Wireless Sensor Networks based IoT

Subjects: Computer Science, Artificial Intelligence
Contributor: Himanshu Sharma

The WSN based IoT (WSN-IoT) design problems include network coverage and connectivity issues, energy consumption, bandwidth requirement, network lifetime maximization, communication protocols and state of the art infrastructure. In this paper, the authors propose machine learning methods as an optimization tool for regular WSN-IoT nodes deployed in smart city applications.

Keywords: Internet of Things (IoT) ; sensor nodes ; WSN-IoT ; artificial intelligence ; reinforcement learning ; smart city

1. Introduction

A smart city is an urban area that uses remote sensors and the Internet of Things (IoT) enabling technologies to collect data from different locations and uses to enhance the quality of life of the people. The low power, low data rate wireless sensor networks (WSN) are used for monitoring and control applications in smart cities. The WSN nodes are used as the underlying technology infrastructure in the IoT. In the IoT, the *"things"* refer to the tiny embedded physical sensing devices (i.e., WSN nodes) connected to the internet to perform a specific application. Currently, a new revolutionary technique known as artificial intelligence (AI) and machine learning (ML) is evolving as the future of fully automated IoT applications. Machine learning is a part of AI, in which, the computer algorithms learn by themselves by improving from past experiences. A detailed survey of ML algorithms was performed in [1] until the year 2013. As the ML and IoT, technologies are emerging rapidly, therefore, the authors extend their survey work also. The IoT applications in smart cities are smart traffic monitoring [2], smart grids [3], smart waste management [4], smart agriculture [5], smart medical healthcare [6], etc.

The major problems in WSN based IoT (WSN-IoT) are fully autonomous operation, maximum network lifetime, energy efficiency, quality of service (QoS), cross-layer optimization, high bandwidth requirement, sensor data analysis, cloud computing, communication protocol design, etc. Currently, the industrial IoT (IIoT) or industry 4.0 is the biggest revolution for smart industries, smart manufacturing sector, automobile sector, smart cities and medical healthcare sector. Worldwide, various major companies like Microsoft, Google and Amazon are working on the development of AI and ML-based algorithms in advanced IoT applications for smart cities.

Machine learning can be applied in WSN-IoT for dynamic updating of routing tables in WSNs, node localization in mobile WSN-IoT nodes, identification and separation of faulty nodes for network optimization and prediction of the amount of energy harvesting in energy harvesting WSN (EH-WSN). Through this paper, the authors have tried to answer the following research questions: Why machine learning methods are used in WSN-IoT? What is its superiority of using ML over traditional optimization methods in WSN-IoT? Why is the smart city a typical use case of IoT applications?

IoT offers new opportunities for smart cities to use data to manage traffic, reduce pollution and make better use of infrastructure. The following are the advantages of using machine learning in traditional WSN-IoT:

- WSNs are generally deployed in a dynamically changing environment. Therefore, self-adaption to the new environment is expected from a fully automated IoT scenario.
- Unknown parameter monitoring requires automatic adjustment of network topology and configurations, e.g., temperature measurement in a glacier or volcano monitoring.
- Lack of accurate mathematical models of the unknown parameters in WSN-IoT.
- WSN-IoT deals with a large amount of sensor data, therefore the correlation between different data set may be of critical concern.
- Integration of WSN in IoT using cloud-based services for better monitoring and control.
- Future predictions and possible actions in WSN-IoT.

- The IoT generates a large amount of data from millions of sensor nodes. Machine learning is powered by data and generates useful information from previous data. Machine learning uses past IoT data to identify hidden patterns and builds models that help predict future behavior and events.

As WSN-IoT are resource-limited (finite bandwidth and power availability) therefore, there are some limitations for running ML-based inferences on IoT nodes also such as:

- A large number of computations are required to process the more amount of data, hence computation complexity increases.
- Additional power consumption.
- Training of WSN-IoT nodes for various ML algorithms requires complex operations and multi-domain skilled programmers.

2. Summary of Literature Survey of ML Techniques for WSN-IoT

We provides a summary of all machine learning (ML) techniques proposed as an optimized solution for WSN-IoT problems. In a smart city, the major challenges are as follows: smart education, smart classrooms, smart traffic monitoring, rain water harvesting, smart grids in smart buildings smart healthcare in hospitals, smart agriculture, industrial IoT (or Industry 4.0), smart waste management, smart governance, smart environment monitoring, etc. Now, we will map each problem of smart cities with the solution provided by machine learning algorithms in WSN-IoT. The WSN node localization problem is considered as a classification or multivariate regression task in the ML domain. Therefore, SVM classification [7] or SVM regression model [8] algorithms are applied as a solution for the node localization problems in WSN-IoT.

The security issues are tackled by correlation techniques and handled by using the Bayesian learning technique as [9][10][11]. Cluster head selection tasks in WSN-IoT are considered clustering tasks in the ML domain. The k-NN [12][13][14], PCA [15][16][17] and ANN [18][19] have been used for clustering. WSN node energy management is considered a prediction problem in the ML domain. The Q-Learning [20][21] has been applied to predict the energy issues. Similarly, in energy harvesting based WSN (EH-WSN) predicts future energy availability using reinforcement learning algorithms like Q-Learning [22], SARSA [23] and deep Q-learning [24] have been applied. Event monitoring and fault detection problems are considered as classification models. These are solved by SVM [25][26] and rule-based Learning [27][28][29][30] algorithms.

The routing of data packets in WSN-IoT is considered a classification problem in the domain of machine learning. The routing optimization algorithms such as genetic algorithms [31] and classification algorithms such as Markov decision process (MDP) in decision tree [32], random forest [33] and Q-learning (QELAR) [34] have been used.

At the MAC layer, the packet scheduling task is considered a regression task in the machine learning context. Therefore, SVM [35], deep neural networks [36] have been applied at the MAC layer. The QoS (latency, bandwidth and coverage) in IoT is considered a prediction problem in IoT. Therefore, Q-Learning, ANN [37] and SVM [38] have been used as the solution. Spectrum sharing in WSN-IoT is a self-learning problem, which can be solved by a deep reinforcement learning [39][40] technique. Data aggregation is a technique in which redundant information is removed before processing by the server. Data aggregation is treated as a regression problem and is solved by SVM [41] and reinforcement [42] respectively. Table 1 shows the summary of the literature survey of ML techniques for WSN-IoT.

Table 1. Summary of literature survey of ML techniques for WSN-IoT.

S. No.	Smart City Applications	WSN-IoT Issues in Smart Cities	Addressed ML Algorithms as Solutions by Researchers Worldwide	Our Remarks
1	**Smart traffic Monitoring**	**WSN Node Localization**	**SVM Classification [7] and SVM regression model [8]**	**Localization is considered as Classification and Multivariate Regression task in ML context.**
2	**Rain Water Harvesting**	**Security Issues in WSN**	**Bayesian Learning [9][10][11]**	**Security is dealt with Correlation, Encoding, Decoding task in ML**
3	**Smart Grids in Smart Buildings**	**Node Clustering, Cluster Head Selection, Data Pattern Analysis**	**k-NN [12][13][14], PCA [15][16][17] and ANN [18][19]**	**Classification problem**

S. No.	Smart City Applications	WSN-IoT Issues in Smart Cities	Addressed ML Algorithms as Solutions by Researchers Worldwide	Our Remarks
4	Smart Healthcare in Hospitals	WSN Node Energy Management	Q-Learning [20][21]	Energy Management is considered a Prediction task in ML
5	Smart Agriculture	Energy Harvesting	Q-Learning [22], SARSA [23] and Deep Q-Learning [24]	The Energy Harvesting process is considered a Prediction task in ML
6	Industrial IoT (Industry 4.0)	Event/Condition Monitoring, Object/Fault Detection,	SVM [25][26] and Rule based Learning [27][28][29][30]	Event detection is handled by Classification techniques in the ML domain
7	Smart Waste Management	Routing of data packets	Genetic algorithms [31], MDP in Decision Tree [32], Random Forest [33] and Q-Learning (QELAR) [34]	Route optimization, Routing as a Classification problem in ML.
8	Smart Governance	Scheduling and Heterogeneity at MAC Layer	SVM [35] and Deep Neural Networks [36]	Scheduling and Heterogeneity problems are Regression tasks in ML
9	Quality of Life of People	QoS (Latency, Bandwidth, Coverage, Link Quality) in IoT	Q-Learning and ANN [37], SVM [38]	QoS in IoT is solved by Prediction, Classification tasks.
10	Energy Efficient Street Lighting, Smart environment monitoring	Spectrum Sharing	Deep Reinforcement Learning [39][40]	Spectrum sharing is Self-learning, rewards system tasks in ML.
11	Pandemic medical treatment (e.g., COVID-19 or Corona Virus)	Data Aggrigation	SVM [41] and Reinforcement [42]	Data Aggregation is treated as a Regression task in the ML context.

The ML and WSN-IoT pair can act as a boon for the medical healthcare sector in smart hospitals in smart cities. For example, as per a world health organization (WHO) report [43], an international pandemic called corona virus disease (COVID-19) caused the death of 716,075 people worldwide until the end of the year 2020. In smart hospitals, the advanced ML techniques with efficiently deployed WSN-IoT can be applied for the treatment of infected patients placed in quarantine. The sensors attached to biomedical instruments can send patient's data over the internet to the doctors for medical diagnosis. Thus, doctors need not go near to the patients and hence avoid/reduce the virus spread in the smart cities and society.

References

1. Alsheikh, M.A.; Lin, S.; Niyato, D.; Tan, H.-P. Machine learning in wireless sensor networks: Algorithms, strategies, and applications. IEEE Commun. Surv. Tutor. 2014, 16, 1996–2018.
2. Du, R.; Santi, P.; Xiao, M.; Vasilakos, A.V.; Fischione, C. The sensable city: A survey on the deployment and management for smart city monitoring. IEEE Commun. Surv. Tutor. 2019, 21, 1533–1560.
3. Morello, R.; Mukhopadhyay, S.C.; Liu, Z.; Slomovitz, D.; Samantaray, S.R. Advances on sensing technologies for smart cities and power grids: A review. IEEE Sens. J. 2017, 17, 7596–7610.
4. Anagnostopoulos, T.; Zaslavsky, A.; Kolomvatsos, K. Challenges and opportunities of waste management in IoT-enabled smart cities: A survey. IEEE Trans. Sustain. Comput. 2017, 2, 275–289.
5. Horng, G.-J.; Liu, M.-X.; Chen, C.-C. The smart image recognition mechanism for crop harvesting system in intelligent agriculture. IEEE Sens. J. 2020, 20, 2766–2781.
6. Pal, D.; Funilkul, S.; Charoenkitkarn, N.; Kanthamanon, P. Internet-of-things and smart homes for elderly healthcare: An end user perspective. IEEE Access 2018, 6, 10483–10496.
7. Zidi, S.; Moulahi, T.; Alaya, B. Fault detection in wireless sensor networks through SVM classifier. IEEE Sens. J. 2018, 18, 340–347.
8. Tran, D.A.; Nguyen, T. Localization in wireless sensor networks based on support vector machines (SVM). IEEE Trans. Parallel Distrib. Syst. 2008, 19, 984–994.

9. Wang, Y.; Yang, A.; Li, Z.; Chen, X.; Wang, P.; Yang, H. Blind drift calibration of sensor networks using sparse bayesian Learning. IEEE Sens. J. 2016, 16, 1.
10. Liu, J.; Li, D.; Xu, Y. Collaborative online edge caching with bayesian clustering in wireless networks. IEEE Internet Things J. 2020, 7, 1548–1560.
11. Mohanraj, R.; Babulak, E. A secure energy-efficient IoT based fractional correlated bayesian data transmission in WSNs. J. Commun. Inf. Netw. 2019, 4, 54–66.
12. Qin, J.; Fu, W.; Gao, H.; Zheng, W.X. Distributed k-means algorithm and fuzzy c-means algorithm for sensor networks based on multiagent consensus theory. IEEE Trans. Cybern. 2017, 47, 772–783.
13. Ray, A.; De, D. Energy efficient clustering protocol based on K-means (EECPK-means)-midpoint algorithm for enhanced network lifetime in wireless sensor network. IET Wirel. Sens. Syst. 2016, 6, 181–191.
14. Paek, J.; Ko, J. K-means clustering-based data compression scheme for wireless imaging sensor networks. IEEE Syst. J. 2017, 11, 2652–2662.
15. Yu, T.; Wang, X.; Shami, A. Recursive principal component analysis (PCA)-based data outlier detection and sensor data aggregation in IoT systems. IEEE Internet Things J. 2017, 4, 2207–2216.
16. Morell, A.; Correa, A.; Barceló, M.; Vicario, J.L. Data aggregation and principal component analysis (PCA) in WSNs. IEEE Trans. Wirel. Commun. 2016, 15, 2207–2216.
17. Ferng, H.-W.; Chuang, J.-S. Area-partitioned clustering and cluster head rotation for wireless sensor networks. In Proceedings of the International Conference on Machine Learning and Cybernetics (ICMLC), Ningbo, China, 9–12 July 2017; Volume 2.
18. Sanhaji, F.; Satori, H.; Satori, K. Cluster head selection based on neural networks in wireless sensor networks. In Proceedings of the International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS), Fez, Morocco, 3–4 April 2019.
19. Wu, J.; Li, G. Drift calibration using constrained extreme learning machine and kalman filter in clustered wireless sensor networks. IEEE Access 2020, 8, 13078–13085.
20. Prabuchandran, K.J.; Meena, S.K.; Bhatnagar, S. Q-Learning Based Energy Management Policies for a Single Sensor Node with Finite Buffer. IEEE Wirel. Commun. Lett. 2013, 2, 82–85.
21. Kosunalp, S. A new energy prediction algorithm for energy-harvesting wireless sensor networks with Q-learning. IEEE Access 2016, 4, 5755–5763.
22. Aslam, N.; Xia, K.; Hadi, M.U. Optimal wireless charging inclusive of intellectual routing based on SARSA learning in renewable wireless sensor networks. IEEE Sens. J. 2019, 19, 8340–8351.
23. Chen, S.; Tang, W. A 64 × 64 pixels UWB wireless temporal-difference (TD) digital image sensor. In IEEE Transactions on Very Large Scale Integration (VLSI) Systems; IEEE: Piscataway, NJ, USA, 2012; Volume 20.
24. Zhu, J.; Song, Y.; Jiang, D.; Song, H. A new deep-Q-learning-based transmission scheduling mechanism for the cognitive internet of things. IEEE Internet Things J. 2018, 5, 2375–2385.
25. Kim, W.; Stanković, M.S. A distributed support vector machine (SVM) learning over wireless sensor networks. IEEE Trans. Cybern. 2015, 45, 2599–2611.
26. Liu, S.; Xu, L. Fault diagnosis of water quality monitoring devices based on multiclass support vector machines (SVM) and rule-based decision trees. IEEE Access 2018, 6, 22184–22195.
27. Hodge, V.J.; O'Keefe, S.; Weeks, M.; Moulds, A. Wireless Sensor Networks for Condition Monitoring in the Railway Industry: A Survey. IEEE Trans. Intell. Transp. Syst. 2015, 16, 1088–1106.
28. Liang, L.; Gao, D.; Zhang, H.; Yang, O.W.W. Efficient event detecting protocol in event-driven wireless sensor networks. IEEE Sens. J. 2012, 12, 2328–2337.
29. Diddigi, R.B.; Prabuchandran, K.J. Novel sensor scheduling scheme for intruder tracking in energy efficient sensor networks. IEEE Wirel. Commun. Lett. 2018, 7, 712–715.
30. Hu, L.; Ni, Q. IoT-driven automated object detection algorithm for urban surveillance systems in smart cities. IEEE Internet Things J. 2018, 5, 747–754.
31. Yang, S.; Cheng, H.; Wang, F. Genetic algorithms with immigrants and memory schemes for dynamic shortest path routing problems in mobile Ad Hoc networks. IEEE Trans. Syst. Man Cybern. Part C Appl. Rev. 2010, 40, 52–63.
32. Rout, R.R.; Krishna, M.S.; Gupta, S. Markov Decision process-based switching algorithm for sustainable rechargeable wireless sensor networks. IEEE Sens. J. 2016, 16, 2788–2797.

33. Pramod, M.S.; Khurram, M. Random node deployment and route establishment in receiver-based routing protocol for WSNs. In Proceedings of the IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), Bangalore, India, 20–21 May 2016.
34. Hu, T.; Fei, Y. QELAR: A machine-learning-based adaptive routing protocol for energy-efficient and lifetime-extended underwater sensor networks. IEEE Trans. Mob. Comput. 2010, 9, 796–809.
35. Yang, B.; Cao, X.; Han, Z.; Qian, L. A machine learning enabled MAC framework for heterogeneous internet-of-things networks. IEEE Trans. Wirel. Commun. 2019, 18, 3697–3712.
36. Yang, B.; Cao, X.; Li, X.; Zhang, Q.; Qian, L. Mobile Edge Computing based hierarchical Machine Learning Task distribution for IIoT. IEEE Internet Things J. 2019, 7, 2169–2180.
37. Ozturk, M.; Akram, M. Novel QoS-aware proactive spectrum access techniques for cognitive radio using machine learning. IEEE Access 2019, 7, 70811–70827.
38. Shu, J.; Liu, S. Research on link quality estimation mechanism for wireless sensor networks based on support vector machine (SVM). Chin. J. Electron. 2017, 26, 377–384.
39. Li, X.; Fang, J.; Cheng, W.; Duan, H.; Chen, Z.; Li, H. Intelligent power control for spectrum sharing in cognitive radios: A deep reinforcement learning approach. IEEE Access 2018, 6, 25463–25473.
40. Mennes, R.; Claeys, M.; De Figueiredo, F.A.P.; Jabandzic, I.; Moerman, I.; Latre, S. deep learning-based spectrum prediction collision avoidance for hybrid wireless environments. IEEE Access 2019, 7, 45818–45830.
41. Frej, M.B.H.; Elleithy, K. Secure data aggregation model (SDAM) in wireless sensor networks. In Proceedings of the IEEE 14th International Conference on Machine Learning and Applications (ICMLA), Miami, FL, USA, 9–11 December 2015.
42. Atoui, I.; Ahmad, A. Tree-based data aggregation approach in wireless sensor network using fitting functions. In Proceedings of the Sixth IEEE International Conference on Digital Information Processing and Communications (ICDIPC), Beirut, Lebanon, 21–23 April 2016.
43. Coronavirus Disease 2019 (COVID-19) Pandemic Situation Report no. 89, a World Health Organisation (WHO) Report; WHO: Geneve, Switzerland, 2020.