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A novel context-aware RPL algorithm based on a triangle module operator*

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Abstract: For the use in low-power and lossy networks (LLNs) under complex and harsh communication conditions, the routing protocol for LLNs (RPL) standardized by the Internet Engineering Task Force is specially designed. To improve the performance of LLNs, we propose a novel context-aware RPL algorithm based on a triangle module operator (CAR-TMO). A novel composite context-aware routing metric (CA-RM) is designed, which synchronously evaluates the residual energy index, buffer occupancy ratio of a node, expected transmission count (ETX), delay, and hop count from a candidate parent to the root. CA-RM considers the residual energy index and buffer occupancy ratio of the candidate parent and its preferred parent in a recursive manner to reduce the effect of upstream parents, since farther paths are considered. CA-RM comprehensively uses the sum, mean, and standard deviation values of ETX and delay of links in a path to ensure a better performance. Moreover, in CAR-TMO, the membership function of each routing metric is designed. Then, a comprehensive membership function is constructed based on a triangle module operator, the membership function of each routing metric, and a comprehensive context-aware objective function. A novel mechanism for calculating the node rank and the mechanisms for preferred parent selection are proposed. Finally, theoretical analysis and simulation results show that CAR-TMO outperforms several state-of-the-art RPL algorithms in terms of the packet delivery ratio and energy efficiency.

Key words: Triangle module operator; Membership function; Context-aware; Routing protocol for low-power and lossy networks (RPL); Routing metrics
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1 Introduction

Low-power and lossy networks (LLNs) (Monowar and Basheri, 2020; Seyfollahi and Ghaffari, 2020) are a kind of communication network for harsh and complex communication conditions, which result in the constraint of nodes and interconnecting links. Constraint means that nodes are limited in memory, processing power, and energy. The interconnecting links are characterized by low data rate, high packet loss ratio, low bandwidth, and instability. Therefore, it is particularly important to study the routing protocol for LLNs (RPL). RPL (Memon et al., 2020; Pereira et al., 2020), standardized by the Internet Engineering Task Force, is specially designed for the use in LLNs.

To improve the performance of LLNs, in this study, a novel context-aware RPL algorithm based on a triangle module operator (CAR-TMO) is designed. The main contributions of this paper are as follows:

1. A novel composite context-aware routing metric (CA-RM) is designed.

(1) CA-RM synchronously evaluates the residual energy index (REI), buffer occupancy ratio (BOR), expected transmission count (ETX), delay (D), and hop count (HC).

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(2) CA-RM proposes that REI and BOR of a candidate parent (neighbor) and their preferred parent (the next hop) should be evaluated recursively to reduce the influence of upstream parents.

(3) CA-RM proposes that the sum, mean, and standard deviation of ETX and *D* of links in a path can be synthetically used in a lexical manner to ensure a better performance.

2. Novel membership functions of routing metrics are designed. CAR-TMO designs the corresponding membership functions of the routing metrics mentioned above.

3. A comprehensive membership function is constructed. CAR-TMO designs a triangle module operator to construct the comprehensive membership function.

4. A comprehensive context aware objective function (CA-OF) is designed. CAR-TMO constructs CA-OF based on the comprehensive membership function, maximum membership principle, and network characteristics.

5. Novel rank calculation mechanisms are designed. CAR-TMO designs the node's rank calculation mechanisms based on CA-OF to determine the location of a node relative to the root and to select the preferred parent (the next hop).

6. Novel preferred parent selection mechanisms are proposed. CAR-TMO proposes novel preferred parent selection mechanisms according to the comprehensive CA-OF, the rank values of nodes, and the number of nodes in the candidate parent set.

7. Simulation evaluations of CAR-TMO and state-of-the-art algorithms are implemented. The evaluation results show that CAR-TMO outperforms state-of-the-art RPL algorithms and improves the LLN performance in terms of the packet delivery ratio and energy efficiency.

2 Related work

The main features of RPL and the problems associated are introduced in this section.

2.1 Overview of RPL

1. RPL control message

In RPL, the ICMPv6 control messages used include mainly the destination-oriented directed acyclic graph (DODAG) information object (DIO), DODAG information solicitation (DIS), destination advertisement object (DAO), and destination advertisement object acknowledgement (DAO-ACK) (Winter et al., 2012; Ganesh et al., 2019). The main functions of these control messages are listed in Table 1.

Table 1 RPL control messages

Control message	Function(s)
DIO	Broadcasted by parents, containing the information about instance, maintaining DODAG, and used for selecting a parent set
DIS	Soliciting DIO from neighbors
DAO	Transmitting destination information upward and building uplink routing
DAO-ACK	Sent by the DAO receiver to acknowledge DAO

2. Objective function

The objective function, an important tool of RPL, is used to define how several routing metrics should be combined and transformed into a rank which is used to construct DODAG and select the optimal routes. Moreover, the objective function can be designed in different forms according to various application requirements. For example, objective function 0 (OF0) (Thubert, 2012) and minimum rank with hysteresis objective function (MRHOF) (Gnawali and Levis, 2012) are designed based on HC and ETX, respectively. They can be applied to different network application scenarios.

3. Network construction

Fig. 1 shows an example of RPL network topology. RPL uses DODAG (Wadhaj et al., 2020) to construct and maintain network topology. DODAG, a directed graph, wherein all edges are oriented in such a way that no cycles exist, is built based on RPL control messages and objective functions. Fig. 2 illustrates the simple construction process of DODAG. The specific construction process is as follows:

Step 1: The root broadcasts DIO to its neighbors. DIO contains relevant information to construct and maintain DODAG.

Step 2: A neighbor such as node 1 receiving DIO determines whether to select the root as its parent according to the objective function. If node 1 selects the root as its parent, it will unicast DAO to the root to build a complete route.

Step 3: Node 1 re-broadcasts DIO to its neighbors, such as node 2. Then, node 2 performs the same operation as node 1 does.

Step 4: After receiving DAO_2 from node 2, node 1 unicasts DAO_{12}, which contains the updated routing information, to the root again.

Step 5: Other nodes such as node 3 perform the same operation.

Step 6: If node 4 does not receive DIO from other nodes within a certain period of time, it will broadcast DIS to solicit DIO from its neighbors (node 3) to join DODAG.

Step 7: After node 4 joins DODAG, node 3 will unicast DAO_{34}, which contains the updated routing information, to its parent (node 2). Then, node 2 unicasts DAO_{234} to node 1 and node 1 unicasts DAO_{1234} to the root.

Repeat the above steps until the network covers all nodes.

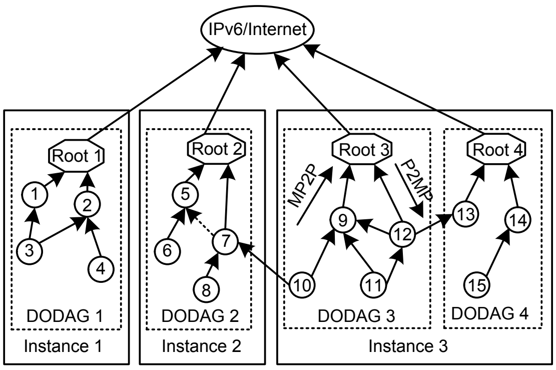

Fig. 1 RPL network topology with four DODAGs in three instances

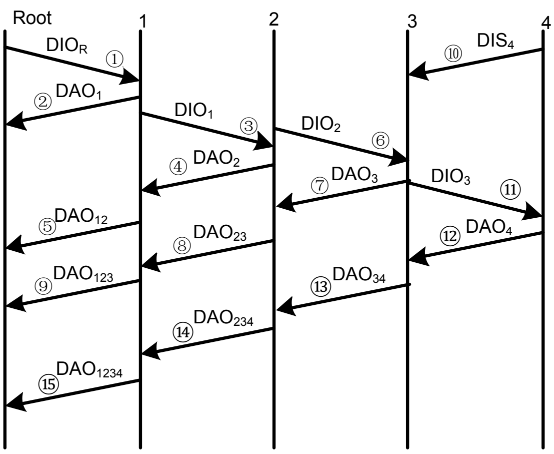

Fig. 2 DODAG simple construction process

2.2 Problem description

While there have been many research studies on RPL, many problems exist.

1. Energy consumption problem

Several studies (Alishahi et al., 2018; Gao et al., 2018; Lamaazi and Benamar, 2018; Taghizadeh et al., 2018) have addressed the energy consumption problem of RPL to improve the energy efficiency. Residual energy and other routing metrics are combined for selecting a preferred parent. The importance of each routing metric is determined by its corresponding weighting coefficient. However, the weighting coefficient is determined mainly by the experience of experts. Therefore, it is subjective and unreasonable. Moreover, several important routing metrics, such as the child node count of the candidate parent (neighbor), are not evaluated.

2. Load balancing problem

The packet queue length in a node's buffer has been studied to relieve the congestion and to balance the load (Al-Kashoash et al., 2016; Kim et al., 2017; Bhandari et al., 2018). However, several other important routing metrics that influence the network performance to a certain extent are not evaluated.

3. ETX calculation problem

ETX represents the number of transmissions (re-transmissions) that a node expects to successfully transmit and acknowledge a packet. As shown in Eq. (1), D_f and D_r are the probabilities of successfully receiving and acknowledging a packet, respectively. ETX of a path is the sum of the ETX values of all the links in that path:

$$\mathrm{ETX}=\frac{1}{D_\mathrm{f}\cdot D_\mathrm{r}}. \tag{1}$$

ETX and other routing metrics have been evaluated to improve the network performance (Araújo et al., 2018; Kheaksong et al., 2018; Nassar et al., 2018). However, there is still no reasonable theoretical basis for determining the importance of each routing metric. The use of ETX standard deviation (SIGMA-ETX) (Sanmartin et al., 2018) instead of the summation method has been proposed to avoid a long single hop. For example, consider two candidate paths from source node S to destination node D (path 1: S-1-2-D; path 2: S-3-4-D), as shown in Fig. 3. Suppose that the ETX of each link is as follows:

$$\begin{cases}\mathrm{ETX}_1=\mathrm{ETX}_3=2,\ \ \mathrm{ETX}_2=3,\\ \mathrm{ETX}_4=\mathrm{ETX}_6=1,\ \ \mathrm{ETX}_5=5.\end{cases} \tag{2}$$

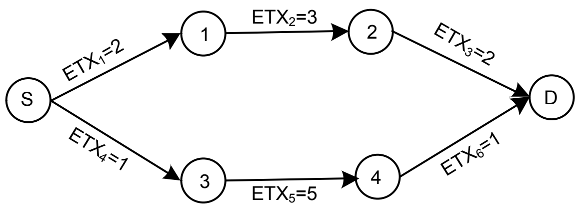

Fig. 3 ETX example

The ETX values of these two candidate paths are equal (through the summation method), so the objective function may randomly select a path to transmit packets and path 2 may be selected. However, ETX_5, between nodes 3 and 4 in path 2, is so large that it may be the bottleneck of the whole network. So, this selection may not be the optimal in these circumstances. Therefore, SIGMA-ETX can be used:

$$\sigma_{\mathrm{ETX}}=\sqrt{\frac{1}{h-1}\sum_{k=1}^{h}\left(\mathrm{ETX}_k-\overline{\mathrm{ETX}}\right)^2}, \tag{3}$$

$$\overline{\mathrm{ETX}}=\frac{1}{h}\sum_{k=1}^{h}\mathrm{ETX}_k, \tag{4}$$

where h is the HC in a path from the source to the destination, and $\overline{\mathrm{ETX}}$ is the average ETX of a path. Then, the standard deviations of path 1 and path 2 are σ_{ETX}(path 1)=0.527 and σ_{ETX}(path 2)=2.309. Thus, path 1 with the smaller ETX standard deviation is more stable, no longer has a single hop, and can be selected as the optimal route.

However, based on SIGMA-ETX, the path with the minimum ETX sum value may not be selected as the optimal path. This will influence the link quality and the network performance. Moreover, SIGMA-ETX does not evaluate other important routing metrics when deciding a route.

4. Delay calculation problem

Similar to ETX, in most studies, delay of a path is calculated by summing the delay values of all links in that path. Then, the path with the minimum delay value will be selected as the optimal route. However, the optimal path may include one or more links that encounter a large delay. Fig. 4 illustrates an example. Consider two candidate paths from source node S to destination node D. Suppose that delay of each link is as follows:

$$\begin{cases}\mathrm{Delay}_1=\mathrm{Delay}_2=\mathrm{Delay}_3=3.1\ \mathrm{s},\\ \mathrm{Delay}_4=\mathrm{Delay}_6=0.1\ \mathrm{s},\ \ \mathrm{Delay}_5=9\ \mathrm{s}.\end{cases} \tag{5}$$

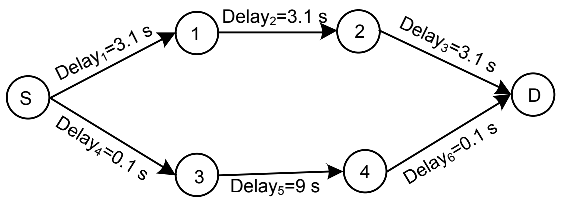

Fig. 4 Delay example

The delay values of path 1 (S-1-2-D) and path 2 (S-3-4-D) are as follows:

$$\begin{aligned}\mathrm{Delay}_{\mathrm{path\ 1}}&=\mathrm{Delay}_1+\mathrm{Delay}_2+\mathrm{Delay}_3\\&=(3.1+3.1+3.1)\ \mathrm{s}=9.3\ \mathrm{s},\end{aligned} \tag{6}$$

$$\begin{aligned}\mathrm{Delay}_{\mathrm{path\ 2}}&=\mathrm{Delay}_4+\mathrm{Delay}_5+\mathrm{Delay}_6\\&=(0.1+9+0.1)\ \mathrm{s}=9.2\ \mathrm{s}.\end{aligned} \tag{7}$$

$\mathrm{Delay}_{\mathrm{path\ 1}}>\mathrm{Delay}_{\mathrm{path\ 2}}$, so path 2 will be selected as the optimal route. However, the delay between nodes 3 and 4 is too large, and may be the bottleneck of the whole network. Therefore, using the summation method to calculate the delay of each path and selecting the path with the minimum delay may not be appropriate.

5. Objective function design problem

At present, most studies construct the objective function by evaluating several routing metrics in a lexical or additive manner (Zahariadis and Trakadas, 2012; Karkazis et al., 2013; Velivasaki et al., 2014; Hassan et al., 2016; Solapure and Kenchannavar, 2020). The network performance of an additive method is better than that of a lexical method. However, reasonably determining the importance of each routing metric is still a challenge, as well as constructing an appropriate objective function.

6. Preferred parent selection problem

Before selecting a preferred parent, the rank of nodes through each candidate parent (neighbor) can be calculated according to the objective function. Then the candidate parent corresponding to the minimum or the maximum rank will be selected as the preferred one (the next hop). Such a selection method is too crude to be suitable for several special cases.

Despite the improvements in RPL, problems still exist. Therefore, a novel CAR-TMO is proposed in this paper. CAR-TMO proposes a novel CA-RM, novel membership functions of routing metrics, a comprehensive membership function, a comprehensive CA-OF, novel rank calculation mechanisms, and novel preferred parent selection mechanisms. Through these new mechanisms, CAR-TMO can select the optimal route and achieve the best network performance.

3 CAR-TMO

3.1 Outline of CAR-TMO

Fig. 5 illustrates the CAR-TMO flowchart, which can be outlined as follows:

(1) introduce the triangle module operator and membership function;

(2) design the novel CA-RM;

(3) design the novel membership functions of routing metrics;

(4) construct the comprehensive membership function;

(5) construct the new comprehensive CA-OF;

(6) propose the novel rank calculation mechanisms;

(7) propose the novel preferred parent (the next hop) selection mechanisms;

(8) analyze the computational complexity of CAR-TMO and several state-of-the-art RPL methods.

CAR-TMO will be described in detail below according to the above-mentioned outline.

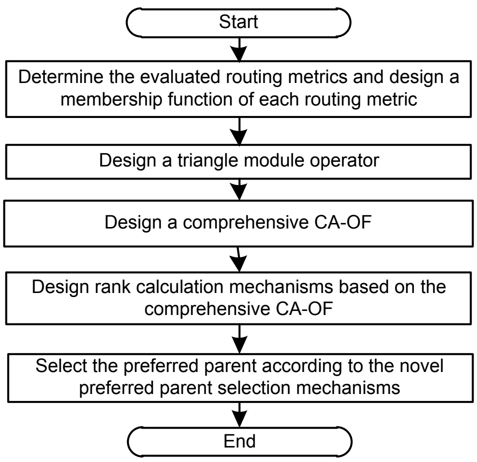

Fig. 5 CAR-TMO flowchart

3.2 Membership function and triangle module operator

1. Membership function

If $F(x)\in[0, 1]$ corresponds to any element x in domain U (the study scope), then F is called the fuzzy set based on U and $F(x)$ is called the membership of x. The closer the $F(x)$ is to 1, the higher the degree to which x belongs to F. The closer the $F(x)$ is to 0, the lower the degree to which x belongs to F. So, $F(x)\in[0, 1]$ can represent the degree to which x belongs to F (Huynh et al., 2020; Nikolić et al., 2020).

2. Triangle module operator

The mapping T: $[0, 1]^2\rightarrow[0, 1]$ is the triangle module operator (Cao and Wu, 2018), if the following four conditions are true $\forall a, b, c, d\in[0, 1]$:

(1) $T(0, 0)=0$ and $T(1, 1)=1$;
(2) $T(a, b)\leq T(c, d)$, if $a\leq c$ and $b\leq d$;
(3) $T(a, b)=T(b, a)$;
(4) $T(T(a, b), c)=T(a, T(b, c))$.

For the convenience of practical application, the triangle module operator can be extended to multiple dimensions. For example, CAR-TMO uses a four-dimensional (4D) triangle module operator.

Moreover, to obtain comprehensive evaluation of a system, the triangle module operator can be used to fuse multiple membership functions of several metrics related to this system, and the strengthening and reconciliation of these metrics are achieved. That is, the evaluation result is not absolutely positive or negative, but it is rather a fuzzy set. Therefore, through these technologies, CAR-TMO can effectively fuse several membership functions of routing metrics to evaluate candidate parents comprehensively and select the most optimal one as the preferred parent to improve the network performance.

3.3 Composite context-aware routing metric

CAR-TMO proposes a novel CA-RM which synchronously evaluates REI, BOR, ETX, D, and HC. CA-RM proposes that REI and BOR of a candidate parent (neighbor) and their preferred parent (the next hop) should be evaluated recursively to reduce the influence of upstream parents. CA-RM also proposes that the standard deviation, sum, and mean values of ETX and delay of links in a path can be synthetically used in a lexical manner to ensure better performance.

In the following, the designs of REI, BOR, ETX, D, and HC are described at length. Suppose that node c has n candidate parents (neighbors).

1. REI

REI can be designed as

$$\begin{cases} \mathrm{REI}(i)=\begin{cases} \dfrac{E_{\text{initial}}(i)-E_{\text{current}}(i)}{E_{\text{initial}}(i)}, & i=\text{root},\\ \max\left\{\dfrac{E_{\text{initial}}(i)-E_{\text{current}}(i)}{E_{\text{initial}}(i)},\ \mathrm{REI}(i_{\mathrm{p}})\cdot\beta\right\}, \\ \qquad\qquad i=1,2,\ldots,n, \end{cases}\\ 0\le \mathrm{REI}(i)\le 1, \end{cases} \tag{8}$$

where $E_{\text{initial}}(i)$ is the initial energy of candidate parent i, $E_{\text{current}}(i)$ is the current energy of candidate parent i, i_{p} is the preferred parent (the next hop) of candidate parent i, and β=0.21 is the adjustment parameter. REI(i), including the REI of candidate parent i and its preferred parent i_{p}, can recursively evaluate the remaining energy of nodes. So, the influence of the parent's remaining energy diminishes as it gets farther down the path. This recursive manner can effectively avoid choosing a candidate parent or route with lower remaining energy as the optimal route.

2. BOR

BOR is constructed as

$$\begin{cases} \mathrm{BOR}(i)=\begin{cases} Q(i), & i=\text{root},\\ \max\left\{Q(i),\ \mathrm{BOR}(i_{\mathrm{p}})\cdot\beta\right\}, & i=1,2,\ldots,n, \end{cases}\\ 0\le \mathrm{BOR}(i)\le 1, \end{cases} \tag{9}$$

$$Q(i)=\frac{\text{packet number in buffer } i}{\text{total buffer size of buffer } i},\quad 0\le Q(i)\le 1, \tag{10}$$

where $Q(i)$ is the buffer utilization. BOR(i), including the BOR of buffer i and its preferred parent i_{p}, can recursively evaluate the buffer utilization of nodes. So, the influence of the parent buffer diminishes as it gets farther down the path. This recursive manner can effectively relieve congestion and balance load.

3. ETX

In CA-RM, the sum, mean, and standard deviation of ETX of links in a path are comprehensively evaluated to avoid long single hops and to ensure the network performance. Suppose that ETX(i), $\overline{\mathrm{ETX}}(i)$, and $\sigma_{\mathrm{ETX}}(i)$ are the sum, mean, and standard deviation, respectively, of ETX of links in a path from c through candidate parent i (i=1, 2, …, n) to the root:

$$\begin{cases} \mathrm{ETX}(i)=\mathrm{ETX}_1+\mathrm{ETX}_2+\cdots+\mathrm{ETX}_{h_i},\\ \overline{\mathrm{ETX}}(i)=\mathrm{ETX}_i/h_i,\\ \sigma_{\mathrm{ETX}}(i)=\sqrt{\dfrac{1}{h_i-1}\displaystyle\sum_{k=1}^{h_i}\left(\mathrm{ETX}_k-\overline{\mathrm{ETX}}(i)\right)^2}, \end{cases} \tag{11}$$

where h_i is the HC of path P_i from c through candidate parent i to the root. Then, the specific lexical rules of ETX(i), $\overline{\mathrm{ETX}}(i)$, and $\sigma_{\mathrm{ETX}}(i)$ are as follows:

Step 1: Calculate ETX(i), $\overline{\mathrm{ETX}}(i)$, and $\sigma_{\mathrm{ETX}}(i)$ of path P_i from c through candidate parent i (i=1, 2, …, n) to the root.

Step 2: Arrange ETX(i) values in ascending order. Then the paths with the first three minimum ETX(i) values are composed into the alternative path set. If n≤3, select all of them into the alternative path set.

Step 3: The path in the alternative path set with the minimum $\sigma_{\mathrm{ETX}}(i)$ will be selected as the optimal one. For example, if $\sigma_{\mathrm{ETX}}(f)$ is the minimum in the alternative path set, then path P_f (the path from c through candidate parent f to the root) can be selected as the optimal one, and candidate parent f is the preferred parent.

Clearly, comprehensive evaluation of the sum, mean, and standard deviation of ETX of links in a path not only ensures the link quality, but also avoids the selection of an optimal path with large ETX links. To facilitate combining ETX with other routing metrics, normalization is required as shown in Eq. (12), and the final ETX routing metric is shown in Eq. (13):

$$\underset{\text{normalization}}{\sigma_{\mathrm{ETX}}(i)}=\frac{\sigma_{\mathrm{ETX}}(i)}{\displaystyle\sum_{i=1}^{n}\sigma_{\mathrm{ETX}}(i)},\quad 0\le \underset{\text{normalization}}{\sigma_{\mathrm{ETX}}(i)}\le 1, \tag{12}$$

$$\psi(i)=\begin{cases} 0, & i=\text{root},\\ \underset{\text{normalization}}{\sigma_{\mathrm{ETX}}(i)}, & i=1,2,\ldots,n. \end{cases} \tag{13}$$

4. Delay D

Similar to the ETX calculation rules, the sum, mean, and standard deviation of delay of links in a path are comprehensively evaluated to avoid selecting an optimal path that encounters one or more large delay links. Suppose that $D(i)$, $\overline{D}(i)$, and $\sigma_D(i)$ are the delay sum, mean, and standard deviation, respectively, of delay of links in the path from c through candidate parent i (i=1, 2, …, n) to the root:

$$\begin{aligned} &D(i)=D_1+D_2+\cdots+D_{h_i}, \\ &\overline{D}(i)=\frac{D_i}{h_i}, \\ &\sigma_D(i)=\sqrt{\frac{1}{h_i-1}\sum_{k=1}^{h_i}\left(D_k-\overline{D}(i)\right)^2}. \end{aligned} \tag{14}$$

The specific lexical rules of $D(i)$, $\overline{D}(i)$, and $\sigma_D(i)$ are as follows:

Step 1: Calculate $D(i)$, $\overline{D}(i)$, and $\sigma_D(i)$ of path P_i from node c through candidate parent i to the root.

Step 2: Arrange $D(i)$ values in ascending order. Then the paths with the first three minimum $D(i)$ values are composed into the alternative path set. If $n\leq 3$, select all of them into the alternative path set.

Step 3: Path in the alternative path set with the minimum $\sigma_D(i)$ will be selected as the optimal path. For example, if $\sigma_D(f)$ is the minimum in the alternative path set, then path P_f (the path from c through candidate parent f to the root) can be selected as the optimal path, and candidate parent f is the preferred parent.

Clearly, comprehensive evaluation of the sum, mean, and standard deviation of delay of links in a path not only ensures real-time performance, but also avoids selecting an optimal path with large delay links. To facilitate combining delay with other routing metrics, normalization is required as shown in Eq. (15), and the final delay routing metric formula is shown in Eq. (16):

$$\underset{\text{normalization}}{\sigma_D(i)}=\frac{\sigma_D(i)}{\sum_{i=1}^{n}\sigma_D(i)},\ 0\leq \underset{\text{normalization}}{\sigma_D(i)}\leq 1, \tag{15}$$

$$\xi(i)=\begin{cases}0, & i=\text{root},\\ \underset{\text{normalization}}{\sigma_D(i)}, & i=1,2,\ldots,n.\end{cases} \tag{16}$$

5. HC

HC, the number of hops between a candidate parent and the root, can be used to avoid selecting a candidate parent with a large HC as the preferred parent. HC is evaluated in the process of calculating ETX and delay standard deviation. Therefore, we will not evaluate the HC routing metric.

In summary, CAR-TMO evaluates all the above important routing metrics, resulting in better network performance.

3.4 Novel membership functions of routing metrics

CAR-TMO uses an assignment method to determine membership functions of routing metrics used in CA-RM. The membership functions are as follows:

1. REI membership function

CAR-TMO selects an arctangent membership function as the REI membership function, as shown in Eq. (17). REI(i) can be calculated according to Eq. (8). The greater the REI(i), the greater the probability that the neighbor becomes the preferred parent, and vice versa (Fig. 6).

$$\begin{cases}\varphi_1(i)=\begin{cases}0.01, & \alpha<\text{REI}(i)<1,\\ F(\text{REI}(i))-F(\alpha)+0.5, & 0<\text{REI}(i)\leq\alpha,\end{cases}\\ F(\text{REI}(i))=\dfrac{1}{\pi}\arctan[\lambda(\alpha-\text{REI}(i))],\ \lambda=25, \alpha=0.6.\end{cases} \tag{17}$$

2. BOR membership function

CAR-TMO selects a Gaussian membership function as the BOR membership function, as shown in Eq. (18). BOR(i) can be calculated according to Eq. (9). The smaller the BOR(i), the greater the probability that the neighbor becomes the preferred parent, and vice versa (Fig. 6).

$$\varphi_2(i)=\exp\left(-\frac{\left(\text{BOR}(i)-c\right)^2}{2\sigma^2}\right),\ c=0,\ \sigma^2=0.0625. \tag{18}$$

3. ETX membership function

CAR-TMO selects a descending semi-normal distribution membership function as the ETX membership function, as shown in Eq. (19). $\psi(i)$ can be calculated according to Eq. (13). The smaller the $\psi(i)$, the greater the probability that the neighbor becomes the preferred parent, and vice versa (Fig. 6).

$$\varphi_3(i)=\exp\left(-k(\psi(i)-a)^2\right),\ k=15,\ a=0.01. \quad (19)$$

4. Delay membership function

CAR-TMO selects a Gaussian membership function as the delay membership function, as shown in Eq. (20). $\xi(i)$ can be calculated according to Eq. (16). The smaller the $\xi(i)$, the smaller the probability that the neighbor becomes the preferred parent, and vice versa (Fig. 6).

$$\varphi_4(i)=\exp\left(-\frac{\left(\xi(i)-c\right)^2}{2\sigma^2}\right),\ c=0,\ \sigma^2=\frac{1}{30}. \quad (20)$$

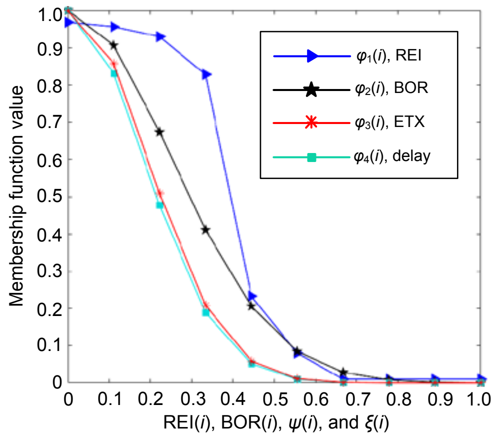

Fig. 6 Membership function curves

3.5 Novel comprehensive membership function

According to the triangle module operator, CAR-TMO fuses the membership function of each routing metric designed above into a comprehensive membership function. As shown in Eq. (21), CAR-TMO designs a 4D triangle module operator. It conforms to the definition of the triangle module operator and can be used to fuse the membership functions of routing metrics to evaluate candidate parents comprehensively.

$$f[\varphi_1(i),\ \varphi_2(i),\ \varphi_3(i),\ \varphi_4(i)]=\frac{\prod_{j=1}^{4}\varphi_j(i)}{\prod_{j=1}^{4}\varphi_j(i)+\prod_{j=1}^{4}(1-\varphi_j(i))}, \quad (21)$$

where $\varphi_j(i)$ (i=1, 2, …, n, j=1, 2, 3, 4) is the membership function of the j^{th} routing metric of the i^{th} candidate parent. Eq. (21) has the following characteristics:

(1) shrinking the dimension mapping: f: $[0, 1]^4 \to [0, 1]$;

(2) $f[\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)]=0$, if $\varphi_j(i)=0$; $f[\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)]=1$, if $\varphi_j(i)=1$;

(3) $f[\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)]\le f[\varphi_1(i'), \varphi_2(i'), \varphi_3(i'), \varphi_4(i')]$, if $\varphi_j(i)\le\varphi_j(i')$;

(4) $f[\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)]=f[\varphi_2(i), \varphi_1(i), \varphi_3(i), \varphi_4(i)]=f[\varphi_3(i), \varphi_2(i), \varphi_1(i), \varphi_4(i)]=\ldots$;

(5) strengthening the similar information: $f[\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)]\ge\max\{\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)\}$, if $\varphi_j(i)>0.5$, and $f[\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)]\le\min\{\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)\}$, if $\varphi_j(i)<0.5$;

(6) reconciling the contradictory information: $\min\{\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)\}\le f[\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)]\le\max\{\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)\}$, if $\min\{\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)\}<0.5<\max\{\varphi_1(i), \varphi_2(i), \varphi_3(i), \varphi_4(i)\}$.

Among them, $\varphi_j(i), \varphi_j(i')\in[0, 1]$, j=1, 2, 3, 4.

Through the triangle module operator, the selection probabilities of preponderant nodes can be enhanced and those of poor nodes can be weakened. Meanwhile, contradictions appearing in REI, BOR, ETX, and D among candidate parents can be reconciled, and the selection criteria of the preferred parent are balanced. For instance, if REI, BOR, ETX, and D of a candidate parent are all favorable (their membership function values are all greater than 0.5), the probability of selecting this candidate parent as the preferred one will increase, and vice versa. If there are contradictions among REI, BOR, ETX, and D of a candidate parent (several of their membership function values are greater than 0.5 and several are less than 0.5), the probability of selecting this candidate parent as the preferred one is determined by their neutral value. Therefore, through the triangle module operator, CAR-TMO can comprehensively evaluate routing metrics in different aspects of candidate parents. Then the optimal preferred parent can be selected and the network performance can be improved effectively.

3.6 Context-aware objective function

According to the comprehensive membership function in Eq. (21) and the maximum membership principle, the novel comprehensive CA-OF can be designed as

$$\mathrm{OF}_{\mathrm{CA}}(i)=\frac{1}{f[\varphi_1(i),\ \varphi_2(i),\ \varphi_3(i),\ \varphi_4(i)]+1},\ i=1,2,\cdots,n, \tag{22}$$

$$\mathrm{OF}_{\mathrm{CA}}=\min\left\{\mathrm{OF}_{\mathrm{CA}}(i)\right\},\ i=1,2,\cdots,n. \tag{23}$$

The objective function is the basis for obtaining and updating the routing metric information, calculating the node rank value, constructing the network topology, and selecting the optimal route. The newly proposed CA-OF can comprehensively evaluate REI, BOR, ETX, and D of candidate parents through the triangle module operator and the maximum membership principle. Then the node rank value, network topology, and optimal route can be calculated optimally.

3.7 Novel rank calculation method

The rank of a node represents its position relative to the root. To avoid loops, the rank value should strictly increase in the down direction (from the root towards the leaf nodes) and decrease in the up direction (from the leaf nodes to the root). It can be calculated according to the objective function. Therefore, based on CA-OF, a novel rank calculation method is proposed.

First, the rank of the root is set as 1.0. Then the rank of other non-root nodes such as c can be calculated according to Eq. (24). $R_c(i)$ is the rank of c, which is based on the route from c through candidate parent i to the root. $R_{\mathrm{cp}}(i)$, advertised by i through DIO, is the rank of i. $\mathrm{OF}_{\mathrm{CA}}(i)+1$ is the calculated CA-OF value of the link from c to candidate parent i.

$$R_c(i)=R_{\mathrm{cp}}(i)+(\mathrm{OF}_{\mathrm{CA}}(i)+1),\quad i=1,2,\cdots,n. \tag{24}$$

According to Eq. (24), $R_c(1)$, $R_c(2)$, …, $R_c(n)$ can be obtained. If $\min\{R_c(1), R_c(2), \ldots, R_c(n)\}=R_c(f)$, then the candidate parent f can be selected as the preferred one.

3.8 Novel preferred parent selection mechanisms

From Section 3.7, it can be seen that through n candidate parents, c can obtain n rank values $R_c(1)$, $R_c(2)$, …, $R_c(n)$. If $\min\{R_c(1), R_c(2), \ldots, R_c(n)\}=R_c(f)$, then f will be selected as the preferred one. However, this preferred parent selection method is not applicable to all cases, such as when there are two or more equal and minimum rank values. Therefore, CAR-TMO proposes novel preferred parent selection mechanisms as follows:

1. If the rank calculated by c through its current preferred parent is greater than that calculated through a candidate parent, but the difference value between these two ranks is less than the threshold of the preferred parent replacement, then the current preferred parent will not be replaced. In this way, the stability of the network topology is guaranteed, as well as the network performance.

2. If the rank calculated by c through its current preferred parent is the minimum and is equal to the rank calculated by c through several other candidate parents, then to guarantee the stability of the network topology, the current preferred parent will not be replaced.

3. If the rank calculated by c through a candidate parent is less than 1.0 or greater than 1000 (the node number in LLNs), then this candidate parent must be eliminated from the candidate parent set. Because the quality of this candidate parent is too poor to deliver any packets or the rank calculated through this candidate parent is incorrect, it needs to be recalculated or become a leaf.

4. When selecting the preferred parent, if there are two or more equal and minimum rank values, then the candidate parent with the largest candidate parent set will be selected as the preferred parent. The larger the candidate parent set, the larger the selection range of the preferred parent, and the more likely it is to select the optimal node as the preferred parent.

5. If c has only one candidate parent, then c waits for a period of time to obtain more candidate parents. After that, if c has two or more candidate parents, c selects its preferred parent through CAR-TMO. Otherwise, c directly chooses this candidate parent as its preferred parent without executing CAR-TMO, and the rank of c equals the rank of this candidate parent plus 1.

3.9 Computational complexity analysis

The computational complexity of CAR-TMO and several state-of-the-art RPL methods can be represented as $O(nh)$, where n is the number of candidate parents and h is the number of hops. The computational complexity of the RPL algorithm increases with increasing network size. However, CAR-TMO does not increase the computational complexity compared to existing algorithms.

4 Performance evaluation

To quantitatively evaluate and compare the newly proposed CAR-TMO algorithm and several popular RPL methods, such as ETXOF (in an MRHOF manner), OF0, and 0.8ETX+0.2REI, we carried out a series of simulations using OPNET14.5.

4.1 Statistic metrics

We selected six important statistic metrics (Table 2) to comprehensively evaluate the performance of CAR-TMO and compared it with those of several state-of-the-art RPL methods.

To improve the accuracy of the experimental results without loss of generality, the average values from simulations were taken as the final result.

4.2 Simulation parameters

Nodes were randomly deployed in a 500 m×500 m network area. The arrival of packets conformed to a Poisson distribution. The initial energy of the nodes was between 0.5 and 15 J. If the residual energy of a node was less than 5% of its initial energy, the node was considered dead. Other key parameters used in CAR-TMO are shown in Table 3.

In Table 3, $E(v, d)$ can be computed as follows (Nayak and Devulapalli, 2016):

$$E(v,d)=\begin{cases}2E_{\text{elec}}v+\varepsilon_{\text{amp}}vd^2, & d<d_0,\\ 2E_{\text{elec}}v+\varepsilon_{\text{fs}}vd^4, & d\geq d_0.\end{cases} \quad (25)$$

The parameters used in Eq. (25) are explained in Table 4.

Table 3 Simulation parameters

Parameter	Value
Simulation scenario area	500 m×500 m
Numbers of nodes	20, 40, 80, 100
Simulation time (s)	1800
Traffic arrival rate (packet/s)	10
Initial energy (J)	0.5–15
Energy consumption of relaying v-bit message	$E(v, d)$
Packet format	IPv6
Physical and data link layer	IEEE 802.15.4g
Size of packet (bit)	1024
Maximum buffer size (packet)	16
Minimum buffer size (packet)	0
Queue type	FIFO
Transmission range (m)	50

Table 4 Parameters used in $E(v, d)$

Parameter	Explanation	Value
E_{elec} (nJ/bit)	Energy consumption of relaying a 1-bit message	50
ε_{amp} (pJ/(bit·m^2))	Energy consumption of the transmission amplifier sending 1-bit message ($d<d_0$)	10
ε_{fs} (pJ/(bit·m^4))	Energy consumption of the transmission amplifier sending 1-bit message ($d\geq d_0$)	0.0013
d_0 (m)	Threshold	87
d	Communication distance between nodes	
v (bit)	The size of relayed message	

Table 2 Statistic metrics

Statistic metric	Explanation	Formula
Average packet delivery ratio (PDR)	Ratio of the number of packets successfully received to the total number of packets sent	$\text{PDR}=\frac{\text{Number of packts received}}{\text{Number of packts sent}}\times 100\%$
Average network latency	Average time required for a packet to reach its destination	$\text{Latency}=\frac{\sum(\text{time}_{\text{receive}}-\text{time}_{\text{send}})}{\text{Number of packets received}}$
Average energy efficiency	Tested by node average remaining energy or the number of live nodes	
Average hop count (HC)	Average number of hops from the source to the destination	$\text{HC}=\frac{\sum\text{Number of hops}}{\text{Number of nodes}}$
Average preferred parent change (PPC)	Average number of preferred parent changes per node	$\text{PPC}=\frac{\sum\text{Number of preferred parent changes}}{\text{Number of nodes}}$
Average control overhead (CO)	Average number of control messages needed to be transmitted per second	$\text{CO}=\frac{\sum\text{DIO}+\sum\text{DIS}+\sum\text{DAO}}{\text{Network running time}}$

4.3 Results and analysis

1. Average packet delivery ratio (PDR)

Fig. 7 shows the average PDR values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI. At the initial network operation stage, the average PDR of each algorithm is unstable. It gradually reaches a stable state after 1000 s. After 1000 s, the average PDR value of CAR-TMO is higher than those of the other algorithms. This is because CAR-TMO evaluates REI and BOR recursively, and evaluates the sum, mean, and standard deviation of ETX and *D* comprehensively. Then, CAR-TMO uses the triangle module operator and the maximum membership principle to fuse the context-aware composite routing metrics, and constructs CA-OF. Therefore, CAR-TMO can comprehensively evaluate routing metrics in different aspects of candidate parents and select the optimal route to transmit packets. So, the average PDR of CAR-TMO is higher than those of the other algorithms.

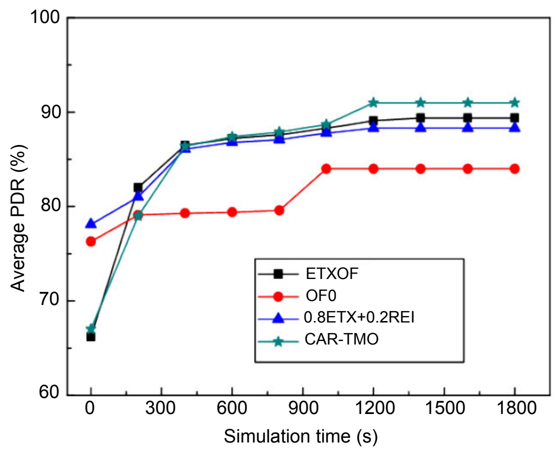

Fig. 7 Average packet delivery ratio (PDR)

The average PDR values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI with different numbers of nodes are shown in Fig. 8. The average PDR value of CAR-TMO is higher than those of the other algorithms at different node densities.

2. Average network latency

Fig. 9 illustrates the average network latency values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI. The network latency value of CAR-TMO is lower than those of the other algorithms. CAR-TMO improves the path delay calculation method and comprehensively evaluates the sum, mean, and standard deviation of *D*. Then the triangle module operator and the maximum membership principle are used. Thereby, CAR-TMO can clearly improve the network latency performance.

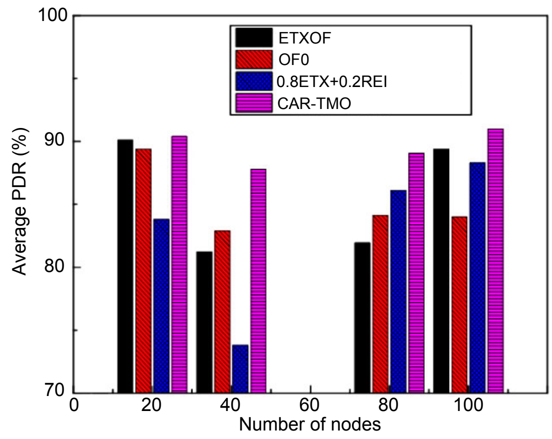

Fig. 8 Average packet delivery ratio (PDR) at different node numbers

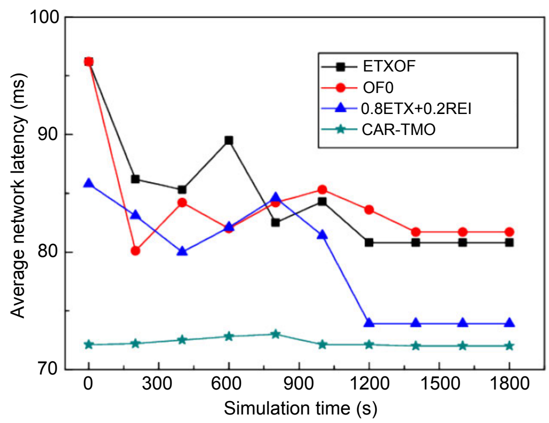

Fig. 9 Average network latency

Fig. 10 shows the average network latency values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI for different numbers of nodes. The average network latency of CAR-TMO is lower than those of the other algorithms at different node densities.

3. Energy efficiency

The average live node number and average remaining energy can represent the energy efficiency effectively. Figs. 11 and 12 show these two statistic metrics of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI. After 600 s, the average remaining energy value and the average live node number of CAR-TMO are higher than their counter parts of ETXOF, OF0, and 0.8ETX+0.2REI. CAR-TMO comprehensively evaluates REI, BOR, ETX, and *D* of a candidate parent, proposes the triangle module operator and the maximum membership function to construct CA-OF, and designs a preferred parent selection mechanism to improve the energy efficiency.

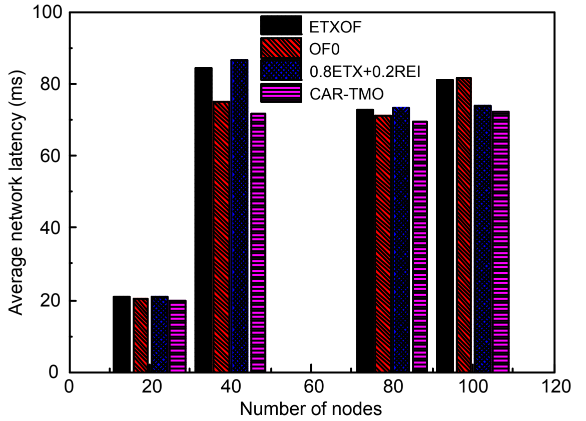

Fig. 10 Average network latency at different node numbers

Fig. 13 shows the average live node numbers of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI for different numbers of nodes. The average live node number of CAR-TMO is higher than those of the other algorithms at 80 and 100 nodes. Meanwhile, the average live node numbers of these algorithms are close to each other at 20 and 40 nodes.

4. Average HC

The average HC values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI are shown in Fig. 14. The HC values of OF0 and CAR-TMO are lower than those of ETXOF and 0.8ETX+0.2REI. Because OF0 selects the next hop based only on the hop metric, the candidate parent with the lowest HC will be selected as the preferred parent. CAR-TMO fuses HC, ETX, and *D* routing metrics, and evaluates them using the triangle module operator and the maximum membership principle. Therefore, the average HC values of CAR-TMO and OF0 are lower than those of ETXOF and 0.8ETX+0.2REI.

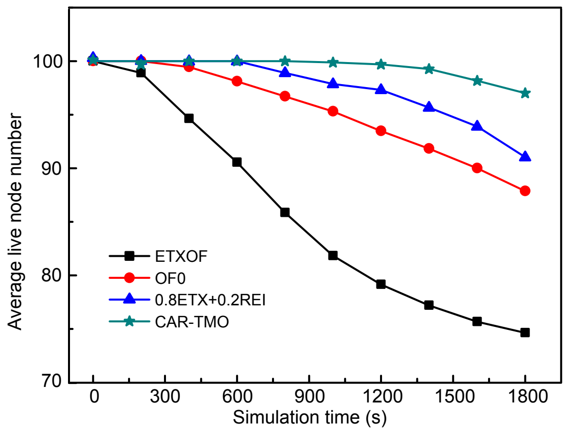

Fig. 11 Average live node number

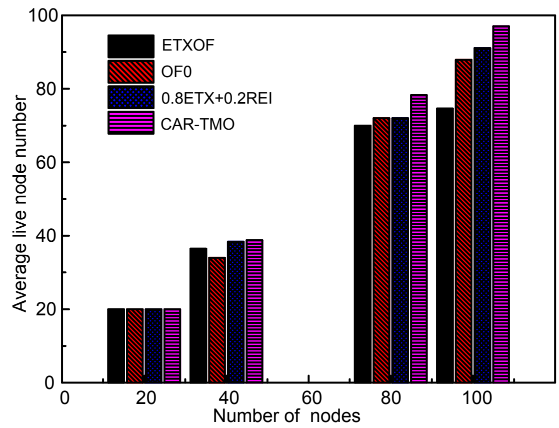

Fig. 13 Average live node number at different node numbers

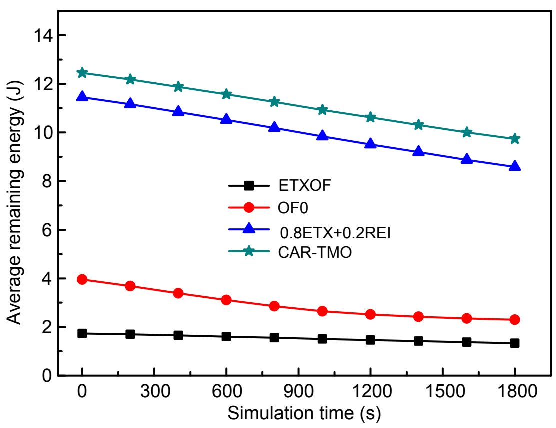

Fig. 12 Average remaining energy

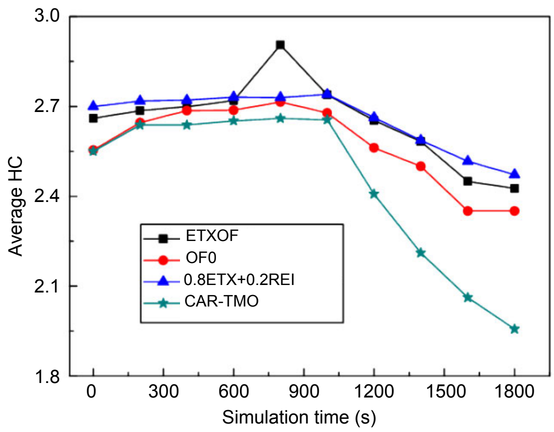

Fig. 14 Average hop count (HC)

The average HC values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI for different numbers of nodes are shown in Fig. 15. The average HC value of CAR-TMO is lower than those of the other algorithms at different node densities.

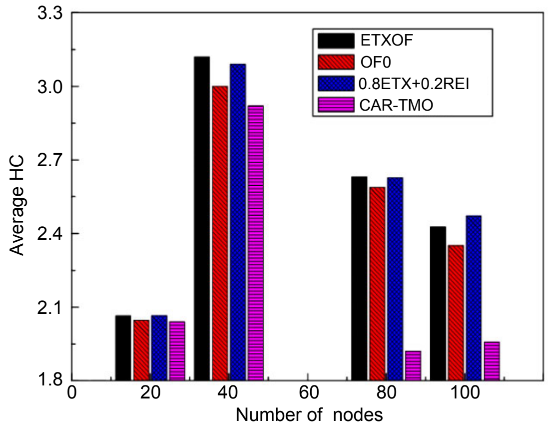

Fig. 15 Average hop count (HC) at different node numbers

5. Average preferred parent changes (PPC)

The average PPC reflects the stability of the network topology, and can be used to reconcile the network performance and network topology stability. Fig. 16 shows the average PPC values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI. At the initial network operation stage, network topology is constructed, so the average PPC value is relatively high. When the network topology gradually reaches a stable state after 1000 s, the average PPC value of CAR-TMO is lower than those of ETXOF, OF0, and 0.8ETX+0.2REI. Therefore, CAR-TMO can guarantee the network topology stability as well as improve the network performance.

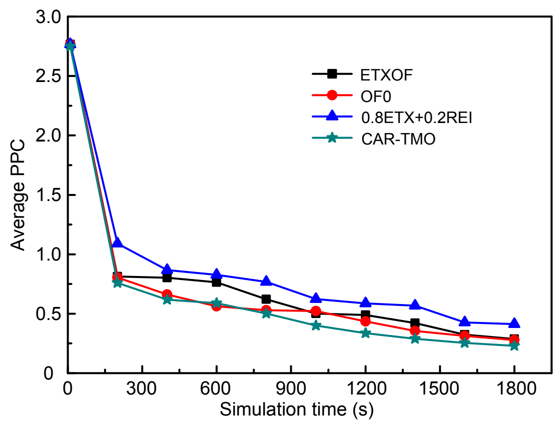

Fig. 16 Average preferred parent changes (PPC)

Fig. 17 shows the average PPC values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI for different numbers of nodes. The average PPC value of CAR-TMO is lower than those of the other algorithms at different node densities.

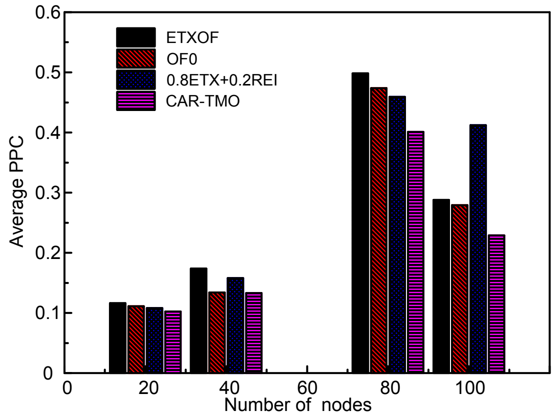

Fig. 17 Average preferred parent changes (PPC) at different node numbers

6. Control overhead (CO)

CO values of CAR-TMO, ETXOF, OF0, and 0.8ETX+0.2REI for different numbers of nodes are shown in Fig. 18. The CO value of CAR-TMO is lower than those of ETXOF, OF0, and 0.8ETX+0.2REI at different node densities.

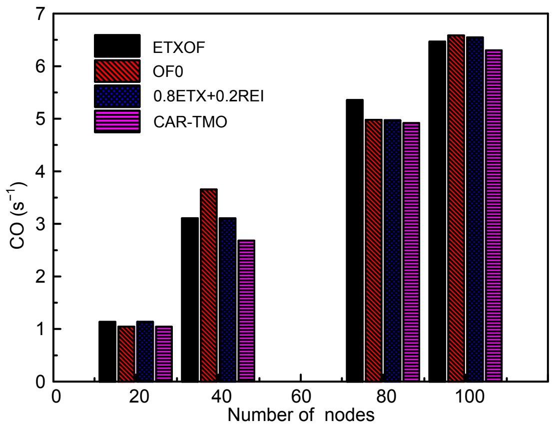

Fig. 18 Control overhead (CO) at different node umbers

5 Conclusions

In this paper, we propose a novel context-aware RPL algorithm based on a triangle module operator (CAR-TMO). We design a novel composite context-aware routing metric (CA-RM), novel membership functions of routing metrics, a comprehensive membership function, a new comprehensive context-aware objective function (CA-OF), novel rank calculation mechanisms, and novel preferred parent (next hop) selection mechanisms. Through these newly designed mechanisms, CAR-TMO can improve the network performance and guarantee the stability of the network topology.

In future work, we will combine 5G or quantum mechanics with RPL to improve the use of LLNs.

Contributors

Yanan CAO designed the research. Yanan CAO and Hao YUAN processed the data. Yanan CAO drafted the paper. Hao YUAN helped organize the paper. Yanan CAO and Hao YUAN revised and finalized the paper.

Compliance with ethics guidelines

Yanan CAO and Hao YUAN declare that they have no conflict of interest.

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