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# Applications of Big Data Analytics for Large-Scale Wireless Networks

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## ABSTRACT

The proliferation of various wireless communication technologies and devices has ushered in the big data era in large-scale wireless networks. Researchers face new challenges when working with big data from large-scale wireless networks compared to traditional computer systems. This is because big data has four essential characteristics: high value, real-time velocity, immense variety, and great volume. The goal of this article is to survey all the new stuff about big data analytics (BDA) methods for massive wireless networks. Data collecting, data preprocessing, data storage, and data analytics are the four distinct phases that make up the BDA life cycle. We next provide an exhaustive review of the technical solutions that have been created to address the difficulties associated with BDA for large-scale wireless networks, organised according to each stage of the BDA life cycle. We also explore the research questions that remain unanswered and provide an overview of the potential future possibilities in this exciting field.

**Keywords:** Big data analytics (BDA), Data collecting, data preprocessing, data storage.

## 1. Introduction

With the proliferation of smartphones and other IoT devices, there has been a noticeable uptick in mobile data creation via wireless networks[1]. The cumulative growth of mobile networks from 2012 to 2017 was seventeen times higher, with data traffic increasing by 71% between 2016 and 2017. Wi-Fi offloaded 54% of traffic from devices that enable cellular and Wi-Fi connectivity in 2017, and that number is projected to rise to 59% by 2022, according to recent studies[2]. This means that IEEE 802.11 networks are the backbone of many different types of end-user networks. In most businesses, the wireless network is used by the majority of users to access internal services or the Internet. An example of a campus Wi-Fi network is the one at Universidade Federal Fluminense, which has 547 access points and 5 Internet gateways. The network can support over 60,000 users, 5,000 users connected at once at its peak, and over 100 Mb/s per gateway in terms of data generation.

The information gleaned from the tracking and administration of such a massive wireless network provides a treasure trove of details regarding users, connections, consumption, and movement patterns[3]. There are a number of differences between wired and wireless network monitoring. If you want to know how the wireless network is doing right now, you can't use the same old wired methods-like measuring metrics after data has gone over the wired network-to do so. For instance, when using conventional approaches, it is impossible to differentiate between a network that is not actively transmitting frames and one that is severely overloaded. Since the measurement alters the wireless network's status, suggestions for evaluating the network's health take active measurements into account, but they also suggest adjusting the evaluated parameters.

There is a trade-off in the precision of the data collected when utilising indirect measurements, such as counting access points to gauge channel utilisation or collecting frames using sensors for spectrum analysis. In contrast, gathering network metadata does not change the status of the network and enables the development of context-aware apps, which in turn facilitates monitoring on all fronts. Finding nearby access points, deducing their physical distance, and determining their radio coverage area are all made possible by passively scanning for beacons and adding data about the signal strength with which they were received. Essential network functions including service charge collection, threat identification and isolation, and problem mitigation are also made possible by data collecting. Wireless mobile networks enhance our knowledge of the network's long-term dynamics by supplementing it with space-time user and network condition data, providing end-to-end visibility and intelligence. For example, geolocation[4] or user positioning information[5] might be helpful for assessing usage trends and identifying outliers.

In addition, by assessing the data given by the network, entities and activities inside the network are able to self-coordinate, leading to the development of more proactive and efficient networks. Analysing enormous amounts of data from large-scale wireless networks allows one to discover usage trends, create user profiles, detect defects or performance declines at specific network sites, and optimise channel allocation, among other things. This study is hindered by various aspects of the wireless environment, such as user mobility issues, background noise, and data redundancy. Volume, velocity, diversity, value, and truthfulness are five essential elements of big data processing that are affected by these traits[6].

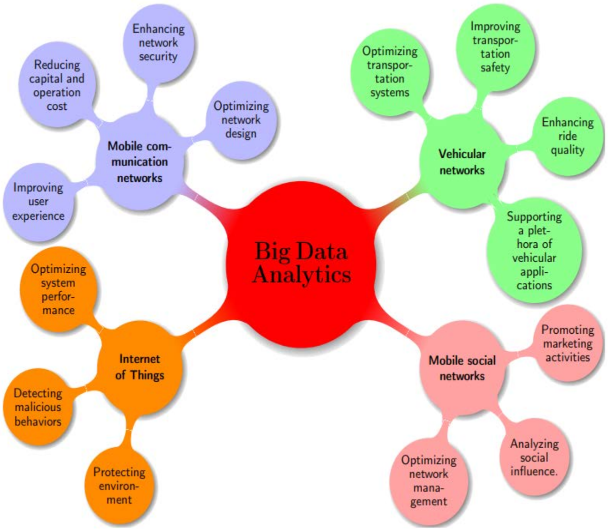

**Figure 1**: Big data analytics is essential for wireless networks on a grand scale.

The desire for thorough analysis of such "big data" is driven by the necessity to derive useful and enlightening insights from the vast amounts of data produced daily. Specifically, we review the various wireless network types and their respective BDA explanations in **(Figure 1).** Lack of network intelligence and fast-reaction mechanisms, frequently associated with the limited perspective of flow management tools, has a negative effect on both the quality of experience (QoE) of large-scale wireless network users and the extraction of knowledge about users and networks[7]. Therefore, monitoring large-scale wireless networks requires real-time processing and rapid responses to adjust the network to peak demand and infrequent user concentrations.

While huge data streaming processing methods may work in some situations, they are absolutely necessary for real-time network analysis. Data sets that may include an unlimited amount of samples and attributes are what big data streaming processing is all about. In characteristics space, samples come in an infinite number of ways and at any time. We are thus in the dark regarding the universe of data attributes and the statistical distribution of the traits. Instead of using a massive data processing platform to sequentially handle a handful of well-known datasets, stream processing takes a different approach.

There is an increase in processing latency and the amount of memory needed to store data when using batch processing. As a result, there are no memory restrictions when it comes to streaming data processing, and the processing delay for each data sample is reduced. In a streaming data scenario, there is an endless amount of samples and processing each new one requires very little latency, thus regular machine learning algorithms can't search the training dataset. Hence, streaming data processing solutions such as Apache Spark Streaming[8] and Apache Flink[9] provide two distinct types of streaming data processing: micro-batch processing and sample-by-sample processing.

Concept drifts in real-time input data can cause learning mistakes in machine learning systems[10]. Thus, it is important for machine learning apps to be cognizant of the attribute distribution statistics in the input data and to monitor any changes to these statistics.

## 2. Literature Review

As a subset of ad hoc networks, wireless sensor networks (WSNs) enable a distributed network of sensor nodes to wirelessly collect, process, and transmit environmental data to a master node (the "sink")[11].

The field, also known as the area of interest, is the geographical region in which the sensor nodes function. Wireless sensor networks (WSNs) allow sensor nodes to self-organize in order to gather data about their surrounding environment. Depending on the application in question, the data transmission can be done on an as-needed basis or at predetermined intervals. A node with two or more network interfaces is termed a sink, and it is used to connect the end-user's network to the WSN. This end-user's network could be a local area network or the Internet. For example, the user can specify the data type to be gathered by requesting it from other network nodes through the sink. For clarity's sake, Figure 2 shows the basic layout of a WSN.

Recovering the data acquired by the sensors is the job of the randomly deployed sensor nodes in an area of interest and the sink at the zone's conclusion. The sink often gathers data from the network and processes it, allowing it to provide the user only relevant information. On top of that, it may take user commands and run them on the internal network. The acquired data is processed and analysed by the user.

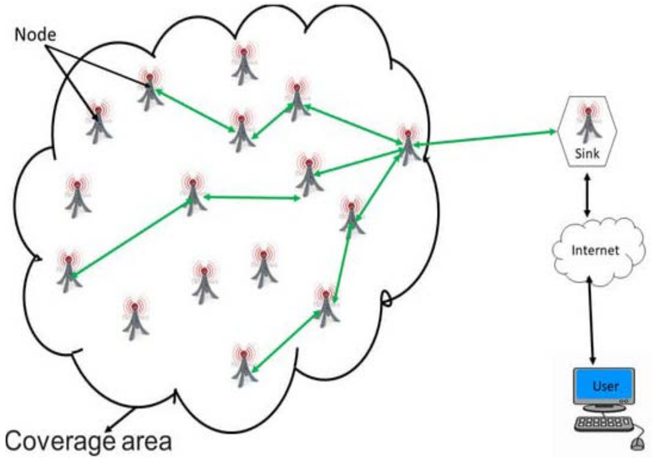

**Figure 2**: The general architecture of a wireless sensor network (WSN).

### 2.1. Hardware architecture of a wireless sensor

Wireless sensors are tiny electronic devices that can measure physical quantities (such as light, temperature, or pressure) and transmit that data either directly to a data centre or through other sensor nodes that function as routers[12]. Thanks to advancements in microelectronics, software, and wireless transmission technologies, tiny, inexpensive microsensors with a volume of just a few cubic millimetres can now function in a network[13]. According to[14], there are six components that make up a sensor node **(Figure 3)**:

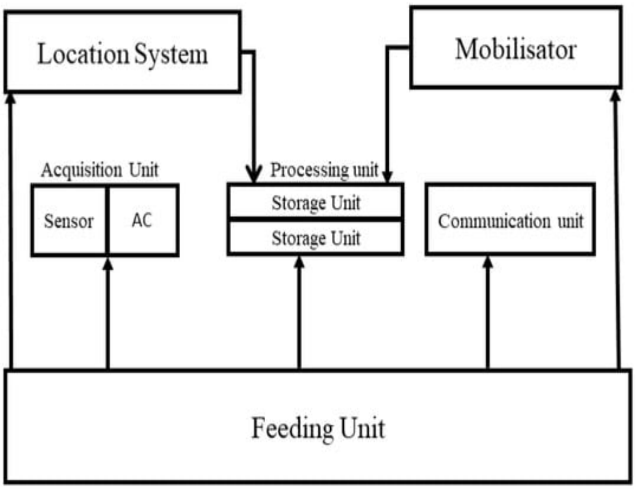

**Figure 3**: Architecture of a wireless sensor.

- **Unit for acquisitions:** Here we have a sensor and an ADC, the two main components. This sensor takes digital readings of several environmental variables and converts them into analogue signals. The ADC is responsible for digitising analogue signals. Unit for processing data. A data-storage unit and a processor are also part of this, with the processor handling data-processing and the control processes that enable the sensor to work with the others to complete acquisition duties.
- **The unit responsible for communication:** Its purpose is to transmit and receive data. It has a set of antennas and a receiver. In our situation, it enables radio frequency (radio wave) communication inside the network. Other transmission modes, such as optical and infrared, do exist, though.
- **Power source:** An essential part of every sensor design is the power source. It powers all the other units in the system. This is a unique issue for this kind of network since it usually correlates to a battery that supplies power to the sensor. The recent development of solar-panel power units, however, offers hope for a solution to the problem of shortening the lifespan of sensors[14].
  - **Mobile device:** As an optional step, this is utilised to relocate the node in order to finish processing the task.
  - **A system that can find its way:** As an optional extra, it gives the application and/or routing the location data they need.

### 2.2. Types of WSNs

Figure 4 shows the various kinds of WSNs that can be deployed in different environments, such as on land, underground, or underwater:

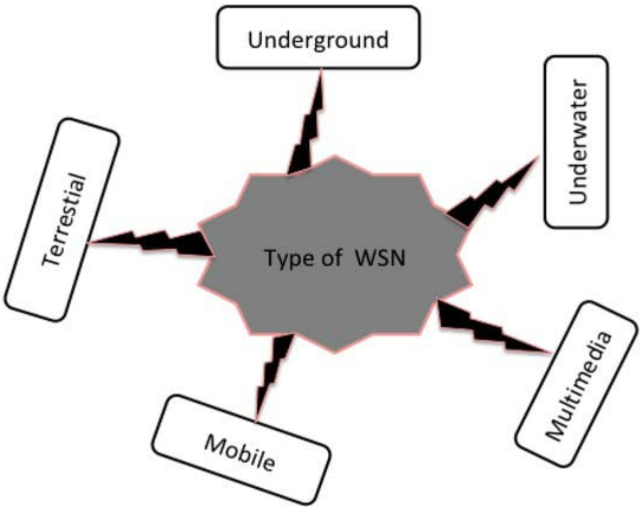

**Figure 4**: Types of WSNs.

- **Terrestrial:** These WSNs are expected to be deployed in a terrestrial space. These networks scatter hundreds of thousands of sensors across an area, either randomly or according to a predefined pattern. Despite its greater utility in environmental monitoring and natural occurrences, this kind of WSN poses a threat to the network›s long-term viability in energy management[15].
- **Subterranean:** Extremely specialised sensor nodes make up these networks, and their installation and upkeep are notoriously difficult and expensive. Typically, sensor nodes in such a network would be buried. In order to keep tabs on soil conditions, they are useful in agricultural settings and mines. However, in this network architecture, data detected by underground nodes is relayed to the base station by a ground node[16].
- **Below the surface:** Submarine networks are one kind of wireless sensor network. This type of network continues to be an intriguing research problem due of the hostile environment in which they are deployed. Compared to sensors located on land, these nodes are more costly, have acoustic wireless communication, a limited bandwidth, frequent signal loss, and frequent synchronisation and propagation delays[17].
- **Moving images**: Data including photos, movies, and audio can be tracked and monitored by these WSNs. These little devices have built-in cameras and microphones. Data processing and compression in such a network type consume a lot of power because of the high bandwidth and quality of service requirements. The installation of these sensors necessitates prior preparation[18].
- **Portable:** This latest WSN variant makes use of mobile nodes that are capable of self-organization and can move around inside the network. The nodes spread to collect data after first deployment. Additionally, there is a hybrid network that uses both stationary and mobile sensors[19,20].

## 3. Big Data Collection in LS-WSNS

A WSN relies on a clearly defined architecture to gather data. Deciding on the best possible design is the main challenge. Here we outline the many literature-proposed designs for identifying those that work with large-scale WSNs. References presented several data-collecting network designs in their study. These designs are primarily based on two approaches: one that relies on a static network and another that relies on network mobility. Figure 5 depicts the various data-collection topologies proposed in the literature.

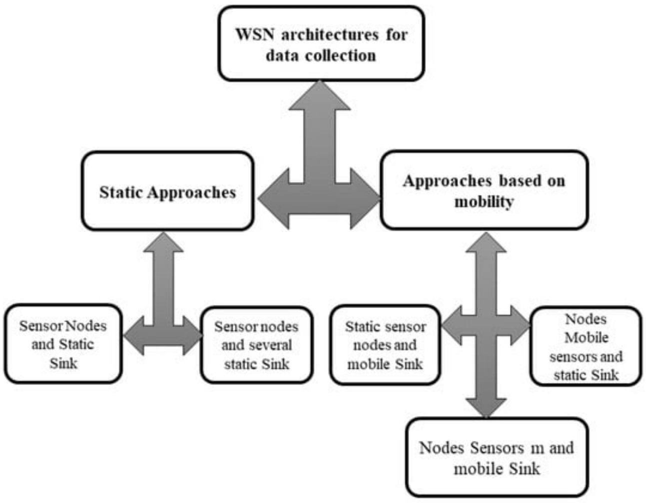

**Figure 5**: Various approaches to WSN design.

### 3.1. Static Architectures

The literature typically encounters this classical technique. It is a method of collecting data that involves placing a network of sensors in a target area. There are no dynamic components in this architecture's network. Conversely, there are two possible approaches to network deployment: deterministic and random.

### 3.2. Static-Sink and static-sensor architecture

A vast network of sensors that can independently gather and transmit data about their surroundings makes up this design. These sensor nodes' locations aren't always set in stone. You have the option to scatter them around the target region at random. A high density is a hallmark of this design style, which ensures that every pair of network nodes will have access to at least one path. In addition, the network's lifespan is reduced, which is a big negative of this design. The issue of nearby sensor nodes' fast battery drain was reported to the washbasin. The nonuniform energy usage in the network originates from the data relay from the source sensor to the washbasin. Because they get the greatest requests for data transfer to the washbasin, nearby sensor nodes quickly run out of juice, rendering the washbasin inoperable. The network's lifetime is diminished due to this circumstance. Uses of this design include the Habitat Monitoring on GDI (Great Duck Island) programmes, the VOLCANO and GLACSWEB apps, and others.

### 3.3. Architecture with sensor nodes and several static sinks

The new design, which differs from the previous one by including sensor nodes and numerous static sinks (see Figure 6), aims to extend the lifetime of the network by increasing the number of sinks. But the problem of sensor nodes' batteries dying while they're far from sinks is still there. It is still difficult to choose amongst the several sinks, which are the sensor nodes in this design.

### 3.4. Architecture based on mobility

Several works have included mobility into WSNs to increase network lifetime and decrease latency. Thanks to its many benefits, such as improved connection, lower deployment costs, reliability, and energy efficiency, mobility in WSNs is a great asset. Despite the fact that mobility increases the lifetime of networks, it poses a number of problems for sensor networks. See Figure 7 for a list of these difficulties. They include things like contact detection, location, energy consumption, reliability of data transfer, quality of service, and mobility-oriented power management.

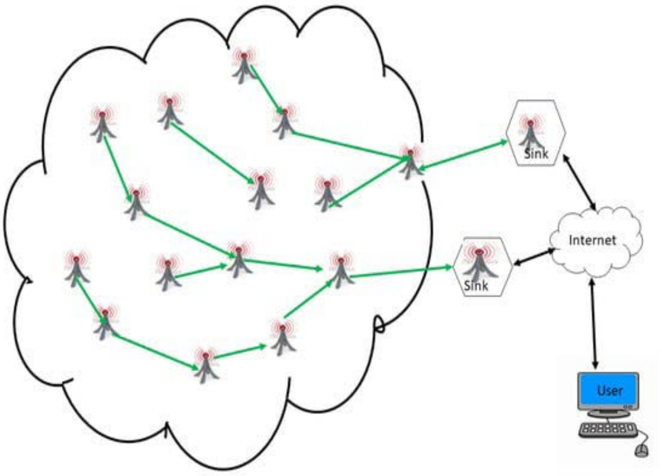

**Figure 6**: Design including many static sinks and sensor nodes.

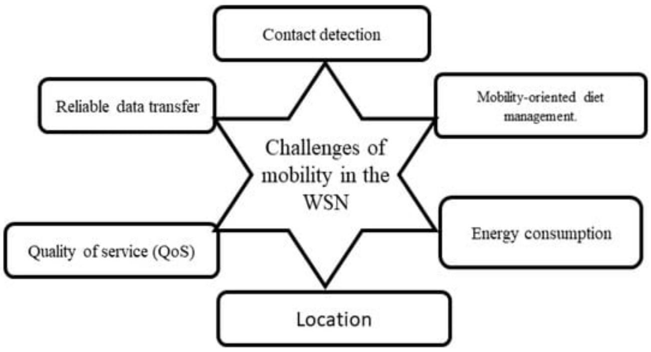

**Figure 7**: Travelling in a WSN: Difficulties.

Many different kinds of mobility have been proposed for WSNs, such as static-sink designs with mobile sensor nodes, mobile-sink and sensor node designs, sensor designs, hybrid designs, and other static-sink designs with sensors and mobile sinks.

### 3.5. Static sink architecture and moving sensor nodes

The mobility of the sensors is a unique feature of this design. A lot of research in recent years has focused on this strategy. This design drastically cuts down on the amount of sensors needed to be deployed due to the mobility of the sensors. This architecture allows for direct communication. This design aids in keeping the network covered well. With this design, energy consumption can be evenly distributed among sensors, and the washbasin may gather a substantial amount of data. Projects like COW and CENWITS adopt this design, in which sensor nodes are mobile but the washbasin remains stationary.

### 3.6. Architecture with a mobile sink and static sensor nodes

The washbasin can be moved about in this arrangement, but the nodes themselves stay put. It is possible to start collecting data after the sink has arrived at a designated sensor node and the sensor has detected it. This layout has a major flaw: the sensor nodes are unable to locate the washbasin. But it's a fascinating notion to employ mobile agents to get data from the sensors. According to[21], agents like MULEs (Mobile Ubiquitous LAN Extensions), mobile sinks, and mobile data collectors move in a predetermined pattern or at random to collect data from the sensors. Mobile agents are used by the permanent sensor nodes to collect data.

These agents on the move can take the form of people, machines, animals, or even cars. One benefit of this design is that it allows for greater connectivity to the WSN placed in a region of interest by removing the constraint of high density. According to References[23], a WSN architecture like this one helps keep data integrity and prevents collusion in densely populated networks of wireless sensors.

### 3.7. Architecture with a mobile sink and mobile sensor nodes

Both the sensor node and the sink levels are considered for mobility in this architecture. This architecture provides advantages similar to those of the mobile sink and static sensor node systems. Several projects in both academia and business have utilised this layout. Using this layout, researchers in Kenya tracked zebras as they rode in a vehicle from the Sweetwaters Reserve to Mpala in central Kenya, with the use of sensors attached to the animals.

When it came to environmental monitoring, this study was among the first to include node and sink mobility in tandem. Naturally, we bring up this zebra tracking project (ZebraNet)[24] as an example of an application that uses this design.

### 3.8. Architecture with sensors and multiple static sinks

This design is unique in comparison to all the others that have been showcased thus far. A dense network of sensor nodes is used in conjunction with several sinks. One of the network sinks takes in data from the sensor nodes and sends it on to the consumers. Selecting the washbasin is a major challenge with this design. Reference[25] adds to the impression of the solution's complexity by suggesting a multi-to-many architecture for routing optimisation. Another obvious flaw with this idea is its lack of evolution. In fact, adding sinks is not something that can be automated as the sensor network expands; otherwise, we risk reverting to the issues of a single-sink architecture. Also, the end user and the sensor nodes can't connect directly with this solution.

### 3.9. Architecture with sensors and multiple mobile sinks

The only real difference between this method and the last one is that in this one the sinks can move about. One possible option is to use a single WSN to house multiple mobile sinks. The solution's inability to easily route sensor data is a major drawback. In an effort to address this, the authors of[26] proposed a method to enhance routing efficiency.

### 3.10. Hybrid architectures

A multisink architecture is another option. Using a number of mobile receivers to gather data instead of a few static ones could significantly extend the lifespan of the WSN. The goal of other efforts involving many mobile sinks was to either increase the global network's lifetime or decrease the energy consumption of sensors. A lack of scalability is a common source of these proposals. The reason behind expanding the sensor network is to circumvent the challenges associated with single-sink architectures, which cannot be solved automatically. Additionally, there is no way for the user to establish a direct connection with the sensor using this technique.

## 4. Comparison of Data-Collection Architectures in the Context of LS-WSNS

Each of the designs discussed here has its own set of pros and cons; this is mostly due to the fact that our objectives inform the design of these structures. Apart from that, LS-WSNs have a dense network of sensors spread out across a large area. Accordingly, we conclude that fewer nodes need to be deployed if mobility benefits sensor nodes rather than sensor networks, even when the benefits outweigh the disadvantages. This leads us to the conclusion that LS-WSNs are not a good fit for this type of design. No matter how much power the sensor and static-sink networks use, they are modified to accommodate the growing network. Getting this network's energy consumption under control is still a major hurdle. This can only be achieved by modifying the various methods employed within the framework of so-called traditional WSNs so that they can cope more effectively with a sensor-rich setting.

### 4.1. Data Transferring in LS-WSNs

The data collected by the nodes needs to go to a central location in the network called a sink. Using routing, we can determine the most efficient way to send data from the sensor nodes to the sink while minimising energy consumption. Connecting the washbasin to a faraway user is also possible by another wide transmission technology, such Wimax, LTE, or even a satellite. The user can specify the kind of data that needs to be harvested and the sink node can transmit the request to other nodes in the network.

Many different routing protocols have been suggested for use in LS-WSNs, which is still an active field of study. Numerous papers have recently been published on the topic of routing methods for WSNs. The network architecture and the intended action are the two primary criteria for categorising these protocols[27,28] **(Figure 8).**

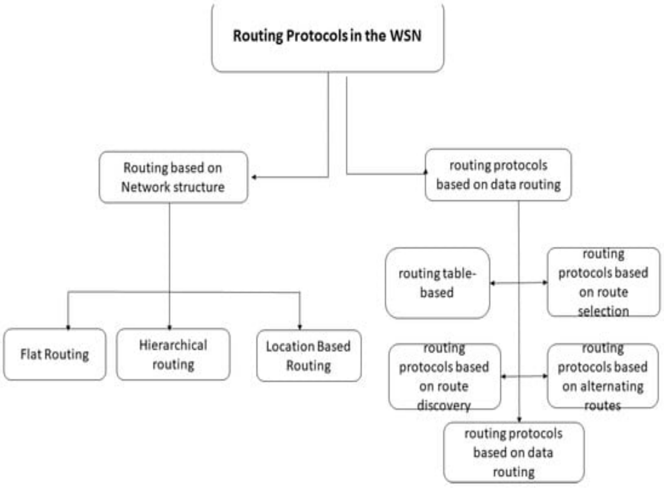

**Figure 8**: Classification of WSN routing protocols.

### 4.2. Network structure-based routing protocols

Data routing relies heavily on the distribution of routing protocols in accordance with the topology of the network. In terms of how networks are structured, there are primarily three types of protocols. Below are the protocols:

- **Direct routing**: Here, all sensor nodes are likewise referred to as "data centric," and they all have identical responsibilities. This is the original approach used for data routing in the WSN. It can only work if all the nodes in the network work together. The massive number of nodes makes it impractical to assign a unique identity to each one, thus instead, data properties are defined using a naming scheme based on attributes (attribute, value). Their ease of use is one of their many benefits; this makes it possible to set up connections with no out-of-pocket expense, as each node simply needs data from its immediate neighbours. Since all traffic must flow via the nodes in close proximity to the base station in order to reach the latter, this drains their energy supplies. Hierarchical routing is a way to organise data. The establishment of clusters (shared regions) is the foundation of this method. Data collected by nodes in a cluster should first be directed to their respective area heads, known as the Cluster Heads (CH), who should then process the data and send it on to the next destination. If the CH is unable to immediately access the station, basic information should be forwarded to the next zone leader. By applying aggregate functions to the cluster's data, CHs are able to integrate it, which reduces communication and energy costs by minimising the number of messages flowing on the network. One drawback is that the network is too big. Furthermore, CH election becomes resource hungry and crucial as network size increases.

- **Routing Based on Location**: It is critical for the WSN data-routing algorithms to be able to pinpoint exactly where the sensor nodes are on the collecting region. The shortest routes between two nodes can be constructed using this location data by calculating the positions of the sensors and the distances between them. Because it eliminates the need for sensor nodes to employ random or probabilistic methods to search for routes, this routing solution is more energy-efficient. Furthermore, the nodes' locations (and, by extension, their regions) allow for the restriction of broadcast requests to certain regions rather than the entire network, drastically cutting down on transmissions. One drawback is the high energy consumption of the satellite tracking systems that are required to be installed on sensor nodes, such GPS.

## 5. Conclusions

There is a vast array of possible uses for wireless sensor networks (WSNs). Implementing these networks within the Big Data framework showcases their ability to tackle and surpass inherent restrictions to meet unique needs. Big Data refers to the expectation of a diverse dataset that is continuously generated by the Internet of Things (IoT) to a degree that it cannot be gathered, managed, or analysed by conventional methods.

The features of such data present an intriguing challenge for the gathering and processing of such data via low-power wireless sensor networks (LS-WSNs). A more effective strategy for the collecting of Big Data is proposed in this study, which is the result of a complete review that we did. Given this background, we set out to solve the issue of big data collection by publishing horizontal overviews of WSNs and big data. Soon after, we covered the numerous approaches to data transportation and the different designs for gathering Big Data. Furthermore, the challenges of Big Data collection in LS-WSNs have been investigated. In an effort to inspire and guide scholars of the future, we provided a comprehensive assessment of the open questions along with the associated barriers. In order to offer direction, this study relied on a systematic assessment of the viewpoints of different authors dealing with the gathering of Big Data in LS-WSNs.

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