A Fuzzy-Based Simulation System for IoT Node Selection in Opportunistic Networks and Testbed Implementation

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Abstract. In opportunistic networks the communication opportunities (contacts) are intermittent and there is no need to establish an end-to-end link between the communication nodes. The enormous growth of nodes having access to the Internet, along the vast evolution of the Internet and the connectivity of objects and nodes, has evolved as Internet of Things (IoT). There are different issues for these networks. One of them is the selection of IoT nodes in order to carry out a task in opportunistic networks. In this work, we implement a Fuzzy-Based System for IoT node selection in opportunistic networks. For our proposed system, we use four input parameters: Node's Distance from Task (NDT), Node's Remaining Energy (NRE), Node's Buffer Occupancy (NBO) and Node Inter Contact Time (NICT). The output parameter is Node Selection Decision (NSD). We also implemented a testbed with the same input and output parameters and compared its results with the simulation results. The results show that the proposed system makes a proper selection decision of IoT nodes in opportunistic networks. The IoT node selection is increased up to 40% and decreased 38% by decreasing NBO and increasing NICT, respectively.

1 Introduction

Future communication systems will be increasingly complex, involving thousands of heterogeneous nodes with diverse capabilities and various networking technologies interconnected with the aim to provide users with ubiquitous access to information and advanced services at a high quality level, in a cost efficient manner, any time, any place, and in line with the always best connectivity principle. The Opportunistic Networks (OppNets) can provide an alternative way to support the diffusion of information in special locations within a city, particularly in crowded spaces where current wireless technologies can exhibit congestion issues. The efficiency of this diffusion relies mainly on user mobility. In fact,

L. Barolli et al. (Eds.): BWCCA 2019, LNNS 97, pp. 32–43, 2020.
https://doi.org/10.1007/978-3-030-33506-9_4

mobility creates the opportunities for contacts and, therefore, for data forwarding [1]. OppNets have appeared as an evolution of the MANETs. They are also a wireless based network and hence, they face various issues similar to MANETs such as frequent disconnections, highly variable links, limited bandwidth etc. In OppNets, nodes are always moving which makes the network easy to deploy and decreases the dependence on infrastructure for communication [2].

In Internet of Things (IoT), the traffic is going through different networks. The IoT can seamlessly connect the real world and cyberspace via physical objects embedded with various types of intelligent sensors. A large number of Internet-connected machines will generate and exchange an enormous amount of data that make daily life more convenient, help to make a tough decision and provide beneficial services. The IoT probably becomes one of the most popular networking concepts that has the potential to bring out many benefits [3,4].

OppNets are the variants of Delay Tolerant Networks (DTNs). It is a class of networks that has emerged as an active research subject in the recent times. Owing to the transient and un-connected nature of the nodes, routing becomes a challenging task in these networks. Sparse connectivity, no infrastructure and limited resources further complicate the situation [5,6]. Routing methods for such sparse mobile networks use a different paradigm for message delivery. These schemes utilize node mobility by having nodes carry messages, waiting for an opportunity to transfer messages to the destination or the next relay rather than transmitting them over a path [7]. Hence, the challenges for routing in OppNet are very different from the traditional wireless networks and their utility and potential for scalability makes them a huge success.

In mobile OppNet, connectivity varies significantly over time and is often disruptive. Examples of such networks include interplanetary communication networks, mobile sensor networks, vehicular ad hoc networks (VANETs), terrestrial wireless networks, and under-water sensor networks. While the nodes in such networks are typically delay-tolerant, message delivery latency still remains a crucial metric, and reducing it is highly desirable [8].

The Fuzzy Logic (FL) is unique approach that is able to simultaneously handle numerical data and linguistic knowledge. The fuzzy logic works on the levels of possibilities of input to achieve the definite output. Fuzzy set theory and FL establish the specifics of the nonlinear mapping.

In this paper, we propose and implement a Fuzzy-based system for selection of IoT nodes in OppNet considering four parameters: Node's Distance from Task (NDT), Node's Remaining Energy (NRE), Node's Buffer Occupancy (NBO) and Node Inter Contact Time (NICT) for IoT node selection. We show the simulation results for different values of parameters.

The remainder of the paper is organized as follows. In the Sect. 2, we present IoT and OppNet. In Sect. 3, we introduce the Fuzzy-based simulator system and testbed implementation. The evaluation results are shown in Sect. 4. Finally, conclusions and future work are given in Sect. 5.

2 IoT and OppNets

2.1 IoT

IoT allows to integrate physical and virtual objects. Virtual reality, which was recently available only on the monitor screens, now integrates with the real world, providing users with completely new opportunities: interact with objects on the other side of the world and receive the necessary services that became real due the wide interaction [9]. The IoT will support substantially higher number of end users and nodes. In Fig. 1, we present an example of an IoT network architecture. The IoT network is a combination of IoT nodes which are connected with different mediums using IoT Gateway to the Internet. The data transmitted through the gateway is stored, processed securely within cloud server. These new connected things will trigger increasing demands for new IoT applications that are not only for users. The current solutions for IoT application development generally rely on integrated service-oriented programming platforms. In particular, resources (e.g., sensory data, computing resource, and control information) are modeled as services and deployed in the cloud or at the edge. It is difficult to achieve rapid deployment and flexible resource management at network edges, in addition, an IoT system's scalability will be restricted by the capability of the edge nodes [10].

2.2 OppNets

In Fig. 2 we show an OppNet scenario. OppNets comprises a network where nodes can be anything from pedestrians, vehicles, fixed nodes and so on. The data is sent from the sender to receiver by using communication opportunity that can be Wi-Fi, Bluetooth, cellular technologies or satellite links to transfer the message to the final destination. In such scenario, IoT nodes might roam and opportunistically encounter several different statically deployed networks and perform either data collection or dissemination as well as relaying data

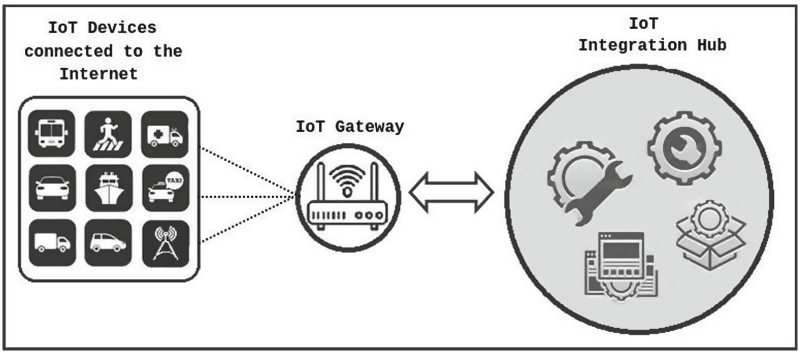


Fig. 1. An Iot network architecture.

between these networks, thus introducing further connectivity for disconnected networks. For example, as seen in Fig. 2, a car could opportunistically encounter other IoT nodes, collect information from them and relay it until it finds an available access point where it can upload the information. Similarly, a person might collect information from home-based weather stations and relay it through several other people, cars and buses until it reaches its intended destination [11].

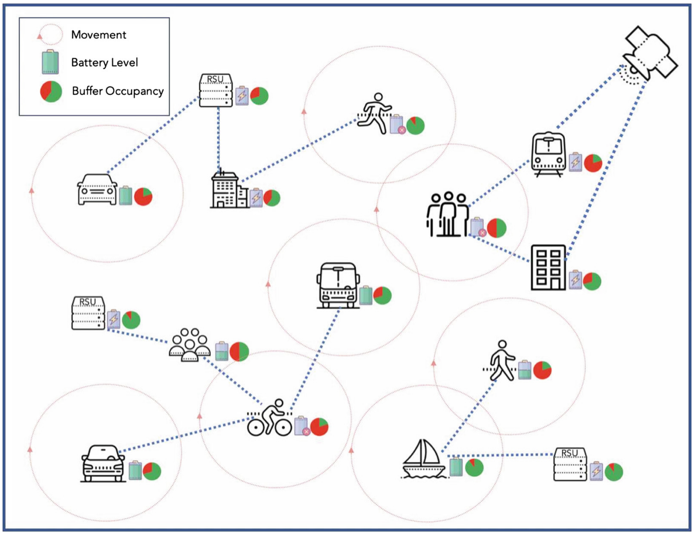


Fig. 2. OppNets scenario.

OppNets are not limited to only such applications, as they can introduce further connectivity and benefits to IoT scenarios. In an OppNet, due to node mobility network partitions occur. These events result in intermittent connectivity. When there is no path existing between the source and the destination, the network partition occurs. Therefore, nodes need to communicate with each other via opportunistic contacts through store-carry-forward operation.

3 Proposed Fuzzy-Based Simulator and Testbed Implementation

In this work, we use fuzzy logic to implement the proposed system. Fuzzy sets and fuzzy logic have been developed to manage vagueness and uncertainty in a reasoning process of an intelligent system such as a knowledge based system, an expert system or a logic control system [12–25].

3.1 Proposed Fuzzy-Based Simulation System

The structure of the proposed system for the node selection is shown in Fig. 3. Based on OppNets characteristics and challenges, we consider the following parameters for implementation of our proposed system:

Node's Distance to Task (NDT): The distance of a node from the task is an important parameter. An IoT node will be selected to carry out a task with high possibility if the node is close to the task.

Node's Remaining Energy (NRE): The IoT nodes are active and can perform tasks and exchange data in different ways from each other. Consequently, some IoT nodes may have a lot of remaining power and other may have very little, when an event occurs.

Node's Buffer Occupancy (NBO): In an network that consists of diverse IoT nodes with different resources, buffer occupancy at a certain time is very important. Some IoT nodes are in more advantageous position than others, making them more likely to deliver messages thus making them busier than others. Due to high amount of traffic, these nodes's buffer may overflow affecting the average throughput and the dropping ratio.

Node Inter Contact Time (NICT): The inter-contact time measures the time between the end of previous contact and the beginning of a new one between two IoT nodes. Shorter inter-contact time means having more opportunities to forward the message to the next IoT node.

Our proposed system consists of one Fuzzy Logic Controller (FLC), which is the main part of our system and its basic elements which are shown in Fig. 4. They are the fuzzifier, inference engine, Fuzzy Rule Base (FRB) and defuzzifier. The FRB forms a fuzzy set of dimensions $|T(NDT)| \times |T(NRE)| \times |T(NBO)| \times |T(NICT)|$, where $|T(x)|$ is the number of terms on $T(x)$. We have four input parameters, so our system has 81 rules. The term sets for these parameters are shown in Table 1. The control rules which are shown in Table 2 have the form: IF "conditions" THEN "control action".

These parameters will be represented from numerical form into linguistic variables. We use fuzzy membership functions to quantify the linguistic term. The fuzzy membership functions of our system our shown in Fig. 5. We use triangular and trapezoidal membership functions for FLC, because they are suitable for real-time operations [26].

3.2 Testbed Implementation

In order to evaluate the simulation system, we have implemented a Testbed as shown in Fig. 6. The testbed setup consists of the hardware and software part. Different data sensing sensors, are mounted on Arduino Uno via IoT Tab Shield 4. This sensed data gets collected by a processing device which is connected to Arduino Uno via USB cable. The processing device consists of Raspberry Pi 3 model B+ which operates on an optimized Debian based system, or a Mac os laptop. For the software part, we used Arduino IDE to collect the sensed data, Processing language to read this data and FuzzyC [12] to evaluate which

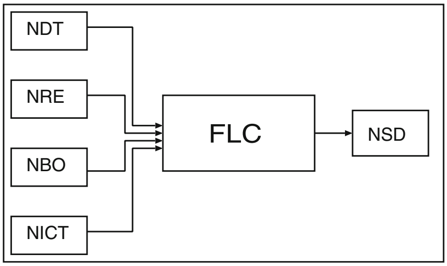


Fig. 3. Proposed system model.

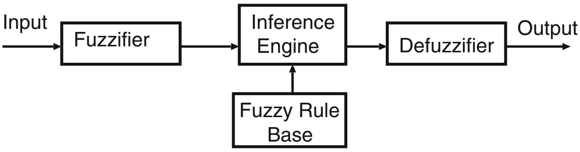


Fig. 4. FLC structure.

Table 1. Parameters and their term sets for FLC.

Parameters	Term sets
Node's Distance to Task *(NDT)*	Near *(Nr)*, Close *(Cl)*, Far *(Fr)*
Node's Remaining Energy *(NRE)*	Low *(Lo)*, Medium *(Md)*, High *(Hg)*
Node's Buffer Occupancy *(NBO)*	Minimum *(Min)*, Medium *(Med)*, Maximum *(Max)*
Node Inter Contact Time *(NICT)*	Short *(Sh)*, Medium *(Mdm)*, Long *(Lng)*
Node Selection Decision *(NSD)*	Extremely Low Selection Possibility *(ELSP)*, Very Low Selection Possibility *(VLSP)*, Low Selection Possibility *(LSP)*, Medium Selection Possibility *(MSP)*, High Selection Possibility *(HSP)*, Very High Selection Possibility *(VHSP)*, Extremely High Selection Possibility *(EHSP)*

of the nodes based on the data is more likely to be selected for a certain task. The hardware is mounted on different IoT nodes to mimic a real life scenario. In Fig. 6(a) and (b) are shown static and mobile IoT nodes, respectively. In static IoT nodes, the data is sensed by the sensor mounted in Arduino with IoT Tab Shield 4, read and processed using the laptop. For mobile IoT nodes, we use Raspberry Pi 3 model B+ for data reading and processing, which is power supplied by a 24000 mAh battery with a lcd display for battery level reading.

Table 2. FRB.

No.	NDT	NRE	NBO	NICT	NSD	No.	NDT	NRE	NBO	NICT	NSD	No.	NDT	NRE	NBO	NICT	NSD
1	Nr	Lo	Min	Sh	EHSP	28	Cl	Lo	Min	Sh	VHSP	55	Fr	Lo	Min	Sh	VHSP
2	Nr	Lo	Min	Mdm	VHSP	29	Cl	Lo	Min	Mdm	MSP	56	Fr	Lo	Min	Mdm	LSP
3	Nr	Lo	Min	Lng	VHSP	30	Cl	Lo	Min	Lng	MSP	57	Fr	Lo	Min	Lng	LSP
4	Nr	Lo	Med	Sh	EHSP	31	Cl	Lo	Med	Sh	HSP	58	Fr	Lo	Med	Sh	MSP
5	Nr	Lo	Med	Mdm	HSP	32	Cl	Lo	Med	Mdm	VLSP	59	Fr	Lo	Med	Mdm	VLSP
6	Nr	Lo	Med	Lng	HSP	33	Cl	Lo	Med	Lng	VLSP	60	Fr	Lo	Med	Lng	VLSP
7	Nr	Lo	Max	Sh	HSP	34	Cl	Lo	Max	Sh	LSP	61	Fr	Lo	Max	Sh	VLSP
8	Nr	Lo	Max	Mdm	LSP	35	Cl	Lo	Max	Mdm	ELSP	62	Fr	Lo	Max	Mdm	ELSP
9	Nr	Lo	Max	Lng	LSP	36	Cl	Lo	Max	Lng	ELSP	63	Fr	Lo	Max	Lng	ELSP
10	Nr	Md	Min	Sh	EHSP	37	Cl	Md	Min	Sh	EHSP	64	Fr	Md	Min	Sh	VHSP
11	Nr	Md	Min	Mdm	EHSP	38	Cl	Md	Min	Mdm	HSP	65	Fr	Md	Min	Mdm	MSP
12	Nr	Md	Min	Lng	EHSP	39	Cl	Md	Min	Lng	HSP	66	Fr	Md	Min	Lng	MSP
13	Nr	Md	Med	Sh	EHSP	40	Cl	Md	Med	Sh	VHSP	67	Fr	Md	Med	Sh	HSP
14	Nr	Md	Med	Mdm	HSP	41	Cl	Md	Med	Mdm	LSP	68	Fr	Md	Med	Mdm	VLSP
15	Nr	Md	Med	Lng	HSP	42	Cl	Md	Med	Lng	LSP	69	Fr	Md	Med	Lng	VLSP
16	Nr	Md	Max	Sh	VHSP	43	Cl	Md	Max	Sh	MSP	70	Fr	Md	Max	Sh	LSP
17	Nr	Md	Max	Mdm	MSP	44	Cl	Md	Max	Mdm	VLSP	71	Fr	Md	Max	Mdm	ELSP
18	Nr	Md	Max	Lng	MSP	45	Cl	Md	Max	Lng	VLSP	72	Fr	Md	Max	Lng	ELSP
19	Nr	Hg	Min	Sh	EHSP	46	Cl	Hg	Min	Sh	EHSP	73	Fr	Hg	Min	Sh	EHSP
20	Nr	Hg	Min	Mdm	EHSP	47	Cl	Hg	Min	Mdm	EHSP	74	Fr	Hg	Min	Mdm	VHSP
21	Nr	Hg	Min	Lng	EHSP	48	Cl	Hg	Min	Lng	EHSP	75	Fr	Hg	Min	Lng	VHSP
22	Nr	Hg	Med	Sh	EHSP	49	Cl	Hg	Med	Sh	EHSP	76	Fr	Hg	Med	Sh	EHSP
23	Nr	Hg	Med	Mdm	EHSP	50	Cl	Hg	Med	Mdm	VHSP	77	Fr	Hg	Med	Mdm	HSP
24	Nr	Hg	Med	Lng	EHSP	51	Cl	Hg	Med	Lng	VHSP	78	Fr	Hg	Med	Lng	HSP
25	Nr	Hg	Max	Sh	EHSP	52	Cl	Hg	Max	Sh	EHSP	79	Fr	Hg	Max	Sh	VHSP
26	Nr	Hg	Max	Mdm	VHSP	53	Cl	Hg	Max	Mdm	MSP	80	Fr	Hg	Max	Mdm	LSP
27	Nr	Hg	Max	Lng	VHSP	54	Cl	Hg	Max	Lng	MSP	81	Fr	Hg	Max	Lng	LSP

4 Proposed System Evaluation

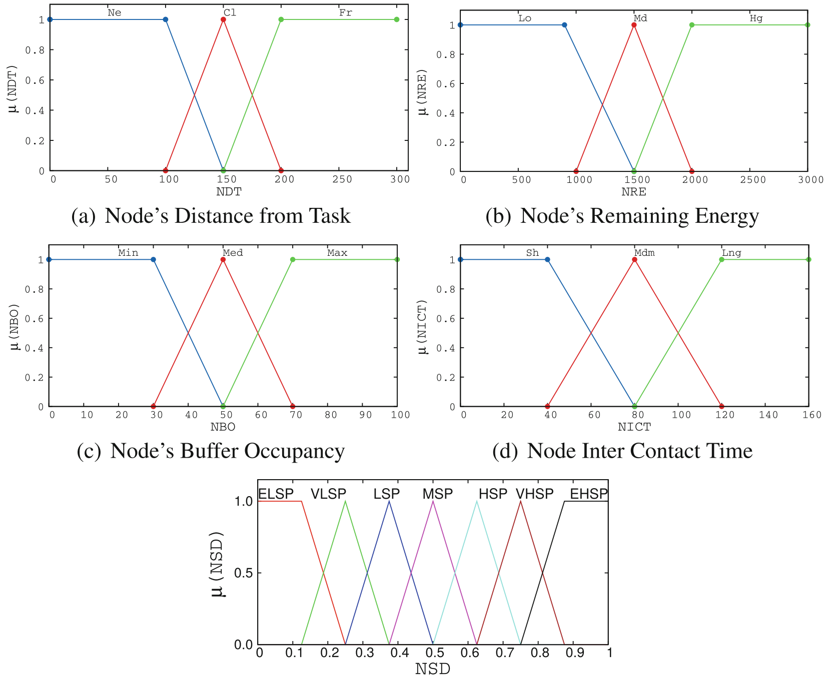
4.1 Simulation Results

We present the simulation results in Fig. 7. We show the relation between the possibility of an IoT node to be selected (NSD) to carry out a task, versus NDT, NRE, NBO and NICT.

In Fig. 7(a) and (b), we show how the output parameter NSD is affected by NRE. IoT nodes with more remaining energy, have a higher possibility to be selected for carrying out a job. To show how remaining energy affects the selection of an IoT node, we compare Fig. 7(a) with Fig. 7(b) for NICT = 0.4, NBO = 0.9. We see that NSD is increased 37%.

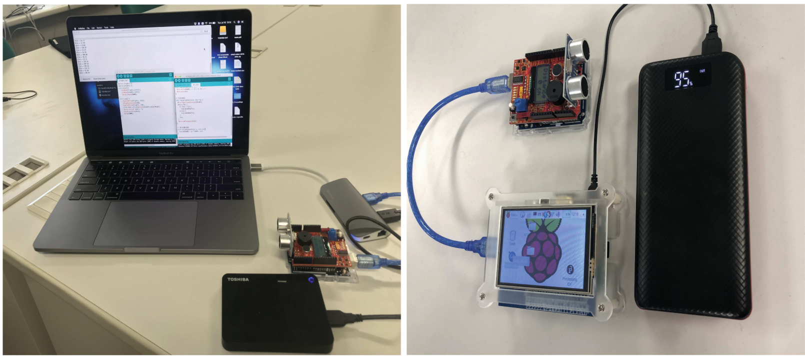
In Fig. 7(c) and (d) are shown the simulation results for NDT = 0.5. Comparing Fig. 7(c) with (a), when NICT = 0.4 and NBO = 0.1, we see that that NDS is decreased 16%. This means that nodes which are far from task, are less likely to be selected since these IoT nodes will need more resources to reach this task.

In Fig. 7(e) and (f), the NDT is increased to 0.9. We have a further decrease of NSD with the increase of NDT. In Fig. 7(e), for NICT = 0.2 to NICT = 0.4 and NBO = 0.1, we see that NSD is decreased 38%. IoT nodes that take a longer



(a) Node's Distance from Task
(b) Node's Remaining Energy
(c) Node's Buffer Occupancy
(d) Node Inter Contact Time
(e) Node Selection Decision

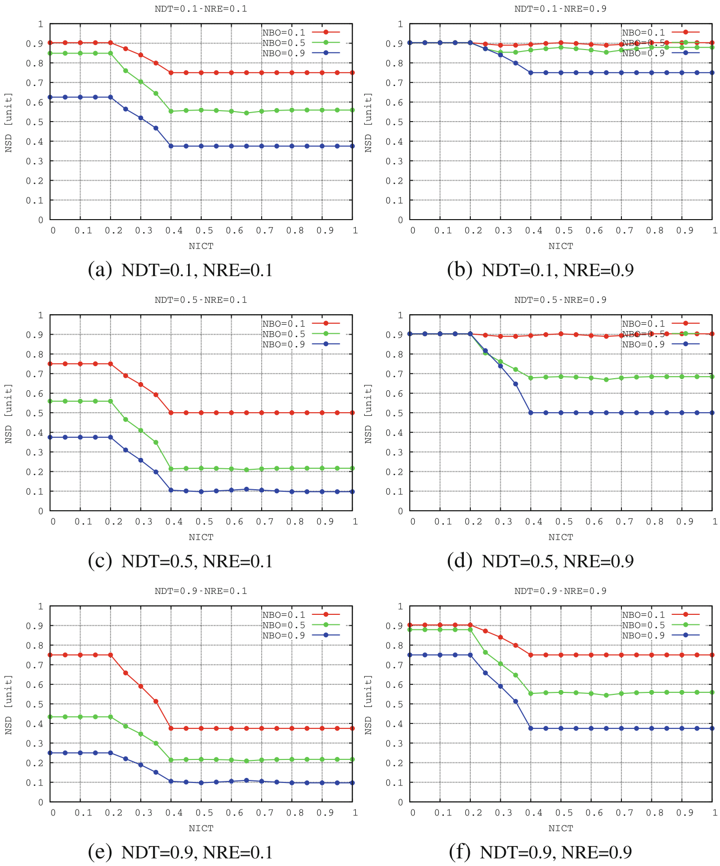
Fig. 5. Fuzzy membership functions.



(a) Statically deployed IoT Nodes.
(b) Mobile IoT Nodes.

Fig. 6. Testbed Implementation.

time to come in contact with other nodes will create less connections, thus the possibility that the IoT node be selected decreases. To see the effect that buffer occupancy has on NSD, we take NICT = 0.4 for NBO = 0.9 and NBO = 0.1 in Fig. 7(f). We see that NSD is increased 40% with the decrease of NBO from NBO = 0.9 to NBO = 0.1. The buffer of some IoT nodes may be occupied or fully



(a) NDT=0.1, NRE=0.1

(b) NDT=0.1, NRE=0.9

(c) NDT=0.5, NRE=0.1

(d) NDT=0.5, NRE=0.9

(e) NDT=0.9, NRE=0.1

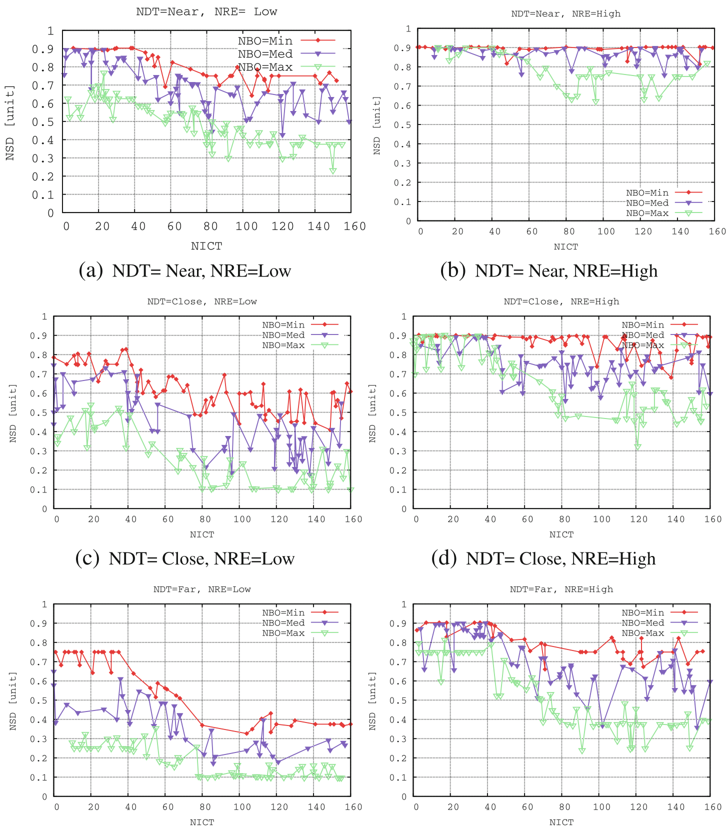
(f) NDT=0.9, NRE=0.9

Fig. 7. Simulation results.

occupied. Since these networks use store-carry-forward mechanism, an occupied buffer will cause a congestion due to buffer overflow.

4.2 Experimental Results

The experimental results are shown in Fig. 8. In Fig. 8(a) and (b) are shown the results for NDT = Near, NRE = Low and NDT = Near, NRE = High, respectively. During the testbed implementation we gathered a lot of data from the sensors. The simulation results in Fig. 7(a) and (b) are close with experimental results in Fig. 8(a) and (b). However, there are some variations from point to point which represent the different outside factors that affect experimental results. In Fig. 8(c) and (d), are shown results for NDT = Close, NRE = Low and NDT = Close, NRE = High. In Fig. 8(e) and (f), are shown results for NDT = Far, NRE = Low and NDT = Far, NRE = High. For all the above results, we can see that the simulation results are close to the experimental results.



(a) NDT= Near, NRE=Low
(b) NDT= Near, NRE=High
(c) NDT= Close, NRE=Low
(d) NDT= Close, NRE=High
(e) NDT= Far, NRE=Low
(f) NDT= Far, NRE=High

Fig. 8. Experimental results.

5 Conclusions and Future Work

In this paper, we proposed a fuzzy-based IoT node selection system for OppNets considering four parameters: NDT, NRE, NBO, NICT. We implemented a testbed and compared experimental results with the simulation results for the selection of IoT nodes in an Oppnet scenario. The simulation results and experimental results are close, but in experiment there are some variations.

In the future work, we will also consider other parameters for IoT node selection and make extensive simulations and experiments to evaluate the proposed system.

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