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Research Article

Prediction Approach of Critical Node Based on Multiple Attribute Decision Making for Opportunistic Sensor Networks

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Predicting critical nodes of Opportunistic Sensor Network (OSN) can help us not only to improve network performance but also to decrease the cost in network maintenance. However, existing ways of predicting critical nodes in static network are not suitable for OSN. In this paper, the conceptions of critical nodes, region contribution, and cut-vertex in multiregion OSN are defined. We propose an approach to predict critical node for OSN, which is based on multiple attribute decision making (MADM). It takes RC to present the dependence of regions on Ferry nodes. TOPSIS algorithm is employed to find out Ferry node with maximum comprehensive contribution, which is a critical node. The experimental results show that, in different scenarios, this approach can predict the critical nodes of OSN better.

1. Introduction

In Opportunistic Sensor Network (OSN), the critical nodes are very important to keep normal operation of networks. In practical applications, if the critical nodes can be predicted, the network could be optimized according to the attributes of critical nodes, which helps improving the robustness of the network. In network maintenance, maintainers can focus on monitoring the status of critical nodes so that the failures of the network could be resolved immediately, which can dramatically reduce the time and the cost of network maintenance. Therefore, predicting critical nodes of OSN has great significance.

2. Related Work

OSN is a kind of Wireless Sensor Networks. It perceives the surrounding environment by sensor nodes and transports messages by the meeting opportunities of Ferry nodes. Hence, it has the characteristics of Mobile Opportunity Network [1] and Wireless Sensor Network [2]. The current study of OSN critical nodes is very little. Nevertheless, in some related fields, researchers have made some progress such as node importance evaluation [3–7] and network cut-vertex judgement [8–14].

Corley and Sha [15] proposed that the critical nodes in a weighted network are those whose removal from the network results in the greatest increase in shortest distance between two specified nodes. This method could be applied to estimate the end-to-end nodes. However, it is powerless to estimate the critical nodes in the whole network. Chen et al. [16] studied a method to estimate the relative importance of nodes by comparing the number of spanning trees. Although this method could estimate the critical nodes of the whole network, it has the problem of high computing complexity. So it is not suitable in practical applications. In resistance network, Xiao et al. [17] did the research on the energy consumption model to evaluate the importance degree of nodes. This method estimates the critical node by comparing the increase of the average energy consumption of the network after the nodes are removed. Goyal and Caffery [18] discussed the split of ad hoc networks. They utilized network survivability concepts to detect the critical links in an ad hoc wireless network. This method is based on the precondition

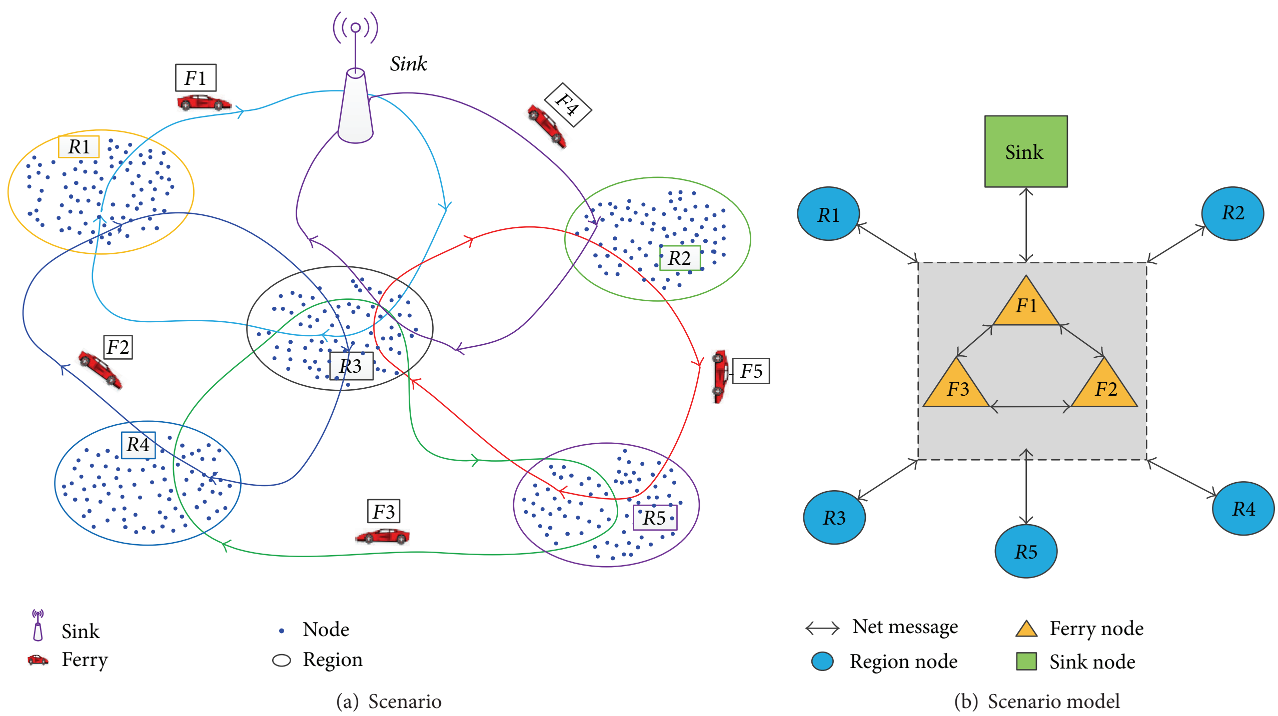


Figure 1: OSN scenario.

that the nodes can locate themselves, which has great application limitations.

With the research above, it is always one-sided to evaluate the network through a single evaluation index. Considering the influence of node degree, node closeness, node betweenness, equivalent topology, and neighbor lists, Hu et al. [19] conducted experiments with three real typical networks to show that their method is more accurate than using a single evaluation index. Liu et al. [20] proposed a method to estimate critical nodes by combining the residual lifetime of nodes and the network energy consumption. Due to the shortcomings of the methods of node deletion and node contraction, Zhou et al. [21] exploited the evaluation matrix of node efficiency and node importance to determine the critical nodes in complex network. This method reflects the significance of divergences between two nodes and can evaluate the importance exactly. In a similar way, Fan and Liu [22] discussed the local and global importance of nodes and presented an evaluation method based on transfer efficiency matrix which takes not only the interactions between adjacent nodes but also the nonadjacent nodes' contributions into account, thus obtaining a more accurate node importance evaluation result.

As a dynamic network, current static prediction methods of critical nodes are not appropriate for OSN. Depending upon the researches above, in this paper, the stage contribution and the region contribution are proposed to evaluate the node importance. Then an algorithm is designed which is based on the multiple attribute decision making (MADM) to predict the critical nodes of OSN.

3. Scenario Model and Definitions

3.1. Scenario Model. The monitoring areas of application scenarios like environmental monitoring are very large. Therefore, the maintainers tend to monitor the key regions instead of the whole network. In OSN, the messages of the network are collected through the communication opportunities supported by mobile nodes. As shown in Figure 1(a), our research is proposed for the OSN with multiple regions and the nodes in the regions are fixed. There are Ferry nodes between regions supporting communication opportunities to Sink nodes and the trajectory of Ferry nodes could be a specific way or a random way.

In Figure 1(b), $R1$~$R5$ are region nodes; $F1$~$F3$ are Ferry nodes. The region nodes and Sink nodes are fixed and isolated. Those two kinds of nodes cannot communicate with each other without Ferry nodes. The Ferry nodes can move among regions, carrying and transporting messages between Sink nodes and other regions.

In this paper, the following assumptions are made:

(1) In our research, each region is abstracted as a "super node" called region node.

(2) Regardless of the Ferry nodes' memory, it is assumed that Ferry node can collect all the messages from each node it meets.

(3) Regions and Ferry nodes and Sink nodes in the network have unique identity information.

(4) The network has a time synchronization mechanism.

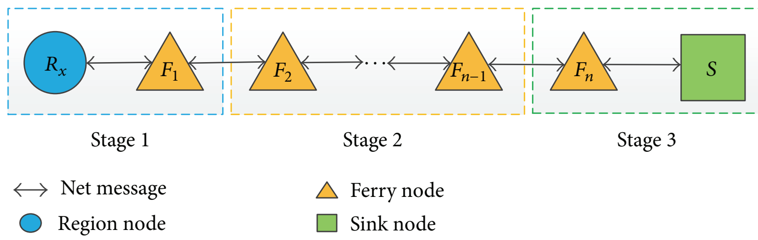


FIGURE 2: OSN message transmission.

In Figure 1, Ferry nodes in the whole network play a role of transport medium so that the Ferry nodes are the key to ensure the connectivity of the whole network. Besides, as a kind of "super node," the region nodes consist of a group of sensor nodes. Individual sensor node's failure in regions will have little impact on the whole network. Therefore, we can learn from the research above that the critical node of OSN could be a Ferry node.

3.2. Definition of Critical Nodes. Define Opportunistic Sensor Networks as G. Define F as a critical node of G when the possibility of network split caused by the removal of node F is the largest. According to the definition above, when the cut-vertices of OSN are removed, the network will be divided. Therefore, we can learn that the cut-vertices of OSN must be critical nodes.

OSN is a dynamic network which transfers data by the "Store-Carry-Forward" mechanism. The traditional parameters such as node degree [23, 24], node betweenness [25–29], node closeness [30], aggregation [31, 32], and other network parameters are not suitable for OSN. Therefore, it is necessary to set up an appropriate evaluation index for OSN.

In OSN, Ferry nodes are transport mediums. So their job is to transport messages between Sink nodes and region nodes. In order to accurately estimate each Ferry node's importance to the network, the effect of Ferry nodes on OSN must be considered properly. With intensive analysis of OSN's routing mechanism, the region messages' life cycle can be divided into three stages as shown in Figure 2.

In the first stage, Ferry nodes receive network messages from regions and then carry them out. In the second stage, the network messages will be forwarded among Ferry nodes. At last, Ferry nodes transport messages to the Sink nodes. These three stages can not only depict the message propagation of OSN clearly but also show the important role of Ferry nodes obviously.

3.3. Definition of First Stage Contribution. Define a time slice as T and the Sink node receives M_j pieces of messages from region R_j in T. If the Ferry node F_i has forwarded messages in the first stage, the total number of the forwarding messages is n_{ij} ($n_{ij} \leq M_j$). Define the First Stage Contribution (FSC) of node F_i to region R_j as n_{ij}/M_j, denoted by $\mathrm{FSC}(F_i, R_j)$.

3.4. Definition of Second Stage Contribution. Define a time slice as T and the Sink node receives M_j pieces of messages from region R_j in T. If the Ferry node F_i has forwarded messages in the second stage, the total number of the forwarding messages is m_{ij} ($m_{ij} \leq M_j$). Define the Second Stage Contribution (SSC) of node F_i to region R_j as m_{ij}/M_j, denoted by $\mathrm{SSC}(F_i, R_j)$.

3.5. Definition of Third Stage Contribution. Define a time slice as T and the Sink node receives M_j pieces of messages from region R_j in T. If the Ferry node F_i has forwarded messages in the third stage, the total number of the forwarding messages is k_{ij} ($k_{ij} \leq M_j$). Define the Third Stage Contribution (TSC) of node F_i to region R_j as k_{ij}/M_j, denoted by $\mathrm{TSC}(F_i, R_j)$.

3.6. Definition of Region Contribution. Define a time slice as T. The stage contributions of Ferry node F_i to region R_j are $\mathrm{FSC}(F_i, R_j)$, $\mathrm{SSC}(F_i, R_j)$, and $\mathrm{TSC}(F_i, R_j)$. Define region contribution (RC) of node F_i to region R_j as $\mathrm{RC}(F_i, R_j) = \mathrm{FSC}(F_i, R_j) + \mathrm{SSC}(F_i, R_j) + \mathrm{TSC}(F_i, R_j)$, denoted by $\mathrm{RC}(F_i, R_j)$.

The region contribution can reflect both the Ferry nodes' contributions to regions and the dependence of the regions on Ferry nodes. It means that the bigger region contribution the node has, the higher possibility leading to the network split the node possesses and the node is more likely to be a critical node. If the region contribution from node F_x to region R_y equals 1, it means that region R_y is fully dependent on node F_x; that is to say, if node F_x is removed, region R_y will be isolated from the whole network.

According to the researches above, we can infer that the node is a cut-vertex of the network when the region contribution equals 1 and it must be a critical node.

4. MADM Based Prediction Method of Critical Node of OSN

According to the research mentioned above, the critical node prediction method for OSN can be described as the following steps.

Step 1. Calculate each Ferry node's region contributions in order to determine whether the network has cut-vertexes or not. If there are no cut-vertexes in the network, go to Step 2.

Step 2. Find out a node which most likely leads to the network split and it must be a critical node. The region contribution shows the dependence of regions on Ferry nodes. We can learn that the higher region contribution the node has, the higher risk of network split it will have. Based on the theory above, we first take each Ferry node as a single evaluation scheme. Then, the TOPSIS method is applied to evaluate the comprehensive region contribution of Ferry nodes.

4.1. Algorithm Description. It is meaningless to predict such a dynamic network like OSN by calculating region contributions within a single time slice such as ΔT. However, a single prediction result can be defined as a suspected critical node. After setting $N \cdot \Delta T$ as the total time length of prediction, N suspected critical nodes will be found. Then, the frequency of each node to be estimated as a suspected critical node can be recorded.

We assume an OSN with d Ferry nodes. Each node may lead to network split. If node F_i has been estimated as a suspected critical node q times, the appearance probability of node F_i could be figured out as $P_s(F_i)$:

$$P_s(F_i) = \frac{q}{N\left(c_d^1 + c_d^1 c_{d-1}^1 + c_d^1 c_{d-1}^2 + \cdots + c_d^1 c_{d-1}^{d-1}\right)}. \quad (1)$$

Denote the maximum of $P_s(F_i)$ as $\max(P_s)$ and the corresponding node as F_k, $k \in \{1, 2, 3, \ldots, d\}$. We define this node as a predicted critical node.

ΔT is a single time slice of the network. The details of ΔT are defined as follows: it is assumed that there are n Ferry nodes to be determined in the network so that the corresponding solution sets can be denoted by $F = (F_1, F_2, \ldots, F_n)$ and there are m regions in the network so the region contribution of each Ferry node can be denoted by an attribute set $S = (S_1, S_2, \ldots, S_m)$. j_{th} attribute of i_{th} node is defined as $F_i(S_j)$ $(i = 1, 2, \ldots, n;\ j = 1, 2, \ldots, m)$. The decision matrix is as follows:

$$E = \begin{pmatrix} F_1(S_1) & \cdots & F_1(S_m) \\ \vdots & \ddots & \vdots \\ F_n(S_1) & \cdots & F_n(S_m) \end{pmatrix}. \quad (2)$$

For comparison, the decision matrix could be optimized by the following normalization processing:

$$r_{ij} = \frac{F_i(S_j)}{\sqrt{\sum_{i=1}^{n} F_i(S_j)^2}}. \quad (3)$$

Then the decision matrix could be updated to $R = (r_{ij})_{n\times m}$.

Due to the different importance of different regions to the whole network, weight is assigned for each evaluation index to make the algorithm more universal. We denote the j_{th} index weight as ω_j $(j = 1, 2, \ldots, m)$, and $\sum_{j=1}^{m} \omega_j = 1$. Then we denote the weighted normalized matrix as

$$C = (c_{ij}) = (\omega_j r_{ij}) = \begin{pmatrix} \omega_1 r_{11} & \cdots & \omega_m r_{1m} \\ \vdots & \ddots & \vdots \\ \omega_1 r_{n1} & \cdots & \omega_m r_{nm} \end{pmatrix}. \quad (4)$$

According to matrix C, the positive ideal solution F^+ and the negative ideal solution F^- are denoted as follows:

$$F^+ = \{c_1^+, c_2^+, \ldots, c_m^+\}, \quad (5a)$$

$$F^- = \{c_1^-, c_2^-, \ldots, c_m^-\}, \quad (5b)$$

where $c_j^+ = \max_{i\in k}(c_{ij})$, $c_j^- = \min_{i\in k}(c_{ij})$, and $k = (1, 2, \ldots, m)$.

We denote the distance from every solution F_i to the positive ideal solution F^+ and the negative ideal solution F^-, respectively, denoted by

$$D_i^+ = \left\| F_i - F^+ \right\| = \sqrt{\sum_{j=1}^{m} \left(c_{ij} - c_j^+\right)^2}, \quad (6a)$$

$$D_i^- = \left\| F_i - F^- \right\| = \sqrt{\sum_{j=1}^{m} \left(c_{ij} - c_j^-\right)^2}. \quad (6b)$$

Then we calculate and sort the ideal solutions similarity degree Z_i, denoted by

$$Z_i = \frac{D_i^-}{\left(D_i^- + D_i^+\right)}. \quad (7)$$

According to the TOPSIS method, the node with maximum Z_i is the suspected critical node.

4.2. Algorithm Process. It is assumed that OSN has n Ferry nodes and m regions. TOPSIS based synthetic evaluation of region contributions algorithm can be described as follows:

(1) At first, denote the length of time as ΔT. With the sampling analysis on the data of Sink node, the normalization matrix $R = (r_{ij})$ can be figured out by (2).

(2) Construct weighted normalized matrix C by (2), (3), and (4).

(3) Determine the positive ideal solution F^+ and the negative ideal solution F^- by (5a) and (5b).

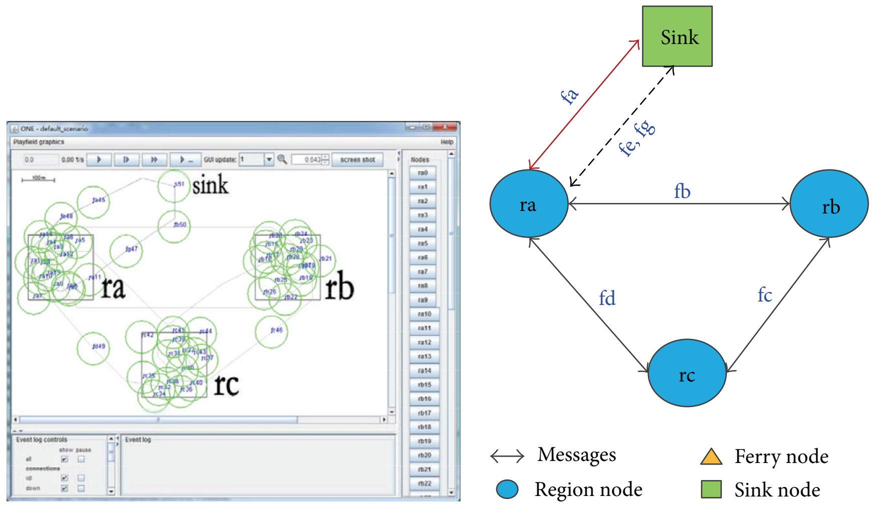
(4) Calculate the distance from every solution F_i to the positive ideal solution F^+ and the negative ideal solution F^- by (6a) and (6b).

(5) Calculate the similarity degree between each solution and ideal solution by (7). The node with maximum Z_i is the suspected critical node.

(6) Repeat the above steps and denote the length of prediction time as $N \cdot \Delta T$. According to (1), the emergence probability of each node can be recorded so that the node with maximum (P_s) is the critical node of the network.

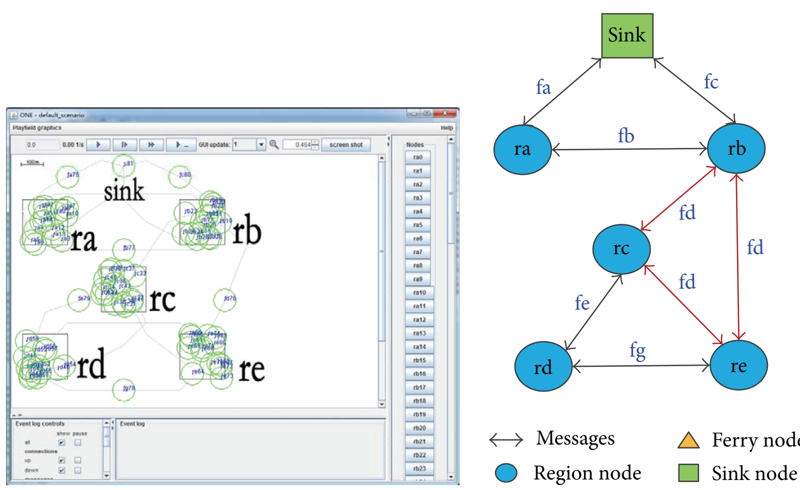
5. Experiments and Analysis

5.1. Experimental Scenarios and Related Parameters. As is shown in Figures 3–6, four typical scenarios are simulated on the Opportunistic Networking Environment (ONE).



(a) Simulation (b) Model

FIGURE 3: Scenario A.



(a) Simulation (b) Model

FIGURE 4: Scenario B.

In Figure 3, there is no cut-vertex in Scenario A and there are three region nodes including ra, rb, and rc and four Ferry nodes including fa, fb, fc, and fd. Among the Ferry nodes, fb, fc, and fd only provide the communication opportunities among the regions of ra, rb, and rc. However, Ferry nodes fa, fe, and fg provide the communication opportunities between region ra and Sink node which lead to the connection of the whole network. In addition, the black thick lines show that most of the communication opportunities of region ra are provided by Ferry node fa and the dotted lines show that the communication opportunities supported by fe and fg between ra and Sink node are very few, which indicates that node fa is the critical node of the network in Scenario A.

In Figure 4, Scenario B shows that node fd is the critical node. If node fd is failure or removed, regions rc, rd, and re cannot communicate to Sink node anymore. The network split occurs so that node fd is the cut-vertex as well as the critical node of the network.

In some more complex situations like Scenario C and Scenario D, in Figure 5, there is no cut-vertex in Scenario C and most of the communication opportunities among regions ra and rb and Sink node are provided by node fa; thus it can be seen that fa is the critical node of the network in Scenario C.

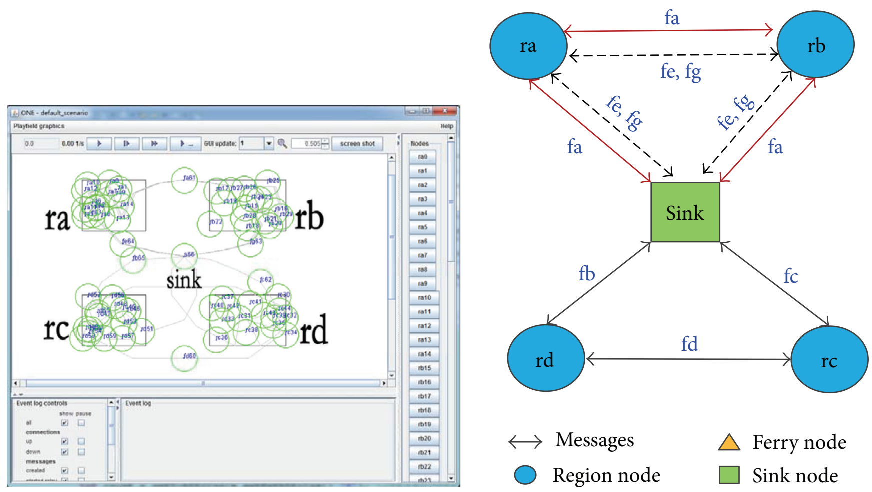
In Figure 6, there are several cut-vertexes in Scenario D such as nodes fc, fd, and fe and they are the critical nodes as well.

5.2. Results Analysis. We have made experiments 100 times for each scenario. Table 1 shows the experimental results after the statistical analysis of experimental data.

As shown in Table 1, the maximum appearance possibility $\max(P_s)$ is 0.33% in Scenario A and 0.44% in Scenario C. Meanwhile, the corresponding prediction results are both fa.

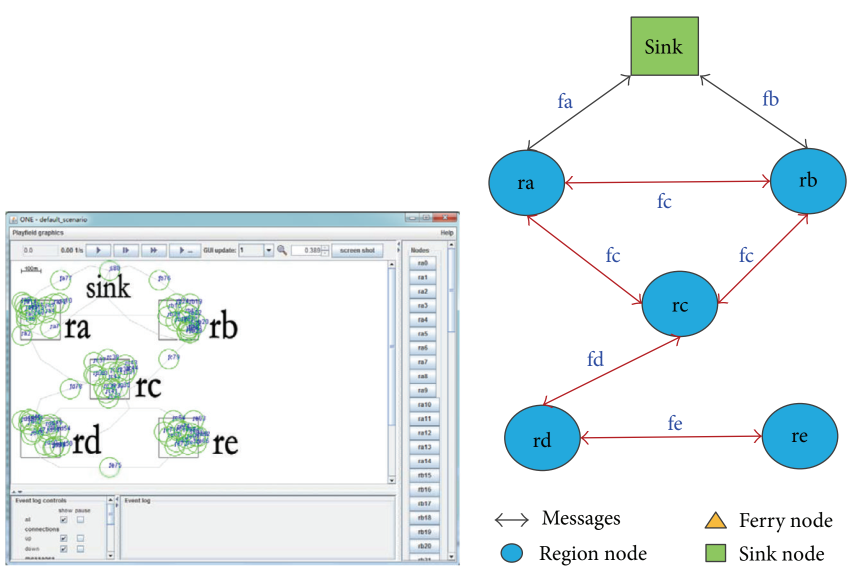
Table 1: Experiment results.

Scenario	CN	Appearance possibility P_s (%)						$\max(P_s)$ (%)	Result
		fa	fb	fc	fd	fe	fg		
Scenario A	fa	0.33	0.04	0	0.06	0.03	0.06	0.33	fa
Scenario B	fd	0.31	0	0.35	0.52	0.02	0	0.52	fd
Scenario C	fa	0.44	0.02	0.24	0.01	0	0	0.44	fa
Scenario D	fc, fd, fe	0.22	0.17	0.52	0.52	0.52	—	0.52	fc, fd, fe



(a) Simulation (b) Model

Figure 5: Scenario C.



(a) Simulation (b) Model

Figure 6: Scenario D.

In Scenario B and Scenario D, the max appearance possibility $\max(P_s)$ is for both 0.52%. The prediction result in Scenario B is fd and the results in Scenario D are fc, fd, and fe. Thus it can be seen that the predicted results of these four scenarios are completely the same with the actual value mentioned above. Therefore, our algorithm can well predict the critical nodes of OSN.

6. Conclusions

Considering the dynamic of OSN, this paper proposed a MADM based method to predict critical nodes. First, the region contribution is introduced to present the dependency of regions on Ferry nodes. Then, the comprehensive region contributions are estimated by the MADM method. At last, the experimental results show that, for different OSN scenarios, our method can predict the critical nodes of the network effectively.

Competing Interests

The authors declare no competing interests.

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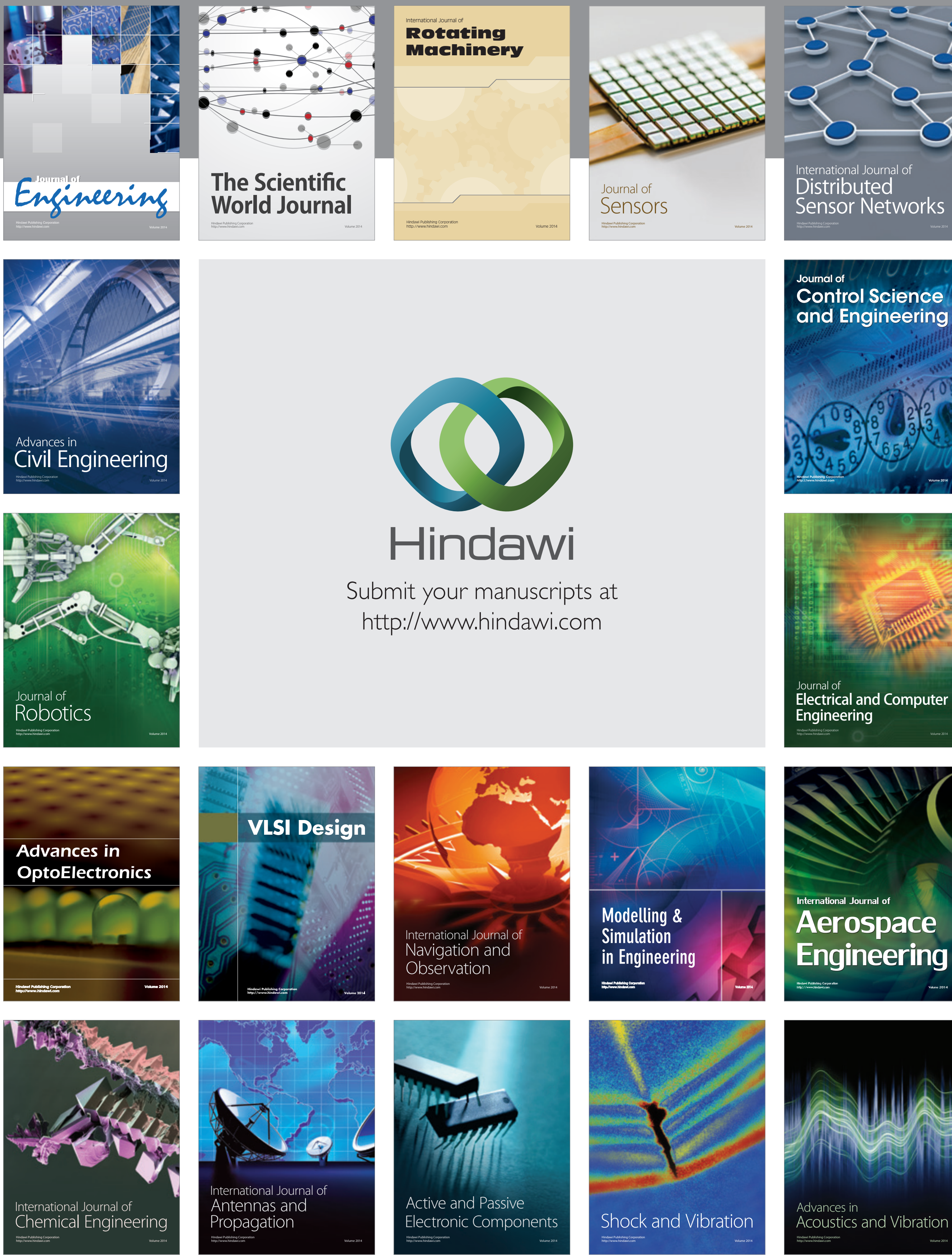
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