Global Journal of Computer and Engineering Technology (GJCET)

Vol. 2, No. 1, January, 2022 ISSN: 2767-1933

ANALYSIS OF ENERGY EFFICIENT WIRELESS SENSOR NETWORKS USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Environment monitoring, military, health, home, smart city, industry, commercial applications, and so on all employs wireless sensor networks. The sensor nodes are battery-powered. It is not possible to remove the batteries from sensor nodes that have been deployed in a hazardous environment. As a result, in order to extend the life of WSNs and make them work in a variety of settings, we will need to create energy-efficient and dynamic WSNs. Machine Learning (ML) approaches are crucial in the development of dynamic, intelligent, and energy-efficient WSNs. Our primary research goal is to use machine learning to solve problems in WSNs such as node deployment, clustering, routing, designing mobile sinks, detection of failure nodes, energy harvesting and network services.

Keywords: WSN, Machine learning, Data aggregation, Clustering, Routing, Energy efficiency.

1. INTRODUCTION

Wireless sensor networks (WSNs) are the most effective technology for a wide range of real-time applications because of their compact size, cheap cost, and ease of deployment. WSN's job is to keep an eye on a certain area of interest, gather data, and send it back to the sink for analysis. Some WSN applications utilise a large number of sensor nodes. As a result, a scalable and power efficient algorithm is required to manage such a vast number of nodes (Akyildiz et. al., 2002; Yick et al., 2008; Rawat et al., 2014). Furthermore, the WSNs may change dynamically as a result of external factors or as the system designers intended. As a result, network routing techniques, localization, latency, cross-layer design, coverage, Services of network and connection quality may all be harmed. Because of the network's high dynamic nature, non-essential reconfiguration may be required; however classic WSN systems are coded to avoid this. As a result, in a dynamic environment, the network does not work properly.

Machine learning (ML) is a technology which helps to train a machine by sample data. As a result, the machine can solve different types of problems easily. ML is part of Artificial Intelligence (AI). Machine learning algorithms helps to design a mathematical model which returns predicted value. By the help of predicted value, we can predict the future like whether forecasting, stock market analysis etc. WSN issues like localization, data aggregation, clustering, routing, energy harvesting etc can be resolved by ML and also uses in IoT applications. ML solves different applications and saves money and time. WSNs' performance is enhanced through machine learning, which reduces the need for retraining of system. The following are some of the ML applications in WSNs:

- Machine learning algorithms are used to deploy minimal sensor nodes in selected field.
- Localization problems can be solved by machine learning algorithms.
- The network faults in WSNs can be identified by using machine learning.
- The overhead of sending all of the data to the sink will be incurred by the network. Machine learning can aid data aggregation at the cluster head level as well.
- Because WSNs are self-powered and have a long lifespan, they benefit from energy harvesting. Machine learning techniques resolves energy harvesting issues.
- When it comes to extending the life of a network, data routing is crucial. The dynamic behaviour of sensor networks needs dynamic routing strategies to increase system performance.

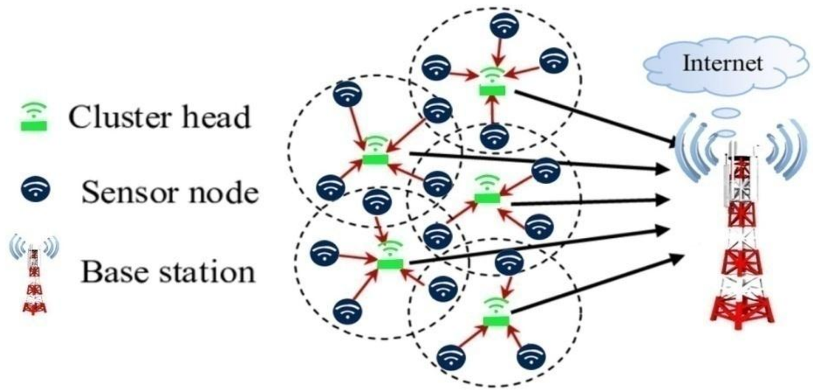

Figure 1: WSNs model

Remaining of the paper is structured as follows: Section 2 Machine learning approaches, Section 3 Machine learning techniques, Section 4 Machine learning algorithms, Section 5 Result analysis, Section 6 Statistical analysis, Section 7 Open issues, Section 8 Conclusion.

2. MACHINE LEARNING APPROACHES

In ML techniques have been classified into four categories based on learning style: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Ayodele (2010).

Table 1: Symbols

Symbols	Description
AD	Anomaly Detection
ACO	Ant colony optimization
ABC	Artificial bee colony
ANN	Artificial Neural Networks
CHs	Cluster heads
CNN	Conventional Neural Network
DL	Deep learning
DT	Decision trees
EC	Evolutionary Computation
FCM	Fuzzy *c*-means
GA	Genetic Algorithm
ICA	Independent Component Analysis
MAC	Medium Access Controller
ML	Machine Learning
PCA	Principle Component Analysis
PDR	Packet delivery ratio
PSO	Particle Swarm Optimization
QoS	Quality of Service
RBF	Radial Basis Function
RF	Random Forest
RL	Reinforcement learning
RPs	Rendezvous points
SVD	Singular Value Dicomposition
SVM	Support Vector Machine
WSNs	Wireless Sensor Networks

2.1 Supervised Learning

One of the most essential data processing methodologies in machine learning is supervised learning. We feed the machine a set of inputs and outputs (datasets with labels) and it learns to associate them over time using supervised learning. We can get predicted result after completion of training. Two types of supervised learning are regression and classification. By using regression and classification different applications such as localization, target tracking, medium access control, security QoS services etc. can be resolved.

2.2 Unsupervised Learning

In unsupervised learning, data will input without output data to the system. To classify a group of homogenous data types into clusters, reduce dimensionality and find anomalies in the data, researchers used unsupervised learning approaches. Connection, anomaly detection, routing, and data aggregation are just a few of the problems that unsupervised learning solves for WSNs. Unsupervised learning includes clustering (k-means, hierarchical, and fuzzy-c-means) and dimensionality reduction (PCA, ICA and SVD).

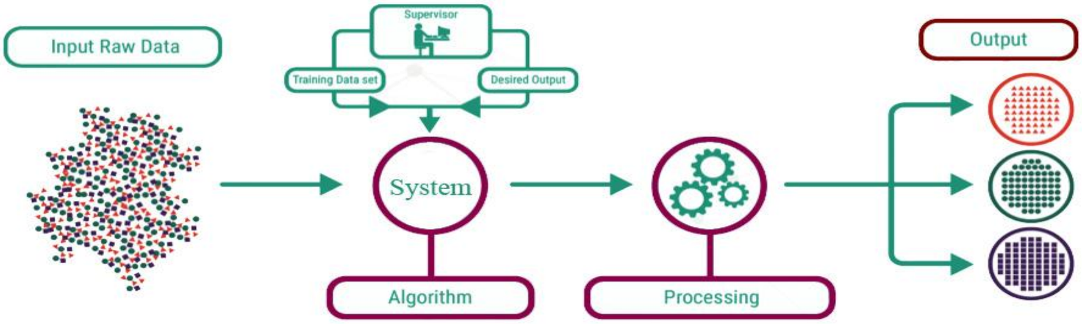

Figure 2: Supervised learning

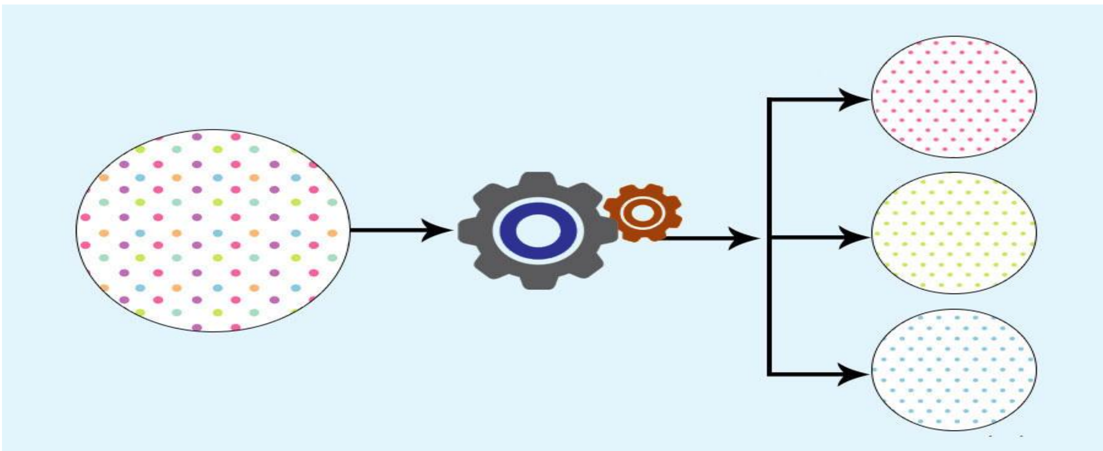

Figure 3: Unsupervised learning

2.3 Semi-Supervised Learning

Semi-supervised learning was first used on data that was labelled and then works on unknown data. It contains semi-supervised classification for partially labelled data, constrained clustering for both labelled and unlabeled data, regression for unlabeled data, and dimensionality reduction for labelled data. It is costly when it works on real-time application. Natural language processing, web content categorization, speech recognition, spam filtering, video surveillance, and protein sequence classification are all semi-supervised learning applications. This learning mechanism is used by WSNs to solve problems like fault detection and localisation (Hady et. al., 2013; Feldman et al., 2013).

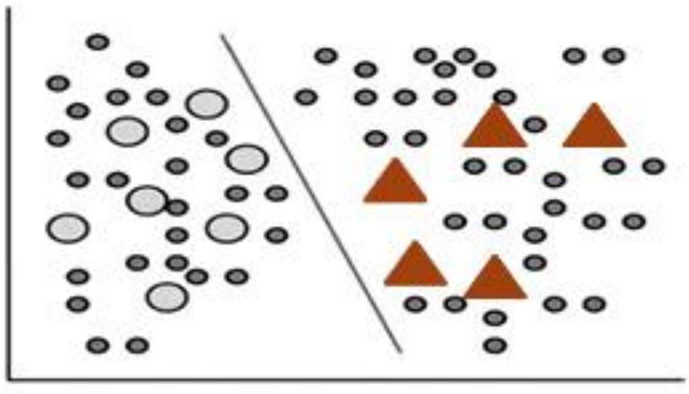

Figure 4: Semi-supervised learning

2.4 Reinforcement Learning

The Reinforcement Learning (RL) algorithm learns by interacting with the environment and collecting data in order for an agent to do specific behaviours. RL boosts performance by figuring out how to get the optimum result from a given situation (Forster et al., 2007). RL performs well in distributed environment. RL resolves routing issues of WSNs very effectively. Q-learning is RL learning.

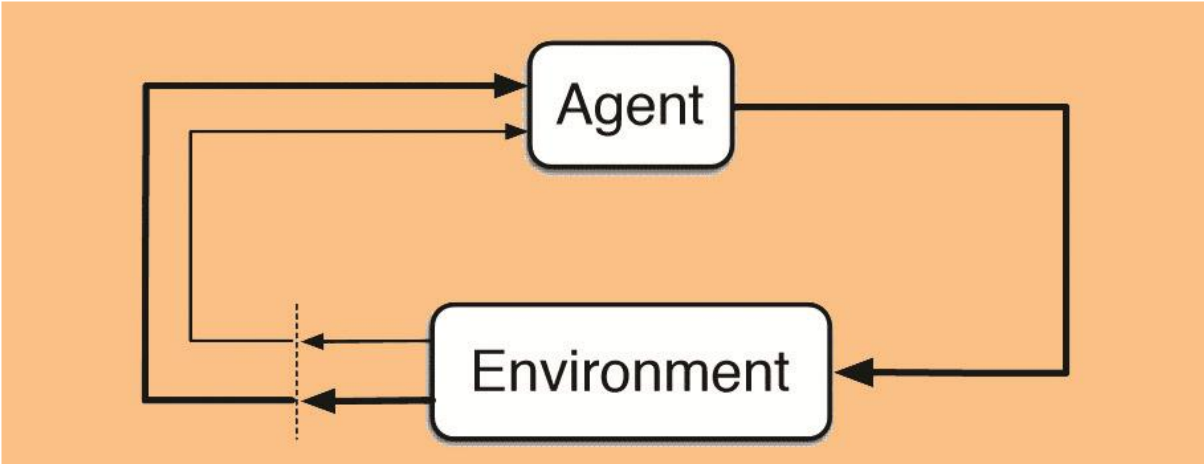

Figure 5: Reinforcement Learning

2.5 Evolutionary Computation

Computational models based on nature and biological evolution is used to tackle problems in evolutionary computation. Evolutionary computing is a type of artificial intelligence that makes use of a variety of combinatorial optimization techniques to solve real life applications. EC is population based and better than traditional computing to get optimal solution. GA, PSO, ACO etc are example of EC. The issues like Localization, coverage, routing, target tracking, and mobile sink are just a few of the WSN difficulties that have recently been handled utilising evolutionary or nature-inspired algorithms.

3. MACHINE LEARNING TECHNIQUES

Machine learning helps analysis data, trains the machine by data sets and solves different types WSNs issues, IoT applications and other applications using different techniques which are explained below (Mitchell, 1997, Ayodele, 2010).

3.1 Regression

The technique of regression is used to discover the link between input and output. It also helps to design a model to predict the future vale of dependent variables. There are different types of regression. They are linear regression, nonlinear regression, logistic regression, ride regression, lasso regression, polynomial regression. Regression technique is unable to identify when the relation is complex among data.

3.2 Decision Tree

DT technique contains if – then rules to improve readability. In DT, there are two types of nodes which are leaf node and decision node. DT solves various problems in WSNs like data aggregation, connectivity, anomaly detection and mobile path selection.

3.3 Random Forest

RT is generated by taking number of DTs to solve regression and classification problems with the help of large data set and returns high accuracy. It requires less training time than other ML algorithms. It solves MAC and coverage problems of WSNs. It also applied in banking, health, marketing sectors to resolves issues.

3.4 Artificial Neural Network

ANN is based on a layer model with a large number of nodes that process data and generate exact outputs. Ann is based on layers, which are connected by nodes. Every node has an activation function connected with it. There are input layer, output layer and middle layer. There may a single middle layer or more middle layer between input and output. The input layer receives data, middle layer process data and the output layer returns output. If generated output is not equal to desired output, modification required in weight of edge to get expected output. ANN solves real life problems in efficient manner. ANN also helps with data aggregation, routing, localisation, detecting problematic nodes, and congestion control in WSNs.

3.5 Naive Bayes Classifier

The Naive Bayes Classifier is a type of classification technique which is based on Bayes' theorem and strong independence assumptions. It's a straightforward probabilistic classifier that calculates conditional class probabilities before determining the most likely categorization. To put it another way, the descriptive attribute probability models values will be used to give a class to an object.

3.6 Deep Learning

Deep learning is subset of ANN. It is also layer based which is inspired by human nerve system. It is applied in various WSN applications like routing, energy harvesting, medical image processing, speech recognition etc.

3.7 Support Vector Machine

SVM divides the dataset into two groups, separated by a linear border that maximises the margin between the classes. The hyper plane with the greatest distance between it and the closest positive and negative samples is the one that SVM seeks out. The kernel activating function is utilised instead of the exponential activating function in the fundamental design of an SVM network, which is similar to that of a standard RBF network (which is commonly Gaussian). To activate the kernel, you can use different types of kernel functions as per applications.

3.8 K-Nearest Neighbour (K-NN)

KNN is instance base learning system which is used in regression and classification. This technique is based on various distance functions like Euclidean distance, Hamming distance. K-NN technique solves various problems like data aggregation, fault detection and anomaly detection of WSNs.

3.9 K-means Clustering

In this technique, K number of positions are selected as centroids form given data set randomly to form clusters. It halts crating and optimizing clusters when either:

- The centroids have stabilized.
- The defined number of iterations has been achieved.

It's a simple clustering technique that's used in Wireless Sensor Networks to figure out how many cluster heads are needed to construct energy-efficient WSNs, as well as for mobile sinks.

3.10 Hierarchical Clustering (HC)

HC is another important technique of machine learning to solve the problems of K-means clustering. It uses two techniques i.e agglomerative and divise. Agglomerative uses bottom – up approach whereas divise uses top-down method to design clusters. The HC resolves various issues of WSNs like data aggregation, energy harvesting and mobile sink

3.11 Fuzzy –c-means Clustering (FCM)

FCM is developed by Bezdek in 1981 which is based on fuzzy set theory. Clusters are characterised by equal measurements such as intensity, distance, and connection, which are based on the number of clusters, dimension, data points and iterations and address a variety of WSN challenges including localization, connectivity and mobile sink.

4. MACHINE LEARNING ALGORITHMS

4.1 Localization

Localization is the process of estimating the location of sensor nodes in target area to design WSNs. To design large sensor WSNs, the sensor nodes can't be deployed manually. There are different methods applied to deploy the sensor nodes. Machine learning algorithms are applied to deploy sensor nodes to design energy efficient WSNs. Classification and regression model are used to deploy the sensor nodes in target area. The following table defines different techniques to design energy efficient WSNs. (Wang Z. et al., 2018) have designed a novel algorithm LSVM-PCS which is based on support vector machine and polar coordinate system to solve localization issues of WSNs. It provides better result over traditional localization algorithms. According to (Wang Z. et. al., 2017) RSS based DSL is right method to localize the person without attaching any electronic device. They have purposed a method by which less amount of data can be sent to sink collected by sensors. They have also two localization methods which are based on GML and PF to global optimum and track the targeted objects.

Table 2: Localization for WSNs

Techniques Applied	Environment	Mobility of Nodes	Complexity	Benefits
SVM	Centralized	Static	High	Extends life of WSNs
Bayesian	Centralized	Static or Mobile	High	Enhance power of WSNs

4.2 Data Aggregation

Data aggregation is the process of collecting and combining data from sensor nodes. In WSNs, data aggregation has an impact on a variety of characteristics such as power consumption, processing time and delay. In WSNs, data aggregation plays an important role in reducing the number of transmissions and communication overhead. An efficient data aggregation method balances sensor node energy consumption and extends lifetime of network. There are different types of data aggregation methods that are dependent on the network topology and applications. In (Song X. et al., 2013, Atoui et al., 2016, Gispan L. et al., 2017), the authors have designed energy efficient WSNs by applying different regression techniques. In (Yang H. et al., 2013), the authors have proposed energy efficient

WSNs by applying decision tree. In (Morell A. et al., 2016) the authors have proposed to control imbalanced class problem in WSNs. In (Morell A. et al., 2016, Anagnostopoulos C. et al., 2014, Chidean M. I. et al., 2015), the author have designed energy efficient WSNs by using PCA method. In (Pinto A. et al., 2014), using a genetic algorithm, the authors suggest a method for implementing data fusion techniques in WSNs.

Table 3: Data aggregation for WSNs

Technique Applied	Environment	Topology	Mobility of nodes	Benefits
Regression	Distributed	Tree	Static	Improved network lifetime
Decision tree	Distributed	Tree	Static	Enhanced network lifetime
ANN	Distributed	Tree	Static	Enhanced network lifetime
Bayesian	Distributed	Hybrid	Static	Enhanced network lifetime
Genetic classifier	Distributed	Star	Static or mobile	Extended network lifetime

4.3 Clustering in WSN

In the case of battery-powered sensors, a fundamental challenge in WSNs is that they have limited or no energy sources available. WSN protocols must perform by lowering CPU load in the situation of mobile sensor nodes with limited battery power. WSNs face a significant power management challenge because they are battery-powered devices. The group of sensor nodes is known as cluster which consumes less power and improves network lifetime of WSNs.

In (Abbasi A. et al., 2007), clustering technique is applied to minimize the power consumption of sensor nodes and extends the lifetime of WSNs. In (Mohammed N. et al., 2011), leader election mechanism is used for intrusion detection in MANET. In (Hajami A. et al., 2010), an enhanced algorithm is designed for MANET clustering using multi-hop and network density. In (Pani N. K. et al., 2014), the authors have designed hybrid routing protocol for protection of MANET. In (Sethi S. et al., 2010), the authors have designed optimized routing protocol for MANET. In (Safa H. et al., 2010), the authors have designed a cluster based trust aware routing protocol for mobile ad hoc network. In (Zhang Y. et al., 2009) the authors have solved routing problems using clustering and detected intrusion of clusters. In (Younis O. et al., 2004), the authors have proposed energy efficient distributed protocol using residual energy and node degree for WSNs. In (Heinzelman W. B. et al., 2002), the popular protocol LEACH is designed which is better than HEED. In (Rajan M. A. et al., 2008), the authors have designed cluster based protocol using graph theory for MANET. In (Reese J. et al., 2006), the authors have solved p-median problem.

Table 4: Clustering in WSNs

Techniques Applied	**Data Noise**	**Speed of Clustering**	**Accuracy**
K-Means	High	Fast	Low
Fuzzy – c- means	Low	Slow	High
Hierarchical clustering	Low	Low	High

4.4 Routing in WSN

Because sensor nodes have limited memory, bandwidth, and processing capabilities, design concerns like as energy consumption, data coverage, scalability, and fault tolerance must be considered while creating a routing protocol (AI-Karaki J. et al., 2004).

In (Mehmood A. et al., 2017), the authors have designed energy efficient routing protocol based on ANN. ANN training the protocol with various parameters like residual energy, distance between nodes, boarder nodes, cluster heads and sink. In (Gharajeh, M. et al., 2016), the authors have designed DFRTP protocol which is based on fuzzy system. This protocol reduces packets sent by nodes to sink and minimizes power depletion of sensor nodes of

WSNs. In (Srivastava J. et al., 2015), the authors have designed ZEEP protocol for mobile sensor networks which is fuzzy based. The cluster heads are selected by using GA. Hence, ZEEP is energy efficient protocol. In (Lee, Y. et al., 2017), deep learning based routing algorithm is designed for mobile sensor network which controls packet loss, power management and congestion. In (Khan F. et al., 2016), SVM based routing protocol is designed to control power consumption and improve the network lifetime which is better than LEACH protocol. In (Jafarizadeh V. et al., 2017), cluster head selection algorithm based on Naive Bayes for power conscious routing protocol that enhances network lifetime. In (Li uZ. et al., 2014), a new routing frame is designed for data collection using Bayesian method. In (Kazemeyni F. et al., 2014), a new routing model is designed using Bayesian method for decentralized system as compare to centralized system. In (Hammoudeh M. et al., 2015), K-means classification algorithm is used for optimality of clusters. This algorithm is energy efficient and improves throughput. In (Liu X. et al., 2017), The authors employed the k-means technique to create energy-efficient clustering and used a multi-hop path from the cluster heads to the sink. In (Jain B. et al., 2018), the author has designed EKMT protocol using k-means which minimizes delay and improves the throughput. (Nayak, P. et al., 2021) has explained routing challenges of WSNs can be solved by using ML techniques to design intelligent WSNs which is base of IOT applications.

Table 5: Routing Algorithms for WSNs

Technique Applied	Topology	Environment	Mobility of Nodes	Complexity
ANN	Tree	Centralized	Static	High
	Tree	Distributed	Static	Moderate
	Tree	Distributed	Static	Moderate
Deep Learning	Hybrid	Centralized	Mobile	High
SVM	Hybrid	Distributed	Static	Moderate
Bayesian	Tree	Distributed	Static	Moderate
	Hybrid	Centralized	Static	Low
	Hybrid	Centralized	mobile	Moderate
K-Means	Hybrid	Distributed	Static	Low
	Tree	Distributed	Static	Moderate
	Hybrid	Centralized	Static	Moderate

4.5 Energy Harvesting

In WSNs, battery power is a key source of energy for sensor nodes, and the amount of energy consumed by the sensor nodes dictates lifetime of networks. The bulk of WSN applications call for network lifetimes ranging from months to years. We use power saving protocols or provide power saving technologies for sensor nodes to extend the lifetime of WSNs. For energy efficiency, intelligent techniques will be applied at time of designing WSNs. For real time applications existing battery power is not enough, so external power source is highly essential. Energy harvesting provides continuous power to sensor nodes of WSNs. Now energy harvesting is a feature of WSNs.

There are two types of energy harvesting: supply of electricity to nodes and with energy storage (rechargeable battery). Several machine learning-based models have been developed to track the most successful energy harvesting methods for wireless sensor networks. Many algorithms are used for energy harvesting. In(Sharma A.et al., 2018), the authors have designed solar irradiance prediction system by using ML technique which provides better result than conventional method by taking data set of national renewable energy laboratory (NREL). In (Tan, W. et al., 2017), the authors have designed an indoor test methodology for solar powered wireless sensor networks using linear regression technique which will work both centralized and distributed environment. But it provides better result in distributed than centralized environment. In (Kosunalp, S. et al., 2016), the author has designed Q-SEP algorithm using reinforcement technique for energy harvesting in wireless sensor networks which returns better harvested energy in particular time period. In (Hsu, R. C et al., 2014), the authors designed energy harvesting algorithm using reinforcement learning technique for controlling duty cycles of WSNs. In (Aoudia, F. A., et al., 2018), the authors have designed a model using deep learning technique for wind power generation for IOT which produces better result than other conventional model. In (Chen, F., et al., 2019), the authors have designed power saving algorithm by applying clustering technique for wireless sensor networks with different types nodes. In this network, renewable energy provides energy to cluster heads and non-renewable energy provides rest of nodes. The less number of cluster heads are deployed to minimize the power consumption of WSNs.

Table 6: Energy harvesting for WSNs

Technique Applied	**Environment**	**Complexity**	**Source of Energy**
Regression	Centralized/Distributed	High	Solar
Reinforcement Learning	Centralized	Low/Moderate	Solar
Deep Learning	Centralized	High	Wind
Hierarchical clustering	Distributed	Low	Solar/Wind

4.6 Mobile Sink

Mobile sink is used to solve energy-hole problem in WSNs. In large WSNs, mobile sink movement from node to node is tedious task. So scheduling mobile sink or use rendezvous point to design energy efficient WSNs. In (Kim S. et al., 2017), the authors have designed naive Bayesian based data collection model using mobile sink from sensor nodes which is better than tradition model and energy efficient. This model also used IoT application. In (Tashtarian F. et a., 2015), the authors are purposed ODT algorithm for selection of RV points for mobile sink which improves lifetime of WSNs. In (Almiani K.et al., 2010), the authors designed energy efficient cluster based algorithm for data collection of mobile nodes in WSNs. In (Zhang R. et al., 2016), the authors have purposed hybrid algorithms for data collection in large scale WSNs using mobile sink which improves network life time. In (Zhang R et al., 2015), The authors created methods for data collecting in large WSNs employing mobile sinks. In (Nayak P. et al., 2016), the authors have purposed a method for WSNs which energy efficient and improves network life time and produces better result than LEACH. In (Wang J. et al., 2017) , To extend the network life time of WSNs, the authors used a PSO-based clustering method with a mobile sink, which outperformed TTDD and LEACH. In (Praveen D. K. et al., 2018), the authors have purposed ACO based algorithm for tour of the mobile sink of WSNs which is energy efficient and extends network life time. In (Ha I. et al., 2017), the authors have proposed an algorithm which is based on k – means algorithm and minimum spanning tree to improve network lifetime of WSNs.

Table 7: Mobile Sink for WSNs

Techniques Applied	**Benefits**
Decision Tree	Mobile path selection for mobile sink
Bayesian	Mobile path selection for mobile sink
K-mean clustering	RV points, optima RV points for mobile sink
Hierarchical clustering	Data collection for mobile sink
Fuzzy c-means clustering	Data collection for mobile sink
Evolutionary computing	Minimize tour length for mobile sink

4.7 Medium Access Control

The MAC layer is part of data link layer of WSNs. There are three sorts of access methods based on the medium access mechanism: non-contentional, contentional, and hybrid. Sensor networks use a contention-free approach in which nodes can only access their assigned carrier slots and so interact with the sink node in a collision-free way. Nodes compete for access to the wireless channel in contention-based sensor networks. The aforementioned two techniques are combined in Hybrid MAC protocols. Our primary objective is to design energy aware MAC for WSNs to enhance the life of WSNs by applying intelligent techniques of ML.

According to (Alotaibi B. et al., 2013), MAC using random forest for minimizing complexity without synchronization which returns better result than existing clustering techniques. It is hybrid type protocol. (Mustapha I. et al., 2017) have designed a hybrid protocol using reinforcement learning which is better channel utilization and extends life of networks. (Kosunlap S. et al., 2016) purposed a protocol using Q-learning which minimizes loss of packets, better topology control and better channel utilization. (Rovcanin S. et al., 2014) have designed a protocol using reinforcement learning which is dynamic in nature and requires synchronization due to centralization system. (Blondia c. et al., 2015), have created a dynamic protocol based on Reinforcement Learning that reduces latency, increases network efficiency, and eliminates the requirement for synchronisation. (Phung K. H. et al., 2015) have developed an RL-based protocol for better topology control that requires synchronisation. (Savaglio C. et. al., 2019) have designed intelligent QL-MAC protocol using Q-learning to extend life of WSNs, topology control, duty cycle is adjusted.

Table 8: MAC for WSN

Techniques Applied	**Benefits**
Random Forest	Reduces complexity, synchronization will not required for decentralized system.
Reinforcement Learning	Complexity will be application dependent. Energy aware MAC protocol will be developed

4.8 Quality of Service

The quality of service in wireless sensor networks is a large study topic with many challenges that could lead to new breakthroughs. This is an important area. It is possible to employ a variety of tactics. WSNs' main operation characteristics and their performance are being improved its components take into account how QoS measurements change as a consequence of each and every application The application of these strategies implies a compromise that may or may not be supported Depending on the application.

The key issues to achieve QoS are minimizing End-to-End delay, the packet Deadline Miss Ratio (DMR), the Bandwidth utilization, Channel Access Delay, Reducing Collisions, reducing Interference and maximize the End-to-End Reliability, energy utilization, load balancing among the sensors and Concurrent Transmissions of WSNs.
(Asif M. et al., 2017) have explained research challenges to maintain QoS in routing of WSNs. (Collotta M. et al., 2017) have purposed fuzzy logic technique for wireless sensor networks which minimizes power depletion , controls data aggregation and provides QoS. (Sun W.et al., 2017) have designed WSN using NN which improves link quality, minimizes power depletion and maintains QoS for WSNs and smart grids. (Lee E.K. et al., 2016) have designed WSN using RL with multi- agents which reduces power consumption, communication overhead for better quality of networks. (Renolad A.P. et al., 2017) have purposed multi agent based algorithm using RL which controls topology management, minimizes power and provides QoS for betterment of networks. (Ren L. et al. 2017) have purposed algorithm using Q-learning which maintains QoS of WSNs in dynamic environment (Razzaque M. A. et al., 2014) have designed routing protocol using RL which maintains QoS for best performance of WSNs. (Cedeno N. Z. Er al., 2019) have designed

Table 9: QoS for WSN

Techniques Applied	**Benefits**
ANN	We can easily find out faulty nodes, improves life of nodes and better communication of WSNs for quality improvement.
RL	We can design cross layer platform, better topology control, good routing protocol for distributed environment and provides QoS of WSNs.

5. RESULT ANALYSIS

We are taking data set of smart house with six sensors such as water flow sensor, an energy control sensor, a gas sensor, a motion sensor, a sound sensor, and a temperature sensor must be monitored to ensure that it delivers suitable comfort and safety for its residents while also lowering energy use. From fig. 6 we have observed that energy consumption is high in August and maximum in September and lowest in January, from fig. 7 we have observed that home office consumes more energy in September month. From fig. 8, it is clear that weather per month data in 2016-07 to 2016-09 fluctuates from July to September. From fig. 9, it is clear that power consumes more in 10 to 16 hours per day. From fig. 10 shows solar consumption month wise, fig.11shows power consumption for room wise and fig.12 shows power consumption for device wise.

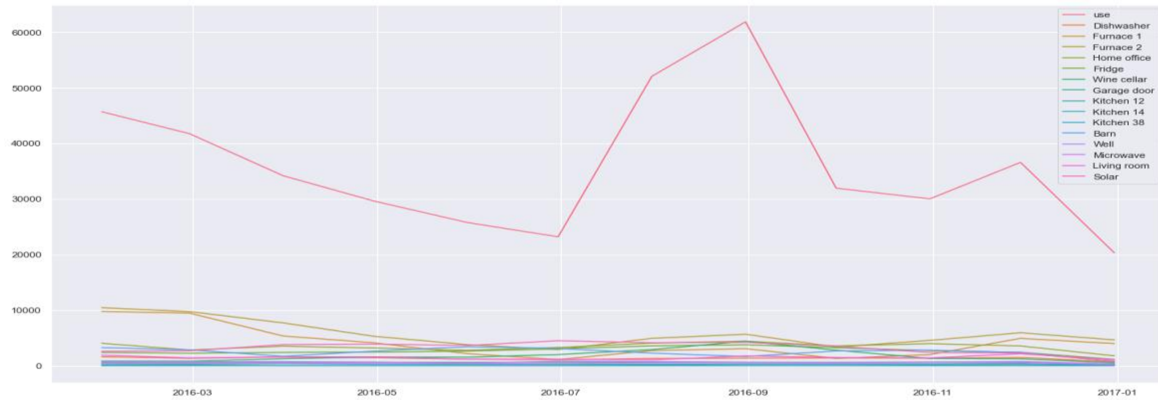

Figure 6: Power consumption month wise

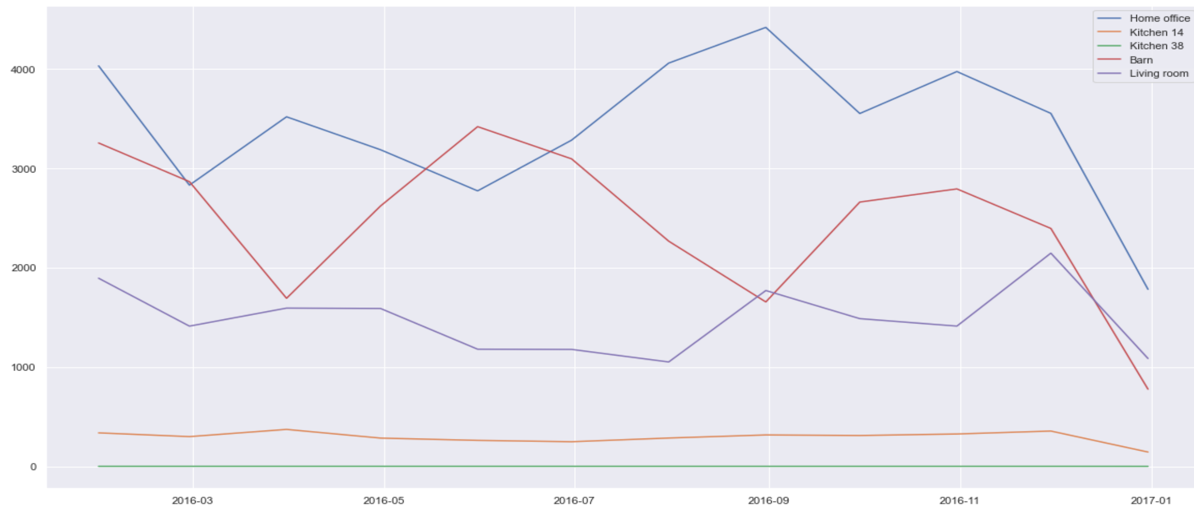

Figure 7: Power consumption room wise

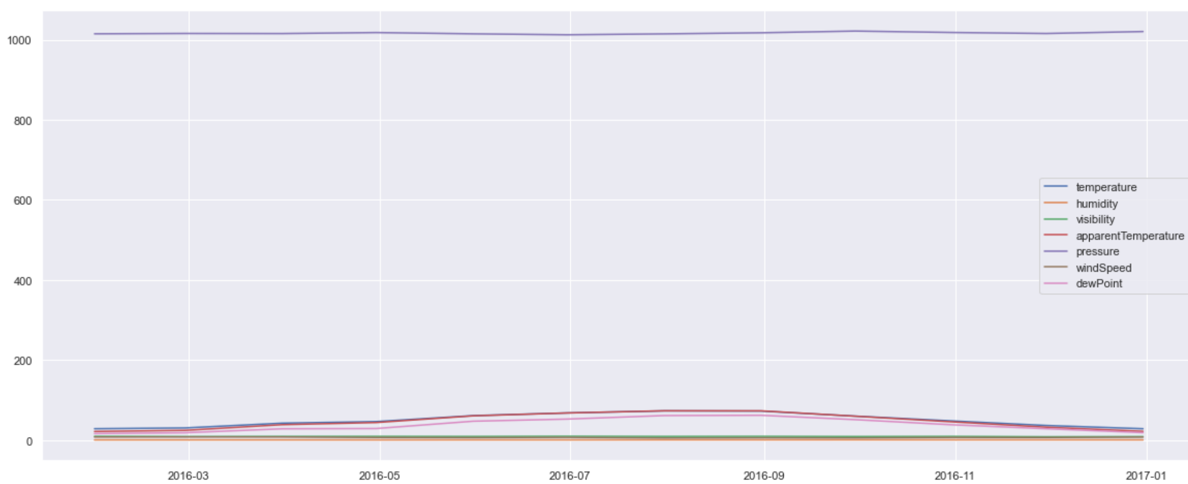

Figure 8: Weather month wise

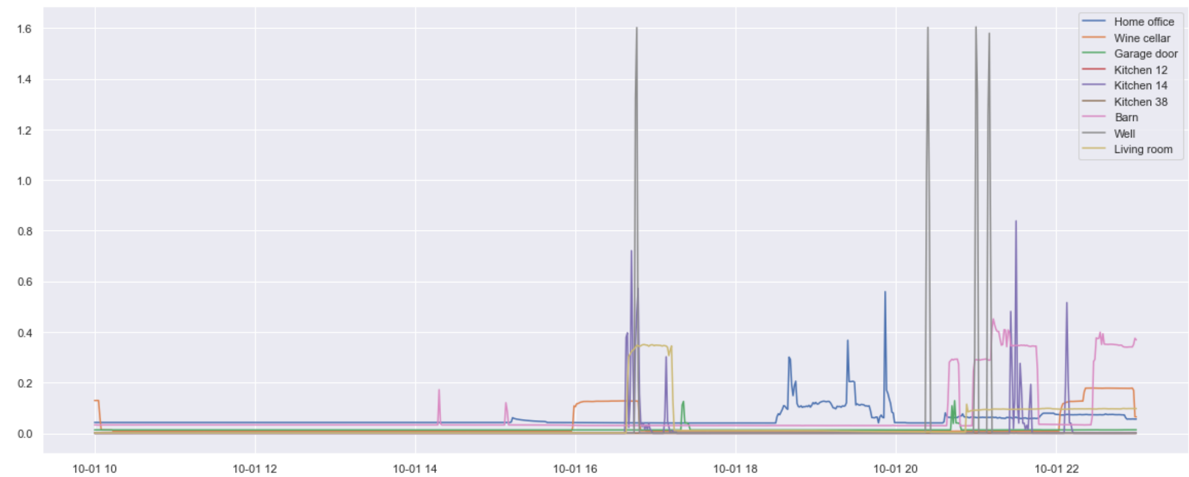

Figure 9: Power consumption on hourly

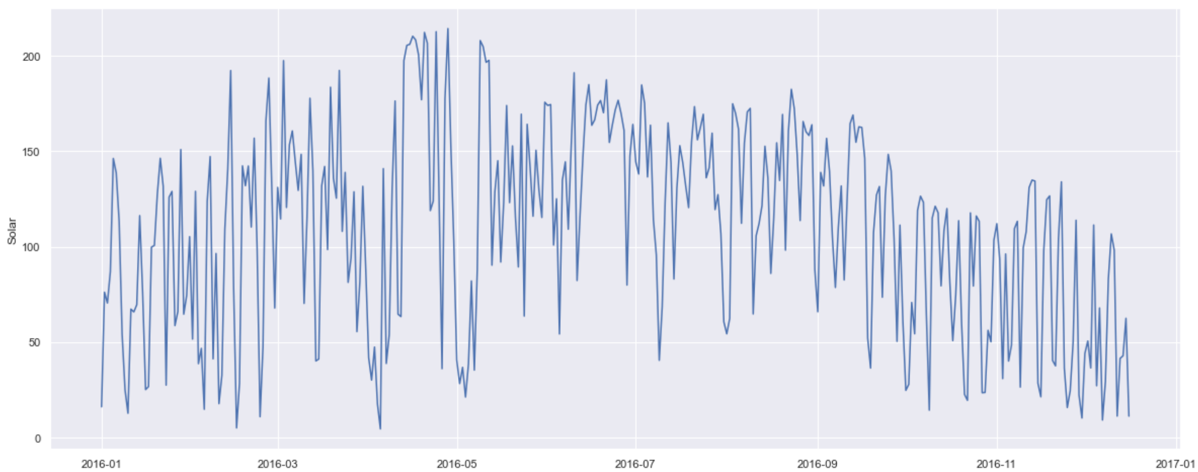

Figure 10: Solar power consumption month wise

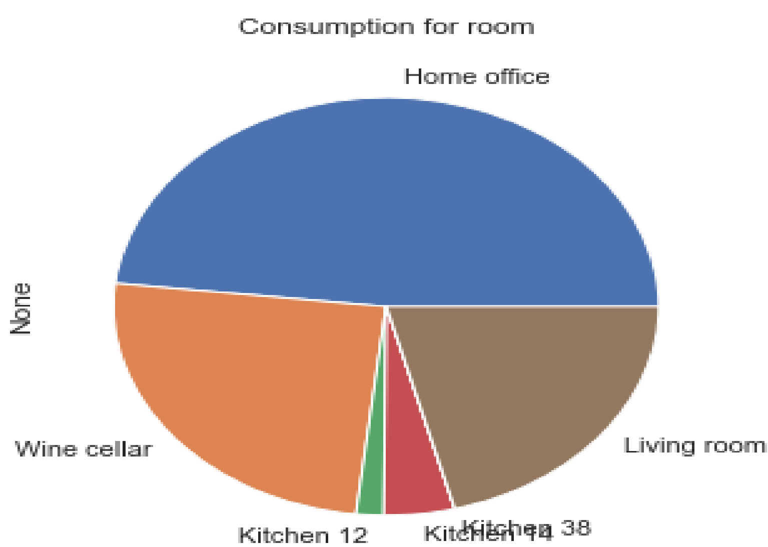

Figure 11: Room wise power consumption

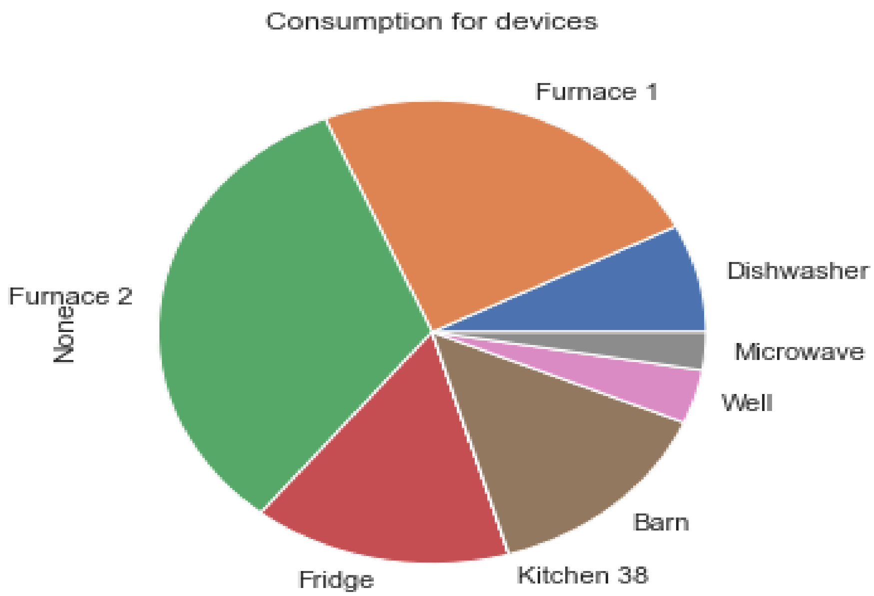

Figure 12: Power consumption device wise

6. STATISTICAL ANALYSIS

We believe that supervised learning techniques will solve the majority of WSN concerns. In recent years, supervised learning algorithms have overcome 67% of WSN difficulties. Unsupervised learning approaches answered 18% of WSN issues, whereas reinforcement learning approaches solved 15%.

7. OPEN ISSUES

There are several challenges in wireless sensor networks. So, further research desirable in area of WSNs using intelligent techniques like machine learning and soft computing. The WSNs issues are localization, coverage and connectivity, data aggregation, routing, target tracking, energy harvesting etc. shown in below table.

Table 10 : Research challenges

Sl. No.	WSN Challenges	ML Techniques	Objectives
1	Localization	SVM, Bayesian	Energy Efficient
2	Data aggregation	Regression Decision tree ANN Bayesian Genetic classifier	Less power consumption, extend life time, Data compression
3	Clustering	K-Means Fuzzy – c- means Hierarchical clustering	Less power consumption, extend life time
4	Routing	ANN Deep Learning SVM Bayesian K-Means	Improve packet delivery ratio, less delay, extend life, reliable, QoS, topology control
5	Energy harvesting	Regression Reinforcement Learning Deep Learning	Energy supplying using different sources

		Hierarchical clustering	
6	Mobile Sink	DT Bayesian K-mean clustering Hierarchical clustering Fuzzy c-means clustering EC	Data collection from sinks using shortest path
7	MAC	RF, RL	Intelligent power minimization techniques
8	QoS Management	ANN, RL	Improve quality services in each layer of networks
9	Security & anomaly detection	Q-learning, Bayesian, Deep learning, SVM, k-NN, DT, SVM, K-Means, Regression	To provide high security to sensitive data and find faulty nodes in networks, maintain accuracy in dynamic environment
10	Coverage & connectivity	DT, DL, EC	Optimal number of nodes in target area

8. CONCLUSION

We presented latest work in WSNs based on machine learning. We have discussed numerous challenges in WSNs that have arisen as a result of the use of ML approaches, such as location, data aggregation, clustering, routing, and energy harvesting. It has been discovered that genetic algorithms are successful in clusters of sensor nodes and can improve the energy efficiency of WSNs when clustering methodologies for WSNs using ML algorithms are used. In future, we will focus on data analysis using different machine learning algorithms using different data sets in different applications.

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