Annals of Emerging Technologies in Computing (AETiC)
Vol. 3, No. 2, 2019

Research Article

IoT Energy Efficiency through Centrality Metrics

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Received: 12th February 2019; Accepted: 5th March 2019; Published: 1st April 2019

Abstract: The Internet of Things is the current and next revolution in integrating various technologies and wireless communications. It has been shown to make an important contribution in various modes of communication, in homes, offices and other buildings. However, certain research issues are still remain, such as life span of the network and a definition of the most influential nodes in communications, which affect the overall energy distribution. This paper introduces a new approach to enhance the communication over the internet of things, by combining two different domains, the computer network and network science. Various scenarios have been thoroughly implemented and tested over different network topologies. The results show clear enhancements on network centrality and overall energy distribution.

Keywords: ***Internet of Things; Computer Networks; Network Science; Energy Efficiency***

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1. Introduction

The Internet of things (IoT) paradigm has recently been gaining considerable attention in both emerging technologies and science. It has been very effective in different domains, such as eHealth, home and retail, among other sectors. The main idea of this paradigm is to have sensors around people where they can identify, communicate and interact with end users. It is considerable that IoT would have impact on users in their daily life on everything and that would be a strength of IoT, where the utilization will be adapted onto various paradigms such as tags, sensors, controllers, actuators and RFIDs [1][2].

According to Gartner (2015) growth is predicted to be very significant, in terms of the number of devices and applications, for both users and businesses [3]. Reports have indicated that there is expected to a large increase in the number of devices, from 20 to 25 billion by 2020 [4]. However, a recent report released by "Help Net Security" [5] has shown that by 2021, the number of IoT devices is expected to increase by 140% to 50 billion. The growth of IoT has exceeded expectations. It has been very effective on food packages, paper documents and furniture, where IoT has started its strength.

However, just like any other paradigms, such as mobile ad hoc networks, IoT has some limitations due to power consumption, the life spans of sensors and the range of sending and

Majed Alhaisoni, "IoT Energy Efficiency through Centrality Metrics", *Annals of Emerging Technologies in Computing (AETiC)*, Print ISSN: 2516-0281, Online ISSN: 2516-029X, pp. 14-21, Vol. 3, No. 2, 1st April 2019, Published by International Association of Educators and Researchers (IAER), DOI: 10.33166/AETiC.2019.02.002, Available: http://aetic.theiaer.org/archive/v3/v3n2/p2.html.

transmitting data in the network [4]. These issues directly or indirectly affect the energy efficiency and the overall budget of nodes in the network. Therefore, this paper introduces a new method to address IoT the energy efficiency problem, by drawing on knowledge from a network science perspective. The results have shown a clear improvement on network centrality and overall energy distribution.

2. Related Work

The Internet of things has been an important area of research over the past decade. Various IoT issues have been examined by different researchers. This paper focuses specifically on power efficiency and rescheduling. The authors of [6] focused on the detection of unanticipated sensor data, which results of either from the sensor system or the environment under scrutiny. Managing and monitoring the links and connections in low wireless communications has been examined by [7]. The authors examined this issue by monitoring the edge service, then rescheduled certain links that were affected by the low power mode.

The authors in [8] studied the centrality metrics and showed how it could be computed in a very dynamic, decentralised environment. A decentralised system was also examined in [9], where they gained useful information in a very unsupervised environment. This information would be useful in managing dynamic complex IoT.

Machine learning has also been adapted to improve the communication in sensor networks, which represents an IoT paradigm among nodes. In machine learning reduces the human intervention and makes the system react and adapt itself, based upon collected information from the targeted nodes. Various techniques of machine learning are applied in [10]. The application of ML was highlighted in various issues, such as coverage problems, power energy issues and faulty node problems.

Minimizing power consumption in wireless sensors network with consideration for keeping an acceptable Quality of Service (QoS), is another way to enhance IoT networks. This approach has been proposed in [11], where machine learning is utilized to monitor the network by strategic agents collecting information over the nodes. In return for this useful information, a heuristic algorithm is developed to maintain the minimum possible power by nodes with an acceptable QoS of transmission.

The authors in [12] have proposed a method to enhance the scheduling and efficiency in surveillance, by considering different factors to balance the distribution among nodes in a very dynamic topology. Node importance was also considered for each sample, where nodes make a decision, based on their importance within the cluster. This way of managing the wireless sensors has contributed to energy efficiency and node reliability.

Other studies such as [13] have also examined connectivity coverage problems and energy efficiency issues, where nodes are either supposed to keep the data or forward it to the appropriate receiver. In [13], various techniques of saving power and energy with consideration of QoS parameters are further investigated and demonstrated.

The life span duration of IoT is another problem which has attracted more attention. It concerns the amount of time the network can survive due to the nature of sensors, which are very small devices sensing and acting at the same time. Recent research as in [14] has developed a heuristic to improve the network life time, by determining the locations of sinks.

Another issue which deserves attention in wireless sensors networks is node mobility, which affects the sink positioning and directions. This behaviour subsequently not only leads to power consumption and energy deduction of nodes, but also has a significant impact on the network, due to frequent updates among nodes. Various techniques were proposed in [15], including a new algorithm which uses a multi-ring shaped infrastructure to announce the sink positions regularly. As a result, low energy consumption is achieved on the overall network.

Other work such as [16] has investigated the power consumption in the case of WSN clustering, where a group of nodes are led by one node as a base station. It is responsible for sending, receiving, and forwarding information in the network. The proposed methods concentrated on moving nodes among clusters periodically, which saves power consumption and balances the load on cluster head nodes.

Energy consumption can also be affected in those nodes close to the sink, where they have to send and receive a huge amount of data. This affects energy consumption and depletes power that would impact the network and lead to the segregation of the network sink nodes. Authors in [17] have looked into this problem. They have proposed an algorithm, which is based upon selecting certain nodes virtually. This plays a role in keeping the latest information on the sinks. Therefore, their results have enhanced energy efficiency and reduced delay.

Other work has focused on prolonging the lifetime of wireless sensors networks, such as [18]. They maximize the life span, by determining the sink and adjusting the transfer rates between nodes to guarantee that they stay longer in the network. Other research studies have looked at enhancing energy efficiency. In [19], a protocol was designed to monitor the nodes, in order to reduce the listening time. It reduced the average communication time over the network.

In contrast to above-mentioned related works, this paper examines energy efficiency issues in IoT, where sensors are communicating with each other in a high-density network. Therefore, a new technique based on network science is employed to enhance the energy efficiency. This combination of two different domains (networking and network science) has contributed to enhancing the overall energy distribution of nodes and the network life span.

3. Proposed Algorithm

IoT consists of sensor nodes which may be interconnected with each other within a building, office, home, etc. These nodes contribute their own energy, power, bandwidth, and budgeting. Therefore, one of the main issues is how to maintain energy at a minimum level, while producing an acceptable Quality of Service (QoS) over the network. It takes into consideration that these nodes could be overwhelmed by either low energy or a high volume of traffic. This would cause collisions and depleted nodes. Such behaviour can lead to a disruption of the network life span and, the overall network efficiency. Since the nodes are interconnected with each other, this incurs redundant links. A high volume of traffic will be generated, which consumes the nodes' energy. This overwhelms the network with packet overheads, which degrades the quality and generates signalling overheads.

In contrast to the works highlighted in Section 2, our proposed algorithm considers introducing a network science methodology to enhance the energy efficiency in wireless sensor networks. A network centrality metric [20] was the key to measure the efficiency of a dense network. We then evaluate the communicability [21], which measures the interconnectivity among nodes all over the network topology. In return, after evaluating the communicability values for all nodes, an additional step is taken by the algorithm, to rank the nodes in the network based upon the communicability, from top to low values.

Thereafter, the algorithm re-measures the network centrality and keeps reshuffling up to a point of having a more evenly distributed centrality over the whole network.

However, it's very important to point out that this step does not neglect the main metric, which is network centrality. It keeps on trading off between communicability and energy efficiency. It is worth mentioning that the ultimate goal would be to never adversely affect the quality of service metrics in the network. Further demonstration of the algorithm is introduced next in the experimental section.

4. Evaluation Method

The proposed algorithm has been prototyped in Python[1]. It is fully capable of creating various types of topology, as well as being high level language with the support of many built-in libraries. To ensure the credibility of the experimental work, all experiments are randomized over different network sizes. The Erdős–Rényi model[2] was used to generate the graphs. The algorithm was then tested by generating N nodes, with the full distribution of values among them all. At the initial phase of the algorithm, communicability[3] is gauged to examine network centrality. This indicates the condition of all nodes in the network and how they are interconnected to each other. After each measurement of the communicability, the algorithm defines the nodes with high and low values. Subsequently, the efficiency gained is then calculated to check the network efficiency. The algorithm then defines those nodes with low values of communicability, then initiates a reshuffling phase, which is known as "rewiring". This operation allows those nodes with low communicability to enhance their situation, by redirecting links from nodes with high communicability values to those nodes achieving low communicability values. This action takes place iteratively, up to the point where communicability is no longer changing significantly. With each reshuffling, gained efficiency is calculated, to see whether the network efficiency is improving. To ensure the validity of this algorithm, the number of nodes are changed frequently to test the robustness and computational efficiency of the algorithm.

5. Results

This section provides more details on the proposed algorithm, by introducing the results of the various metrics. It compares the proposed algorithm to a randomised scenario, where no change is considered over the network under all conditions. The following metrics were examined over various types of network conditions and sizes.

5.1. Communicability

In order to guarantee that the proposed algorithm is well-examined, a topology of various network size (50, 100, 150, 200) nodes were generated. At the initial start-up phase, the topology was

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1 https://www.python.org/

2 https://en.wikipedia.org/wiki/Erd%C5%91s%E2%80%93R%C3%A9nyi_model

3 https://networkx.github.io/documentation/networkx-1.10/reference/algorithms.centrality.html

randomly created with the defined network size. However, two scenarios were introduced. The first scenario is randomised, where no change is made over the network condition, and all nodes are interconnected randomly. The second scenario is the proposed algorithm called "reshuffling," as explained and discussed in Sections 3 and 4.

Figure 1 shows the results of the two scenarios with various network sizes. It shows that the proposed algorithm "with reshuffling" has a steady decrease in the overall communicability compared to the randomised scenario "without reshuffling". Therefore, the results show that the values change very little in the randomised scenario. However, to ensure the validity of the results, the average and standard deviation of several runs were taken for both scenarios across network size. The reason for the steady decrease in overall communicability in the proposed algorithm, is that the weight of the network (in terms of energy and power) is fully distributed among all nodes. The default condition of the network in the no reshuffling scenario indicates that some nodes are always carrying out tasks over the network. This affects both the gained efficiency and power energy.

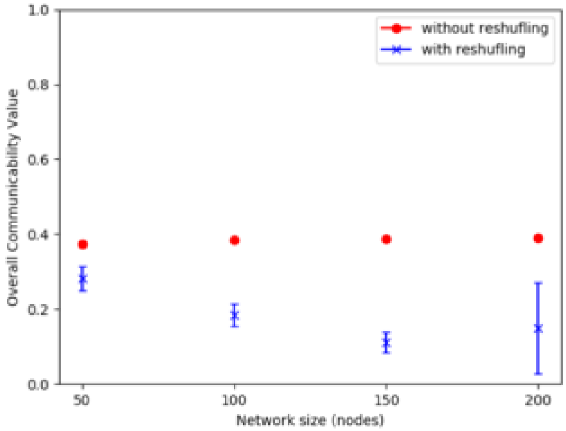

Figure 1. Overall Communicability value

5.2. Gained Efficiency (GE)

In the proposed algorithm, gained efficiency (GE) is defined as follows:

$$GE = (\Delta/\text{max values}) * 100$$

Where Δ is (*MAX - the overall communicability value*).

Max value in this case is 1 (depending on the metrics scale).

The purpose of this metric is to show the network efficiency and how the nodes are contributing to the overall network. It is interlinked with the overall communicability each time. Therefore, one of the main goals of the proposed algorithm is to enhance the network efficiency. Two scenarios have been introduced in this metric to provide meaningful results. It will show how the proposed method results in a very significant improvement in the overall network efficiency. The same network conditions and topology were used, with various network size (50, 100, 150, 200) nodes. Figure 2 indicates the gained efficiency of two scenarios. The proposed algorithm "with reshuffling" is achieves very significant improvements. The overall communicability for the proposed algorithm is going against gained efficiency which proves the validity of this algorithm. By contrast, the randomised scenario without reshuffling shows a decrease in the overall gained efficiency. This is consistent with the results shown in Figure 1.

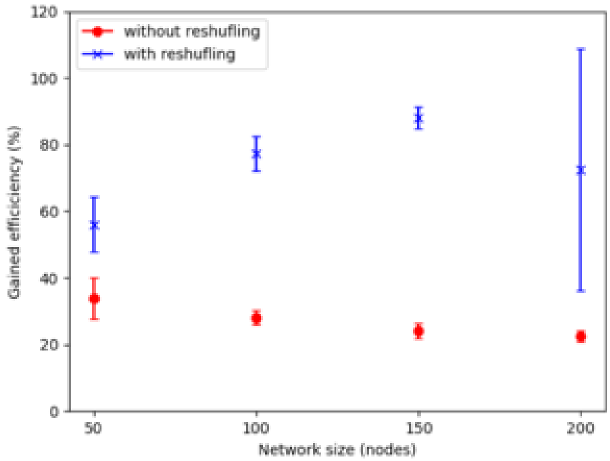

Figure 2. Gained Efficiency

5.3. Computational efficiency

Computational time is another critical factor of the proposed algorithm, since it shows the robustness of the proposed approach. Therefore, dealing with a large scale network size has a significant impact on the performance of executing very complicated scenarios. This metric was very valuable in measuring the computational efficiency of the proposed algorithm, in terms of running time and execution.

Figure 3 indicates that the running time increases linearly against the network size. A careful examination of the amount of elapsed time necessary to run, execute, and achieve the best results over many runs, demonstrates that the algorithm performs very well despite the network size and the complexity of connections among the nodes.

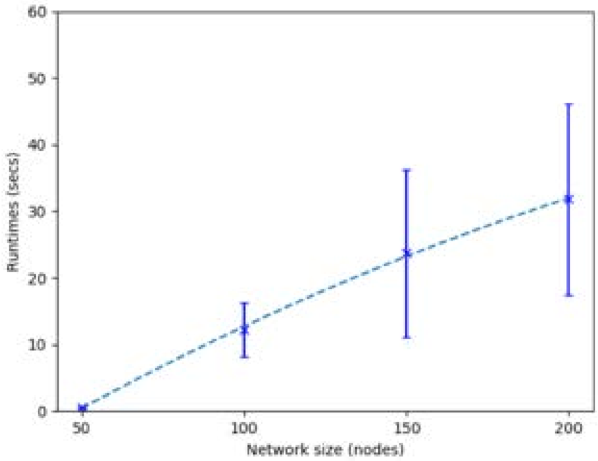

Figure 3. Computational time

5.4. Reshuffling iterations

In order to execute the proposed method, reshuffling is done through a set of iterations. It was, therefore, essential to set a condition of process exit. Reshuffling was repeated up to the point where the gained efficiency was not changing significantly. This threshold indicates that the algorithm was reaching its optimum value, so process is exit. Figure 4 shows the total number of iterations for various network node sizes. The number of iterations is almost the same for the different network sizes. This demonstrates that the proposed algorithm is capable stabilising and achieving outstanding results for any network size, with near-constant performance.

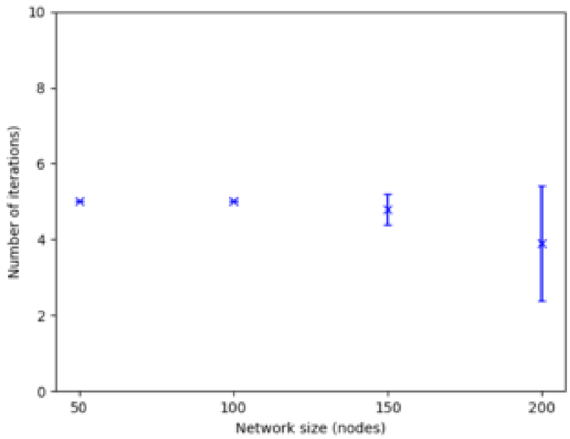

Figure 4. Number of reshuffling Iterations

6. Concluding remarks

This paper examines energy efficiency and power depletion from a network science perspective. Network centrality plays a key role in the overall network communicability. A heuristic is presented that enhances the network centrality, by looking at the communicability and overall gained efficiency. A reshuffling technique was proposed to enhance the network distribution, and subsequently, the overall gained efficiency. The proposed technique was also compared to a default scenario (randomised) to provide insightful results on the proposed method. The results clearly demonstrate the excellent performance of the proposed method in enhancing the network efficiency and communicability over various network sizes. Future research work will explore additional techniques to improve scalability for the IoT paradigm. Since the type of network (i.e. dense, sparse) has a crucial impact on communication among nodes (which results in high traffic and signalling), a priority would be given to investigate this in various types of networks.

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