathrm{sin}})$. In addition, if the advertising start time did not fall into the effective ScanWindow, it would be expected to take several times of T_{adv} to meet the scanner's scanning window. Via some algebra and deduction, the average discovery latency was derived from the possibilities. The model results showed the average discovery latency of BLE NDP versus the varied advertising duty ratio and scanning duty ratio. When T_{adv} came close to T_{sin}, it was shown that a coupling procedure may occur and lead to a large discovery latency. Furthermore, with the condition $T_{\mathrm{adv}} \leq \omega_{\mathrm{SW}}$, the larger T_{sin} led to the larger latency, and continuous scanning could decrease the discovery latency. However, the analysis results only work with the condition $T_{\mathrm{adv}} \leq \omega_{\mathrm{SW}}$, since the effective ScanWindow-based model only holds when the condition is satisfied, as previously mentioned.

Following [10], Liu and Chen proposed the energy consumption analysis model in [24] by using the same model. The

TABLE IV
MAIN PARAMETERS OF THE EFFECTIVE SCANWINDOW-BASED MODEL [27]

Channel	d_{early}	d_{late}	d_e
CH37	0	d_a	$\omega_{SW} - d_a$
CH38	$d_a + d_{ch}$	$2d_a + d_{ch}$	$\omega_{SW} - d_a$
CH39	$2d_a + 2d_{ch}$	$3d_a + 2d_{ch}$	$\omega_{SW} - d_a$

current waveform was captured during an Advertising Event on Texas Instruments CC2540. In addition, the discovery average energy consumption was derived from the probability with the same condition as in [10]. The results showed the average energy consumption for advertisers dropped quickly as the AdvInterval and the ScanWindow increased when $T_{\text{adv}} \leq \omega_{\text{SW}}$ was satisfied. In contrast, the energy consumption almost increased linearly with the ScanInterval.

According to [10] and [24], it could be concluded that with the condition $T_{\text{adv}} \leq \omega_{\text{SW}}$, the average discovery latency and energy consumption have a clear relationship with the AdvInterval, ScanWindow, and the ScanInterval. However, there is still no resolution for the situation when $T_{\text{adv}} > \omega_{\text{SW}}$.

Kindt *et al.* [27] presented a performance analysis model for both the NDP and the connected communication mode. For BLE NDP, the effective ScanWindow-based model was used to analyze the probability of the success discovery of the advertiser. In the proposed probabilistic algorithm, the discovery latency was divided into two parts, the advertiser DL and $t_{\text{advevent}}(ch)$. The advertiser DL denoted the duration time between the start of the first advertising event and the start of the advertising event received, and $t_{\text{advevent}}(ch)$ denoted the duration time when the advertising packet was successfully received by a scanner in the advertising event. The total discovery latency could be obtained by the sum of these two parts. Meanwhile, the model considered that the advertiser started at a given phase offset that was called ϕ after $t = 0$, the moment at which the scanner started scanning on channel 37. The value of ϕ increased from 0 to $3T_{\text{sin}}$ with a step Δ. Then, all possible values of ϕ were calculated for a given T_{sin}, T_{adv}, and ω_{SW}. A numerical integration was then performed by multiplying the results with Δ and computing the sum of the values.

A key contribution of the algorithm in [27] was providing an estimated discovery latency and energy consumption for BLE NDP with all possible parameter settings, including the condition $T_{\text{adv}} \geq \omega_{\text{SW}}$. The model results showed, when $T_{\text{adv}} \geq \omega_{\text{SW}}$, coupling peaks occurred with some parameter configurations. This algorithm was useful for choosing the right parameter value to avoid these peaks to obtain the expected performance for BLE NDP.

However, the computational cost of the algorithm in [27] is high, and it may take a few minutes to hours to obtain the results when the values of parameters are large. Meanwhile, the algorithm in [27] also has a parameter condition such that the offset ϕ should be larger than 0. Thus, the algorithm only satisfies the situation when the advertiser starts earlier than the scanner. Both Campo *et al.* [21] and Liendo *et al.* [23] provided improvement analysis models based on [27].

In [21], the models for both the broadcast communication mode and the connected communication mode have been merged to obtain an algorithm that was able to estimate the discovery latency for event-driven sensors. The analysis model for neighbor discovery in this article was also based on the effective ScanWindow-based model. Based on the analysis model in [27], an iterative probabilistic model was proposed to estimate the discovery latency for the advertiser, aiming to reduce the algorithm computational complexity. The model results showed a linear relationship between T_{adv} and the expected latency. Instead of using any kind of average, the model directly inserted ϕ into the probabilistic model. From the comparison of the results of the models in [21] and [27], it shows that the model in [21] can generate a trend of the discovery latency without any peaks, which is easier to integrate than the model in [27]. In addition, it is obvious that the model in [27] is much better than [21] in accuracy. Therefore, both of the models can be used to estimate the discovery latency and energy consumption of BLE NDP. Importantly, it depends on the situation and expected characteristics of the application when choosing the proper model.

The analysis model in [23] focused on improving the offset condition in [27], providing the performance analysis from the scanner perspective under the condition $\phi \in [-T_{\text{adv}} + 10\text{ ms}, 0]$. Since the precision of the model results depended on the step Δ, the model in [23] adjusted Δ for the analysis algorithms of the advertiser and the scanner.

The models mentioned above are all based on the 1:1 network, and the performance is analyzed between only one advertiser and one scanner. Since more and more BLE devices are deployed in dense IoT applications, the performance of the BLE NDP may be affected by the number of the devices. Shan *et al.* simulated the broadcast signal collision under continuous scanning mode in [32]. The simulation results show that the increasing number of advertisers leads more serious signal collisions. Meanwhile, the experiments in [33] evaluated the successful packet delivery rate above 99% even when over 200 advertisers broadcasted simultaneously in the BLE broadcast communication mode. For a larger network size, the BLE parameters need to be adjusted to achieve a high data reception. Therefore, it is essential to explore the performance theoretical analysis models of BLE NDP with multiple advertisers.

Pérez-Diaz de Cerio *et al.* [17] attempted to achieve an upper bound for the discovery capacity under one-scanner coverage with several advertisers by using a simple mathematical model. There were scan gaps observed during the scanning event on the real BLE chipset. In addition, these nonideal cases had a severe impact on the discovery process performance. The model proposed in [17] could meet the standard specification and the practical BLE chipset. The mean discovery latency was analyzed with a feasible parameter setting that involved the advertising interval and the size of the advertising frame under the continuous scanning scenario. Based on the model proposed in [17] and [34] modeled the broadcast communication mode with request and response based on BLE 5.0. The theoretical and simulation results show that the backoff mechanism has a significant impact on the discovery probability and latency in high-density networks. As a further study, Hernández-Solana *et al.* [35] analyzed the backoff mechanism in detail and improved the active scanning to reduce the collision in dense IoT tracking applications.

Shan and Roh [22] proposed an advertising interval optimization method to minimize the discovery latency for the whole set of advertisers in a 1:N network (one scanner and N advertisers). In [22], the effective ScanWindow-based model was used to calculate the probability that the scanner successfully received a complete message from any advertiser; then, the expected time interval between two consecutive ADV_PDUs successfully received by the scanner was derived. Finally, the whole discovery time could be expressed by the product of the expected number of ADV_PDUs that were successfully captured and the time interval. However, this model was also constrained by two conditions. One was that the scanner was assumed to be under a continuous scanning mode, which meant that the value of ScanWindow was equal to the ScanInterval. The other condition was that the length of a ScanInterval should be larger than that of the AdvInterval.

In addition to [22], Cho *et al.* devised a full attendance performance analysis with three configuration networks in [18] and [25], including the 1:N network, M:1 network, and M:N network. An analysis model based on the residual time was proposed in this articles. Assuming that the scanner received the first ADV_IND packet at an arbitrary time instance of t_0, the residual time was the interval between t_0 and the completion of ScanWindow. Then, the probability that there was sufficient residual time and the probability of the first successful discovery were given under the assumption of a continuous scanning scenario. The probabilities of successful discoveries on the second and third advertising channels were introduced as well. In this model, without the constraint of the effective ScanWindow, the analysis for $T_{\text{adv}} > \omega_{\text{SW}}$ was attempted. However, the probability that an ADV_IND was successfully received within a scan window had been assumed to be constant on a particular channel. Given the BLE periodic nature, this probability has a strong correlation with the offset between the start time of the advertising event and the scanning event.

By taking into account of all possible initial offsets between the first advertising packet and the first scanning, the upper bound discovery latency of the periodic interval-based protocol was calculated using analytical methods in [12]. The key idea of the proposed model was to track the change in the temporal distance between neighboring advertising packets and the ScanWindow over time rather than considering the effective ScanWindow. This model provided a method to calculate the upper bound latency with all possible parameter values. However, the theory has not been applied to an analysis of the BLE NDP, which has its unique issues such as multiple channels.

To solve the problem of the infinite offset between the first advertising packet and the first scan window, quantizing the time unit into a discrete component is another common method. The model in [20] was assumed to be time slotted, as mentioned in the previous section. In addition, the model provided the state transition diagram for BLE NDP; therefore, the probabilities of the transitions among the states were calculated. However, the probability that the advertising packet was sent on a specific channel was assumed to be constant, as in the models in [18] and [25]. As a result, the model in this article was unable to predict any latency peaks.

C. CRT-Based Analysis Models

As mentioned in the previous section, the probabilistic models pose difficulties in analyzing the performance of BLE NDP without any constraints due to the infinite offset, especially when $T_{\text{adv}} > \omega_{\text{SW}}$. To overcome the nondeterminism of the periodic interval-based protocol, some models were proposed to configure the BLE NDP parameter values based on CRT [36].

CRT states that for any two coprime numbers n_i and n_j, there exists an integer X satisfying the pair of simultaneous congruences [29]

$$\begin{aligned} X &\equiv m_i (\text{mod} n_i) \\ X &\equiv m_j (\text{mod} n_j). \end{aligned} \tag{2}$$

Here, we have the solution X as $X = x_0 + kn_in_j, k \in Z^+$. According to the slotted BLE NDP model, a common idea to apply CRT is that making the parameters in BLE NDP fulfill the conditions of the values of n_i, n_j, m_i, and m_j and there is a solution X that represents the slots where two nodes wake up together. The CRT provides a theoretical solution for the slotted models, that motivated many researchers to apply CRT to analyze the performance of BLE NDP.

In CRT-based analysis models, if the parameter values of BLE NDP can fulfill the CRT, there would be a solution X to guarantee the discovery. x_0 represents the first slot where two nodes meet. However, there is a restrictive precondition of coprime that lead to that CRT-based models only cover a very small part of the possible parameter values.

Kandhalu *et al.* [16] was the first to apply CRT to analyze the bound discovery latency of BLE NDP for an in-vehicle network. The model provided the value mapping method for BLE NDP. n_i and n_j denoted the active period slots of the advertiser and the scanner, m_i and m_j denoted the offset slots, and the solution X would be the slot in which two nodes meet. The experiments in [16] showed that the BLE with coprime parameter values had a low discovery latency under the same duty cycle. However, there were no detailed performance analyses on the impact of parameter values.

The model in [28] analyzed the mean discovery latency and the energy consumption based on CRT and compared the experimental results with the probabilistic model in [10]. Shan and Roh [31] analyzed the NDP in Bluetooth 5.0 based on the model in [28]. In addition to providing the discovery time in primary channels using CRT, the probability that the scanner can receive an AUX_ADV_IND packet in the secondary channel was calculated. The model provided the discovery latency and energy consumption of the NDP in Bluetooth 5.0. In both models, the effective ScanWindow-based model was used to derive the discovery latency, with a constraint $T_{\text{adv}} \leq T_{\text{sin}}$.

TABLE V
PARAMETER VALUE IN [16], [28], [29], [31] MAPPING WITH THE CRT

Model	n_i	n_j	m_i	m_j
[16]	$\frac{T_{adv}}{t_{slot}}$	$\frac{T_{sin}}{t_{slot}}$	pseudorandom integer	pseudorandom integer
[28][31]	$\frac{T_{adv}}{t_{slot}}$	$\frac{3T_{sin}}{t_{slot}}$	t	ch37: i ch38: $T_{sin} - d_a - d_{ch} + i$ ch39: $2(T_{sin} - d_a - d_{ch}) + i$ $(0 < i \leq \omega_{SW} - d_a)$
[29]	$\frac{T_{adv}}{\tau_{wa}}$	$\frac{3T_{sin}}{\omega_{SW}}$	ch37: $\frac{t_0}{t_{slot}}$ ch38: $\frac{t_0+\tau_{wa}}{t_{slot}}$ ch39: $\frac{t_0+2\tau_{wa}}{t_{slot}}$ $(0 < t_0 \leq T_{adv})$	ch37: $\frac{t_1}{t_{slot}}$ ch38: $\frac{t_1+T_{sin}}{t_{slot}}$ ch39: $\frac{t_1+2T_{sin}}{t_{slot}}$ $(0 < t_1 \leq 3T_{sin})$

To address the problem of constraints of the effective ScanWindow-based model, the latest CRT-based model was proposed in [29]. This article provided a 3-channel-distributed model to analyze the discovery latency instead of using the effective ScanWindow-based model. In addition, the experimental results showed the mean discovery latency and energy consumption varied with several key parameters, including the situation when $T_{\text{adv}} \geq T_{\text{sin}}$.

Although all the three models have applied the CRT, they differed regarding the mapping scheme. Table V summarizes the mapping values between CRT parameters and the BLE NDP parameters. In [16], both the advertiser and the scanner offset values were set as pseudorandom integers, since the BLE NDP operated in an unsynchronized manner. The values of m_i and m_j in [28] and [29] were related to the BLE NDP models that were proposed in this articles, respectively. The values of n_i and n_j denoted the duty cycle of advertisers and scanners in CRT. The model in [16] only considered the single channel, which caused the results to not correlate well with the actual performance. Meanwhile, the values of n_i and n_j in [28] and [29] differed from each other, which led to the different results.

D. Discussion of BLE Neighbor Discovery Performance

From the reviews so far, the state-of-the-art studies of BLE NDP are based on experiments, simulations, and theoretical analysis. Some typical performance analysis results, simulation results, and the constraints will be summarized in this section.

Simulations and measurements on testbeds are effective in evaluating the performance of the BLE broadcast communication mode, especially in a dense network. From the simulation and experimental results in [32], [33], and [37], the number of the advertisers and scanners has a significant impact on the packet reception rate. However, the packet delivery probability can achieve 99%, despite the signal collision, when the network size is small or medium. In addition to the number of devices, the distance between advertisers is another factor that can lead a fast growth of discovery latency. Based on these simulation and experiment results, BLE broadcast communications protocol can ensure a promising packet reception rate and is well suited for IoT applications with a medium-size network.

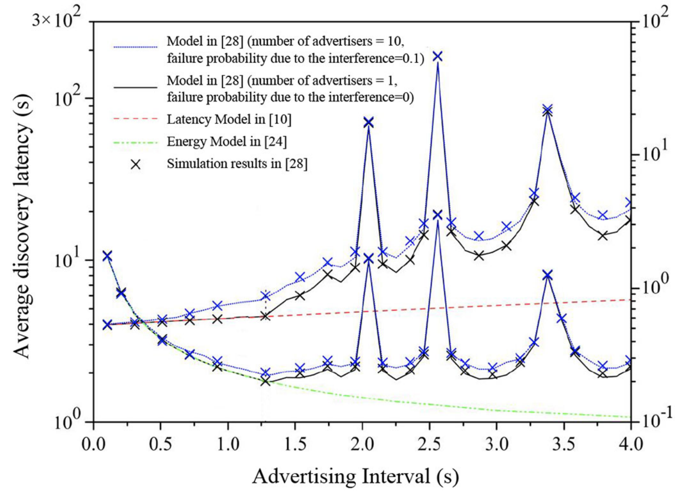

Fig. 7. Comparison of the models in [10], [28], and [24]. The comparison is under the scenario that $\omega_{\text{SW}} = 1.28$ s and $T_{\text{sin}} = 10.24$ s. The blue and black lines represent the average discovery latency results analyzed in [28]; the red line shows the discovery latency result in [10]; the green line shows the energy result analyzed in [24]. Cited from [28].

Nevertheless, for dense IoT applications with a large number of devices, improving the backoff mechanism and adjusting the BLE parameters are required to reduce the collision happening during the BLE broadcasting in the BLE NDP [35], [38]. Due to the large range of the parameters, simulations and experiments are usually used to evaluate the accuracy of theoretical analysis models under some fixed parameter settings.

The main results of the surveyed theoretical models can be summarized into two categories: 1) the linear results and 2) the peak results.

The analysis results are shown in Fig. 7. In Fig. 7, when $T_{\text{adv}} > T_{\text{sin}}$, the discovery latency and energy consumption results of the models in [10], [24], and [28] are different. The average discovery latency keeps growing with the increasing advertising interval when $T_{\text{adv}} \leq \omega_{\text{SW}}$ [10], [24], [28]. Once the parameter setting is out of this range, there is no promise on the discovery latency. These simulation results reflect that $T_{\text{adv}} \leq \omega_{\text{SW}}$ and $T_{\text{adv}} \leq T_{\text{sin}}$ raise some concerns in [10], [22], [24], and [28].

In addition, the models proposed by Kindt *et al.* [12] and Cho *et al.* [18] failed to predict the peaks when $T_{\text{adv}} \geq T_{\text{sin}}$. With the absence of the constrains $T_{\text{adv}} \leq T_{\text{sin}}$, models in [12] and [27] obtain the peak results for the average discovery latency in BLE NDP. Also, peak results appear in the discovery latency analysis of some other models [4], [23], [28], [29].

Table VI shows the model analysis results, applications, and constraints of surveyed models; it is clear that all the models have some constraints for their applications.

The models in [21] and [27] had a constraint condition of the offset between advertisers and scanners $\phi \in [0, 3T_{\text{sin}}]$, which was further considered in [23] with $\phi \in [-T_{\text{adv}} + 10 \text{ ms}, 0]$. In addition, Campo *et al.* [21] simplified the model in [27]

TABLE VI
APPLICATIONS AND CONDITIONS OF SURVEYED MODELS

Model results	Applications	Conditions	Models
Linear results	Estimate of average energy and average discovery latency	$T_{adv} \leq \omega_{SW}$	[10, 24, 28]
		$\phi \in [0, 3T_{sin}]$	[21]
	Estimate of upper bound discovery capacity	For one channel	[16, 22]
		Continuous scanning scenario	[17]
	Estimate of the trend of energy and discovery latency	Assumed constant probability	[18, 20, 25]
Peaks results	Estimate of average energy and average discovery latency	$T_{adv} > T_{sin}$	[28]
		$\phi \in [0, 3T_{sin}]$	[27]
		Coprime duty cycle	[4, 29]
		$\phi \in [-T_{adv} + 10\ ms, 0]$	[23]
	Estimate of upper bound discovery capacity	For one channel	[12]

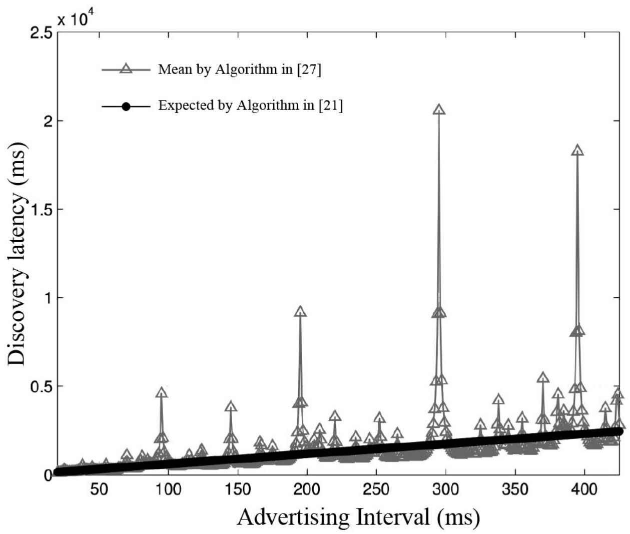

Fig. 8. Comparison of the models in [21] and [27]. Cited from [21].

to estimate the expected performance of BLE NDP. Fig. 8 compares the discovery latency results of models in [21] and [27] in a possible scenario. The simulations are performed for the following configuration: $T_{\sin} = 100$ ms, $\omega_{\rm SW} = 25$ ms, $d_a = 10$ ms. It can be seen that the periodical peaks are obtained by the model in [27], and the result of model in [21] shows a linear trend that is close to the results in [27].

Since BLE NDP is a typical periodic interval-based protocol, there is an infinite number of initial offsets, which makes it hard to determine the bound performance. The models in [12], [16], [17], and [22] provided the bound discovery latency under some constraints, such as under the continuous scanning scenario or constrained on one channel. However, the models still revealed the latency was bounded for all parameters, which was supposed to be considered during the design of IoT applications.

The results from the models in [18], [20], and [25] showed the performance with the whole range of parameters. However, the probability that the advertising packet hit on a specific channel was assumed to be constant, which made the analysis results inaccurate on the coupling conditions.

Comparing the two categories of methods, the probabilistic models have the advantage of accuracy but have more assumptions and constraints than CRT-based models. The CRT-based models transferred the slotless periodic interval problem to the slotted scenario, guaranteeing the discovery between two nodes with the coprime duty cycle. Meanwhile, the CRT-based strategies were widely used in other configurable protocols, such as Disco [36], Hello [39], searchlight [40], and U-connect [41].

E. Use Case

One of the most important motivations to study the performance analysis of BLE NDP is to guide the parameter setting for IoT applications. According to the discussions on the performance of BLE NDP, it is possible to use these models to set the parameter values carefully for the purpose of avoiding the peaks of discovery latency and energy consumption. Some surveyed models are used to provide results for realistic IoT applications [4], [21], [23].

Campo *et al.* [21] presented a tool based on the performance analysis model to support the design and configuration for BLE wireless Home Automation application. The possible scenario is that two cited networks share a central node. Using the tool, the suggested values of scanning interval and scanWindow are 100 and 79.55 ms. The obtained value of expected discovery latency quantitatively shows the suitability of this possible configuration.

Liendo *et al.* [23] proposed two test cases based on the parameter optimization and compare them with results using the recommended parameter in SIG profile. In the retail store use case, a reference discovery latency value is used for parameter optimization. Then, using the model proposed in this article, the simulation results of average energy consumption, average discovery latency, worst-case latency, and lifetime for

TABLE VII
RETAIL STORE USE CASE SIMULATION RESULTS. CITED FROM [23]

		TI		**BlueNRG**	
SIG configurations		Advertiser	Scanner	Advertiser	Scanner
$T_{sin} = 60ms$ $\omega_{SW} = 30ms$ $T_{adv} = 20ms$	E_{avg}	231.16 μJ	1.1 mJ	66.711 μJ	452.11 μJ
	DL_{avg}	34.9 ms	22.5 ms	34 ms	20 ms
	DL_{we}	51.6 ms	34.2 ms	50.7 ms	31.7 ms
	lifetime	3.82 days	1.76 days	9.55 days	2.56 days
$T_{sin} = 60ms$ $\omega_{SW} = 30ms$ $T_{adv} = 30ms$	E_{avg}	202.38 μJ	1.24 mJ	57.78 μJ	467.78 μJ
	DL_{avg}	41 ms	23.6 ms	40.1 ms	21.1 ms
	DL_{we}	71.6 ms	39.2 ms	70.7 ms	36.6 ms
	lifetime	5.54 days	1.76 days	13.82 days	2.56 days
Proposed in [23]		Advertiser	Scanner	Advertiser	Scanner
$T_{sin} = 10.24s$ $\omega_{SW} = 2.56s$ $T_{adv} = 2.2s$	E_{avg}	192.11 μJ	58.4 mJ	60.07 μJ	25.7 μJ
	DL_{avg}	2.17 s	1.11 s	2.22 s	1.11 s
	DL_{we}	4.41 s	2.21 s	4.41 s	2.21 s
	lifetime	1.1 years	4.05 days	2.32 days	5.62 days

TABLE VIII
WILD MEASUREMENTS USE CASE SIMULATION RESULTS. CITED FROM [4]

$T_{adv,OPT}$	T_{sin}	ω_{SW}	τ_{wa}	E_{exp}	E_{sim}
118.125 ms	10.24 s	5.12 s	0.746 ms	100 A*ms	98.4 A*ms
230 ms	5.12 s	2.56 s	0.746 ms	200 A*ms	201.3 A*ms
257.5 ms	2.56 s	1.28 s	0.746 ms	250 A*ms	256.4 A*ms
292.5 ms	1.28 s	500 ms	0.746 ms	300 A*ms	298.1 A*ms
200.625 ms	500 ms	300 ms	0.746 ms	350 A*ms	355.8 A*ms
230.62 5ms	200 ms	150 ms	0.746 ms	400 A*ms	403.2 A*ms

the nodes are presented in Table VII. From the statistics, it can be seen the beacon can operate for more than two years on a single coin cell battery, which is much longer than the configuration of Bluetooth SIG recommendation.

Based on the performance analysis model, parameter optimization is presented in [4]. Wild measurement as a typical IoT application, BLE-nonconnected communication may be used to broadcast data to an object or an area and connected communication may be introduced to transfer data between two specific nodes. Both nodes, in this case, are energy sensitive BLE nodes. In this energy-primary case, an optimal AdvInterval was obtained using the energy-primary procedure with the input parameters in Table VIII. Then, the energy consumption E_{sim} was obtained from simulations, which is very close to the expected performance.

IV. CONCLUSION

This article reviewed the performance theoretical analysis methods for neighbor discovery in BLE networks, including both the BLE NDP models and performance analysis models. For BLE NDP models, the slotted model and slotless model were summarized. For performance analysis models, the probabilistic analysis models and CRT-based models were reviewed in detail.

Based on our survey, several performance analysis methods were identified for different applications and constraint conditions were considered when applying the models. For slotless models, probabilistic models are the conventional methods to analyze the performance of BLE NDP. Whereas, it cannot be ignored that the performance analysis results depend on the assumption and the conditions, such as the parameter setting range, designated channel, and continuous scanning scenario. Due to the multichannel and asynchronous communications for BLE NDP, slotted models provide another option to analyze the performance. According to the survey, the CRT-based methods are very popular, which also consider the constraints of the coprime parameter with the protocol.

The performance analysis results also reflect the constraints in the models. When the parameter setting satisfies the condition $T_{\mathrm{adv}} \leq \omega_{\mathrm{SW}}$, the discovery latency increases linearly with advertising interval. Without the condition, the performance peaks are observed in the analysis results. These peaks should be avoided during the application configuration.

Despite the significant attention on the BLE NDP performance analysis, the research is still very limited. We believe that there are some important issues required for further studies. First, all the models reviewed in this article only focus on the specification of Bluetooth 4.2 and Bluetooth 5.0. However, there are many changes in Bluetooth 5.1 and Bluetooth 5.2, particularly the advertising channels use with a randomized channel index sequence in Bluetooth 5.1, which can significantly impact the performance of NDP. To the best of our knowledge, so far, performance models of BLE NDP, according to the specification of Bluetooth 5.1 and Bluetooth 5.2 have not been proposed. Meanwhile, there is still a lack of relevant simulation and experimental results to evaluate the improvement on the broadcast collision and NDP performance. Additionally, more efforts are also required to analyze the impact of the backoff mechanism in BLE NDP, including theoretical models and simulations. It is essential to guarantee a higher successful collision-free reception rate, especially in IoT applications with a large number of devices.

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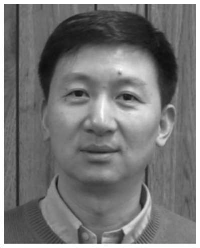

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