FACETED AND CROSS NETWORK SIGNIFICANCE ASSESSMENT, THE CROSS -LAYER EXPOSURE OF THE POWER COMMUNICATION SYSTEM

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ABSTRACT:

A "smart city" is created when a city's physical and social infrastructures are connected with information technology, allowing the city to pool its resources and expertise. Smart cities depend largely on wireless sensor networks for the management and upkeep of their infrastructure. Air pollution, garbage collection, traffic flow, and power consumption are just some of the issues that may benefit from the use of today's sensor technology. The data acquired by sensors does not magically organize itself in a database, despite the smart city movement's reliance on sensor technology. Complex database architecture is required for such attempts to provide effective outcomes. In addition, with little forethought, a wireless sensor network's energy efficiency might be improved. This design will extend the life of wireless networks. To better organize geographical database data gathered by wireless sensor networks (WSN), for this research we came up with a new strategy. In order to tackle the several issues that arise from strategically placing sensors across the city's three-dimensional urban landscape, the smart city makes use of a specific algorithm called the 3D geo - clustering algorithm. The algorithm's objective is to minimize the number of overlapping clusters. It's hard to exaggerate the benefits of overlap when it comes to cost-cutting. As a result, only one signal will be sent to the cluster's head node even if the sensors are discovered to be members of two or more group clusters. It has been shown that this method would only provide a 5-10% overlap between various groupings. In this study, we put the algorithm through its paces in a variety of scenarios. The simulation results demonstrate that this approach may keep the nodes' energy usage consistent, which eventually results for better resilience for of the network. In addition, it has great scalability and stability. In order to ensure that the approach used to evaluate the database's performance is reliable, it is tested several times.

1. INTRODUCTION

It is called a "smart city" when it is run in an environmentally responsible and technologically advanced way. A smart device is one that incorporates and monitors several infrastructures and services (Giffinger et al., 2007). The urbanization of the world's population has had a disproportionately detrimental impact on resources like climatic change and other environmental challenges. By next couple of years, more than 68% of the global mankind is projected to resides in cities, according to the United Nations (Nations, 2018). Because of this growth, present energy consumption and environmental changes will be significantly impacted. Hence, to overcome this difficulty, we need to build greener and more energy- efficient cities with superior infrastructure.

Based on the work of P Hancke and Silva (2012), sensing may be thought of as the central processing unit (CPU) of smart infrastructures. It can maintain a watch on the city's public infrastructure, such as roads, bridges, and buildings, by monitoring itself. A real-time monitoring system has the potential to save expenses by eliminating the need for periodic inspections. In addition, it would help with accurate load forecasting and energy conservation via its calculation of energy. This is especially important for smart machines.

Simply said, a sensor is an object that can detect and respond to changes in its surrounding conditions. The modification is a piece of data that will be processed and sent. Binary (on/off), acceleration, or other values like temperature, humidity, or location might be derived from the signal. Sensors that work in 'real time' Hence, it may produce a large amount of data. The main job of a sensor is to collect data. Energy management, environmental preservation, and human health are just few of the many issues that sensors are employed to investigate (Ho et al., 2005, Patel et al., 2012, Zhang et al., 2017).

Distributed, highly specialized sensors form the basis of a wireless sensor network. In smart cities, wireless sensors are essential for the management of services. For smart cities to function, wireless sensor network must be used for various forms of communication and data collection. For instance, sensor may be used to determine which lanes to close off open up in order to ease traffic congestion. When equipped with sensors, a route-planning system, and the appropriate staff and tracks, dumpsters may be useful for garbage management.

Figure 1 depicts how sensors are used in smart cities. The infographic illustrates how important sensors are to the backbone of smart city infrastructure. Despite the importance placed on sensor technology in a smart city, the data collected by sensors does not necessarily organize itself in a database. It takes a sophisticated database design to make any useable information from such operations. In this research, we will develop a unique method for storing data collected by wireless sensor networks in ageographical database.

The following section of this article discusses the difficulty and motivation behind smart cities and wireless sensor networks. In section 3, the concept of the proposed method and its application are introduced. Results from the analysis and experiments are reported in Section 4. Part 5 gives the results.

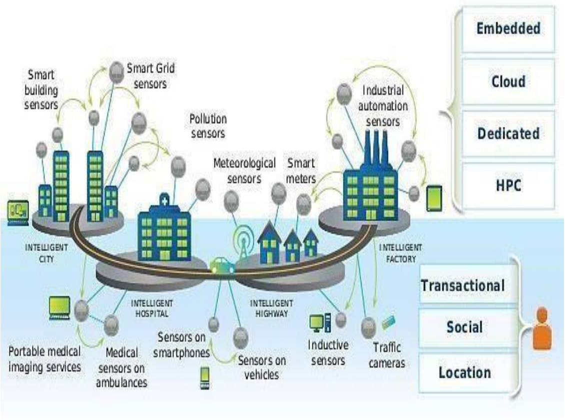

Figure 1. Sensors in smart city.

2. RESEARCH PROBLEMS AND MOTIVATIONS

In this part, we will examine the history of the problem in wireless sensor networks and explore the many clustering methods that have been proposed to far. After that, we'll talk about how we've come up with a solution for 3D geo- clustering, which we've identified as a key part.

The Architecture of Wireless Sensor Network

Smart cities rely heavily on sensor technology. It may produce a wide variety of data types for use in many contexts. For instance, camera sensors may create still images or even real-time video streams. Sensors in the smart grid may detect outages, flaws, and load, and then report that information in real time and trigger warnings if necessary.

Sensor data is an essential part of the IoT. (IoT). An IoT device may be assigned a unique identifier (UID) and can share information with other devices through a network. Sensors supply most of the communicated data, per (Zaslavsky and Georgakopoulos, 2015). Large amounts of sent data may give a wealth of information. This is reportedly the next obstacle in the way of data management.

The city is represented by a web of linked sensors. The difference between them lies in their networks, both wired and wireless. In recent years, researchers in the fields of networking and operating system design have shown a great deal of interest in the wireless sensor network (Baccelli et al., 2013, Dutta and Dunkels, 2012). This is because it is impossible to set up a wired network in particularly challenging or dangerous terrain, making the process of setting up the network much easier. Connected sensors, for instance, would be impractical to set up in a forest, but wireless ones might be dropped from a plane.

Most wireless sensors will operate in an unmonitored and unrestricted environment. As saving electricity will be a top priority, the sensor will run on batteries. According to, transmission costs must be higher than the cost of computing locally (Pourmirza and Brooke, 2012; Miettinen and Nurminen, 2010). This is because sending massive volumes of data over long distances may put a strain on a network and shorten its useful life.

Across sensor networks, nodes serve as hubs for processing, acquiring data from sensors, and interacting with other nodes. Each node has a limited number of resources at its disposal, including memory, transceiver, central processing unit, and power. In addition, a node might have either a homogeneous or heterogeneous composition. The location of nodes in a network is very important. A greater degree of overlap will exist between nodes that are physically close together, since they share the same environment and hence get identical sensor data. This situation would lead to a lot of redundant data entry. Locating the nearest sensor nodes is essential for maintaining network equilibrium and maximizing energy efficiency.

Wireless sensor networks' aforementioned characteristic exemplifies the value of a well-organized network. As stated by the research team of (Govindan et al., 2002), sensor networks benefit most from bottom-up, data- centric routing algorithms. Yet, database applications use a top-down approach to data modeling. When seen as a whole, however, it is obvious that a database can readily accommodate the structure of a wireless sensor network. The nodes and the wireless sensor network are shown in Figure 2.

Clustering the Wireless Sensor Network

Moreover, data aggregation may help reduce energy consumption and overhead transmission in wireless sensor networks. Clusters may be used to realize this concept, which allows for the grouping of sensors into a wide variety of configurations. Network clustering refers to the process through which groups of nodes are divided up. The lifespan of the sensor network may be prolonged by using clustering (Keynes and Punithavathani, 2017, Abbasi and Younis, 2007, Gupta and Pandey, 2016). It's also possible that the network's scalability and upgrade plans will pan out.

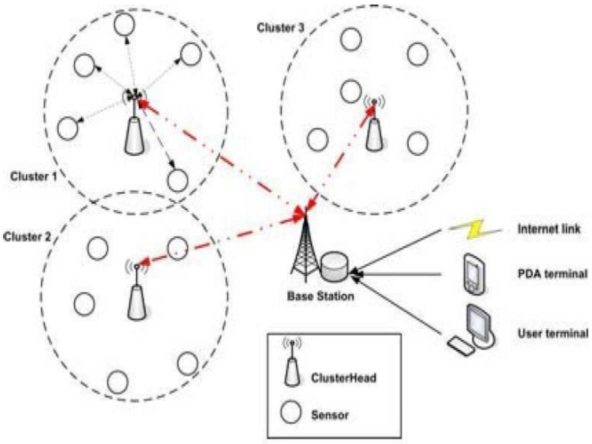

Figure 2. Wireless sensor network and nodes (Dechene et al., 2007).

There are a variety of applications for wireless sensor network segmentation. Algorithms like LEACH (Low Energy Adaptive Clustering Hierarchy), PEGASIS (Power Efficient Gathering in Sensor Information Management), and LCA (Low Complexity Algorithms) have been designed for this same purpose (Linked Clustering Algorithm). Here, we go into detail about how each algorithm works.

PEGASIS

PEGASIS, or Power Efficient Gathering in Sensor Information Systems, organizes sensors into grids in order to more effectively collect data (Lindsey and Raghavendra, 2002). Hence, clustering like this is included into location-aware routing. An important characteristic is that it may operate independently of a predefined routing table. PEGASIS uses a near-perfect chain-based protocol. In comparison to LEACH, this is a significant improvement. Communication between nodes occurs only between adjacent nodes; signals and information are sent between nodes in sequence.

LEACH

Low-Energy Adaptive Clustering Hierarchy (LEACH) is a hierarchical approach for grouping data. One of the main aims of this kind of clustering is to maintain the same amount of energy while using multiple-hop paths (Rhim et al., 2018). Using this strategy, data may be sent while minimizing energy use. The LEACH algorithm utilizes cluster-head node rotation at random to ensure that power in sensor networks is distributed fairly (Heinzelman et al., 2000). Localized coordination is employed to improve the method's scalability and robustness.

LCA

Linked Clustering Algorithm (LCA) is a heuristic algorithm, therefore it may make snap judgments (Singh et al., 2010). This method is designed to find the optimal solution in a practical amount of time. The search does not depend on a single deterministic feature, which might possibly increase its effectiveness. In an LCA network, each node has a specific label. There are two possible routes to it becoming the leader of the cluster. Unless one of the neighboring nodes is already the cluster leader, the node with the higher ID takes charge of the group (Dechene et al., 2007).

Nevertheless, the aforementioned techniques are typically designed for 2D network sensors. Placement of sensors in the real environment is a three - dimensional problem. A few examples of probable placements include the building's front, the tower's peak, or the roof of a moving vehicle. A 3D-like data clustering is required for this purpose. The use of a 2D coordinate system to position sensors raises the possibility of erroneous readings and unnecessary interventions. Sensors on a building may not all be represented in a 2D image. If the scenario is shown in two dimensions, overlapping sensors will seem to be a single sensor.

The clustering process also often disregards overlaps criteria. We consider this to be an important step in reducing the amount of human intervention required to identify nearby nodes with whom to make contact. Thus, this research suggests a clustering method based on 3D sensors. This approach almost eliminates the possibility of overlapping groups. In the next section, we'll discuss our chosen approach in further detail.

3. 3D GEO-CLUSTERING

3D geo-clustering is a method for organizing sensor data that considers its geographical environment. These days, sensor clustering techniques typically employ a 2D clustering approach. The main issue with this approach is that it ignores the objects' actual locations. In the real world, sensors are often placed and positioned in a three- dimensional space. Video surveillance sensors, or closed-circuit television (CCTV) systems, are often put in visible locations such as the outside of buildings, the summit of mobile phone towers, and the tops of cars. Advantages of three-dimensional placement have been highlighted by(Stoter and Zlatanova, 2003). They found that users and decision-makers had a better understanding of the information when it was presented in 3D. That's why reducing its size will result in a loss of information. This study proposed 3D geo-clustering as a means of arranging sensor data. Figure 3 displays the findings of several urban sensor simulations. Sensor data and geographic coordinates are kept in a database. Using the collected data, the precise positions of the sensors are calculated and sent into a 3D geo-clustering algorithm. After that, a parallelepiped in three dimensions is drawn around each of these spots

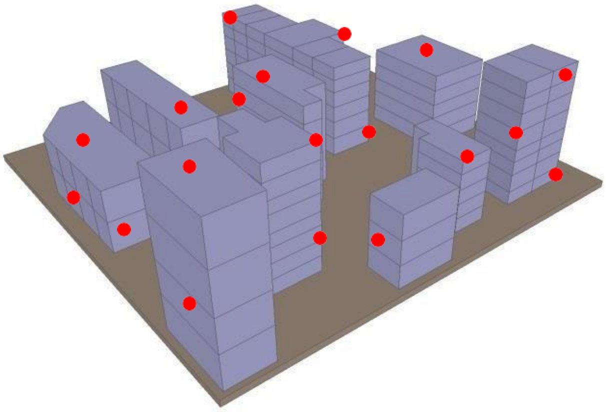

Figure 3. Sensors location in urban area

The information is then used to classify the sensors as either low- or high-power (GE). In this setup, the "head node" of the network is determined by taking the sensor nodes with the highest GMax values (Head Node). The sensors are then organized into groups according on their proximity to the Head Node. In the event that there are many Greater Energy nodes in close proximity to one another, the one with the highest value is designated as Head Node, and the others are placed in sleep mode. At this step, the objects are categorized using the k-means++ technique. In any event, sensors with GMax support are the nerve centers of cluster hubs. Previous studies (Suhaibah et al., 2015) suggest that k-means++ can achieve minimal overlap across different groupings. We'lldive deep into the 3D geo-clustering procedure in the next paragraph.

In Figure 4, we see 540 sensors clustered using a 3D geo- clustering approach. Every one of the four clusters have a unique Head Node once it is divided (in black color). As we can see by comparing the percentages of overlapping clusters, the overlap is relatively little (between 5 and 10 percent).

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Algorithm-1 HORA
Input Location of  sensor in 3d, energy value
Output Group Cluster
1. get the min and max point bounding parallelepiped (in 3D, 3 points are needed to define a parallelepiped)
2. find sensor with Less Energy and Greater Energy
3. classify into group
4. choose Max Greater Energy as Head Node
5. initialize Head Node as cluster center $C1, C2, \ldots Ck \in \mathbb{R}^3$
6. repeat until convergence:
   {
      forevery i, set
         $c^{(i)} := \arg\min_{j} ||x^{(i)} - \mu_j||^2$
      for every j, set
         $\mu_j := \frac{\sum_{i=1}^{m} 1\{c^{(i)} = j\} x^{(i)}}{\sum_{i=1}^{m} 1\{c^{(i)} = j\}}$
7. end if all completed.
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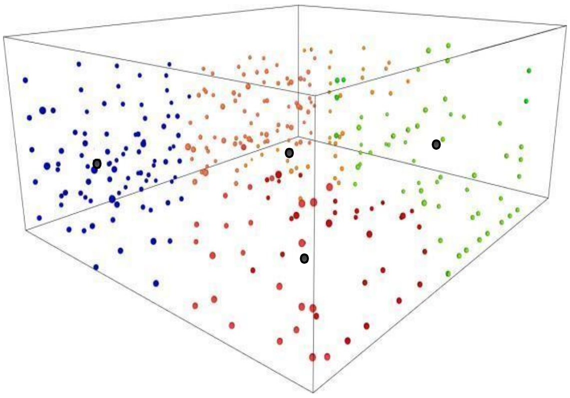

Figure 4. Clustered sensor using 3D geo-clustering.

4. EXPERIMENT AND ANALYSIS

Many analyses and testing are conducted on the proposed 3D geo-clustering of sensor sites.

As was said before, overlap plays a significant role in maximizing efficiency. Low-power sensor nodes are isolated in an experiment. In areas where more than one group cluster coexists, this sensor will report its findings to the nearest Head Node. The sensor won't have to send data to the furthest Head Node, saving power. The location of three sets of sensors with varying numbers are used to identify several low-energy sensors in overlapping clusters. As seen in Figure 5, on average, only 10% of sensors detect LE in the overlap zone. This percentage rise to 23%in 500 sensors and 48% in 1000 sensors. This illustrates that 3D location-specific overlap is rather small.

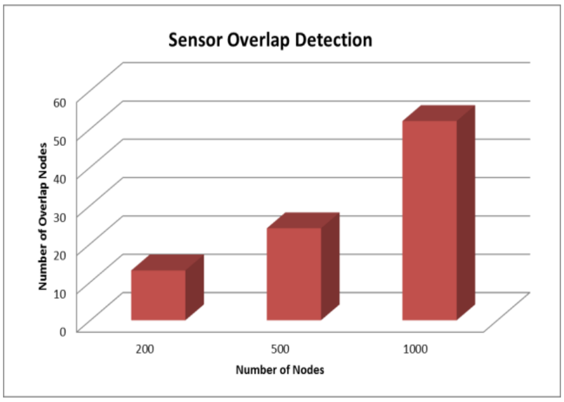

Figure 5. Number of Low energy sensors inoverlapping areas.

Detection of Greater Energy Sensor

Head Node status is awarded to the node with the highest energy detection threshold relative to the other nodes. Nonetheless, the sensors may be in a side-by-side arrangement during the actual detection. There is probably just one cluster where this kind of sensor may be found. Even if the sensors are spread out throughout many different clusters, there will still be a high degree of group-level overlap thanks to their involvement. As a result, one node in the network (a sensor) is designated as the network's Head Node. We placed the second gadget into slumber to preserve juice. In this study, three separate sensor networks, each with a unique number of nodes, are used (200, 500, and 1000). The first set consists of 35 nearby Greater Energy sensors. Out of a total of 1,000 bigger Energy sensors, the second group is able to identify 78, while the third group is only able to identify 48. Figure 6 displays the results of detecting high-energy sensors. As soon as the detection is made, many sensors are instructed to turn off, so preventing them from draining the battery any further. The tabulated outcomes of the experiments are shown in Table 1. This experiment shows that over fifty percent of the target population was sleeping throughout the night.

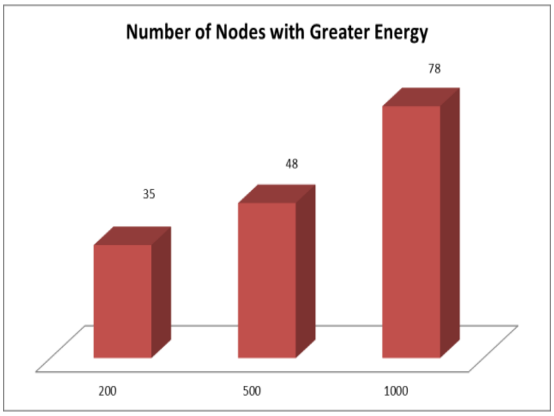

Figure 6. Sensors with greater energy

Table 1. Number of sensors that are set to sleep mode.

Number of Sensors	Greater Energy (G_E) Sensor	Sensor on Sleep Mode
200	35	25
500	48	36
1000	78	53

5. CONCLUSION

We introduce a 3D geo-clustering method for a network in this research (WSN). The proposed technique may be used to organize sensors into clusters based on their energy consumption or geographic proximity. The purpose of the method is to reduce the number of overlapping clusters in the network to lessen the amount of data sent and to identify the sensor head node to save power.

The research and testing of a 3D geo-clustering approach show how challenging it is to find overlap cluster. As a consequence, there are very few sensors used by several communities. Data transmission costs are calculated for a single sensor cluster, even though the sensor might possibly belong to many clusters. It sends information, which is the only component in the network called Head Node. Finding high-energy nodes or sensors has also been found to benefit from 3D geo-clustering. When choosing a Head Node, a sensor with a lower detection threshold is preferable. On the occasion of detection, a number of powerful sensors in close proximity are integrated into a single powerful sensor. This is done to avoid sending data to too many sensors or the furthest possible Head Node. By this technique, we can reduce energy consumption and maybe lengthen the life of the network.

Based on our findings, the proposed 3D geo-clustering method is a great option for clustering purposes in wireless sensor networks. Nevertheless, further research and testing are needed to reach the full potential of this area.

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