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A Classical Machine Learning Model Scheduling in Industrial Wireless Sensor Networks

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Abstract: Time synchronization is a primary issue in industrial wireless sensor networks (IWSNs). It helps to optimize the connection and preserve battery consumption, and thus increase the network lifetime. This study aims to identify the most effective factors that decrease the battery consumption and monitor the critical targets in wireless sensor networks (WSNs) through addressing the coverage and connectivity aware scheduling of sensor nodes (SNs). On the other hand, this paper aims to get a scheduling algorithm for industrial wireless sensor networks of SNs by using classical machine learning in the proposed model like support vector machine, decision tree, and RProp (resilient back-propagation) algorithms. In this paper, classical machine learning methods are applied for testing the extracted features and the affected degree for network configurations. An extensive simulation run showed high accuracy for machine learning measurements and extracted the most affected features that play a big role in the sensor node scheduling in industrial wireless sensor networks. For testing, we used the KNIME (KoNstanz Information MinEr) model that gives a result with high accuracy. The SVM (Support Vector Mashine), Decision Tree, and RProp classifiers give an accuracy of 92.489%, 97.979%, and 98.335%, respectively.

Keywords: resilient back-propagation algorithm, wireless sensor networks, classical machine learning.

工業無線傳感器網絡中的經典機器學習模型調度

摘要：時間同步是工業無線傳感器網絡中的主要問題。它有助於優化連接並節省電池消耗，從而延長網絡壽命。本研究旨在通過解決傳感器節點的覆蓋和連接感知調度問題，確定降低電池消耗的最有效因素並監控無線傳感器網絡中的關鍵目標。另一方面，本文旨在通過在所提出的模型（如支持向量機、決策樹和彈性反向傳播算法）中使用經典機器學習來獲得傳感器節點的工業無線傳感器網絡的調度算法。在本文中，經典的機器學習方法用於測試提取的特徵和網絡配置的影響程度。廣泛的模擬運行顯示了機器學習測量的高精度，並提取了在工業無線傳感器網絡中的傳感器節點調度中發揮重要作用的受影響最大的特徵。對於測試，我們使用了恆常信息挖掘者模型，該模型給出了高精度的結果。支持向量混搭、決策樹和彈性反向傳播分類器的準確率分別為 92.489%、97.979% 和 98.335%。

关键词：彈性反向傳播算法，無線傳感器網絡，經典機器學習。

1. Introduction

Since the inception of WSNs, they became the focus of attention and caught the attention of such fields as industry, agriculture, health, and others [1]. Among the common uses of sensor nodes (SNs) in the field of industry, it seeks to monitor and disclose data that are of utmost importance, such as the possibility of fire and prior notification [2, 3]. The main objective of this achievement was to extend the grid spirit as much as possible so that the SNs actuate on the power compartment source, such as small batteries. The short life of these batteries makes them not desirable for most applications. Therefore, researchers focused on energy-efficient methods that extend the lifetime of WSN [4, 5].

One energy-saving and frequently used WSN applications method is sensor node scheduling. Through this scheduling, it is possible to extend the

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spirit of the network with high quality through SNs usage time modeling. Therefore, when starting to monitor and disclose a specific place, the necessary nodes for that area will be activated at a specified time; thus, any unnecessary node in that area will not be operational, leading to energy saving. Therefore, while saving energy, this process will also extend the life of the WSN network. The most important and difficult scheduling life cycle is establishing appropriate data detection and connection between the SNs and the base station (BS). Also, the sensor nodes' energy must be considered because the near-expiring energy makes the group perform less and forces them to start a new schedule [6, 7]. Hence, the sensor node may fail due to its low capacity, and due to obstacles, the network connection may be affected [8]. Therefore, the scheduling and connecting issue of WSNs is an NP-hard problem [6, 9].

Coverage and connectivity are of great importance in the life cycle of wireless sensor networks, so the correct connection of sensor nodes positively affects how the network functions. Consequently, it will reduce the amount of energy used for the grids. Because the sensor nodes have limited capacity and communication space, it is not easy to maintain the network's required coverage and connection flow. Therefore, due to the failure to which the sensor nodes are exposed, it is necessary to place enough sensor nodes in the area to be monitored to avoid losing coverage and contact when one or more nodes fail [10, 11]. Coverage is one of the problems that affect the power consumption of sensor nodes and the consumption of network life in wireless sensor networks. Hence, the coverage problem's goal is to efficiently monitor network quality [12, 13].

NSGA-II is called a non-controlled sorting genetic algorithm. It is an algorithm that is classified among the optimization algorithms. Hence, its function is to indicate the set of solutions and address solutions simultaneously. Therefore, every polarized solution will be represented as a chromosome; the chromosome comes in a series of symbols. Therefore, chromosomes are presented based on a binary form composed of 0 and 1 [14].

This study aims to schedule industrial wireless sensor networks of sensor nodes (SNs) for monitoring the critical targets in industrial wireless sensor networks (WSNs), where classical machine learning used in the proposed model like support vector machine, decision tree, and RProp algorithms as a measurement for the network performance and testing the efficiency for the dataset.

2. Literature Review

In [15] study, they proposed a model for time synchronization in IWSNs based on the energy-efficient reference node selection (EERS) algorithm. The proposed method worked selected and scheduled a minimal series of linked reference nodes responsible for spreading timing messages. The experiment results showed that a large sensor network of 450 nodes demonstrates that EERS reduces the number of transmitted messages by 52%, 30%, and 13% compared to R-Sync, FADS, and LPSS.

While in [16] study, they proposed a sleep scheduling scheme IWSNs that ensures a covering degree requirement according to the dangerous degree of the toxic gas leakage area while keeping the minimal awake nodes connected with the global network. The experiment results showed that the proposed method outperforms the CKN-based sleep scheduling scheme with the same required coverage degree for the toxic gas leakage area.

In [17], the authors established an Energy-Efficient Dynamic Scheduling Hybrid MAC Protocol (EDS-MAC) that adopting the EDS-MAC protocol in a WSN can assist users in extending network life and reducing overall network energy and overhead usage. This protocol is divided into two steps: cluster formation and data transmission. For constructing energy-aware clusters through optimal cluster head selection, a variable step size firefly algorithm (VSSFFA) is proposed in the first step. The data transmission stage reduces latency, delay, and control overhead in data transfer.

3. Dataset and Configuration

The dataset contains the most important features of the network that extracted from measurements for the WSN at an industrial environment during the period 05-06/06/2014, where the extraction process for data based on the splitting of the raw instances of the network into windows of monitoring with length equals 500 sequential entries per node of the sensor. The dataset contains each network monitoring for the traffic, MAC, NWK layers, and metrics from physical and ambient sensors readings (humidity and temperature) and voltage threshold on each sensor node. The traffic recorded is related to the links established at the application layer (dataset) between each node (id = 1, 2...10) and a sink node (Fig.1), where the traffic is recorded at the sink node.

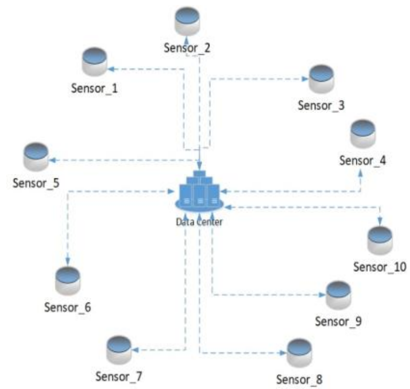


Fig. 1 Sensor nodes

The network configuration contains each sensor node platform, network size, a transmission protocol stack. Table 1 below shows the configuration for the proposed network.

Table 1 Network configuration

Features	**Description**
Sensor Nodes Platform	AdvanticSyS XM1000 and CM5000-SMA (IEEE 802.15.4-compliant devices)
Network Size	Ten sensor nodes (node id = 1, 2,...10) and a sink node (running on a PandaBoard)
Transmission Period	6sec
Protocol Stack	Customized, based on Contiki OS-version 2.6- and incorporating the IETF Standard for Routing over Low-Power and Lossy Networks

The dataset contains each of the following features:

- The received signal strength value over the multi-hop path between a node (i) and sink node (dBm);
- The value of link quality indicator over the multi-hop path between a node (i) and the sink node;
- The value of the noise floor over the multi-hop path between a node (i) and sink node (dBm);
- The transmission rate at the MAC layer (bpm) at the 1:10 node (unicast traffic only);
- The reception rate at the MAC layer (bpm) at the 1:10 node (unicast traffic only);
- The value of the routing path length (number of hops) between a node (i) and the sink node;
- The estimated Packet Reception Ratio, using WMEWMA estimator [19];
- The value of temperature on the 1:10 node (Celsius degrees);
- The value of humidity on the 1:10 node (%);
- The value of voltage level on the 1:10 node (V);
- The Recorded Packet Reception Ratio.

4. Methodology

This study addresses the coverage and connectivity-aware scheduling of sensor nodes (SNs) for monitoring the critical targets in industrial wireless sensor networks (WSNs). The SNs with relatively higher energy levels are preferred to be selected to serve full rounds. Considering the multi-objective nature of the problem, the proposed model used the classical machine learning (support vector machine, decision tree, and RProp) algorithms to calculate the network performance and test the efficiency for the dataset. Fig. 2 depicts the general framework for the proposed model.

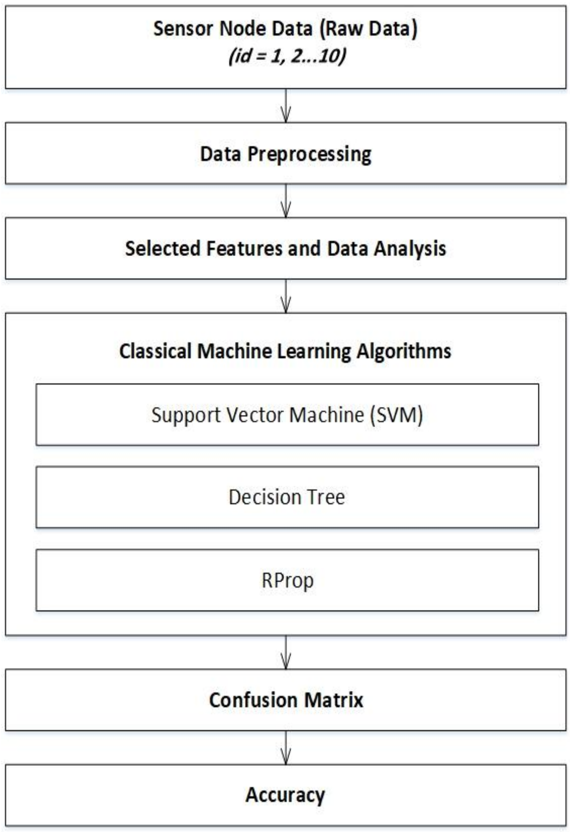


Fig. 2 General framework

The main goal of the proposed model is to extract the most affected features (received signal, link quality indicator, floor noise, transmission MAC, reception MAC, routing path length, estimated packet reception, temperature, humidity, voltage, and the recorded packet reception). They play a big role in network scheduling and calculating the accuracy of the dataset to improve the scheduling in industrial wireless sensor networks. Table 2 describes the classifier model of supervised machine learning using the KNIME Analytics Platform.

Table 2 Supervised machine learning model

Algorithm	**KNIME node**	**Description**
SVM	SVM Learner SVM Predictor	This node trains a support vector machine on the input data (Refined Dataset). It supports several kernels (Hyper Tangent, Polynomial, and RBF), and uses an SVM model generated by the SVM learner node to predict the output for given values.
RProp	RProp MLP Learner. Multi-LayerPerceptron Predictor	Implementation of the RProp algorithm for multilayer feedforward networks. RPROP performs a local adaptation of the weight updates according to the behavior of the error function.
Decision Tree	Decision Tree Learner Decision Tree Predictor	This node induces a classification decision tree in the main memory. The target attribute must be nominal (classes of sensors).

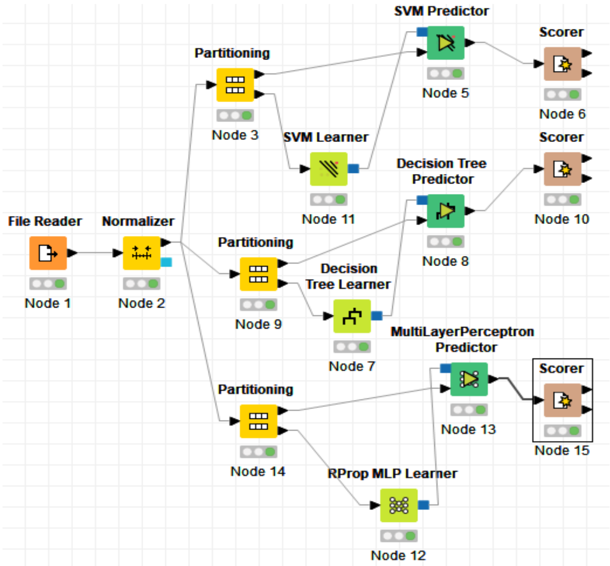


Fig. 3 KNIME analytics model

In this research, the main idea behind the KNIME analytics model (Fig. 3) is to calculate a confusion matrix (the number of matching for the attribute rows with their classification match) containing each correct and wrong classified accuracy and the error. Where the accuracy measurement depends according to the following measurements:

- *True-Positives:* the value of the result where the proposed model correctly prophesies the positive class.
- *False-Positives:* the value of the result where the proposed model incorrectly prophesies the positive class.
- *True-Negatives:* the value of the result where the proposed model correctly prophesies the negative class.
- *False-Negatives:* the value of the result where the proposed model incorrectly prophesies the negative class.
- *Recall:* the total number of relevant instances that were retrieved.
- *Precision:* the relevant instances among the retrieved instances.
- *Sensitivity:* the number of actual positives that are correctly identified.
- *Specificity:* the number of actual negatives that are correctly identified.
- *F-measure:* a combination of each precision and recall into one measure.

5. Results and Analysis

In this section, we will make a full analysis of the dataset and testing results using the proposed model in KNIME Analytics. This section aims to extract all features that affect the scheduling for industrial wireless sensor networks.

5.1. Temperature & Humidity

Table 3 shows the relation between each of temperature (Celsius degrees) and humidity (%), and the node of sensors:

Table 3 The average temperature and humidity

Sensor	Temperature	Humidity
Sensor_1	18.52360804	67.48392965
Sensor_2	18.66901005	54.71281407
Sensor_3	18.64507	57.03429
Sensor_4	18.14116	69.924385
Sensor_5	18.75105	66.23385
Sensor_6	18.878295	55.245245
Sensor_7	18.558055	71.198335
Sensor_8	18.639025	66.40776
Sensor_9	18.506795	54.202205
Sensor_10	18.765255	52.081695

Table 3 shows the convergence of results for the temperature values for all sensors, with the significant variation for the results for the humidity values for all sensors (Fig. 4).

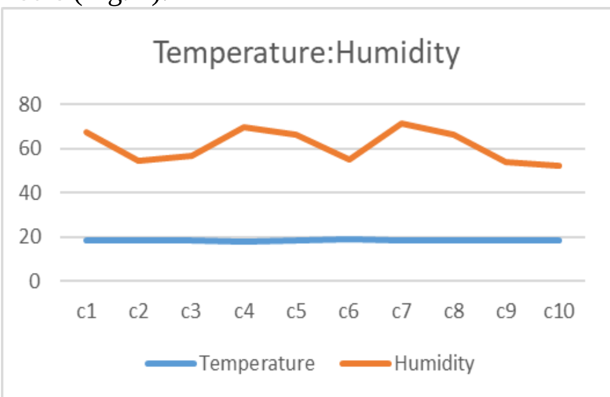


Fig. 4 Temperature and humidity percentage

5.2. Recorded Packet Reception & Estimated Packet Reception

Table 4 shows the comparison of values between each of the recorded packet reception and the estimated packet reception for all sensors:

Table 4 The average of recorded packet reception and the estimated packet reception

Sensor	Recorded Packet Reception	Estimated Packet Reception
Sensor_1	0.927648543	0.929756382
Sensor_2	0.921503116	0.923267688
Sensor_3	0.9212376	0.9219941
Sensor_4	0.93571605	0.9373106
Sensor_5	0.9255054	0.92708265
Sensor_6	0.9337663	0.93630265
Sensor_7	0.9235966	0.92572625
Sensor_8	0.94135405	0.9430637
Sensor_9	0.9329652	0.9350768
Sensor_10	0.9239234	0.92584455

We can notice the convergence of results for the recorded packet reception and the estimated packet reception for all sensors, which mean there is no big impact for these features on the scheduling in industrial wireless sensor networks (Fig. 5):

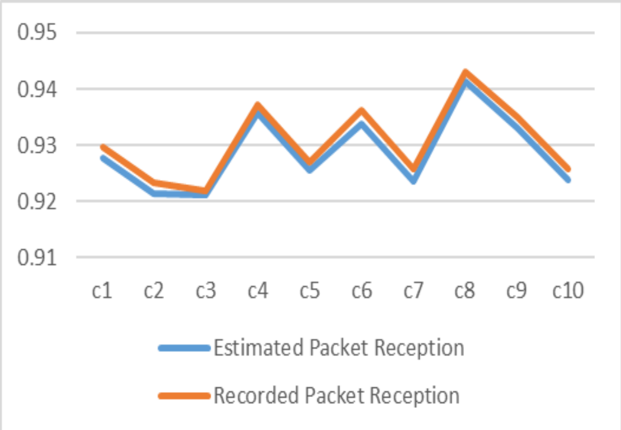


Fig. 5 Recorded packet reception and the estimated packet reception values

5.3. Transmission & Reception MAC Layers

Table 5 shows the difference for each transmission MAC layer (unicast traffic only) and the reception MAC layer (unicast traffic only):

Table 5 The average transmission & reception MAC layer

Sensor	Transmission MAC	Reception MAC
Sensor_1	279.1578894	150.5554874
Sensor_2	149.8915578	23.00052764
Sensor_3	416.8487	139.6315
Sensor_4	152.3443	23.095395
Sensor_5	134.21135	4.711055
Sensor_6	151.87365	22.95482
Sensor_7	264.9166	135.95115
Sensor_8	1387.34565	1221.18765
Sensor_9	697.1805	559.19513
Sensor_10	132.6446	4.64779

We can notice the big difference between each of the transmission and the reception MAC layers that effect directly on the scheduling in industrial wireless sensor networks (Fig. 6):

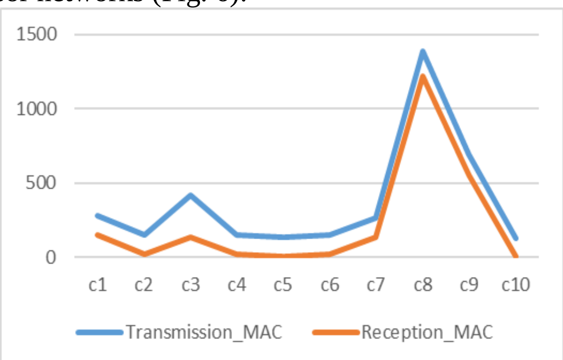


Fig. 6 Recorded packet reception and the estimated packet reception values

5.4. Received Signal Strength & Noise Floor

Table 6 shows the difference for each of received signal strength over the multi-hop path between a node (i) and sink node (dBm), and the noise floor over the multi-hop path between a node (i) and sink node (dBm).

Table 6 The average received signal strength & noise floor

Sensor	Received signal strength	Noise floor
Sensor_1	-85.5591005	-97.47270352
Sensor_2	-85.40829648	-95.27441709
Sensor_3	-86.33442	-93.39855
Sensor_4	-86.68147	-97.56427
Sensor_5	-85.459465	-95.497715
Sensor_6	-86.63261	-95.86175
Sensor_7	-86.01895	-90.271755
Sensor_8	-87.462285	-95.726705
Sensor_9	-85.11303	-94.877075
Sensor_10	-86.796655	-98.2337

We can notice the big difference between each received signal strengths and the noise floors that directly affect the scheduling in industrial wireless sensor networks (Fig. 7):

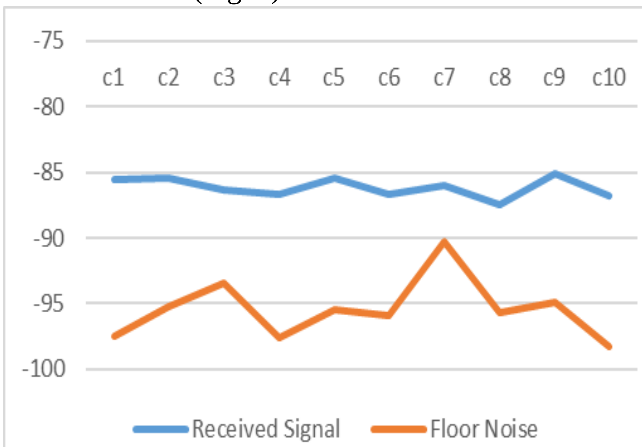
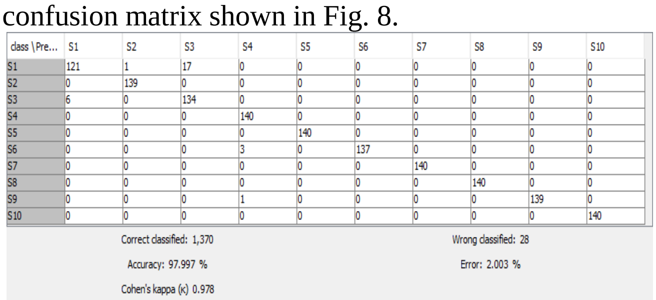


Fig. 7 Received signal strength and the noise floor

5.5. KNIME Analytics Model

KNIME model contains three different classifiers (support vector machine, decision tree, and RProp). Each classifier gives a different result, represented as a confusion matrix shown in Fig. 8.



class \Pre...	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
S1	121	1	17	0	0	0	0	0	0	0
S2	0	139	0	0	0	0	0	0	0	0
S3	6	0	134	0	0	0	0	0	0	0
S4	0	0	0	140	0	0	0	0	0	0
S5	0	0	0	0	140	0	0	0	0	0
S6	0	0	0	3	0	137	0	0	0	0
S7	0	0	0	0	0	0	140	0	0	0
S8	0	0	0	0	0	0	0	140	0	0
S9	0	0	0	1	0	0	0	0	139	0
S10	0	0	0	0	0	0	0	0	0	140

Correct classified: 1,370 Wrong classified: 28
Accuracy: 97.997 % Error: 2.003 %
Cohen's kappa (κ) 0.978

Fig. 8 KNIME confusion matrix

Table 7 shows the results of confusion matrices for all classifiers (support vector machine, decision tree, and RProp).

Table 7 Confusion matrices results

Classifier	Correct Classified	Wrong Classified	Accuracy	Error
SVM	1293	105	92.489%	7.511%

Continuation of Table 7

DT.	1370	28	97.979%	2.003%
RProp	1375	23	98.335%	1.645%

6. Conclusion

In this paper, classical machine learning methods (SVM, RProp, and Decision Tree) are applied for testing the extracted features to an affected degree for network configurations. This study tried to extract the most affected features (received signal, link quality indicator, floor noise, transmission MAC, reception MAC, routing path length, estimated packet reception, temperature, humidity, voltage, and the recorded packet reception). They play a big role in network scheduling and calculating the accuracy of the dataset to improve the scheduling in industrial wireless sensor networks. The proposed dataset contains different fractures like the sensor nodes platform, network size, transmission period, and the protocol stack.

The experiment results showed the convergence for the temperatures values for all sensors, with the significant variation for the results for the humidity values for all sensors, and the convergence of results for the recorded packet reception and the estimated packet reception for all sensors, which mean there is no big impact for these features on the scheduling in industrial wireless sensor networks. While the big difference in results between each of the transmission and the reception MAC layers that effect directly on the scheduling in industrial wireless sensor networks.

The testing measurements using the KNIME model give a high accuracy in results according to the available dataset, where SVM classifier reached (92.489%) with (7.511%) for error rate, while decision tree classifier reached (97.979%) with (2.003%) for error rate, but the RProp classifier gives a higher rate for accuracy reached to (98.335%) with (1.645%) for error rate.

The results are considered good during the limitation of the lack of data and features. In the future, we will apply another scenario with collecting a big dataset using the Artificial Neural Networks (ANN) that its many data characteristics can impact the efficiency of the results.

References

[1] QUEIROZ D.V., ALENCAR M.S., GOMES R.D., FONSECA I.E., and BENAVENTE-PECES C. Survey and systematic mapping of Industrial Wireless Sensor Networks. *Journal of Network and Computer Applications*, 2017, 97: 96-125. https://doi.org/10.1016/j.jnca.2017.08.019

[2] LI K., NI W., DUAN L., ABOLHASAN M., and NIU J. Wireless power transfer and data collection in wireless sensor networks. *IEEE Transactions on Vehicular Technology*, 2017, 67(3): 2686-2697. https://doi.org/10.1109/TVT.2017.2772895

[3] KADDI M., KHALILI Z., and BOUCHRA M. A Differential Evolution Based Clustering and Routing Protocol for WSN. In: *2020 2nd International Conference on Mathematics and Information Technology* (ICMIT). IEEE, 2020. p. 190-195. https://doi.org/10.1109/ICMIT47780.2020.9047006

[4] HARIZAN S., and KUILA P. Coverage and connectivity aware energy-efficient scheduling in target-based wireless sensor networks: an improved genetic algorithm-based approach. *Wireless Networks*, 2019, 25(4): 1995-2011. https://doi.org/10.1007/s11276-018-1792-2

[5] WANG Q., LIU W., WANG T., ZHAO M., LI X., XIE M., MA M., ZHANG G., and LIU A. Reducing delay and maximizing lifetime for wireless sensor networks with dynamic traffic patterns. *IEEE Access*, 2019, 7: 70212-70236. https://doi.org/10.1109/ACCESS.2019.2918928

[6] XU Y., JIAO W., and TIAN M. Energy-efficient connected-coverage scheme in wireless sensor networks. *Sensors*, 2020, 20(21): 6127. https://doi.org/10.3390/s20216127

[7] SINGH S.P., and SHARMA S.C. A particle swarm optimization approach for energy-efficient clustering in wireless sensor networks. *International Journal of Intelligent Systems and Applications*, 2017, 11(6): 66. https://doi.org/10.5815/ijisa.2017.06.07

[8] AL-AZZAM S., and SHARIEH A. A data estimation for failing nodes using fuzzy logic with integrated microcontroller in wireless sensor networks. *International Journal of Electrical and Computer Engineering*, 2020, 10(4): 3623-3634. https://doi.org/10.11591/ijece.v10i4.pp3623-3634

[9] HARIZAN S., and KUILA P. Coverage and connectivity aware critical target monitoring for wireless sensor networks: Novel NSGA-II-based approach. *International Journal of Communication Systems*, 2020, 33(4): e4212. https://doi.org/10.1002/dac.4212

[10] CARLSON J., DAEHLER K.R., ALONZA A.C., BARENDSEN E., BERRY A., BOROWSKI A., CARPENDALE J., CHAN K.K.H., COOPER R., FRIEDRICHSEN P., GESS-NEWSOME J., INEKE H.-R., HUME A., KIRSCHNER S., LIEPERTZ S., LOUGHRAN J., MAVHUNGA E., NEUMANN K., NILSSON P., PARK S., ROLLNICK M., SICKEL A., SUH J.K., SCHNEIDER R., VAN DRIEL J., and WILSON C. The refined consensus model of pedagogical content knowledge in science education. In: *Repositioning pedagogical content knowledge in teachers' knowledge for teaching science.* Springer, Singapore, 2019: 77-94. https://doi.org/10.1007/978-981-13-9574-1_11

[11] YARINEZHAD R., and HASHEMI S.N. A sensor deployment approach for target coverage problem in wireless sensor networks. *Journal of Ambient Intelligence and Humanized Computing*, 2020, 1-16. https://doi.org/10.1007/s12652-020-02195-5

[12] ELHABYAN R., SHI W., and ST-HILAIRE M. Coverage protocols for wireless sensor networks: Review and future directions. *Journal of Communications and Networks*, 2019, 21(1): 45-60. https://doi.org/10.1109/JCN.2019.000005

[13] FAYAZIBARJINI E., GHARAVIAN D., and SHAHGHOLIAN M. Target tracking in wireless sensor networks using NGEKF algorithm. *Journal of Ambient Intelligence and Humanized Computing*, 2019, 1-13. https://doi.org/10.1007/s12652-019-01536-3

[14] ELSHARIEF M., MOHAMED A., EL-GAWAD A., KO H., and PACK S. EERS: Energy-Efficient Reference Node Selection Algorithm for Synchronization in Industrial Wireless Sensor Networks. *Sensors*, 2020, 20(15): 4095. https://doi.org/10.3390/s20154095

[15] MUKHERJEE M., SHU L., HU L., HANCKE G.P., and ZHU C. Sleep scheduling in industrial wireless sensor networks for toxic gas monitoring. *IEEE Wireless Communications*, 2017, 24(4): 106-112. https://doi.org/10.1109/MWC.2017.1600072WC

[16] TOMAR V., and SINGH D. Coverage and connectivity aware data gathering protocol for wireless sensor networks. In: *2016 2nd international conference on next-generation computing technologies* (NGCT). IEEE, 2016. p. 432-438. https://doi.org/10.1109/NGCT.2016.7877455

[17] SUNDARARAJ V., MUTHUKUMAR S., and KUMAR R.S. An optimal cluster formation based energy-efficient dynamic scheduling hybrid MAC protocol for heavy traffic load in wireless sensor networks. *Computers & Security*, 2018, 77: 277-288. https://doi.org/10.1016/j.cose.2018.04.009

参考文:

[1] QUEIROZ D.V.、ALENCAR M.S.、GOMES R.D.、FONSECA I.E. 和 BENAVENTE-PECES C. 工業無線傳感器網絡的調查和系統製圖。網絡與計算機應用雜誌, 2017, 97: 96-125. https://doi.org/10.1016/j.jnca.2017.08.019

[2] LI K.、NI W.、DUAN L.、ABOLHASAN M. 和 NIU J. 無線傳感器網絡中的無線電力傳輸和數據收集。電氣和電子工程師學會 車輛技術彙刊, 2017, 67(3): 2686-2697. https://doi.org/10.1109/TVT.2017.2772895

[3] KADDI M.、KHALILI Z. 和 BOUCHRA M. 基於差分進化的無線傳感器網絡聚類和路由協議。在：2020 年第二屆數學與信息技術國際會議。電氣和電子工程師學會，2020 年。 190-195。 https://doi.org/10.1109/ICMIT47780.2020.9047006

[4] HARIZAN S. 和 KUILA P. 基於目標的無線傳感器網絡中的覆蓋和連接感知節能調度：一種改進的基於遺傳算法的方法。無線網絡, 2019, 25(4): 1995-2011。 https://doi.org/10.1007/s11276-018-1792-2

[5] WANG Q., LIU W., WANG T., ZHAO M., LI X., XIE M., MA M., ZHANG G., 和 LIU A. 減少動態無線傳感器網絡的延遲和最大化壽命交通模式。 電氣和電子工程師學會使用權, 2019, 7: 70212-70236. https://doi.org/10.1109/ACCESS.2019.2918928

[6] XU Y., JIAO W., 和 TIAN M. 無線傳感器網絡中的節能連接覆蓋方案。傳感器, 2020, 20(21): 6127. https://doi.org/10.3390/s20216127

[7] SINGH S.P. 和 SHARMA S.C. 一種粒子群優化方法，用於無線傳感器網絡中的節能聚類。國際智能係統與應用雜誌, 2017, 11(6): 66. https://doi.org/10.5815/ijisa.2017.06.07

[8] AL-AZZAM S. 和 SHARIEH A. 在無線傳感器網絡中使用帶有集成微控制器的模糊邏輯對故障節點進行數據估計。國際電氣與計算機工程雜誌, 2020, 10(4): 3623-3634。 https://doi.org/10.11591/ijece.v10i4.pp3623-3634

[9] HARIZAN S. 和 KUILA P. 無線傳感器網絡的覆蓋和連接感知關鍵目標監控：基於非支配排序遺傳算法-II 的新型方法。國際通信系統雜誌, 2020, 33(4): e4212。 https://doi.org/10.1002/dac.4212

[10] CARLSON J., DAEHLER K.R., ALONZA A.C., BARENDSEN E., BERRY A., BOROWSKI A., CARPENDALE J., CHAN K.K.H., COOPER R., FRIEDRICHSEN P., GESS-NEWSOME J., INEKE H.-R., HUME A., KIRSCHNER S., LIEPERTZ S., LOUGHRAN J., MAVHUNGA E., NEUMANN K., NILSSON P., PARK S., ROLLNICK M., SICKEL A., SUH J.K., SCHNEIDER R., VAN DRIEL J., 和 WILSON C. 科學教育中教學內容知識的精煉共識模型。在：重新定位教師知識中的教學內容知識以進行科學教學。施普林格，新加坡，2019：77-94。 https://doi.org/10.1007/978-981-13-9574-1_11

[11] YARINEZHAD R.和 HASHEMI S.N.一種針對無線傳感器網絡中目標覆蓋問題的傳感器部署方法。環境智能和人性化計算雜誌，2020 年，1-16。 https://doi.org/10.1007/s12652-020-02195-5

[12] ELHABYAN R.、SHI W. 和 ST-HILAIRE M. 無線傳感器網絡覆蓋協議：回顧和未來方向。通信與網絡雜誌, 2019, 21(1): 45-60. https://doi.org/10.1109/JCN.2019.000005

[13] FAYAZIBARJINI E.、GHARAVIAN D. 和 SHAHGHOLIAN M. 使用廣義擴展卡爾曼濾波器算法的無線傳感器網絡中的目標跟踪。環境智能與人性化計算學報，2019，1-13。 https://doi.org/10.1007/s12652-019-01536-3

[14] ELSHARIEF M.、MOHAMED A.、EL-GAWAD A.、KO H. 和 PACK S. 工業無線傳感器網絡中用於同步的節能參考節點選擇算法。傳感器, 2020, 20(15): 4095. https://doi.org/10.3390/s20154095

[15] MUKHERJEE M.、SHU L.、HU L.、HANCKE G.P. 和 ZHU C. 用於有毒氣體監測的工業無線傳感器網絡中的睡眠調度。電氣和電子工程師學會 無線通信, 2017, 24(4): 106-112. https://doi.org/10.1109/MWC.2017.1600072WC

[16] TOMAR V. 和 SINGH D. 無線傳感器網絡的覆蓋和連接感知數據收集協議。在：2016 第二屆下一代計算技術國際會議。電氣和電子工程師學會，2016 年。 432-438。 https://doi.org/10.1109/NGCT.2016.7877455

[17] SUNDARRAJ V.、MUTHUKUMAR S. 和 KUMAR R.S.一種基於最優簇形成的節能動態調度混合MAC協議，用於無線傳感器網絡中的大流量負載。計算機與安全, 2018, 77: 277-288. https://doi.org/10.1016/j.cose.2018.04.009