

# Machine Learning in Wireless Sensor Networks: A survey

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**Abstract:** Wireless Sensor Network (WSN) is a network which consists of multiple sensors which are small in size, autonomous, low power and low cost. Main objective of WSN is to measure or sense change in environmental or physical conditions overtime. WSN are often used in applications where remote data collection is required such as military applications, health monitoring, smart homes, environment monitoring etc. Often WSNs is use to monitor dynamic change in environment parameters which occur over period time. Many practical solutions which enhance the lifespan of the network and maximize resource utilization can be achieved using Machine Learning algorithms. In this paper, we present and literature review of Machine Learning methods that were used to address in general problems in WSN. The advantages and disadvantages of each algorithm are evaluated.

Key words —Wireless sensor networks, machine learning, clustering, security, data aggregation.

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## **INTRODUCTION**

Wireless Sensor Network (WSN) is a network which consists of multiple sensors which are small in size, autonomous, low power and low cost. Generally WSN is having distributed autonomous devices for the purpose of to sense or monitor physical or environmental parameters cooperatively [1]. There are various applications such as military applications, health monitoring, smart homes, environment monitoring, habitat monitoring, prediction and detection of natural calamities [2] where WSNs are used. WSN composed of thousands of tiny, inexpensive, disposable and autonomous sensor nodes which are arranged using ad hoc manner in any hostile terrain. These nodes senses data of their environment and these collaborative data are to be forwarded to centralized units which are called as Base Station (BS) or sink node for further data processing. The sensor nodes are equipped with different types of sensors, transceiver or other wireless devices, a small micro controller, limited energy sources usually a battery. WSN have enormous potential to build powerful applications. For WSN it is always challenging task to design efficient protocols which are suitable for various application. WSN protocol designers have to face common problems related to data aggregation, localization, data reliability, node clustering, events scheduling, energy aware routing.

Machine learning (ML) was introduced as a technique for artificial intelligence (AI) in the late 1950's [3]. Over time, Machine Learning algorithms are shifted to algorithms which

are robust and viable in terms of computation. Task like classification, regression and density estimation were major domain in which machine learning techniques have been used broadly during last decade. In these domains, machine learning techniques are improving performance of applications such as fraud detection, speech recognition, computer vision, bioinformatics, and spam detection. There are two classical definitions of machine learning as follow:

- 1) “The development of computer models for learning processes that provide solutions to the problem of knowledge acquisition and enhance the performance of developed systems” [4].
- 2) “The adoption of computational methods for improving machine performance by detecting and describing consistencies and patterns in training data” [5].

Based on these definitions, machine learning can be applicable to historical data to achieve performance enhancement of WSN for specific function without the requirement of re-programming. In addition, machine learning is very useful in the domain of WSN because of following main reasons:

- Main objective of WSN is to measure dynamic environments that change quickly after some time. For example, due to soil disintegration or ocean turbulence a node’s position may differ. For such applications it is convenient to design sensor networks so that network can modify and perform efficiently in such unpredictable environments.
- Another application of WSNs is to be used for collection of new data of unreachable, dangerous locations [6] (e.g., hostile environment, volcano eruption and waste water monitoring). Because of the abrupt behaviour of such environment, system designers needs design machine learning algorithms which are robust and self-adaptive in nature and these algorithms are able to adjust as per newly gained knowledge of environment.
- WSNs are generally used in harsh environments for which researchers cannot find out exact mathematical models which define the behaviour of system. Meanwhile, some tasks or function of WSNs can be defined with some simple mathematical models but it may still require complicated functions to solve them (e.g., the routing problem [7], [8]). For such scenario, machine learning techniques may provide effective solutions.
- Wireless Sensor network developers frequently have to deal with huge amounts of data so that it is difficult to identify similarities between them. Sensor nodes are having limited hardware resources [9]. With this hardware, WSN applications often has to offer energy sustainability and communication connectivity. Machine learning techniques can then be used to find out important similarities in the sensor data and propose improved sensor deployment scheme to obtain optimum data coverage.
- Another application of WSNs are in machine-to-machine (M2M) communications, Internet of things Technologies (IoT), cyber physical systems (CPS) have been introduced to support more intelligent decision-making and autonomous control [10]. For this, machine learning techniques are important to identify the different levels of abstractions needed to perform the Artificial Intelligence tasks with less or no human intervention.

However, designers of WSN have to consider few drawbacks while designing system in which machine learning techniques are used. Some of these are:

- WSN is a resource limited framework. While predicting the accurate hypothesis and extract the consent relationship within the data samples, WSN drains a considerable percentage of its energy budget. Thus, the designers should consider the trade-off between the learned model's accuracy and the algorithm's computational requirement. Specifically, the higher accuracy is achieved with higher computational requirements, and the higher computational requirements need higher energy consumptions. Otherwise, the developed systems might be developed using centralized and resource capable computational units to perform the learning task. But generally this is not preferable of typical WSN.
- In general, the intended generalization capabilities (i.e., fairly small error bounds) can be achieved by learning by examples techniques. On the other hand, learning by examples requires a large data set of samples. The machine learning algorithm's designer may not have the full control over the knowledge formulation process [11].

While designing of WSNs, parameters like power resource, limited memory, communication link failures, and change in topology are important to consider. Machine learning techniques have been successfully used to solve problems of different operational issues of WSNs such as energy efficient routing, node clustering and data aggregation, query processing and event detection, real-time routing, and localization.

#### A. Routing in WSNs

While developing routing algorithms for WSNs, designers has to deal with various design issues like scalability, fault tolerance, energy consumption and data coverage [12]. Sensor nodes in sensor network are equipped with limited resources. These resources are processing power, memory capacity and less bandwidth. In WSNs, distance between the base station and sensor node is more so it is advisable to multipath routing approach. In general, a routing problem is defined as a graph  $G$ . This graph  $G$  is define as  $G = (V,E)$ . For this graph  $G$ ,  $V$  is the collection of all nodes and set of communication channels (bidirectional) which connects all sensor nodes together is represent as  $E$ . Using this model, the routing problem can be defined as "the process of finding the minimum cost path starting from the source vertex, and reaching towards all destination vertices, with the help of available graph edges". The path in which vertices includes the source node (i.e. parent node) and destination nodes (i.e. child nodes that do not have any further child nodes) is called as spanning Tree  $T$ . This spanning tree is denoted as  $T = (V,E)$ . To solve such spanning tree with effective data aggregation is difficult when knowledge of full topology is available [7].

Using machine learning techniques, a WSN can learn from previous occurrences or experiences and accordingly decide optimized routing actions. WSN algorithms can also be modified according to the dynamic change in environment. The advantages of machine learning for WSNs can be summarized as follows:

- WSN algorithms are able to get knowledge about for optimized routing paths which in turns reduce energy consumption and so increasing the lifetime of rapidly changing WSNs.
- If routing problem is divided into simpler and smaller sub-routing problems, complexity of routing problem is decreased significantly. For each sub-routing problem, nodes develop the graph structures by considering only their local neighbours, thus achieving low cost, efficient and real-time routing.

Fig. 1(a) and (b) illustrate a simple sensor network routing problem using a graph, and the traditional spanning tree routing algorithm, respectively. Routing information is exchange within sensor nodes to find the optimal routing paths. In the other side, Fig. 1(c) demonstrates how machine learning techniques can reduce the complexity of a typical routing problem by only considering neighbouring nodes' information that will be used to predict the full path quality. Each node will independently perform the routing procedures to decide which channels to assign, and the optimal transmission power.

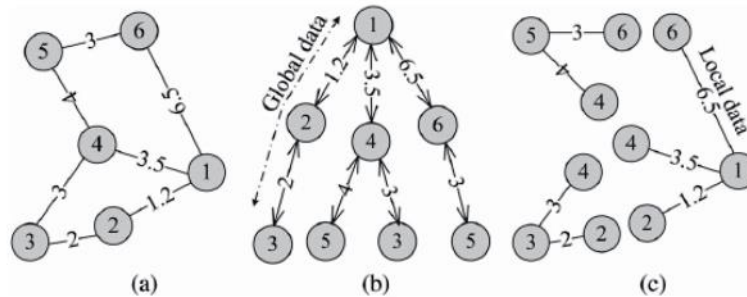


Fig. 1. Example of a sensor network routing problem using a graph along with each path routing cost, traditional spanning tree routing, and the generated sub-problems using machine learning that require only local communication to achieve optimal routing (i.e., require only single-hop neighborhood information exchange). (a) Original graph. (b) Traditional routing. (c) Simplified problems using machine learning.

**Distributed Regression Framework:** In [12], Guestrin et al. come up with a general framework for sensors data modeling. To meet a global function to match their own measurement, this distributed framework depends on the network nodes. The nodes are used to execute a kernel linear regression in the form of weighted components. Kernel functions map the training samples into some feature space to facilitate data manipulation (refer to [13], [14] for an introduction to kernel methods). The proposed framework exploits the fact that the readings of multiple sensors are highly correlated. This will minimize the communication overhead for detecting the structure of the sensor data. The main advantages of utilizing this algorithm are the good fitting results, and the small overhead of the learning phase. However, it cannot learn non-linear and complex functions.

**Data routing Using Self-Organizing Map (SOM):** Barbancho et al. [15] introduced “Sensor Intelligence Routing” (SIR) by using SOM unsupervised learning for detection of optimal routing paths as illustrated in Fig. 2. SIR introduces a minor modification of the Dijkstra’s algorithm to form the network backbone and to find shortest paths from a base station to every node in the network. During route learning phase, the second layer neurons compete with each other to reserve high weights in the learning chain. Accordingly, the weights of the winning neuron and its neighboring neurons are updated to further match the input patterns. Clearly, the learning phase is a highly computational process due to the neural network generation task. As a result, it should be performed within a resourceful central station. However, the execution phase does not incur computational cost, and can be run on the network nodes. As a result, this hybrid technique (i.e., a combination of the Dijkstra’s algorithm and the SOM model) takes into account the QoS requirements

(latency, throughput, packet error rate, and duty cycle) during the process of updating neurons' weights. The main drawback of applying such an algorithm is the complexity of the algorithm and the overhead of the learning phase in the case that the network's topology and setting change.

Routing Enhancement Using Reinforcement Learning (RL): In multicast routing, the message transfer mechanism is a node sends the message to several other nodes. Sun et al. [16] demonstrated a method to increase multicast routing for wireless ad hoc networks using Q-learning algorithm. Basically, the Q-MAP multicast routing algorithm guarantees reliable resource allocation. Generally, mobile ad hoc network are heterogeneous in nature. In other words it has different nodes with different capabilities. It is not appropriate to maintain a overall and up-to-date knowledge for the whole network architecture all the time. The multicast routes are defined in two phases. The first phase, called as "Join Query Forward" that detects an optimal route and the Q-values (a prediction of future rewards) of the Q-learning algorithm. The second phase is "Join Reply Backward" which creates the optimal path to allow multicast transmissions. As a result of using Q-learning for multicast routing in mobile ad hoc network, overhead is reduced while searching for route. However, WSNs requires energy efficiency protocols so Q-MAP algorithm needs to be changed significantly by considering constraints of WSNs.

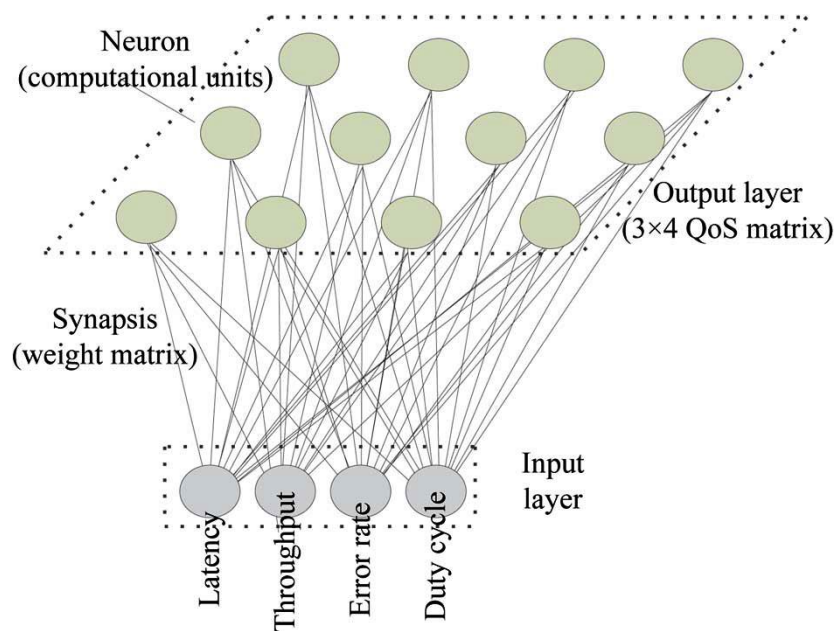


Fig. 2. Self-Organizing Map construction of the Sensor Intelligence Routing [15].

### B. Clustering and Data Aggregation

As WSNs are having limited power source, it is always preferable to transmit only relevant data to sink node [17]. One effective solution of this is to send the sense data from sensor node

to a local aggregator node which is generally called as a cluster head. This cluster head performs data aggregation process on data collected from the sensors nodes within its cluster. This aggregated data will transmit from cluster head to the sink node. Using this approach energy of sensor node is consumed less and so finally it results in energy savings of whole network. Data aggregation from a source node to a based station in Cluster based network is shown in Fig 3.

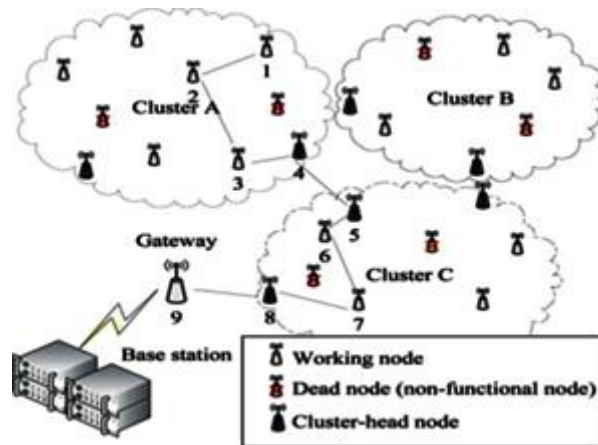


Fig. 3. Data aggregation scenario for a clustered network with the working nodes, dead nodes and cluster heads

In a network, there are chances of having some nodes as faulty in nature. Such faulty nodes should be removed from the network as they will generate incorrect data and affect accuracy and operation of a whole network. The task of data aggregation and node clustering can be enhanced using Machine Learning techniques as follow:

- Cluster head selection is critical parameter for Cluster based WSN. Machine learning techniques can be implemented for efficient selection of cluster head, where relevant cluster head selection will automatically reduce energy utilization and enhance lifespan of a network.
- Using machine learning techniques, at cluster head level data compression can be done efficiently. This data compression detects similarity and dissimilarity (generally provided by faulty nodes) in sensor nodes' readings.

Large Scale Network Clustering Using Neural Network: Hongmei et al. [18] have used neural networks for the development of self-managed clusters. This method can be used to a large scale sensor network in which sensors are having short transmission radius because for such network centralized algorithm may not work effectively. On the other hand, for a sensor network in which sensors are having large transmission radius performance of this algorithm is more or less equal to centralized algorithm.

Applying Decision Tree for selection of a Cluster Head: Ahmed et al. [19] have solved critical problem of cluster head selection problem using a decision tree algorithm. In decision tree algorithm, some critical parameters like distance between node and cluster, remaining power source, the degree of mobility are used at the time of iterating the input vector. The simulations shows that this approach of selecting cluster head increase the overall performance as compared to “Low Energy Adaptive Clustering Hierarchy” (LEACH) [20] algorithm.

Application of “Learning Vector Quantization for Online Data Compression”: Some WSNs protocols require an updated full knowledge of the network topology, on the other side there are some protocols which may not need full knowledge of the network topology.

Lin et al. [21] proposed a technique called “Adaptive Learning Vector Quantization (ALVQ)” for effective fetching of compressed data from sensor nodes. ALVQ uses the Learning Vector Quantization algorithm for prediction of code-book using pervious training samples. The ALVQ algorithm minimizes the bandwidth requirement at the time of transmission. This algorithm also boosts up accuracy of retrieval of original data from compressed data. The main disadvantage of Learning Vector Quantization while doing online data aggregation is dead neurons, which are at distance from the training samples. These dead neurons will never participate in competition. So it is very important to design algorithm that are robust against such outliers.

## **Conclusion**

There are significant difference between Wireless Sensor Network and traditional network. Therefore it is necessary to develop protocols that address general limitations and challenges of WSNs. As a result, WSNs needs innovative solutions for general challenges such as security, real-time routing, localization, data aggregation. Machine Learning techniques provide reasonable solution to enhance overall performance of the network. Moreover, number of issues is still open and needs to explore by researchers to develop robust protocols for WSNs.

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