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Enhanced Capsule Neural Network for WSN/IoT

Journal of Electrical Systems

Abstract: - The development in the field of information technology has led to a rapid development in wireless sensor networks (WSN) that are deployed in many applications for their sensing capabilities and other features. In WSN models, each sensor node communicates in a variety of ways to transfer information from the Internet of Things to virtual modules. The clustering process in sensor networks helps improve the quality of the network by controlling the energy consumption rate and improving the data accuracy rate. This research aims to present a model to improve the capsule neural network (caps Net) algorithm by training the capsule weights to obtain the best communication path to the base station (power supply) and selecting the cluster head To model the wireless sensor networks for the Internet of Thing in addition to pruning data and links by improving the link pruning algorithm and thus reducing the network energy level mainly.

Keywords: WNS. Caps Net· Internet of things · Energy· Link-pruning.

1. INTRODUCTION

As a result of the tremendous development in the field of information and communication technology and the computer and mobile phone industry, there has been a rapid development in the field of the Internet of Things (IoT),[1]. which is a modern wireless communication platform containing a set of sensor nodes connected to the wireless sensor network (WSNs). These methods divide the sensor nodes into groups, where each group consists of a cluster head CH node Figure (1) represents a group in wireless sensor networks. The formal scope of this task is to provide a new CH selection in WSN applicable to the Internet of Things using a self-adaptive metaheuristic algorithm [2]. The wireless sensor network, which is essential for collecting data in areas that are difficult to reach and outside the range of communications, is used in applications such as monitoring, detecting objects and events, agriculture, capturing and distributing geographic information, monitoring human and machine health All minor changes in the physical world and even the prevention and control of natural disasters.

It includes many advantages of a wireless sensor network and is more beneficial with energy efficiency, scalability, responsiveness, reliability, and mobility [3]. To address financial constraints, a number of researches have been developed. of these wireless sensor networks and advanced methods to establish cooperation with nodes with the aim of increasing the lifetime and reliability of sensor nodes to reduce energy usage through the availability of energy-aware routing protocols enhanced with quality of service [4].The main focus is to increase the lifetime of the network in any way and for this purpose many protocols are presented which can be classified based on their applications into the following:

A. Proactive routing protocols which are suitable for applications that require information on a regular basis.

B. Reactive routing protocols Nodes sense data continuously but do not send it except at the time when there is a radical change.

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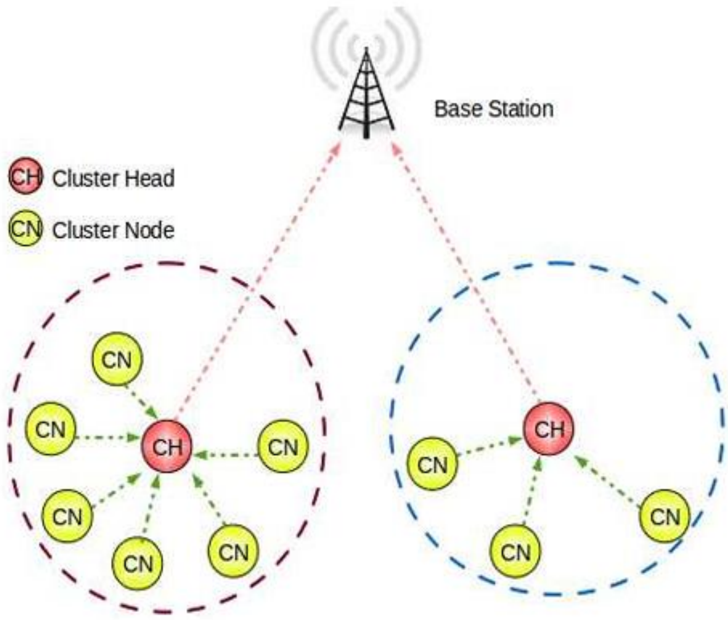

Figure (1): cluster formations in WSN [5].

Recently, artificial intelligence (deep learning and machine learning) has been used to build applicable neural models which is the design of CNN (capsule neural networks) which is effective in improving routing problems to obtain better performance of the sensor network and reduce the network overhead [6].

The use of the neural model of the capsule is to determine the better choice of networks nodes by analyzing the historic behavioral of the driver SNs,[7].

2. RELATED WORK

There are a number of studies and researches that have dealt with the neurons of the capsule network and what is related to them, using a different group of techniques, including the following.

- ***Akyildiz et al,(2008),[8].***

The researchers proposed a wireless sensor network that assists in multimedia data retrieval, To improve, develop, and integrate prototypes to evaluate the protocol and algorithm related to the wireless multimedia network.

- ***Ortega-Zamorano et al,(2014),[9].***

The researchers proposed a study of the fire alarm and weather forecasting situation using an artificial neural network algorithm. The results were analyzed and evaluated, as well as the evaluation of the proposed system.

- ***S.Sabour and S.N.Deepa,(2017),[10]***

In their study, the researchers proposed a description of the possibility The reason is to Use vector activations length of capsules due to the presence in the feature. In their study, they proposed the concept of a capsule network to represent each case of the direction of the capsule's particular activation vector.Umamaneswari S,(2019),[3].

The researcher suggested and demonstrated learning techniques for data and sensors, as well as explained the machine learning system (capsule network). (WSN) to obtain an intelligent way to deal with the dynamic and real environment without human intervention. Due to reducing energy use, this system extends the life of the network, improves energy efficiencies, and improves productivity. The proposed system was validated in network simulation and the effectiveness of wireless sensors with data pruning based on capsule networks was demonstrated. S. Govindaraj and S. N. Deepa, (2020),[11].

The researchers presented a network energy optimization scheme for IoT sensor nodes. A capsule neural network architecture model was proposed to achieve better performance by reducing the energy cost of an IoT-assisted wireless sensor network (WSN). The simulation results obtained demonstrated the reliability and effectiveness of the proposed CNN learning to improve the energy optimization of IoT sensor networks compared with previous studies and research.

- ***Arivazhagu, U. ,(2023),[12].***

The researchers proposed a novel Gated Capsule Networks (GCN) to improve the accuracy of abnormal behavior detection of wireless networks and design an efficient intrusion detection system that can achieve a good balance between energy and accuracy. A comparative analysis was conducted using learning for different attack predictions in WSN_IOT. The proposed framework achieved an ideal performance in terms of accuracy (99.99%).

- ***K. Saritha and V. Sarasvathi ,(2024),[13].***

The researchers proposed a Hybrid Cross-Layer Air Quality Prediction Protocol (HCL-AQP) framework where the Wireless Sensor Network (WSN) topology is built by the Adaptive Spherical Clustering (AB-KC) algorithm to reduce the power consumption and thus enhance the sensor coverage. Then, the lifetime of the sensor and the UAV are guaranteed.

3. Capsule Networks (Caps Net)

Capsule Networks were proposed by Hinton and his colleagues[14]. as a substitute for CNNs. A network of neurons that accepts and outputs vectors as opposed to CNNs' scalar values makes up capsules, which are equivariant. A capsule's ability to learn an image's features in addition to its deformation and viewing conditions is made possible by this property. Each capsule in a capsule network consists of a collection of neurons, with each neuron's output representing a distinct aspect of the same feature. This gives the benefit of perceiving the entire element by first perceiving its parts. The output (or features) of a CNN is the input to a capsule. Depending on the type of capsule used, these features are processed. A case's result is made out of the likelihood that the element encoded by the container is available and a bunch of vectors esteems ordinarily called launch boundaries. The probability of the capsule's feature being present is responsible for guaranteeing the network's invariance. The network's equivariance, or capacity to recognize poses, textures, and deformations, is represented by the instantiation parameters. A model's decision to remain unchanged in the face of input modifications is known as invariance. CNNs are unique in their translational invariance type. For instance, if a CNN is to recognize a face, no matter where the eye is positioned, it will still recognize the face. However, equivariance guarantees that the face's features' spatial location is taken into account. Therefore, the location of an eye in the image is taken into account by equivariance as well as its presence in the image. For Caps Nets, equivariance is a desirable property.

In the literature, there is a set of three methods used for so-called capsule applications. Their function is to change the autoencoders [14]. Capsules based on dynamic orientation, or what are known as vector capsules, [15], and capsules based on expectation-maximization orientation, or what are known as matrix capsules [16].

CNNs create structures similar to neural networks using hierarchical connections. In contrast to convolutional neural networks, which significantly lose information regarding the spatial location of the object, which is a critical element in both detection and segmentation. With the development of the capsule neural network by Geoffrey Hinton, it is believed that the drawbacks of the convolutional neural network have been solved. The CNN architecture consists of three basic layers: input, hidden, and output. The three additional layers added to the hidden layer are the convolutional layer, the initial capsules, and the lower and upper layers, which are commonly referred to as digitizers [17]. More accurately than a convolutional neural network, Caps Net recognizes overlapping images and sounds. Convolutional neural networks are less effective than capsule neural networks in identifying and measuring structural defects due to the presence of measurement within both objects and the latter's inability to calculate the rotation of objects.

The process of collecting information in the current CNN capsule is similar to the human brain during the process of collecting the necessary data, through the hierarchical form resulting from segmenting and linking the set of images into smaller units or parts, and this provides the possibility of obtaining a higher and more accurate level of learning than convolutional neurons. What increases the classification accuracy characteristic of the capsule, increases the accuracy in classification [18].

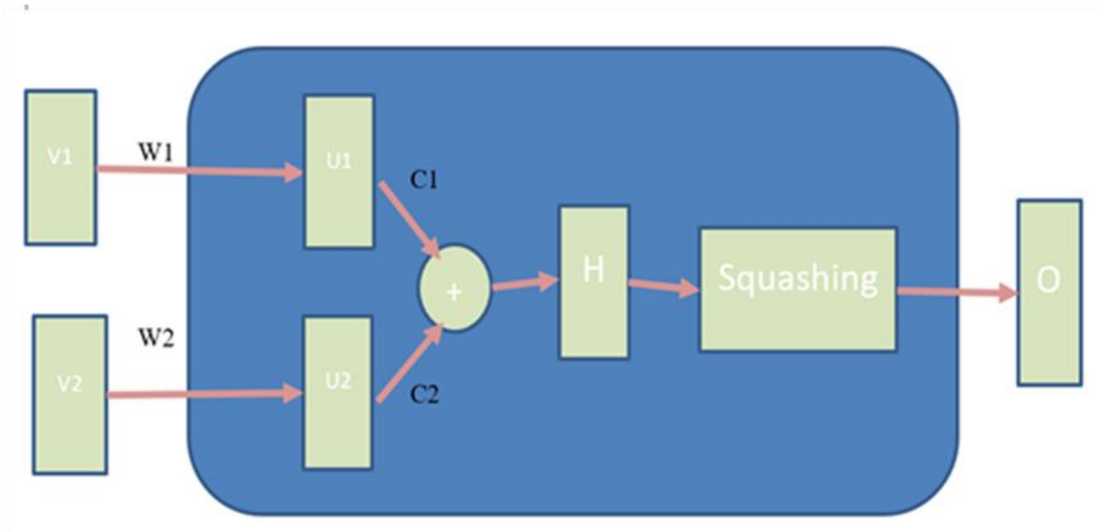

Figure (2): Capsule

CNNs consist of more capsule than the previous neural network, which consists of neurons. Each CNN capsule has a distinct meaning and direction. Different aspects of a given object are represented in the image through the activation of neurons within the capsule. These properties can contain a wide range of compositional features, such as mode (position, size, and direction), reflection, distortion, tone, texture, and speed. At the network level, CNN has a large number of layers. The lowest level of the capsule, known as the perceptual domain, uses only a small portion of the image as input and attempts to determine whether a particular pattern is present and how to subtract it. The Higher levels of the capsule, known as vector capsules, use the entire image as input. At higher levels, this is used to detect larger and more complex objects. The output vector of capsule length indicates whether an object is present, and its direction indicates the object's orientation properties. If the position of the model changes slightly, the capsule vector product will remain the same length instead of changing direction slightly. If the output capsule in a CNN is eight-dimensional, the effect of the capsules is isotropic as a result, for example, the probability that there is an object represented by its vector length, and various properties of this object are also represented, such as in the angles of rotation or the exact location of the object, In terms of classification accuracy, the capsule network is superior to the convolutional neural network and has interpretable activation vectors when using the MNIST dataset. Despite the advantages presented by the study, it also turned out that the capsules do not deal with huge sets of data. Figure (2) shows the capsule diagram.

Equation No. (1) represents the relationship between the inputs and outputs of the capsule [3]

$$Oj = \frac{\|Hj\|^2}{1+\|Hj\|^2} \frac{Hj}{\|Hj\|} \tag{1}$$

Where Oj this is considered ejection of the capsule and Hj This is considered the total of his input.

“For all but the first layer of capsules, the total input to a capsule sj is a weighted sum over all “prediction vectors” ˆuj|i from the capsules in the layer below and is produced by multiplying the output ui of a capsule in the layer below by a weight matrix Wij” [3] .

$$Hj = \sum_i Cij \times \mathrm{Uj|i} \tag{2}$$

$$\mathrm{Uj|i} = \mathrm{Wij} \times \mathrm{Ui} \tag{3}$$

By performing an iterative dynamic routing process, Cij is determined as coefficients [3]. The formulas are used in [19]. To be able to define group heads in a wireless sensor network. Threshold Sensitivity, an interactive protocol, was used to modify the protocol of LEACH to fine-tune cluster heads in a wireless sensor network.

A minimal, interactive protocol for modifying the protocol of LEACH to, Identifying group heads in a wireless sensor network.

$$Nnrm = \frac{Nopt}{1+m.\alpha+b.\mu} \tag{4}$$

$$Nint = \frac{Nopt.(1+\mu)}{1+m.\alpha+b.\mu} \tag{5}$$

$$Nadv = \frac{Nopt.(1+\alpha)}{1+m.\alpha+b.\mu} \tag{6}$$

The quantum formulas in [19] are intended to determine different energy levels of nodes in WSN by using three levels of heterogeneity and the different energy levels of nodes are:

1- regular nodes.

2- Intermediate nodes.

3- Advanced nodes.

Since they have a greater power level than that of regular nodes as well as intermediate nodes, advanced nodes are often used to form a cluster head in the network.

3.1. Capsule's Calculation

$$U1= W1V1$$

$$U2= W2V2$$

$$S= C1U1 + C2U2$$

$$O = Squash (H)$$

$$O = \frac{||H||^2}{1+||H||^2}\frac{H}{||H||}$$

The output of the capsule is represented by O, while the input vector given to the capsule is represented by H.

The Parameters Equation

1- ***Packet delivery rates (PDR)***

At the base station, the number of received packets is measured as a ratio of the total number of packets as well as the packet delivery ratio (PDR).

$$PDR = \frac{No.of\ Received\ Packets}{Total\ No\ Of\ Packets} \tag{7}$$

2- ***Productivity***

WSN transport parameters measure the delay in packet deliveries to base stations.

$$Throughput = \frac{No.of\ Received\ Packets}{Delay\ Time} \tag{8}$$

3- ***Delays***

Delays are considered to be the time differences between the beginning of data collection in the sensor until it is delivered to the base stations.

$$Delay\ Time = T_{PacketReceived} - T_{packetSent} \qquad (9)$$

4- *energy*

1. The initial node energy is $E_o = 2\ Joules$
2. This indicates that each node consumes 5 nanojoules of energy when transmitting and receiving, and thus:

$$E_{T_X} = E_{R_X} = 50 \times 10^{-10}\,Joules \qquad (10)$$

When transmitting, There are two types of energy consumption present in each node

a. If the distance of the transmissions D It is considered less than d_o, this generates new energy called wasted energy.

$$E_{diss} = E_{T_X} + 10^{-11} \times D^2 \qquad (11)$$

b. When the transmission distances D is greater than d_o, the results for dissipation energy are as follows:

$$E_{diss} = E_{T_X} + 1.3\ \times 10^{-15} \times D^4 \times Packet_{Size} \qquad (12)$$

The data collection capacity consumes all its nodes upon reception E_{aggr} which is:

$$E_{aggr} = E_{R_X} + 5 \times 10^{-9} \times Packet_{Size} \qquad (13)$$

3. No of alive Sensors

No of alive Sensors is

$$AliveSensors = no\ of\ sensors\ that\ have\ energy > 0 \qquad (14)$$

Figure (3) represents the probability of convolution with the original capsule outputs.

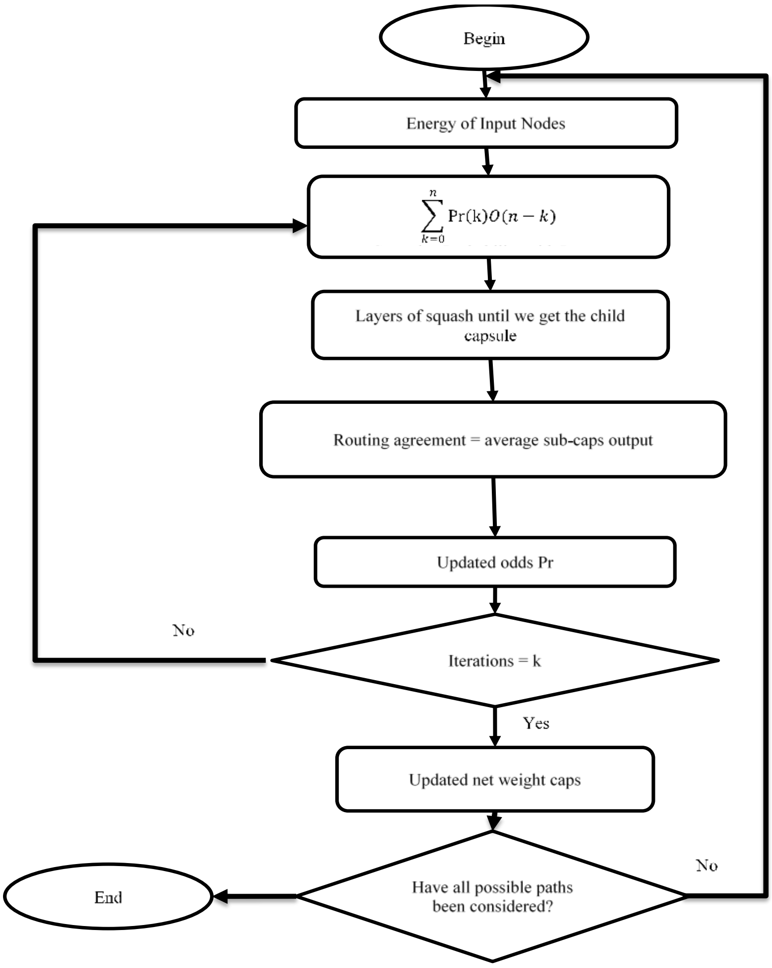

Figure (3): Capsule paths.

4. Proposed model

The proposed model aims to improve the capsule neural network algorithm (Caps Net) and improve the link pruning algorithm as shown below.

4.1 Proposed Caps Net Algorithm

In this section, a proposal for improving the capsule neural network algorithm (Caps Net) is presented by training the capsule weights to obtain the best connection path to the base station (energy provider) and selecting the cluster head Wireless sensor networks model for the Internet of Thing in addition to pruning the data and thus reducing the energy level of the network basically. Algorithm (1) shows the main steps that were taken to improve the capsule algorithm.

Algorithm (1): The Algorithm Proposed for Caps Net

Input: Shows node energies data

Output: shows all the net weight trained for the a best path until we reach the basic stations (conservative energies)

Step 1: Input the nodes' energy

Step 2: The algorithm combines the probability with the outputs from the parent capsules.

using the following equation:

$$\sum_{k=0}^{n} \mathbf{Pr(k)}\boldsymbol{O}(\boldsymbol{n}-\boldsymbol{k})$$

Step 3: Squash the input values in the squash layer to get the child

capsule probabilities O. The squash layer output is:

$$\boldsymbol{O} = \frac{\left|\left|\boldsymbol{H}\right|\right|^2}{\mathbf{1} + ||\boldsymbol{H}||^2} \frac{\boldsymbol{H}}{||\boldsymbol{H}||}$$

where H is the input of the squash layer.

Step 4: The average ejection time of the subcapsules is the orientation agreement.

Step 5: The squash output is 0 and this is the probability update

Step 6: If the number of repetitions= m

Then perform the procedure to update the net weights in Caps and then go to step number 7

Eles requirement is not done, go to step 2

Step 7: If we take all path from the live node into account

Then after that step 8 (the end)

Else If not, go back to step 1

Step 8: END

4.2 Proposed Link-Pruning Technique

The routing procedure in WSNs represents the majority of energy consumption, so it is better to suggest improving the network lifetime and energy usage. This technique is used after the Caps Nets training step. Sensor nodes that consume a higher energy level and that are far from the head of the group (the link to it is broken) are cut off to give the best energy paths to preserve the network lifetime.

In Figure 4, the correlation pruning is shown in a step after obtaining the probability from learning using Caps Nets. The sensor will be selected as CH if the probability is greater than 0.01 (pruning). Algorithm (2) represents link pruning.

Algorithm (2): The Link Of Pruning

Input: Sensors' Energy **Output: Pruned Clusters WSN**
Step 1: Input the sensors' energy **Step 2: i=0** **Step 3: If energy of the ith Sensors E(Si)> 0 then Go To Step 4** **Else Go To Step 7** **Step 4: If the ith Sensor was cluster head then Go To Step 5** **Else Go To Step 7** **Step 5: Get Probability (Pr) using algorithm (1)** **(The proposed Caps Net Algorithm)** **Step 6: If Pr < 0.01 Go To Step 7** **Else pick the ith sensor (Si) as a cluster head and Go To Step 7** **Step 7: i =i+1** **Step 8: If i >= No of Sensors then Go To Step 9 (END)** **Else Go To Step 3** **Step 9: END**

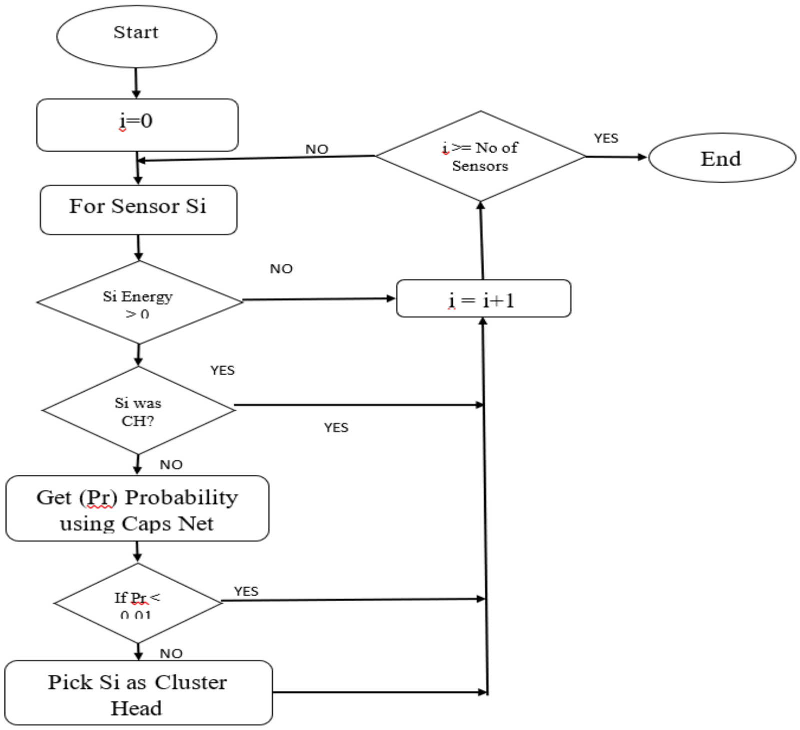

Figure (4): The flow diagram of the Link-pruning

4.3 Optimization method with group head selection: Energy optimization method with group head selection in WSN

To improve energies and choose the head of groups in wireless sensor networks (WSNs), this is considered a relatively new field of study that still uses Capsule Neural Networks (Caps Nets). However, we can apply the mathematical formulas used in Caps Nets (which were discussed in Section 3).

5. THE RESULTS OF SIMULATION

In MATLAB environments, the activities of educational neural networks (Caps Nets) have been verified and developed to select head groups in a wireless sensor network. To compare the results of Caps Nets with LEACH and the improved LEACH protocol by arranging 100 nodes in an area of a 1000×1000 grid with initial parameters, as shown in Table 1.

Table 1: Proposed network parameters

Simulation parameters	**The value of the Parameter**
Node	100
Area	1000 * 1000
Initial energy	2 J
This is considered the upper limit for the number of all rounds until we compare with Leach and modified Leach LEACH and Modified LEACH	500
It is considered the upper limit on the number of rounds of capsule neural network scenarios	1000
Comparing Pruned-Caps with Firefly in seconds of simulation.	1000

5.1. Results

Below are the results of the simulation implementation of the proposed model

1. Comparing the remaining energy in joules for each round of the different orientation protocols and comparing it to the proposed caps and pruned caps approaches. Figure (5) shows the comparison between rounds and the residual energy in Joules for each leach, modified leach, caps and pruned caps.

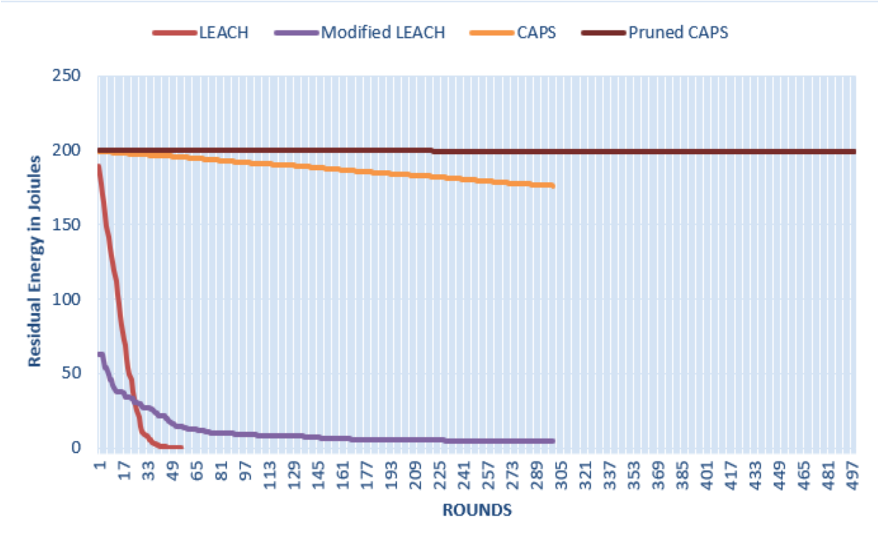

Figure (5): Comparison between residual energy and rounds

2. The figure (6) shows alive sensor per round for different routing protocols and compare it to the proposed CAPS and Pruned CAPS approaches.

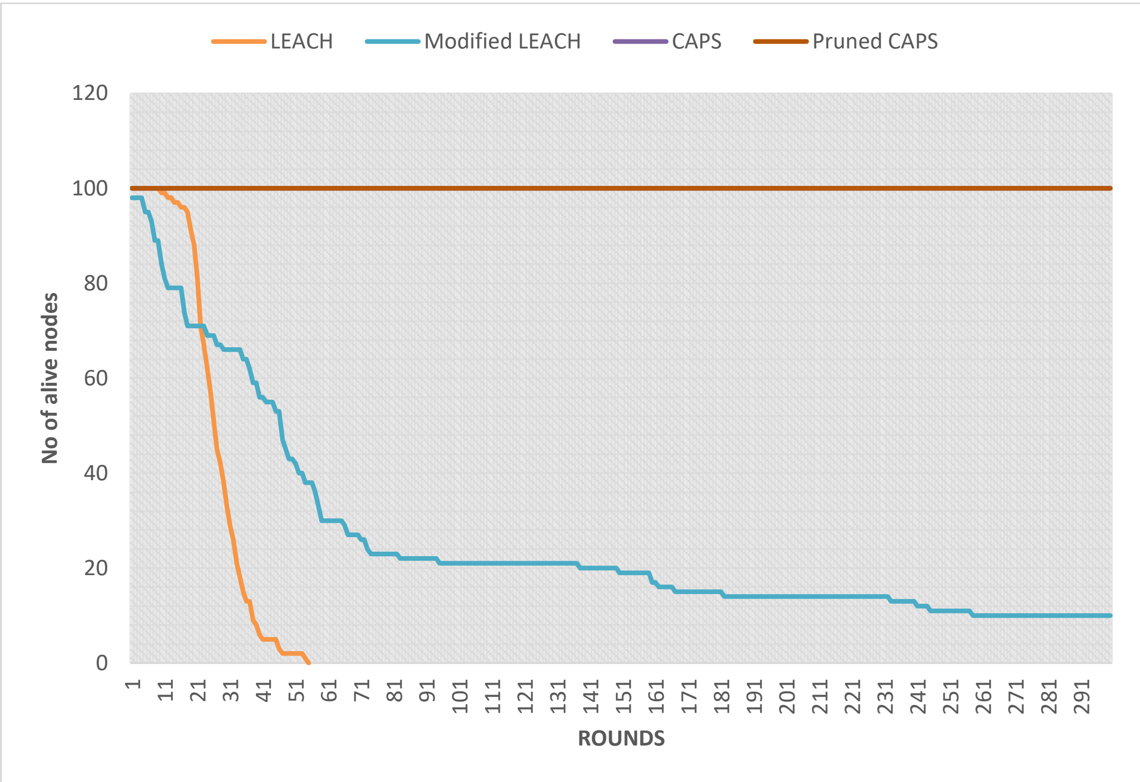

Figure (6): The relationship between no of alive nodes and rounds

3. Figure (7) shows a comparison between Compare packet delivery ratio (PDR) for CAPS and pruned CAPS

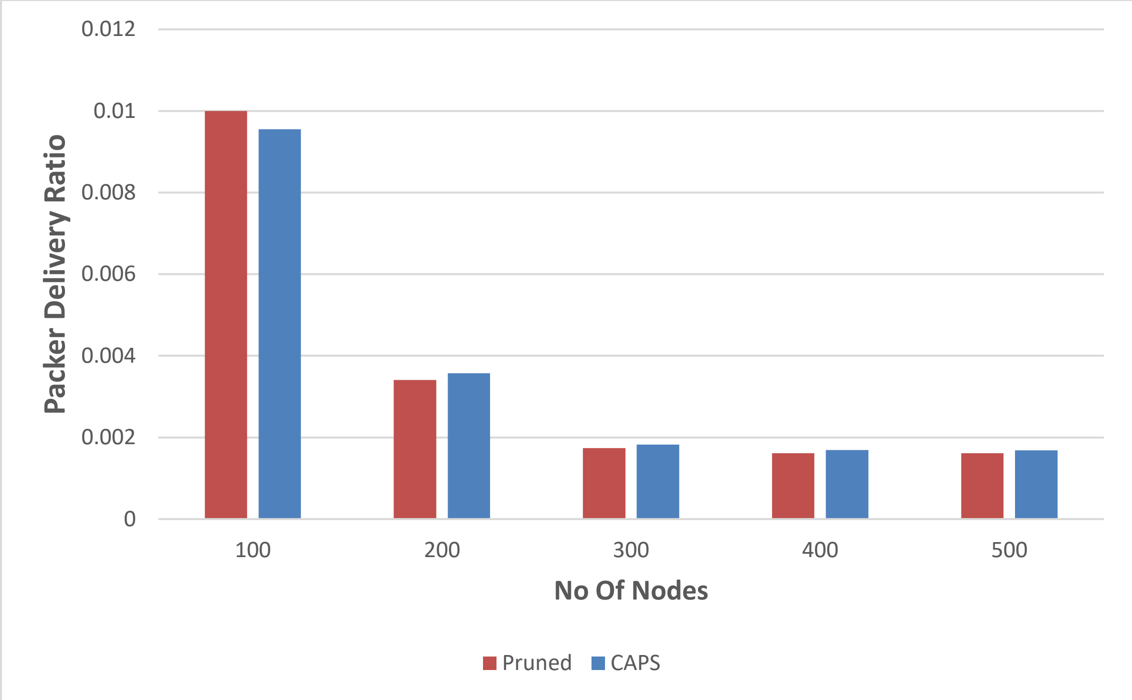

Figure (7): The relationship between PDR and no of nodes

4. Figure (8) shows a comparison between delay time for CAPS and pruned CAPS

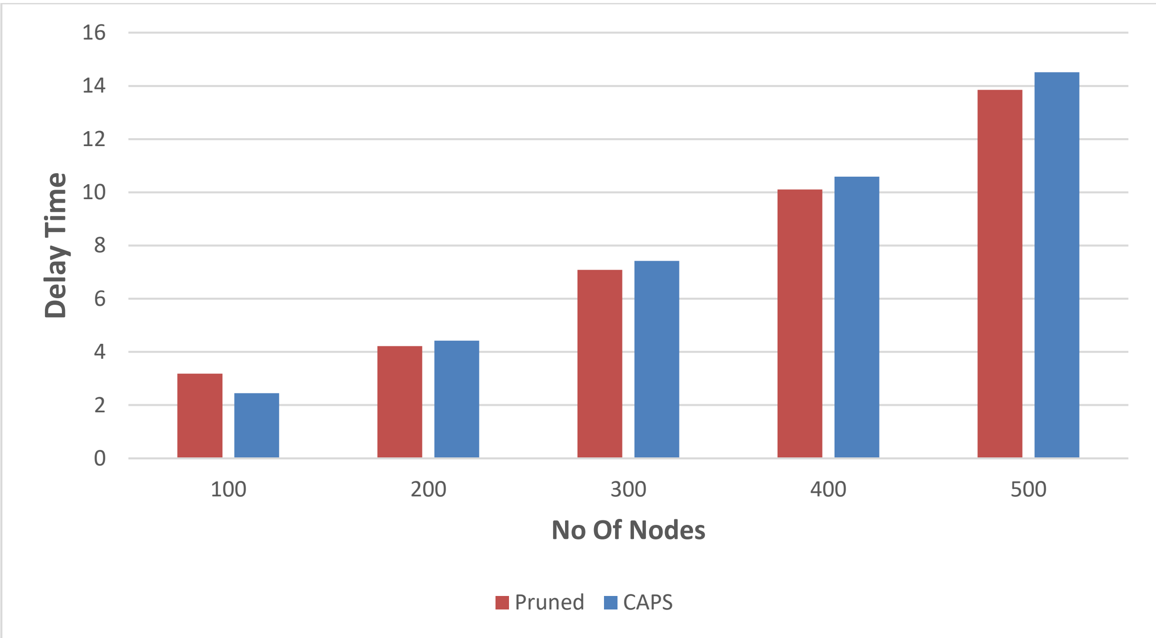

Figure (8): The relationship between delay time and no of nodes

5. Figure (9) shows a comparison between average throughput for CAPS and pruned CAPS

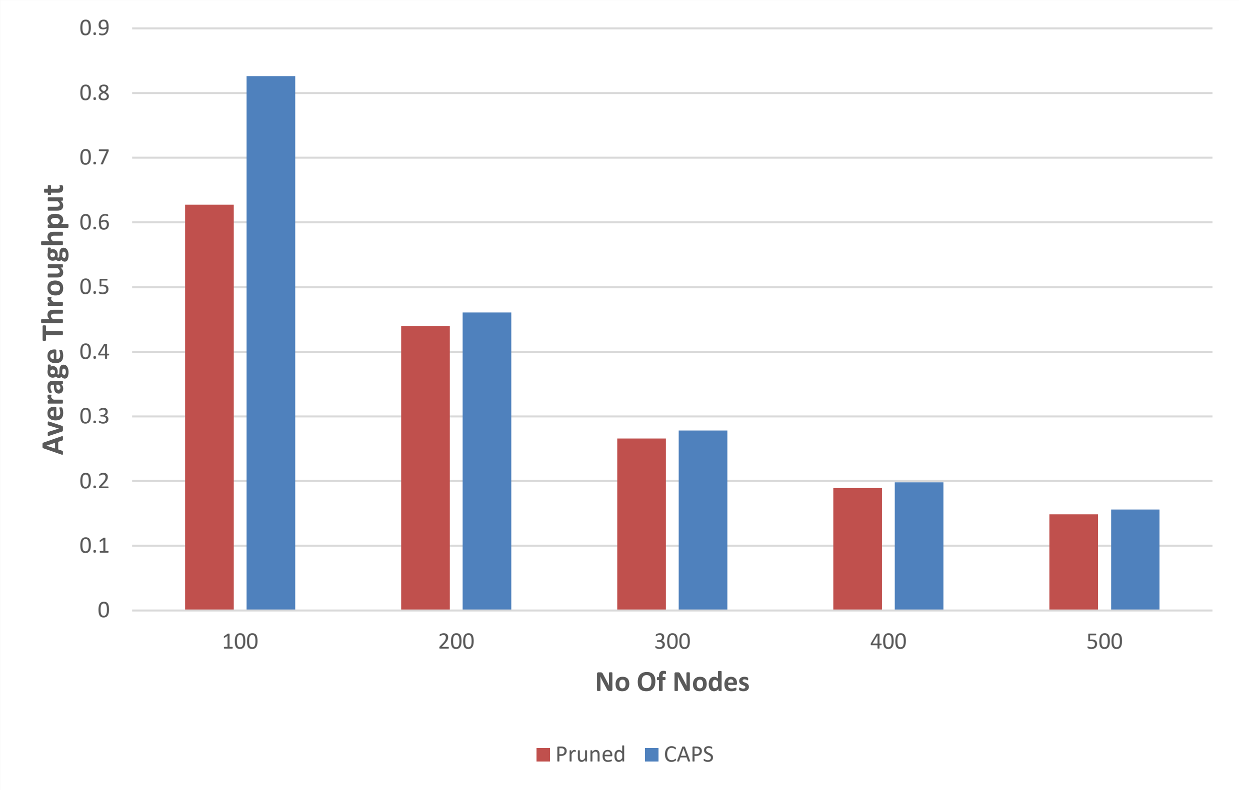

Figure (9): The relationship between average throughput and no of nodes

5.2 Discussion of the results

In the Caps Nets algorithm, the simulation results were more improved in the remaining energy as well as the number of parameters in the live sensor nodes in the WSN network compared to the LEACH and MOD-LEACH algorithms, and the throughput parameters, the results showed an improvement in delay time and PDR than the LEACH and MOD-LEACH algorithms, due to the complexity. The problems of sensor nodes in networks are considered to be grouped to conserve energy. The proposed model (Caps Nets) is considered to conserve energy as much as possible for CH.

To enhance the Caps Nets algorithm, link pruning was proposed, and this technique gave results of a significant improvement in the number of remaining energy. Of the sensor nodes alive.

When the numbers of nodes increases (more than 100 nodes) in the WSN network, we notice the results of the Link-Pruning technique and the Caps Nets algorithm in the case of the packet receipt ratio parameter. By making a comparison between them, it turns out that Link-Pruning is better than the Caps Nets algorithm in cases of the delay factor at Increasing the number of nodes (more than 100 nodes). So, we will get results close to each other.

6. Conclusion

Wireless sensor networks that are involved in sensing, processing, and running real-time applications include a set of vulnerabilities because they operate on a battery. The proposed method, in order to improve the capsule networks and prune the data and links, enables the cluster routing of the wireless sensor network to work on building an efficient model with low power. This results in a longer lifespan for the network. In the proposed research, the effectiveness of the developed Caps Nets learning neural network for selecting the cluster head in wireless sensor networks was verified by arranging 100 nodes in a 1000 × 1000 network area to compare the results of Caps Nets with LEACH and improved LEACH protocol with initial parameters. The results of the Caps Nets algorithm showed a significant improvement in the remaining energy parameters and the number of live sensor nodes for wireless sensor networks when compared to the LEACH and MOD-LEACH algorithms links were given an improvement in the Caps Nets algorithm and this led to an improvement in the score

In the remaining energies and the number of live sensor nodes, so when the number of nodes increases to more than 100 nodes, this indicates that the link pruning algorithm is better than the Caps Net algorithm.

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