Applications of Hidden Markov Model in Wireless Sensor Network

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Abstract--- *WSN is now widely used, due to its cost effectiveness and ease of deployment. Traditional sensor network approaches fail to respond dynamically; hence machine learning can be new techniques to be explored. The benefit of machine learning is that they can self learn, without human intervention or reprogramming. A concise introduction of classification of Machine learning algorithm is discussed. A review of one of the most promising technique Hidden Markov Model is covered. In recent decades, Hidden Markov model is being explored as the new technique for Wireless Sensor Networks. Hidden Markov model can efficiently perform time series prediction with generalization. This work emphasizes on recent applications of Hidden Markov Model to solve various issues and challenges in Wireless Sensor Networks.*

Keywords--- *Machine Learning (ML), Hidden Markov Model (HMM), Wireless Sensor Networks (WSN).*

I. INTRODUCTION

Machine Learning (ML) is the process that can learn on its own, based on the study and experience. The strength of ML algorithm is, they can act and improve their performance. ML algorithm can model complex data and provide quick and more accurate results as compared to other algorithm. ML technique is reliable, fast and cost effective. ML can be applied diverse interdisciplinary problems from various fields like medical, engineering and computing. In the recent years, ML has been applied to solve various issues in WSN. Sensor nodes transmit vast amount of data to the Base station. ML algorithms are appropriate for extracting meaningful information and inferences from the available data.

ML can be classified into three types based on the learning style i.e. supervised, unsupervised and reinforcement learning

1. Supervised Learning: For supervised learning technique, the learning algorithm is provided with labeled training data set. The system being modeled is build by creating rules from training dataset. Model is selected and training is performed to make the machine learn the relationship between input, output and system parameters.

2. Unsupervised Learning: For unsupervised category, no labeled dataset is provided. The algorithm learns by clustering various set of data into various groups or clusters, and by discovering similarities between input data samples.

3. Reinforcement Learning: Is an interactive reward based learning technique, it learns by interacting with the environment to maximize the rewards.

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DOI: 10.37200/IJPR/V24I4/PR2020465
Received: 12 Mar 2020 | Revised: 25 Mar 2020 | Accepted: 10 Apr 2020

Apart from this, learning can be combination of both supervised and unsupervised learning also known as hybrid or semi supervised learning.

There are various supervised and unsupervised learning algorithm available. Depending on the problem statements and scenarios one can select best algorithm by trial and error. Simple algorithms are easy to implement but have low accuracy. Highly flexible model are hard to implement and can over fit the data.

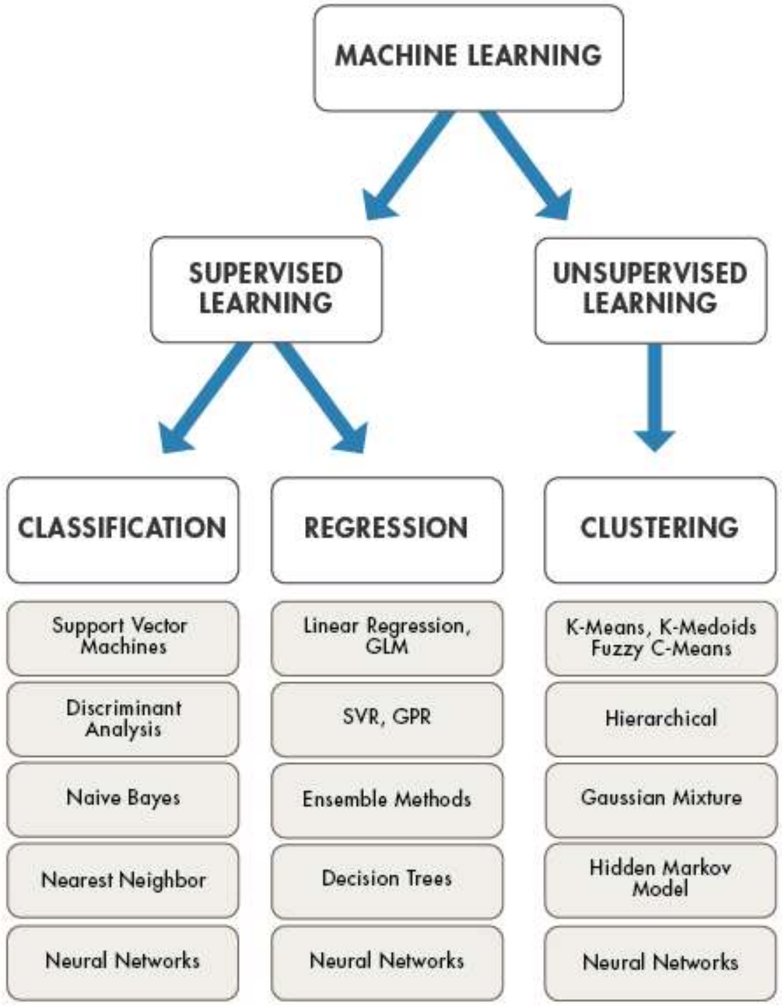

Figure 1: Classification Machine Learning Algorithm Adapted from [1]

The Supervised learning problem can be categorized as classification or regression problem. Unsupervised problems are generally clustering problems. A generic classification of machine learning algorithm is given in Figure 1.This paper describes a review on unsupervised learning based Hidden Markov Model and their applications in WSN.

II. HIDDEN MARKOV MODEL (HMM)

HMM is the probabilistic framework, computationally simple but having strong mathematical formalism. HMM are used for sequential data modeling, as they can manage multivariate data of variable length and are capable in identifying hidden properties of time series. It provides a good statistical framework for solving a wide range of problems, including bioinformatics, financial trend analysis, optical character recognition, activity recognition and speech recognition etc.

The Hidden Markov Model is a well known statistical model of great practical value [2]. It is widely used for diverse learning problems both supervised and unsupervised paradigms. The HMM is double stochastic process with one stochastic process as hidden and modeled as Markov chain, and the second stochastic process is observable. A HMM is denoted by

$$\lambda = (\pi, A, B) \qquad Eq. 1$$

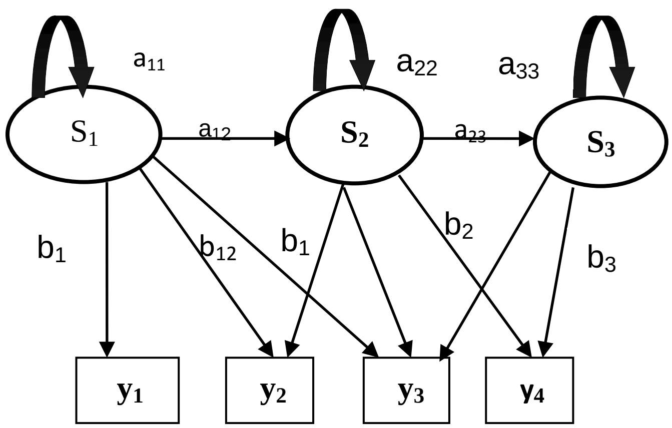

Figure 2: Hidden Markov Model Architecture

- $S = \{S_1, S_2, \ldots\ldots\ldots, S_N\}$ represents a set of hidden states.
- Y is a set of observable parameters. $Y = \{ y_1, y_2, \ldots, y_T\}$
- A is the transition matrix where, $A = \{a_{ij}\}$ stands for the probability of transition from state S_i to S_j

$$a_{ij} = P[S_j(t+1)|S_i(t)] \qquad 1 < i, j \le N$$

- B represents emission matrix where $B = \{b_{jk}\}$ stands for the probabilities of emission symbols y_k in hidden state S_j,

$$b_j(k) = P[y_k(t)|S_j(t)] \qquad 0 \le j \le N, 0 \le k \le T$$

- Where π represents initial hidden state probabilities, $\pi_i = P[S_i]$, $0 \le i \le N$
- Constraints are $\sum_j a_{ij} = 1 \; \forall \; i$ and $\sum_k b_{jk} = 1 \forall \; j$

III. HMM TOPOLOGIES

HMM is a probabilistic model of observable symbols whose probability is determined by underlying hidden states of Markov chain. For any HMM model, there exist a directed graph of states and allowed transitions between states. This corresponds to respective zero and non zero entries of transition matrix of that HMM Model. It is difficult to choose a topology and number of states for HMM Model. It becomes easy to select HMM parameters if prior knowledge about data to be modeled is available.

DOI: 10.37200/IJPR/V24I4/PR2020465
Received: 12 Mar 2020 | Revised: 25 Mar 2020 | Accepted: 10 Apr 2020

1. Fully Connected Model

An HMM is termed fully connected when all states are connected and there is no distinguishable starting or ending states. All possible transitions between the states are allowed and underlying digraph is complete. Transition matrices have no zero entries except for the diagonal elements. If self loop are allowed, fully connected model will have all N x N elements with non zero values.

2. Left to Right Model

For any N state HMM model, transition matrix consist of N x N elements. As amount of computations are directly proportional to transitions probabilities. Depending on the problem being modeled, there may be some zero transition. To reduce computation, it will be practical to disallow such transitions, when it is appropriate. In left to right structure states follow a sequential order, and transition goes from “left” to “right”. Another option is transition back to same state. A stringent left to right model is the one in which self loops are not allowed, and transitions occur only to the next consecutive state in the model**.**

3. Circular Model

It has no unique starting or terminating state, and the underlying directed graph is ergodic.

IV. APPLICATION OF HMM IN WSN

Advanced machine learning is being adopted increasingly for solving WSNs problems. There are various issues in WSN such as limited memory, low battery power, dynamic topology and link failures [3]. HMM has been utilized to overcome the challenges and improve performance of the network. HMM based approach can be used to deal with functional issues in WSN, such as data aggregation, Clustering, routing and localization [4]. HMM can be equally helpful for addressing non functional requirements in WSN like improving data quality and quality of service.. A brief overview of application of HMM in WSN is presented below

1. Enhancing Sensor Data Quality

Data Failures in WSN are inevitable; one possible way to deal with it is using prediction. Prediction can help in recovering missing data values, and predicting upcoming data values. Generally prediction is based on the analysis of historical data. Prediction can contribute to enhance the data quality and message reduction in WSN scenario. An improved HMM based multi step prediction model is proposed to predict and analyze varying data patterns in WSN [5]. The parameters of HMM are optimized using particle swarm optimization. The model was evaluated on agriculture and industrial datasets. The model consist of four main procedures Preprocessing, Training, optimizing and predicting. The proposed model is compared with back propagation, neural networks; Naïve Bayesian, Grey System, and traditional HMMs. Ahmed, et al. [6] used an approach to optimize energy consumption of WSNs, by predicting power available in the battery of each sensor node. The approach is based on HMM and Fuzzy Logic. The first step is learning WSN behavior and second step is predicting QOS parameters. The feasibility of the approach is illustrated by a use case of deployment of WSN in data centre.

DOI: 10.37200/IJPR/V24I4/PR2020465
Received: 12 Mar 2020 | Revised: 25 Mar 2020 | Accepted: 10 Apr 2020

2. Energy Level Modeling

Hu et al. [7] proposes a HMM based approach for energy level prediction in WSN. The approach can predict the energy state of individual nodes and network which can be helpful for designing energy efficient routing protocols. Gustavo et al. [8] proposed a method to construct an energy map for software defined wireless sensor network. For this, an energy consumption prediction model is implemented into the controller, which acquires information of each node and estimates its energy consumption rate. Node processing overhead and memory usage is greatly reduced.

3. Clustering and Cluster Head (CH) Selection

A CH performs complex tasks, hence consumes more energy than an ordinary node. In order to balance energy utilization CH rotation is essential. The WSN topology is dynamic due to insertion of new node, node failures and death /loss of nodes. To manage the operations of network, control messages are exchanged periodically to identify energy left in each sensor node. The criteria of selecting cluster head depend on the objective of clustering.

The choice of Cluster Head is difficult and CHs are generally chosen dynamically based on residual energy or battery left in the sensor node. The network size/dynamics keep on changing; hence a log of dead and alive nodes is maintained periodically. Based on the gathered information new CHs are selected. Overall communication energy in WSN can be considerably be reduced by formation of clusters and choosing appropriate cluster heads [9]. Hence numerous works on energy efficient clustering algorithms on WSN exist in the literature. Predicting sensor data and messages are studied exclusively to deal with data failure and noise reduction in WSN [10]. Goudarzi et al. [11] proposed a centralized clustering algorithm based on HMM. HMM parameters are optimized using particle swarm algorithm; the approach is then used to predict the energy level of the sensor nodes. PSO is applied again with new cost function to elect the cluster head. The combined approach minimizes the cost of clustering and improves the clustering performance.

Veena K et al. [12] propose a dynamic clustering algorithm based Kohenan self organizing map. The sensor node parameters memory, processing speed, available power and residual energy are fuzzified. The result obtained from fuzzy logic system is used as observation sequence for Hidden Markov model to estimate the application coefficient of each sensor nodes. The application coefficient serves as criteria to decide best application that is suitable for that node. According to the application requirement, KSOM cluster nodes for different types of application such as precision agriculture, critical applications etc.

C. B. Vinutha [13] proposes a cluster based adaptive power control protocol for CH selection. The cluster head are selected considering parameters such as received signal strength (RSS) values, residual battery power and node distances. Weight based approach is used and node with least weight is selected as cluster head (CH). RSS values are the observation states of the nodes and hidden states are the transmitted power levels of the nodes. Once the HMM is trained the CH can estimate the initial power of its cluster members. CH constantly monitors the Quality of link and RSS of the cluster members, in case of any variations in these parameters, the transmission power level are recomputed by HMM and information is provided to all the cluster members. This dynamic power control technique reduces packet drops and optimizes consumption of energy in the network. A combined Particle swarm optimization and HMM based approach is used for clustering in WSN.[14]. HMM is used for energy level prediction of sensor

DOI: 10.37200/IJPR/V24I4/PR2020465
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nodes, based on energy level CH are selected.

4. Localization

Localization is the process of estimating the geographic location of the node. The position of node plays an important role in various operations of WSN. A large sensor networks comprises of thousands of nodes, using GPS for localization in such scenarios increases energy consumption and deployment cost. It is practically not feasible to use GPS for large scale WSN, hence localization algorithm plays important role. Location requirement can be relative or accurate based on the application of WSN

Zang et.a [15] l proposes HMM based hybrid model and takes time factor into consideration, when receiving RSS sequence and then performs classification. RSS values are compared with preset threshold values, based on it if value is above threshold values then signal propagation model is used, else trained HMM is used for distance calculations.

Arthi and Murugan [16] proposes a localization technique using HMM and algorithm is compared with particle filter algorithm. The Received Signal Strength Indicator (RSSI) level is used for localization. The analysis depicts that Semi Markov Smooth (SMS) mobility model can achieve better localization using HMM in WSN. The work was extended further by [17] using heterogeneous sensors and incorporating various mobility models with Hidden Markov Model. The mobility models considered are random waypoint, reference point group mobility model (RPGM) and random walk semi markov mobility model. The performance metrics like overhead, energy control error, and density of node are calculated.

5. Intrusion and Anomaly Detection System

Rapid increase in network devices has increased the probability of security threats and violations. Computer networks and communication links if not secured can lead to loss of precious and critical information of important organizations. Hence various business and military organization require Intrusion Detection System (IDS) competent of automatically detecting intrusions. The key tool for intrusion detection system is anomaly detection which works on simple principle of finding abnormalities in system, user and network behavior.

Debin Gao et al. [18] proposed an approach of detecting anomalies in network or in the packets using behavioral distance based HMM. Anomaly detection is performed based on the behavioral distance between two states. Anomaly is detected only if distance is greater than the threshold value. The results depict HMM based approach detects anomalies with good accuracy.

YanLing et al. [19] proposes intrusion detection system based on HMM to compute the output probability of short sequence of system calls. It uses two state HMM, where one state represents normal while another represents anomalous behavior. Observation sequences are short and fixed in length. A set of observed system behavior are represented by a set of discrete symbol handled by HMM. The system computes average probability of occurrence of these sequences. On the basis of average probability the normality of the system is defined. If the statistical characteristic of sequence sent by process is different the behavior is considered as anomalous.

HMM in combination with theory of rough sets for anomaly detection is proposed [20]. A normal fixed length

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sequence of system calls are transformed into a decision table. This table is reduced and used to deduce certain norms. These norms are applied to define normal behavior and are used to detect anomalies. For on time detection of anomalies, a detection engine based on HMM is used. This HMM engine is designed with 30 states, with observation sequence of length 182.

6. Activity Recognition

Human activity recognition is required in the health care systems, human computer interaction, robotics for human behavior characterization and in video surveillance. Human activity recognition system has ability to interpret human gestures or motion via sensors and determine the human action or activity.

Cho et al. [21] propose an activity recognition technique to detect body gestures and motion. The sensors are placed throughout the body and they provide accelerometer readings with three axis measurements. The HMM model is used which uses these sensor readings as observation sequence and predicts the activity at each sensor. The features are extracted from the accelerometer sensors. These features are compared with predefined threshold values. Each raw sensor reading is thus converted into either positive, negative or null. For improving classification and accuracy, a naïve bayes classifier is used for final gesture decision.

Kabir et al. [22] uses a two layer HMM model for identification of Activities of Daily Living (ADL) in Home Environment. First layer predicts the activity class based on location data of object, and the second layer is used to determine activity from the selected class. This approach reduces time complexity as the first layer identifies activity class, and the second layer concentrates only on the variables related to selected class only. For the evaluation of the approach three real datasets were used.

V. CONCLUSION

In this survey, the recent HMM based approaches used in wireless sensor network were summarized. The work highlights various issues in WSN addressed by HMM like localization, intrusion detection, anomaly detection, and clustering. The performance of the HMM primarily depends on the selection of initial transmission and emission matrix. Apart from this number of states, HMM topology and training data size also affects the performance of HMM model. HMM algorithms are generally used at the base station as high computation is required for processing training data and implementing these algorithms. Machine learning techniques can be applied to solving different problems of WSN. It is difficult to identify the appropriate ML techniques for the problem. Future work involves exploring other Machine learning algorithms and discovering their strengths and weaknesses.

REFERENCES

[1] J. Brownlee, “a-tour-of-machine-learning-algorithms,” 15 January 2020. [Online]. Available: https://machinelearningmastery.com/a-tour-of-machine-learning-algorithms/.

[2] L. R. Rabiner, “A tutorial on hidden Markov models and selected applications in Speech recognition,” *in SIAM interdisciplinary Journal*, 1989.

[3] B. T. &. B. V. &. K. S. &. J. V.Bala, “ A survey: Issues and challenges in wireless sensir network,” *International Journal of Engineering and Technology(UAE)* , vol. 7, pp. 53-55, 2018.

[4] S. L. N.-P. T. Mohammad Abu Alsheikh, “Machine Learning in Wireless Sensor Networks:Algorithms, Strategies, and Applications,” *IEEE Communications Surveys & Tutorials,* vol. 16, no. 4, pp. 1996 - 2018, 2014.

DOI: 10.37200/IJPR/V24I4/PR2020465
Received: 12 Mar 2020 | Revised: 25 Mar 2020 | Accepted: 10 Apr 2020

[5] Z. Z. Y. C. &. L. L. Xiaofei Xu, " HMM-based predictive model for enhancing data quality in WSN," *International Journal of Computers and Applications.,* 2017 .

[6] M. H. R. B. H. A. H. K. K. D. a. M. J. J. Ahmed, "Energy Saving In WSN Using Monitoring Values Prediction," *Procedia Computer Science,* pp. vol. 32,1154-1159, 2014.

[7] Z. Z. L. L. Peng Hu, "The HMM-based Modeling for the Energy Level Prediction in Wireless Sensor Networks," *in Second IEEE Conference on Industrial Electronics and Applications.,* 2007.

[8] G. A. N. a. C. B. Margi, "Energy Map Model for Software-Defined Wireless," *XXXV Brazilian Symposium on Telecommunications ...,* 2017.

[9] V. &. K. S. &. J. V. Bhatia, " Comparative study of cluster based routing protocols in WSN," *International Journal of Engineering & Technology,* vol. 7, p. 171, 2017.

[10] S. Hugtenburg, "Reducing the need for communication in wireless sensor networks using machine learning and planning techniques," *DElFT,* 2017.

[11] B. J. a. M. S. Rouhollah Goudarzi, "An Efficient Clustering Algorithm using Evolutionary HMM in wireless sensor Networks," *in International Conference on Embedded and Ubiquitous Computing IEEE,* 2010.

[12] V. K. B. Veena K.N., " Hidden Markov Model with Computational Intelligence for Dynamic Clustering in Wireless Sensor Networks," *in International Conference on Advances in Computing,* Bangalore, 2012.

[13] N. N. a. M. N. C. B. Vinutha, "Cluster-based adaptive power control protocol using Hidden Markov Model for Wireless Sensor Networks," *International Journal of Electronics,* pp. vol. 104, no. 6,, 2017.

[14] D. V. J. S. K. a. D. K. S. K. Varsha Bhatia, "A Hidden Markov Model based Prediction Mechanism for Cluster Head Selection in WSN," *International Journal of Advanced Science and Technology,* vol. 28, no. 15, pp. 585 - 600, 2019.

[15] Y. &. W. J. &. L. L. &. L. P. Zang, "The Hybrid HMM for RSS-based Localization in Wireless Sensor Networks," *Applied Mechanics and Materials.,* pp. 347-350., 2013.

[16] A. a. K.Murugan, " Localization in Wireless Sensor Networks by Hidden Markov Model," *in ICoAC,* 2010.

[17] R. &. M. K. Arthi, Scenario Based Analysis of Localization of Sensor Nodes *Using HMM,* 2010.

[18] M. K. R. a. D. S. Debin Gao, "Behavioral Distance Measurement Using Hidden Markov Models," *LNCS* 4219, p. 19–40, 09 2006.

[19] S. D. a. S. YanLing, "Detection of Network Intrusion Based on a HMM Model," *in 2010 Second International Conference on Multimedia and Information Technology,* Kaifeng, 2010 .

[20] Z. C. a. X. Ji, "An Efficient Intrusion Detection Approach Based on Hidden Markov Model and Rough Set," in *International Conference on Machine Vision and Human-machine Interface, Kaifeng, 2010*.

[21] Y.-S. L. a. S.-B. Cho, "Activity Recognition Using Hierarchical Hidden Markov Models on a Smartphone with 3D Accelerometer," in Hybrid Artificial Intelligent Systems: *6th International Conference, HAIS* 2011, Wroclaw Poland , 2011.

[22] M. R. H. K. T. a. S.-H. Y. M. Humayun Kabir, "Two-Layer Hidden Markov Model for Human Activity Recognition in Home Environments," *International Journal of Distributed Sensor Networks,* p. 12, 2016.

[23] L. D. Alahakoon, "Controlling the spread of dynamic self-organizing maps," *Neural Computing & Applications,* vol. Volume 13, no. 2, pp. 168-174, 2004.

[24] A. P. C. a. H. B. W. B. Heinzelman, "An application-specific protocol architecture for wireless micro sensor networks," *IEEE Transactions on Wireless Communications,* vol. 1, pp. 660-670, 2002.

[25] S. K. H. a. B. S. D. Alahakoon, "Dynamic self-organizing maps with controlled growth for knowledge discovery," *Neural Networks, IEEE Transactions,* vol. 11, pp. 601-614, 2000.

[26] Siddeswara Mayura Guru, Arthur Hsu, and Saman Halgamuge, "An Extended Growing Self-Organizing Map for Selection of Clusters in Sensor Networks," *International Journal of Distributed Sensor Networks ,* vol. 1, pp. 227-243, 2005.

[27] A. H. S. H. a. S. F. Siddeswara Mayura Guru, "Clustering Sensor Networks Using Growing Self-Organizing Map," *ISSNIP* , 2004.

[28] E. U. A. M. &. T. K. Warriach, " A Machine Learning Approach for Identifying and Classifying Faults in Wireless Sensor Networks," *in International Conference on Computational Science and Engineering,* 2012.

[29] B. Y. a. T. Sasikala, " Intrusion detection system for mitigating attacks using energy monitoring in wireless sensor networks," *International Journal of Mobile Network Design and Innovation,* vol. 6, no. 4, 2016.

[30] B. A. a. M. Ponnavaikko, "Energy Efficient Hidden Markov Model Based Target Tracking Mechanism in Wireless Sensor Networks," *Journal of Computer Science,* vol. 5, no. 12, pp. 1082-1090, 2009.

DOI: 10.37200/IJPR/V24I4/PR2020465
Received: 12 Mar 2020 | Revised: 25 Mar 2020 | Accepted: 10 Apr 2020

[31] K. D. a. Y. H. Victor Obado, “Hidden Markov Model for shortest paths testing to detect a Wormhole Attack in a localized Wireless Sensor Network,” *in IST-AWSN,* 2012.
[32] S. D. a. B. N. Nilayam Kumar Kamila, “Neural network Enabled WSN Management for Energy Effcient Routing Mechanism,” *Indian Journal of Science and Technology,* vol. 9, no. 26, July 2016.
[33] A. L. Q. F. a. B. J. K. Mengxue Cao, “Growing Self-Organizing Map Approach for Semantic Acquisition Modeling,” *in International Conference on Cognitive Info communications, Budapest, Hungary,* 2013.
[34] M. A. F. D. P. V. S. Bernard Robles, “HMM Framework, for Industrial Maintenance Activities,” *in QUALITA,* 2013.
[35] A. K.Murugan, “Localization in Wireless Sensor Networks by Hidden Markov Model,” *in ICoAC,* 2010.