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COMPARISON OF EXISTING CLUSTERING AND OPTIMIZATION ALGORITHMS IN IoT NETWORKS

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Abstract
The "wireless sensor networks (WSNs)" are the most important aspect of the growth of "Internet of Things (IoT)" over the recent years with an increasing range of applications like agriculture, healthcare, etc., especially for tracking and monitoring, which are usually associated with security issues. Sensors can be used in large, remote, and unpopulated areas in some applications and track congested and busy spaces. It is very important to cluster the nodes of a sensor network into multiple clusters for common scalability reasons. They can also devise usage or maintenance schedules that might improve the lifetime of the network.
The WSNs are an important aspect of the daily lives of people in the future. The sensor nodes need very little energy. Failure of a single node of the network or WSN can pose serious damage to the operation, especially when it is used in healthcare and the military. Power-saving is a major issue in wireless networks. Various optimization techniques can be used to get ample output in every situation where it is possible to save energy. Sensor deployment and routing are two major issues to get fruitful results with optimization models. This paper briefly discusses optimization algorithms used in IoT networks. This paper also compares existing and advanced clustering algorithms to analyze their performance.
Keywords: *Internet of Things, optimization algorithms, clustering algorithms, sensors, IoT, wireless sensor networks*

1. Introduction

IoT or Internet of Things consists of different interrelated wireless devices, users, and smart objects that can exchange information over the wireless network automatically. It is possible to realize the vision of IoT with WSNs. WSN is among the promising technologies in wireless networks. There are several deliberations that future WSN applications should adopt software and hardware (Parwekar et al., 2018). Hence, network designers manage to harmonize the trade-offs to save implementation costs and boost performance. Sensor nodes are spread in WSN randomly in large amounts from hundreds to thousands in a network.

In different areas, the sensors can be used to gather data from environmental aspects like pressure and temperature. It is possible to use multi-hop routing to transmit the data using other nodes from source to destination. Ultimately, users can access the data using the web in real time (Ahmad et al, 2015). WSN takes a lot of resources like bandwidth, memory, and energy.

Energy is a vital resource as nodes are operated by batteries in WSN. The sensor nodes rely on non-rechargeable batteries and it is not possible to replace them. The sensors or the network last longer with effective approaches in energy storage.

1.1 Background

Data can be shared with neighbors with a set of "wireless mobile nodes (WMNs)" and "wireless sensor network-enabled Internet of Things (WSNIoT)", which can manage various applications like flood control, rescue operations, international border monitoring, disaster management, and communication in the battlefield. The clustering techniques can do wonders once the WSN-IoT size turns into a vast network as compared to flat WSNs despite implementing a routing structure (Gupta & Kumar, 2000). In flat WSN, scalability is a serious issue when a huge number of mobile knots should be moved to various directions.

In WSN-IoT, when the number of wireless mobile networks is x with a flat routing setting, the complexity of the "proactive routing network" is going to be $O(x^2)$ (Belding-Royer, 2002). With the growth of wireless mobile networks in WSN-IoT, there is also a rise in routing overhead with the ratio of double the WMN count. Similarly, the reactive routing models cause delays in route setup with the rise in WMNs in WSN-IoT. In addition, the request for flooding route packets may simultaneously increase to cause slowdowns in the network. A hierarchical structure is needed to achieve the assurance of elementary performance in the large size of WSN-IoT (Perkins, 2008). The clustering organization is a simple implementation of a hierarchical plan. It is challenging to form clusters to design "cluster-based routing" schemes as choosing the right CH-set is hard (Basagni, 1997).

It is very important to plan a clustering model for routing the details related to "Quality of Service (QoS)" for studies related to WSN-IoT. The main prototype here is clustering and there are two ways to list its importance. First, clustering structure can be used to manage WSN-IoT structure meritoriously. Secondly, there are hundreds or thousands of wireless mobile networks in an ordinary WSN-IoT. Extra packets are transmitted to sink nodes from the source in a flat WSN-IoT configuration (Shah et al, 2017). There are chances that scalability issues may take place with flat WSN when it comes to elevating the WMNs in wireless networks and it may saturate the network. In WSN-IoT, the wireless mobile networks may move and make it extra stimulating to control the scalability in terms of static networks. So, cluster-based routing can be effective in managing WSN-IoT. In addition, clustering can solve queries like developing a virtual network, controlling topology, and discovering intrusion (Azni et al., 2016).

2. Literature Reviews

Considering the recent advancement of smart networks and "Software Defined Networking (SDN)", **Al-Janabi & Al-Raweshidy (2017)** further investigated the high-density WSNs. WSNs have their issues which affect their performance like limitations of sensor resource which affect memory, power supply, processing, and communications. They proposed "Whale Optimization Algorithm (WOA)", a new clustering method based on SDN. It considers both random diversification of density of nodes and sensor resource limitations in an area. It splits

the area of sensing by SDN controller into "virtual zones (VZs)" to manage the "cluster heads (CHs)" as per the node density in each virtual zone.
It became important to choose cluster head in IoT devices connected to WSNs with the rise in use of IoT devices in different applications like monitoring, industries, and smart homes in recent years. **Janakiraman (2018)** proposed a "Hybrid Ant Colony and Artificial Bee Colony Optimization Algorithm-based Cluster Head Selection (HACO-ABC-CHS)" technique for selection of cluster head while avoiding issues of ABC and ACO mutually. Employee bee agents are used to prevent the stagnation issue in intensification of ACO and to resolve the problem of delayed convergence in "onlooker bee stage" of ABC by splitting the exploitation process in two levels by using the "employee bee phase".

There are usually a lot of challenges in giving better energy optimization and performance in IoT for smart cities. The nodes are categorized as clusters in WSNs and IoT which form "cluster head (CH)" to gather data from all nodes and transmit the same to base station. **Alazab et al. (2021)** used a clustering model on inter-distance and intra-distance between nodes and CH to achieve various objectives like reducing delays and energy sustainability. In IoT devices, optimization variables like delay, distance, and use of energy are considered for selection of desired CH.

In an IoT network, sensor nodes constantly generate data which directly affects the longevity of the network. Despite the significant potential of IoT applications, there are various challenges like load balancing, privacy, security, storage, energy optimization and heterogeneity of devices. Energy utilization should be optimized and is very important. The power consumption of sensor nodes affect various factors like temperature, residual energy, number of nodes alive, cost function, and load of CH. **Maddikunta et al. (2020)** designed "Moth Flame Optimization (MFO)", a hybrid "Whale Optimization" model to choose the right cluster head, which ultimately optimizes the above factors.

IoT is widely used in agriculture, weather forecasting, smart city, waste management, and smart grids. Although IoT has significant potential in some areas, it still needs improvement. **Iwendi et al. (2021)** conducted a study to reduce the power consumed by IoT sensors which increases network lifespan. They have selected the best possible CH in the IoT network to save energy. They used a hybrid model "Whale Optimization Algorithm (WOA)" while using "Simulated Annealing (SA)". They have used various performance metrics like load temperature, alive nodes, cost function, and residual energy to choose the right CH in IoT network clusters.

2.1 Research Gap

Clustering is common in studies conducted on IoT and WSNs as a subroutine of scalable routing and they have various specialized roles in academia. However, there is a lack of comparisons and general overviews of existing optimization and clustering models. In addition, a lot of studies present state-of-the-art methods and the popular K-means method without proper assessments of issues of this method. This study is aimed to fill this gap.

2.2 Research Question

- What are the existing clustering methods used in IoT networks?
- What are the use cases and pros and cons of clustering techniques?
- What optimization algorithms are used for "Wireless Sensor Networks" or IoT networks?

2.3 Research Objectives

- To discuss modern clustering methods used in IoT networks
- To compare use cases and pros and cons of clustering techniques
- To compare optimization algorithms for "Wireless Sensor Networks (WSNs)"

3. RESEARCH METHODOLOGY

To fulfill the above objectives, this study is based on secondary data collected from various relevant studies on optimization algorithms and clustering models used in wireless sensor networks and IoT networks. The data has been collected from various databases like Science Direct, ELSEVIER, SciHub, Google Scholar, etc.

4. ANALYSIS OF STUDY

There has been a rise in a number of connected devices and objects that generate big data to identify trends and gather data for different purposes. This is where clustering is very important for IoT devices (Wang et al., 2019; Sakthidasan et al., 2019; Zhang et al., 2018; Amaxilatis & Chatzigiannakis, 2018). There are different benefits of clustering as it makes IoT network scalable and saves routing overhead by handling the routing decisions on the selected "cluster heads (CHs) (Yang et al., 2017; Lin et al, 2018). In addition, it saves bandwidth and reduces expenses for maintaining topology. Additionally, just the gateway and cluster heads are the lifeblood of the network to make topology easier and reduce flooding, overhead, and clash. The only task of devices is connecting to the cluster head and forwarding the information without having any impact of changes in the inter-cluster head tier. The number of exchanged data packets is reduced with the combination of collected data on the cluster head. In the end, several management strategies like scheduling can save energy sources to implement on cluster head level and improve the network lifetime (Rajasegarar et al., 2006; Bakaraniya & Mehta, 2013; Pavithra & Ghuli, 2015).

4.1. Existing Clustering Methods used in IoT networks

Clustering is helpful in different ways to improve the operational safety and quality of WSNs, while improving their lifespan. The situation varies network to network, as per the scope, number of sensors, resources, and quality of data generated. It is not worth relying only on one way of clustering for all situations for different reasons like hop-by-hop routing, aggregation, and data clustering for implementation. Hence, several modern clustering techniques are introduced or recalled with interest in IoT.

4.1.1. K-Means

The data is clustered by K-Means to separate people into groups with reduced inertia or total intra-cluster squares. Table 1 has presented its common use case and Table 2 represented its pros and cons. With k as initial centers, the "$\Omega = \{x_1, \ldots, xm\}$" is partitioned in "$k$ disjoint subsets" in order to reduce "Euclidean distance" among each x_i and its center which is assigned. The following equation helps reduce the criterion -

$$\min\left\{\sum_{i=1}^{k}\sum_{x_j\in C_i}||x_j-c_i||,(C_1,...,C_k)\in P(\Omega)\right\}$$

Here,

- $P(\Omega)$ refers to a range of potential Ω subsets.
- c_i is at the core of C_i cluster.

One can choose the initial centers in different ways and the algorithm iterates in the following ways –

- Each x_i is assigned to the closest center c_j.
- Each center is revaluated as average of closest x_i.

4.1.2. K-Means++

It is very important to elect initial centers for K-means which significantly affects the outcomes. Here, "K-Means++" is an initialization model, which avoids selection of first centers. Here are some of its principles –

- Random selection of initial centers with "non-uniform probability" principle.
- Proportional chance of selecting an initial center point to the square of distance to the selected centers.

Here is the algorithm for writing this –

Algorithm 1 K-means++ initialization

Require: K: Number of clusters
Require: m elements x_i to be clustered
  $c_1 \leftarrow x_1$
  for $k = 1, ..., K-1$ **do**
    $s_0 \leftarrow x_0$
    for $i = 1, ..., m$ **do**
      $s_i = s_{i-1} + min(||x_j - c_1||^2, ..., ||x_j - c_i||^2)$
    end for
    pick r randomly in $[s_1, s_m]$
    find l such that r belongs in $[s_l, s_{l+1}]$
    $c_j \leftarrow x_l$
  end for

4.1.3. K-Medoids

The "Partitioning Around Medoids (PAM)" or K-Medoids helps in adopting K-Means to reduce the distance between cluster points and their center (26). Medoids are important for clustering sets, which is not common in K-means. Hence, a Medoid is an individual cluster with minimal average to the individuals of other clusters.

4.1.4. Gaussian Mixture Model (GMM)

It makes K-means more flexible with an assumption that each point has been collected from Gaussian distribution in the observed sample and its parameters rely on the cluster it comes from. Hence, circular clusters are no longer assumed for elliptical shapes in 3D. Then, the probability associated with its mean vector defines each cluster.

4.1.5. Hierarchical Clustering

These algorithms are either bottom-up or top-down. It is started from simple clusters where it is aggregated in pairs until a final cluster is reached. The bottom-up method is known as "agglomerative hierarchical clustering" and is shown as a dendrogram. The root is the last cluster with leaves in the form of data points.

4.2. Use Cases and Pros and Cons of Clustering Techniques

There are various clustering techniques listed in Table 1 along with their parameters, size, numbers and geometry.

Table 1 – Clustering Techniques and their Use Cases

Techniques	Parameters	Size	No. of Clusters	Geometry
Birch	Several	Large	Large numbers	Non-flat
"Affinity propagation"	"Damping sample preference"	Diverse	Large numbers not scaling up with individuals	Non-flat
DBSCAN	"Neighborhood size"	Diverse	Very large range of individuals; average no. of clusters	Non-flat
Hierarchical	Distance, link type	Diverse	Several samples and clusters	Hierarchical
GMM	Number of clusters	Non-scalable	Non-scalable	Flat
K-Means	-do-	Regular	Not too many clusters	-do-
K-Medoids	-do-	-do-	-do-	-do-
Spectral	-do-	Diverse	Small	Non-flat
Mean-shift	Bandwidth	-do-	Many	-do-

Table 2 illustrates the pros and cons of each clustering technique that is widely used in existing IoT systems these days.

Table 2 – Clustering Techniques and their Pros and Cons

Clustering Technique	Pros	Cons
Birch	- Reduces data and deletes outliers - Ideal when plenty of subclusters are needed	- Not adaptable to large datasets (generally used for "MiniBatchKMeans")

Affinity Propagation	- Doesn't need a number of clusters - The damping factor is the main parameter. The number of clusters is reduced by increasing it.	- Quadratic complexity - Convergence may be non-existent
GMM	- Intuitive algorithm with enhanced likelihood - Soft clustering with all clusters - Estimation of density	- Not so scalable
DBSCAN	- Priority to the number of clusters is not needed - Helpful to identify noise or outliers - Helps to find clusters of arbitrary shapes and sizes - Ideal for homogenously dense clusters	- Not sufficient when various densities of clusters are to be found - Not sufficient for ultra-high dimension
Hierarchical clustering	- Does not need a number of clusters - One can choose the most appropriate number of clusters afterward - Doesn't need to choose distance - Compatible for naturally hierarchical data to recover hierarchy	- Ideal for hierarchical data - Outliers have vast impact on it - Comparatively slow
K-Medoids	- Ideal when outliers are present and against noise	- Requires choosing number of clusters
K-Means	- Fast - Easy to deploy - Proven for a lot of applications - Scalable for plenty of individuals and reasonable no. of clusters	- Requires choosing the number of clusters - Not so good out of spherical clusters - Not so consistent due to random initialization and different clustering is produced by different runs
Mean-shift	- Doesn't need to prioritize no. of clusters - Convergence of centers of balls for highest density	- Not easy to fix window size
Spectral	- Effective for limited affinity matrix	- Requires number of clusters

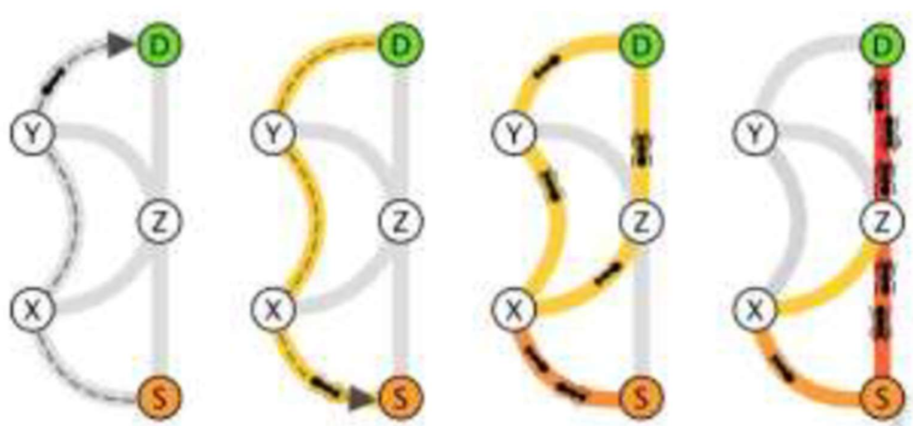
- Ideal with non-convex cluster	- Cannot work when no. of clusters is too many

4.3. Optimization Algorithms for IoT Networks

There are so many optimization algorithms provided based on swarm behavior. When it comes to IoT network, a sensor node has two important operations to perform – as data transmitter and data generator. Both the operations are energy-hungry. Some minimum energy is needed for data sensing. By choosing the path between receiver and sender wisely, it is possible to save enough energy. This way, the sensor can be deployed wisely in the field to cover maximum area by least number of sensors to save energy. Optimization algorithm is applied in both cases to find the right solution.

Kassabalidis et al. (2001) proposed an optimization algorithm which relies on ant routing behavior. The shortest path is considered to transfer the data to save energy. The result was better than traditional approaches like broadcasting or flooding. As illustrated in Figure 1, Ant should find the path from source to destination. Various ants follow various paths and share data with other ants. They eventually find the shortest available path from source to destination. Though they find the shortest path from sender to receiver, they divert all the traffic to the shortest path which causes congestion which leads to maximum consumption of energy at a specific path, which leads to node death.

Figure 1 – Ant Routing for Path Selection



Source - Kassabalidis et al. (2001)

Later, Camilo et al (2006) modified the "ant colony algorithm" suggested by Kassabalidis et al. (2001). Along with considering the shortest routing path, they also considered sustainable path. This algorithm has been named as "Energy Efficient Ant-based Routing Algorithm (EEABR)". This algorithm performs better than previous one. Then, this optimization algorithm was compared with "Basic Ant Based Routing (BABR)" and "Improved Ant Based Routing (IABR)" algorithms (Table 3). They used 50, 30 and 20 Joules of energy on each network. The output was compared for "Energy Efficiency, Minimum Energy, Standard Deviation, and Average Energy". It is observed that EEABR was found to perform better than other optimization algorithms for IoT networks. There is a catch with that algorithm as they haven't considered the issue of balancing energy. Each node consumes energy to send and sense data. So, energy balancing is important among them.

Table 3 – Difference between EEABR, BABR and IABR Algorithms

Criteria	**EEABR**	**IABR**	**BABR**
Average Energy	High	Medium	Low
Minimum Energy	High	Medium	Low
Energy Efficiency	Good	Good	Poor
Deviation	Low	Medium	High

Agraval et al (2010) combined an optimization algorithm and a typical routing algorithm. This way, the "LEACH model" is combined with the "ant colony algorithm" for best output. The "LEACH-Ant" model is used in vast networks for better output than using just the LEACH algorithm (Table 4). Initially, the rate of data transfer is almost similar. However, there was a rise in the rate of data transfer for "Ant-LEACH algorithms". In the "Ant-LEACH algorithm", there is a higher lifetime of nodes and there is a larger number of nodes after a while in active mode.

Table 4 – Difference between LEACH and LEACH-Ant Optimization Algorithms

Criteria	**LEACH**	**LEACH-Ant**
Capacity of Data Transfer	Low	High (performance improves as time passes in comparison to LEACH)
Lifetime	Low	High (50% growth as compared to LEACH)

5. RESULTS

For helping in communication infrastructure, the evolution of IoT is helpful for new services for different fields like smart city, home network, medical, logistics, retail, and aeronautics. However, this evolution has become a new challenge for handling management and usage of the network. Apart from Carnot Institute, there are joint ventures like Orange, Alcatel, and Thales which identified some of the major challenges in IoT networks for awareness among several academicians (IMC Alliance, 2011). Here are some of the open challenges to deal with for optimizing IoT networks –

- **Routing** – An efficient network depends upon network architecture and topology. There is a need to address an efficient routing mechanism to send data packets in mesh topology as IEEE 802.15.4 is the best IOT technology.
- **Mobility** – It consists of changing the subnet of mobile IP from its attachment point to the IP backbone network. The common mobile structure consists of various or single nodes

and routers of the network with specified topology. A mobile network is visited by mobile nodes or other structures in complex structures. Handover is widely needed for mobility, i.e., changing the point of attachment of the mobile node to the network (Manjula et al., 2008).

- **Multicast** – It is used to notify or show the presence to other nodes or to send resource requests from the given source (IMC Alliance, 2011).
- **Security** – It is the most important requirement for any connected device because of higher vulnerability. People trust the secured data of the product or technology to avoid malicious activities. IoT devices that are not secured can cause attack to the entry point and attackers may cause malfunctioning or reprogramming of devices. Poor design exposes applications or devices to data theft as it is connected to the internet (Porambage et al., 2016). For example, a smoke detector which is not secured is more prone to network attacks when connected to the internet and sends fake alarms or notifications once it is infected.
- **Interoperability** – It is caused due to heterogeneity among communication and protocols of devices or objects. Various IoT devices use various network technology. So, there are several interoperability issues to deal with (Ishaq et al., 2013).

6. Conclusion

IoT networks have advanced significantly in this day and age with a lot of real-time applications where mobile devices and sensors are interlinked and connected to the web with IP-based protocols. Organizing networks is one of the major challenges for IoT in the future. This paper has discussed some of the modern clustering and optimization algorithms used in IoT networks. This study has highlighted use cases and the pros and cons of those models. The researchers observed a vast diversity in clustering algorithms. There is no single rule to choose the best clusters. Several optimization algorithms are compared for optimizing IoT networks in routing to save energy.

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