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Applications of Prediction Approaches in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) collect data and continuously monitor ambient data such as temperature, humidity and light. The continuous data transmission of energy constrained sensor nodes is a challenge to the lifetime and performance of WSNs. The type of deployment environment is also and the network topology also contributes to the depletion of nodes which threatens the lifetime and the also the performance of the network. To overcome these challenges, a number of approaches have been proposed and implemented. Of these approaches are routing, clustering, prediction, and duty cycling. Prediction approaches may be used to schedule the sleep periods of nodes to improve the lifetime. The chapter discusses WSN deployment environment, energy conservation techniques, mobility in WSN, prediction approaches and their applications in scheduling the sleep/wake-up periods of sensor nodes.

Keywords: prediction models, wireless sensor networks, time series models

1. Introduction

Wireless Sensor Networks (WSNs) is made up of sensor nodes that are capable of sensing environmental phenomena and cooperatively transferring the sensed data to a base station without the use of wires. The sensor nodes are spatially distributed in their deployable environment to observe some phenomena within their immediate neighborhood. They can be deployed in the tens, hundreds or thousands depending on the application requirements. These sensor nodes are smart devices and may monitor environments such as homes, inventory, transportation, traffic situation, health of humans, structural health, track animals, air quality, water quality, military, and may even serve as surveillance systems [1]. Over the years, WSNs is gradually becoming the technology of choice for industrial applications and research, for environmental monitoring (EM) applications considering the number of advantages that comes with its use [2, 3]. For example, a WSN is resilient (i.e., adaptive to node failures), scalable (i.e., easy to add nodes to the network), robust (i.e., can withstand harsh environmental conditions), flexible to setup and deploy, cheap, and the network requires no infrastructure [4]. Despite the large number of advantages, WSNs are challenged with a number of issues. These include but are not limited to communication, memory size, energy, processing capacity, and security [5].

2. Types of deployment environments

Wireless Sensor Networks may be classified according to the deployment environment. **Figure 1** shows the classification of WSN according to the deployment environment. WSNs may be classified according to the type and environment of the data being acquired. The sensor nodes may either be deployed terrestrially, that is either aboveground or underground. They may be underwater or multimedia (when deployed to capture videos, images, and audios) or simply numeric data.

WSNs have also been classified according to their mobility, mobile (when the sensor nodes move in their deployment environment) and stationary [6]. In both underground and underwater wireless sensor networks (**Figure 1**), the sensor nodes are buried either in the soil or placed underwater to measure the condition of their respective environments. The buried sensor nodes communicate with a sink above ground and send data through it to a monitoring station [7].

2.1 Wireless underground sensor networks (WUSN)

Wireless Underground Sensor Networks (WUSNs) as shown in **Figure 2** is a well-studied area [4]. They are used in different applications which include intelligent agriculture, power grid maintenance, pipeline fault diagnosis, etc. [8, 9].

Compared with traditional terrestrial Wireless Sensor Networks, WUSNs suffer special communication challenges characterized by the weak signal propagation in soil, rocks and other underground materials. Underground signal propagation is challenged with strong attenuation and signal losses [7]. Traditionally, WUSNs use electromagnetic (EM) waves to establish connection among transceivers underground. However, EM waves have several shortcomings; antenna sizes, short communication range, and the channel conditions are highly unreliable. There are new techniques such as magnetic induction (MI) that have the potential to overcome the challenges posed by the use of EM waves in WUSNs. Underground sensors are equipped with batteries which are difficult to charge or replace when the sensor nodes energy are depleted. Conserving underground sensor nodes' energy is crucial to extending the lifetime of the network and to achieving optimal performance.

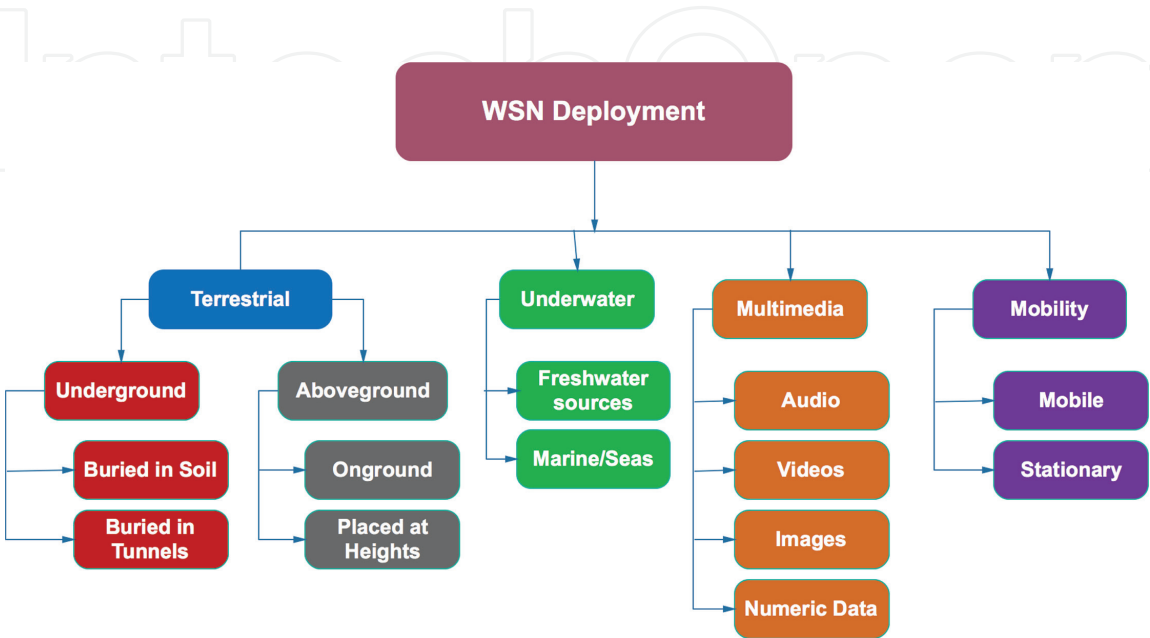


Figure 1.
WSN deployment types.

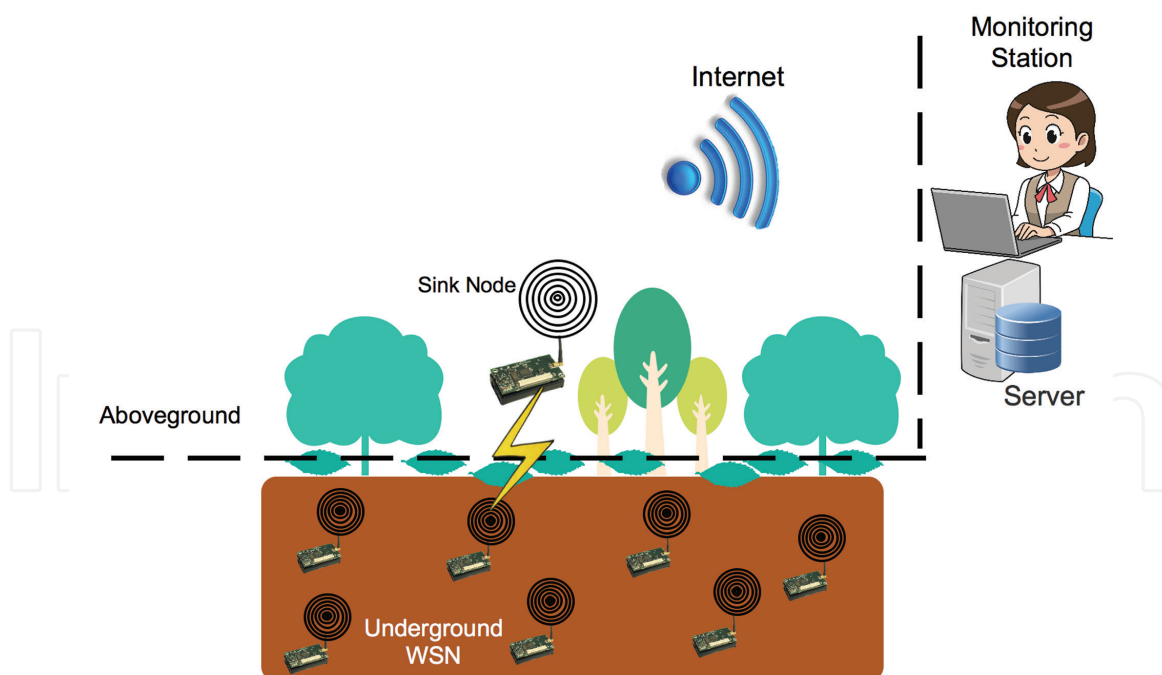


Figure 2.
 Underground deployment.

2.2 Wireless underwater sensor networks

Wireless Underwater Sensor Networks (**Figure 2**) is an area that has caught the attention of researchers in recent times [10, 11]. Underwater Sensor Networks are useful due to their several implementation areas which include marine pollution monitoring, marine data gathering, tsunami detection, threat detection at seaports, and underwater telemetry.

The monitoring is usually performed using navigation assistance such as autonomous underwater vehicles (AUV) and vehicle surveillance. Wireless Underwater Sensor Networks (e.g., marine monitoring) suffer from limited bandwidth, node failures due to harsh environmental conditions, signal fading, and propagation delay [12].

Underwater sensor nodes normally communicate using acoustic waves to a surface buoy or sink above the water. It is also possible to employ non-acoustic communication techniques such as radio frequency (RF), magnetic induction (MI), and underwater free-space optics in underwater sensor networks [13].

The dynamic nature of the water environment is related to the content salt, and its turbidity. Hence, the communication channel also becomes dynamic. RF signals, when exposed to these environmental characteristics, suffer high attenuation. Magnetic Induction may also be used for underwater propagation but requires the use of large-sized antennas which is somewhat impractical in such environments. Acoustic communication is the preferred method for underwater communication since acoustic waves suffer less attenuation and are able to travel long distances due to their low frequencies. Nodes that are connected using acoustic waves constitute underwater acoustic sensor networks (UASNs). UASN nodes are energy hungry nodes which consume a great deal of power compared to sensor nodes deployed to monitor environmental conditions on land. There are several techniques discussed in the literature to overcome the energy problem in UASN and to minimize the energy consumed by the UASN to improve on the network lifetime. Energy efficient routing protocols and clustering protocols are two such techniques adopted to minimize the energy consumed by sensor nodes deployed in WUSNs and UASNs [13]. Current existing routing protocols are group into receiver-based and sender-based which are further categorized based on energy, geographic information, and hybrid routing protocols [10].

An Energy Optimized Path Unaware Layered Routing Protocol (E-PULRP) that minimizes the energy consumed in a dense 3D-WUSN is described in [14] as a typical example of an energy-based routing protocol. E-PULRP uses on the fly routing to report events to a stationary sink node.

E-PULRP has two phases: layering and communication. Nodes occupy layers in a concentric shell around the sink node in the layer phase. The nodes within one layer have the same number of hop counts to the sink node. The E-PULRP protocol is designed to follow a network model in which the total volume in the area of interest is subdivided into small-sized cubes with a binomial probability distribution for a node occupancy. The protocol assumes that the number of cubes is large. Following Poisson approximation to the binomial distribution, we can calculate the probability of k nodes occupying a volume V as:

$$Pr[x=k] = \frac{(\int_V \rho dv)^k}{k!} \exp - \int_V \rho dv \quad (1)$$

where:

ρ = is the volume density of the sensor nodes.

\int_V = indicates integral over the volume V .

Physical properties such as temperature and chemical properties affect underwater communication. Another key factor that affects underwater communication is the depth of transceivers. In E-PULRP, for a transmitted energy of E_T , the received energy E_R at distance R , is modeled as follows:

$$E_R = \frac{E_T}{R^{(B/10)} 10^{(\alpha R + \beta)/10}} \quad (2)$$

where:

B = takes values 10, 15 or 20 depending on the type of propagation.

α = is a range-independent absorption coefficient.

β = is a constant independent of range.

E_T = the transmitted energy.

E_R = the received energy/power of the control packet.

In this layering phase, the protocol allows communication to occur only when energy levels of layers close to the sink are chosen. Concentric circles are formed around the central sink and the structure ensures packet forwarding towards the central sink. The layers in this phase are formed as follows: 1) Layer 0 initiates a probe of energy; 2) Nodes with energy equal to the detection threshold (E_D) assign layer 1 to themselves; 3) The nodes in layer 1 communicates with the sink using a single hop and 4) waits for time k to transmits a probe with energy to create layer 2 (i.e., made of nodes in layer 1 with energy equal to E_D).

The detection threshold, (E_D) and the waiting time k are calculated as follows:

$$E_D = \frac{E_{pl}}{\alpha_l^{(B+10)} 10^{(\alpha \alpha_l + \beta)/10}} \quad (3)$$

where

E_{pl} = the probing energy

$l = \text{the layer}$

$$k = \frac{\lambda_{\min}(E_R - E_D)}{\gamma} \quad (4)$$

γ = energy dependent factor which is the ratio of the energy remaining in the node to the total initial energy

λ_{\min} = constant.

In the communication phase, intermediate relay nodes are selected to send packets to the sink using multiple hop routing path to determine nodes *on the fly*. In this phase, nodes at the lower layers nearer to the source node are first identified as potential forwarding relay nodes. For example, if a source node, S in layer l sends a control packet, a node, N in the network who receives this control packet may declare itself as a potential forwarding node. This self-declared potential node waits at a time period given in Eq. (4) to listen if any other node has not declared itself as a relay node. It does this by comparing its signal strength Received Signal Strength Indication (RSSI) with other nodes' RSSI.

Once its RSSI value is less than all others, then it forwards the data packet, otherwise it will go into silent mode. A classic example of a cluster-based energy efficient UWSN is SEEC: Sparsity-aware energy efficient clustering protocol for underwater wireless sensor networks. SEEC was proposed by [15] to search sparse regions in the network. The network is divided into subregions of equal sizes. With the use of sparsity search algorithm (SSA) and density search algorithm (DSA), sparse and dense regions in the network. The lifetime of the network is improved through sink mobility in the sparse regions and through clustering in the dense regions. SEEC minimizes the energy consumed in the overall network by balancing the two sparsity search algorithm (SSA) and density search algorithm (DSA).

In SEEC, random nodes are deployed underwater and the network formed is divided into 10 regions. The position of each node in the network is dynamic due to the dynamic nature of the deployable environment. The 10 regions are created to determine the sparse and dense regions. SEEC employs three sinks (i.e., a static sink at the top of central point of the sensor network field and two mobile sinks positioned at the sparse regions). Each sensor nodes coordinate is first determined in order to know its current region in the network field (i.e., sparse or dense).

A simple algorithm that checks the number of nodes in a region is used to determine a sparse or a dense region. If the number of nodes is minimum, then then node is in a sparse region other the node is considered to be in a dense region. When the searching is completed, then the nodes in the dense region are placed into clusters. To conserve energy and increase the lifetime of the network, SEEC is designed to cluster the top four (4) densely populated regions. Nodes in a dense region collaborate to select their cluster head (CH). The CH is the node with low depth and high residual energy.

$$E_{ave} = \frac{\text{Total Residual Energy}}{\text{Number of Alive Nodes}} \quad \text{rand Th} \quad (5)$$

$$Th(i) = \frac{p}{1 - p \left(\text{mod} \left(r, \frac{1}{p} \right) \right)}$$

2.3 Wireless multimedia sensor networks (WMSNs)

Another type of WSN is the Wireless Multimedia Sensor Networks (WMSNs). These types of sensor networks are designed to monitor multimedia events and

are capable of retrieving images, videos, audios, and scalar wireless sensor data. WMSNs come with additional challenges on top of the challenges of traditional WSNs. WMSN challenges include real-time delivery, high bandwidth demand, security, tolerable end-to-end delay, coverage, and proper jitter and frame loss rate [16]. Video streaming requires high bandwidth for it to be delivered. Streaming at high data rate also means that more energy will be consumed.

Several approaches have been proposed to also reduce the amount of energy consumed for delivering the content. Current studies have looked into the design of energy efficient MAC and routing layer protocols that are capable of handling low data rates [17, 18]. Also, to overcome the other challenges apart from the amount of energy utilized during content capturing and delivery, new approaches have been proposed in WMSNs to ensure data sharing security, quality of service assurance in providing real-time multimedia data and to ensure algorithms are designed to compress the images, videos, and audios before transmission to reduce the amount of energy consumed for such operations [19].

2.4 Mobile wireless sensor networks (MWSNs)

There are some application domains that static wireless sensors may not be a good option to deploy, hence, the introduction of Mobile Wireless Sensor Networks (MWSNs). Mobile sensors are capable of moving freely in their environment. This type of WSNs are good for deployments that require maximum coverage to monitor the physical environmental conditions since the mobile nodes can spread out when gathering information and reposition themselves. Mobile sensors improve coverage, energy efficiency, and channel usage [12]. In the last decade, studies into MWSNs have focused on sensor node coverage, energy efficiency, sensor relocation and deployment [20]. Following the studies conducted, the energy efficiency schemes discussed in this area is of key interest. There are two main approaches of improving the energy efficiency in MWSNs: reducing the energy consumption and harvesting energy to power sensor nodes.

2.5 WSN topologies

The arrangement of wireless sensor nodes in a Wireless Sensor Network is critical for maximizing the network lifetime. The network topology adopted in a deployment environment affects factors such as network connectivity. Network connectivity becomes more reliable if the proper topology is chosen for the deployment [13]. The topology also affects the energy consumed by nodes in network. For example, if a network is designed in such a way that the wireless sensor nodes are distributed far from their neighbors and the sink, the nodes will require high energy budget to establish connections and communicate [13].

Wireless Sensor Networks employ mesh (also known as peer-to-peer), star, star-mesh, and tree topologies, as show in **Figure 3**. Static network topologies do not suffer from topological changes but they suffer from minimum battery power and MAC layer problems.

In a star topology (**Figure 3**), the nodes are one-hop away from the sink. The sink or base station is at the central point and all the nodes in the network broadcast data through the sink to other nodes in the network. The star topology is energy efficient when adopted in WSN projects. But in situations where the sensor nodes are far from the sink node, the sensor nodes in the star topology requires a ton of energy compared to multi-hop through mesh. The challenge with this topology is that it is susceptible to failures when the sink node fails [21].

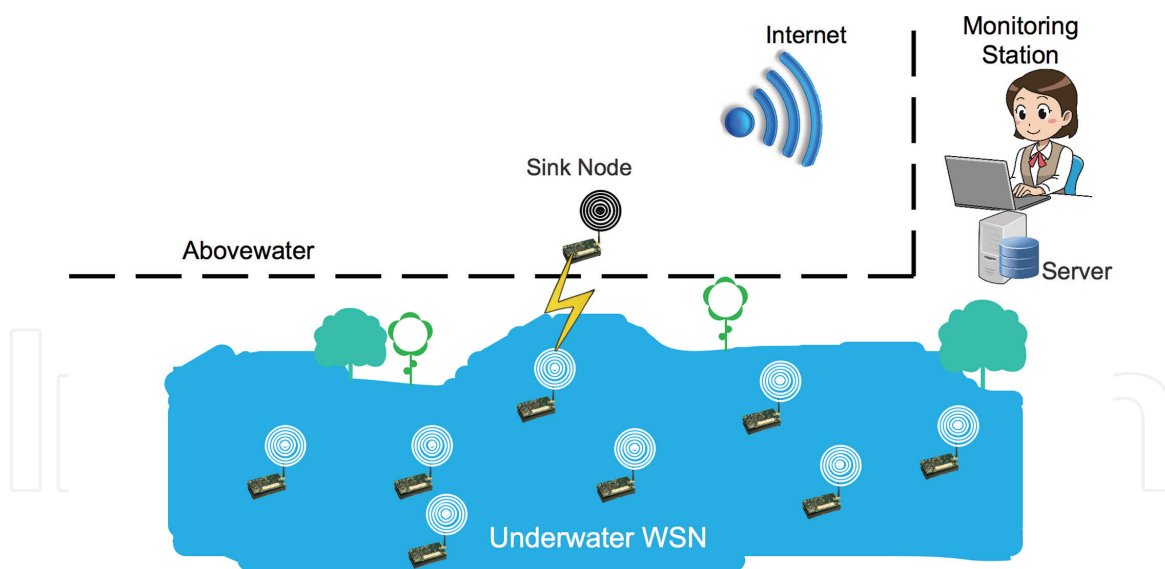


Figure 3.
 Underwater deployment.

In **Figure 3**, the sink serves as the root of the tree and all other nodes are considered as child nodes. In **Figure 3**, the sink or base station is a hop away from some of the nodes, which are its nearest neighbors. The other nodes require multiple hops to reach the sink. In a full mesh, every sensor node is connected to every other sensor node in the network. Finally, in **Figure 3**, the sink node is at the central point. Some nodes broadcast to the sink directly whilst other nodes require a hop to reach the sink.

3. WSN deployment techniques

In WSNs, sensor node deployment is the process of setting up or positioning wireless sensor nodes to be fully functional and operational in either real-world using testbeds, laboratory or simulated environments [22, 23]. Deploying sensor nodes in the environment (i.e., land, air, water) may differ from one application domain to the other. In some cases, deploying the sensor nodes to communicate from one medium to the other (i.e., air/land to water, water to air/land, water to land and vice versa, and water to water) require the right selection of the deployment strategy [23].

The sensor nodes are deployed to collect data/information about their environment and transmit to a base station for onward processing. Nevertheless, the primary objective for node deployment consideration in WSN is to gain energy advantage since the sensor nodes are low powered devices. There are several deployment strategies for static and mobile sensor networks (**Figure 4**). Sensors in their physical environment play several roles in the network (i.e., act as a source node, relay node, cluster head, or sink/base station node) are deployed with any of the approaches or methodologies in **Figure 4**.

The objective function for selecting the desired methodology or approach should be based on the coverage area, network connectivity, network lifetime, and data fidelity (ensuring that the data gathered is credible) [24]. Unlike static environments, placing and controlling sensor nodes in mobile environments is challenging. Similarly, node replacement is also a difficult task. The best deployment strategy for any implementation must meet the following criteria: 1) have clear objectives to meet the application requirements; 2) improve system

performance and maximization of network lifetime; 3) enable the detection of failures and errors in the network topology [13, 24]. Sensor node deployment techniques in WSNs may also be determined based on the algorithms used. Current algorithms that have gained proper consideration for sensor node deployment include greedy, adaptive, probabilistic, centralized, distributed, incremental, and genetic algorithms [25].

In [23], the authors classified four (4) possible WSN deployment problems that are likely to be encountered during the lifetime of the wireless sensor network (**Table 1**). The deployment problems were classified into: 1) node problems which general involve only one node; 2) link problems which occurs between two neighboring nodes; 3) path problems which typically occurs in a multi-hop environment (i.e., where paths are formed by more than three sensor nodes within the network); and 4) global problems affecting the entire sensor nodes in the network. Advances in algorithms for reduction in energy consumption, bandwidth utilization, routing and clustering, quality of service have seen the improvement of sensor node deployment issues related to coverage, network connectivity, energy efficiency, and data fidelity. A recent survey conducted by [26], has provided the state-of-the-art in four main wireless sensor node deployment strategies mentioned earlier in this dissertation and provides the approach, the load balance strategy, the lifetime, cost, redundant nodes, deployment space (i.e., 2D or 3D), the energy distribution, sensor range, and scalability of some of the work done so far in the area.

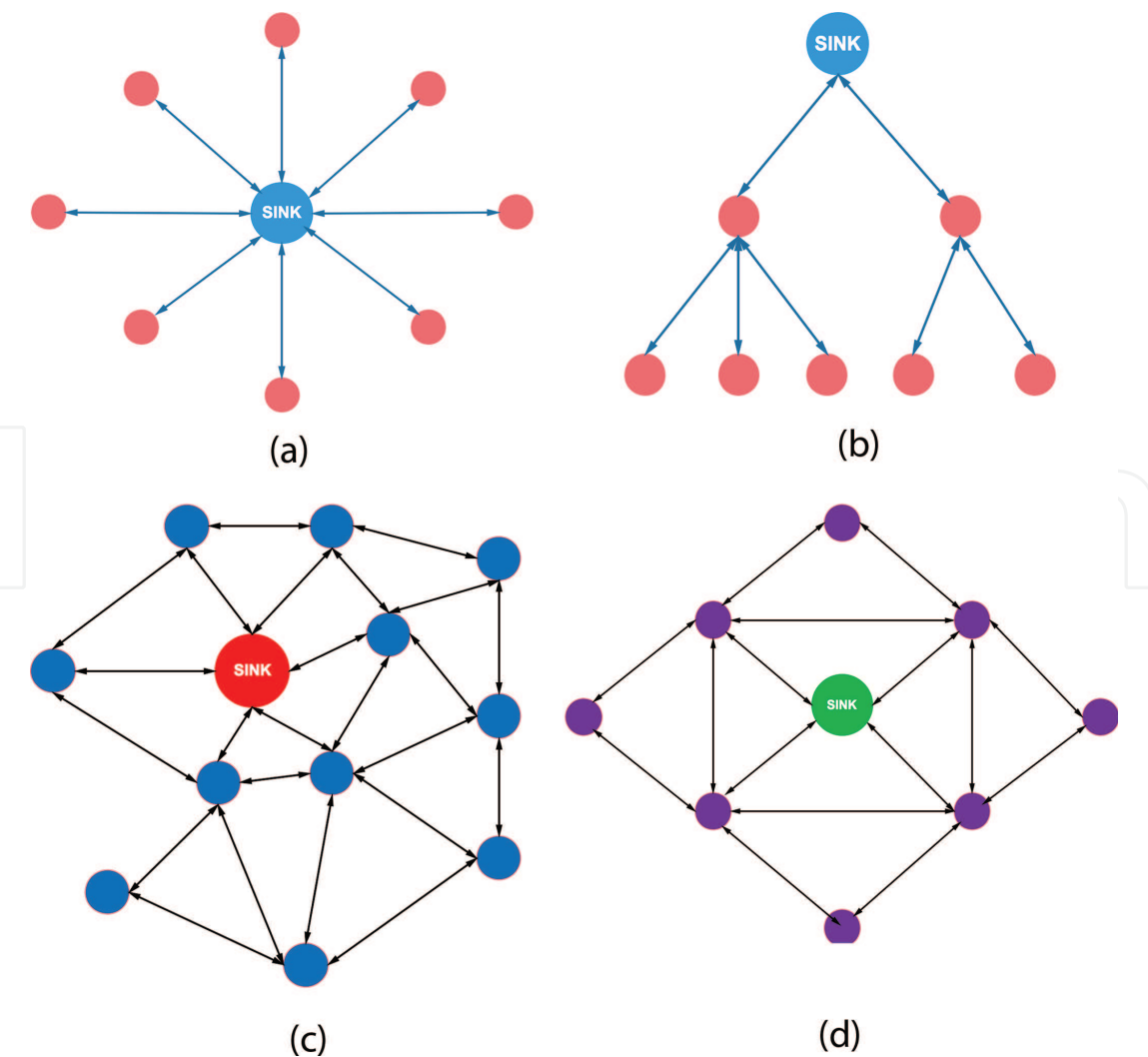


Figure 4. WSN topologies. (a) Star topology, (b) Tree topology, (c) Mesh topology, and (d) Star mesh topology.

Sensor deployment problems	Causes	Effects	Possible solution
Node Problems	Low battery, increased network traffic, software bugs, and sinks acting as gateway between WSN and the Internet	Wrong sensor readings which affects the performance of the network; battery depletion due to overhearing, bugs results in hanging or kill threads, data loss	Node duty cycle Energy harvesting Power management schemes
Link problems	Network congestion due to traffic bursts, neighbor nodes frequently changing, asymmetric links	Message loss, broadcast to discover and maintain links	Efficient MAC protocol
Path problems	Bad path to sink bad path to node, routing loops, asymmetric paths	Greedy nodes not forwarding packets received message loss, inconsistent paths	Direct diffusion Rebooting nodes to clear cached data
Global problems	Low data yield High reporting latency Short network lifetime	Network delivering insufficient data Message loss Node dies	Energy efficiency schemes Energy harvesting

Table 1.
Sensor network deployment problems. Adapted from [3, 5].

4. Energy conservation

Energy conservation techniques or methods mitigate the consumption of energy from the sensor node through careful use of resources available to the individual components of the sensor node to reduce energy consumption. The different components that make up the subsystems of a sensor node are the sensing, computational and radio circuitry. The radio circuitry is responsible for operations such as transmission, reception, sleep and idle. The energy consumption of these aforementioned components is presented in **Figure 5**.

The sensing component is made of sensor(s) for acquiring data from the environment that may include an analog-to-digital converter. The CPU with some memory is responsible for the processing of all computations and local memory allocations. Significant energy may be consumed by these components and subsystems, but the transmission and reception systems which are a function of the radio consumes the most energy.

4.1 Energy conservation schemes

Energy is a scarce resource in WSN applications and the judicious use of the energy available in a sensor node is important to ensure the continuous and prolonged use. Energy conservation schemes employ techniques to reduce the consumption of energy by the component. Classification of conservation schemes for energy in WSN mainly duty cycling, data-driven and mobility as shown in **Figure 6** [3, 27].

Duty Cycling approaches intuitively adapt the sleep/wake-up schedules of sensor nodes to mitigate the energy consumed through the distribution of overhead packets. This exchange of packets occurs during synchronization, frequent switching between sleep/wake-up schedules, overhearing and idle listening. Mobility schemes, however, consider the movement of the sink or relay nodes to positions closer to network nodes to reduce energy consumed. Mobility schemes are best discussed in mobility sensor networks in Section 5.



Figure 5.
WSN deployment techniques.

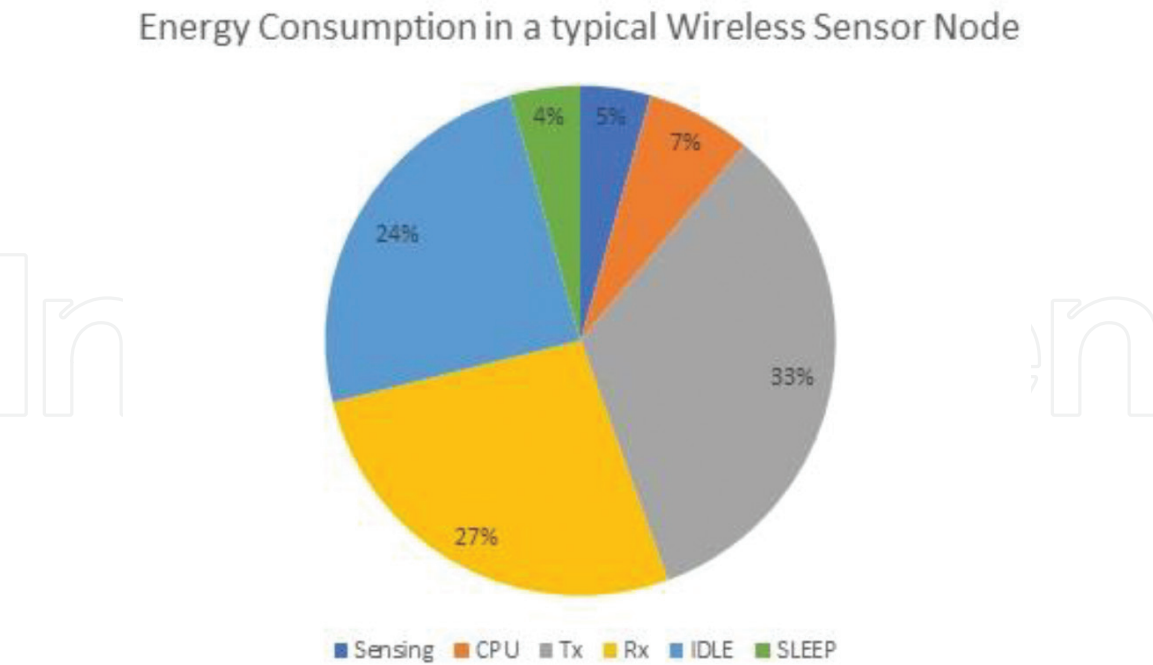


Figure 6.
Energy consumption by the components of a sensor node.

5. Mobility in wireless sensor networks

Mobility may be an important consideration in the energy conservation scheme of sensor networks. Mobility becomes necessary in energy conservation when the

sink or nodes are mobile in the network [28, 29]. Static nodes with multi-hop communication usually have the energy hole problem where nodes closer to the sink are depleted of their energy [30]. The energy hole problem occurs when nodes further away from the sink use them as intermediate nodes to hop data to the sink. Mobile sinks, therefore, go round the network to collect data samples from the nodes to reduce the cost of communication and hence energy lost [31]. The challenge of implementing mobile sinks is to ensure optimum paths are maintained within the network [29].

5.1 Mobility models

The design, deployment and evaluation of sensor nodes in WSNs depend on the environment and the designed objectives for the intended application (e.g., water quality monitoring, fire detection applications, etc.). The sensor network in their deployable environments becomes successful when the stakeholders take into account the network size, the topology, and the communication models used for achieving the application goals. Mobile sensor nodes move to form mobile sensor networks and reposition/reorganize themselves in the sensor network. For example, nodes placed in the ocean are capable of measuring parameters such as ocean current speed, temperature, salinity, pressure, and other chemicals. These sensors move about collecting data in real-time and transmitting the data to a central repository for real-time data analysis [28].

Terrestrial WSNs mobility occurs differently from aquatic WSN mobility. For example, sensor nodes deployed in freshwater sources are affected by the water current. The node movement affects the sensor network design, the distance between the nodes (i.e., during route discovery), propagation, energy utilization among others. In an aquatic environment, electromagnetic wave propagation to sinks above water is challenging. Energy conservation and mobility in this type of network create challenges in the design of routing protocols. Routing protocols that are capable of minimizing the energy consumed by nodes, managing the random variation in the network topology and minimizing the delay in communication are therefore required in an aquatic environment.

In designing and evaluating mobility models for aquatic environments, our work took into consideration the conditions and characteristics of freshwater sources. Freshwater sources such as rivers are in constant motion. The velocity of the river depends on the slope of the land, the size and shape of the bed, and the quantity of water in the river [4, 32]. Sensor nodes may be deployed in one of the following environments; 1) slow but deep water bodies, 2) swift but deep water bodies, and 3) swift but shallow water bodies. Freshwater sources are characterized by three key factors: velocity, gradient, and discharge. Velocity is the distance that the water in a river travels in a given amount of time. The velocity relates to the energy levels of the water in the river. For example, objects (small or large) deposited in a swift or fast-moving river are carried downstream or along the river path quickly as compared to slow-moving rivers. The velocity of a river is affected by the gradient, discharge, and the shape of the river path that the water travels. The gradient is a measure of the steepness of a river, and a river's discharge is expressed as the quantity of water that moves through the different points along the river path at any given time. The discharge varies along the length of the river [32].

Mobile sensor nodes continue to move with water currents after the initial deployment. There are different mobility models used to simulate WSN projects. These include constant acceleration, constant position, constant velocity, Gauss Markov, hierarchical, random direction 2D, random waypoint, steady state random waypoint, random walk2D, and waypoint mobility models. Although these mobility

Terrestrial environment				Aquatic Environment
Parameters	Random waypoint	Random walk	Random Direction	Modified random walk
Selection of destination	Node selects destination (uniformly distributed)	Pre-defined destination (uniformly distributed)	MN travels to boundary of scenario (destination)	Region of interest
Selection of destination	To specified destination in environment	Selects a direction (uniformly distributed)	Selects uniform direction from boundary	Depends on water current (randomly chosen directions)
Selection of Speed	Selects speed (uniformly distributed)	Pre-defined speed (Uniformly distributed)	Selects uniform speed	Depends on river current/speed
Moving to destination	Moves until it reaches the destination	Node moves until reaching the boundary/a certain distance	Moves until it reaches the boundary	Nodes move to boundary and redirected by bouncing effects to change course (x, y)
Waiting time	Stays in a location for a period of time (Uniformly distributed)/Pause time	Wait a certain amount of time	Wait a certain amount of time	No waiting time since node movement is dependent on the flow motion
Next destination	Stays in a location for a period of time (Uniformly distributed)/Pause time	Node selects new direction after reaching boundary/ a certain distance	—	Node floating to the bank (Boundary) and bouncing effects determines (x, y) destination

Table 2.
Random mobility models compared.

models are designed for terrestrial WSN projects, they may be modified for use in aquatic WSN projects. In considering the random walk mobility model, the mobile sensor node after the initial travel time stays at a point for a given period known as the pause time. In other models, the mobile sensor node chooses a new direction and a new speed throughout the travel time and travels towards the destination with this new direction and speed. A comparison of some random mobility models and their characteristics are presented in **Table 2**.

Random walk mobility model is designed in a way that the mobile sensor nodes move freely and randomly in the defined simulation field. In our application domain (i.e., river network monitoring), the mobile sensor node’s movement is affected by the characteristics of the water environment. Notably, the movement is affected by the velocity of the water. Therefore, the sensor nodes are not expected to move in a

- The time and distance that a mobile sensor node moves are short.
- The node’s movement pattern is limited to an only small area in the simulation environment

- The node’s directional movement is randomly generated
- The mobile sensor node moves independently of other nodes

Hence, there is a need to design models that have different mobility characteristics (i.e., such as destination, velocity, and direction). In an aquatic model defined in [33], the speed increases incrementally and the change in direction may not be smooth but fraught in some scenarios as shown in **Figure 7**. The Random Walk mobility model defined proposes node movements that depend on speed, discharge and gradient of the river. The speed and direction of the mobile sensor nodes are critical parameters that aids in the determination of a sensor nodes’ mobility behavior.

Energy conservation schemes in WSN include approaches that depend on characteristics of the data values produced in the network to mitigate energy consumption. Data-Driven techniques, shown in **Figure 8**, involve the use of data characteristics of a sampled data stream to mitigate energy consumption [27]. They include data reduction and energy efficient data acquisition. While data reduction schemes save energy by taking out the redundant data, energy efficient data acquisition reduces the energy spent by the sensing subsystem or sometimes through communication.

Energy efficient data acquisition schemes work on the premise that the sensing subsystem, in some instances, consume significant amount of energy. These may include energy hungry transducers that require high power to sample data. Examples include multimedia sensors or biological sensor. Sensors that require active transducers like radar or laser rangars require active sensing and applications that require long acquisition time that may run into several hundred milliseconds or even seconds [33]. Reducing the energy consumption through frequent/continuous sensing translates into reducing the number of communication as well. The authors of [27, 34] argue that many energy efficient data acquisition schemes have been classified as methods to reduce the energy consumption of the radio. Therefore, WSNs assume the sensing subsystem has negligible energy consumption.

Data acquisition and reduction approaches have been used individually or simultaneously to mitigate energy consumption. The acquisition schemes measure data samples that are correlated spatially or temporally [35]. Temporally because subsequent data samples may not differ much from each other while data from neighboring sensor nodes may not differ much in spatial-correlation.

The inherent characteristics of the data that influence the data received at the sink may be classified as data reduction schemes. Data reduction approaches are generally categorized as In-networking processing, Data Compression and Data Prediction schemes. In-network processing applications are designed to be application specific. In-network data processing operations such as fusion and aggregation incorporate sensing and networking to reduce unnecessary data forwarding from

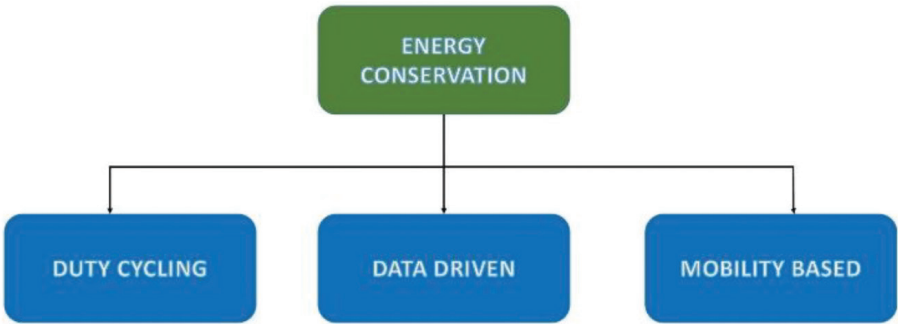


Figure 7.
Energy conservation in wireless sensor networks.

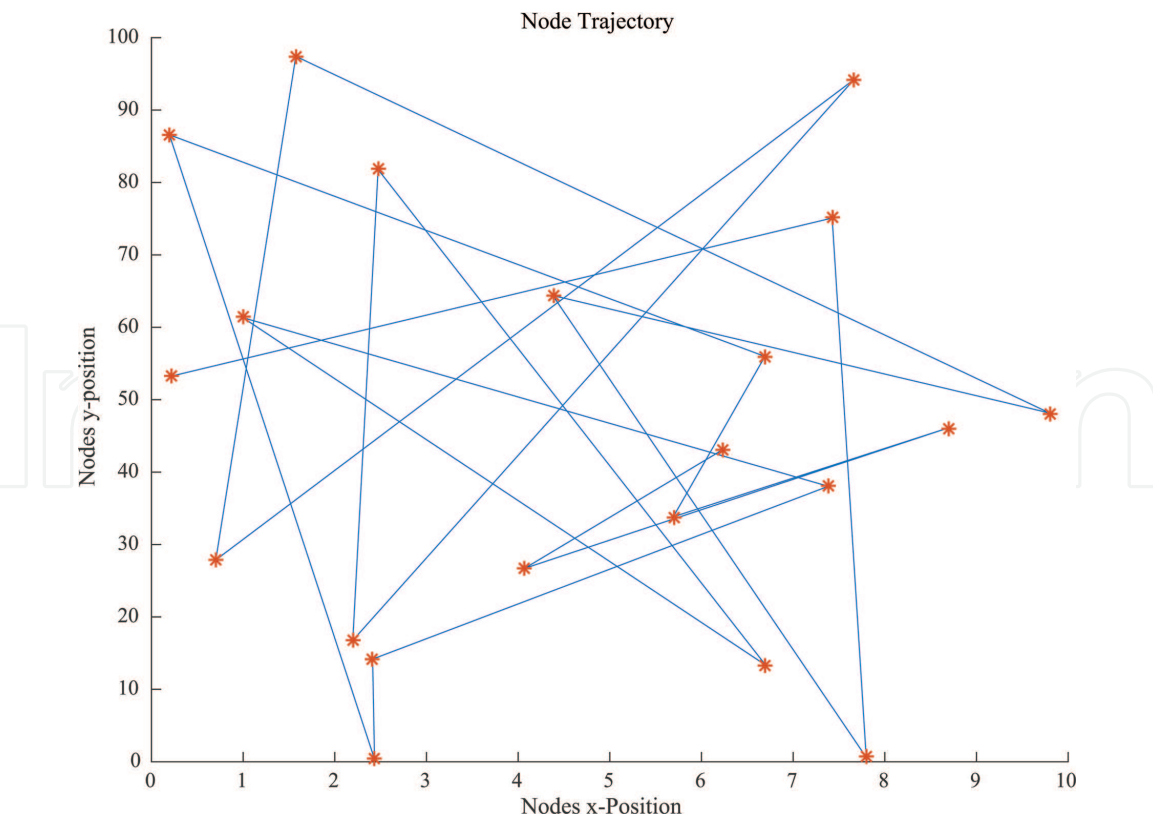


Figure 8.
Node mobility trajectory with random waypoint model.

source nodes to the sink as they traverse the network. A survey of data aggregation methods was presented in [36], and present clustering-based aggregation protocols in WSN. The clustering protocols were classified as homogeneous, heterogeneous, and single and multi-hop.

Data compression is the reduction of the amount of data that traverses a network. It may be classified into lossless, loss and unrecoverable compression. In lossless compression, the data obtained after decompression is the same as data after the compression operation [37]. An example of lossless compression is the Huffman coding. In loss compression [38, 39], some details of the data are changed as a result of compression. Unrecoverable compression occurs when no decompression operation is applied such final data cannot be derived from the initial data [40, 41].

6. Data prediction approaches

Data prediction is a data reduction method in WSNs that reduces the number of data that is sent from sources to the sink. They are concerned with the building of models for forecasting sensed parameters of sensor nodes using historical data. The main aim of predictive wireless sensor networks is to exploit the temporal and spatial correlation characteristics of the observed environment. Prediction also capitalizes on the redundancies of environmental parameters to compute future parameter readings thereby reducing the frequency of required readings.

The forecasted values are adopted when they fall within some acceptable thresholds. Some predictive models are based on the sink and on the nodes themselves. Prediction is therefore performed on the sink node and since the same model is kept on the nodes by synchronization, it is assumed the same predicted values are generated. In some instances, prediction is done by the nodes and model is sent to the sink; hence the sink also computes the same predicted readings. When nodes take readings

beyond some threshold, it is sent to the sink otherwise the sink uses the predicted values. When the model deteriorates such that the model does not reflect the current readings, fresh data is read from the environment and the model is updated. This requires frequent update and re-synchronization of the sensor nodes and the sink which introduces energy consumption overheads in the network [2]. To overcome the energy lost by synchronization, some predictive models are only kept on the nodes, which determine when readings from the sensors are transmitted to the sink.

The prediction schemes surveyed in [22] on data reduction were not concerned with the medium access control challenges of radio energy consumption. In their classification, forecasting methods were not fully explored in WSN by the time of their publication as well as machine learning tools as argued in [42]. This is the basis for the new classification presented in **Figure 9**. Predictions studied in this chapter are limited to methods to predict data for the purposes for reducing data transmission (**Figure 10**).

6.1 Stochastic approaches

Stochastic approaches characterize the sensed data as a random process from which a probabilistic model is applied to predict the data values. An example of a stochastic approach is proposed in [43] where KEN (a range of perception, understanding and knowledge based model) a robust approximation technique minimizes

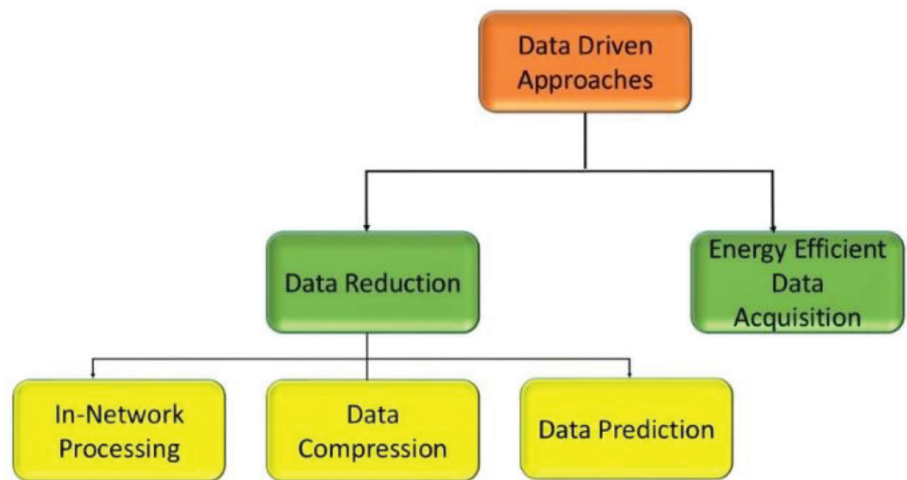


Figure 9.
Data-driven approaches in WSN.

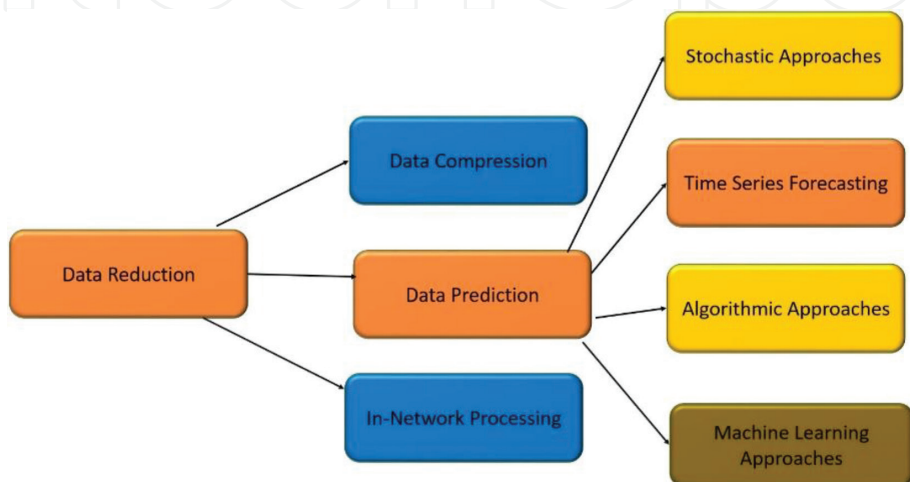


Figure 10.
Predictive approaches in wireless sensor networks.

the communication from sensors to sink using replicated dynamic probabilistic models KEN exploits the spatial correlations across sensor nodes to boost coordination that minimizes communication cost. The Kalman filter, Dynamic Probabilistic Models and Monte Carlo are some algorithms that have been used in some stochastic models [38, 39]. Due to randomness and probabilities of data used in stochastic applications, they are usually energy consuming and care must be taken in applying them to WSNs. They are mostly used in heterogeneous networks where specialized nodes that have high energy levels run these models.

6.2 Algorithmic approaches

Algorithmic approaches are predictive methods that depend on algorithms that consider the heuristic or behavioral characteristics of the data collected from the environment. One of the first works based on the algorithmic approach is Prediction-based Monitoring (PREMON) [44]. PREMON is a prediction-based monitoring algorithm which is inspired by concepts from MPEG (also known as the Moving Pictures Experts Group [MPEG]), a standard for video compression. Algorithmic approaches are usually application specific. A spatiotemporal data map of data stream from sensors at the sink node is obtained by generating periodic snapshots at a given time granularity [45]. An Energy efficient data collection framework (EEDC) is proposed in [46] that exploits the spatiotemporal correlation of data to form clusters and a randomized scheduling algorithm to conserve energy. A lightweight greedy algorithm that minimizes the energy consumed through data transmission is modeled as an optimization problem called Piecewise Linear Approximation with minimum number of Line Segments (PLAMLiS). The algorithm is integrated into EEDC framework to further save energy. In [47] a data collection method is proposed that exploits the trade-off between QoS of applications and energy consumption by progressively exposing power saving states in a network while minimizing the energy consumption. Since algorithms are application specific, more work may be done in the future in real applications to standardize the approaches. In [48], the challenge of selecting the efficient prediction model for a particular time series is addressed by an adaptive lightweight and online model selection algorithm. The algorithm statistically selects an optimal model among a list of candidates. The Dual Prediction Scheme (DPS) has been used severally in WSN applications and yield high communication and energy savings.

6.3 Machine learning approaches

Machine learning uses tools, techniques and algorithms with computational viability to improve on themselves by learning through their experience on data and is used for creating predictive models. They are able to carry out predictions while learning from streams of data patterns. Machine learning presents strategies for WSNs to better make informed decisions from the data in the network to improve network performance. These strategies learn the behavior of the networks and improve on its experiences of the environment without explicit programming. It is based on statistical models and probabilities to make predictions of future data occurrences.

In literature, machine learning approaches are categorized as supervised learning, unsupervised learning and reinforcement learning [Under supervised learning approaches such as K-nearest neighbor (k-NN), Decision Trees, Neural Networks, support vector machines and Bayesian statistics are the most commonly used Unsupervised learning techniques include K-Means clustering, and Principal Component Analysis (PCA). Reinforcement learning approaches have been used with the most common approach in WSN being Q-learning. Most of

Mechanisms	Classification	Machine leaning algorithms	Complexity	Balancing energy consumption	Delay	Overhead	Topology
Large scale network clustering	Supervised Learning	Bayesian Networks	Moderate	Yes	High	Low	Yes
Location-aware activity recognition			Moderate	Yes	High		Yes
Localization based on Neural Networks	Supervised Learning	Neural Networks	High				Yes
Soft Localization			Moderate				Yes
Cluster Head election	Supervised Learning	Decision Trees	Low	Yes	Low	Low	Yes
Underwater surveillance systems			Moderate				No
Clustering using SOM and sink distance	Unsupervised learning	SOM	Moderate	No	High	Moderate	Yes
Path Determination	Reinforcement Learning	Reinforcement Learning	Low	No	Low	Low	Yes
Role-free clustering	Reinforcement Learning	Q-learning	Low				No
Localization using SVM	Supervised learning	SVM	Moderate				Yes

Table 3.
Feasibility of machine learning approaches in wireless sensor networks.

these approaches have been applied in sensor node clustering and data aggregation mechanisms as presented in the **Table 3**.

In [46], the authors present surveys of machine learning approaches that have been applied to WSN to address known challenges such as outlier detection in data, computational efficiency, and errors in collected data. They are used in tasks including classification and regression and applied in bioinformatics, computer science, spam detection, anomaly detection, and fraud detection. Machine learning approaches have provided a means for wireless sensor networks to dynamically adapt its behavior to the environment. They are used to solve WSNs challenges such as limited resources and the diversity of the learning themes and patterns developed from the vast data collected. In [46], the authors identified challenges with machine learning approaches in wireless sensor networks which include developing lightweight and distributed message passing techniques, online learning algorithms, hierarchical clustering pattern and to develop solutions that take into consideration the resource limitation of WSN.

7. Sleep scheduling based on prediction

Sleep scheduling algorithms reduce the energy consumption in wireless sensor nodes due to idle listening and overhearing. Traditionally, sleep scheduling algorithms require frequent sleep/wake-up transitions; however, they consume extra energy due to the frequent state transitions. Sleep scheduling algorithms determine some nodes to be awake in a given epoch, while the remaining nodes maximize their sleep periods to reduce the energy consumed in the network.

Several sleep scheduling approaches have been proposed in literature since nodes in sleep (low power) modes consume significantly lower energy than active nodes. Some scheduling algorithmic approaches in literature propose means of turning off redundant nodes in the network, leaving some active nodes to continue network operations. Initial works include [49] where longer sleep cycles were proposed for a network with redundant nodes. The authors explored the relationship between the level of redundancy and the low duty cycles. The approach synchronizes nodes for a robust performance for large networks as opposed to a random scheduling approach. But the cost of synchronizing sensor nodes is high when the control overhead increases with increasing size of the network.

Idle listening, which occurs when nodes stay awake for longer periods waiting for packets, is a major source of energy waste in WSN. Authors in [49, 50] suggests idle listening consumes just as much energy required for receiving packets. Hence nodes are turned off when the radio module is not in use. Several approaches have been introduced by authors to mitigate idle listening.

One such approach is to put nodes in low-power listening (LPL) low duty cycle (LDC) mode (when nodes are made to sleep for longer periods when there is no activity in the network) that makes nodes wake up periodically to check the channel for activity. Characteristics of LDC include networks in periodic and relatively low frequency of network activity. One challenge of such networks is synchronization of receiver and sender nodes. Since sections of the network may be turned-off to conserve energy, remote communication may result in packets not reaching their destination, or have increased end-to-end delays. An example is Berkeley-MAC (B-MAC) makes nodes independently sample the channel for activity, by sending a preamble longer than the listening time of the duty cycle of the receiver node. This ensures the receiver is awake to receive its intended message. But this increases energy waste when the load in the network increases and collisions occur as a result of the increased preambles.

Low-power listening with Wake-Up After Transmission (LWT-MAC) was developed in [51] that alerts all nodes that overheard the last transmitted packets to wake-up to receive the new message. This approach does not depend on preambles but on the local synchronization of the nodes. This approach does not consider remote communication beyond the local nodes that overhear the latest transmission. Other protocols like X-MAC [52], S-MAC [42] and T-MAC [53] uses the Request-to-Send (RTS) and Clear-to-Send (CTS) to keep receiver nodes active when a message is intended for them. Other low-power listening protocols include Scheduled Channel Polling Mac (SCP-MAC) that increases the duty cycle after a successful message delivery to cut down on end-to-end delays.

TDMA protocols used in duty cycle algorithms reduce idle listening, over hearing and also avoid collisions. But they also increase the number of dropped packets in transmissions since nodes may only receive packets when they are active. Synchronization of receiver nodes and sender nodes ensures nodes are active to receive packets when transmitted from the sender nodes.

The medium access therefore is one key challenge in the era of Internet of Things (IoTs) due to the huge number of device connectivity with different traffic profiles. It is therefore, of necessity, an urgent requirement of these sensor nodes to reduce the number of transmissions from devices using data reduction approaches. However, prediction models, which forecast future data values may be a promising tool to reduce transmissions while maintaining optimum levels of trust and reliability of the data received [53].

In the past, researchers avoided the implementation of complex algorithms in WSN due to their limited computational capabilities. However, with recent advances in hardware, data mining techniques are increasing used in WSN to discover patterns in sensor data to improve on its successful delivery [54]. Even though not all data mining approaches include predictions, machine learning tools that implement prediction in WSN is currently an open research area. Authors in [54] discussed the implementation of machine learning in the routing and medium access layers.

In the implementation of prediction models, time series models have been used together with machine learning to forecast data values. This is because, machine learning-based approaches uncover and learn patterns in data to evolve their predictions in response to changes in the deployed environment. On the other hand, time series methods depend on the statistical and probabilistic tendencies of the data to make predictions. The survey by [55] introduced current prediction techniques for reducing data transmission in WSN.

Time series models sequentially model observed data over successive time. The successive data is analyzed to extract meaningful statistics and probabilities that may influence calculated forecasts. Time series data may be seasonal, trend, cyclical or irregular. Trend analysis tends to increase, decrease or remain stagnant over a long period. Seasonal analysis shows fluctuations that change during repeatable periods in the period under observation. Under cyclical, the patterns observed describe medium-term changes that may repeat in cycles, where cycles may extend over long periods. Irregular patterns fluctuate unpredictably and hence are difficult to be predicted using time series methods.

Examples of time series models implemented in WSN include the naive approaches, autoregressive and moving average approaches (AR and MA), Autoregressive Integrated Moving Average (ARIMA), Exponential Smoothing, Gray Series, and Least Mean Square (LMS). In time series analysis, Autoregressive Integrated Moving Average (ARIMA) generalizes the Autoregressive moving average (ARMA) with a differencing. However, ARMA is a combination of the Autoregressive (AR) and Moving Average (MA) models into a single equation.

Predictive Model	Examples	Classification of data	Characteristics	Advantages	Disadvantages	Applications in WSN
ARIMA models	AR, MA, ARMA, ARIMA	Seasonal, Trend	Univariate, linear and non-linear, discrete	Independence from external data. Does not require extended analysis	Assumes univariate data analysis	Data gathering applications Water Quality monitoring
Naïve algorithms	Naïve bayes	Trend	Distributed, partially independent	Independence of input data if trained. Useful in applications with frequent topology changes if model is well trained.	Assumes independent predictor features.	Medical data monitoring Agricultural monitoring
Exponential Smoothing	Single Exponential smoothing Double Exponential smoothing Triple exponential smoothing	Trends and seasonal data	Univariate	More significant to recent observations. Best for short-term forecasts	Ignores random variations of data. May not handle trends well	Environmental monitoring Multimedia VANETS
Gray Series	GM (1,1) Rolling GM (1,1) Adaptive Gray	Trend, seasonal,	Univariate and multivariate data.	Requires limited samples for short term prediction. Can make near accurate prediction with poor information of the data.	Homogenous exponent simulative deviation	Energy-map applications Water quality monitoring Environmental monitoring Internet of Things
Least Mean Square	LMS Hierarchical LMS	Trend	Univariate	Distributed algorithm Does not require a-priori knowledge of the environment	Not robust frequent change is trends	Target tracking Temperature measurements.

Table 4.
Time series classification.

These models are best for stochastic data sets that may be linear or non-linear. ARIMA models have several applications in WSN due to their simplicity of use, and near accurate prediction for linear data.

Exponential smoothing prediction is a time series forecasting method that can be used to forecast univariate data to support data with systemic or seasonal trends [56]. It is a model where predictions are weighted sums of past observations, such that weights exponentially decrease as they get older. Weights of predictions decrease at a geometric ratio. They may be considered peers or alternatives to other Box-Jenkins models. Three exponential smoothing models are generally used, that is the single, double and triple exponential smoothing models. The single exponential smoothing methods add no systemic structure to the univariate data without trend or seasonality. A smoothing factor, alpha is set to values between 0 and 1, with larger values indicating model is dependent more on recent observations and the vice versa. The single smoothing method is used when the observed data is either stationary or changes slowly with time.

The double smoothing method adds trends and seasonality to the univariate data. A beta value is added to the alpha value to control the decay of the influence of change in the trend of data. The change may be additive or multiplicative. When the change is additive, the Holt's linear trend model. In longer forecasts, the double smoothing method may reduce the size of the trend to straighten it, prevent unrealistic trends. In the triple smoothing, a gamma value is added to the alpha and beta to influence the seasonality of the observed data.

Gray series are time series prediction model with superiority to other statistical methods of prediction [57] due to its accuracy in predicting small data sets with lower errors. Gray models are preferable for data where statistical methods may not be appropriate or if the data does not satisfy conventional distributions [57]. In WSN, gray series are preferred due to their minimum complexity and low computational capacity. **Table 4** present some selected classification of time series models used in WSN based on their popularity and frequency of use.

8. Conclusion

The chapter focuses on the various deployment environments and the challenges that the implementation of WSNs brings about when adopted for use. The chapter also discussed WSN topologies and explored ways in which network topology impacts energy consumption and communication issues. The chapter highlights the different techniques mainly used when implementing WSNs to maximize lifetime, coverage, and connectivity while ensuring data fidelity. The chapter also describes the energy conservation techniques, data prediction approaches, and mobility models. Various data prediction models such as the time series models are discussed in detail. A classification of some time series models based on their popularity and recent use highlights their applications. Advantages and disadvantages of the selected time series models and reasons of their implementations are discussed.

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