Wireless Networks
https://doi.org/10.1007/s11276-018-1864-3

Neighbor discovery latency in bluetooth low energy networks

Bingqing Luo[1] · Jia Xu[1] · Zhixin Sun[2]

Abstract

Bluetooth Low Energy (BLE) networks have shown great promise as the Internet of Things (IoT) takes center stage. BLE devices featuring low-power are suitable for IoT applications. Meanwhile, the standard neighbor discovery protocol provides a wide range settings of parameters, which chould meet the variety of IoT applications. Whereas the different settings also have a great influence on neighbor discovery latency. This paper presents a theoretical model based on the Chinese Remainder Theorem (CRT) for analyzing the neighbor discovery latency in BLE networks, where the scanner and the advertiser are modeled in 3-distributed channels. The neighbor discovery latency in BLE is derived by applying the CRT to each specific channel. According to the simulations of the proposed model, we found some interesting results, which offers a better understanding of the relationship between parameters and latency performance. Meanwhile, the results provide a valuable clue to optimize the neighbor discovery latency.

Keywords Internet of Things · Bluetooth Low Energy · Neighbor discovery · Performance · Latency

1 Introduction

Bluetooth Low Energy (BLE) is incorporated into Version 4.0 of the Bluetooth Core Specification [1]. In contrast to regular Bluetooth, BLE is designed to be a low-power, low-cost short-range radio capability for devices in Internet of Things (IoT) systems. According to the statistics, BLE technology will be used in one-third of IoT devices in the future [2], which has attracted academic attention.

BLE operates in the 2.4 GHz ISM band using 40 radio channels, in which three advertising channels (CH37, CH38 and CH39) are used for neighbor discovery, and the others for data transmission. The Neighbor Discovery Process (NDP) is the first step for BLE devices to set up a connection or to exchange information with each other. The BLE NDP standard provides a wide range of parameter options to balance energy consumption and latency to support different applications. Improper parameter settings could seriously impact the performance of NDP, which motivates our study on modeling the BLE NDP to analyze the relationship between NDP performance and the parameter settings.

In recent years, several analytical models have been proposed to optimize the BLE neighbor discovery process. In [3], Liu et al. developed a 3-channel-based analytical model to determine performance metrics and further enhanced the model in [4] by using the CC2540 Mini-Development Kit to analyze the energy performance metric. Following [3, 4], an adaptive device discovery mechanism was proposed in [5]; this mechanism enabled BLE scanner/initiator to learn the network contention and adjusted parameters accordingly, so as to achieve lower latency.

In [2, 6], Cho et al. suggested an analytical model to investigate discovery probability and discovery latency, where multiple BLE pairs (advertisers and scanners) are considered. Based on the work in [2, 6], an adaptive parameter-setting algorithm was proposed in [7] to

✉ Zhixin Sun
sunzx@njupt.edu.cn

Bingqing Luo
luobq@njupt.edu.cn

Jia Xu
xujia@njupt.edu.cn

1 Jiangsu Key Laboratory of Big Data Security and Intelligent Processing, Nanjing University of Posts and Telecommunications, Nanjing 210023, Jiangsu, China

2 Laboratory of Broadband Wireless Communication and Sensor Network Technology, Nanjing University of Posts and Telecommunications, Nanjing 210003, Jiangsu, China

Published online: 01 November 2018

improve the performance of neighbor discovery in crowded BLE networks [8].

The analytical model in [9] considered that the additional scanning gaps in the scanning process reduced the discovery capabilities, and a model was suggested to obtain an upper bound for the discovery capacity and to select the desired parameters values according to a particular BLE application.

Literature [10] introduced a mapping mechanism between the Chinese Remainder Theorem (CRT) and the asynchronous neighbor discovery protocol and proposed Disco, a protocol that ensured that two nodes would have some overlapping radio on-time within a bounded number of periods, even if nodes independently set their own duty cycle. Then, the BLE neighbor discovery process is exactly an asynchronous discovery problem. In [11], Kandhalu et al. suggested a model to ensure bounded latency of BLE NDP using CRT. However, the model ignored the possibility that the scanner and the advertiser were in different channels. The model also had a strong constraint: the length of scan window should be longer than the advertising event. As a result, this model has some limitations in accuracy. The most recent work in [12] improved the model in [11] also using CRT. This work proposed a discrete analysis model of BLE NDP and analyzed the best tradeoff between discovery latency and energy consumption. In [12], the time slot length is set to a fixed value, but in practice, slots will rarely be aligned since nodes are run independently and do not adjust clock skews or set up a global time reference.

In [13], Philipp et al. suggested a mathematical theory to compute the neighbor discovery latency in slotless protocols such as BLE. However, it considers a one-channel discovery procedure, rather than three channels as used in the BLE discovery procedure.

This paper proposed a theoretical model based on CRT to analyze the latency performance of neighbor discovery in BLE networks, where the scanner and the advertiser are modeled in 3-distributed channels. We use CRT to compute the discovery latency in each channel, and the overall discovery latency is derived, assuming that the advertiser and the scanner initially start at any time with the same probability. The modeling results are important to provide guidance for the configuration of the parameters in BLE neighbor discovery process.

The remainder of the paper is organized as follows: Sect. 2 briefly reviews the standard BLE neighbor discovery process [14]. In Sect. 3, we propose a simple analytical model based on Chinese Remainder Theorem and derive the average latency of neighbor discovery in BLE. Numerical results from the mathematical model and simulation results are presented and discussed in Sect. 4. Finally, the paper concludes with Sect. 5.

2 Background

According to the Bluetooth Core Spec. V4.2 [14], a BLE device normally operates in three different modes in the discovery state, i.e. advertising, scanning and initiating states. An advertiser is a device in advertising mode, which periodically transmits advertising information in three advertising channels (CH37, CH38, CH39), and then listens for responses from other devices. A scanner or initiator is a device in scanning or initiating mode, respectively, which periodically scans the advertising channels with the same channel order and listens to advertising information of others. Since the scanner and initiator have similar basic discovery functionalities in the discovery state, both will be called scanners in this paper.

As shown in Fig. 1, AdvInterval T_{ADV} is the time between the start of two consecutive advertising events, which is composed of a fixed interval ω_{AI} and a pseudo random delay μ. At each advertising event, the advertiser broadcasts Adv_PDUs in each of the predefined advertising channels. The time the advertiser spends in each channel is denoted by τ_{wa}.

In the scanning state, the time between the start of two scanning events is called ScanInterval T_{SIN}, and the time listening to the advertising message for a fixed duration of length ω_{SW} is called ScanWindow. It is noteworthy that the advertiser broadcasts in all three channels during one T_{ADV}, while the scanner listens in one specific channel during each T_{SIN}.

According to the standard [14], there are two kinds of advertising events for BLE: undirected and directed. The Undirected Advertising Event is used for detecting unknown devices, while the Directed Advertising Event is used for establishing connections with already-known devices. Since the directed advertising event is simpler than the undirected advertising event, we only discuss undirected advertising events in this paper.

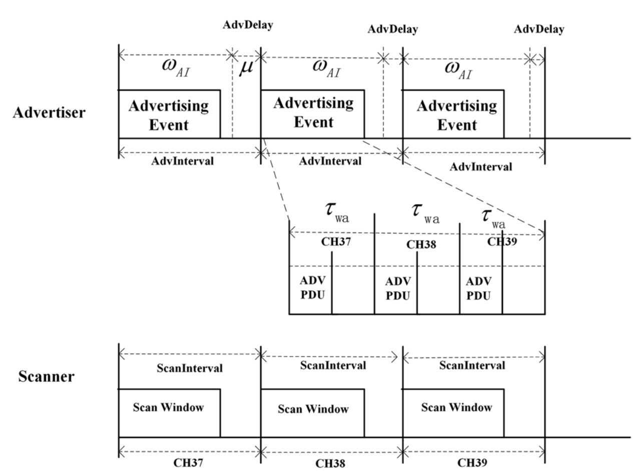

Fig. 1 The standard process of BLE neighbor discovery

The BLE standard specifies a wide range of feasible parameter values for NDP, such as AdvInterval, advertising cycle, Scan Window and ScanInterval. Based on the standard [14], the AdvInterval should be an integer multiple of 0.625 ms in the range of 20 ms to 10.24 s, and the AdvDelay should be within the range of 0–10 ms. For scanners, the Scan Window should be less than ScanInterval within the range of 0 ms to 10.24 s. The advertising time τ_{wa} depends on the size of an Adv_PDU and the tolerable time for the advertiser to wait for the response. Table 1 shows the list of major timing parameters for undirected advertising event specified in BLE standard.

Low-cost, low-power BLE devices could support a variety of applications with such wide-ranging parameters. In the meantime, the initial appropriate parameter setting should meet practical needs for low latency while avoiding unnecessary energy usage. This motivates our study for modeling the neighbor discovery process of BLE and discussing its performance.

3 Modeling the neighbor discovery process

In this section, we inspect the discovery latency performance of BLE devices from the perspective of a theoretical model based on CRT.

CRT [10] states that for any two coprime numbers n_i and n_j, there exists an integer X satisfying the pair of simultaneous congruences:

$$\begin{aligned} X &\equiv m_i(mod n_i) \\ X &\equiv m_j(mod n_j) \end{aligned} \tag{1}$$

For example, the pair of simultaneous congruences, $X \equiv 1(mod 3)$ and $X \equiv 2(mod 7)$ has the solution $X = 16 + 21k, k \in Z^+$.

In BLE neighbor discovery process, two nodes, the advertiser and the scanner, pick two numbers n_i and n_j such that the nodes wake up and beacon at n_i and n_j time intervals. Then, m_i and m_j will be the phase offsets that the advertiser and the scanner enter the advertising mode and the scanning mode, respectively. Therefore, there will be an X satisfying the pair of simultaneous congruences 1 if n_i and n_j are relatively prime. We can express X as

$$X = x_0 + kn_in_j, k \in Z^+ \tag{2}$$

when $X = x_0$, the advertiser and the scanner are turned on and can discover each other. Therefore, according to the Eq. 2, x_0 will be the minimum slot time that the two nodes meet. It is easy to see that there is exactly one such overlapping period for every n_in_j periods.

However, the BLE discovery process is different from regular asynchronous neighbor discovery. The BLE advertiser will broadcast on three channels in order during each duty cycle, while the scanner only listens on a specific channel in a duty cycle. Therefore, when $X = x_0$, both nodes are turned on, but there is a possibility that the two nodes are in different channels, which makes it impossible to directly apply CRT to BLE NDP.

3.1 The distributed neighbor discovery model

To solve the above problem, we proposed a distributed neighbor discovery model for BLE networks. As shown in Fig. 2, according to the same timeline, the neighbor discovery process in a cycle is separated into three components based on different channels. Then, we can apply CRT to the BLE neighbor discovery process in one specific channel, and the minimum solution of all the three pairs of simultaneous congruences is the beacon time when two nodes find each other.

In Fig. 2, we assume that the advertiser entered advertising mode at time t_0, and the scanner entered scanning mode at time t_1. According to CRT, the enter times of the two nodes determine the phase offset of the solution X. Therefore, to apply CRT to the distributed model, it is necessary to address the nodes enter time in each distributed channel. Consistent with the advertising order, for channel 37, the enter times of advertising and scanning are t_0 and t_1, respectively; for channel 38, $t_0 + \tau_{wa}$ and $t_1 + T_{SIN}$; for channel 39, $t_0 + 2\tau_{wa}$ and $t_1 + 2T_{SIN}$.

Another key parameter for CRT is the duty cycle. As shown in Fig. 2, for all channels, the advertiser has the same period T_{ADV} and the same duty time τ_{wa}. It is easy to see that the duty cycle of the advertiser is $\frac{\tau_{wa}}{T_{ADV}}$ in each of the three channels. Similarly, for all channels, the scanner has the same period T_{SCAN} and the same duty time ω_{SW}. The duty cycle of the scanner in each channel is $\frac{\omega_{SW}}{3T_{SIN}}$ ($T_{SCAN} = 3T_{SIN}$).

In [10], to apply CRT, time is quantized into a discrete component, called a slot time. The nodes wake up and beacon every nth slot, so the duty cycle is $\frac{1}{n_i}$. In our continuous model, with the purpose of correlating the model parameters to the CRT, we can express the duty cycle as $\frac{\alpha}{\beta}$.

Table 1 BLE major parameters and recommended values

Item	Notation	Value
Fixed interval	ω_{AI}	$20\,\text{ms} \le \omega_{AI} \le 10.24\,\text{s}$
AdvDelay	μ	$0 \le \mu \le \mu_{MAX} \le 10\,\text{ms}$
AdvInterval	T_{ADV}	$\omega_{AI} + \mu$
Advertising period per channel	τ_{wa}	$0 \le \tau_{wa} \le 10\,\text{ms}$
ScanWindow	ω_{SW}	$0 \le \omega_{SW} \le T_{SIN}$
ScanInterval	T_{SIN}	$0 \le T_{SIN} \le 10.24\,\text{s}$

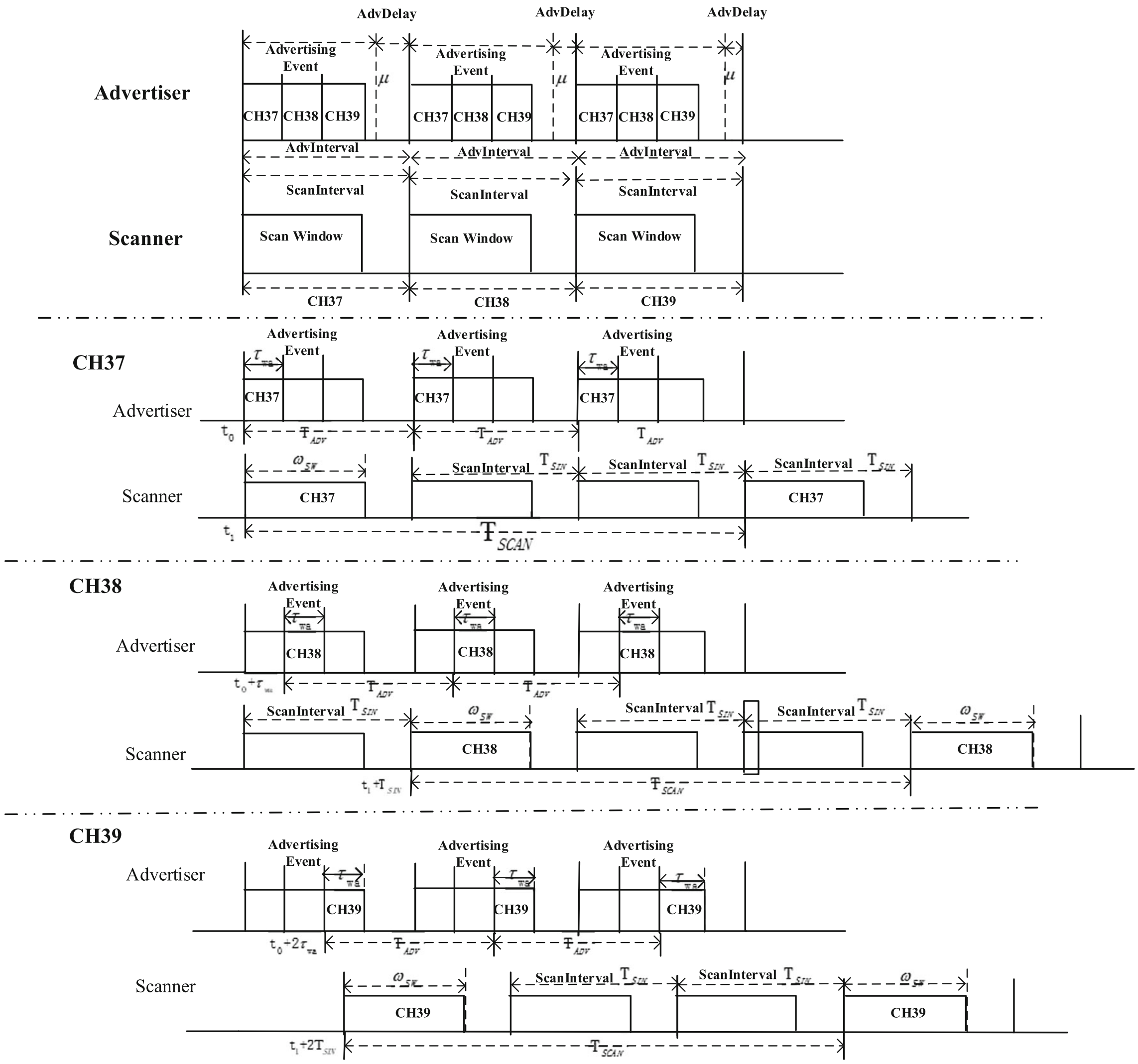

Fig. 2 Distributed neighbor discovery model in BLE

For example, the advertiser's duty time is denoted by $\alpha = \frac{\tau_{wa}}{t_{slot}}$ and the period is denoted by $\beta = \frac{T_{ADV}}{t_{slot}}$, so the discrete duty cycle is also $\frac{\tau_{wa}}{T_{ADV}}$. The phase offset to the solution X can then be expressed as $\frac{t_{entertime}}{t_{slot}}$. For an advertiser in channel 37, the discrete phase offset is $\frac{t_0}{t_{slot}}$; for channel 38 is $\frac{t_0+\tau_{wa}}{t_{slot}}$; for channel 39 is $\frac{t_0+2\tau_{wa}}{t_{slot}}$. Table 2 shows the key parameters of the distributed neighbor discovery model based on CRT.

Table 2 Key parameters of distributed neighbor discovery model

Item	CH37	CH38	CH39
$\frac{1}{n_i}$ (advertiser duty cycle)	$\frac{\tau_{wa}}{T_{ADV}}$	$\frac{\tau_{wa}}{T_{ADV}}$	$\frac{\tau_{wa}}{T_{ADV}}$
$\frac{1}{n_j}$ (scan duty cycle)	$\frac{\omega_{SW}}{3T_{SIN}}$	$\frac{\omega_{SW}}{3T_{SIN}}$	$\frac{\omega_{SW}}{3T_{SIN}}$
m_i (advertiser phase offset)	$\frac{t_0}{t_{slot}}$	$\frac{t_0+\tau_{wa}}{t_{slot}}$	$\frac{t_0+2\tau_{wa}}{t_{slot}}$
m_j (scanner phase offset)	$\frac{t_1}{t_{slot}}$	$\frac{t_1+T_{SIN}}{t_{slot}}$	$\frac{t_1+2T_{SIN}}{t_{slot}}$

3.2 The value of slot time

The slot time is a discrete component denoted by t_{slot} with a fixed length. In [10], it has been explained that the slots could not be aligned because of the asynchronization for BLE nodes. Even if slots are generally non-aligned, nodes that are in phase may come into contact with each other from time to time. If the slot time is small enough, the effort skewed by the clock is reduced.

In our model, the advertiser and the scanner would be turned on at the time, and the handshaking process should be finished during a slot time. Theoretically, an advertising PDU and a consequent response can be transmitted successfully, if only an interval is provided with at least length of

$$T_s = T_{adv\_ind} + T_{scan\_req} + T_{scan\_rsp} + 3T_{IFS} \tag{3}$$

During which there are zero transmission-attempts.

Here, T_{IFS} denotes the inter-packet guard time, T_{adv_ind} denotes the time for sending ADV_IND packet,T_{scan_rep} denotes the time for sending SCAN_REQ message, and T_{scan_rsp} denotes the time for sending SCAN_RSP message [7].

The transmission time of these kinds of PDUs is related to the length of PDUs. Based on Bluetooth Specification v4.2 [14], the PDUs of undirected advertising event are of maximal payload in length, i.e. the largest is 37 octets. Hence, the maximum length packets containing these PDUs are 47 octets [5]. Then, it could be derived by 47 octets over 1 Mbps bit rate that the minimum handshaking time is 1.578 ms. That means the minimum slot time t_{slot} is 1.578 ms.

3.3 Discovery latency

The discovery latency is defined as the interval from the initiation time of the advertiser to the time when the advertising information being received by a scanner. As shown in Fig. 3, $X = x_0$ is the beacon time for the advertiser and the scanner, and t_0 is the entering time when advertiser initially starts advertising.

As shown in Fig. 3, advertiser starts advertising at time t_0 and turn on every six slots, and the scanner is waked every five slots after time t_1. The x_0 slot is their beacon time, and the latency L could be expressed as

$$L = x_0 * t_{slot} - t_0 \tag{4}$$

From this point, we can develop the discovery latency described by our model. According to Table 2, we have

$$\begin{aligned} X_{on}^{37} &= \Gamma\left(\frac{t_0}{t_{slot}}, \frac{t_1}{t_{slot}}, \frac{T_{ADV}}{\tau_{wa}}, \frac{3T_{SIN}}{\omega_{SW}}\right) \\ X_{on}^{38} &= \Gamma\left(\frac{t_0 + \tau_{wa}}{t_{slot}}, \frac{t_1 + T_{SIN}}{t_{slot}}, \frac{T_{ADV}}{\tau_{wa}}, \frac{3T_{SIN}}{\omega_{SW}}\right) \\ X_{on}^{39} &= \Gamma\left(\frac{t_0 + 2\tau_{wa}}{t_{slot}}, \frac{t_1 + 2T_{SIN}}{t_{slot}}, \frac{T_{ADV}}{\tau_{wa}}, \frac{3T_{SIN}}{\omega_{SW}}\right) \end{aligned} \tag{5}$$

Thus, $x_0 = min(X_{on}^{37}, X_{on}^{38}, X_{on}^{39})$. Let $\theta(t_0, t_1)$ denotes the smallest slot among all matching slots. Therefore,

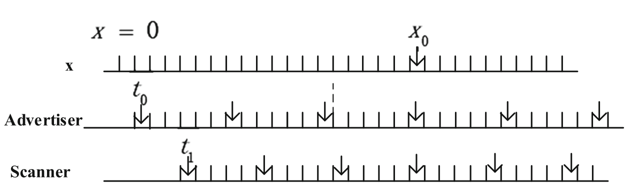

Fig. 3 Example of the beacon process

$$L(t_0, t_1) = \theta(t_0, t_1) * t_{slot} - t_0 \tag{6}$$

Finally, we assume the advertiser and scanner initially start at any slot within $[0, T_{ADV}]$ and $[0, 3T_{SIN}]$ respectively, independently with the same probability. We can calculate the average discovery latency using Eq. 5 as

$$\bar{L} = \frac{1}{3T_{ADV}T_{SIN}} \sum_{t_0=0}^{T_{ADV}} \sum_{t_1=0}^{3T_{SIN}} L(t_0.t_1) \tag{7}$$

3.4 Energy consumption

In this section, we present the energy consumption waveform during an advertising event. As the measurement in [4], an energy consumption waveform could be presented as shown in Fig. 4.

For an advertising event, it is noticed that Tx, Rx and Tx to Rx are repeated on Channels(37,38,39), which reflects the advertiser periodically transmits ADV-PDU and listens for responses with the channel order 37–38–39. The other peaks contains the changes before and after the advertising.

With the peaks described, the energy consumption within a period E_{ADV-P} could be computed as

$$\begin{aligned} E_{ADV-P} = E_{wake} + E_{pre} + E_{pre-Tx} + 3E_{Tx} + 3E_{Rx} \\ + 3E_{Tx-Rx} + E_{post} \end{aligned} \tag{8}$$

And if the beacon happens on one specific channel, the energy consumption within the period could be expressed as

$$\begin{aligned} E_{ADV-37} &= E_{wake} + E_{pre} + E_{pre-Tx} + E_{Tx} + E_{Rx} \\ &\quad + E_{Tx-Rx} + E_{post} \\ E_{ADV-38} &= E_{wake} + E_{pre} + E_{pre-Tx} + 2E_{Tx} + 2E_{Rx} \\ &\quad + 2E_{Tx-Rx} + E_{post} \\ E_{ADV-39} &= E_{wake} + E_{pre} + E_{pre-Tx} + 3E_{Tx} + 3E_{Rx} \\ &\quad + 3E_{Tx-Rx} + E_{post} \end{aligned} \tag{9}$$

As discussed in formal section, the energy consumption for advertisers could be expressed as

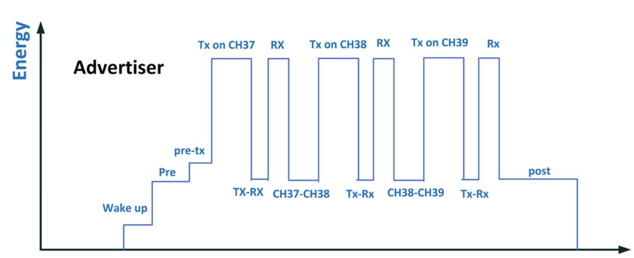

Fig. 4 The energy consumption in BLE NDP for an advertising event

$$E^X_{ADV} = \left(\frac{L(t_0, t_1) * \tau_{wa}}{T_{ADV} - 1}\right) * E_{ADV-P} + E_{ADV-X}$$
$$X = 37, 38, 39 \tag{10}$$

Therefore, the average energy consumption for adversers is

$$\overline{E_{ADV}} = \frac{1}{T_{ADV}} \sum_{t_0=0}^{T_{ADV}} E^X_{ADV} \tag{11}$$

4 Simulation results

In this section, we demonstrate the latency performance of neighbor discovery in BLE and then reveal its setting principle of related parameters.

We conduct realistic simulations of neighbor discovery with 10,000 repetitions. To analyze the relationship between latency and related parameters, we set AdvInterval, ScanWindow and ScanInterval to the values recommended by the Bluetooth Special Interest Group(SIG) [15] and calculate the average latency based on the every specific parameter setting. In the simulation, the starting times of the scanner and of the advertiser are all randomly chosen from the intervals $[0, T_{SIN}]$ and $[0, 3T_{ADV}]$, respectively. As derived before, the slot time t_{slot} is set as its minimum value 1.578 ms. The other default parameter setting is $\tau_{wa} = 7.46$ ms.The detailed parameter settings in simulation are listed in Table 3.

Figure 5 illustrates that the average of neighbor discovery delay has a regular variation with the increase of the AdvInterval. In contrast to the intuition that neighbor discovery latency should simply and steadily increase with AdvInterval,C the discovery delay has many local minima and maxima, whose values grow linearly. This result very closely matches the simulation results in [16], which first reported the performance anomaly of neighbor discovery in BLE by capturing BLE's essential procedures and features. However, this paper first validates the performance pattern according to the performance analysis model. Meanwhile,

Table 3 Simulation parameters and their values

Notation	Meaning	Value
T_{ADV}	AdvInterval	$20\,\text{ms} \le T_{ADV} \le 10.24\,\text{s}$
T_{SIN}	ScanInterval	$0 \le T_{SIN} \le 10.24\,\text{s}$
τ_{wa}	Advertising period per channel	7.46 ms
ω_{SW}	ScanWindow	$0 \le \omega_{SW} \le T_{SIN}$
t_{slot}	Slottime	1.578 ms
t_0	Start time of advertisers	$[0,3T_{ADV}]$
t_1	Start time of scanners	$[0,T_{SIN}]$

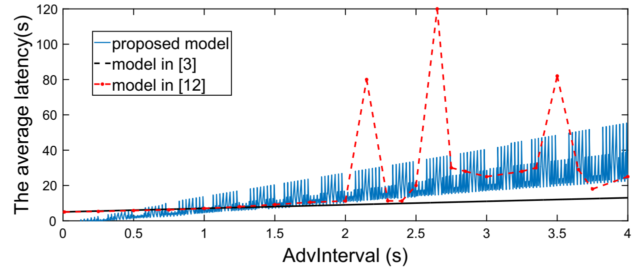

Fig. 5 Average discovery latency according to advInterval ($T_{SIN} = 10.24\,\text{s}, \omega_{SW} = 1.28\,\text{s}$)

there are further complexities that could not be revealed by the analysis in [16]: (1) The local minima and maxima recur with a certain period, where each period contains several minima and several maxima. (2) There are intermediate values that recur with the same period and growth rate as the local minima and maxima. (3) The local minima occur more frequently than the intermediate values or the local maxima.

Furthermore, by comparing these results with those of the models in [3, 12], we can observe the overall performance trend. The model in [3] showed a linear trend between the AdvInterval and the average latency, which failed to predict any latency peaks. And from the simulation results, some latency peaks were shown in [12], while the accuracy of the model was low.

According to the above discuss, we simulated the energy consumption model respect to different ScanInterval settings. Figure 6 shows the average energy consumption fluctuates with the rise of AdvInterval. However, it is obvious that the average energy consumption for advertisers during the neighbor discovery process shows a upward trend when the ScanInterval declines. When we set the ScanInterval 1.28 s, the energy consumption fluctuates from 3mA*ms to 5mA*ms. While when the ScanInterval is 10.24 s or 5.12 s, the average energy consumption is below 1mA*ms. That means ScanInterval is the key parameter to

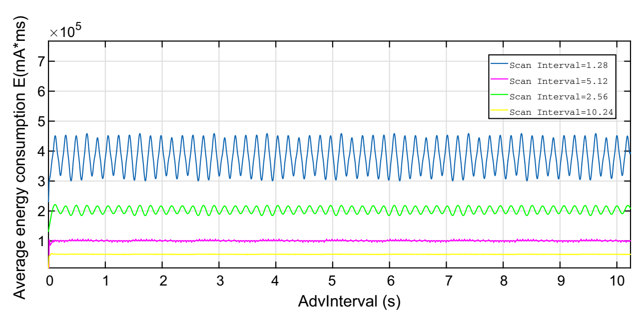

Fig. 6 Average discovery energy with respect to scanning interval ($T_{SIN} = 10.24\,\text{s}, \omega_{SW} = 4.28\,\text{s}$),($T_{SIN} = 5.12\,\text{s}, \omega_{SW} = 1.28\,\text{s}$), ($T_{SIN} = 2.56\,\text{s}, \omega_{SW} = 1.28\,\text{s}$),($T_{SIN} = 1.28\,\text{s}, \omega_{SW} = 1.28\,\text{s}$)

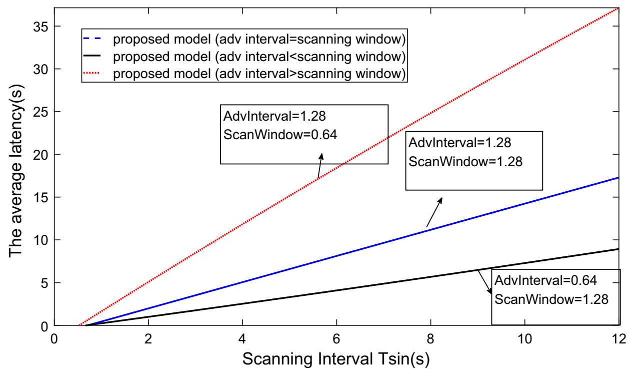

Fig. 7 Average discovery latency with respect to scanning interval($T_{ADV} = 1.28$ s,$\omega_{SW} = 0.64$ s),($T_{ADV} = 1.28$ s,$\omega_{SW} = 1.28$ s), ($T_{ADV} = 0.64$ s,$\omega_{SW} = 1.28$ s)

the average energy consumption. Since the longer ScanInterval, the discovery latency is lower, and the energy consumption for advertisers is lower.

Figure 7 shows the average latency according to the ScanInterval with three different parameter settings. It is obvious that the average latency steadily increases when the ScanInterval grows. While an interesting found is that under a fixed ScanInterval, the average delay is higher when $T_{ADV} > \omega_{SW}$; the average delay is lower when $T_{ADV} < \omega_{SW}$.

From the model of neighbor discovery process, the longer ScanWindow means the scanner have a longer time to find the advertiser, which increases the chance to have a success pairing on one specific channel theoretically. So under a fixed ScanInterval and AdvInterval, the larger ScanWindow leads a lower average latency. Particularly, as illustrated in Fig. 6, when the value of AdvInterval is lower than the ScanWindow, the average latency is better than others. Finally, it is apparent that the lower average latency could be achieved with a fixed ScanInterval, if we set a longer ScanWindow than AdvInterval.

Figure 8 shows the effect of ScanWindow on NDP performance. The average latency of neighbor discovery in

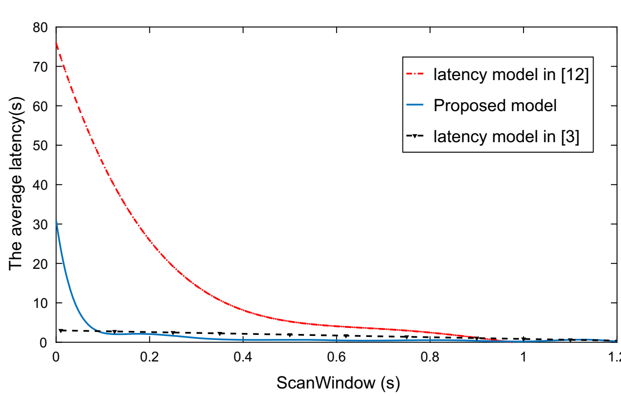

Fig. 8 The average latency with respect to ScanWindow ($T_{ADV} = 0.64$ s, $T_{SIN} = 2.56$ s)

BLE consistently shows a decline with the longer ScanWindow under a fixed ScanInterval ($T_{SIN} = 2.56$ s). In particular, for ScanWindow values greater than 0.1 s, the decrease of average latency is slight. The similar results could been seen in [3, 12]. The reason is that ScanWindow mainly affect the rendezvous chance of the advertiser and the scanner on one of the three advertising channels, but have a simple impact on the discovery latency [2].

In summary, Fig. 5, 6, 7 and 8 show that neighbor discovery in BLE can achieve good performance when the parameters are set properly. From the figures, it is easy to observe that AdvInterval and ScanInterval have a great influence on the average latency, but the influence of ScanInterval is simpler than that of AdvInterval.

For this reason, a parameter-setting strategy is recommended. A scanning interval could be chosen as the first control parameter; then, according to the scanning interval, an appropriate ScanWindow can be set that is larger than advInterval. Based on the range of advInterval, the NDP performance could be evaluated based on the model proposed in this paper. Using the model results, the AdvInterval value is easy to choose.

5 Conclusions

We have proposed a theoretical model based on CRT to analyze the latency performance of neighbor discovery in BLE networks, where the scanner and the advertiser are modeled in 3 distributed channels. According to compute the discovery latency in each channel based on CRT, the discovery latency is derived, assuming the advertiser and the scanner initially starts at any time and with the same probability. The modeling results reveal the variation of latency performance with different parameter settings. In particular, the parameter induces a complex but regular pattern in the average latency, which is unexpected in contrast to intuition. In addition, our model is applicable for any feasible parameter values and could provide practical guidance to improve the efficiency of BLE advertising.

Acknowledgements This research is funded by "Research of Neighbor Discovery Mechanism for Bluetooth Low Energy Mesh Network based on 6LoBLE" project by National Natural Science Foundation of China(No. 61702281)and "The abnormal flow detection method research in Software defines big data network." project by National Natural Science Foundation of China (No. 61672299).

References

1. Bluetooth Special Interest Group. (2014). Bluetooth specification version 4.0.

2. Cho, K., et al. (2014). Analysis of latency performance of bluetooth low energy (BLE) networks. *Sensors*, *15*(1), 59–78.
3. Liu, J., Chen, C., & Ma, Y. (2012). Modeling neighbor discovery in bluetooth low energy networks. *IEEE Communications Letters*, *16*(9), 1439–1441.
4. Liu, J., & Chen, C. (2012). Energy analysis of neighbor discovery in Bluetooth Low Energy networks. *Nokia (nd)*, *5*(10), 10.
5. Liu, J., et al. (2013). Adaptive device discovery in bluetooth low energy networks. In *Vehicular technology conference (VTC Spring), 2013 IEEE 77th, Dresden, Germany, 2–5 June 2013* (pp. 1–5).
6. Cho, K., et al. (2016). Performance analysis of device discovery of bluetooth low energy (BLE) networks. *Computer Communications*, *81*, 72–85.
7. Park, G., et al. (2016). An adaptive parameter setting algorithm to enhance performance in self-organizing bluetooth low energy networks. *Wireless Personal Communications*, *87*(3), 953–969.
8. Kouche, A. E. (2012). Towards a wireless sensor network platform for the Internet of Things: Sprouts WSN platform. In *2012 IEEE international conference on communications (ICC), Ottawa, ON, Canada, 10–15 June 2012* (pp. 632–636).
9. Perez-Diaz de Cerio, D., et al. (2017). Analytical and experimental performance evaluation of BLE neighbor discovery process including non-idealities of real chipsets. *Sensors*, *17*(3), 499.
10. Dutta, P., & Culler, D. (2008). Practical asynchronous neighbor discovery and rendezvous for mobile sensing applications. In *Proceedings of the 6th ACM conference on Embedded network sensor systems, Raleigh, NC, 05–07, NOV 2008* (pp. 71–83).
11. Kandhalu, A., Xhafa, A.E., & Hosur, S. (2013). Towards bounded-latency Bluetooth Low Energy for in-vehicle network cable replacement. In *International conference on connected vehicles and expo (ICCVE), Las Vegas, NV, 02–06, Dec 2013* (pp. 635–640).
12. Jeon, W. S., Dwijaksara, M. H., & Jeong, D. G. (2017). Performance analysis of neighbor discovery process in bluetooth low-energy networks. *IEEE Transactions on Vehicular Technology*, *66*(2), 1865–1871.
13. Kindt, P. H., et al. (2018). Neighbor discovery latency in BLE-like protocols. *IEEE Transactions on Mobile Computing*, *17*(3), 617–631.
14. Bluetooth Special Interest Group. (2014). Bluetooth core specification v4.2.
15. The website of Bluetooth Special Interest Group. https://www.bluetooth.com/zh-cn
16. Lee, H., et al. (2016). Performance anomaly of neighbor discovery in bluetooth low energy. In *2016 IEEE international conference on consumer electronics (ICCE), Las Vegas, NV, USA, 7–11 Jan. 2016* (pp. 341–342).

Bingqing Luo received the Ph.D. degree from Nanjing University of Posts and Telecommunications, Nanjing, China, in 2016. Currently, she is a faculty member of School of Computer Science, Nanjing University of Posts and Telecommunications. Her research interests include Wireless Network Communications and Internet of Things.

Jia Xu received the M.S. degree in School of Information and Engineering from Yangzhou University, Jiangsu, China, in 2006 and the Ph.D. degree in School of Computer Science and Engineering from Nanjing University of Science and Technology, Jiangsu, China, in 2010. He is currently a professor in the School of Computer Science at Nanjing University of Posts and Telecommunications. He was a visiting Scholar in the Department of Electrical Engineering and Computer Science at Colorado School of Mines from Nov.2014 to May.2015. His main research interests include Crowdsourcing, Opportunistic Networks and Wireless Sensor Networks.

Zhixin Sun was born in Xuancheng, China, in 1964. He received his Ph.D. degree from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 1998. From 2001 to 2002, he was a postdoc in the School of Engineering, Seoul National University, South Korea. Currently, he is a professor and dean of School of Modern Posts, Nanjing University of Posts and Telecommunications. His research interests are in Cloud Computing, Cryptography and Traffic Identification.