October 08, 2019

AN IMPROVED ROUTING METRICS ALGORITHM FOR WIRELESS MESH NETWORK USING PAGE RANK THEORY AND LINEAR REGRESSION

Lele Zhang

Pascal Thubert

Chuanwei Li

Li Zhao

AN IMPROVED ROUTING METRICS ALGORITHM FOR WIRELESS MESH NETWORK USING PAGE RANK THEORY AND LINEAR REGRESSION

AUTHORS:

Lele Zhang
Pascal Thubert
Chuanwei Li
Li Zhao

ABSTRACT

An existing metric algorithm in wireless mesh networks (WMNs) adopts samples generated by itself. In other words, the existing algorithm sends some probe frames and then counts the returned acknowledgments (acks). This leads to two inherent defects: wasting limited bandwidth to send too many probe frames; and detecting metric changes insensitively.

Presented herein is an improved routing metrics algorithm for WMNs that uses page rank (PR) theory and linear regression. To solve the problems mentioned above, PR theory and multiple linear regression (MLR) methods are introduced in metric calculation to generate metrics closer to real values by conditionally referring sibling metrics to a common parent or candidate.

The method may be run in a distributed fashion and/or it may be centralized. The dependency between the A->D metric and the B->D and C->D, or even B->C, may be observed by a learning machine. In that case the controller may push the parameters for the PR algorithm to the device so as to use only the metrics that are cross influential.

DETAILED DESCRIPTION

Wireless Mesh Networks (WMNs) have experienced much growth in the past decade due to their rapid deployment, instant communication capabilities, large coverage, and good scalability. Connected Grid Mesh (CG-Mesh) is being developed for Internet of industrial Things (IIoT) customers, such as smart grid Advanced Metering Infrastructure (AMI) or Distributed Automation (DA) networks. CG-Mesh is a tree-based WMN which complies with Routing Protocol for Low power and Lossy Networks (RPL), i.e., RFC-6550.

In order to get optimal performance, various metric algorithms have been proposed, some of which are listed below:

1. Minimum Hop Counts (MHC)
2. Expected Transmission Count (ETX)
3. Expected Transmission Time (ETT)
4. Weighted Cumulative Expected Transmission Time (WCETT)
5. Metric of Interference and Channel-switching (MIC)
6. Interference Aware (iAWARE)

Regardless of which routing metric algorithm the WMN uses, it aims at obtaining a stable and high quality link in the network. However, the WMN has some inherent weaknesses including those discussed in more detail in the bulleted list below.

- CG-Mesh takes ETX as a metric algorithm, which is addressed in RFC-6551. To get the initial ETX to its neighbors, a node needs to send some probe frames periodically, such as neighbor solicited (NS) frames. This consumes limited bandwidth resources.
- To avoid occupying too much bandwidth in maintenance, the frequency of probe frames transmissions may need to be reduced as much as possible. However, doing so leads to an insufficient amount of samples. Moreover, in RFC-6551, ETX is described with the following formula: ETX = 1 / (Df * Dr), where Df is the measured probability that a packet is received by the neighbor and Dr is the measured probability that the acknowledgment packet is successfully received. Additionally, according to RFC-6551, it needs to multiply 128 as a factor. So, an insufficient sample may generate a non-reasonable ETX. For example, if a node just sends five NS frames and then gets back three Acks, it thinks the ETX is 214 (i.e., 1.67*128). But it is not true in practice. Inadequate samples produce inaccurate metric that makes the WMN unstable.
- Otherwise, transmissions among nodes are usually infrequent because nodes are typically inactive most of time. At the same time, however, the network may always be changing or changing frequently. For example, as illustrated in Figure 1, below, node A has good ETX to its parent node, node B, at the beginning, and it sends packets to node B about every 30 minutes. A few minutes later, the interference

becomes stronger between them, but node A is unaware because it is inactive during this interval. Node A needs to go through many failed transmissions to know that link quality to node B has become bad. So in general, a big problem, which has been difficult to overcome by conventional methods, is that the convergence speed of refreshing ETX is too slow.

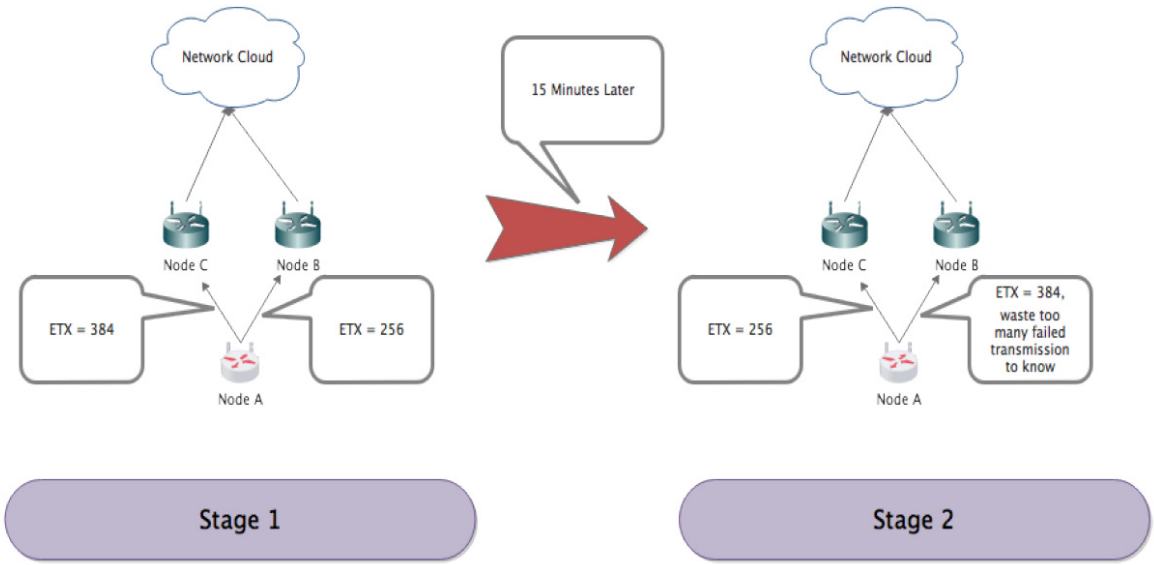

Figure 1

An improved routing metrics algorithm is proposed for WMN to solve this problem, which costs less probe frames and could get faster convergence speed. This proposed algorithm is useful not only for ETX case like CG-Mesh, but also for other metrics methods that have been mentioned above.

PR is a good theory to evaluate routing metrics via referring neighbors' records. With reference to Figure 2, below, it is assumed that there are two siblings, node x and node y (both have similar RANK), and they have a common parent, node z. The link quality between x and y is considered to be perfect, given the metrics (e.g., ETX) between them is around 128. Thus, both x and y are believed to have similar ETX to node z, so if the ETX between node x and z is increasing, it is proposed that the ETX between node y and z is increasing too as long as the ETX between x and y is still good (i.e., 128).

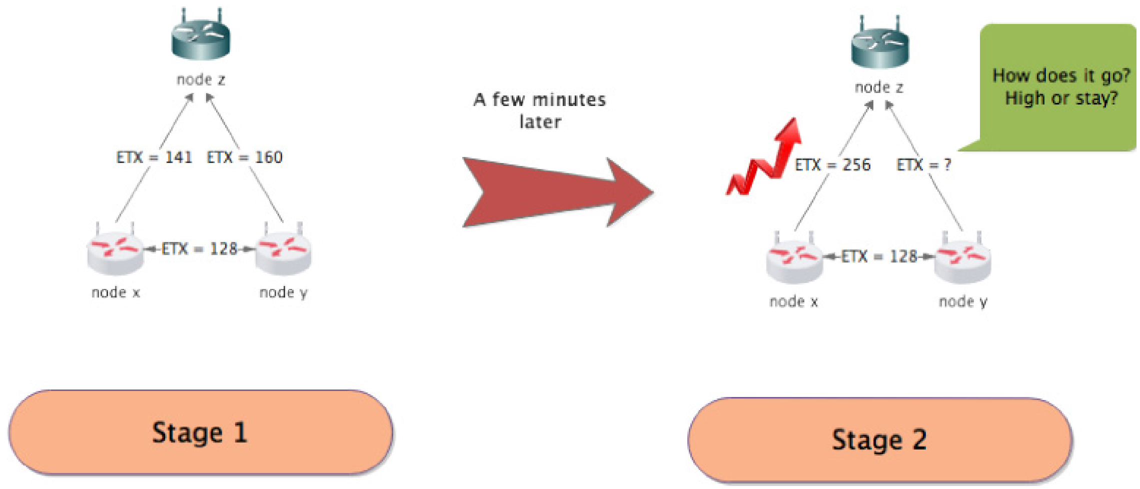

Figure 2

So the native theory in the proposed solutions is that the brothers will share the link qualities with the node as long as both of them have enough good link quality. The proposed solutions are not intended to use the PR algorithm strictly, rather it considers the theory of the PR algorithm.

In statistics, linear regression is a linear approach to modelling the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables). The case of one explanatory variable is called simple linear regression. For more than one explanatory variable, the process is called multiple linear regression. This term is distinct from multivariate linear regression, where multiple correlated dependent variables are predicted, rather than a single scalar variable.

In the model proposed herein, neighbors' link metrics are attempted to be absorbed in order to determine more accurate ETX for a node, and it is suitable to use MLR method.

Currently, in CG-Mesh, ETX is used to measure the link quality between two nodes. As proposed herein, sibling nodes could help a brother to correct link quality metric via sharing their metrics to a common parent.

Techniques presented herein leverage PageRank (PR) theory for correcting an existing metric(s) by using neighbors' metrics.

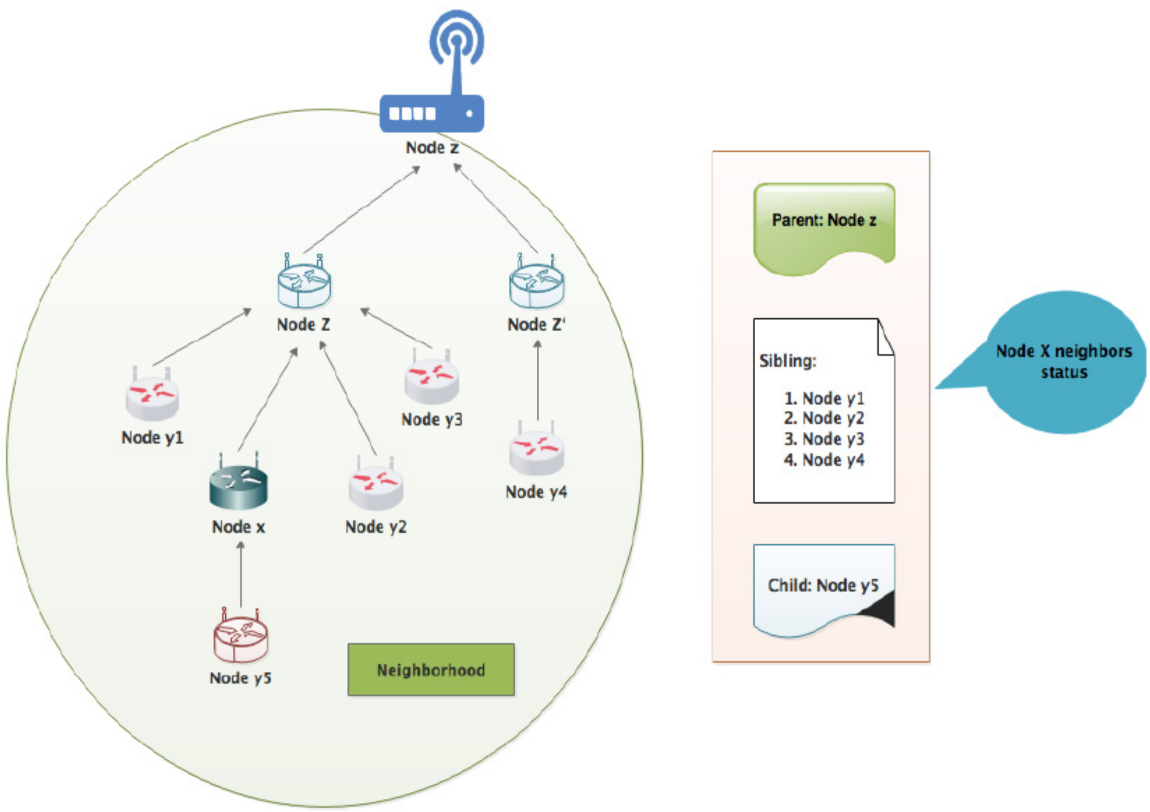

Figure 3

For example, as shown in Figure X, below, node x has a set of neighbors,

$$S = \{y_1, y_2, y_3, \cdots, y_n, z\} \quad (1)$$

Node z is its preferred parent (i.e., root). However, node x needs to refresh ETX frequently to see whether node z still has the smallest ETX in its neighbor list, and if not, node x will switch its parent to another neighbor.

The proposed techniques are explained in more detail below in steps 1-3.

Step 1

The node x collects tripe-dimension tuple from its neighbors except node z. This tuple is [E_x, E_z, H_y], where E_x indicates the ETX between node x and node y_n, E_z indicates the ETX metric between node z and node y_n, and H_y indicates whether this neighbor is a sibling or not. Therefore, a new set S_e is composed of these tuples,

$$S_e = \{[E_x^1, E_z^1, H_y^1], [[E_x^2, E_z^2, H_y^2\ ], \ldots, [E_x^n, E_z^n, H_y^n]\} \quad (2)$$

Table 1, below, is an example sample :

Node	E_x	E_z	H_y
y_1	128	256	2
y_2	144	288	2
y_3	156	264	2
y_4	256	1024	2
y_5	128	768	3
...	...	...	...
y_n	256	1024	m

Table 1

Hints: in the table 1, 1024 represents the maximum metric to a target node, which means the target node could not be heard.

Additionally, there are various methods to collect this information from neighbors. Some example options for collecting this information are listed below, in a non-exhaustive list:

1. using NS frames among neighbors.
2. using DIO frames to broadcast in the area of neighborhood.
3. using IE fields of MAC frame when transmitting ucast frame.
4. using other self-defined probe frames among neighbors.

Step 2

Effective neighbors from set Se are picked, which need to abide by the following rules:

1. The desired neighbors must be siblings rather than children (e.g., node y5) or uncles (e.g., node z'). An example unexpected situation is illustrated in Figure 4, below. As shown in Figure 5, white node is a child of blue node, and they have good link quality. White node, however, has bad link quality to brown node (because it is its grandfather). According to the proposed solution model, white node may mislead blue node that the link quality to brown node is bad.

2. Some siblings could not hear node z, like node y4, so their E are meaningless, because they are all 1024. These nodes should be dropped from list.
3. Some siblings have a large EXT to node x, due to poor link quality, their ETXs to node z is valueless. So, it is proposed herein to define a threshold (e.g., 256), and if siblings exceed this value, these nodes will be dropped either.

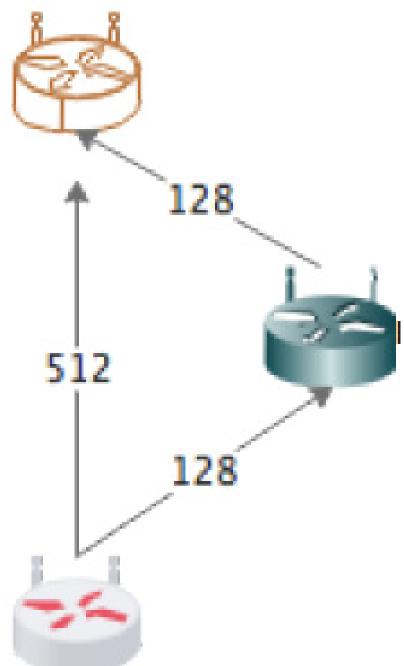

Figure 4

Based on the above rules, usable neighbors are picked up to reform a new set as S'e.

$$S'e = \{x_0, x_1, x_2, x_3 \cdots, x_n\} \tag{3}$$

In formula (3), x_0 denotes the ETX from node x to node z, and the other are ETXs from selected neighbors to node z.

Step 3

The proposed solution uses multiple linear regression (MLR) to calculate expected ETX for target node (e.g., node x).

MLR is a basic machine learning (ML) method, which may be used to find a solution with multiple inputs.

The solution presented herein use MLR to determine a desired ETX with neighbors' ETXs, because it is very suitable within our model. The following formulas are provided to calculate our wanted ETX between node x and node z.

$$f(x) = w_0 x_0 + w_1 x_1 + \cdots + w_n x_n + b \tag{4}$$

$$f(x) = w^T x + b \tag{5}$$

In order to figure out f(x), parameter "w" and "b" are to be determined. However, MLR gives the solutions for calculating them with the following formulas.

$$w = \frac{\sum_{i-0}^{n} y_i (x_i - \overline{x})}{\sum_{i=0}^{n} x_i^2 - \frac{1}{n} \left(\sum_{i=o}^{n} x_i\right)^2} \tag{6}$$

$$b = \frac{1}{m} \sum_{i=0}^{n} (y_i - w x_i) \tag{7}$$

These formulas have already been proven by mathematics in theory. For each node x, it collects metrics from selected neighbors periodically, and then adjusts "w" and "b" per round. After several rounds, the result becomes more and more accurate.

So far as we know, each node of WMN measures its routing metric just according to its own statistics data. Whatever, we think neighbors' experience are also meaningful for one node, thus we propose a novel of routing metric algorithm for WMN, which partly refers to Page Rank Algorithm.

Some testing with proposed algorithm was conducted by the authors, and the resulting performance of the proposed algorithm is in Figure 5, below, along with performance of an existing algorithm and real ETX. The results indicate that the proposed algorithm is more sensitive than existing algorithm when network link quality is changing. It has faster convergence speed and more accurate value as well.

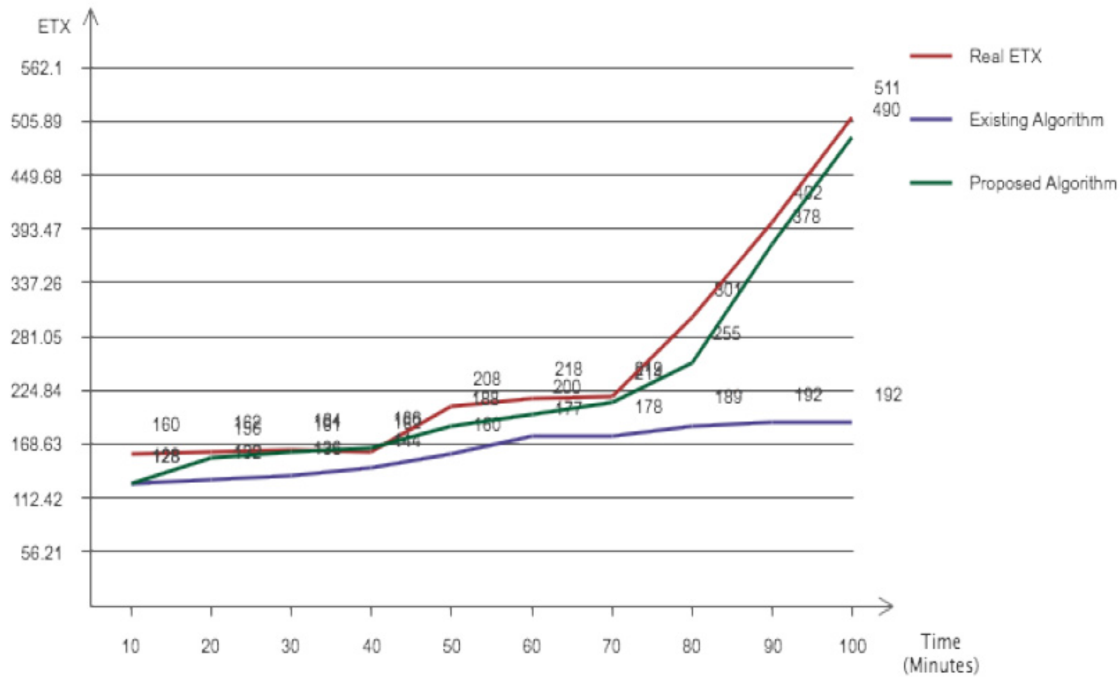

Figure 5

Centralized approach

The proposed solution allows to expose the measured ETX to a controller that would replicate the distributed computation and compare with real numbers, and adjust if necessary. The information would be piggy backed in OAM headers of small packets directed to the root.

The controller would run a classical deep learning system that rewards when the distributed computation is correct.

From the central position the controller can assess correlations and find which neighbors actually provide meaningful hints (which variations of ETX between A and B impact C and D, and tell the nodes to use only those).

Additionally, the controller would run linear regressions to assess the degree of impact of each neighbor and provide the coefficients to the nodes for their computation.

As mentioned above, known methods to maintain routing metric in WMN generally have two inherent defects:

1. producing too many probe messages; and
2. insensitive detectability.

In the proposed techniques, the corrected ETX comes from other neighbors' records; it leverages the experience what is shared by other neighbors. The proposed techniques shift the vision from the target neighbor records to other neighbors' experience

In the proposed techniques, different weights for different neighbors respectively are assigned, and this model is more suitable for linear regression method.

The proposed solutions improve metrics calculation by involving neighbors' relevant metrics. The proposed solutions still use single routing path to distribute packets.

The proposed solutions address how to improve ETX performance in short time.

The proposed solution uses neighbors' metrics to correct its ETX.