Information Fusion 49 (2019) 1–25

Contents lists available at ScienceDirect

Information Fusion

journal homepage: www.elsevier.com/locate/inffus

Machine learning algorithms for wireless sensor networks: A survey

D. Praveen Kumar, Tarachand Amgoth*, Chandra Sekhara Rao Annavarapu

Department of Computer Science and Engineering, Indian Institute of Technology (Indian School of Mines), Dhanbad, India

A R T I C L E I N F O

Keywords:
Wireless sensor networks
Machine learning
Energy efficiency
Network lifetime
Data aggregation

A B S T R A C T

Wireless sensor network (WSN) is one of the most promising technologies for some real-time applications because of its size, cost-effective and easily deployable nature. Due to some external or internal factors, WSN may change dynamically and therefore it requires depreciating dispensable redesign of the network. The traditional WSN approaches have been explicitly programmed which make the networks hard to respond dynamically. To overcome such scenarios, machine learning (ML) techniques can be applied to react accordingly. ML is the process of self-learning from the experiences and acts without human intervention or re-program. The survey of the ML techniques for WSNs is presented in [1], covering period of 2002–2013. In this survey, we present various ML-based algorithms for WSNs with their advantages, drawbacks, and parameters effecting the network lifetime, covering the period from 2014–March 2018. In addition, we also discuss ML algorithms for synchronization, congestion control, mobile sink scheduling and energy harvesting. Finally, we present a statistical analysis of the survey, the reasons for selection of a particular ML techniques to address an issue in WSNs followed by some discussion on the open issues.

1. Introduction

Wireless sensor network (WSN) is one of the most promising technologies for some real-time applications because of its size, cost-effective and easily deployable nature [2]. The job of WSN is to monitor a field of interest and gather certain information and transmit them to the base station for post data analysis [3,4]. Some of the WSN applications consists of a large number of sensor nodes. Therefore managing such a large number of nodes requires a scalable and efficient algorithms. In addition, due to the external causes or intended by the system designers, the WSNs may change dynamically. Therefore it may affect network routing strategies, localization, delay, cross-layer design [5], coverage, QoS, link quality, fault detection, etc. [6]. Because of the highly dynamic nature, it may require depreciating dispensable redesign of the network, but the traditional approaches for the WSNs are explicitly programmed, and as a result, the network does not work properly for the dynamic environment.

Machine Learning (ML) is the process that automatically improves or learns from the study or experience, and acts without being explicitly programmed [7–9]. ML was making our computing processes more efficient, reliable and cost-effective. ML produce models by analyzing even more complex data automatically, quickly and more accurately. It is mainly classified into supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. The strength of ML lies in their ability to provide generalized solutions through an architecture that can learn to improve its performance. Because of the interdisciplinary nature, it plays a pivotal role in various fields including engineering, medical, and computing. Recent advances in ML have been applied to solve various issues in WSNs [1]. Applying ML not only improves the performance of WSNs and also limits the human intervention or re-program. Access vast amount of data collected by the sensors, and extract the useful information from the data is not so easy without ML. It also uses to integrating Internet of things (IoT), cyber-physical systems (CPS) and machine to machine (M2M) [1]. Some of the applications of ML in WSNs are:

- For target area coverage problem, deciding an optimal number of sensor nodes to cover the area is easily obtained by ML techniques.
- Energy-harvesting provides a self-powered and long lasting maintenance for the WSNs deployed in the harsh environment. ML algorithm improves the performance of WSNs to forecast the amount of energy to be harvested within a particular time slot.
- Sensor nodes may change their location due to some internal or external factors. Accurate localization is smooth and rapid with the help of ML algorithms.
- ML used to segregate the faulty sensor nodes from normal sensor nodes and improve the efficiency of the network.
- Routing data place a major role in improving the network lifetime. The dynamic behavior of sensor network requires dynamic routing mechanisms to enhance the system performance.

* Corresponding author.
E-mail address: tarachand@iitism.ac.in (T. Amgoth).

https://doi.org/10.1016/j.inffus.2018.09.013
Received 17 April 2018; Received in revised form 17 September 2018; Accepted 20 September 2018
Available online 21 September 2018

Table 1
Abbreviations.

AD	Anomaly Detection	ABC	Artificial bee colony
ACO	Ant colony optimization	ANN	Artificial Neural Networks
ANOVA	Analysis of variance	AOGE	Angle optimized global embedding
BCS	Bayesian compressive sensing	BSN	Body sensor network
BTMS	Bayesian-based trust management strategy	CHs	Cluster heads
CNN	Conventional Neural Network	CPS	Cyber physical systems
DACR	Distributed adoptive cooperative routing	DBSCAN	Density-based Spatial Clustering of Applications with Noise
DFRTP	Dynamic 3D fuzzy routing-based on traffic probability	DFTDT	Distributed functional tangent decision tree
DL	Deep learning	DLRDG	Distributed linear regression-based data gathering
DoS	Denial-of-Service	DT	Decision trees
FCM	Fuzzy *c*-means	FCMTSR	Fuzzy *C*-means training sample reduction
FDS	Fault detection scheme	FIS	Fuzzy information system
FLI	Fuzzy location indicator	GPS	Geographical position system
HMM	Hidden Markov Model	ICA	Independent component analysis
IDS	Intrusion detection system	IoT	Internet of Things
LEACH	Low Energy Adaptive Clustering Hierarchy	LQI	Link quality indicator
MAC	Medium Access Controller	MDBN	Multi-layer dynamic Bayesian network
ML	Machine Learning	MST	Minimum spanning tree
NREL	National renewable energy laboratory	ODT	Optimal deadline-based trajectory
PCA	Principle Component Analysis	PCRB	Posterior CramerRao bound
PDR	Pocket delivery ratio	PPM	Parts Per Million
PSO	Particle Swarm Optimization	QoS	Quality of Service
RBF	Radial Basis Function	RF	Random forests
RL	Reinforcement learning	RMSE	Root mean square error
RPs	Rendezvous points	RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator	SHM	Structural health monitoring
SLT	Shallow light tree	SMC	Sequential Monte Carlo
SMO	Sequential minimal optimization	SVD	Singular Value Decomposition
SVDD	Support Vector Data Description	SVM	Support Vector Machine
THMSO	Two-hop mass spring optimization	VBEM	Variational Bayesian expectation maximization
VOC	Volatile organic compound	WEH	Wireless energy harvesting
WH	Wormhole	WNN	Wavelet neural networks
WSNs	Wireless Sensor Networks	ZEEP	Zone-based energy efficient routing

- Transmitting the entire data to the base station will lead to transmission overhead in the network. ML also helps to reduce the dimensionality of the data at the sensor or cluster head level.

In [1], a detailed survey of the ML for WSNs has been covered for the period 2002–2013 in which various issues were discussed. The covered issues are localization, object tracking, routing, clustering and data aggregation, event detection, query processing, and MAC protocols as a functional challenge and whereas security, anomaly detection, fault node detection, and QoS as non-functional challenges. We present a survey on various ML-based algorithms for WSNs with their advantages, drawbacks, and parameters effecting the network lifetime, covering the period from 2014–March 2018. In this survey, we also discuss ML algorithms for synchronization, congestion control, mobile sink scheduling and energy harvesting for WSNs. Finally, we present a statistical analysis of the survey, the reasons for selection of ML to solve various issues in WSNs, and some of the open issues to be addressed by ML techniques for WSNs.

The rest of the paper organized as follows. For the readers convenient, abbreviations used in this paper are listed in Table 1. The necessary background of the ML approaches discussed in Section 2. In Section 3, a brief survey of various applications of ML in WSNs issues are discussed. In Section 4, statistical analysis and limitations are presented. In Section 5, we present open issues for ML-based algorithms for WSNs. Finally, in Section 6, we conclude the paper.

2. Machine learning techniques

In this section, we explore various ML techniques and their learning procedures that will helps to understand the later sections. We also given a brief description of evolutionary computing techniques for WSNs. Based on the learning styles, ML techniques have been categorized into supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. Fig. 1 shows the taxonomy of ML techniques.

2.1. Supervised learning

Supervised learning is one of the most important data processing approaches in ML. In supervised learning, we provide a set of input and outputs (datasets with labels), and it finds the relation between them while training the system. At the end of the training process, we can find a function from an input x with a best estimation of output y (f: $x \rightarrow y$). A major responsibilities of supervised learning algorithms are to generate the model which represents relationships and dependency links between input features and forecast objective outputs. Supervised learning solve various challenges in WSNs such as localization [10–25], coverage problems [26–31], anomaly and fault detection [32–45], routing [46–53], MAC [54], data aggregation [55–67], synchronization[68–71], congestion control [72–74], target tracking [75–78], event detection [79–81], and energy harvesting [82,83]. Supervised learning categorized into regression and classification. Classification can be divided into logic-based (decision tree and random forest), perceptron based (ANN and deep learning), statistical learning (Bayesian and SVM) and instance-based (k-NN) algorithms.

2.1.1. Regression

Regression is a supervised learning method, and it will predict some value (Y) based on a given set of features (X). The variables in the regression model are continuous or quantitative. Regression is very simple ML approach and predicts accurate results with minimum errors. The mathematical notation for linear regression [84] is shown in Eq. (1).

$$Y = f(x) + \varepsilon \tag{1}$$

where Y is the dependent variable (output), x indicates independent variable (input), f is a function that it makes the relation between x and Y, and ε represents the possible random error. The working model of a simple linear regression is shown in Fig. 2. Regression is applied to solve various issues in WSNs such as localization [85], connectivity problem [26,27], data aggregation [55–57], and energy harvesting [82,83].

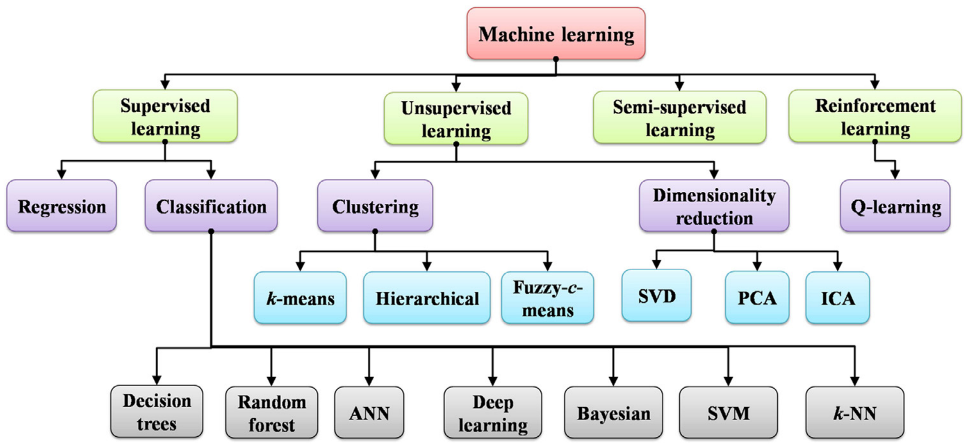

Fig. 1. Taxonomy of ML techniques.

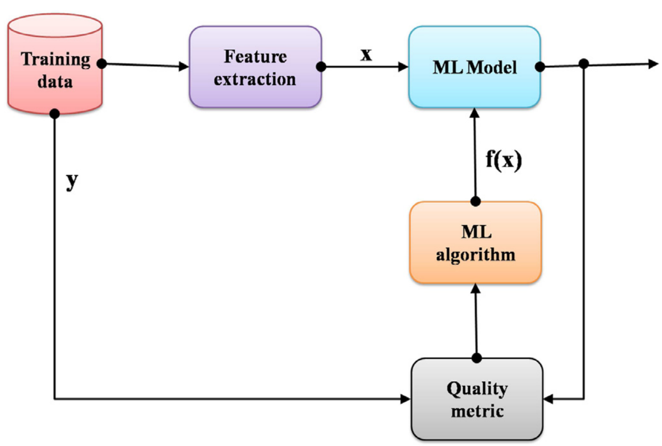

Fig. 2. The simple linear regression model [86].

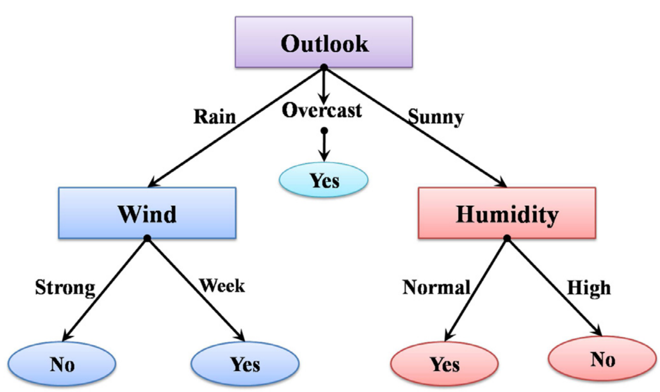

Fig. 3. Graphical representation of a decision tree [87].

2.1.2. Decision trees

Decision trees (DT) are a class of supervised ML approach for classification based on a set of if-then rules to enhance the readability. A decision tree contains two types of nodes called as leaf nodes (final outcomes) and decision nodes (choice between alternatives) [87]. Decision tree uses to predict a class or target by creating a training model based on decision rules inferred from training data. An example graphical representation of a decision tree is shown in Fig. 3. The major advantages of the decision tree are transparent, reduces ambiguity in decision-making, and allows for a comprehensive analysis. Decision trees are adopted to solve various issues in WSNs such as connectivity [29], anomaly detection [33], data aggregation [59,60], and mobile sink path selection [88].

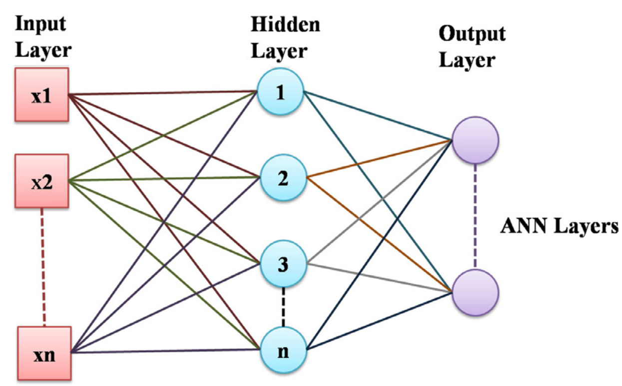

Fig. 4. A simple ANN architecture with different layers.

2.1.3. Random forest

Random forest (RF) algorithm is a supervised ML technique with a collection of trees and each tree in the forest gives a classification. RF algorithm works in two stages, creation of random forest classifier and prediction of results [89]. RF works efficiently for the larger datasets and heterogeneous data. This approach accurately predicts the missing values. The impact of randomly selecting a subset of training samples and isolating variables at each tree node will produce a large number of decision trees. Therefore, the sensitivity level of RF classifier is less with appraising to other streamline ML classifiers because of the quality of training samples and to over robust decision trees. Existing classification methodologies are facing significant challenges due to a curse of dimensionality and highly correlated data. RF classifier will be the best appropriate method for classifying hyperspectral data [90]. RF algorithm has been applied to solve various issues in WSNs such as coverage [30] and MAC protocol [54].

2.1.4. Artificial neural networks

An artificial neural network (ANN) is a supervised ML technique based on the model of a human neuron for classifying the data [91,92]. ANN connected with a huge number of neurons (processing units) that process information and produce accurate results. ANN typically operates on layers, these layers connected with nodes and each node associated with an active function. Fig. 4 shows the basic layer structure of an ANN. Each ANN contains three layers called input layer, one or more hidden layer(s) and output layers. ANN classifies complex and nonlinear data sets very easily, and there is no restriction for the inputs like other classification methods. Several real-time WSN applications have using ANN though it has higher computation requirement. ANN can be applied to improve the efficiency of various issues in WSNs including localization [10–15], detecting faulty sensor nodes [44], routing [46–49], data aggregation [61], and congestion control [72,73].

2.1.5. Deep learning

Deep learning is a supervised ML approach used for classification, and it is a subcategory of ANN. Deep learning approaches are the data learning representation methods with multi-layer representations (between the input layer and output layer). It compose with simple non-linear modules that transforms the representation from lower layer to higher layer to achieve the best solution [93]. It is inspired by communication patterns and information processing in human nerve systems [94]. The key benefits of deep learning are extracting high-level features from the data, work with or without labels, and it can be trained to fulfill multiple objectives. It can be useful in various domains such as Bioinformatics, social network analysis, business intelligence, medical image processing, speech recognition, handwriting recognition. The advantages of deep learning have attracted researchers of WSNs. Deep learning have addressed various issues in WSNs such as anomaly and fault detection [95,96], routing [49], data quality estimation [97], and energy harvesting [98].

2.1.6. Support vector machine

Support vector machine (SVM) is a supervised ML classifier which finds an optimal hyperplane to categorize the data. SVM performs the best classification using hyperplane and coordinate individual observation [99]. Most of the training data is redundant once a boundary established and a set of points helps to identify the boundary. The points which are used to find the boundary called as support vectors. SVM provides the best classification from a given set of data. Therefore, the model complexity of an SVM is unaffected by the number of features encountered in the training data. For this reason, SVMs are well suited to deal with learning tasks where the number of features is large with respect to the number of training instances. Applying SVM for WSNs have addressed issues in WSNs such as localization [15–20], connectivity problem [28,29], fault detection [39,40,100,101], routing [50], and congestion control [74].

2.1.7. Bayesian

Bayesian is a supervised ML algorithm based on statistical learning approaches [102]. A Bayesian learning finds the relationships among the datasets by learning the conditional independence using several statistical methods (example: Chi-square test). A set of inputs $X_1, X_2, X_3 \dots, X_n$ returns a label θ the probability $p(\theta|X_1, X_2, X_3 \dots, X_n)$ to be maximize. Bayesian learning allows different probability functions for different variables of class nodes. Recently, several WSNs problems are solved based on the Bayesian learning strategies to improve the efficiency of the network. The issues are localization [21–25], coverage [31], anomaly & fault detection [37,38,41–43], routing [51–53], data aggregation [63–67], synchronization [71], target tracking [75–78,103], event detection [104], and mobile sink path selection [105].

2.1.8. k-Nearest neighbor

K-Nearest Neighbor (*k*-NN) is the most straightforward lazy, instance-based learning method in regression and classification. The *k*-nearest training set consider as an input from the feature space. K-NN commonly classifies based on the distance between specified training samples and the test sample. The *K*-NN method uses various distance functions such as Euclidean distance, Hamming distance, Canberra distance function, Manhattan distance, Minkowski distance and Chebychev distance function. The complexity of the *k*-NN algorithm depends on the size of input dataset and optimal performance if the same scale of the data. This approach finds the possible missing values from the feature space and also reduces the dimensionality [106–108]. In WSNs, anomaly detection and fault detection [32,45] and data aggregation [58] approaches are used the *k*-NN algorithm.

The comparisons of classification algorithms with respect to various parameters are tabulated in Table 2. The number 4 indicates the best performance whereas 1 indicates poor performanc, 3 indicates very good and 2 can be considered as satisfactory.

2.2. Unsupervised learning

In unsupervised learning, there is no output (unlabeled) associated with the inputs; even the model try to extract the relationships from the data. Unsupervised learning approach used as classifying the set of similar patterns into clusters, dimensionality reduction, and anomaly detection from the data. The major contributions of unsupervised learning in WSNs are to tackle various issues such as connectivity problem [110], anomaly detection [111], routing [112–115], and data aggregation [116–125]. Unsupervised learning further categorized into clustering (*k*-means, hierarchical and fuzzy-*c*-means) and dimensionality reduction (PCA, ICA and SVD).

2.2.1. k-means clustering

The *k*-means algorithm easily forms a certain number of clusters from a given dataset [126]. Initially *k* number of random locations are considered and all the remaining points associated with the nearest centers. Once the clusters are formed by covering all the points from the dataset, a new centroid from each cluster is re-calculated. The centroid of the cluster change in each iteration, and repeat the algorithm until no more changes in the centroid of all clusters. The time complexity of the *k*-means algorithm is $O(n^*k^*i^*d)$, where n represents the number of points, k indicates the number of centroids, i indicates a number of iterations, and d represents the number of attributes. The minimization function for the sum of squares of errors [127] is presented in Eq. (2).

$$min \quad f(X) = \sum_{i=1}^{k} \sum_{j=1}^{N} ||x_i - y_j||^2 \tag{2}$$

where $||x_i - y_j||$ indicates the Euclidean distance between x_i and y_j, N represents the number of data points from i^{th} cluster. *k*-means clustering is the simplest clustering and useful in WSNs to find optimal cluster heads (CHs) for routing the data towards to base station [112–114]. This approach also useful to find the efficient rendezvous points for mobile sink [128].

2.2.2. Hierarchical clustering

Hierarchical clustering technique groups the similar objects into clusters that have a predetermined top-down or bottom-up order. Top-down hierarchical clustering also called *divisive clustering*; in this clustering, a large single partition split recursively until one cluster for each observation. Bottom-up hierarchical clustering also called as *agglomerative clustering*; in this approach, each observation assigns to its cluster based on density functions [129,130]. In the hierarchical clustering approach, no prior information needed about the number of clusters and it is easy to implement. The worst case time complexity of this clustering method is $O(n^3)$ and the space complexity is $O(n^2)$. The hierarchical clustering used to solve various problems in WSNs, such as data aggregation [131], synchronization [132], mobile sink [133,134], and energy harvesting [135].

2.2.3. Fuzzy-c-means clustering

Fuzzy-*c*-mean (FCM) clustering also called as soft clustering developed by Bezdek in 1981 using fuzzy set theory, which assigns the observation to one or more clusters [136]. In this technique, clusters are identified based on the similarity measurements such as the intensity, distance or connectivity. Depends on the applications or data sets, the algorithms may considered for one or more similarity measures. The algorithm iterates on the clusters to find the optimal cluster centers. FCM

Table 2
Comparisons of ML techniques with various specifications [109].

Specifications	DT	RF	ANN	DL	SVM	Bayesian	k-NN
Handling parameters	3	3	1	2	1	4	3
Accuracy	2	2	3	3	4	1	2
Learning speed	3	2	1	1	1	4	4
Classification speed	4	4	4	4	4	4	1
Handling missing values	3	2	1	2	2	4	2
Handling redundant variables	2	2	2	2	3	1	2
Dealing over-fitting	2	2	1	1	2	3	3
Handling noise	2	3	2	3	2	3	1
Handling highly independent attributes	2	2	3	3	3	1	1
Handling irrelevant variables	3	3	1	2	4	2	2

Table 3
Comparisons of various clustering algorithms.

Specifications	k-means	Hierarchical clustering	Fuzzy-c-means
Accuracy	Low	High	High
Speed of clustering	Fast	Fast	Slow
Average prediction accuracy	High	Low	Low
Performance with small observations in datasets	High	Moderate	Moderate
Quality with huge datasets	High	Moderate	Moderate
Results of randomness in the datasets	Moderate	Good	Moderate
Sensitivity of noise data	High	Low	Low

produce the optimal clustering as compared to k-means for the overlapped datasets. Like k-means clustering, it also requires prior knowledge about the number of clusters. The time complexity of the FCM is higher than the other clustering approaches, and it mainly depends on the number of clusters, dimensions, data points and iterations. This clustering approach used in various fields such as pattern recognition, image segmentation, Bioinformatics, and business intelligence, etc. FCM technique used to solve several issues in WSNs such as localization [16,137], connectivity [110], and mobile sink [138]. Comparisons of clustering algorithm summarized in Table 3.

2.2.4. Singular value decomposition

Singular value decomposition (SVD) is a matrix factorization method which is used to reduce the dimensionality. Matrix factorization means representing a matrix into a product of matrices. In Eq. (3), a $m \times n$ matrix M's SVD has been represented as.

$$M = U \sum V^* \tag{3}$$

where U is a $m \times m$ left unitary matrix, Σ is a $m \times n$ diagonal matrix (the diagonal values of Σ called as singular values of M), V is a $n \times n$ right unitary matrix and V^* is conjugate transpose of V. SVD can be used efficiently for reducing the data dimensionality of the given feature space. SVD guarantees the optimal low-rank representation of the data [139]. SVD used in WSNs to address various issues like routing [115] and data aggregation [125].

2.2.5. Principle component analysis

Principle component analysis (PCA) is a multivariate analysis feature extraction method for dimensionality reduction[140]. The PCA combine all the information and drops the least priority information from the feature space to reduce the dimensionality. The output of PCA is a linear combination of observed variables (principal components). PCA sometime used to detect anomalies from the data as well as in regression. In WSNs, sensors continuously gather information from the environments and transmitting to the base station. Applying PCA in WSNs can reduce the dimensionality of the data either at sensor level or at cluster head level to reduce the communication overheads. It reduce the buffer overflows at the sensor nodes or cluster heads in event-driven applications, which avoids the congestion problem. Several algorithms of WSNs such as localization [141], fault detection [100,101], data aggregation [117–124], and target tracking [142] have adopted PCA.

2.2.6. Independent component analysis

Independent component analysis (ICA) finds a new basis for data representation and decomposes multivariate observations into additive subcomponents. Here the subcomponents are non-Gaussian observations [143]. ICA is a more powerful technique than PCA, in other words, it is an extended version of the PCA. ICA will remove the higher order dependencies, whereas PCA was unable to do. ICA analyzed data from various application fields such as web content, digital images, psychometric measurements, business intelligence, and social networking, etc. In many application data, the observations are time series or set of parallel observations; to characterize these observations, the blind sources separation method is used.

2.3. Semi-supervised learning

Most of the real-world application's data is the combination of labeled and unlabeled. The supervised learning algorithms work efficiently on the labeled information, and unsupervised learning works efficiently on unlabeled data. The semi-supervised learning introduced to work on the data with the combination of both labeled and unlabeled. It encompasses semi-supervised classification to perform classification on partially labeled data, constrained clustering to performs clustering with both labeled and unlabeled data, regression with unlabeled data and dimensionality reduction for labeled data [144,145]. There are two distinct goals of semi-supervised learning that are to predict the labels on unlabeled data in the training set and to predict the labels on future test data sets. Concerning these goals, semi-supervised learning divided into two categories: *Transductive learning* and *inductive semi-supervised learning*. Transductive learning is used to predict the exact labels for a given unlabeled dataset, whereas the inductive semi-supervised learning learns a function f: $X \mapsto Y$ so that f expected to be a good predictor on future data. Semi-supervised learning fits with several real-time applications such as natural language processing, classifying the web content, speech recognition, spam filtering, video surveillance, and protein sequence classification, etc [144]. Recently, WSNs uses this learning process to solve localization [146–149] and fault detection [150] problems.

2.4. Reinforcement learning

Reinforcement learning (RL) algorithm continuously learn by interacting with the environment and gathers information to take certain

Fig. 5. Visualization of reinforcement learning.

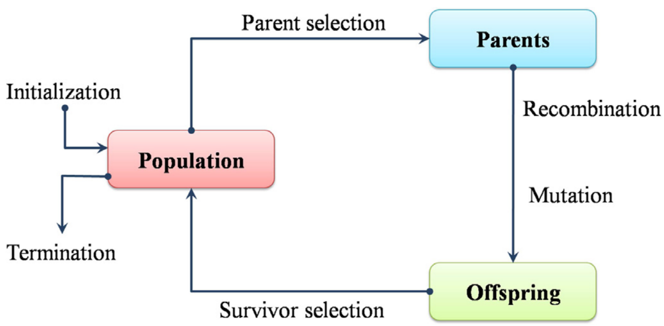

Fig. 6. General scheme of evolutionary algorithms [165].

actions. RL maximize the performance by determining the optimal result from the environment. Fig. 5 shows the functionality of the reinforcement learning. Q-learning techniques is one of the model-free reinforcement learning approach [151]. In Q-learning, each agent interact with environment and generate a sequence of observation as *state-action-rewards* (for example: $< s_0, a_0, r_1, s_1, a_1, r_2, s_2, a_2, r_3, \dots >$) [152]. The reward matrix $R(S, A)$, where A and S indicate a set of actions and a set of states respectively. The actions of the agent in Q-learning shown in the matrix $Q(S, A)$ form, it is equal to the size of R with initial values of zeros. The rows and columns of the matrix Q are current state of agent and possible next state respectively. The transaction rule that update each entry of the matrix Q with sum of the corresponding value in matrix R and the learning parameter γ, multiplied by the maximum value of Q for all possible actions in the next state, as shown in Eq. (4).

$$Q(s_i, a_i) = R(s_i, a_i) + \gamma * Max[Q(next\_state, A)] \tag{4}$$

2.5. Evolutionary computation

Evolutionary computation is a problem-solving approach that uses the computational models inspired from nature and biological evolution. Evolutionary computing is a subcategory of artificial intelligence and it uses various combinatorial optimization techniques. In evolutionary computation, the solution of a particular problem generates over iteration by iteration [153]. Initially it generates a random set of solutions, in every iteration it removes less fit solutions as per objective functions by the trail-and-error basis to achieve optimal results. Fig. 6 shows the general scheme of an evolutionary algorithm in the form of a flowchart. The dialects of evolutionary or nature inspired algorithms include genetic algorithms, genetic programming, evolutionary algorithms, evolutionary programming, ant colony optimization, particle swarm optimization, artificial bee colony, firefly algorithm, artificial immune systems, memetic algorithms, and differential evolution, etc. Evolutionary computation successfully implemented various applications including WSNs. In [154], the authors provided the survey of different evolutionary approaches for WSNs. Recently, an evolutionary or nature inspired algorithms used to solve WSNs issues such as localization

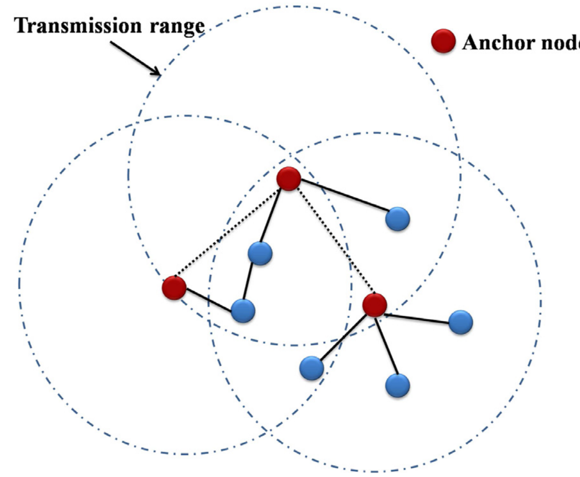

Fig. 7. Example of localization.

[155], coverage [156], routing [157,158], target tracking [159,160], and mobile sink [161–164].

3. Machine learning algorithms for WSNs

In this section, we explore applications of ML in WSNs. In each subsection, we discuss the advantages of selecting a ML technique to address the issues in WSNs and also presents the features of existing approaches in the tabular form.

3.1. Localization

Localization in WSNs can be defined as recognizing the physical/geographical location of a sensor node. In many applications of WSNs, the sensor nodes placed in a field without knowing their positions and there is no sufficient infrastructure available to locate them after the deployment. However, identifying the location of the sensor node is very important task. Location of sensor nodes can be known by means of manual assignment or geographical position system (GPS), some special sensor nodes known as Anchor node or Beacon node. An example is shown in Fig. 7. Localization mainly categorized as proximity-based localization, range based localization, angle and distance based localization and known location based localization [166]. The position of sensor nodes in the environment can change dynamically due to some external causes. To handle such situations, we may require the reprogramming or reconfiguration of the network, so applying ML techniques in such scenarios improve the accuracy of location [167]. Along with this, ML also provides some benefits:

- ML algorithms can easily classify the anchor nodes and unknown nodes in the network.
- ML algorithms are used to create clusters in the sensor networks, and each cluster is training separately to find the sensor node coordinates rapidly.
- Mobile sensor nodes dynamically change their positions in WSNs, so to identify the accurate localization in such an environment is more contented, and it is rapid with ML approaches.
- Table 4 summarizes the ML-based algorithm for localization in WSNs.

In [137], authors have introduced a method to improve the accuracy of localization using k-means algorithm and fuzzy c-means technique. These two clustering are used only at the sink to train the system. The total field divided into clusters based on RSSI values, and each region is trained separately to find the sensor node coordinates. This approach requires RSSI data to train the system. A new PSO-based Neural Network (LPSONN) scheme has been developed using neural networks in

Table 4
ML-based localization techniques for WSNs.

ML Technique	Studies	Complexity	Environment	Mobility	Remarks
k-means + fuzzy-*c*-means	[137]	High	Centralized	static nodes	Improved accuracy
ANN	[10]	Low	Distributed	static nodes	Reduced error-rate
	[11]	Moderate	Centralized	static nodes	Improved accuracy
	[12]	Moderate	Centralized	mobile nodes	Improved accuracy
Fuzzy logic	[13]	Low	Distributed	static nodes	Reduced time complexity
	[14]	High	Centralized	mobile nodes	Improved accuracy
CNN+SVM	[15]	Moderate	Centralized	static nodes	Improved accuracy
fuzzy-*c*-means + SVM	[16]	Low	Centralized	static nodes	Improved accuracy and minimize time complexity
SVM	[17]	High	Distributed	static nodes	Improved accuracy
	[18]	High	Centralized	static nodes	Energy-efficient
	[19]	Moderate	Distributed	static nodes	Improved accuracy
	[20]	Moderate	Centralized	static nodes	Improved accuracy
Bayesian	[21]	Moderate	Centralized	static nodes	Energy-efficient
	[22]	Low	Centralized	static nodes	minimize time complexity
	[23]	High	Centralized	static or mobile nodes	Energy-efficient
	[24]	Moderate	Distributed	static nodes	Improved accuracy
	[25]	High	Distributed	static nodes	Improved accuracy
PCA	[141]	Moderate	Distributed	static nodes	Outlier detection
Regression	[85]	Moderate	Distributed	static nodes	Improved accuracy
Semi-supervised	[146]	Moderate	Distributed	mobile nodes	Improved accuracy
	[147]	Low	Centralized	mobile nodes	Optimal time complexity
	[148]	Moderate	Centralized	mobile nodes	Improved accuracy
	[149]	High	Centralized	mobile nodes	Improved accuracy and reduced error-rate

[10] for WSNs. In this scheme, each anchor node finds its hop count with other anchor nodes and sends the information to head anchor node. LP-SONN trains only the head anchor nodes using neural networks, and a PSO algorithm used to find the optimal number of hidden layers. The performance of the algorithm is good as compared to the other existing algorithms interns of error rate. A range-free localization with energy-efficient distance estimation using ANN has been developed in [11]. This algorithm used to solve the anisotropic signal attenuation interference for shadow and fading. This algorithm is robust in various parameters including accuracy. Authors in [12] have presented a localization of mobile sensor nodes using ANN and improved the performance of the proposed algorithm with PSO. Here the use of PSO was to find the optimal number of neurons needed to find the accurate localization in WSNs. This algorithm improved the accuracy and performance as compared to other traditional approaches.

In [13], authors have used a fuzzy logic along with vector PSO to range-free localization for a non-uniform node deployment in WSNs. This algorithm mainly focuses on heterogeneous scenarios, and achieves lower complexity as compared to other localization techniques. Authors in [14] have focused on fuzzy linguistic modeling for indoor localization of mobile sensor nodes for WSNs. This approach mainly carries out in two ways: initially to handle RSSI variations using an interval type 2 fuzzification and after that by considering fuzzy location indicator (FLI) identification of geometric re-partitions. In [15], authors have presented a graph based localization algorithm using conventional neural networks (CNN) and SVM. The usage of heterogeneous dual classifiers in this approach is to analyze the target signals and improves the classification accuracy. By enhancing signal strength, the graph-based algorithm used to identify the leakage location in the network and reduced the error. Even if the leakage happens in the same position more than once, it does diagnosis results and produces the accurate results. This approach also overcomes the time synchronization errors. A localization method has been presented in [16] using SVM for large-scale WSNs. A fuzzy *c*-means training sample reduction (FCMTSR) method was used to reduce the training overhead and learning calculation. FCMTSR-SVM algorithm improves the localization accuracy and reduces the training samples time. This algorithm also effectively overcome the coverage-hole problem and border problem.

A range-free localization based on SVM (RFSVM) has been presented in [17]. In this approach, a transmit matrix was introduced to show the relation between hops and distances. Transmit matrix was used to train the system and SVM was used to find the unknown nodes in WSNs. A range-free localization method has been developed using SVM classifier, and polar coordinate system (PCS) referred as LSVM-PCS in [18]. In LSVM-PCS, the region of WSNs divided into a finite number of polar grids and each sensor node labeled into any one of the grids using SVM. The efficiency of the localization was improved by using a two-hop mass-spring optimization (THMSO) approach. A fast-SVM based localization algorithm has been presented in [19] for large-scale WSNs. The fast-SVM divide the feature space into support vector groups based on the maximum similarities. Because of the separate groups, it is easy to apply the SVM and improves the performance. Fast-SVM also overcomes the coverage-hole problem and border problem. In [20], a device-free localization technique has been developed using multi-class SVMs. This algorithm uses a fingerprinting method along with SVM. Based on the signal eigenvector at a receiver, an antenna array was used instead of received signal strength (RSS). RSS is mainly affected temporal and spatial fluctuations because of noise and multi-path fading. This method also improves the accuracy of the localization compared with conventional approaches.

In [21], authors have focused on the localization of unknown nodes by using the Bayesian approach. To estimate the source location, posterior CramRao bound (PCRB) was used, and sequential Monte Carlo (SMC) identifies the unknown nodes which gathers the data from the sources. PCRB improves the efficiency of the SMC. A variational Bayesian expectation-maximization (VBEM) approach has been presented in [22] to solve compressed sensing (CS) based localization. VBEM iterate over two phases: VBE-phase and VBM-phase. In each iteration, VBE-phase updates the sparse signals whereas the VBM-phase updates the grid parameters. The efficiency of VBEM algorithm mainly depends on the number of iteration. This algorithm is remarkable achievement when the number of grids increases. In [23], a device-free localization method has been proposed using Bayesian approach. In this work, sensor nodes send link state signals to the base station instead of transmitting the RSS measurement to reduce the data delivery rate. This approach work for either static or mobile target or sensor nodes.

A Bayesian compressive sensing (BCS) framework has been introduced in [24], for adaptive localization in WSNs. BCS framework estimates the target locations as well as the noise in the environment. This approach provides better accuracy than the traditional methods. In [25], counting and localization techniques were presented based on the iterative variational Bayesian interface. An accurate sparse approximation method was implemented to reduce the faults caused by off-grid. In this strategy, a three-level hierarchical prototype used to recover the faulty prior information. A non-convex Robust PCA algorithm has been developed in [141] to eliminate the outliers. The primary goal of the PCA is dimensionality reduction, the low-dimension gives efficient and accurate results. This approach identifies the outliers between the original data matrix and preprocessed data matrix. A localization method has been developed using weighted linear regression in [85]. To improve the accuracy of the localization, this approach increases the weights of neighboring anchor nodes. This method outperforms the different topologies of anisotropic networks. An artificial bee colony (ABC)-based optimal relay node placement algorithm has been proposed in [155]. In this algorithm, ABC uses to find the position where the relay node fits to give optimal energy consumption while routing the information from the source node to base station.

A semi-supervised learning based localization approach has been developed in [146] for mobile WSNs. This approach can easily incorporate the newly added sensor, or any environmental changes affects on the network without any explicit or implicit changes in the algorithm. This algorithm achieves the best accuracy even the low label data in the input. In [147], authors have presented a semi-supervised hidden Markov model (HMM) based localization technique for mobile sensor nodes in WSNs. This model works with various conditions, even the less training data. This algorithm works for both indoor and outdoor environment with the time complexity of $O(n)$. A localization algorithm has been proposed in [148] based on the semi-supervised learning algorithm for mobile WSNs. This algorithm produces an accurate location of the sensor nodes using large unlabeled data with the small amount of labeled data collected from the signal and physical space in the network. Authors in [149] have proposed a localization algorithm using semi-supervised learning and support vector regression. Initially, they used a semi-supervised learning algorithm for training the system with a small amount of labeled data and then they applied support vector regression approach to finding the target localization. Combination of the algorithms provides accurate results and minimal error rate. This algorithm also utilizes less memory because of using a simple support vector regression method.

3.2. Coverage & connectivity

Apart from the energy efficiency, coverage and connectivity are also the challenging issue in WSNs. Coverage means how efficiently each deployed sensors monitoring the area of interest. The deployment of sensor nodes in a network has either deterministically or randomly depended on the application [168,169]. Most of the WSNs application random deployment was feasible as compared to deterministic deployment. Coverage mainly classified into two categories such as full coverage and partial coverage [159,168]. Partial coverage further categorized into focused coverage, sweep coverage, target coverage and barrier coverage. Connectivity means no isolated sensor node in the network; it means every node in the WSNs is sending its data to sink node directly or through relay nodes. Fig. 8 demonstrates coverage and connectivity. In Fig. 8 node *A* and node *B* are isolated nodes (disconnected nodes), and coverage hole in the network represented is in white. In WSNs, several algorithms have been proposed to solve coverage and connecting problems[170]. trying to address static sensors in WSNs whereas, in [169,171] trying to solve a mobile WSNs. Using ML techniques for coverage [172] and connectivity problems have the following advantages:

- To find a minimum number of sensor nodes to cover the target area can be obtained rapidly and dynamically in WSNs.
- Classifying nodes either connected or disconnected in the network and changing routes dynamically without data loss.
- Table 5 summarizes the ML approaches for coverage and connectivity in WSNs.

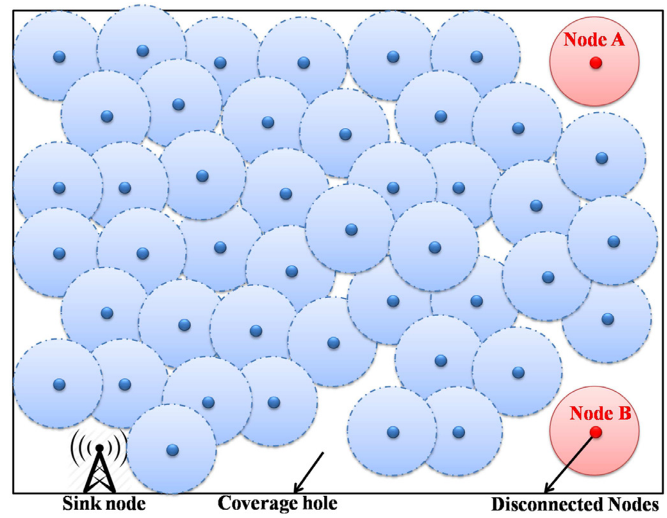

Fig. 8. Example of coverage and connectivity.

In [26], end-to-end data delivery reliability (E2E-DDR) algorithm has been presented for link quality control in WSNs. E2E-DDR algorithm captures the mapping function between the background noise, packet reception ratio, and RSS. These studies optimize the network quality and reliability in deployment of sensor nodes. The results of E2E-DDR method was tested using linear regression technique. In [27], a new regression-based accuracy-aware interface design has been developed for WSNs. This method has reduced the overhead of in-network aggregation technique while measuring the connectivity. In [28], a fully distributed SVM learning algorithm has been presented to a simple communication mechanism for WSNs. In order to prove the global optimality, the joint operations of convex hulls have used. This algorithm also improves the efficiency of connectivity by reducing the communication complexity, and shorter message exchange with local nodes. In [29], an SVM with decision tree based algorithm has been presented to estimate a link quality in WSNs. In this method by considering estimation parameters as RSSI and link quality indicator (LQI), SVM performs the classification to determine the communication quality. This method produced the best link quality accuracy, reduced energy consumption and improved the network lifetime.

In [30], RF-based algorithm has been used to monitor the WSNs. In the context of changing the quantity of the features randomly, RF produces the best performance. This algorithm improves the accuracy of the coverage target area in WSNs. In [31], Naive Bayes Classifier has been used to track the location of the human in the sensor networks. In this approach, the area of the WSNs divided into consistent static subregions. By using the Naive Bayes in the static regions, the algorithm tracks the initial location of the human. This approach has taken substantially less computational complexity to trace the target by covering the area. In [110], a distributed *k*-means algorithm has been used along with the fuzzy *c*-means algorithm for the WSNs with a strongly connected network. To classify the data of sensor nodes, *k*-means algorithm has been used. The fuzzy *c*-means algorithm used for partitioning the workload depends on the different measurements.

A two-stage sleep scheduling approach [173] based on reinforcement learning for area coverage has been presented. In this approach, sensors sparsely cover the area without knowing their geographical location. Q-learning algorithm selects the appropriate nodes that cover the target area with a limited number of sensor nodes. This algorithm was providing the desired area coverage and enhances the network lifetime. In [174], the authors have presented a reinforcement learning-Probe (RL-Probe), to measures the accurate quality of a link with minimal energy wastage and overheads. To maintain the up-to-date information about link quality, RL-Probe combines both synchronous and asynchronous

Table 5
ML-based coverage & connectivity algorithms for WSNs.

ML Technique	Studies	Coverage or Connectivity	Complexity	Mobility	Environment	Remarks
Regression	[26]	Connectivity	Low	Static	Centralized	Optimize network quality and reliability
	[27]	Connectivity	Moderate	Static	Centralized	Improved accuracy
SVM	[28]	Connectivity	Moderate	Static	Distributed	Connection efficiency
SVM + Decision tree	[29]	Connectivity	High	Static	Centralized	Improved network lifetime
Random forest	[30]	Coverage	Moderate	Static	Distributed	Improved accuracy
Bayesian	[31]	Coverage	Moderate	Static	Distributed	Reduced time complexity
k-means + fuzzy-*c*-means	[110]	Connectivity	Low	Static	Distributed	Reduced work load
Reinforcement learning	[173]	Coverage	Low	Static	Distributed	Improved network lifetime
	[174]	Connectivity	Moderate	Static or mobile	Centralized	Improved network lifetime

monitoring mechanisms, and then it minimizes the measurement overhead without interrupting the routing changes. RL-Probe reduces the energy consumption and provides the accurate link quality in WSNs. The coverage control algorithm has been proposed in [156] for WSNs using hybrid multi-objective evolutionary algorithms. In this, the Evolutionary algorithm used to optimize the randomly generated weights and the search direction.

3.3. Anomaly detection

An inconsistent observation appears significantly from the particular data readings are called as an anomaly [175–179]. In WSNs, misbehavior identified either in measuring the sensor data or in traffic-related attributes. Most of the applications in WSNs, sensors continuously gathering the data from the environment and transmit it to the base station through relay nodes. While data transmission there is a possibility of data loss because of abnormal attacks, therefore there is need for protecting sensing data. Anomaly detection in WSNs minimizes the communication overhead while sharing the information between the sensor nodes. The survey of intrusion detection for energy efficient WSNs have presented in [180].

Some of the possible attacks in WSNs are blackhole attack, misdirection Attack, wormhole attack, sinkhole attack, and hybrid anomaly [177]. Fig. 9(a) shows the general data flow of WSNs. In blackhole attack, a block receives the packets instead of forwarding it to the base station as shown in Fig. 9(b). A misdirection attack is shown in Fig. 9(c), in this the attackers routes the packets with distinct nodes rather than its neighbor nodes. It may construct the longer route and reduces the throughput. A wormhole (WH) attack, a WH tunnel is formed between two distinct nodes and misapprehension that they are very close. This WH can bypass or attract a number of packets from the network and attackers perform the manipulations [181]. In Fig. 9d, a wormhole attack is shown. A particular node (Sinkhole) advertises an optimal route to its neighbor nodes to the base station. In sinkhole attack, it tampers the data and damages the network. We represent a sinkhole in Fig. 9e. In hybrid attack, different types of attacks such as blackhole, misdirection, WH, and SH attack affects at a time.

ML approaches have used to detect anomalies in WSNs, protecting from various attacks and misapprehensions. In WSNs, several algorithms have used to protect from anomalies such as self-learning threshold and sleep scheduling approaches [182] for a heterogeneous sensor network based on geological sensor nodes, [183] for sinkhole attack as well as denial-of-service (DoS), by detecting inconsistent data [184] provides resilience and genuine information. The survey of anomaly detection on non-stationary datasets using ML presented in [179]. Using ML for anomaly detection in WSNs significantly improved as compared to other approaches, benefits listed as follows:

- A hybrid anomaly is the combination of various attacks, therefore detecting the node which effects and type of anomaly are happening. Employing clustering algorithms minimizes the complexity and communication overhead for the problem.
- For detecting the anomalies in non-stationary environments, ML approaches guarantee to handle faults, attacks, and outliers in WSNs.
- For online anomaly detection, it is possible to adjust the parameters dynamically using the historical information.
- Table 6, summarizes the ML approaches for detecting an anomaly in WSNs.

In [177], authors have proposed a method to detect hybrid attack using a popular k-means clustering approach. In this approach, authors used Opnet modeler dataset for training and testing the system. This algorithm works efficiently to detect malicious nodes automatically when blackhole and misdirection attacks happen in WSNs. Authors in [32] have used a hypergrid *k*-NN algorithm for online anomaly detection to monitor WSNs, which mainly protect from random faults and cyber-attacks. Using hypergrid over original *k*-NN improves and meets the specific requirements to detect anomalies in WSNs. In this approach to lower the computational and communication overhead, hypersphere detection region redefined to a hypercube detection region for online anomaly detection. In [33] authors have designed a new architecture called intrusion detection systems (IDS) uses decision tree classification approach to ensure high detection rate. This approach mainly used in environmental monitoring.

Authors in [111] have used two ML-based algorithms such as least squares-SVM along with sliding window and PCA to detect outlier in WSNs. In this work, modified RBF kernel has been used along with least squares-SVM to improve the performance of anomaly detection in non-stationary time-series. PCA has been applied for tracking subspace recursively in WSNs. Support vector data description (SVDD) classifier has been used in [34] to detect anomalies of node's data. The primary goal of this approach is to minimize the complexity of training and testing phases. A two-order approximation based sequential minimal optimization (SMO) algorithm has been used to reduce the complexity of training phase. In the testing phase, a fast decision-making technique was presented using the center point of a hypersphere in kernel feature space. In [35], authors have provided a detailed analysis of various outlier (event or error) detection methods using one-class SVM in harsh environments. They also analyzed different planes like hyper-sphere, hyperplane, hyper-ellipsoidal and quarter-sphere they found that quarter-sphere formulations are low computational complexity and communication overhead as compared to others for outlier detection.

In [36], authors have proposed a DBSCAN algorithm for detecting anomalies by evaluating various features in WSNs. They also used a well-known classification technique of SVM to improve the detection accuracy in DBSCAN. The efficient learning feature of SVM used to train the system with standard and general data. DBSCAN is accurate to detect low-density regions in the network, and removes the anomaly. Detecting DoS attacks in distributed WSNs is an extremely challenging task with traditional approaches. In [185], a combination of game theoretic method and reinforcement learning based fuzzy *Q*-learning approach has been used to detect malicious behavior in WSNs. Compared with Markovian game-theory, ML based approaches noted the best performance in various parameters like accuracy, lifetime, energy consumption, efficiency, and visibility. In [37], Bayes Classifiers have been used

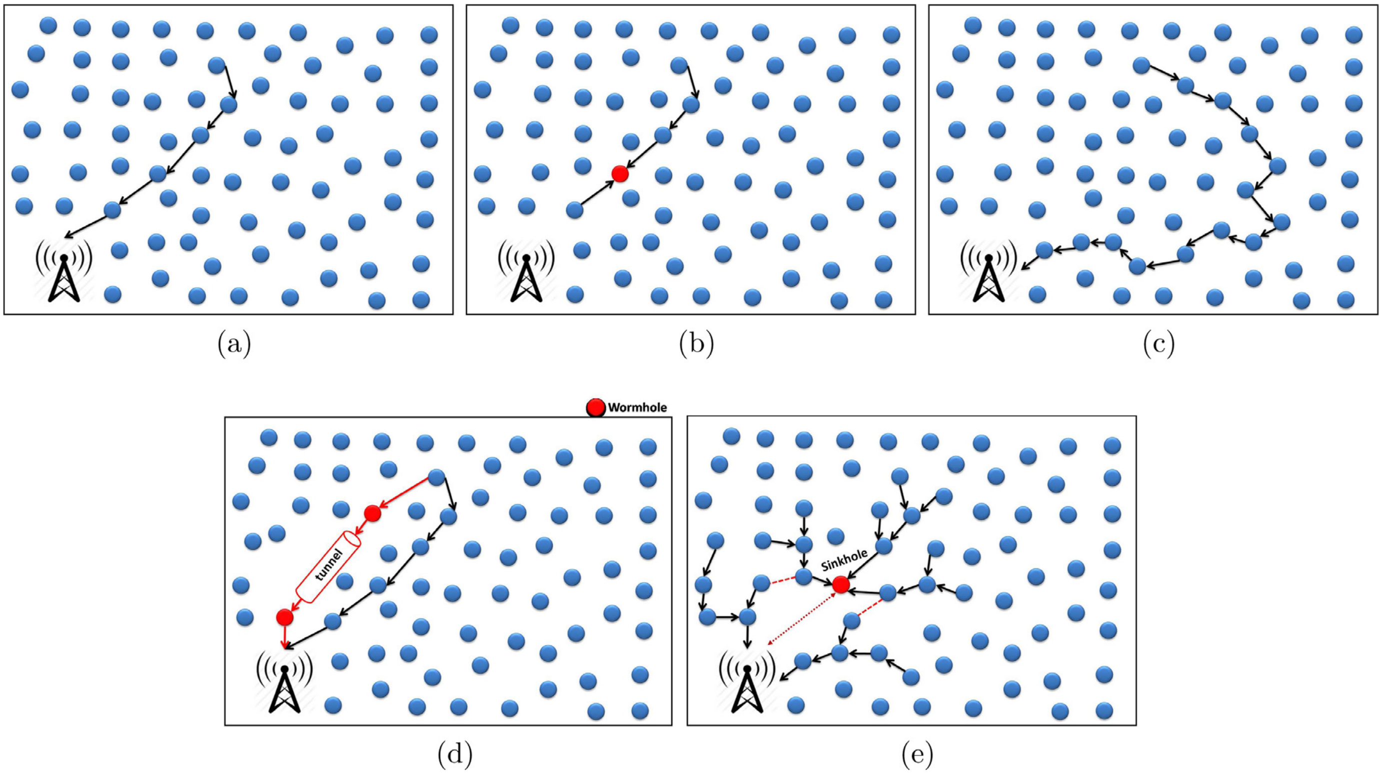

Fig. 9. Anomaly detection in WSNs (a) normal flow (b) blackhole attack (c) misdirection attack (d) wormhole attack (e) sinkhole attack.

Table 6
ML-based anomaly detection techniques for WSNs.

ML Technique	Studies	Anomaly	Complexity	Environment	Remarks
k-Means	[177]	Hybrid anomaly	Moderate	Centralized	Improved accuracy
k-NN	[32]	Random faults, Cyberattacks	Low	Distributed	Reduced time complexity
Decision tree	[33]	Sinkhole	Moderate	Centralized	Improved accuracy
SVM + PCA	[111]	Outliers detection	Moderate	Distributed	Improved accuracy
SVM	[34]	Anomaly detection	High	Centralized	Reduced time complexity
	[35]	Error detection	Low	Centralized or Distributed	Reduced time complexity
	[36]	Intrusion detection	High	Centralized	Improved accuracy
Q-learning	[185]	DoS	High	Distributed	Improved network lifetime
Bayesian	[37]	outlier detection	Moderate	Distributed	Improved accuracy
	[38]	Trust management	High	Distributed	Improved accuracy
Regression	[186]	Anomaly detection	Moderate	Centralized	Improved accuracy
Deep learning	[95]	Intrusion detection	High	Centralized	Improved accuracy

to detect outliers for WSNs application. This method performs outlier detection in two levels; one at the sensor nodes level and the second one at the gateway. This approach produces a high outlier detection accuracy for WSNs.

Bayesian-based trust management strategy (BTMS) has been proposed for WSNs in [38]. BTMS perform the trade-off between the energy consumption of sensor nodes and security. From the overall data gathered from the nodes, it evaluates the trust and identifies direct and indirect trust information. In [186], authors have used SMO regression technique to detect an anomaly of sensor data for healthcare application. In this technique, based on the historical data, the algorithm predicts false positive and true negatives. The detection rate of this approach reach 100% accuracy rate and providing rapid results as compared to traditional approaches. In [95], authors have proposed a method to detect intrusion by combining a special clustering and deep neural network approaches. Initially this algorithm divide the entire data set into *k*-subset using special clustering method, and then deep neural network perform the intrusion detection operation by comparing the testing set with the training set data. The results of this algorithms show that the accuracy is improved as compared to random forest, and SVM.

3.4. Fault detection

WSNs have been deployed in a various application-specific environment such as harsh, hostile, and unattended. Consequently, faults may occur in WSNs such as communication failures, battery failures, hardware failures, software failures, inefficient base station or topological changes [187]. Detecting the fault in WSNs is challenging because of several reasons such as resource limitation, a different type of environment (forest, indoor), changes in deployment, detection accuracy between the normal and faulty nodes [39]. Several fault detection methods [188–190] are presented by the researcher without using any ML approaches, whereas applying ML for detecting faults have the following:

- Brisk detection and categorization of faults.
- Improves accuracy in detecting faults.

Table 7
ML-based fault detection mechanisms for WSNs.

ML Technique	Studies	Fault detected	Accuracy	Complexity
SVM	[39]	Negative alerts	99%	Low
	[40]	Fault nodes	98%	High
SVM + PCA	[100]	Hardware faults	99.8%	Moderate
	[101]	Online fault diagnosis	99%	High
Bayesian	[41]	Body sensors	-30% fault rate	Moderate
	[42]	faulty sensor nodes	100%	High
	[43]	faulty sensor nodes	98%	Moderate
ANN	[44]	faulty sensors	98%	High
Deep learning	[96]	Faulty data	99%	High
k-NN	[45]	fault nodes	99%	Moderate
Semi-supervised	[150]	Faulty node detection	99%	Moderate

- Several ML-based fault detection mechanisms for WSNs are shown in Table 7.

To detect the faults in WSNs, a well-known SVM classifier has been proposed in [39]. A significant advantage of using SVM is to classify the data as well as decision making. This approach detects faults in sensor data very accurately and rapidly. In this approach, a kernel function was used for detecting the faults in non-linear classification data and the accuracy rate of detecting defects exceeds 99%. An error prediction method has been developed in [40] using SVM and cuckoo search algorithms. In this approach, SVM used to predict the errors in sensor dynamically; however, it depends on the parameter comparisons. To optimize the key parameter, this method adopted cuckoo search algorithm to avoid local minimum value. In [100] authors have presented a technique for diagnosis induction motor (signal processing) faults using multi-class SVM classifier and PCA. Here, the multi-class SVM classifier was used for classifying and training the various faults affected by the induction motor in the sensor node. SVM increases the fault classification accuracy and PCA was used to extract more dominant feature dimensions. This approach achieves very high accuracy (99.80%) as compared to other traditional strategies.

Authors in [101] have presented an online fault detection method for real-time data streams using recursive PCA and multi-class SVDD classification method. Recursive PCA method was used to detect the fault in WSNs, and it is lightweight. SVDD classifier used to identify the fault categories. Fault detection in body sensor network (BSN) causes a false medical diagnosis, therefore it is very important to detect a fault in BSN. In [41], Bayesian network based fault detection method has been presented for BSNs. A Bayesian network method was used to capture the temporal and spatial correlation of body sensor. Based on an optimal threshold value, sensor faults can be identified. Authors in [43] have proposed efficient malicious nodes identification for Smartphone network based on the Bayesian network model. To ease the security and a trust computation proposed method has been implemented by the hierarchical method. This method provides an accurate faulty node detection and energy-efficiency.

Authors in [42] have presented a fault detection scheme (FDS) which detect the faulty nodes in WSNs with their batteries and sensing information. In FDS, faulty nodes can be found in two-level verification. In the first phase, a Naive Bayesian classifier was used to detect the fault inside the sensor node, while the second phase the cluster head or gateway evaluated fault detection. This method shows the 100% accuracy rate through simulation results. In [44], a fault node distribution and management approach have been presented based on the fuzzy rules in WSNs. This algorithm mainly concentrated on re-usability of faulty nodes by implementing the efficient route towards base station. It provides a better QoS and network lifetime. A *k*-NN classifier was used to separate fault sensor nodes from the normal sensor nodes based on the abnormal behavior of sensors [45]. This approach mainly focus on error rate of the sensors to decide faulty sensor nodes.

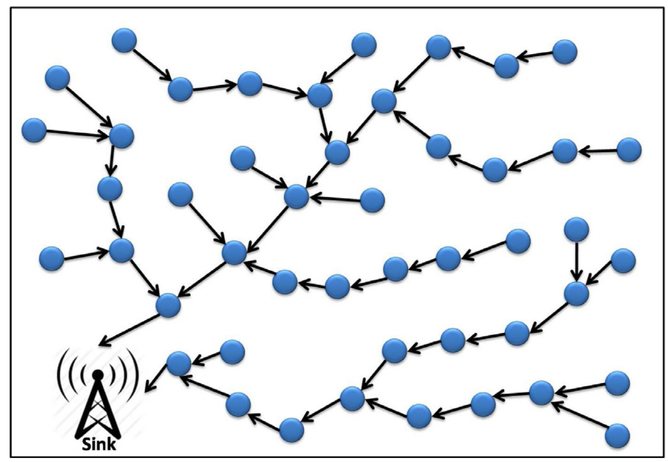

Fig. 10. Example of routing in WSNs.

In [96], a centralized solution has been developed by the authors to detect the faults in WSNs using deep neural networks. The objective of this method is to improve the fault detection accuracy and reduce the power consumption. This approach achieves 99% of detection accuracy. In [150], authors have introduced an efficient label propagation method for faulty node detection method using semi-supervised learning approach. A kernel density based function used in this approach to label the unlabeled data in the input data set.

3.5. Routing

Routing is one of the primary challenges in WSNs because of the limited power supply, low transmission bandwidth, less memory capacity, and processing capacity. In WSNs, sensors deployed randomly in the environment, each sensor node collects the data from the environment and transmits to the base station for further processing. Fig. 10 shows the multi-hop transmission from sensor nodes to base station. In general, the nodes which are near to the base station consume more energy because they serve as a relay nodes. The goal of routing protocol design is to reduce the energy consumption of sensor nodes and increase the network lifetime. Recently, several routing methods [191–193] are developed for WSNs by the researcher using different approaches. But employing the ML techniques for WSNs to develop routing protocols. Some of the benefits of ML-based routing for WSNs are as follows:

- To select an optimal set of CHs for routing in WSNs, ML algorithm adopts changes in the environment without re-programming.
- ML has a wide range of applications in WSNs such as optimal routing, lowering communication overhead and delay-aware [194].
- Several ML-based routing protocols for WSNs are summarized in Table 8.

Table 8
ML-based routing algorithms for WSNs.

ML Technique	Studies	Topology	Complexity	QoS	Environment	Mobility
ANN	[46]	Tree	High	No	Centralized	static nodes
	[47]	Tree	Moderate	Yes	Distributed	static nodes
	[48]	Tree	Moderate	No	Distributed	mobile nodes
Deep learning	[49]	Hybrid	High	No	Centralized	mobile nodes
SVM	[50]	Hybrid	Moderate	No	Distributed	static nodes
Bayesian	[51]	Tree	Moderate	No	Distributed	static nodes
	[52]	Hybrid	Low	No	Centralized	static nodes
	[53]	Hybrid	Moderate	No	Centralized & decentralized	mobile nodes
k-means	[112]	Hybrid	Low	Yes	Distributed	static nodes
	[113]	Tree	Moderate	No	Distributed	static nodes
	[114]	Hybrid	Moderate	No	Centralized	static nodes
SVD	[115]	Arbitrary	Moderate	No	Distributed	static nodes

In [46], authors have developed ELDC approach based on artificial neural networks (ANN) to determine energy-efficient and robust routing for WSNs. In ELDC, the usage of ANN is to train the protocol. ANN training the protocols using various parameters in WSNs such as residual energy and the distances between nodes, cluster heads (CH), border nodes and sink or base station. It generates a massive amount of training set, even ANN an efficient threshold values for selecting a group of reliable CH based on backpropagation. ELDC is highly energy-efficient and balances the energy consumption of the sensor nodes and avoids the data loss in the WSNs. Authors have presented a dynamic 3D fuzzy routing based on traffic probability (DFRTP) routing protocol in [47] using the fuzzy system. The fuzzy system takes neighbor nodes and distances as an input and produces routing probability as an output. One of the neighbor nodes of every node in the network which provide optimal (lowest) traffic probability is chosen as data forwarding node towards to sink. DFRTP increases the data delivery ratio and reduces the energy consumption of the sensor nodes.

The zone-based energy efficient routing (ZEEP) protocol has been developed in [48] using a fuzzy system for mobile sensor networks. ZEEP selects a set of CHs using fuzzy inference system (FIS) by considering parameters such as mobility, density, distance, and energy. Finally, a genetic algorithm was used to finalize the optimal set of CHs, from the collection of CHs nominated by FIS. ZEEP balance the energy consumption by selecting the optimal set of CHs and enhance the network lifetime. In [49], a deep learning based routing protocol has been introduced with the base station as an infrastructure. It means the route maintained, assigned and recovered by the base station. Proposed deep learning based algorithm adopts dynamic routing in a mobile sensor network. The base station initially creates a list of virtual routing paths, and from them it identifies the optimal route. This algorithm overcomes the congestion and packets loss and power management. An efficient SVM based routing protocol has been developed in [50] which balance the energy consumption of the nodes by assigning the nodes to nearest CH. This algorithm achieves higher network lifetime as compared to LEACH protocol.

A Naïve Bayes based optimal cluster heads selection for efficient routing has been presented in [51]. The optimal set of CHs always balances the energy consumption of sensor nodes and enhances the network lifetime. Naïve Bayes guarantees that even new features added or changed in the network dynamically. A new adaptive integrated routing framework has been presented in [52] for data collection based on a Bayesian technique. In the projected technique, an adaptive projection vector is constructed in each iteration of routing by introducing a new target node selection. In [53], a Bayesian learning method based optimal routing prediction model has been developed for both decentralized and centralized versions. This approach also performs the scheduling approach while routing the data to balance energy consumption. This algorithm is much more suitable for decentralized than centralized.

Authors in [112] have used a well-known *k*-means classification algorithm to find optimal clustering in WSNs for routing. This algorithm provides a better packet delivery ratio, throughput, lowering the energy consumption and controls the traffic overhead. In [113], authors have proposed energy efficient clustering protocol using k-means (EECPK-means) algorithm to find the optimal center point from the cluster from a random initial center point. It selects optimal CHs based on the Euclidean distance and residual energy of the sensor nodes in WSNs. EECPK-means algorithm finds the efficient multi-hop communication path from the CHs to base stations. This algorithm avoids the data loss and balances the energy consumption of the sensor nodes. An energy efficient *k*-means technique (EKMT) has been presented in [114] to find the optimal cluster heads (CH), which are near to the member nodes as well as the base station. EKMT measure sum of squared distances between nodes and choose CH based on minimum distance. This technique improves the throughput and reduces the delay by re-selecting the CHs dynamically.

Authors in [115] have developed singular value decomposition (SVD) based in-network routing protocol of WSNs with an arbitrary topology where the shallow light tree (SLT) used along with SVD to route the information towards to base station. This can implement especially for smart cities and structural health monitoring (SHM) using IoT devices. Due to a large number of sensor nodes, this is quite a high transmission overhead. In [195], a secure cluster based routing protocol has been developed to enhance the network lifetime for WSNs. In this approach, CHs selected based on their distances and residual energy. This algorithm mainly focuses on the isolated CH and edge node to balance the node energy consumption. In [157] authors have presented an efficient routing mechanism based on the transmission range of the sensor nodes and the data forwarding load. In this mechanism, efficient clustering method was used which based on the particle swarm optimization, to balances the load of the sensor nodes in the networks. An ACO-based routing algorithm has been presented in [158] for WSNs. In order to find the optimal routing, they consider various parameters such as the residual energy of a node, transmission distance, transmission path, and the shortest path between the source nodes to the base station. This algorithm results in minimum energy consumption and prolongs the network lifetime.

3.6. MAC

In WSNs, the network lifetime can maximize by developing energy efficient medium access control (MAC) protocols. MAC layer is a sublayer of data link layer with the primary functions are addressing, data transfer from upper layers, channel allocation, predict errors, and frame recognition. Consequently, designing energy efficient MAC protocols is a challenging for WSNs because of the dynamic behavior of adding or removing (maybe dying) sensor nodes, noise data transmission and so forth [196]. MAC protocols mainly classified as contention-based (no need for central coordination) and schedule-based (each node communicates during specific time slot) protocols. ML approaches for MAC layer protocol design guarantees the energy efficient and avoids latency. The

Table 9
ML-based MAC designs for WSNs.

ML Technique	Studies	Complexity	Category	Type	Synchronization
Random forest	[54]	Low	contention-based	Hybrid	No
Reinforcement learning	[197]	Moderate	schedule-based	Hybrid	Yes
	[198]	Low	contention-based	ALOHA	Yes
	[199]	High	contention-based	Hybrid	Yes
	[200]	Moderate	contention-based	ALOHA/ CSMA-CA	No
	[201]	Low	schedule-based	CSMA	Yes

summary of ML based MAC protocols listed in Table 9 and benefits of ML-based MAC protocol designs are as follows:

- Reduces the additional burden to reconfigure of any newly joined or died nodes in the network.
- Improves the efficiency of self-learning process of the network and reduces the end-to-end delay.

In [54], authors have proposed MAC address spoofing detection mechanism based on random forest. This method performs better regarding prediction time, and accuracy compared to traditional cluster-based methods. Authors have suggested the one-class SVM to train the system without the whole network range. An optimal channel allocation scheme has been proposed in [197] based on reinforcement learning for sensor networks. This approach adopts the dynamic behavior of the network and considers various parameters to allocate the channel such as availability of the channel, cost of sense, and impairment of sense. This method improves the network lifetime by balancing the energy of the sensor nodes and enhances the accuracy of channel allocation. MAC layer protocols (ALOHA) extended using the Q-learning approach in [198], in order to extend the channel performance and accuracy. This protocol efficiently works for any new sensor nodes added into the network and balances the energy consumption of the nodes in WSNs. The ALOHA-Q reduces the packet loss and works dynamically according to the changes happen in the network.

In [199], reinforcement learning based cooperative approaches for WSNs has been proposed. This method works for both the distributed and centralized sensor networks. The parameters of the system are dynamically activated or deactivated depends on the situation of the network. Due to dynamic activation or deactivation policy, the performance of the network may be positive or negative. Reinforcement learning-based self-learning techniques for an optimal set of services have been presented in [200]. This method is highly dynamic in nature and provides a well efficient compelling set of services from the network. This algorithm reduces the end-to-end delay of multi-hop transmission and improves the reliability of the network. In [201], a channel hopping method developed based on reinforcement learning approach to improve the performance of the network has been presented. This method efficiently works without any additional configuration even if any new node joins in the WSNs. This method controls the message exchange based on time synchronization.

3.7. Data aggregation

The process of collecting and aggregate data from the sensor nodes called data aggregation. Data aggregation in WSNs affects various parameters such as power, memory, communication overhead and computational units. In order to reduce the number of transmission and communication overhead, data aggregation places a significant role in WSNs. An efficient data aggregation method balances the energy consumption of the sensor nodes and enhances the network lifetime. There are several types of data aggregation methods depends on the network structure like cluster-based data aggregation, tree-based data aggregation, in-network data aggregation, and centralized data aggregation [202]. Several approaches to data aggregation in WSNs have been proposed in [203–205]. ML algorithms for data aggregation in WSNs are summarized in Table 10 and their benefits are listed below:

- ML approaches select efficient CHs in the network for data aggregation that will significantly balance the energy of the sensor nodes.
- ML algorithms helpful for dimensionality reduction of the data at the sensor node level, therefore it reduces the communication overhead in the network. The reduction may be performed at sensor nodes or cluster heads to minimize the delay in transmission of data.
- ML adopts the environment and work accordingly without reconfiguring or reprogramming in the context of data aggregation.

In [55], a distributed linear regression based data gathering (DL-RDG) algorithm has been presented to enhance the CHs functionality in WSNs. Based on the past data at each CH in WSNs, the regression method predicts the actual monitoring measurements and broadcast to the base station. Linear regression model also chooses the faulty nodes in the network during the data gathering process. An energy efficient multivariate data reduction model has been developed in [56] based on periodic data aggregation using polynomial regression functions. The reduction of data in sensor level will reduce the communication overhead during the transmission of the data between the nodes or CHs towards to base station. Euclidean distance only not sufficient in all cases of the WSNs, it is also required to determine a temporal and spatial correlation between the sensor nodes in the complex WSNs deployments. A linear regression model has been used in [57] to estimate the non-random parameters during information gathering. Before transmitting the data to the base station, the CHs compress the data. This method specially designed for the decentralized network, with sufficient condition, centralized approach also achieve good performance.

In [59], authors have focused on agriculture and health monitoring application. Heterogeneous WSNs are utilized to collect the data from the fields. For agriculture application, decision tree analysis was used and for the health monitoring application, a honeybee soft computing method was used. The decision tree used to classify the data, and the classification accuracy is 95.38% for different cases. Authors in [60] have developed a distributed data fusion framework for heterogeneous WSNs. This framework has the capability of a self-organizing using decision tree for proving optimal computational scalability, data flow, data quality, running time and energy consumption. This framework adopts the dynamic changes in the network automatically. In [61], a low-cost data gathering and decision making approach have been developed using fuzzy set theory for wireless body sensor networks. Decision making on the gathered data from the bio-sensors improves the data quality and transmission overhead. In [62] authors have presented a decision tree based imbalanced data classification and predict imbalanced data classes using Naïve Bayes to reduce imbalance class of data. This approach also reduces the communication overhead in the network and balances the energy consumption of sensor nodes.

Authors in [63] have proposed multi-sensor data fusion techniques using the Bayesian system to collect and analyze the heterogeneous data. This technique self-organize or configure according to the dynamic changes in the network. This method provides a context-aware, adaptive system for efficient data fusion process for WSNs. In [64], sparse Bayesian-based compressive sensing approaches have been proposed to decrease the active sensor nodes while gathering data. This method also

Table 10
ML-based data aggregation approaches for WSNs.

ML Technique	Studies	Mobility	Environment	Complexity	Topology	Remarks
Regression	[55]	static	Distributed	Low	Tree	Improved network lifetime
	[56]	static	Distributed	Low	Tree	Improved network lifetime
	[57]	static	Distributed/ Centralized	Moderate	Hybrid	Improved network lifetime
k-NN	[58]	static	Distributed	Moderate	Hybrid	
Decision tree	[59]	static	Distributed	Moderate	Tree	Improved accuracy
	[60]	static	Distributed	Low	Tree	Improved network lifetime
ANN	[61]	static	Centralized	High	Hybrid	Improved accuracy
	[72]	static	Distributed	High	Tree	Improved network lifetime
Naïve bayes + Decision tree	[62]	static	Distributed	High	Tree	Improved network lifetime
Bayesian	[63]	static or mobile	Distributed	Moderate	Hybrid	Improved accuracy
	[64]	static	Centralized	Low	Hybrid	Improved time complexity
	[65]	static	Distributed	Moderate	Hybrid	Reliable data transmission
	[66]	static	Distributed	Moderate	Hybrid	Improved network lifetime
	[67]	static	Centralized	Moderate	Tree	Improved accuracy
k-means	[116]	static	Distributed	Moderate	Tree	efficient redundancy elimination
Hierarchical clustering	[131]	static	Distributed or centralized	Moderate	Hierarchical	Reduce unnecessary transmissions
PCA	[117]	static	Distributed	Low	Tree	Improved network lifetime
	[118]	static	Distributed	Moderate	Tree	Improved network lifetime
	[119]	static	Distributed	High	Tree	Improved network lifetime
	[120]	static	Distributed	Moderate	Tree	Efficient drift findings
	[121]	static	Distributed	Moderate	Tree	Reduce unnecessary transmissions
	[122]	static	Distributed	Moderate	Tree	Improved network lifetime
	[123]	static	Distributed	Low	Hybrid	Improved network lifetime
	[124]	static	Distributed	Moderate	Hybrid	Improved network lifetime
SVD	[125]	static	Centralized	High	Hybrid	Reduce unnecessary transmissions
Genetic classifier	[206]	static or mobile	Distributed	Moderate	Star	Improved network lifetime

minimizes the estimation error while gathering the data from sensor nodes. It outperforms the traditional approaches and has lower computational complexity. A Bayesian model has been presented in [65] for reliable data transmission between the node and base station. This method achieves channel-aware data transmission between the sensor nodes either single-hop or multi-hop manner. In [66], a distributed Bayesian network model has been used to compress the sensing data at each sensor node level before transmitting to the CH. To avoid the non-existing packet paths, this algorithm adopts arithmetic coding. This algorithm reduces the communication overhead and improves network lifetime.

Temporal sparse Bayesian learning based sensor drift estimation method has been proposed in [67] from under-sampled observations for WSNs. This method identifies the drifting sensor without dense deployment or prior knowledge of data models. Authors in [58] developed a novel *k*-NN based missing data estimation method for WSNs by determining the temporal and spatial correlation between the sensor nodes. For the optimal computational search and measuring the missing data percentage, weighted *k* dimensional-tree data structure has been used. In [116], a *k*-mean and ANOVA-based clustering approach have been proposed for efficient data gathering in underwater WSNs. This approach eliminates redundancies at each sensor node before transmitting to CHs. Once the data set received by CH, it performs *k*-means and ANOVA to identify the similar datasets before sending it to the base station.

In [117], PCA based data aggregation technique has been proposed. The primary goal of this approach is to reduce the energy consumption of the sensor nodes, and it is achieved by data compression and signaling. In this method, the sensor nodes send their data to CHs, and the CHs take the compression responsibility before transmitting to the base station. Authors in [118] have devised a PCA-based data compression model for stationary WSNs. The primary design goal of this approach is to reduce the communication overhead among the sensor nodes. This approach successfully achieves energy efficiency and maximizes the network lifetime. In [119], self-organizing algorithms using distributed PCA for WSNs have been implemented to minimize unnecessary transmission and improving network lifetime. This approach better for any compression rate and able to solve principal component in CHs. This method achieved to improve the network lifetime and communication overhead between sensor nodes, CHs and base station. In [120], a PCA-based drift detection technique and angle optimized global embedding (AOGE) have been presented. PCA and AGOA analyze projection variance and projection angle respectively to determine principle component. This method efficiently finds the drift from data streams.

A PCA-based distributed adaptive algorithm has been developed in [121] to find Q smallest and highest eigenvalues for the sensor network. This approach dynamically determines the eigenvectors without any explicit constructions. A controlled number of transmissions for producing quality data using Compressive-Projections PCA has been developed in [122] to reconstruct data. This approach provides an energy efficient quality data reconstruction. This method also constructs the clusters for in-network processing. A recursive-PCA (R-PCA) method has been developed in [123] for energy efficient data gathering and outlier detection. R-PCA algorithm runs in CHs to aggregate data as well as outlier detection. R-PCA performs the data aggregation with high recovery accuracy and efficient outlier detection. In [124], a novel PCA-based framework has been proposed for data recovery, prediction and compression. The primary goal of this approach is to reduce the communication overhead. By compressing the data at CHs, this algorithm achieves lower communication overhead. This approach provides an accurate prediction, recovery and efficient compression mechanism for enhancing the network lifetime.

In [125], SVD based numerical analysis has been performed to investigate the missing information in an image. This method is very accurate and also avoids noisy data from the image sensed by sensors but inaccurate when the sensor nodes are less. Neural networks based data compression technique have been proposed in [72] for avoiding the congestion in the network as well as balancing the energy consumption of the sensor nodes in WSNs. This algorithm provides accurate results compared with various traditional algorithms for spatial and temporal data compressions. A novel power-aware hybrid data aggregation approach investigated in [131] using compression sensing along with hierarchical clustering approach for large scale WSNs. In this method, cluster sizes vary at each leave with the help of different threshold values to optimize the number of data transmissions in the network. This algorithm especially reduces communication overhead on the cluster head. In [206], authors have used genetic ML approach for parallel data gathering for

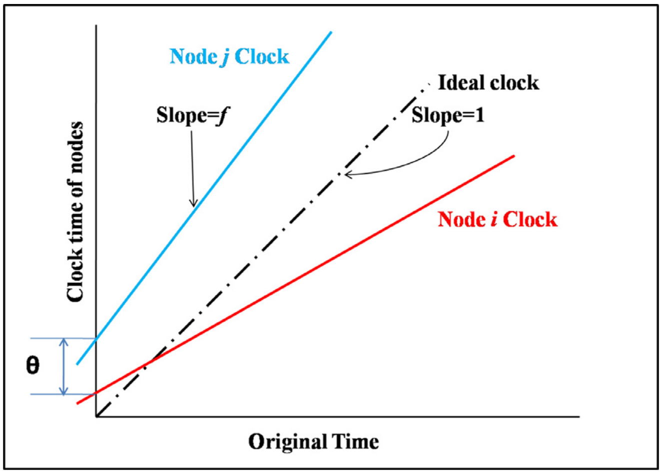

Fig. 11. Clock model of sensor nodes.

WSNs. This approach work dynamically according to the topological changes of the WSNs, save energy of the sensor nodes, and reduce the packet loss.

3.8. Synchronization

Clock synchronization is one of the major components of WSNs, it mainly used in protocols design. Synchronization was used in various parameters such as data aggregation, power management (sleep scheduling), transmission scheduling, localization, security and target tracking. In WSNs, each sensor node has a common time frame, and it may be different from others as shown in Fig. 11. The clock rate in WSNs measured using PPM. The clock rate of a sensor node i is represented as $C_i(t)$ calculated [207,208] as in Eq. (5).

$$C_i(t) = \theta + f.t \tag{5}$$

where the parameter θ indicates offset, and f means frequency difference (clock skew).

Fundamental time synchronization methods are classified into three categories such as one-way messaging, two-way messaging and receiver-receiver synchronization. Synchronization achieved with various techniques without using ML [209–212]. However, there are several advantages of using ML approaches for WSNs are listed as follows:

- ML improves the accuracy of the synchronization for WSNs.
- ML adopts the changes in the environment and resynchronizes accordingly.

A regression-based synchronization protocol has been developed in [68] to analyze various factors affect the performance synchronization. The factors considered here are clock frequency noise, latency, and clock drift. This method is particularly useful for the low-cost WSNs. In [69], a linear regression model-based long-term synchronization method has been proposed. Because of external factors, the WSNs will change dynamically, and the clock drift between the sensor nodes also can change dynamically it may affect synchronization in the network; therefore this algorithm resynchronizes according to the variation. This approach also reduces the synchronization error and produces the high accuracy rate as compared to other conventional methods.

In [70], regression-based synchronization method has been presented for low-cost applications of WSNs. To improve the synchronization performance, this algorithm focuses mainly on clock drift, resolution of clock, latency, clock wander and jitter. In [71], a Bayesian interface along with linear regression methods used to improve the accuracy of synchronization in WSNs. The major constraints consider in this work are clock and power consumption. Because of using Bayesian interface the algorithm improve 12% accuracy compared with conventional synchronization methods. A clustering task-scheduling mechanism has been introduced in [132] for WSNs using hierarchical clustering. This method mainly reduces the energy consumption of the sensor nodes in the network for applying the unnecessary clustering process.

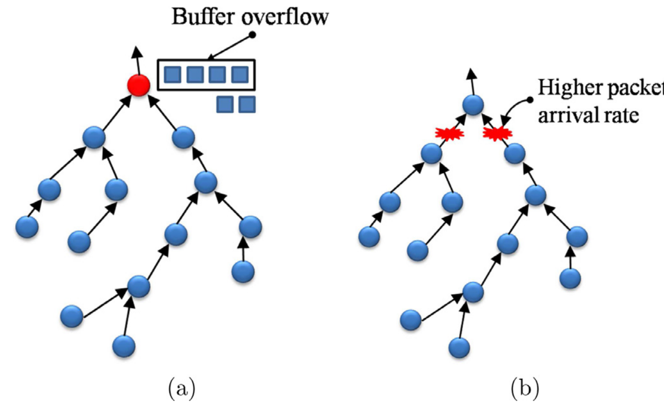

Fig. 12. Congestion in WSNs (a) Node level congestion (b) Link level congestion [213,214].

3.9. Congestion control

In WSNs, congestion happens when a sensor node or communication channel handles more data transmission than its capacity. There are several causes for the occurrence of congestion such as node buffer overflow, many-to-one data transmission scheme, transmission channel contention; packet collision, dynamic time variation, and transmission rate [213–215]. Fig. 12, illustrates the node level congestion and link level congestion. Node level congestion happens because of high packet arrival rate to a particular node (Figure. 12(a)) whereas link-level congestion occurs because of the collision and lower bit transmission rate between two nodes (Figure. 12(b)). Congestion affects various parameters of WSNs such as energy consumption, QoS, end to end delay, and packet delivery ratio (PDR). Congestion control is one of the most significant challenges in WSNs. Recently, some of the control congestion approaches have been proposed in [216–218] for WSNs to improve and energy-aware data routing. However, ML approaches more promising for congestion control and have following benefits:

- ML approaches are more accurate to estimate the traffic and also can find optimal path for minimized end-to-end delay between the nodes and base station.
- Using ML techniques, transmission ranges may change dynamically due to dynamic changes in the network.
- Table 11 briefs a comparison of ML approaches for congestion control in WSNs.

Congestion affects directly to the pocket loss, energy consumption and end-to-end delay. Neural networks based data compression technique has been proposed in [72] for avoiding the congestion in the WSNs as well as balancing the energy consumption of the sensor nodes. Transmitting the compressed data between the nodes or CHs will reduce the communication overhead. Therefore it reduces the energy consumption rate and also protects from the congestion occurrence. This algorithm performs the better in congestion control as compared to various traditional algorithms for spatial and temporal data compressions.

In [73], fuzzy logic based congestion detection and control mechanism have been developed to minimize packet loss ratio using efficient and active queue management. This approach performs in three phases. Initially, it manages the queue with the fuzzy system used to detect the congestion. In the second phase it adjusts the congestion control, and finally, it recovers from the congestion by balancing the flow. In [74], authors have presented an SVM based congestion control method

Table 11
ML-based congestion control strategies for WSNs.

ML Technique	Studies	Congestion control	Parameter metric	Data flow	Control pattern
ANN	[72]	traffic control	end-to-end delay, energy consumption	continuous	Hop-by-hop
Fuzzy logic	[73]	queue length	packet loss ratio	continuous	Hop-by-hop
SVM	[74]	transmission rate	throughput, latency, energy consumption	continuous	Hop-by-hop
Reinforcement learning	[219]	traffic control	throughput, energy efficient	continuous	Hop-by-hop

Table 12
ML-based target or node tracking algorithms for WSNs.

ML Technique	Studies	#Targets	#Sensors	Mobility of target	Mobility of sensor	Remarks
Bayesian	[75]	single	single	static	static	Improved accuracy
	[76]	single	single	mobile	mobile	improved accuracy
	[77]	single	multiple	static	static	Reduced communication overhead
	[78]	multiple	single/ multiple	static	static	Improved network lifetime
Bayesian + RL	[103]	single	multiple	static	static or mobile	Improved network lifetime
PCA	[142]	single	multiple	static	static	Improved network lifetime
Q-learning	[224]	single	multiple	static	static	efficient task scheduling
Genitic algorith	[159]	single	multiple	static	static	Improved network lifetime
memetic algorithm	[160]	single	single	static	static	Improved network lifetime

for WSNs. In this method, transmission rates of each node are adjusted due to dynamic changes in traffic. As compared with other classification methods, SVM produces the accurate results. An energy-efficient data gathering approach has been proposed in [219] using multi-agent reinforcement learning approach. This approach controls traffic at the cluster-ring level and takes the optimal routing decision. This approach also adopts routing patterns for the dynamic changes in network topologies.

3.10. Target tracking

Target tracking indicates detecting and monitoring a particular static or mobile phenomenon in the network. Target tracking in WSNs may perform with single or multiple sensor nodes depends on the application. Using single node for tracking the target benefits consumes less energy as compared to multiple sensor nodes, whereas multiple sensor nodes provide accurate results. The quality of target tracking invites some of the challenges such as node failure, target missing, coverage and connectivity, data aggregation, tracking latency, and energy consumption. A comparative study of target tracking has been provided in [220]. Target tracking using divide-and-conquer approach solved in [221], target tracking based on estimation presented in [222]and information fusion for target tracking in large-scale WSNs has been presented in [223]. Recently, several approaches are adopted ML techniques to improve the accuracy of target tracking in WSNs; some of them are listed below:

- ML approaches reduce the computational overhead to track the mobile object with either stationary or mobile sensor nodes.
- Dynamic nature of the targets in a sensor network, ML improves the efficiency of target tracking.
- Table 12 shows ML-based target or node tracking algorithms for WSNs

In [75], authors have proposed a target tracking along with data fusion method using Bayesian posterior for WSNs. The accuracy of the algorithm verified based on computer-generated data as well as the real-time environment. This approach produces an accurate target tracking and data fusion for WSNs. In [76], a multi-layer dynamic Bayesian network (MDBN) has been proposed for mobile target tracking. The target tracking accuracy improved because of Bayesian statistics. This approach also works online mobile tracking in nonlinear observation and time-varying RSS precision. This method promising optimal target tracking approach compared to the conventional approaches. Authors in [77] have presented a node selection algorithm for signal recovery based on Bayesian learning approach for WSNs. This method efficiently selects a subset of a sensor for target selection. This approach reduces the communication overhead and efficient signal recovery approach. A multi-target tracking method has been proposed in [78] for WSNs using Bayesian filtering algorithm. This method developed with two layers; in first layer handling information fusion problem and second layer Bayesian approach adopted for tracking the target. Because of using two-layer approach, computational overhead of this approach will reduce and balances the energy consumption of the sensor nodes in the network.

In [103], two ML approaches, Bayesian and reinforcement learning are used to monitoring an event. A dynamic Bayesian network was used to observe the event and reinforcement learning was used to apply the optimal duration for sleep schedules to the sensor nodes. This approach was more efficient regarding energy consumption of the sensor nodes and data accuracy. Authors in [142] have developed a system for observing a specific volatile organic compound (VOC) in the industrial environment using wireless sensing system. This method adopts PCA to process the sensing information from the field to determine gaseous conditions in the network. In [224], Q-learning-based task model for target tracking has been developed for dynamic WSNs. This method mainly developed for task scheduling for cooperative sensor nodes.

A genetic algorithm based target tracking approach with a k-coverage model for WSNs has been presented in [159]. In this approach, the genetic algorithm used to improve the network life and scheduling the sensor nodes to track the object. In [160], authors have proposed a memetic algorithm based target coverage scheduling strategy for WSNs. The goal of this approach is to organize all the sensor nodes into disjoint subsets and allow one after another to cover the particular target.

3.11. Event detection

In WSNs, sensor nodes continuously monitor the environment, observe a phenomenon and process locally and make certain decisions. The feature of detecting the event or misbehavior from the data refereed as event detection. The requirements to satisfy the event detection are synchronization, low false alarm rate, and high true detection rate. Sensors are of limited power, memory, and computational resources, Therefore event detection is challenging. ML based approaches have the potential to address event detection problems. Some of the benefits are listed below

- ML is very useful to detect an event from the complex forms of sensor data.
- ML improves packet delivery ratio by achieving efficient duty cycles.

In [79], authors have focused to detect a different kind of events for variant WSN applications. The authors have suggested sophisticated regression model to improve the accuracy of the event detection. *k*-NN applied to extract information of interest from the raw sensor data efficiently. In [80], *k*-NN based query processing approach has been proposed to extract information of interest from information storage and in-network rather from the raw sensor data. This approach improves the query processing time and balances the energy consumption of the sensor nodes. Authors in [81] have presented an event detection method for sensor network using fuzzy logic. This method improves the accuracy of event detection by considering neighbor nodes data. This method also applies rule-based approaches to speed up the event detection process.

In [225], a human-activity recognition method has been proposed using deep learning technique and PCA. The dimensionality has reduced using PCA and deep learning approach used for training and testing the Smartphone data. As compared to the traditional methods of human recognition approach, the algorithm provides 94.12% overall accuracy. A deep learning-based projection-recovery network (PRNet) has been developed in [97] to estimate blind online calculations of sensor data. PRNet approach initially focuses on drifted data in feature space; later deep learning recover drifted data from the sensor data. This approach has achieved $2\times$ accurate than conventional methods. In [226], ANN-based groundwater quality estimation method has been proposed for sensor networks. This method used in real-time water quality estimation and provides the accurate result than traditional approaches. ANN was used to train the large set of sample to achieve accurate results.

In [104], Bayesian learning-based motion detection method has been presented for a moving object with different temporal dimensions in a polygon region. This method also works concurrently to detect multiple moving objects in WSNs. This approach balance the energy consumption of the sensor nodes and reduces the latency. Authors in [227] have developed a reinforcement learning-based sleep/wake-up scheduling approach for energy efficient WSNs. The duty cycling approach maintained by reinforcement learning and it has tradeoff with packet delivery delay. This approach also achieves high packet delivery ratio and increases network lifetime. In [228], authors have presented distributed functional tangent decision tree (DFTDT) for estimating the quality of water from the pond using sensors. In DFTDT, the routing determined by using ABC and decision trees.

3.12. Mobile sink

In WSNs, sensor nodes gather information from the environment and transmit the data to the base station directly or multi-hop manner. When the data transmits in a multi-hop manner, the node which is near to the sink will die soon referred as energy-hole problem. To avoid the energy-hole problem, a mobile sink concept has been introduced, a mobile sink visits each sensor node in the network and collects information directly. In large WSNs, visiting every node is difficult, so scheduling mobile sink in an efficient delay-aware manner is a research issue. Therefore instead visiting each sensor node in the network, mobile sink visit only a few nodes or points in the network called rendezvous points (RPs) to collect data, and all remaining nodes send their data to nearest RPs [229,230]. We can also use multiple mobile sinks to avoid delay of mobile sink to visit sensor nodes, but it is cost-effective.

Authors in [231] have proposed multiple mobile sink concepts to gather the information from the WSNs and store it into the cloud. In this, each mobile sink treated as a fog device, and it acts as the bridge between WSNs and cloud. This algorithm designed for parallel data gathering process for minimizing the latency and maximizing the scheduling efficiency. This approach balances the energy consumption and improves the network lifetime. Recently, ML approaches have adopted for WSNs to schedule mobile sink and to choose the optimal set of rendezvous points. This adoption will result from following benefits:

- ML for mobile sink will provide optimal rendezvous points or efficient cluster heads for data collection.
- Mobile sink path selection place a significant role to avoid delay-aware data collection, ML achieve delay aware routing of mobile sink.

In [105] authors have determined optimal deadline-based trajectory (ODT) algorithm for an efficient mobile sink scheduling based on dynamic rendezvous point selection and virtual structures in the WSNs using decision trees. ODT performs the delay-aware data gathering from the network from active sensor node (AN) groups. The ODT obtain a feasible solution by running decision tree with polynomial time complexity. This method improves the network lifetime and also delay-aware path planning of mobile sink. In [88] authors have proposed a data gathering methods using mobile sink based on Naïve Bayesian classifier. This method was efficiently gathering the information from the sensor nodes and outperforms compared to traditional approaches. Authors in [232] find optimal rendezvous points and efficient mobile sink path selection for WSNs. *k*-means algorithm used to perform the clusters and RPs for data gathering. *k*-means useful to reduce the intra-cluster communication. Efficient mobile sink path determined using a minimum spanning tree (MST). This method provides optimal energy balance of sensor nodes and improves network lifetime. An energy efficient PSO based routing algorithm named EPMS has been proposed in [161] for WSNs using a mobile sink. EPMS is the combination of virtual clustering and mobile sink scheduling approach. PSO algorithm used in EPMS to split the network into clusters and then finds the cluster heads.

In [162], authors have proposed an algorithm to determine the mobile sink path for non-uniform data constrained WSNs using Ant colony optimization (ACO) algorithm. In this algorithm, the authors have used ACO to find the rendezvous points for collecting the data as well as the path of the mobile sink. This approach produces optimal results for energy consumption and network lifetime in both uniform and non-uniform data constraints. A mobile sink based data collection algorithm has been presented using discrete firefly algorithm for WSNs in [163]. The firefly algorithm has been used to find the order of visiting the sensor nodes in the network to optimize the mobile sink tour. In [164], authors have presented an ABC based mobile sink path planning algorithm for WSNs to collect the data efficiently. The ABC uses to find the optimal mobile robot visiting points and minimum tour length. Authors in [133,134] have proposed a mobile sink based data collection in WSNs using hierarchical clustering approach. In this, initially, apply the clustering method to identify the cluster heads and then efficient path planning algorithm designed for a mobile sink to collect the data from the CHs. A fuzzy clustering approach has been proposed in [138] for collecting the data using mobile sink. In this approach, it selects super-CHs to reduce the tour length of the mobile sink.

3.13. Energy harvesting

Battery power is one of the significant current source of energy for sensor nodes in WSNs, and the lifetime of the network depends on the energy consumed by the sensor nodes. Most of the applications of WSNs require longer network lifetime ranges from months to years. To prolong the lifetime of WSNs, either we apply the energy-efficient protocols or providing energy harvesting approaches for sensor nodes. Several routing, sleep-scheduling, mobile sink, mobile charger etc., protocols have been introduced for energy-efficiency. However the energy requirement is not filled because of high computational resources, unreachable sensor nodes and additional maintenances. Energy harvesting includes maintenance free, long lasting, and self-powered in WSNs. Energy harvesting gives uninterrupted energy for sensor nodes from an ambient surrounding such as radio frequency energy, wind energy, solar energy, thermal, mechanical and vibrations. Energy harvesting is categorized into two types, without energy storage (sensor nodes directly used the power without any backup) as shown in Fig. 13(a), and pow-

Table 13
ML-based energy harvesting techniques for WSNs.

ML Technique	Studies	Environment	Complexity	Energy source
Regression	[82]	Centralized	High	Solar
	[83]	Distributed/ centralized	High	Solar
Reinforcement learning	[234]	Centralized	Moderate	solar
	[235]	Centralized	Moderate	Solar
	[236]	Centralized	Low	Solar
Deep learning	[98]	Centralized	High	Wind
Hierarchical clustering	[135]	Distributed	Low	Solar/ wind

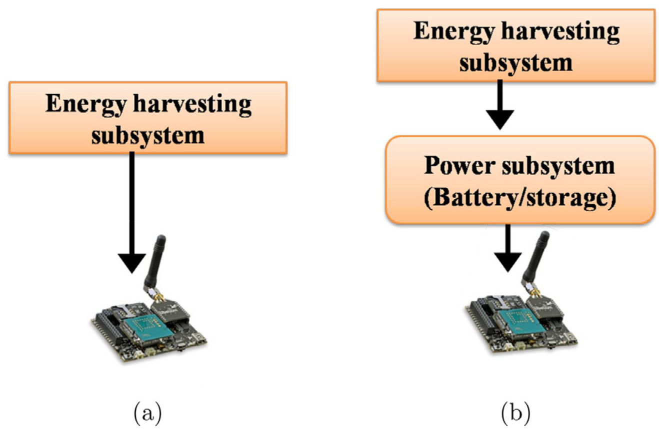

Fig. 13. Types of energy harvesting for sensor nodes (a) energy harvesting without storage (b) energy harvesting with storage [233].

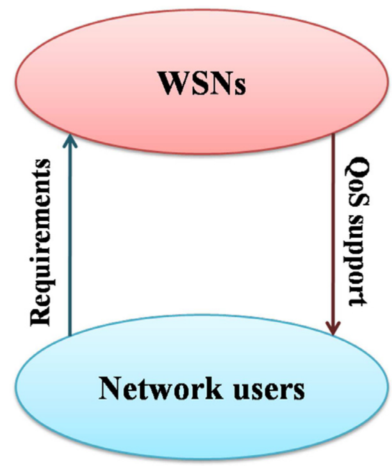

Fig. 14. QoS functionality for WSNs [193].

ered storage (rechargeable battery) as shown in Fig. 13(b). Several ML based models have been used to track effective energy harvesting methods for WSNs. The summary of ML-based energy harvesting methods listed in Table 13. Some of the benefits of ML-based energy harvesting are as follows:

- ML algorithm improves the performance of WSNs to forecast the amount of energy to be harvested within a particular time slot [234].
- ML approaches reduce the computational complexity to calculate the amount of energy harvested and maintain appropriately by balancing the energy consumption.

Authors in [82] have investigated and evaluated solar irradiance prediction using ML-based approaches. This method performs various operations on historical data sets and results out correlation coefficient, forecast accuracy, and root mean square error (RMSE). Authors have collected data sets from national renewable energy laboratory (NREL) to perform the testing operations. The resultant of this algorithm provides best accuracy rate compared with other conventional methods. In [83] authors have presented an indoor test methodology based on astronomical models and PV (photovoltaic) cell design principles for solar-powered WSNs. The experiments were tested for both centralized and distributed networks using linear regression based methods. The result of this algorithm shown to perform better for distributed approaches than the centralized strategies.

A Q-learning-based solar energy prediction (Q-SEP) approach has been proposed in [234] for energy harvesting in WSNs. Q-leaning was used efficiently for prediction based on past observations. The algorithm improves the performance of WSNs to forecast the amount of energy to be harvested within a particular time slot. In [235], a reinforcement learning-based method has been presented for energy harvesting WSNs. The algorithm automatically adjusts duty cycles according to the learning process of reinforcement learning. This method outperforms as compared to conventional approaches. In [236], reinforcement learning-based energy management (RLMan) have been proposed for energy harvested WSNs. RLMan approach balances the energy consumption of the sensor nodes as well as maintains energy harvesting.

A deep learning-based fault prediction and diagnose method for wind power generation in IoT has been developed in [98]. It produces high accuracy rate and low error rate of fault prediction in any conditions without human interaction. In [135], authors have focused on energy harvesting using a hierarchical clustering algorithm for heterogeneous WSNs. The algorithm found static cluster heads for data collection and these cluster heads are using renewable sources and all other sensor nodes are non-renewable. The objective of this approach is to find the optimal locations for the cluster headsto reduce the power consumption of the sensor nodes.

3.14. QoS

The level of service given by WSNs to its users depends on the quality of service (QoS). QoS is mainly classified into two categories such as network-specific and application-specific. The network-specific parameters for QoS are the energy consumption rate of sensor nodes and bandwidth. The application-specific parameters are measurements of sensor nodes, deployment and the number of sensor nodes is active in the network. There are several challenges to maintain the QoS for WSNs are severe resource constraints, unbalanced traffic, data redundancy, dynamic network, energy balancing, scalability, multiple sinks, the difference in traffic types [193]. Fig. 14 demonstrate the QoS functionality for WSNs. The summary of ML-based approaches for QoS in WSNs is shown in Table 14.

In [237], authors have proposed an energy efficient method for data fusion based on fuzzy logic to achieve QoS in WSNs. This method aggregate only true information, instead of gathering complete data from the WSNs. The algorithm is applicable for cluster-based sensor networks where each CH capture information from its members until an event detects. The fuzzy logic controller used in every sensor node to find the true information before it transmits to the nearest CHs. Authors in

Table 14
Summary of ML-based QoS for WSNs.

ML Technique	Studies	Complexity	Objective
ANN	[44]	Moderate	Faulty node detection
	[237]	Moderate	Data fusion and energy balancing
	[238]	Low	Link-quality estimation
Reinforcement learning	[239]	Moderate	Cross-layer communication framework
	[240]	Low	Topology control and data dissemination protocol
	[241]	High	Constraint-satisfied service composition
	[242]	Moderate	Distributed adaptive cooperative routing

[238] have presented a wavelet neural-network-based link quality estimation (WNN-LQE) mechanism to enhance the QoS requirements in WSNs and smart grids. This method estimates different link quality parameters by using the signal to noise ratio (SNR). This method also improves the QoS by reducing the communication overhead and balancing the energy consumptions. A cross-layer communication protocol has been presented in [239] based on multi-agent reinforcement learning for WSNs.

In [240], a multi-agent RL and energy-aware topology control and data dissemination protocols have been developed for effective self-organization of WSNs. The multi-agent RL algorithm used to select the active neighbor nodes to maintain the reliable topology. The connectivity and coverage for the boundary nodes sustained through a convex-hull algorithm. This method provides the optimal QoS and improves the performance of the sensor network. A Q-leaning based mechanism has been used in [241] to solve the uncertainty of QoS and dynamic behavior of a service for WSNs. This method achieves globally optimal for the safety service. Authors in [242] have proposed distributed adaptive cooperative routing protocols (DACR) based on light-weighted reinforcement learning mechanism, to achieve reliable QoS for WSNs. The reinforcement learning algorithm select optimal relay nodes in the network and decides transmission mode at each node to maximize the reliability.

4. Statistical analysis and limitations

In this section, we discuss the statistical analysis of recent research topics for ML-based algorithms for WSNs and their limitations.

4.1. Statistical analysis

Here, we present statistical charts to show the overview of recent research on ML-based algorithms for WSNs, as shown in Fig. 15. From Fig. 15(a) and Figure. 15(b), we notice that the most researchers focus on data aggregation, localization, routing, anomaly and fault detection, event detection, coverage,and connectivity. In contrast, a little amount of research has been done by using ML to solve MAC, target tracking, QoS, energy harvesting, congestion control, synchronization and mobile sink scheduling.

From Fig. 15(c), we estimate that most of the WSNs issues solved using supervised learning algorithms. The supervised learning approaches are solved 67% of the WSNs issues in recent times. Unsupervised learning approaches have solved 18% of the WSNs problems and finally, reinforcement learning approach has solved 15% of the problems of WSNs in recent years. From Fig. 15(d), we see that most of the WSNs issue solved by using the Bayesian learning approach. The reasons are that the Bayesian learning efficiently combine the prior information with the current data. It produces solid decisions with more than 95% of confidence interval. It also handle the parameters successfully, noise, missing values effectively, and classifies the data rapidly. Bayesian learning approach allows different probability functions specific to the problem in WSNs. Table 2. Summarize the benefits of this approach with additional specifications. Because of the faster classification and high accuracy rate in the result, the ANN learning approach also attracted the researcher to address various in WSNs. It can find the unseen relationships from the inputs, and it does not impose restrictions on input data. ANN is also handles the independent attributes efficiently as compared to others.

Reinforcement learning approach does not require any prior knowledge. It can efficiently balance the exploration and exploitation, whereas most of the supervised learning algorithms fail. By interacting with the environment, according to the things happen in the network, it takes decisions accordingly. The computational complexity is low compare to most of the supervised learning approaches. This approach reduce the energy consumption and improves the lifetime of the network. From the literature, we found that SVM also given priority to resolve the various issues in WSNs. It attracts the researcher even for slow learning process; because it produces high accuracy rate and perform the classification faster. SVM provides good results with labeled, semi-labeled or unlabeled data, without any restrictions.

Regression is attracting the WSNs researchers, because of its rapid prediction strategy, efficient decision support, error correctness, and less computational requirements. It produces accurate results for both large and small applications. The dimensionality reduction is the necessary requirement, because it avoids unnecessary data transmissions in the networks. PCA and ICA are used to reduce the dimensionality of the data in the network for improving the network lifetime. The less effort had done with the Random forest approach in the literature; because this algorithm fits and produce a better result to the large-scale WSNs. Because of the large data, it requires additional space to store the data and consumes more time to computation. Simulation of large-scale networks require high computational machines to prove the results. However, there are several benefits with Random forests such as quick training, implicit feature selections, less variance and highly accurate for the large-scale WSNs.

4.2. Limitations

In spite of many benefits, there are some limitations of applying ML in WSNs:

- ML techniques do not produce immediate accurate predictions, because they require to learn from historical data. The performance of the system depends on the amount of historical data. If the data size is large then energy consumed to process the data is also very high. In other words, there is tradeoff between energy limitations of the WSNs and high computation complexities of the ML algorithm. To overcome this tradeoff, ML algorithm are need to run centrally.
- Validating the predictions that produced by the ML algorithm in the real-time environment is a cumbersome task.
- Sometimes identifying a particular ML technique to address an issue in WSNs is very difficult.

5. Open issues

Several challenges still open and require further research in WSNs. Here we listed out some of the open research issues for WSNs that can be solvable using ML approaches. The summary of ML choice to be solve a issue in WSNs are listed in Table 15.

1. *Localization*: It is essential to design efficient path planning for the beacon nodes in the context of mobile sensor nodes. To the best

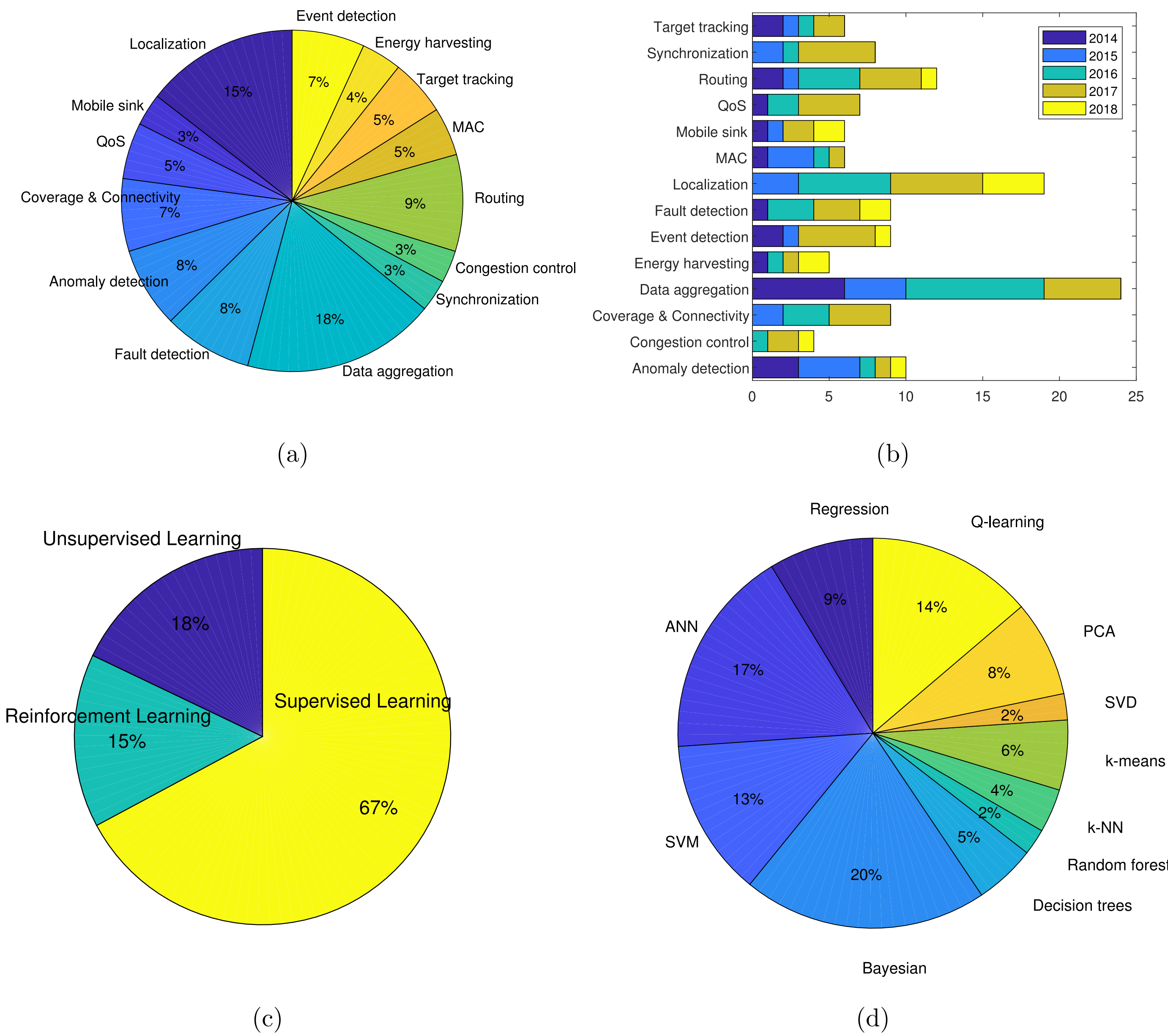

Fig. 15. Statistical charts (a) Issues in WSNs addressed by ML algorithms (2014–March 2018) (b) Year wise research articles (c) Classification of ML algorithms for WSNs (d) ML-based algorithms for WSNs.

of our knowledge, there is no particular predefined path planning strategy available for mobile anchor nodes. Further, ML may provide efficient path planning approaches for each anchor nodes in the sensor networks to achieve higher localization accuracy with minimum energy consumption. Most of the real-time applications deploys sensor nodes in three-dimensional space, but most of the existing localization algorithms examined only for two-dimensional space. Therefore, there is a need to develop localization techniques for three-dimensional spaces for static and mobile WSNs.

2. *Coverage and Connectivity*: A number of recent works have been proposed for coverage and connectivity, still a lot of problems and challenges need to be explored. Predicting the minimum number of sensor nodes require to cover an area of interest or target, and finding its optimal placement of sensor nodes is also a challenging issue. Most of the real-time WSNs applications, the deployment of the sensor nodes are random. This random deployment may cause the coverage hole. Finding such a coverage hole in the network is a challenging task. Due to the dynamic changes in the network, coverage holes may occur. Predicting such situations in the network and finding the remedies require further research. Most of the current researchers have developed coverage algorithms for two-dimensional space, however, three-dimensional coverage with optimal computational complexity is still unexplored.
3. *Anomaly detection*: Anomaly detection is one of the most promising research issues in WSNs, and recently most of the researchers have developed various techniques to detect anomalies. Anomalies in WSNs effects communication overhead, transmission delays, or some time it misleads the sensor nodes data. Authors in [32–38,111,175–179,181–186] focused on anomaly detection, but detection of the anomaly itself is not a complete solution, further research is needed, on what actions need to be taken once the anomaly detects, what are the efforts required to reduce the damages. Anomaly detection method is application specific; therefore the selection of anomaly detection algorithm for heterogeneous WSNs is a challenging task. The detection algorithm needs to fulfill the accuracy and speed of the detection.

Table 15
ML techniques to solve various issues in WSNs.

Sno	WSNs Issues	ML techniques	Remarks
1	Localization	Reinforcement learning	Prior knowledge not required and solution works even for the dynamic environment
		k-NN	Efficient distance estimation for range free localization
2	Coverage & Connectivity	Decision tree	Efficient classification of connected or isolated nodes in the network
		Deep learning	To find the minimum number of sensor
		Evolutionary computation	nodes for well covered area with optimal connectivity
3	Anomaly and fault detection	Random forest	To classify the faulty sensor nodes from the normal nodes
		PCA	To detect anomaly in the network
		ICA	
		Deep learning	Online anomaly or fault detection
4	Routing	Decision tree	To predict the optimal routing paths through dynamic alternative path selection to control the data traffic
		Random forest	
		Evolutionary computation	
5	MAC	SVM	Efficient channel assignment
		Decision tree	
		Deep learning	Reconfiguring newly joined sensor nodes and predict time slots
6	Data aggregation	k-means	To find optimal clusters heads in the network
		SVM	
		Reinforcement learning	To identify the optimal data routing paths within the network without prior knowledge
7	Synchronization	Deep learning	Predict the efficient time slots for channel allocation and resynchronize dynamically
8	Congestion control	Reinforcement learning	To predict the congestion locations in the network, and find the optimal alternative routing paths
		Random forest	Classifying the congestion nodes from the normal nodes in large-scale WSNs.
		Decision tree	
		SVM	
		Evolutionary computation	To find optimal dynamic alternative path selection for congestion avoidance
		PCA	Dimensionality reduction to control unnecessary data transmission
		ICA	
9	Target tracking	Deep learning	Efficient multiple target tracking for mobile WSNs
		SVM	To classify the targets in heterogeneous WSNs
		Decision tree	
10	Event detection	PCA	To detect an event from the complex forms of sensor data
		ICA	
		Deep learning	Efficient duty cycling management
		Evolutionary computation	
11	Mobile sink	Evolutionary computation	To select optimal mobile sink path between sensor nodes or rendezvous points.
		Reinforcement learning	Selecting optimal rendezvous points, and optimal tour selection
		Random forest	To find the data forwarding routes and optimal RPs selection for large-scale networks
12	Energy harvesting	SVM	To forecast the amount of energy to be harvested within a particular time slot
		Deep learning	
		Evolutionary computation	To predict the amount of energy to be harvested.

4. *Routing*: Most of the existing routing mechanisms are developed for collecting data from a single source and transmitting it to a single destination. WSNs with multiple source and multiple destinations, there may be a possibility of packet collision. Developing collision free cooperative routing protocols for a WSNs with multiple source and multiple targets is an emerging research interest. In a mobile WSNs, the position of the nodes changes dynamically. Sometimes due to the external causes the nodes in a WSNs may change their position. Therefore, there is a requirement to develop routing protocols that adopt the dynamic changes in the network.
5. *Data aggregation*: Most of the researchers interested in data aggregation methods for WSNs with uniform data rate sensor nodes. The further research is required in the WSNs with non-uniform data rate sensor nodes. The data collection is more complex in mobile WSNs with the non-uniform sensor nodes. Data gathering and energy efficiency can improve by introducing the mobile sink. Scheduling the mobile sink in a WSNs with non-uniform data is a challenging task. The major goals to consider the efficient data aggregation process with mobile sink are energy efficient, scalability and low-cost.
6. *Congestion control and avoidance*: Due to the dynamic behavior of WSNs operations, efficient and effective congestion control and avoidance approaches should require robustness and phenomenal survivability to internal disturbances and external stimuli or data loss [214]. Due to the limited energy and memory constraints of WSNs, it should require to implement simple congestion control mechanisms at each node level and minimize the transmission rate between the nodes. WSNs require a faster, efficient and effective congestion control and avoidance mechanism for autonomous and decentralized strategies. Congestion control should adopt the self-learning approach to respond according to the dynamic changes in the network. In self-adoption of congestion control mechanism, it must respond to remove or add nodes while congestion detected in the network. There is a need to develop traffic estimation protocols to identify the rapid and dynamic change in route to avoid congestion in the network. Further need for efficient mobile agent approaches to collect the data from sensor nodes rather transmitting data between the nodes.
7. *Energy harvesting*: In WSNs, the tiny sensor nodes deployed in the environment with a limited energy source (battery). Due to limited energy resources of the sensor nodes, it should need a low-cost, highly efficient, small wireless harvesting system (WHS) for operating the network fora long time. There is a need of efficient cross-layer wireless energy harvesting protocols for WSNs. Majority of the existing routing protocols are energy efficient, therefore it should revisit the reliability routing protocols using ML. For the large-scale sensor networks there should be a self-charging and discharging cycles according to the dynamic changes in the environment. Efficient power allocation strategies needed to improve the network lifetime. So, there is a need for synchronization between physical layer power control and MAC layer to adjust the duty cycles.
8. *QoS*: The goal of QoS in WSNs needs to meet the requirements of users and applications. QoS standards vary from different requirements (such as sensor type, data rate, traffic handling methods, or data types) or application for WSNs. Therefore, defining the standards of QoS for different requirement or application is challenging. Designing efficient cross-layer protocols may improve the QoS. For

a large heterogeneous mobile sensor network, developing QoS standards is a challenging issue.

6. Conclusion

In this survey, we have presented recently published ML-based algorithms for WSNs. We have discussed various ML algorithms briefly for reader convenience. We have highlighted various issues in WSNs addressed by ML techniques such as localization, anomaly detection, fault nodes detection, routing, data aggregation, MAC protocols, synchronization, congestion control, energy harvesting and mobile sink path determination. In addition, we have discussed issues like synchronization, congestion control and energy harvesting which are not included in any previous survey papers. Besides, we have compared and summarized the ML-based algorithm for WSNs in the tabular form. The statistical charts have summarized the impact of recent research on ML-based algorithm for WSNs followed sugestions to chose a particular ML techniques to address a issues in WSNs. Finally, we have discussed some of the open issues.

Acknowledgments

We appreciate the time and efforts made by the editor during reviewing this manuscript. We pay our sincere thanks to the esteemed reviewers for their valuable comments and suggestions to improve the quality of this survey paper.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.inffus.2018.09.013.

References

[1] M.A. Alsheikh, S. Lin, D. Niyato, H.-P. Tan, Machine learning in wireless sensor networks: algorithms, strategies, and applications, IEEE Commun. Surv. Tutorials 16 (4) (2014) 1996–2018.
[2] P. Rawat, K.D. Singh, H. Chaouchi, J.M. Bonnin, Wireless sensor networks: a survey on recent developments and potential synergies, J. Supercomput 68 (1) (2014) 1–48.
[3] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, Wireless sensor networks: a survey, Comput. Networks 38 (4) (2002) 393–422.
[4] J. Yick, B. Mukherjee, D. Ghosal, Wireless sensor network survey, Comput. Networks 52 (12) (2008) 2292–2330.
[5] D.K. Sah, T. Amgoth, Parametric survey on cross-layer designs for wireless sensor networks, Comput Sci. Rev. 27 (2018) 112–134.
[6] J.B. Predd, S.B. Kulkarni, H.V. Poor, Distributed learning in wireless sensor networks, IEEE Signal Process. Mag. 23 (4) (2006) 56–69.
[7] T.M. Mitchell, Machine Learning, first ed., McGraw-Hill, Inc., New York, NY, USA, 1997.
[8] T.O. Ayodele, Introduction to Machine Learning, first ed, InTech, 2010.
[9] P. Langley, H.A. Simon, Applications of machine learning and rule induction, Commun. ACM 38 (11) (1995) 54–64.
[10] S.S. Banihashemian, F. Adibnia, M.A. Sarram, A new range-free and storage-efficient localization algorithm using neural networks in wireless sensor networks, Wireless Personal Commun. 98 (1) (2018) 1547–1568.
[11] A. El Assaf, S. Zaidi, S. Affes, N. Kandil, Robust ANNs-based WSN localization in the presence of anisotropic signal attenuation, IEEE Wireless Commun. Lett. 5 (5) (2016) 504–507.
[12] S.K. Gharghan, R. Nordin, M. Ismail, J.A. Ali, Accurate wireless sensor localization technique based on hybrid PSO-ANN algorithm for indoor and outdoor track cycling, IEEE Sens. J. 16 (2) (2016) 529–541.
[13] S. Phoemphon, C. So-In, D.T. Niyato, A hybrid model using fuzzy logic and an extreme learning machine with vector particle swarm optimization for wireless sensor network localization, Appl. Soft Comput. 65 (2018) 101–120.
[14] N. Baccar, R. Bouallegue, Interval type 2 fuzzy localization for wireless sensor networks, EURASIP J. Adv. Signal Process. 2016 (1) (2016) 1–13.
[15] J. Kang, Y.J. Park, J. Lee, S.H. Wang, D.S. Eom, Novel leakage detection by ensemble CNN-SVM and graph-based localization in water distribution systems, IEEE Trans. Ind. Electron. 65 (5) (2018) 4279–4289.
[16] F. Zhu, J. Wei, Localization algorithm for large-scale wireless sensor networks based on FCMTSR–support vector machine, Int. J. Distrib. Sens. Netw. 12 (10) (2016) 1–12.
[17] T. Tang, H. Liu, H. Song, B. Peng, Support vector machine based range-free localization algorithm in wireless sensor network, in: International Conference on Machine Learning and Intelligent Communications, Springer, 2016, pp. 150–158.
[18] Z. Wang, H. Zhang, T. Lu, Y. Sun, X. Liu, A new range-free localisation in wireless sensor networks using support vector machine, Int. J. Electron. 105 (2) (2018) 244–261.
[19] F. Zhu, J. Wei, Localization algorithm for large scale wireless sensor networks based on fast-SVM, Wireless Personal Commun. 95 (3) (2017) 1859–1875.
[20] J. Hong, T. Ohtsuki, Signal eigenvector-based device-free passive localization using array sensor, IEEE Trans. Veh. Technol. 64 (4) (2015) 1354–1363.
[21] T.L.T. Nguyen, F. Septier, H. Rajaona, G.W. Peters, I. Nevat, Y. Delignon, A bayesian perspective on multiple source localization in wireless sensor networks, IEEE Trans. Signal Process. 64 (7) (2016) 1684–1699.
[22] B. Sun, Y. Guo, N. Li, D. Fang, Multiple target counting and localization using variational Bayesian EM algorithm in wireless sensor networks, IEEE Trans. Commun. 65 (7) (2017) 2985–2998.
[23] Z. Wang, H. Liu, S. Xu, X. Bu, J. An, Bayesian device-free localization and tracking in a binary RF sensor network, Sensors 17 (5) (2017) 1–21.
[24] Z. Xiahou, X. Zhang, Adaptive localization in wireless sensor network through bayesian compressive sensing, Int. J. Distrib. Sens. Netw. 2015 (2015) 1–15.
[25] Y. Guo, B. Sun, N. Li, D. Fang, Variational bayesian inference-based counting and localization for off-grid targets with faulty prior information in wireless sensor networks, IEEE Trans. Commun. 66 (3) (2018) 1273–1283.
[26] W. Sun, X. Yuan, J. Wang, Q. Li, L. Chen, D. Mu, End-to-end data delivery reliability model for estimating and optimizing the link quality of industrial WSNs, IEEE Trans. Autom. Sci. Eng. 15 (3) (2018) 1127–1137.
[27] X. Chang, J. Huang, S. Liu, G. Xing, H. Zhang, J. Wang, L. Huang, Y. Zhuang, Accuracy-aware interference modeling and measurement in wireless sensor networks, IEEE Trans. Mob. Comput. 15 (2) (2016) 278–291.
[28] W. Kim, M.S. Stankovi, K.H. Johansson, H.J. Kim, A distributed support vector machine learning over wireless sensor networks, IEEE Trans. Cybern 45 (11) (2015) 2599–2611.
[29] J. Shu, S. Liu, L. Liu, L. Zhan, G. Hu, Research on link quality estimation mechanism for wireless sensor networks based on support vector machine, Chin. J. Electr. 26 (2) (2017) 377–384.
[30] W. Elghazel, K. Medjaher, N. Zerhouni, J. Bahi, A. Farhat, C. Guyeux, M. Hakem, Random forests for industrial device functioning diagnostics using wireless sensor networks, in: Aerospace Conference, 2015 IEEE, IEEE, 2015, pp. 1–9.
[31] B. Yang, Y. Lei, B. Yan, Distributed multi-human location algorithm using naive bayes classifier for a binary pyroelectric infrared sensor tracking system, IEEE Sens. J. 16 (1) (2016) 216–223.
[32] M. Xie, J. Hu, S. Han, H.-H. Chen, Scalable hypergrid k-NN-based online anomaly detection in wireless sensor networks, IEEE Trans. Parallel Distrib. Syst. 24 (8) (2013) 1661–1670.
[33] A. Garofalo, C. Di Sarno, V. Formicola, Enhancing intrusion detection in wireless sensor networks through decision trees, Dependable Comput. (2013) 1–15.
[34] Z. Feng, J. Fu, D. Du, F. Li, S. Sun, A new approach of anomaly detection in wireless sensor networks using support vector data description, Int. J. Distrib. Sens. Netw. 13 (1) (2017) 1–14.
[35] N. Shahid, I.H. Naqvi, S.B. Qaisar, One-class support vector machines: analysis of outlier detection for wireless sensor networks in harsh environments, Artif. Intell. Rev. 43 (4) (2015) 515–563.
[36] H.S. Emadi, S.M. Mazinani, A novel anomaly detection algorithm using DBSCAN and SVM in wireless sensor networks, Wireless Personal Commun. 98 (2) (2018) 2025–2035.
[37] C. Titouna, M. Aliouat, M. Gueroui, Outlier detection approach using bayes classifiers in wireless sensor networks, Wireless Personal Commun. 85 (3) (2015) 1009–1023.
[38] R. Feng, X. Han, Q. Liu, N. Yu, A credible bayesian-based trust management scheme for wireless sensor networks, Int. J. Distrib. Sens. Netw. 11 (11) (2015) 1–9.
[39] S. Zidi, T. Moulahi, B. Alaya, Fault detection in wireless sensor networks through SVM classifier, IEEE Sens. J. 18 (1) (2018) 340–347.
[40] M. Jiang, J. Luo, D. Jiang, J. Xiong, H. Song, J. Shen, A cuckoo search-support vector machine model for predicting dynamic measurement errors of sensors, IEEE Access 4 (2016) 5030–5037.
[41] H. Zhang, J. Liu, N. Kato, Threshold tuning-based wearable sensor fault detection for reliable medical monitoring using bayesian network model, IEEE Syst. J. 12 (2) (2017) 1886–1896.
[42] C. Titouna, M. Aliouat, M. Gueroui, FDS: Fault detection scheme for wireless sensor networks, Wireless Personal Commun. 86 (2) (2016) 549–562.
[43] W. Meng, W. Li, Y. Xiang, K.-K.R. Choo, A bayesian inference-based detection mechanism to defend medical smartphone networks against insider attacks, J. Netw. Comput. Appl. 78 (2017) 162–169.
[44] P. Chanak, I. Banerjee, Fuzzy rule-based faulty node classification and management scheme for large scale wireless sensor networks, Expert Syst. Appl. 45 (2016) 307–321.
[45] W. Li, P. Yi, Y. Wu, L. Pan, J. Li, A new intrusion detection system based on KNN classification algorithm in wireless sensor network, J. Electr. Comput. Eng. 2014 (2014) 1–9.
[46] A. Mehmood, Z. Lv, J. Lloret, M.M. Umar, ELDC: An artificial neural network based energy-efficient and robust routing scheme for pollution monitoring in WSNs, IEEE Trans. Emerg. Top Comput. PP (99) (2017) 1–8.
[47] M.S. Gharajeh, S. Khanmohammadi, DFRTP: Dynamic 3D fuzzy routing based on traffic probability in wireless sensor networks, IET Wireless Sens. Syst. 6 (6) (2016) 211–219.
[48] J.R. Srivastava, T. Sudarshan, A genetic fuzzy system based optimized zone based energy efficient routing protocol for mobile sensor networks (OZEEP), Appl. Soft Comput. 37 (2015) 863–886.

[49] Y. Lee, Classification of node degree based on deep learning and routing method applied for virtual route assignment, Ad Hoc Netw. 58 (2017) 70–85.
[50] F. Khan, S. Memon, S.H. Jokhio, Support vector machine based energy aware routing in wireless sensor networks, in: Robotics and Artificial Intelligence (ICRAI), 2016 2nd International Conference on, IEEE, 2016, pp. 1–4.
[51] V. Jafarizadeh, A. Keshavarzi, T. Derikvand, Efficient cluster head selection using naïve bayes classifier for wireless sensor networks, Wireless Netw. 23 (3) (2017) 779–785.
[52] Z. Liu, M. Zhang, J. Cui, An adaptive data collection algorithm based on a bayesian compressed sensing framework, Sensors 14 (5) (2014) 8330–8349.
[53] F. Kazemeyni, O. Owe, E.B. Johnsen, I. Balasingham, Formal modeling and analysis of learning-based routing in mobile wireless sensor networks, in: Integration of Reusable Systems, Springer, 2014, pp. 127–150.
[54] B. Alotaibi, K. Elleithy, A new MAC address spoofing detection technique based on random forests, Sensors 16 (3) (2016) 1–14.
[55] X. Song, C. Wang, J. Gao, X. Hu, DLRDG: distributed linear regression-based hierarchical data gathering framework in wireless sensor network, Neural Comput. Appl. 23 (7–8) (2013) 1999–2013.
[56] I. Atoui, A. Makhoul, S. Tawbe, R. Couturier, A. Hijazi, Tree-based data aggregation approach in periodic sensor networks using correlation matrix and polynomial regression, in: Computational Science and Engineering (CSE) and IEEE Intl Conference on Embedded and Ubiquitous Computing (EUC) and 15th Intl Symposium on Distributed Computing and Applications for Business Engineering (DCABES), 2016 IEEE Intl Conference on, IEEE, 2016, pp. 716–723.
[57] L. Gispan, A. Leshem, Y. Be'ery, Decentralized estimation of regression coefficients in sensor networks, Digit Signal Process. 68 (2017) 16–23.
[58] Y. Li, L.E. Parker, Nearest neighbor imputation using spatial–temporal correlations in wireless sensor networks, Inf. Fusion 15 (2014) 64–79.
[59] F. Edwards-Murphy, M. Magno, P.M. Whelan, J. OHalloran, E.M. Popovici, b+WSN: smart beehive with preliminary decision tree analysis for agriculture and honey bee health monitoring, Comput. Electron. Agric. 124 (2016) 211–219.
[60] H. He, Z. Zhu, E. Mäkinen, Task-oriented distributed data fusion in autonomous wireless sensor networks, Soft Comput. 19 (8) (2015) 2305–2319.
[61] C. Habib, A. Makhoul, R. Darazi, C. Salim, Self-adaptive data collection and fusion for health monitoring based on body sensor networks, IEEE Trans. Ind. Inf. 12 (6) (2016) 2342–2352.
[62] H. Yang, S. Fong, R. Wong, G. Sun, Optimizing classification decision trees by using weighted naïve bayes predictors to reduce the imbalanced class problem in wireless sensor network, Int. J. Distrib. Sens. Netw. 9 (1) (2013) 1–15.
[63] A. De Paola, P. Ferraro, S. Gaglio, G.L. Re, S.K. Das, An adaptive bayesian system for context-aware data fusion in smart environments, IEEE Trans. Mob. Comput. 16 (6) (2017) 1502–1515.
[64] S. Hwang, R. Ran, J. Yang, D.K. Kim, Multivariated bayesian compressive sensing in wireless sensor networks, IEEE Sens. J. 16 (7) (2015) 2196–2206.
[65] Y. Dingcheng, W. Zhenghai, X. Lin, Z. Tiankui, Online bayesian data fusion in environment monitoring sensor networks, Int. J. Distrib. Sens. Netw. 10 (4) (2014) 945894.
[66] C. Wang, E. Bertino, Sensor network provenance compression using dynamic bayesian networks, ACM Trans. Sensor Netw. (TOSN) 13 (1) (2017) 5.1–5.32.
[67] Y. Wang, A. Yang, Z. Li, X. Chen, P. Wang, H. Yang, Blind drift calibration of sensor networks using sparse bayesian learning, IEEE Sens. J. 16 (16) (2016) 6249–6260.
[68] D. Capriglione, D. Casinelli, L. Ferrigno, Analysis of quantities influencing the performance of time synchronization based on linear regression in low cost WSNs, Measurement 77 (Suppl. C) (2016) 105–116.
[69] J.J. Prez-Solano, S. Felici-Castell, Adaptive time window linear regression algorithm for accurate time synchronization in wireless sensor networks, Ad Hoc Netw. 24 (Part A) (2015) 92–108.
[70] G. Betta, D. Casinelli, L. Ferrigno, Some Notes on the Performance of Regression-based Time Synchronization Algorithms in Low Cost WSNs, Springer International Publishing, Cham, 2015.
[71] J.J. Pérez-Solano, S. Felici-Castell, Improving time synchronization in wireless sensor networks using Bayesian inference, J. Netw. Comput. Appl. 82 (2017) 47–55.
[72] M.A. Alsheikh, S. Lin, D. Niyato, H.P. Tan, Rate-distortion balanced data compression for wireless sensor networks, IEEE Sens. J. 16 (12) (2016) 5072–5083.
[73] A.A. Rezaee, F. Pasandideh, A fuzzy congestion control protocol based on active queue management in wireless sensor networks with medical applications, Wireless Personal Commun. 98 (1) (2018) 815–842.
[74] M. Gholipour, A.T. Haghighat, M.R. Meybodi, Hop-by-Hop congestion avoidance in wireless sensor networks based on genetic support vector machine, Neurocomputing 223 (2017) 63–76.
[75] P. Braca, P. Willett, K.D. LePage, S. Marano, V. Matta, Bayesian tracking in underwater wireless sensor networks with port-starboard ambiguity., IEEE Trans. Signal Process. 62 (7) (2014) 1864–1878.
[76] B. Zhou, Q. Chen, T.J. Li, P. Xiao, Online variational bayesian filtering-based mobile target tracking in wireless sensor networks, Sensors 14 (11) (2014) 21281–21315.
[77] B. Xue, L. Zhang, W. Zhu, Y. Yu, A new sensor selection scheme for bayesian learning based sparse signal recovery in WSNs, J. Franklin Inst. (2017) 1–21.
[78] H. Chen, R. Wang, L. Cui, L. Zhang, EasiDSlT: a two-layer data association method for multitarget tracking in wireless sensor networks, IEEE Trans. Ind. Electron. 62 (1) (2015) 434–443.
[79] V.P. Illiano, E.C. Lupu, Detecting malicious data injections in event detection wireless sensor networks, IEEE Trans. Netw. Serv. Manage. 12 (3) (2015) 496–510.
[80] Y. Li, H. Chen, M. Lv, Y. Li, Event-based k-nearest neighbors query processing over distributed sensory data using fuzzy sets, Soft Comput. (2017) 1–13.
[81] Y. Han, J. Tang, Z. Zhou, M. Xiao, L. Sun, Q. Wang, Novel itinerary-based KNN query algorithm leveraging grid division routing in wireless sensor networks of skewness distribution, Pers. Ubiquitous Comput. 18 (8) (2014) 1989–2001.
[82] A. Sharma, A. Kakkar, Forecasting daily global solar irradiance generation using machine learning, Renewable Sustainable Energy Rev. 82 (2018) 2254–2269.
[83] W.M. Tan, P. Sullivan, H. Watson, J. Slota-Newson, S.A. Jarvis, An indoor test methodology for solar-powered wireless sensor networks, ACM Trans. Embedded Comput. Syst. (TECS) 16 (3) (2017) 82.1–82.25.
[84] D.C. Montgomery, E.A. Peck, G.G. Vining, Introduction to Linear Regression Analysis, 821, John Wiley & Sons, 2012.
[85] W. Zhao, S. Su, F. Shao, Improved DV-hop algorithm using locally weighted linear regression in anisotropic wireless sensor networks, Wireless Personal Commun. 98 (4) (2018) 3335–3353.
[86] C.G. Emily Fox, The Simple Linear Regression Model, Machine Learning : Regression, Coursera, 2018.
[87] J.R. Quinlan, Induction of decision trees, Mach. Learn 1 (1) (1986) 81–106.
[88] S. Kim, D.-Y. Kim, Efficient data-forwarding method in delay-tolerant P2P networking for IoT services, in: Peer-to-Peer Networking and Applications, 2017, pp. 1–10.
[89] L. Breiman, Random forests, Mach. Learn 45 (1) (2001) 5–32.
[90] M. Belgiu, L. Drăguţ, Random forest in remote sensing: a review of applications and future directions, ISPRS J. Photogramm. Remote Sens. 114 (2016) 24–31.
[91] S.S. Haykin, S.S. Haykin, S.S. Haykin, S.S. Haykin, Neural networks and learning machines, vol. 3, Pearson Upper Saddle River, NJ, USA, 2009.
[92] H. White, Learning in artificial neural networks: a statistical perspective, Neural Comput. 1 (4) (1989) 425–464.
[93] Y. LeCun, Y. Bengio, G. Hinton, Deep learning, Nature 521 (7553) (2015) 436–444.
[94] A.H. Marblestone, G. Wayne, K.P. Kording, Toward an integration of deep learning and neuroscience, Front. Comput. Neurosci. 10 (2016) 1–41.
[95] T. Ma, F. Wang, J. Cheng, Y. Yu, X. Chen, A hybrid spectral clustering and deep neural network ensemble algorithm for intrusion detection in sensor networks, Sensors 16 (10) (2016) 1–23.
[96] C. Li, X. Xie, Y. Huang, H. Wang, C. Niu, Distributed data mining based on deep neural network for wireless sensor network, Int. J. Distrib. Sens. Netw. 11 (7) (2015) 1–7.
[97] Y. Wang, A. Yang, X. Chen, P. Wang, Y. Wang, H. Yang, A deep learning approach for blind drift calibration of sensor networks, IEEE Sens. J. 17 (13) (2017) 4158–4171.
[98] F. Chen, Z. Fu, Z. Yang, Wind power generation fault diagnosis based on deep learning model in internet of things (IoT) with clusters, Cluster Comput. (2018) 1–13.
[99] V.N. Vapnik, An overview of statistical learning theory, IEEE Trans. Neural Networks 10 (5) (1999) 988–999.
[100] M.R. Islam, J. Uddin, J.-M. Kim, Acoustic emission sensor network based fault diagnosis of induction motors using a gabor filter and multiclass support vector machines., Adhoc Sensor Wireless Netw 34 (2016) 273–287.
[101] Q.-y. Sun, Y.-m. Sun, X.-j. Liu, Y.-x. Xie, X.-g. Chen, Study on fault diagnosis algorithm in WSN nodes based on RPCA model and SVDD for multi-class classification, Cluster Comput. (2018) 1–15.
[102] F.V. Jensen, An Introduction to Bayesian Networks, 210, UCL Press London, 1996.
[103] S.N. Das, S. Misra, B.E. Wolfinger, M.S. Obaidat, Temporal-correlation-aware dynamic self-management of wireless sensor networks, IEEE Trans. Ind. Inf. 12 (6) (2016) 2127–2138.
[104] B. Avci, G. Trajcevski, R. Tamassia, P. Scheuermann, F. Zhou, Efficient detection of motion-trend predicates in wireless sensor networks, Comput. Commun. 101 (Supplement C) (2017) 26–43.
[105] F. Tashtarian, M.Y. Moghaddam, K. Sohraby, S. Effati, ODT: optimal deadline-based trajectory for mobile sinks in WSN: a decision tree and dynamic programming approach, Comput. Networks 77 (2015) 128–143.
[106] S.A. Dudani, The distance-weighted *k*-nearest-neighbor rule, IEEE Trans. Syst. Man Cybern. SMC-6 (4) (1976) 325–327.
[107] L.E. Peterson, K-nearest neighbor, Scholarpedia 4 (2) (2009) 1883.
[108] J.M. Keller, M.R. Gray, J.A. Givens, A fuzzy *k*-nearest neighbor algorithm, IEEE Trans. Syst. Man Cybern. SMC-15 (4) (1985) 580–585.
[109] S.B. Kotsiantis, I. Zaharakis, P. Pintelas, Supervised machine learning: a review of classification techniques, Emerg. Artif. Intell. Appl. Comput. Eng. 160 (2007) 3–24.
[110] J. Qin, W. Fu, H. Gao, W.X. Zheng, Distributed *k*-means algorithm and fuzzy *c*-means algorithm for sensor networks based on multiagent consensus theory, IEEE Trans. Cybern. 47 (3) (2017) 772–783.
[111] P. Gil, H. Martins, F. Januário, Outliers detection methods in wireless sensor networks, Artif. Intell. Rev. (2018) 1–26.
[112] R. El Mezouary, A. Choukri, A. Kobbane, M. El Koutbi, An energy-aware clustering approach based on the K-means method for wireless sensor networks, in: Advances in Ubiquitous Networking, Springer, 2016, pp. 325–337.
[113] A. Ray, D. De, Energy efficient clustering protocol based on k-means (EECP-K-means)-midpoint algorithm for enhanced network lifetime in wireless sensor network, IET Wireless Sens. Syst. 6 (6) (2016) 181–191.
[114] B. Jain, G. Brar, J. Malhotra, EKMT-k-means clustering algorithmic solution for low energy consumption for wireless sensor networks based on minimum mean distance from base station, in: Networking Communication and Data Knowledge Engineering, Springer, 2018, pp. 113–123.
[115] P. Guo, J. Cao, X. Liu, Lossless in-network processing in WSNs for domain-specific monitoring applications, IEEE Trans. Ind. Inf. 13 (5) (2017) 2130–2139.
[116] H. Harb, A. Makhoul, R. Couturier, An enhanced *k*-means and ANOVA-based clustering approach for similarity aggregation in underwater wireless sensor networks, IEEE Sens. J. 15 (10) (2015) 5483–5493.
[117] A. Morell, A. Correa, M. Barceló, J.L. Vicario, Data aggregation and principal component analysis in WSNs, IEEE Trans. Wireless Commun. 15 (6) (2016) 3908–3919.

[118] C. Anagnostopoulos, S. Hadjiefthymiades, Advanced principal component-based compression schemes for wireless sensor networks, ACM Trans. Sensor Netw. (TOSN) 11 (1) (2014) 7.
[119] M.I. Chidean, E. Morgado, E. del Arco, J. Ramiro-Bargueo, A.J. Caamao, Scalable data-coupled clustering for large scale WSN, IEEE Trans. Wireless Commun. 14 (9) (2015) 4681–4694.
[120] S. Liu, L. Feng, J. Wu, G. Hou, G. Han, Concept drift detection for data stream learning based on angle optimized global embedding and principal component analysis in sensor networks, Comput. Electr. Eng. 58 (2017) 327–336.
[121] A. Bertrand, M. Moonen, Distributed adaptive estimation of covariance matrix eigenvectors in wireless sensor networks with application to distributed PCA, Signal Process. 104 (2014) 120–135.
[122] M.I. Chidean, E. Morgado, M. Sanromn-Junquera, J. Ramiro-Bargueo, J. Ramos, A.J. Caamao, Energy efficiency and quality of data reconstruction through data–coupled clustering for self-organized large-scale WSNs, IEEE Sens. J. 16 (12) (2016) 5010–5020.
[123] T. Yu, X. Wang, A. Shami, Recursive principal component analysis based data outlier detection and sensor data aggregation in IoT systems, IEEE Internet Things J. 4 (6) (2017) 2207–2216.
[124] M. Wu, L. Tan, N. Xiong, Data prediction, compression, and recovery in clustered wireless sensor networks for environmental monitoring applications, Inf. Sci. 329 (2016) 800–818.
[125] G. Gennarelli, F. Soldovieri, Performance analysis of incoherent RF tomography using wireless sensor networks, IEEE Trans. Geosci. Remote Sens. 54 (5) (2016) 2722–2732.
[126] T. Kanungo, D.M. Mount, N.S. Netanyahu, C.D. Piatko, R. Silverman, A.Y. Wu, An efficient *k*-means clustering algorithm: analysis and implementation, IEEE Trans. Pattern Anal. Mach. Intell. 24 (7) (2002) 881–892.
[127] J.P. Ortega, M. Del, R.B. Rojas, M.J. Somodevilla, Research issues on *k*-means algorithm: an experimental trial using matlab, in: CEUR Workshop Proceedings: Semantic Web and New Technologies, 2009, pp. 83–96.
[128] K. Almi'ani, A. Viglas, L. Libman, Energy-efficient data gathering with tour length--constrained mobile elements in wireless sensor networks, in: Local Computer Networks (LCN), 2010 IEEE 35th Conference on, IEEE, 2010, pp. 582–589.
[129] S.C. Johnson, Hierarchical clustering schemes, Psychometrika 32 (3) (1967) 241–254.
[130] R.G. D'Andrade, U-statistic hierarchical clustering, Psychometrika 43 (1) (1978) 59–67.
[131] X. Xu, R. Ansari, A. Khokhar, A.V. Vasilakos, Hierarchical data aggregation using compressive sensing (HDACS) in WSNs, ACM Trans. Sensor Netw. (TOSN) 11 (3) (2015) 45.
[132] P. Neamatollahi, S. Abrishami, M. Naghibzadeh, M.H.Y. Moghaddam, O. Younis, Hierarchical clustering-task scheduling policy in cluster-based wireless sensor networks, IEEE Trans. Ind. Inf. 14 (5) (2018) 1876–1886.
[133] R. Zhang, J. Pan, D. Xie, F. Wang, NDCMC: A hybrid data collection approach for large-scale WSNs using mobile element and hierarchical clustering, IEEE Internet Things J. 3 (4) (2016) 533–543.
[134] R. Zhang, J. Pan, J. Liu, D. Xie, A hybrid approach using mobile element and hierarchical clustering for data collection in WSNs, in: Wireless Communications and Networking Conference (WCNC), 2015 IEEE, IEEE, 2015, pp. 1566–1571.
[135] S.W. Awan, S. Saleem, Hierarchical clustering algorithms for heterogeneous energy harvesting wireless sensor networks, in: Wireless Communication Systems (ISWCS), 2016 International Symposium on, IEEE, 2016, pp. 270–274.
[136] W. Peizhuang, Pattern recognition with fuzzy objective function algorithms (james c. bezdek), SIAM Rev. 25 (3) (1983) 442.
[137] M. Bernas, B. Płaczek, Fully connected neural networks ensemble with signal strength clustering for indoor localization in wireless sensor networks, Int. J. Distrib. Sens. Netw. 11 (12) (2015) 1–10.
[138] P. Nayak, A. Devulapalli, A fuzzy logic-based clustering algorithm for WSN to extend the network lifetime, IEEE Sens. J. 16 (1) (2016) 137–144.
[139] V. Klema, A. Laub, The singular value decomposition: its computation and some applications, IEEE Trans. Automat. Contr. 25 (2) (1980) 164–176.
[140] S. Wold, K. Esbensen, P. Geladi, Principal component analysis, Chemometrics Intell. Lab. Syst. 2 (1–3) (1987) 37–52.
[141] X. Li, S. Ding, Y. Li, Outlier suppression via non-convex robust PCA for efficient localization in wireless sensor networks, IEEE Sens. J. 17 (21) (2017) 7053–7063.
[142] P. Oikonomou, A. Botsialas, A. Olziersky, I. Kazas, I. Stratakos, S. Katsikas, D. Dimas, K. Mermikli, G. Sotiropoulos, D. Goustouridis, et al., A wireless sensing system for monitoring the workplace environment of an industrial installation, Sens. Actuators, B 224 (2016) 266–274.
[143] T.-W. Lee, Independent component analysis, in: Independent Component Analysis, Springer, 1998, pp. 27–66.
[144] X. Zhu, A.B. Goldberg, Introduction to semi-supervised learning, Synth. Lect. Artif. Intell. Mach. Learn. 3 (1) (2009) 1–130.
[145] M.F.A. Hady, F. Schwenker, Semi-supervised learning, in: Handbook on Neural Information Processing, Springer, 2013, pp. 215–239.
[146] J. Yoo, W. Kim, H.J. Kim, Distributed estimation using online semi-supervised particle filter for mobile sensor networks, IET Control Theory Appl. 9 (3) (2015) 418–427.
[147] S. Kumar, S.N. Tiwari, R.M. Hegde, Sensor node tracking using semi-supervised hidden markov models, Ad Hoc Netw. 33 (2015) 55–70.
[148] B. Yang, J. Xu, J. Yang, M. Li, Localization algorithm in wireless sensor networks based on semi-supervised manifold learning and its application, Cluster Comput. 13 (4) (2010) 435–446.
[149] J. Yoo, H.J. Kim, Target localization in wireless sensor networks using online semi–supervised support vector regression, Sensors 15 (6) (2015) 12539–12559.
[150] M. Zhao, T.W. Chow, Wireless sensor network fault detection via semi-supervised local kernel density estimation, in: Industrial Technology (ICIT), 2015 IEEE International Conference on, IEEE, 2015, pp. 1495–1500.
[151] C.J. Watkins, P. Dayan, Q-learning, Mach. Learn. 8 (3–4) (1992) 279–292.
[152] D.L. Poole, A.K. Mackworth, Artificial Intelligence: Foundations of Computational Agents, Cambridge University Press, 2010.
[153] A. Eiben, M. Schoenauer, Evolutionary computing, Inf. Process. Lett. 82 (1) (2002) 1–6. Evolutionary Computation.
[154] R.V. Kulkarni, A. Forster, G.K. Venayagamoorthy, Computational intelligence in wireless sensor networks: a survey, IEEE Commun. Surv. Tutorials 13 (1) (2011) 68–96.
[155] H.A. Hashim, B.O. Ayinde, M.A. Abido, Optimal placement of relay nodes in wireless sensor network using artificial bee colony algorithm, J. Netw. Comput. Appl. 64 (2016) 239–248.
[156] Y. Xu, O. Ding, R. Qu, K. Li, Hybrid multi-objective evolutionary algorithms based on decomposition for wireless sensor network coverage optimization, Appl. Soft Comput. 68 (2018) 268–282.
[157] P. Kuila, P.K. Jana, Energy efficient clustering and routing algorithms for wireless sensor networks: particle swarm optimization approach, Eng. Appl. Artif. Intell. 33 (2014) 127–140.
[158] Y. Sun, W. Dong, Y. Chen, An improved routing algorithm based on ant colony optimization in wireless sensor networks, IEEE Commun. Lett. 21 (6) (2017) 1317–1320.
[159] M. Elhoseny, A. Tharwat, A. Farouk, A.E. Hassanien, *k*-coverage model based on genetic algorithm to extend WSN lifetime, IEEE Sensors Lett. 1 (4) (2017) 1–4.
[160] C.-P. Chen, S.C. Mukhopadhyay, C.-L. Chuang, T.-S. Lin, M.-S. Liao, Y.-C. Wang, J.-A. Jiang, A hybrid memetic framework for coverage optimization in wireless sensor networks, IEEE Trans. Cybern. 45 (10) (2015) 2309–2322.
[161] J. Wang, Y. Cao, B. Li, H.-j. Kim, S. Lee, Particle swarm optimization based clustering algorithm with mobile sink for WSNs, Future Gener. Comput. Syst. 76 (2017) 452–457.
[162] K.D. Praveen, T. Amgoth, C.S.R. Annavarapu, ACO-based mobile sink path determination for wireless sensor networks under non-uniform data constraints, Appl. Soft Comput. 69 (2018) 528–540.
[163] G. Yogarajan, T. Revathi, Nature inspired discrete firefly algorithm for optimal mobile data gathering in wireless sensor networks, Wireless Networks (2017) 1–15.
[164] W.-L. Chang, D. Zeng, R.-C. Chen, S. Guo, An artificial bee colony algorithm for data collection path planning in sparse wireless sensor networks, Int. J. Mach. Learn. Cybern. 6 (3) (2015) 375–383.
[165] A.E. Eiben, J.E. Smith, et al., Introduction to Evolutionary Computing, vol, 53, Springer, 2003.
[166] J. Kuriakose, S. Joshi, R.V. Raju, A. Kilaru, A review on localization in wireless sensor networks, in: Advances in Signal Processing and Intelligent Recognition Systems, Springer, 2014, pp. 599–610.
[167] P. Cottone, S. Gaglio, G.L. Re, M. Ortolani, A machine learning approach for user localization exploiting connectivity data, Eng. Appl. Artif. Intell. 50 (2016) 125–134.
[168] S.M. Mohamed, H.S. Hamza, I.A. Saroit, Coverage in mobile wireless sensor networks (M-WSN): a survey, Comput. Commun. 110 (C) (2017) 133–150.
[169] W. Fang, X. Song, X. Wu, J. Sun, M. Hu, Novel efficient deployment schemes for sensor coverage in mobile wireless sensor networks, Inf. Fusion 41 (2018) 25–36.
[170] H. Li, S. Wang, M. Gong, Q. Chen, L. Chen, IM^{2}DCA: Immune mechanism based multipath decoupling connectivity algorithm with fault tolerance under coverage optimization in wireless sensor networks, Appl. Soft Comput. 58 (2017) 540–552.
[171] M. Abo-Zahhad, N. Sabor, S. Sasaki, S.M. Ahmed, A centralized immune-voronoi deployment algorithm for coverage maximization and energy conservation in mobile wireless sensor networks, Inf. Fusion 30 (2016) 36–51.
[172] A. Farhat, C. Guyeux, A. Makhoul, A. Jaber, R. Tawil, A. Hijazi, Impacts of wireless sensor networks strategies and topologies on prognostics and health management, J. Intell. Manuf. (2017) 1–27.
[173] H. Chen, X. Li, F. Zhao, A reinforcement learning-based sleep scheduling algorithm for desired area coverage in solar-powered wireless sensor networks, IEEE Sens. J. 16 (8) (2016) 2763–2774.
[174] E. Ancillotti, C. Vallati, R. Bruno, E. Mingozzi, A reinforcement learning-based link quality estimation strategy for RPL and its impact on topology management, Comput. Commun. 112 (2017) 1–13.
[175] P. Oluwasanya, Anomaly detection in wireless sensor networks, arXiv:1708.08053 (2017).
[176] A.D. Paola, S. Gaglio, G.L. Re, F. Milazzo, M. Ortolani, Adaptive distributed outlier detection for WSNs, IEEE Trans. Cybern. 45 (5) (2015) 902–913.
[177] M. Wazid, A.K. Das, An efficient hybrid anomaly detection scheme using K-means clustering for wireless sensor networks, Wireless Personal Commun. 90 (4) (2016) 1971–2000.
[178] H.H. Bosman, G. Iacca, A. Tejada, H.J. Wörtche, A. Liotta, Spatial anomaly detection in sensor networks using neighborhood information, Inf. Fusion 33 (2017) 41–56.
[179] C. O'Reilly, A. Gluhak, M.A. Imran, S. Rajasegarar, Anomaly detection in wireless sensor networks in a non-stationary environment, IEEE Commun. Surv. Tutorials 16 (3) (2014) 1413–1432.
[180] I. Butun, S.D. Morgera, R. Sankar, A survey of intrusion detection systems in wireless sensor networks, IEEE Commun. Surv. Tutorials 16 (1) (2014) 266–282.
[181] D. Dong, M. Li, Y. Liu, X.Y. Li, X. Liao, Topological detection on wormholes in wireless ad hoc and sensor networks, IEEE/ACM Trans. Networking 19 (6) (2011) 1787–1796.
[182] Y. Wang, Z. Liu, D. Wang, Y. Li, J. Yan, Anomaly detection and visual perception for landslide monitoring based on a heterogeneous sensor network, IEEE Sens. J. 17 (13) (2017) 4248–4257.

[183] M. Xie, J. Hu, S. Guo, A.Y. Zomaya, Distributed segment-based anomaly detection with kullback -leibler divergence in wireless sensor networks, IEEE Trans. Inf. Forensics Secur. 12 (1) (2017) 101–110.
[184] V.P. Illiano, A. Paudice, L. Muñoz-González, E.C. Lupu, Determining resilience gains from anomaly detection for event integrity in wireless sensor networks, ACM Trans. Sensor Netw. (TOSN) 14 (1) (2018) 5.
[185] S. Shamshirband, A. Patel, N.B. Anuar, M.L.M. Kiah, A. Abraham, Cooperative game theoretic approach using fuzzy Q-learning for detecting and preventing intrusions in wireless sensor networks, Eng. Appl. Artif. Intell. 32 (2014) 228–241.
[186] S.A. Haque, M. Rahman, S.M. Aziz, Sensor anomaly detection in wireless sensor networks for healthcare, Sensors 15 (4) (2015) 8764–8786.
[187] T. Muhammed, R.A. Shaikh, An analysis of fault detection strategies in wireless sensor networks, J. Netw. Comput. Appl. 78 (2017) 267–287.
[188] H. Geng, Y. Liang, F. Yang, L. Xu, Q. Pan, Model-reduced fault detection for multi-rate sensor fusion with unknown inputs, Inf. Fusion 33 (2017) 1–14.
[189] R.R. Swain, P.M. Khilar, S.K. Bhoi, Heterogeneous fault diagnosis for wireless sensor networks, Ad Hoc Netw. 69 (2018) 15–37.
[190] R. Palanikumar, K. Ramasamy, Effective failure nodes detection using matrix calculus algorithm in wireless sensor networks, Cluster Comput. (2018) 1–10.
[191] M. Hammoudeh, R. Newman, Adaptive routing in wireless sensor networks: QoS optimisation for enhanced application performance, Inf. Fusion 22 (2015) 3–15.
[192] X. Liu, Routing protocols based on Ant colony optimization in wireless sensor networks: a survey, IEEE Access 5 (2017) 26303–26317.
[193] M. Asif, S. Khan, R. Ahmad, M. Sohail, D. Singh, Quality of service of routing protocols in wireless sensor networks: a review, IEEE Access 5 (2017) 1846–1871.
[194] K.-L.A. Yau, H.G. Goh, D. Chieng, K.H. Kwong, Application of reinforcement learning to wireless sensor networks: models and algorithms, Computing 97 (11) (2015) 1045–1075.
[195] Shashikala, C. Kavitha, Secure Cluster-based Data Integrity Routing for Wireless Sensor Networks, Springer Singapore, Singapore, 2018.
[196] J. Kabara, M. Calle, MAC Protocols used by wireless sensor networks and a general method of performance evaluation, Int. J. Distrib. Sens. Netw. 8 (1) (2012) 1–11.
[197] I. Mustapha, B.M. Ali, A. Sali, M.F.A. Rasid, H. Mohamad, An energy efficient reinforcement learning based cooperative channel sensing for cognitive radio sensor networks, Pervasive Mob. Comput. 35 (2017) 165–184.
[198] S. Kosunalp, Y. Chu, P.D. Mitchell, D. Grace, T. Clarke, Use of q-learning approaches for practical medium access control in wireless sensor networks, Eng. Appl. Artif. Intell. 55 (2016) 146–154.
[199] M. Rovcanin, E. De Poorter, I. Moerman, P. Demeester, A reinforcement learning based solution for cognitive network cooperation between co-located, heterogeneous wireless sensor networks, Ad Hoc Netw. 17 (2014) 98–113.
[200] M. Rovcanin, E. De Poorter, D. van den Akker, I. Moerman, P. Demeester, C. Blondia, Experimental validation of a reinforcement learning based approach for a service-wise optimisation of heterogeneous wireless sensor networks, Wireless Netw. 21 (3) (2015) 931–948.
[201] K.-H. Phung, B. Lemmens, M. Goossens, A. Nowe, L. Tran, K. Steenhaut, Schedule-based multi-channel communication in wireless sensor networks: a complete design and performance evaluation, Ad Hoc Netw. 26 (2015) 88–102.
[202] M. Ambigavathi, D. Sridharan, Energy-aware data aggregation techniques in wireless sensor network, in: Advances in Power Systems and Energy Management, Springer, 2018, pp. 165–173.
[203] k. xie, L. Wang, X. Wang, G. Xie, J. Wen, Low cost and high accuracy data gathering in WSNs with matrix completion, IEEE Trans. Mob. Comput. 17 (7) (2017) 1595–1608.
[204] H. Lin, D. Bai, Y. Liu, Maximum data collection rate routing for data gather trees with data aggregation in rechargeable wireless sensor networks, Cluster Comput. (2017) 1–11.
[205] E. Kanjo, E.M. Younis, N. Sherkat, Towards unravelling the relationship between on-body, environmental and emotion data using sensor information fusion approach, Inf. Fusion 40 (2018) 18–31.
[206] A. Pinto, C. Montez, G. Arajo, F. Vasques, P. Portugal, An approach to implement data fusion techniques in wireless sensor networks using genetic machine learning algorithms, Inf. Fusion 15 (2014) 90–101.
[207] Y.C. Wu, Q. Chaudhari, E. Serpedin, Clock synchronization of wireless sensor networks, IEEE Signal Process. Mag. 28 (1) (2011) 124–138.
[208] D. Djenouri, M. Bagaa, Synchronization protocols and implementation issues in wireless sensor networks: a review, IEEE Syst. J. 10 (2) (2016) 617–627.
[209] W. Wang, S. Jiang, H. Zhou, M. Yang, Y. Ni, J. Ko, Time synchronization for acceleration measurement data of Jiangyin bridge subjected to a ship collision, Struct. Control Health Monit. 25 (1) (2018) 1–18.
[210] K.-P. Ng, C. Tsimenidis, W.L. Woo, C-Sync: Counter-based synchronization for duty-cycled wireless sensor networks, Ad Hoc Netw. 61 (2017) 51–64.
[211] Y.-P. Tian, Time synchronization in WSNs with random bounded communication delays, IEEE Trans. Automat. Contr. 62 (10) (2017) 5445–5450.
[212] C. Tan, S. Ji, Z. Gui, J. Shen, D.-S. Fu, J. Wang, An effective data fusion-based routing algorithm with time synchronization support for vehicular wireless sensor networks, J. Supercomput. (2017) 1–16.
[213] A. Ghaffari, Congestion control mechanisms in wireless sensor networks: a survey, J. Netw. Comput. Appl. 52 (2015) 101–115.
[214] C. Sergiou, P. Antoniou, V. Vassiliou, A comprehensive survey of congestion control protocols in wireless sensor networks, IEEE Commun. Surv. Tutorials 16 (4) (2014) 1839–1859.
[215] M.A. Kafi, D. Djenouri, J. Ben-Othman, N. Badache, Congestion control protocols in wireless sensor networks: a survey, IEEE Commun. Surv. Tutorials 16 (3) (2014) 1369–1390.
[216] C. Raman, V. James, FCC: Fast congestion control scheme for wireless sensor networks using hybrid optimal routing algorithm, Cluster Comput. (2018) 1–11.
[217] H.A. Al-Kashoash, M. Hafeez, A.H. Kemp, Congestion control for 6LoWPAN networks: a game theoretic framework, IEEE Internet Things J. 4 (3) (2017) 760–771.
[218] M.A. Kafi, J. Ben-Othman, A. Ouadjaout, M. Bagaa, N. Badache, REFIACC: Reliable, efficient, fair and interference-aware congestion control protocol for wireless sensor networks, Comput. Commun. 101 (2017) 1–11.
[219] S.-H. Moon, S. Park, S.-j. Han, Energy efficient data collection in sink-centric wireless sensor networks: a cluster-ring approach, Comput. Commun. 101 (2017) 12–25.
[220] A. Ez-Zaidi, S. Rakrak, A comparative study of target tracking approaches in wireless sensor networks, J. Sensors 2016 (2016) 1–12.
[221] K. Xiao, R. Wang, T. Fu, J. Li, P. Deng, Divide-and-conquer architecture based collaborative sensing for target monitoring in wireless sensor networks, Inf. Fusion 36 (2017) 162–171.
[222] S. Vasuhi, V. Vaidehi, Target tracking using interactive multiple model for wireless sensor network, Inf. Fusion 27 (2016) 41–53.
[223] A. Abrardo, M. Martal, G. Ferrari, Information fusion for efficient target detection in large-scale surveillance wireless sensor networks, Inf. Fusion 38 (2017) 55–64.
[224] Z. Wei, Y. Zhang, X. Xu, L. Shi, L. Feng, A task scheduling algorithm based on Q-learning and shared value function for WSNs, Comput. Networks 126 (2017) 141–149.
[225] M.M. Hassan, M.Z. Uddin, A. Mohamed, A. Almogren, A robust human activity recognition system using smartphone sensors and deep learning, Future Gener. Comput. Syst. 81 (2018) 307–313.
[226] Y. Kılıçaslan, G. Tuna, G. Gezer, K. Gulez, O. Arkoc, S.M. Potirakis, ANN-based estimation of groundwater quality using a wireless water quality network, Int. J. Distrib. Sens. Netw. 10 (4) (2014) 1–8.
[227] D. Ye, M. Zhang, A self-adaptive sleep/wake-up scheduling approach for wireless sensor networks, IEEE Trans. Cybern PP (99) (2017) 1–14.
[228] S.B. Chandanapalli, E.S. Reddy, D.R. Lakshmi, DFTDT: distributed functional tangent decision tree for aqua status prediction in wireless sensor networks, Int. J. Mach. Learn. Cybern. (2017) 1–16.
[229] W. Wen, S. Zhao, C. Shang, C.-Y. Chang, EAPC: Energy-aware path construction for data collection using mobile sink in wireless sensor networks, IEEE Sens. J. 18 (2) (2018) 890–901.
[230] H. Salarian, K.-W. Chin, F. Naghdy, An energy-efficient mobile-sink path selection strategy for wireless sensor networks, IEEE Trans. Veh. Technol. 63 (5) (2014) 2407–2419.
[231] T. Wang, J. Zeng, Y. Lai, Y. Cai, H. Tian, Y. Chen, B. Wang, Data collection from WSNs to the cloud based on mobile fog elements, Future Gener. Comput. Syst. (2017), doi:10.1016/j.future.2017.07.031.
[232] I. Ha, M. Djuraev, B. Ahn, An optimal data gathering method for mobile sinks in WSNs, Wireless Personal Commun. 97 (1) (2017) 1401–1417.
[233] F.K. Shaikh, S. Zeadally, Energy harvesting in wireless sensor networks: a comprehensive review, Renewable Sustainable Energy Rev. 55 (2016) 1041–1054.
[234] S. Kosunalp, A new energy prediction algorithm for energy-harvesting wireless sensor networks with Q-learning, IEEE Access 4 (2016) 5755–5763.
[235] R.C. Hsu, C.T. Liu, H.L. Wang, A reinforcement learning-based ToD provisioning dynamic power management for sustainable operation of energy harvesting wireless sensor node, IEEE Trans. Emerg. Top Comput. 2 (2) (2014) 181–191.
[236] F.A. Aoudia, M. Gautier, O. Berder, RLMan: an energy manager based on reinforcement learning for energy harvesting wireless sensor networks, IEEE Trans. Green Commun. Networking (2018) 1–11.
[237] M. Collotta, G. Pau, A.V. Bobovich, A fuzzy data fusion solution to enhance the QoS and the energy consumption in wireless sensor networks, Wireless Commun. Mobile Comput. 2017 (2017) 1–10.
[238] W. Sun, W. Lu, Q. Li, L. Chen, D. Mu, X. Yuan, WNN-LQE: Wavelet-neural-network-based link quality estimation for smart grid WSNs, IEEE Access 5 (2017) 12788–12797.
[239] E.K. Lee, H. Viswanathan, D. Pompili, RescueNet: Reinforcement-learning-based communication framework for emergency networking, Comput. Networks 98 (2016) 14–28.
[240] A.P. Renold, S. Chandrakala, MRL-SCSO: Multi-agent reinforcement learning-based self-configuration and self-optimization protocol for unattended wireless sensor networks, Wireless Personal Commun. 96 (4) (2017) 5061–5079.
[241] L. Ren, W. Wang, H. Xu, A reinforcement learning method for constraint-satisfied services composition, IEEE Trans. Serv. Comput. PP (99) (2017) 1–14.
[242] M.A. Razzaque, M.H.U. Ahmed, C.S. Hong, S. Lee, QoS-aware distributed adaptive cooperative routing in wireless sensor networks, Ad Hoc Netw 19 (Supplement C) (2014) 28–42.