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Trust and Reputational Model for Online Social Networks and Wireless Sensor Networks Using Machine Learning Approach

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Abstract: Comparing complex systems by representing them as networks is a useful method for determining structural similarity (or dissimilarity). In network analysis, the similarity of two networks is determined by the similarity of their ordering, sizes, and topological properties. The study is done to ascertain the similarities and differences in the two networks. TRM-sim is used to simulate the WSN. The research has visualized, analyzed and compared online social networks (OSNs) and wireless sensor networks (WSNs) and has identified some similarities and differences among them in terms of clustering, trust and reputation. There exists the need to compare network clusters in wireless sensor networks (WSNs) and online social networks (OSNs) in order to detect communities, understand the flow of communication among nodes in the network etc. This research work shown the comparison between WSN and OSN, both the models show a reasonably good performance in terms of efficiency, WSN require high efficiency due to their resource limitations, while OSN due to its very large scale also require high efficiency. From the results obtained in this research work the OSN performs better than the WSN.The result indicates that the OSN in all the cases does better than the WSN, one of the reason is that of power, when it comes to cluster head selection the power consumption gets higher unlike the OSN.

Key words: Model, Machine Learning, Online Social Networks and Wireless Sensor Networks

1. **Introduction**

Comparison and matching are common tasks in the age of big data. Comparing complex systems by representing them as networks is a useful method for determining structural similarity (or dissimilarity). In network analysis, determining the similarity of complex networks is crucial. The similarity of two networks is determined by the similarity of their ordering, sizes, and topological properties Saxena et al. (2019). The use of graph is one of the techniques used in representing networks.

A graph is a form of data structure that keeps track of the interactions between groups of actors. "Complex networks" is a term used to describe these objects. Rather than directly relating the features of individual objects, this sort of data structure relates links between them (Wills & Meyer, 2020). Some scholars such as (Emmons et al., 2016) also suggest that clustering is another approach used in analyzing networks.

Grouping items into groups, usually referred to as classes or categories, is the process of clustering them so that, depending on a predetermined trait, objects in one cluster are more similar to one another than those in other clusters. In several disciplines, such as statistics, data analysis, bioinformatics, and image processing, this is a crucial issue. Early twentieth-century techniques for grouping data include link clustering, centroid clustering, density clustering, and others. A hierarchical or partitioned structure with disconnected or overlapping clusters can be produced through clustering. According to Emmons et al. (2016), the number of clusters, average size, minimum size, maximum size, and other cluster metrics are frequently of interest. Organizing items into communities through the act of clustering makes objects in the same community more similar to one another than objects in other communities. According to Emmons et al. (2016), the goal of clustering approaches is to represent the intuitive notion that nodes should be connected to many nodes within the same community (intra-cluster density), but to few nodes inside different communities (inter-cluster sparsity). The study's objective is to compare WSNs and OSNs utilizing graphs and clustering algorithms.

Researchers' interest in wireless sensor networks (WSNs) has grown recently as they have become more crucial in a range of applications. The components of a WSN are a collection of spatially dispersed autonomous sensor nodes that track environmental variables like temperature, pressure, and humidity and cooperatively transmit their data over the network to a hub known as the sink. The sink of a WSN gathers data from sensor nodes and sends it over the internet or a Virtual Private Network (VPN) to users. According to Akila, Manisekaran & Venkatesan (2017), WSNs fall under the category of (LRWPAN) Low Range Wireless Personal Area Networks.

A wireless sensor network (WSN) is made up of a radio transceiver, which functions as both a transmitter and a receiver, a microcontroller, an electrical circuit for interacting with the sensors, and an energy source, which is frequently a battery or an embedded form of energy harvesting. In essence, sensor networks deliver more comfortable, intelligent views of the environment and substitute human labor in hard-to-reach locations. In the future, sensor networks will take the place of today's personal computers, cell phones, and other computing devices as an integral component of daily life. In a sensor network, sensor nodes can be homogeneous or heterogeneous. They may monitor either things or space, or the interactions between the two. Today, sensor networks are utilized for a variety of purposes, such as weather monitoring, home appliance management, precision agriculture, medical diagnostics, and combat surveillance. Every sensor application calls for a unique set of specifications and features (Akila, Manisekaran & Venkatesan, 2017). The second aspect of the research study is OSNs as described in the next paragraph.

With the introduction of websites like Facebook, etc., online social networks have recently grown in popularity. There are a lot of users active in these networks. As users fill out their websites with personal information, these networks provide a valuable source of data (Azizifard, 2014). Online social networks (OSNs) that are complex are used for the sharing of comments, images, and videos. Examples of OSNs include Facebook, LinkedIn, and Google+. However, users occasionally run into circumstances that call for communication with those who are not immediately related to them. In some situations, people may be aware of the ideal person to help them but are unwilling to approach them due to authority issues or privacy concerns. In other cases, people may not even be aware of who might be able to assist them. Despite the fact that OSN platforms are designed to intuitively aid users, they lack the capacity to swiftly and directly connect their users to the types of people or experts they may seek (Saleem, 2018). In these networks, locating clusters or communities is a major issue. There are many reasons to look for close-knit groups in networks; for instance, target marketing plans can be created using clusters, and it has been suggested that terrorist cells can be found (Azizifard, 2014).

An OSN community (cluster) is a group of people who interact often with one another and participate in some discussions. Understanding the interconnections of groups of people, for example, is one of the many applications of determining such communities in an OSN, Understanding the interactions among group of people, Visualizing and navigating huge networks of node of attractions (NoAs), Forming a basis for other tasks such as data mining, Marketing, and handling law and order situations (Hajeer et al., 2013).

As the life of a WSN depends on the cooperation and trustworthiness of its nodes, trust formation between nodes is a requirement to assess the trustworthiness of other nodes. For WSN, trust management systems may be particularly helpful in identifying malicious or malfunctioning nodes and in aiding decision-making. It has been used recently to track the evolving behaviors of network nodes in WSN.Interactions between nodes in a social network are based on trust connections. In general, the term "trust" refers to human-to-human relationships. According to Gang et al. (2020), interpersonal trust is the expectation and faith placed in one party to make decisions in interpersonal communications.

2. Literature Review

2.1 Clustering Techniques

A hierarchical or partitioned structure with disconnected or overlapping clusters can be produced through clustering. It is frequently interesting to know the count (number of clusters), average size, minimum size, maximum size, and other cluster properties. According to Emmons et al. (2016), clustering is the act of grouping things into communities in order to make them more similar to one another than to objects in other communities.

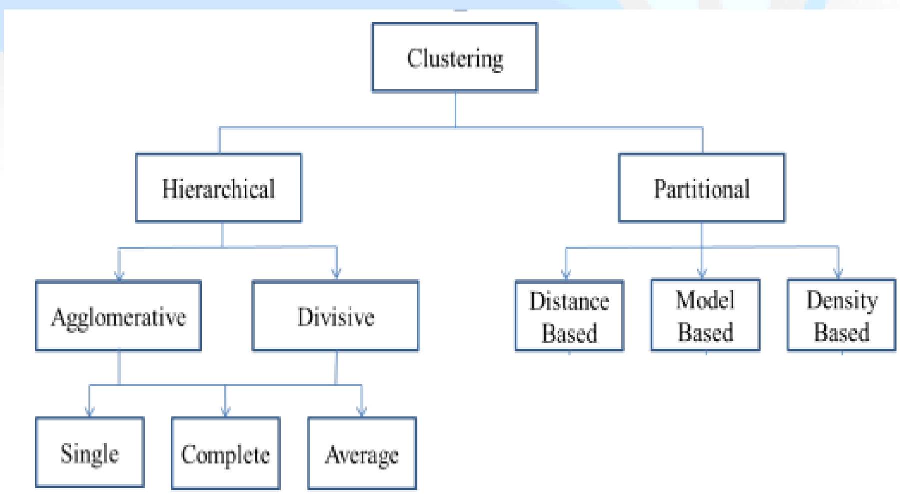

Figure 1: Clustering techniques

Clustering of single-linkages

One of the most fundamental agglomerative hierarchical clustering techniques is single linkage, also referred to as the nearest neighbor method. When only pairs made up of one object from each group are taken into consideration, the distance between two clusters is determined as the shortest distance between two points in each cluster. The single linkage method is used to determine D (r, s) as follows: According to Kumar et al. (2020), D (r, s) = Min d (i, j), where item i is in cluster r and object j is in cluster s.

Clustering of complete linkage

In complete-linkage clustering, sometimes referred to as the diameter, the maximum method, or the furthest neighbor methodology, the distance between two clusters is determined by the longest distance between any member of one cluster and any member of the other cluster (Saxena et al., 2017).

Clustering by average linkage

Average linkage clustering defines the distance between two clusters as the average of all the distances between pairs of objects, where each pair contains one object from each group. The average linkage approach is used to determine D (r, s) as follows: D (r, s) = Trs / (Nr * Ns). The sum of all pairwise distances between clusters r and s is known as Trs. According to Kumar et al. (2020), the letters Nr and Ns stand for the sizes of the clusters r and s, respectively.

2.2 Wireless Sensor Networks

WSN (Wireless Sensor Network) is a new paradigm for developing fault-tolerant mission-critical systems. It's a new area of multidisciplinary research involving people from electrical engineering, computer science, and a variety of other fields (Jiang, & Wu, 2014).

2.2.1 Military applications

It served as the primary impetus behind the founding of WSN. In 1980, the Sensor Information Technology (SENSIT) program was adopted by the Defense Advanced Research Projects Agency (DARPA), and the National Science Foundation (NSF) Programs looked into WSN for improved tracking capabilities. Other applications included intrusion detection and combat surveillance. The assessment of the concentration levels of nuclear, chemical, and biological poisons as well as their detection are more recent projects (Solaiman & Sheta, 2013).

2.2.2 Applications in health care

Advanced medical sensors are used by WSNs in the healthcare industry to monitor patients in a hospital or at home as well as to enable wearable device real-time monitoring of patients' vital signs. the major subcategories of WSNs' health applications, such as patient wearable monitoring, home support systems, and hospital patient monitoring, as well as the most frequently used sensor types in them (Kandris et al., 2020).

2.2.3 Applications in the environment

Recently, environmental monitoring systems have been created and used in many different applications to help people with their tasks and save money and time. Environmental monitoring applications have advanced greatly, with examples including agricultural monitoring, habitat monitoring, interior monitoring, greenhouse monitoring, temperature monitoring, and forest monitoring. Because the community has acknowledged the significance of wireless sensor network technology in their everyday life (Othmana & Shazalib, 2012), it is a laudable endeavor that will be advantageous to the community.

2.2.4 Urban applications

WSNs can acquire unheard-of volumes of data about a target location, whether it be a room, a building, or the outside, because to their diverse range of sensing capabilities. With a virtually limitless number of uses, WSNs are a superb instrument for determining the spatial and temporal features of any phenomena in an urban environment. The most well-known WSN applications in the urban environment are smart houses, smart cities, transportation systems, and structural health monitoring (Kandris et al, 2020).

2.2.5 Applications in agriculture

Precision farming entails employing the right amount of input (such as water, fertilizer, etc.) at the right time and place to boost quality and yield while preserving the environment. It is accomplished using WSN, which tracks variables like air temperature and soil moisture before calculating the necessary amounts of water and nutrients. In order to help farmers prevent crop damage and increase agricultural output, WSNs also use irrigation control (Solaiman et al., 2013).

2.3 Online Social Network

2.3.1 Social Network

A social network is represented by a social network graph G, which consists of n nodes signifying n individuals or network participants. The graph's edge Eij represents the relationship between node I and node j. These relationships between the network's participants can be visualized using a directed or undirected graph. An adjacency matrix A can be used to represent the graph, with $A_{ij} = 1$ if there is an edge between I and j and $A_{ij} = 0$ otherwise. The features of social networks are similar to those of complex networks (Fasmer, 2015). Friends-based, telephone, email, and collaborative networks are some real-life examples of social networks. These networks may be seen as graphs, which can be studied and analyzed to uncover intriguing patterns among the components.

2.3.2 Detection of Online Social Network Community

A community is a group of entities that are more closely related to one another than the other entities in the dataset. Individuals develop communities in which members of a group communicate with one another more frequently than those outside the group. Similarity or distance metrics between entities can be used to determine the proximity of a group's entities. Clusters in networks are equivalent to communities in social networks. An individual represented by a node in a graph may be a member of more than one community or group; it could be a member of several closely related or dissimilar groups in the network. A person may be a member of multiple organizations at the same time, such as college, school, friends, and family. Overlapping communities are all such communities that share similar nodes (Bedi, & Sharma, 2016).

3. Material and Methods

3.1 Research Approach

Quantitative, qualitative, and mixed methodologies are the three most often used research methods. The type of information required to address the study topic is anticipated by the researcher. For instance, is it necessary to have textual, numerical, or both types of data? The researcher chooses one of the three aforementioned techniques to conduct research based on this evaluation. For research issues requiring numerical data, researchers often choose the quantitative technique, for questions requiring textual data, the qualitative approach, and for questions requiring both numerical and textual data, the mixed methodologies approach (Vijay, 2015).

3.2 Quantitative research approach

The idea of number or extent serves as the foundation for quantitative research in the natural and social sciences. It has to deal with something that can be measured or expressed numerically. This type of research is an example of systematic experimental examination of observable phenomena utilizing numerically expressed statistical, mathematical, or computational processes, such as statistics, percentages, and so forth (Shanti & Shashi, 2017). This research will be conducted using a quantitative technique.

3.3 Qualitative research approach

On the other hand, qualitative research focuses on qualitative phenomena, such as those involving or relating to quality or kind. We frequently make reference to "Motivation Study," a type of qualitative research, when examining the factors that influence human behavior (i.e., why people think or act in certain ways). Qualitative research is crucial in the behavioral sciences because it helps to uncover the fundamental causes of human behavior. Through such research, we may assess the various factors that influence people's behavior or determine whether they like or dislike a particular object. Descriptive research is typically more challenging to evaluate than quantitative data. Non-numerical data is carefully analyzed in qualitative research (Shanti & Shashi, 2017).

3.4 Datasets to Be Used

The dataset for wireless sensor network could be extracted from (Snap.stanford.edu), while that of online social network could be extracted from (kaggle.com). In another alternative because of the complexity of obtaining the secondary data, the use of simulation can be adopted.

3.5 Research Instrument

Gephi v 0.9.2 could be used in visualizing and clustering OSN, while igraph or networkx library in python could be used to visualize and cluster WSN. The network graph comparison will be done on the python platform using some metrics common to the two types of networks.Apparently, Trust and Reputation Simulator (TRMSim) will be used in the implementation of the proposed framework.

3.5.1 Python requirements (Packages)

The python packages that will be required include; Matplotlib, Numpy, Scipy, Igraph or Networkx, Sklearn (scikitlearn) etc.

3.6 Clustering Method to Be Adopted

There are basically two main clustering methods as mentioned in the previous chapter: hierarchical and partition clustering methods. This study will adopt partition clustering method.

3.7 Network Comparison Approach

Popular approaches for comparing networks include: (i) Graph Isomorphism, (ii) Graph Edit Distance, (iii) Network Alignment and (iv) Feature Extraction (Saxena, Kaur & Bhatnagar, 2019). A theoretically sound method for determining exact matching between two graphs of the same order or whether two graphs are morphologically identical is graph isomorphism. Isomorphic graphs have one-to-one correspondences between their vertices. Given that the problem is NP-hard, it has only limited application to the huge graphs of today. In recent years, there hasn't been much research done in this field of network comparison.

Graph edit distance is a different way of comparing networks that has been used in pattern detection and analysis. This method, which is essentially an error-tolerant method, discovers approximate matching. The network alignment strategy, which is commonly addressed in bioinformatics, has been widely investigated by biologists. The goal of network alignment methods is to identify a match or alignment between two graphs' vertices.

These three approaches result in algorithms that have a large computational complexity and are thus non-scalable. Their application to big networks is hampered as a result of this. Recent times have seen the community interested in evaluating modern graphs embrace the feature extraction approach. In order to quantify differences, the technique entails extracting features from the compared graphs and calculating distance between them. Modern network similarity algorithms use the following three-step methodology to determine how similar two networks are to one another.

i. Feature Extraction: Map the two graphs to corresponding feature vectors derived from graph topology.
ii. Feature Aggregation: To create network signatures, combine feature vectors.
iii. Distance Computation: To determine how similar the two networks are, calculate the distance between signatures.

The feature extraction approach was adopted for this research work.

3.8 Categories of Feature Extraction-Based Network-Similarity Methods

Network-centric and node-centric methods are the two basic categories into which feature extraction-based network-similarity methods can be divided. While the latter method pulls features from nodes or their surroundings (1- or k-step induced subgraph around the node), the former method derives features from the overall network topology.

3.8.1 Network-centric approaches

Network-centric techniques concentrate on network topology and compare networks using global network attributes. These algorithms use properties including graph Laplacian, eigenvalues, density, transitivity, node connectivity distances, and network edge curvatures under heat kernel embedding to summarize network topology (Saxena et al., 2019).

3.8.2 Node-centric approaches

Node-centric techniques analyze network structure using node-centered subgraphs, motifs, egonets, or graphlets. Graphlets are compact, linked, non-isomorphic subgraphs. Many node-centric algorithms take the distribution of graphlets in the network into account when representing the topology of the network. The methods used to create network signatures from the count of graphlets and to compare those signatures differ. This strategy successfully satisfies the goals of researchers in this field because biological sciences graphs are frequently tiny (Saxena et al., 2019).

As mentioned in chapter two, the network comparison methods are broadly divided into two categories namely; Known Node Correspondence and Unknown Node Correspondence. The former compares two or more networks (graph) of similar size and from the same application domain, while the latter compares any pair of networks (graph) including those of various sizes, densities, and application domains (Tantardini et al., 2019). The Unknown Node Correspondence comparison method will be used in this research work.

3.9 Network Comparison Metrics

The similarity metrics to be used will be distance-based which include: Jaccard distance, Euclidean distance, Manhattan distance, Minkwoski distance, Cosine similarity, Centrality (degree, eigenvector, closeness, betweenness centrality etc.).

3.10 Parameters

There are many networks clustering parameters among which are:

Network diameter: The network's diameter is the separation between its two farthest nodes. The average network path length, also known as the network diameter, is frequently regarded as one of the key characteristic parameters to distinguish between different network types, such as regular networks, stochastic networks, and complex networks, and to measure network performances, such as node importance and network survivability. The following is a popular formula for determining the network diameter:

Equation 1:

$$D = \frac{\sum_{i>j} dij}{\frac{n(n-1)}{2}}$$

(1)

From above, that network diameter is visible. D is the proportion of the total number of node pairs to the lengths of all the shortest paths. The network size is represented by the number of node pairs, or n. The shortest path between nodes i and j has a length of dij. The network diameter measures how close together all of the nodes in a network are by describing the average minimum number of edges that can exist between any two of them.

i. Average clustering coefficient: The clustering coefficient is a term used in graph theory to indicate how closely nodes tend to group together in a graph. It displays the strength of the relationship between a node's neighbors, to be more precise. Theproportion of nodes' neighbors, or clustering coefficient, can be defined as

Equation 2:

$$CCI = \frac{2E\text{i}}{k_{i(k_i-1)}}$$

(2)

where Ei is the number of triangles between node i and its neighbors, ki is the number of neighbors of node i, and CCi is the clustering coefficient of node I represented as

Equation 3:

$$ki = \sum_{j\epsilon G} \delta ij \qquad (3)$$

where δij denotes the connection between node i and node j.

ii. Degree distribution: Degree Distribution p(k) is the fraction of nodes in the network with degree thus if there are n nodes in total in a network and n_k of them have degree k, we have:

Equation 4:

$$P(K) = \frac{n_k}{n}$$

(4)

The degree of a node specifies the number of its connections and the probability distribution of the degrees over the whole network forms the degree distribution. Degree distribution is an important and informative characteristic of a network.Although it does not capture all aspects of the topology of a network, it reflects the overall pattern of connections and is an important determinant of network properties. Degree distribution is also a sign oflink formation process in the network.

iii. Density: Density of a network is the fraction of existing edges out of possible edges in the network. Network density is a measure of the percentage of "optional" edges that exist in the network and is given by:

Equation 5:

$$\text{For undirected graphs} \frac{2E}{N(N-1)}$$

(5)

Equation 6:

$$\text{For directed graphs} \quad \frac{E}{N(N-1)}$$

(6)

N isnumber of nodes E number of edges. Higher value indicates dense graph and lower value indicate sparse graph (Bhattacharya et al., 2020).

The research study will adapt the use of clustering and TRM (Trust and reputation model) for the implementation of the research study.

3.11 Proposed framework for clustering and TRM model

The proposed model integrates WSN and OSN and introduces machine learning technique and trust management API.

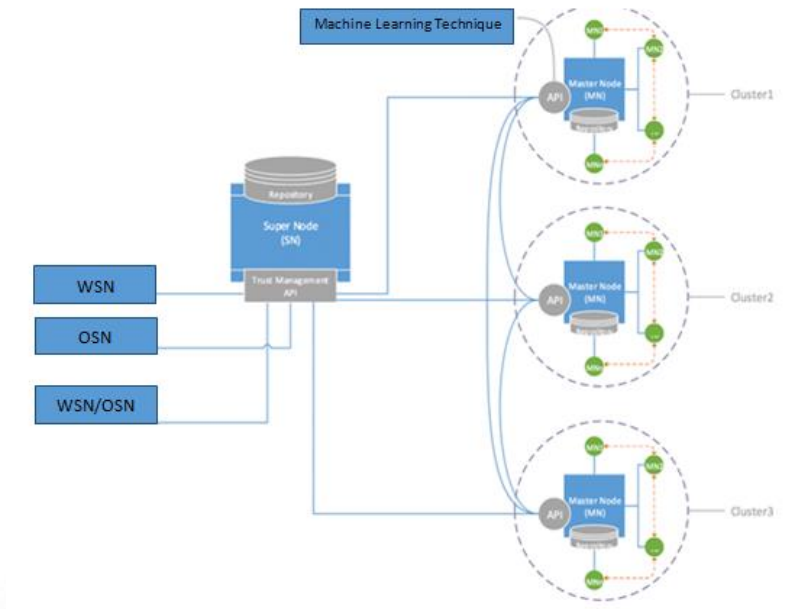

Figure 2: Proposed framework for comparing WSN and OSN

4. Results

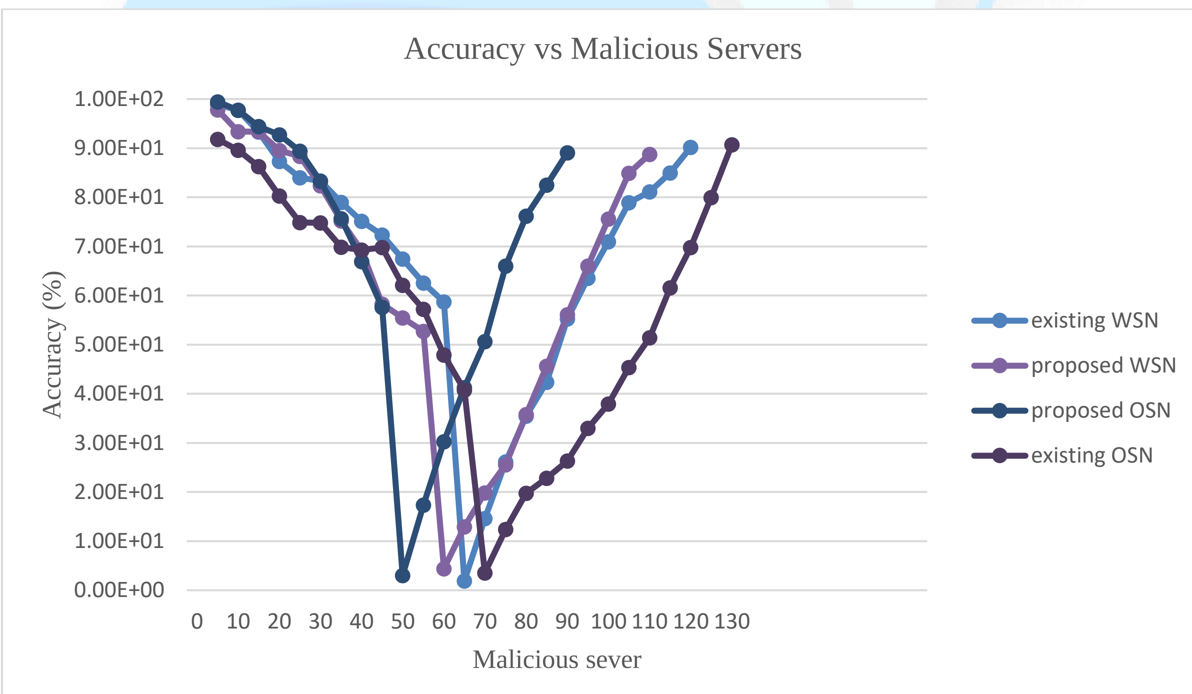

Figure 3: Impact of Malicious Servers on the Network

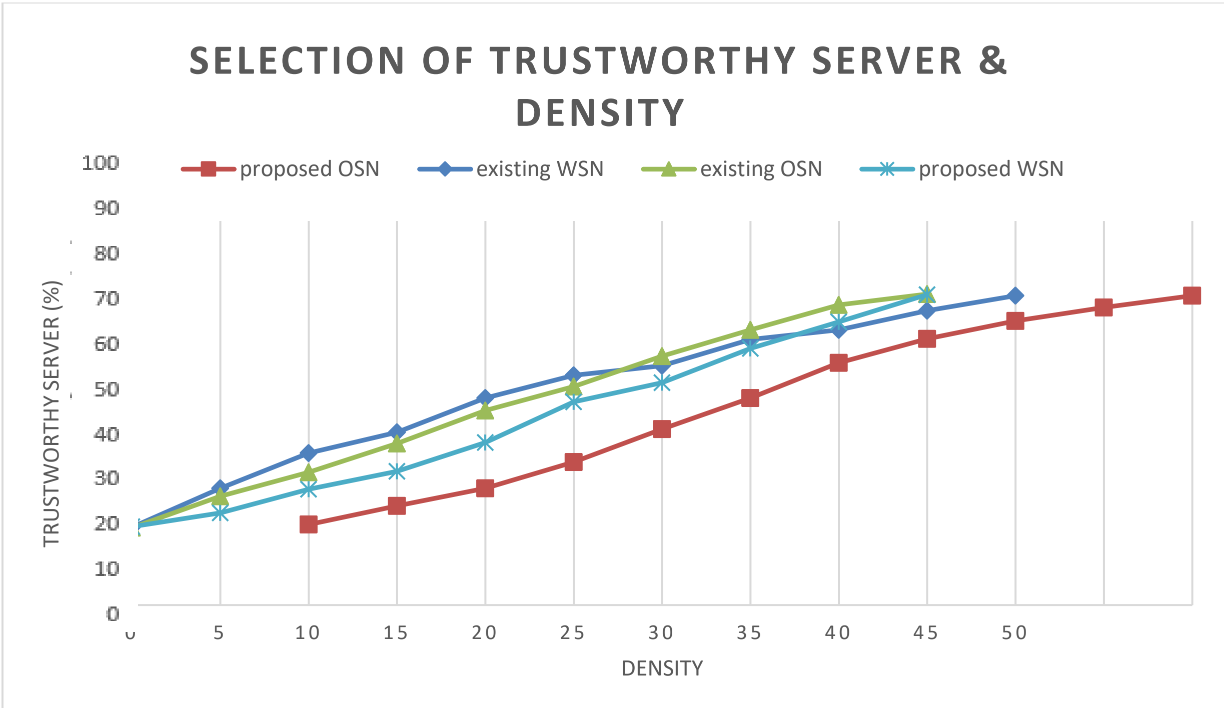

Figure 4: Trustworthiness of Servers and Nodes in the Network

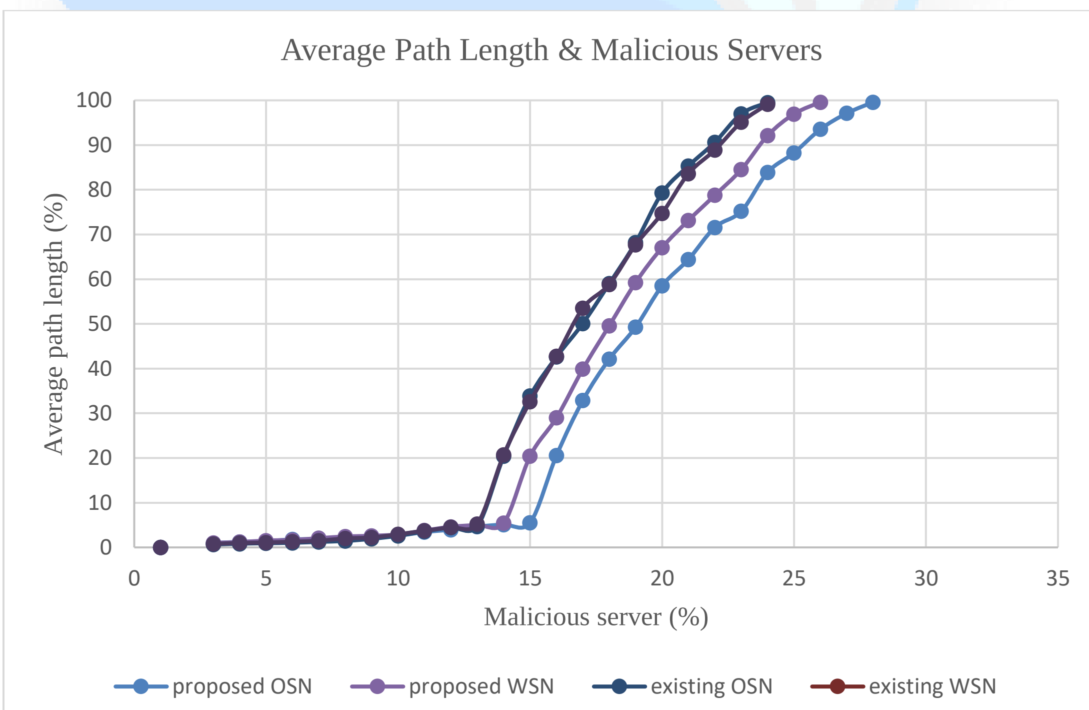

Figure 5: Average Path Length against Malicious Servers

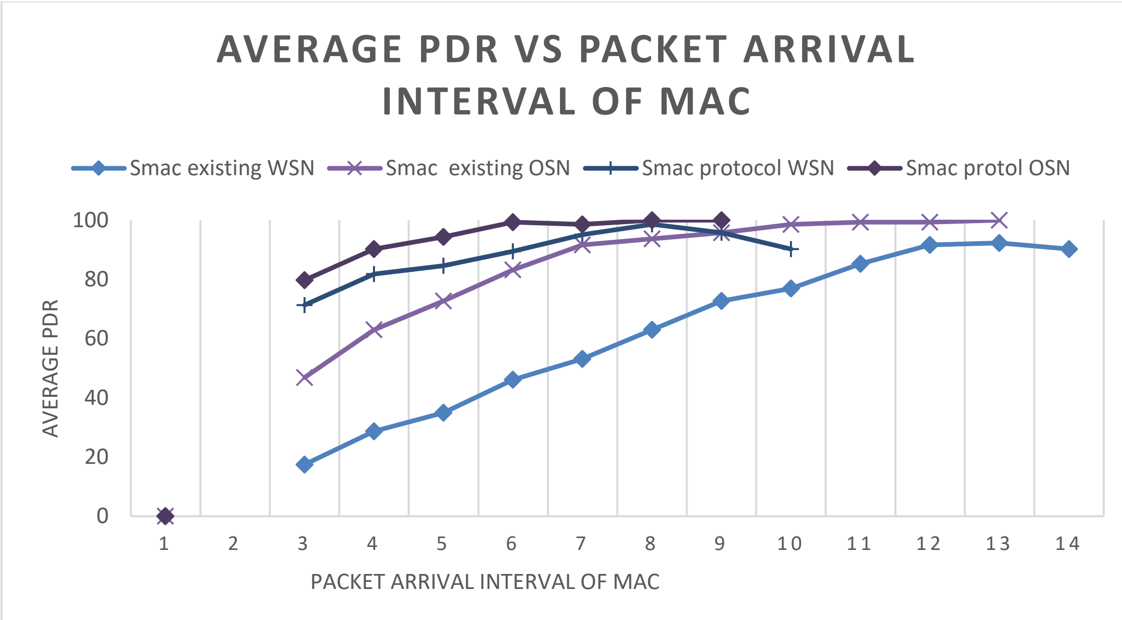

Figure 6: Average PDR against Packet arrival Time.

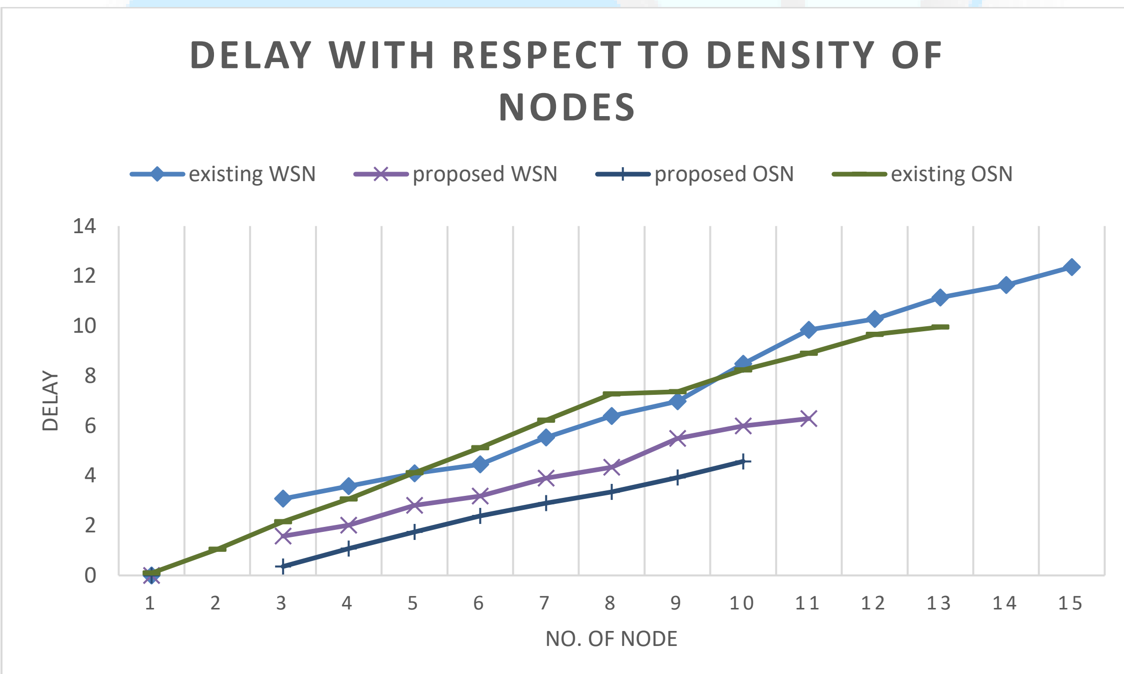

Figure 7: Delay against no of Nodes

4. Discussion

All the four models start with high accuracy, as the number of malicious server's increase, the accuracy of all the models keep dropping. When the malicious servers reach between 50-70 the accuracy level dropped down to almost zero in all the models. And from there the accuracy level start to increase in all the models. The percentage of trustworthy servers gets higher as the density of the network is increasing.

As the number of malicious servers increase the average path length is also increasing in all the four models. Our proposed OSN model seems to perform better than the remaining three model. APL is the average number of steps along the shortest paths for all possible pairs of network nodes. As the percentage of malicious server is too high, the model's performance worsens.

PDR is the ratio of number of packets received at the destination to the number of packets sent from the source. The graph indicates that the average PDR grows higher as the packet arrival interval of mac. Fig 4.11 illustrates the performance of the network in terms of delay by varying number of nodes. As expected, the delay increases as the number of nodes increase.

5. Conclusion

In this research work we have shown the comparison between WSN and OSN, both the models show a reasonably good performance in terms of efficiency, WSN require high efficiency due to their resource limitations, while OSN due to its very large scale also require high efficiency. From the results obtained in this research work the OSN performs better than the WSN. The result indicates that the OSN in all the cases does better than the WSN, one of the reason is that of power, when it comes to cluster head selection the power consumption gets higher unlike the OSN.

6. Recommendations

The work is conducted on simulated network; it is recommended that the study be conducted on datasets as well to see how it will turn out.

It is recommended that the work be implemented in real-life scenario by telecommunication companies.

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