Supplementary

TABLE S1. CHARACTERISTICS OF PROPOSALS FOR OUTLIER DETECTION IN WSNS

No.	Paper	Technique	Base Algorithm	Taxonomy	Centralized / Distributed	Offline/ Online	Num. Vars.[1]	Correlations	Outlier Source
1	[6]	DSS with simplified ODT	N/D	Threshold-based	Centralized	Online	M	Attributes	Events and faults
2	[8]	FTAD	PCM and Interval Method	Hybrid (Statistical-based + Threshold-based)	Distributed	Online	M	Spatiotempora	Events and faults
3	[22]	OCPCC-based detection technique	OCPCC + CCIPCA	Hybrid (Spectral Decomposition-Based + Distance-based)	Distributed	Offline Online	M	Spatial	Events and faults
4	[21]	TSVDD	SVDD + Toeplitz Random Fourier Feature Mapping	Boundary-based	Centralized	Offline	B	Attributes	Events and faults
5	[17]	PSEM and PSk-means Improved algorithms with PSA	EM and k-means. PSA based on Bayesian Optimization (BO)	Clustering-based	Centralized	Offline	B	None	Faults
6	[5]	CKODT	KFDA + OCSVM classifier (the best among 5 evaluated)	Hybrid (Spectral Decomposition-Based + Classification-based)	Centralized	Online	M	Spatial	Events and faults
7	[18]	N-STASVDD	SVDD optimized with Core-sets	Boundary-based	Distributed	Online	M	Spatiotempora and attribute	Faults
8	[20]	CBPM	Copula functions with Bayes' theory	Statistical-based	Distributed	Online	M	Spatiotempora	Events and faults
9	[44]	OPF classifier	Optimum-Path Forest Clustering	Hybrid (Graph-based + Clustering-based)	Centralized	Offline	B	Attributes	Faults
10	[39]	doOCSVM and Sparce doOCSVM	OCSVM	Classification-based	Distributed	Online	M	None	Faults
11	[45]	TOD and SOD	TOD: Hampel Identifier algorithm SOD: Gaussian process model	Hybrid (Statistical-based + Graph-based+ Threshold-based)	Distributed	Online	U	Spatial and temporal	Events and faults
12	[23]	ID-SVDD	SVDD + Parzen-window density + Mahalanobis distance	Boundary-based	Centralized	Offline	M	Attributes	Faults
13	[29]	DODS	Bayes classifier and other classifiers + MAP concept	Classification-based	Distributed	Online	M	Temporal	Faults
14	[46]	iNNE	KNN + isolation principle from Isolation Forest alg.	Hybrid (Nearest Neighbor-based + Isolation-based)	Distributed	Online	B	Spatial	Faults
15	[41]	ANN-based forecast model and ANN-based forecast optimized model	Neural Network	AI-based	Centralized	Online	U	Temporal	Faults
16	[30]	FDP generates solutions: FDPA, FDPC, FDPS, FDPK	AHC optimized with NNB	Clustering-based	Centralized	Offline	B	Attributes	Faults
17	[40]	ST-CE-CKDOT	CKDOT + OCSVM	Classification-based	Distributed	Online	U	Spatial and temporal	Events and faults
18	[31]	INCODE	INCODE + Google PageRank algorithm	Hybrid (Consensus-based + Nearest Neighbor-based + Edge Computing)	Distributed	Online	U	Spatial	Events and faults
19	[37]	Omnibus outlier detection solution (OODS): TWO-MuO, SWO-MuO and SWO-UnO	TACO + LSH	Threshold-based	Distributed	Online	U / M	Spatial, temporal, and attribute	Events and faults
20	[36]	OLWPR based detection with a dynamic threshold method	PCA + Linear Weighted Projection Regression (LWPR)	Hybrid (Spectral Decomposition, Statistical, Threshold-based)	Distributed	Online	M	Attributes	Faults
21	[47]	DBN-OQSSVM	DBN + QSSVM	Hybrid (AI-based + Classification-based)	Centralized	Online	M	Attributes	Faults
22	[25]	LODA	Adaptive Bayesian Network	Hybrid (Statistical and, Classification-based + Select features)	Distributed	Online	M	None	Faults
23	[7]	Ensemble random forest (ERF)	Random Forest + Decision Tree, Naive Bayes, and K-NN	Hybrid (Classification-based + Statistical-based + NN-based)	Centralized	Offline	M	None	Faults
24	[48]	HADF	Hypergrid-Based Detector + Statistical-based detector	Hybrid (Hypergrid-based + Statistical-based)	Distributed	Online	M	Attributes	Faults

25	[49]	A mobile edge-cloud collaboration outlier detection framework for WSNs	FastABOD + f-SVDD package (SVDD+ fuzzy theory)	Hybrid (Angle-based + Boundary-based + Edge Computing-based + Cloud-based)	Distributed	Online	M	Attributes	Faults
26	[42]	OFN	N/D	Nearest Neighbor-based	Distributed	Offline	U/M	Spatial and temporal	Events and faults
27	[50]	Nameless	Algorithms: Coefficient correlation, Random Forest, Threshold and Majority Voting	Hybrid (Statistical-based + Classification-based + Threshold-based)	Centralized	Online	M	Spatial, temporal, and attribute	Faults (false alarms)
28	[51]	CESVM-DR	OCSVM + CCIPCA	Hybrid (Classification-based + Spectral Decomposition-Based)	Distributed	Offline Online	M	Attributes	Faults
29	[38]	MOD	N/D	Statistical-based	Centralized	Online	M	Attributes	Faults
30	[4]	Preprocessed PiForest	Isolation Forest + PCA	Hybrid (Isolation and Spectral Decomposition-Based)	Distributed	Online	M	Attributes	Faults
31	[28]	Time-series analysis, entropy, and random forest-based classification	Random Forest + Time-series analysis and entropy technique	Hybrid (Classification-based + Time-series analysis and the Entropy technique)	Distributed	Online	M	Spatial and temporal	Faults
32	[43]	BS-iForest	Improved Isolation Forest	Isolation-based	Centralized	Offline	M	None	Faults
33	[52]	GANs + Autoencoder neural network with Adam optimizer	N/D	Hybrid (AI-based + Threshold-based)	Distributed	Offline Online	B	None	Faults

[1] Univariate (U), bivariate (B), or multivariate (M).

TABLE S2. THE FREQUENCY DISTRIBUTION OF PROPOSED WSN OUTLIER DETECTION PROPOSALS

Taxonomy	Freq	Approach					The number of variables				Correlations						Outlier Source	
		D	C	Offline	Online	Offline/ Online	U	B	M	U/M	S	T	A	S/T	S/T/A	None	Faults	Events/Faults
Hybrid	18	13	5	2	13	3	2	3	13		4		7	3	1	3	13	5
Classification-based	3	3			3		1		2			1		1		1	2	1
Boundary-based	3	1	2	2	1			1	2				2		1		2	1
Clustering-based	2		2	2				2					1			1	1	1
Threshold-based	2	1	1		2				1	1			1		1			2
Statistical-based	2	1	1		2				2				1	1			1	1
Nearest Neighbor-based	1	1		1						1				1				1
Isolation-based	1		1	1					1							1	1	
AI-based	1		1		1		1					1					1	
Total	33	20	13	8	22	3	4	6	21	2	4	2	12	6	3	6	21	12
Approximate %	100	60.6	39.4	24.2	66.7	9.1	12.1	18.2	63.6	6.1	12.1	6.1	36.4	18.2	9.1	18.2	63.6	36.4

TABLE S3. PERFORMANCE METRICS AND ANALYSIS OF THE COMPLEXITY OF THE DETECTION PROPOSALS

No.	Paper	Taxonomy	Evaluation type	Software	Network structure	Metrics	Better effectiveness results	Efficiency analysis
1	[6]	Threshold-based	Testbed	N/D	Flat	ACC	87.54% < ACC <=91.98%	CPC with real-time dataset = O(1) CPC with static dataset = O(n) CT = 0.1080s
2	[8]	Hybrid	Simulation	Python 2.7	Flat	TPR FNR	TPR >97% FNR <3.7%	Asymptotic complexity O(2n) in th worst case
3	[22]	Hybrid	Simulation	Matlab 2011b	Hierarchical Cluster-based	DR ACC FPR FNR	IBRL Dataset: $\bar{x}$ (DR) using median 99.7% $\bar{x}$ (ACC) using median 98.9% $\bar{x}$ (FPR) using median 2.7%	CMC = (Ok) CPC = (Omd) MC = (Omd)
4	[21]	Boundary-based	Simulation	Matlab 2014a	N/D	FPR TPR ROC	TPR with IBRL: >97% with GSB: >96% FPR with IBRL: <1.88% with GSB: <16.76 ROC: Higher efficiency than others	Less execution time in comparison
5	[17]	Clustering-based	Simulation	N/D	Hierarchical Cluster-based	ACC PRE REC	PSK-means with Synth. Data: ACC:91.3%; REC: 87.3%; PRE: 94.2%. PSEM with Synth. Data: ACC:90.4%; REC:86.9% PRE:94.0%. PSEM with Real Data: ACC:>95% (5% anom ACC: ≈80% (25% anom)	PSA improved the calculation efficiency of OEM in PSEM by [73.9%, 86.3%]. Similarly occurs ir PSK-Means in [51%, 67%]. PSEM: CT = $O(N^3)$ PSK-means: CT = $O(N^2T)$
6	[5]	Hybrid	Real implementation	N/D	Hierarchical Cluster-based	ACC	ACC: 98% using OCSVM	N/D
7	[18]	Boundary-based	Simulation	Matlab + PRtools and Ddtools functions	Hierarchical Cluster-based	FPR TPR ROC AUC	AUC: 0.9883 FPR: 3% TPR: >85%	CPC = O(*l*) TC = 1.536 s CMC = O(1) on each link.

8	[20]	Statistical-based	Simulation	RStudio (R 3.2) and Matlab R2016b	Hierarchical Cluster-based	FPR TPR ROC AUC	IBRL: 87.83% ≤ AUC ≤ 93.07%; GSB: AUC ≤ 97.13%	N/D
9	[44]	Hybrid	Simulation	N/D	N/D	ACC F1	ACC > 99% F1 > 99%	N/D
10	[39]	Classification-based	Simulation	Matlab 2016b	Flat	FPR TPR AUC F1	Synthetic dataset: FPR 0.00 TPR > 0.98 AUC >99.99% F1 > 0.9 Real dataset: AUC > 80 in 6 of 7; AUC > 94 i 3 of 7	N/D
11	[45]	Hybrid	Numerical analysis	None	Flat	AUC	TOD: Outlier detected 3/3 and 16/18 SOD: 86% ≤ AUC ≤ 95%	N/D
12	[23]	Boundary-based	Simulation	Matlab	N/D	TPR TNR ACC	GSB Dataset: TPR > 99.42; TNR: 87.5% - 97.03%; ACC: 99.77% - 99.44% Other datasets: TPR: 91.13%; TNR: 96.29%; ACC: 91.33%	CT = 0.37 to 0.38s
13	[29]	Classification-based	Simulation	TOSSIM tool	Hierarchical Cluster-based	DAR FAR	DAR: Above 90% in all cases FAR: Below 2% in 3 of 4 attributes tested	N/D merely infers low energy consumption.
14	[46]	Hybrid	Simulation	Matlab R2016a	Hierarchical Cluster-based	AUC ACC DAR FAR	ISSNIP dataset: ACC = 100% related two algorithms; ACC: >95 in most cases; DR: 96%-100% in most cases; FAR: 1.3% at best and 11.6% at worst	Training stage: TC = $O(t\Psi^2)$, MC= $O(t\Psi)$ Evaluation stage: TC = $O(nt\Psi)$, MC $O(nt\Psi)$
15	[41]	AI-based	Simulation and Real Implementation	Matlab	Flat	Forecast ACC	Outlier detection as a forecasting problem. Fo ANN model, the mean errors for the training and testing processes are 0.0596◦C and 0.0534◦C, respectively, and the correspondin largest absolute error is 0.1862◦C.	CT for (ANN, optimized ANN): Training phase: (1s, 6s), 5000 temperature records. Testing phase: (0.007787s, 0.009211s) with 2000 temperature records.
16	[30]	Clustering-based	Simulation	N/D	N/D	ROC DR	Synthetic data: Outlier-DR [0.622, 0.80]; AU(with [0.78, 0.89]; Mean AUC values for large data: (FDPA, FDPS) = (0.911, 0.929). Real data FDPC and FDPS: best DR >0.90; AUC better for FDPA, FDPC, FDPS >0.98	SC = O(n) TC = $O(n \log^2 n)$
17	[40]	Classification-based	Simulation	EPANET + Matlab	Hierarchical Cluster-based	ROC ACC FPR	It is not explicitly determined	MC = O(nd+n) at each node CPC = O(k) and O(n)
18	[31]	Hybrid	Simulation	OPNET 18.0 modeler	Hierarchical Group and community based	PRE REC F1	In event detection: REC and PRE >0.97 In fault detection: REC and PRE >0.97 F1 > 0.97	CPC = O(log(d)) + |V|2) CMC = O(log(d) PC = Low due to the use of edge computing and network traffic.
19	[37]	Threshold-based	Simulation	N/D	Hierarchical Cluster-based	PRE REC F1	TWO-MuO: with IBRL: F1> 0.9 in all configurations; with Weather: F1< 0.9 as the angle increases. SWO-MuO with IBRL and Weather data: F1 degrades to 0.7 as the angle increases. SWO-UnO: IBRL data: F1 < angle 20; Weathe data: F1 > 0.8 as angle increases.	Communication costs and energy consumption are analyzed. For multidimensional, the cost of communication decreases and the lifetime of the network increases. For one-dimensional data, the use o unreduced data is better.
20	[36]	Hybrid	Simulation	Python	Hierarchical Cluster-based	PE RMSE ACC PRE DR REC F1 AUC	$\bar{x}$ (PE): The lowest in comparison $\bar{x}$ (RMSE): The lowest in comparison ACC: >0.9 PRE: 0.85 DR: 0.86 REC: 0.86 F1: 0.86 AUC: 0.54	N/D
21	[47]	Hybrid	Simulation	Matlab 2017a	N/D	ROC AUC	$\bar{x}$ (AUC): >0.95	CT = DBN training: ≈0.31s CT = DBN testing: ≈0.002s
22	[25]	Hybrid	Simulation	Matlab and R	N/D	ACC	ACC: 88.9%	N/D
23	[7]	Hybrid	Simulation	Python 3.7.7 with Sci-kit learn 0.23.	N/D	ACC SEN SPE PRE REC F1 GME	ACC: >0.99 SEN: >0.99 SPE: >0.99 PRE: >0.99 REC: >0.99 F1: >0.99 GME: >0.99	N/D
24	[48]	Hybrid	Simulation	Python	Hierarchical Cluster-based	PRE REC F1	PRE, REC, and F1 >0.85 with IBRL and LUC in the detection of outliers due to faults. PRE, REC and F1 >0.85 with IBRL and LUC in the detection of constant failures PRE, REC, and F1 >0.80 with IBRL and LUC in the detection of noisy faults	CPC: O(nlogn)
25	[49]	Hybrid	Simulation	N/D	Hierarchical architecture with three layers	ACC	ACC: 92%	N/D

26	[42]	Nearest Neighbor-based	Simulation	Python	Hierarchical Cluster-based	DR FAR	DR and FAR, 98% and 3.6% on average wit IBRL and r > 50 DR and FAR, 100% and 2.0% on average wit Synthetic1 and r > 50 DR and FAR, 100% and 0.9% on average wit Synthetic2 and r > 80 Classification of errors and events: Regular. Only with r >= 90	ET = With IBRL from 21.3 to 23.7
27	[50]	Hybrid	Simulation	Python and Weka	Flat	ROC	N/D	N/D
28	[51]	Hybrid	Simulation	N/D	Flat	DAR FAR DR FNR FPR ACC	With GSB dataset: $\bar{x}$ (DAR): 96.08%; $\bar{x}$ (FPR 1.2%; $\bar{x}$ (FNR): 3.92%; $\bar{x}$ (ACC): 98.56% With other datasets: DR: 99.1%-100%; DAR 78.6%-100%; FPR: 0%-25.8%; FNR 0%-0.01%	MC = O(mn+nd) CPC = $O(P+m^2d+dn^2)$ CMC = None
29	[38]	Statistical-based	Simulation	OMNET ++	Hierarchical Cluster-based	Aggregated Data Accuracy	Is considered outlier detection as a step prior t data aggregation and is determined the effectiveness of the aggregation process.	N/D
30	[4]	Hybrid	Simulation and Real Implementation	Python	N/D	AUC	Compared to other solutions: AUC is not as effective as the original iForest. Only in two real datasets AUC is > 0.9 The real implementation was done with a singl Arduino node equipped with 4 sensors. In testing with synthetic data and injected anomalies, PiForest achieved an AUC of 0.97	The estimated memory requiremen per node is 20.59 KB with k = 2 an ntrees=10. SC = O(Ψtb)
31	[28]	Hybrid	Simulation	Matlab and R	Flat	ACC	ACC with IBRL data: 99.1% (with 10% noise The algorithm can detect up to 100% of outlie with sigma = 10 and even with 20% noise.	N/D
32	[43]	Isolation-based	Simulation	Java	N/D	ACC AUC	AUC with BreastW dataset: 0.9947 AUC with Campus CRS dataset: 0.989 ACC with BreastW dataset: 0.9653 ACC with Campus CRS dataset: 0.9896	N/D
33	[52]	Hybrid	Simulation	Python with library Pymote 2.0	Hierarchical Cluster-based	ACC PRE REC FPR F1	ACC: 94.11% REC: 95.81% FPR: 22.32% PRE: 97.62% F1: 96.7%	N/D. However, the algorithm prove to increase the lifetime of the networ and to be robust related to channel faults and faulty communication channel distribution.

TABLE S4. SUMMARY OF ADVANTAGES AND DISADVANTAGES OF OUTLIER DETECTION PROPOSALS

No.	Paper	Technique	Advantages	Disadvantages / Limitations
1	[6]	DSS with simplified ODT	Low computational complexity O (1). Does not degrade real-time system performance by avoiding full dataset scans. Improves DSS accuracy by eliminating outliers.	Sensitive to noisy datasets and multiple values. Centralized architecture not very scalable. Susceptible to external factors like extreme weather conditions. Requires proper threshold definition for outlier detection. Lower accuracy compared to more complex algorithms.
2	[8]	FTAD	Fault-tolerant. Capable of detecting events with high node failure rates. Utilizes spatio-temporal correlation to distinguish between events and failures. Divides the network into neighborhoods for targeted detection. Achieves good performance even with low-density networks.	Does not account for detection of multiple simultaneous events. Requires message exchange between neighboring nodes. Dependent on accurate estimation of failure rates. Does not optimize node energy consumption.
3	[22]	OCPCC-based detection technique	Leverages spatial data correlation in nearby neighborhoods to improve effectiveness. Distributes detection workload across the network for enhanced efficiency. Adaptable to dynamic environmental changes by allowing periodic retraining and updates when necessary.	Incorporates additional communication overhead for transmitting model summaries between nodes and the head node. High number of false positives.
4	[21]	TSVDD	Reduces computational complexity. Improves stability in low dimensions.	Need for a representative training dataset. Sensitivity to model parameters. The use of the Toeplitz matrix to reduce time and space complexity in a real application can impact the accuracy and efficiency of the algorithm. Limited to static data. Centralized and offline, not suitable for highly distributed WSNs or those requiring real-time detection.
5	[17]	PSEM and PSk-means Improved algorithms with PSA	Significantly reduces the number of iterations required for clustering. Improves clustering accuracy by finding better initial points.	Requires a priori design for efficient Bayesian optimization. Centralized and offline, not suitable for highly distributed WSNs or those requiring real-time detection.
6	[5]	CKODT	Achieves high classification accuracy. Handles non-linear data better when using KFDA. More efficient due to dimensionality reduction.	Requires a labeled training set. Combining techniques could increase computational complexity.
7	[18]	N-STASVDD	Considers both spatio-temporal and attribute correlations, improving detection performance. The use of "core-sets" is effective in reducing computational complexity.	Preprocessing and initialization in N-STASVDD can be costly for real-time anomaly detection.

			Implements anomaly detection in a distributed manner, reducing communication overhead.	
8	[20]	CBPM	Does not require assumptions about data distribution. Allows for modeling of multidimensional variables. Good performance in AUC and prediction time.	Requires communication with the base station for model training. Complexity increases with dimensions. Selection of an appropriate threshold required. Dependency between captured measurements.
9	[44]	OPF classifier	Does not require a predefined number of clusters. Performs well with non-Gaussian clusters.	Requires fine-tuning of parameters such as neighborhood size and anomaly threshold. Does not provide information on performance in WSN scenarios.
10	[39]	doOCSVM and Sparce doOCSVM	Fully distributed algorithms without the need for a fusion center. Online processing, reducing memory requirements. Good performance in anomaly detection.	Selection of appropriate parameters for the approximate random function and stochastic gradient descent required. Does not address the multi-class classification problem. Requires single-class normal data for training.
11	[45]	TOD and SOD	Able to detect both temporal and spatial outliers. Computationally simple and suitable for WSNs.	Difficulty in setting an appropriate detection threshold with multivariate data. Requires definition and optimization of parameters.
12	[23]	ID-SVDD	Efficiently maps data points from sparse spaces to high-density spaces. The use of Mahalanobis distance in density estimation improves performance by eliminating the interference of correlations between variables. Improves outlier detection accuracy compared to SVDD, D-SVDD, and DW-SVDD.	May not be suitable for real-world applications due to its centralized approach. Higher computational complexity than regular SVDD. Requires appropriate selection of hyperparameters for the algorithm.
13	[29]	DODS	Detects outliers in a distributed and autonomous manner at each node. Does not require neighbor information or inter-node communication. Can handle multiple types of sensed data.	Does not consider the contextual or global information of the network. Requires an offline supervised training phase. The use of small intervals in Bayesian classifiers may increase the false alarm rate.
14	[46]	iNNE	Improves detection accuracy and reduces false alarm rates compared to other frameworks. Reduces resource consumption by using iNNE for the local detector. The proposed combination method avoids transmitting the hyper-sphere structure of local detectors. Adapts to dynamic environmental changes using a sliding window to update the local detector.	Requires setting a threshold for outlier detection. The size of the sliding window is predefined and fixed.
15	[41]	ANN-based forecast model and ANN-based forecast optimized model	Allows for real-time detection and correction of outliers. Does not require prior labeling of normal and abnormal data. The optimized ANN model handles large ambient temperature changes better. Achieves good accuracy in detection.	Requires initial training with a large amount of data. The ANN may overfit the training data. Performance depends on sensor distribution and data quality. High computational complexity due to the use of deep neural networks.
16	[30]	FDP generates solutions: FDPA, FDPC, FDPS, FDPK	Can detect global anomalies without influence from local clusters. Has lower computational complexity by utilizing data structures like quad-tree and kd-tree. Is an unsupervised algorithm that does not require training or labeled data.	Adapting to different data distributions may pose a challenge. Requires appropriate selection of the similarity function in the hierarchical clustering process. Due to its centralized approach, it could have scalability issues in very large WSNs or with high data dimensionality.
17	[40]	ST-CE-CKDOT	Centered ellipsoidal model has better accuracy than spherical models. Distributed approach reduces computational and communication load. Uses spatial and temporal correlation to distinguish between noise, events, and faulty sensors. Useful for monitoring water pipe leaks through WSN.	Implementation and maintenance of this network can be costly and require careful planning. Requires information exchange between neighboring nodes. Needs retraining and updating. Parameters must be optimized for the specific problem.
18	[31]	INCODE	High detection accuracy (98%). Low computational and communication complexity when operating at the network edge. Associates an anomaly degree to provide more information to the user.	Requires community formation and a consensus mechanism. Depends on the spatial correlation of nodes. Omission of temporal correlations could limit its effectiveness in certain contexts.
19	[37]	Omnibus outlier detection solution (OODS): TWO-MuO, SWO-MuO and SWO-UnO	Allows for explicit and predictable balancing of bandwidth and accuracy. Supports various similarity measures for defining outliers. Operates under different window models (sliding and batch). Multidimensional outlier detection.	Higher complexity in parameter configuration (e.g., window size). Requires more local processing on the nodes. Dependent on the quality of the generated random vectors.
20	[36]	OLWPR based detection with a dynamic threshold method	Good performance in detection rate and error rate. Low memory consumption as it does not require storing training data. Dynamic threshold adaptable to changes.	Could require a significant amount of computational resources and face scalability challenges. Requires an offline training phase. Unclear how it would perform against new types of attacks.
21	[47]	DBN-OQSSVM	Reduces data dimensionality through DBN. OQSSVM allows for quick model training through sorting instead of optimization. Detection is performed online without the need for retraining. Improves accuracy compared to other methods. Drastically reduces computational cost.	Might require significant computational capacity to scale to distributed detection. Requires a priori estimation of the outlier rate. Dependent on the quality of DBN's dimensionality reduction.

22	[25]	LODA	Does not require inter-node communication, saving energy. Performs well even with small memory sizes. Robust against increases in noise level.	Requires preprocessing and feature selection. Relies on the Bayesian classifier, which has known limitations. Does not leverage spatiotemporal correlations between nodes.
23	[7]	Ensemble random forest (ERF)	Utilizes an ensemble of heterogeneous algorithms (Decision Tree, Naive Bayes, and KNN) to improve performance. Bootstrap sampling reduces variance and improves results. Outperforms base algorithms when used separately.	Higher computational complexity due to the need to train multiple models. Does not thoroughly analyze scalability to large sensor networks.
24	[48]	HADF	Detects multiple types of anomalies. Combines hypergrid-based and statistical analysis detectors to improve accuracy. Adopts lazy and continuous learning to adapt to data changes. Proposes a more robust L1 detection region than existing ones.	Could have limitations in terms of computational complexity and resource requirements. Requires longer execution time than simpler methods like HGDB. Depends on coordination between sensor nodes and cluster head. Not validated with very large datasets.
25	[49]	A mobile edge-cloud collaboration outlier detection framework for WSNs	Reduces delays and energy consumption by moving intensive tasks to edge nodes. The FastABOD algorithm improves the scalability of ABOD for high-dimensional data. The SVDD model with kernel functions performs well for nonlinear data. Iterative optimization in the cloud improves accuracy.	Demands periodic updates and optimizations of the detection model. Requires additional mobile edge nodes. Unclear how the movement of edge nodes is coordinated. No guarantee on the degree of offloading to edge nodes. Improvement in model accuracy is not quantified.
26	[42]	OFN	Uses spatial and temporal correlation for outlier classification. Considers the resource limitations of WSNs. Is scalable and shape-independent of the data. Classifies outliers into errors or events.	Requires defining parameters like the number of neighbors to consider. Potential sensitivity to variations in the density function. Unclear how they determine the thresholds for outlier detection. Does not allow for online outlier detection.
27	[50]	Nameless	Dynamic thresholds adaptable to each patient and condition. Does not require complex distance or classification algorithms.	Strong dependence on historical data. Its centralized approach could limit its scalability. Does not detail how to select parameters for detection. Does not sufficiently analyze the efficacy and efficiency of the proposed technique.
28	[51]	CESVM-DR	Utilizes OCSVM, which can classify unlabeled data, highly useful in WSNs. Employs the CESVM formulation of OCSVM that is efficient in multivariate data. Uses CCIPCA to reduce dimensionality and complexity. Achieves good detection accuracy. Does not require inter-node communication for detection.	Requires storing model parameters on each node. Reference normal model needs to be updated periodically. Performance depends on well-tuned regularization parameters, for example, the optimal number of principal components when applying the CCIPCA algorithm. Does not consider spatial correlation between nodes.
29	[38]	MOD	Outlier detection prior to aggregation to preserve accuracy. Considers correlations among multiple variables. Higher accuracy of aggregated data compared to other algorithms like FTDA.	Its centralized architecture may impact scalability and effectiveness. Requires more complex statistical calculations. Consumes more computational resources on sensor nodes. Does not consider distributed outlier detection among cluster members.
30	[4]	Preprocessed PiForest	Significantly reduces memory requirements and complexity by working with lower-dimensional datasets. Effectively handles streaming data. Adapts more quickly to data changes, reducing the effect of concept drift.	The use of PCA may affect detection accuracy in datasets with complex structures or nonlinear correlations between features. Slightly inferior performance to conventional iForest in some cases due to dimensionality reduction. Requires manual tuning of some hyperparameters such as sliding window size.
31	[28]	Time-series analysis, entropy, and random forest-based classification	High accuracy in outlier detection. Adaptive to varying levels of noise and dynamics. Utilizes temporal and spatial correlation.	High computational cost of random forest on nodes with limited resources. Does not address the issue of detecting malicious or faulty nodes. Requires storage of historical data on each node. Does not consider temporal correlation between neighboring nodes.
32	[43]	BS-iForest	Improves accuracy and stability compared to traditional iForest. Initial filtering with box plots reduces randomness. Selection of the most accurate trees enhances detection capability. Joint judgments in the fuzzy area improve performance.	Higher computational complexity than traditional iForest. Requires manual tuning of some parameters. Is centralized and offline, which could lead to scalability issues.
33	[52]	GANs + Autoencoder neural network with Adam optimizer	Improves accuracy in outlier detection compared to state-of-the-art techniques. Extends the network lifespan by discarding erroneous data. Robust against communication channel failures.	Requires periodic training of autoencoders, which consumes computational and communication resources. Does not resolve ambiguity in detection when multiple nearby sensors generate abnormal data.