Design of High-Performance Intelligent WSN based-IoT using Time Synchronized Channel Hopping and Spatial Correlation Model

Hamza M. Ridha Al-Khafaji [1,*], Refed Adnan Jaleel [2,3]

[1] Biomedical Engineering Department, College of Engineering and Technologies, Al-Mustaqbal University, Hillah 51001, Babil, Iraq

[2] Commissions of Persons with Disabilities and Special Needs, Ministry of Labor and Social Affairs, Baghdad, Iraq

[3] Information and Communication Engineering, Al-Nahrain University, Baghdad, Iraq

Emails: hamza.alkhafaji@uomus.edu.iq; iraq_it_2010@yahoo.com

Abstract

Wireless Sensor Network (WSN) is one of the most significant contributors to the Internet of Things (IoT), and it plays a significant role in the lives of individuals. There are three main problems in the design of traditional WSN based-IoT. First problem about data; the WSN transmits a huge volume of data to the IoT for processing. The second problem is the energy; since sensor nodes rely on their limited battery, conserving energy is crucial, and the third problem about efficiency of transmission. This paper presents new WSN based IoT framework that integrate important techniques to solve these problems; To increase the effectiveness of data processing and storing, the intelligent Adaptive Boosting stochastic algorithm is applied. IEEE 802.15.4e time slotted channel hopping (TSCH) protocol is used because it has the benefits such as collision-free transmission and multi-hop transmission. Data reduction at the Gateway (GW) level of the network is achieved through spatial correlation between sensors with the goal of conserving energy. Principle idea of this new framework is to identify the advantages of integrating the important techniques; intelligent Adaptive Boosting Stochastic diffusion search algorithm, TSCH, and Special correlation model. As a result, the proposed framework can thereby satisfy the need for a long battery life of low-rate applications and at the same time, the need for high throughput for high-rate uses also for testing it in achieved efficient classification of data, the important performance measures are used.

Keywords: Internet of things; wireless sensor network; time synchronized channel hopping; spatial correlation model; adaptive boosting stochastic algorithm

1. Introduction

In the modern day, Internet is transitioning from linking people to connecting objects, giving rise to the new idea of IoT. This emerging pattern ushers in the IoT, which in turn gives rise to novel online services and commercial endeavors. By 2020, 212 billion devices are anticipated to be installed. From personal wearable within to environmental sensors placed outdoors, these items become new data generators on the Internet, allowing virtual entities to better understand their physical surroundings. This leads to innovations or new applications in a variety of disciplines like as healthcare, transportation, disaster detection/ prevention, agriculture, and so on, can drastically enhance the standard of living. The concept of user-centric software defined IoT (UC-SDIoT) described in (Figure 1) [1].

This form of network exists as an output of the quick development of embedded computer, electronics, and wireless technology [2]. Countless low-cost, low-power sensors, and lightweight are contained in the WSN that are distributed spatially to track the environmental or physical phenomena of a particular region of attention like

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

humidity, temperature, vibration, sound, motion, strain, etc. [3]. The monitored area is outfitted with sensors that gather, process, and relay data to a central hub or "gateway" (GW) for further analysis [4].

The battery's ability to supply energy is the sensor node's most important resource, and its life span directly impacts the WSN as a whole. The primary function of power batteries was to supply the node of sensor with the energy it needed to complete its duty [5]. Since sensor nodes are powered by their fixed battery, and if a large number of sensors are dispersed across a large area, energy conservation is crucial [6]. When sensor nodes must continuously transmit data measurements to the GW over an extended time period, data compression is especially helpful for applications that don't truly need real-time data [7]. Depending on the requirements of application, gathering of data in WSN could be time-driven and event-driven. The model of a temporally-driven data gathering known as periodic is discussed. Every sensor node periodically updates the GW with data gathered from the monitored area [8]. Figure 1 offers the user-centric software defined IoT (UC-SDIoT).

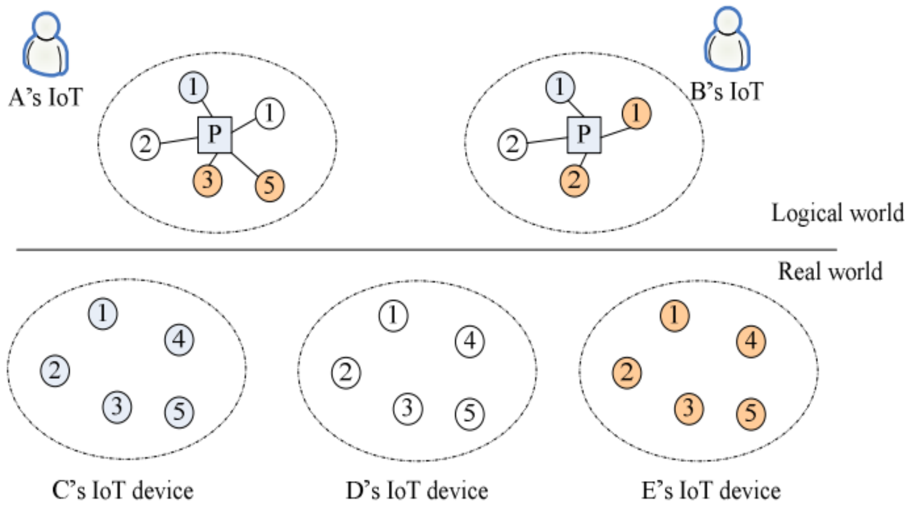


Figure 1**:** UC-SDIoT

Due to the enormous dimensionality of the data, conventional approaches to solving such problems have led to the proposal of meta-heuristic algorithms. These meta-heuristic algorithms have offered a remarkably adaptable method for choosing the best answers. In order to obtain higher-performing systems that integrate and further leverage their complementing qualities of the optimization strategies, all diverse meta-heuristic algorithms were hybridized [9].

Feature selection is another optimization method that breaks down vast sets of the initial rough characteristics into more manageable feature subsets. In contrast to previous nature-inspired algorithms, the SDS will have a robust mathematical foundation, determines how to allocate resources, low-level convergent criteria, problems with linearity of convergence and time to the global optimum [41]. By adapting relatively weak classifiers to various realizations in the data, a "boosting" technique to ML can produce a very potent ensemble of classifiers. Adaptive Boosting (adaptive boosting) is a concept that was proposed to create strong classifiers from a collection of weak classifiers. With the current weak learner system, the number of misclassified samples increases as the weight of samples classified properly decreases; the technique further generates a new set of poor learners to preserve a group of weights. The simplicity, programmability, and mergability of this method make it useful for locating questionable hypotheses [10, 11].

The contributions made by this paper are as follows:

1. Increase the effectiveness of data processing and storing by using the intelligent Adaptive Boosting stochastic algorithm.
2. Data reduction at the GW level of the network is achieved through spatial correlation between sensors with the goal of conserving energy.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

3. IEEE 802.15.4e TSCH protocol is used because of the advantages it provides such as collision-free transmission and multi-hop transmission.
The remaining portion of the paper is divided into sections of similar works, section of materials & methods, which contains subsection about the techniques that have been used in the proposed framework, section for experiment that determine the results and discussion, finally the section of conclusions.

2. Related Works

Many suggested works that try to extend the life of the sensor of network by reducing data transmission are found in the literature, like as aggregation of data, predictive monitoring, compression, routing, scheduling, battery repletion, clustering and optimization of radio [12, 13, and 14].

From the perspective of WSN, a survey was conducted in [15] on the energies, jitters, packet-delivery ratios, jitters, throughput, and performance of routing protocol was assessed using, bandwidth, latencies, delay, and jitter. Ad-hoc On-Demand Distance Vector (AODV) routing has been optimized through the development of a new algorithm. For protocol optimization, two tables—the routing table and the internet access table—were combined into a single table. The primary goal of this work was to examine IoT AODV routing protocol simulation studies. Additionally, to enhance IoT AODV and AODV performance using the NS2 simulator. Furthermore, due to its various constraints, traditional routing protocols cannot be used directly with WSN-assisted IoT. Energy is a serious issue for IoT devices that use WSN. Power is wasted more often on inter-node communication than on actual computation or sensing. As a result, employing efficient energy management strategies is crucial to extending the network's lifespan.

An efficient multi-hop & multi-user hierarchical routing technique was suggested in paper [16], it discusses multi-hop communication with equally distributed energy among sensor nodes forming a cluster, new methods for cluster adaptability and rotation, as well as a method for reducing communication range's energy have been proposed. The study [17] enhanced on the traditional routing protocol and introduced a novel protocol with novel data transport and CH selection techniques. This implied a connection between the real-world WSNs' gap and the actual heterogeneous environment. Performance measurements were used to analyze the simulation results, which highlighted the differences between the proposed protocol and the current Hy-IoT.

In order to cluster data, the paper [18] used a novel method of swarm intelligence called as stochastic diffusion search. In the past, this algorithm served as the multi-agent global search. The algorithm was used in this paper to address clustering issues. The standard Iris dataset was used for testing. Based on robustness and quality in its classification, the comparison's highlights and results were competitive for the approach proposed and showed promise. Additionally, the research provided evidence that the idea may be applied in creative ways to the problem of data clustering.

The authors in [19] built a framework that contains an IoT cloud platform, NB devices, a user app, and an application server. Building a development board that takes part in a subscriber identification module is the primary component, power management modules, a unit of micro-controller, and module of an NB IoT communication. A design of firmware was offered for data sensing, device wake-up of NB, the IoT cloud configuration for data analysis, and computing and communication. By using smart cities as the primary use case, the authors in [20] evaluated the different machine learning approaches that address the issues in data of IoT. A classification scheme for machine learning algorithms is presented, outlining the many approaches that can be taken to the data in order to get more meaningful insights. The possibilities and difficulties of machine learning for IoT analytics of data had been described. To identify the most common opcode sequences used by malicious IoT applications, the paper [21] used a sequential pattern mining technique. Opcode sequences with detected maximal frequent patterns (MFPs) can be utilized to recognize between malicious and good IoT apps. To gauge an MFP's usefulness, we classify its features for Multilayer Perceptron, SVM, RF, K-NN, and Decision Tree, Adaptive Boosting. Unseen IoT malware can be detected with a 99% success rate.
In order to create a system, the authors in [22] used a variety of machine learning algorithms and took into account open health care datasets that were available in the cloud, It uses IoT technology and cloud computing to enable real-time remote health monitoring The system is allowed to use historical and empirical data stored in the cloud to drive references. Disease prediction models are evaluated such as breast cancer, heart disease, spect_heart, diabetes, dermatology, thyroid, liver surgical and disorders data. A variety of input parameters connected to that specific disease. A couple algorithms of machine learning run the results.

Researchers of [23, 24] in the field of evaluation for performance have simulated and experimentally examined the method of TSCH efficacy. The authors of [23] have examined the IEEE 802.15.4e TSCH mode's performance

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

in terms of latency, rate of delivery, and time-to-association using a real-world running in a simulation. So that to explore the security on the link-layer of TSCH, the authors of [24] have constructed a full link-layer security on many platforms utilizing various software/ hardware rules. Time-slotted access is combined with channel hopping and multichannel capabilities in the new MAC protocol, which known as TSCH. To sum up, TSCH is a very promising technology for enabling the IoT of the future because of its ability to support mesh networks. Despite this, there are still a lot of flaws and open issues that need to be resolved. To begin, the vast majority of TSCH network works are geared toward a converge cast situation in which several nodes are responsible for transmitting data to a centralized coordinator of network. Although this situation is real, node-to-node communication will become a typical traffic pattern as the developed of IoTs. Supporting this volume of traffic effectively requires intensive study. To swiftly build node to node paths in networks of TSCH lightweight routing and scheduling methods should be developed. The procedure of establishing networks is another area of TSCH that must be perfected. Truthfully, most frameworks' nodes will be movable, leading to frequent node joins and departs. On the other hand, several nodes of TSCH will likely employ a mechanism of duty-cycling during the joining process to conserve power. Therefore, cutting-edge solutions may be incorrect or ineffective for upcoming real network circumstances.

Finally, big data is a group of data that are extremely massive and complicated and that can be processed faster than traditional database systems. When it comes to the IoT, this data is both massive and extremely fast-moving it won't work with the current system's structure. It refers to a big amount of information that was created using several programmers and is not systematically organized. An effective classifier that classifies the data acquired from the WSN is needed to solve this problem [9]. Table 1 explains the differences between these paper and related ones.

Table 1: Differences between this study and similar works

Reference	**Development Classification**	**Kinds of Applications**	**Architecture**	**Problems, Limitations and Challenges**
[12]	Intelligent factories	Sensor-based Internet of Things applications were discussed.	Wireless Sensor Network using RFID	Communication interference, Energy harvesting, fault tolerance, cost feasibility, higher capacities to handling data processing
[13]	Industry	Discussion of deployment methods employing sensor networks	Wireless Sensors Network	Coverage time, communication cost, and accuracy.
[14]	Intelligent IoT devices	Urban areas	Wireless Sensors Network	The problem with this study is that the WSN nodes aren't powerful enough to cover large areas.
[15]	Intelligent Cities	Internet of Things implementation in intelligent power grids	Internet of Things	The drawback of this effort is that no mobile applications or graphical user interfaces were provided to operate the robot autonomously.
[16]	IoTs Frameworks	Security, Applications, and taxonomy in Internet of Things	Internet of Things	Some problems arise with the layout, and it can't handle real-time data.
[17]	Intelligent factory & Industry	Only investigate and evaluate current solutions to identify sinkhole attacks	Wireless Sensors Network	They had difficulties with node type, depth type,

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

				communication range, and other factors
[18]	Industry	Methods of attack and defense against mobile networks' routing infrastructure are addressed	Wireless Sensors Network	Stack protocol difficulties and potential remedies
[19]	IoTs Frameworks	Models for sensor network deployment, categorization, and operation were studied in order to attain coverage.	IoTs	Attacks on the IoTs and the Wireless Sensor Network: Solutions, Benefits, and Limitations
[20]	Smart IoT devices	Models for categorization, and operation were studied also the sensor network deployment	Internet of Things	Using Prefix-Frequency Filtering (PFF) to filter a collection is a challenging problem.
[21]	Smart IoT devices	IoT's technological and societal perspectives were discussed in order to advance technology	Wireless Sensors Network	The WSN has a substantial challenge in deleting duplicate data without sacrificing accuracy
[22]	Industry	Methods of attack and defence against mobile networks' routing infrastructure are addressed.	Internet of Things	Many network functions, such as time synchronization, localization, and data fusion, are vulnerable to wormhole assaults
[23]	Intelligent factory & Industry	Wi-Fi (802.11) technology for smart cities	Wireless Sensors Network	Energy conservation is of paramount importance during the data capture and transmission processes
[24]	Intelligent factory & Industry	Network protocols, security for Internet of Things systems, and cryptographic techniques are all covered in this article.	Internet of Things	This study's weakness is that it did not address how to address security concerns in a heterogeneous IoT context.
This Paper	Intelligent Healthcare	To address three issues, applications and contributions of both IoT and WSN are thoroughly examined.	Wireless Sensors Network and Internet of Things	The key issue is security since the cost of doing security measurements eats up valuable resources that might otherwise be used to keep the network running quickly

3. Materials and Methods

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

3.1 Proposed Method

Environmental sensing using sensor nodes deployed at monitoring points is a typical IoT application scenario. In the final leg of internet connectivity for IoT devices, a wireless interface is favored for ease of deployment. An IoT system depends heavily on its applications. The applications can be roughly broken down into two groups: low rate of data and high rate of data. The expected level of service quality varies greatly. On the other hand, efficiency of energy is especially important for low-rate applications, which may rely solely on battery power. Because it determines how many nodes are viable, network design is the most crucial aspect of high-rate applications.

A dependable transfer from the nodes of sensor to the base of data will be the standard requirement. Although multi-hop transmission can be used to increase a WSN's coverage, due to repeated deliveries of the same packet, the cost is extremely high, resulting in a drop in network performance and life of battery. If the transmission range can be increased, the number of hops needed to complete a connection can be decreased, which is the preferable option. There can be a lot of nodes. WSN utilized by the building system of energy management to track the temperature of patients in a large facility. As sensor node density rises, the distribution of temperature will become more precise. The deployment density is affected by the cost of the nodes of sensor [1].

The GW employed a data reduction technique that was described in [25]. The concept behind this method is cluster topology. The proposal intentionally avoids discussing how the cluster topology is formed because it is outside the scope of the document and is predicated on the existence of an existing topology. Any clusters generated by a clustering protocol can be used with the provided methods. Primarily concentrating on developing energy-efficient data reduction methods. Specifically, this method aims to extend the WSN's lifespan by decreasing the amount of data detected at the GW level. The suggested approach functions as filtering at the gateway level by allowing the GW to recognize and then eliminate redundant data sets created by nearby nodes so as to reduce the overall number of sets that the sink will receive [26].

To improve Adaptive Boosting efficiency in the proposed framework, we employed SDS to fine-tune the configuration of a set of weak classifiers, including the number and weights of those classifiers. The SDS is an optimization and multi-agent global search method built on a straightforward exchange of information between the doctors. SDS is useful for sidestepping the "local minimum". Initially, a training corona dataset [27] is applied to teach the Adaptive Boosting. After t iterations, we have a set of weak weights and classifiers. Performance evaluations of the proposed system rely on testing of SDS Adaptive Boosting. The SDS algorithm then enters the process, optimizing the weight and quantity of weak classifiers. A vector is used to represent the answer, and the doctors are encoded. If the simple classifier is used, it is written as 1, otherwise it is written as 0. Only the necessary data is kept and handled in the IoT after the suggested classifier has categorized the data aggregated over WSN. Figure 2 offers the flowchart for suggested high-performance framework. Also, the algorithm A and algorithm B offers reduction of data at nodes and at gateway respectively.

Algorithm A: Reduction of Data at Nodes of Sensor

Input: sensor corona data set with n corona data readings.
Output: compressed sensor corona data.
while sensor energy > energy threshold do
for i ← 1 to n do
Corona Data ← Corona Data∪ {capture corona data reading}
end for
for each sensor corona data do
X[1] ←uncompressed corona data[1]
for i ←2 to n do
Delta Encoding = corona data (i) – corona data (i−1)
X[i] ←Delta Encoding
end for
Coding corona data ←RLE(X) (Encoding Technique)
end for
end while
return coding corona data

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

Algorithm B: Reduction of Data at Gateway

Input: n compressed corona data from first node.
Output: reduced corona data.
for i ←1 to n do
corona data (i) ← Decompressed(corona data(i))
end for
while it is not time to stop do
capture best two corona data
gathering those two corona data into one cluster
end while
for every cluster do
transfer uncompressed hypothesis
transfer conditional description (corona data (i)| hypothesis)
end for
return reduced corona data

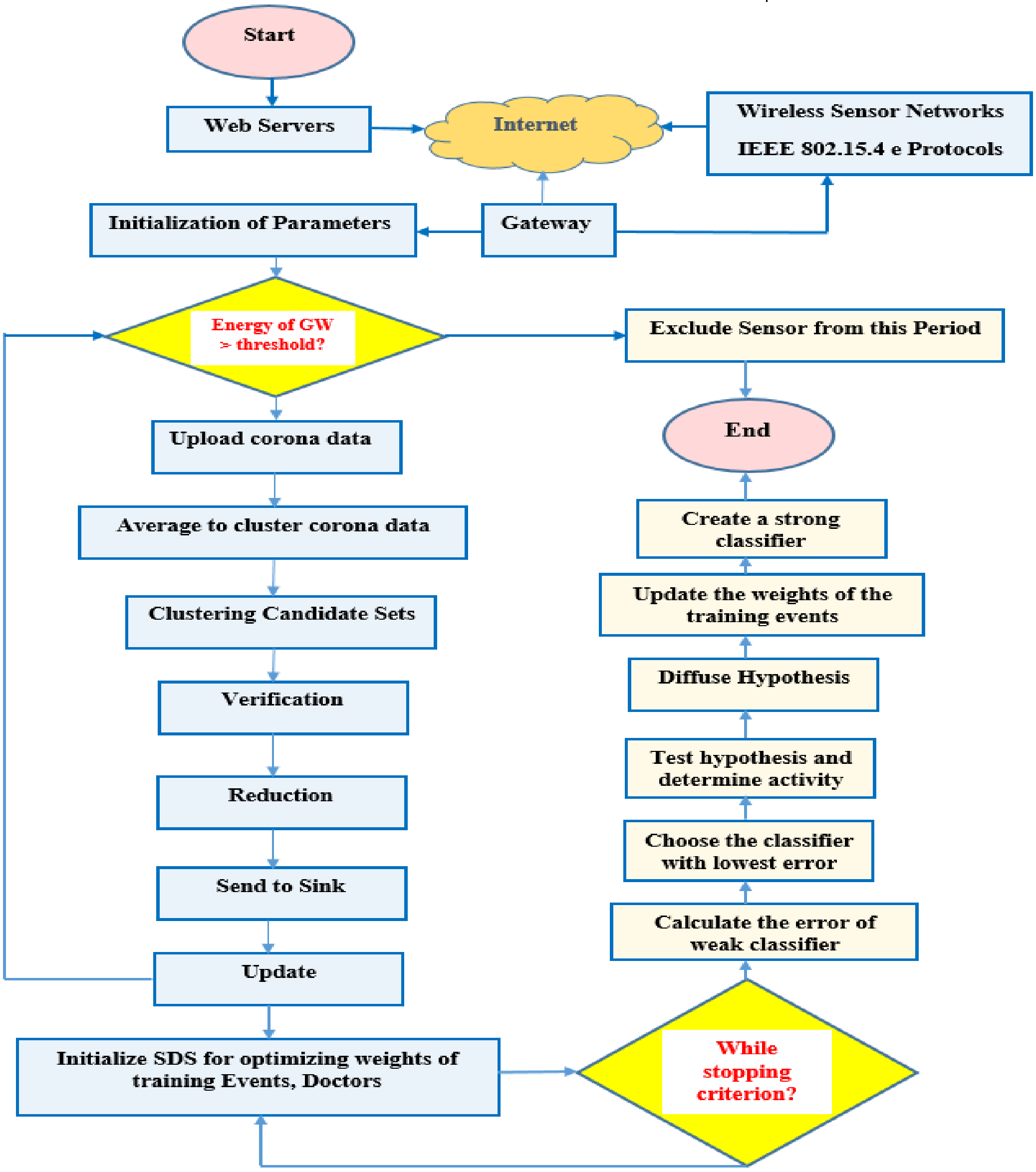


Figure 2: Flowchart of the Proposed High-Performance Framework.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

4. Wireless Sensor Network

The IEEE 820.15.4e [28] standard defines three novel protocols for use in a variety of situations: synchronous and deterministic multi-channel extension, low latency deterministic network, and TSCH. Only TSCH among them can build a mesh network using multi-hop transmission. TSCH, in essence, is a TDMA protocol that requires all nodes to synchronize with the coordinator's time stamp. Time is broken up into intervals of equal duration, as depicted in (Figure 3) contains a complete list of parameter definitions and default settings. In summary, before transmitting, the transmitter must wait for a time equal to mac-Ts-Tx-Offset to guarantee that the receiver is in a state of readiness to receive and before turning on its RF interface for any incoming packets, the receiver should wait an additional period equal to mac-Ts-Rx-Offset.

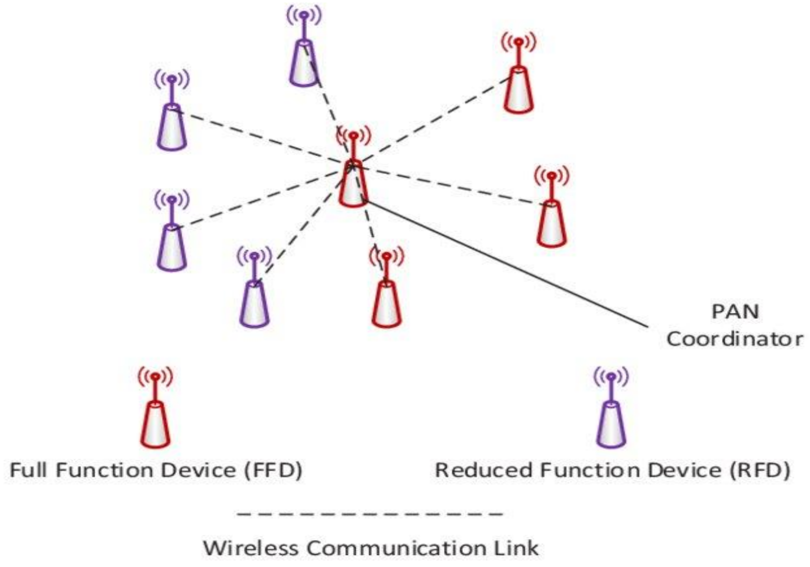


Figure 3: Kinds of Devices for IEEE 802.15.4.

5. Structure and Synchronization of Slot Frame

TSCH mode requires nodes to synchronize with one another on a periodic slot frame. Every node get channel hopping, synchronization, slot frame information and time slot from Enhanced Beacons (EBs) frames that other nodes send on a regular basis to promote the network. Once a node has received a valid EB, it will synchronize with the network, establish the slot frame, and begin broadcasting its own beacons. After this point, the slot frame repeats automatically based on the shared perception of time between the nodes and does not require beacons to start communication. Left of (Figure 4) is a slot frame with four time slots. A node may deliver a data frame of the largest size and obtain the associated acknowledgement during each timeslot (Figure 4 right). If the acknowledgment is not received within a certain amount of time, the data frame will be resent during the next time slot allocated to the same pair of nodes.

Within a timeslot, data packets are sent at the precise instant that is Ts-Tx-Offset microseconds seconds after the start of the timeslot. However, the receiver node begins listening to the channel Guard-Time's before to allow for a little amount of de-synchronization. Additionally, the node turns off its radio to conserve power if packet reception does not start within Guard-Time s after Ts-Tx-Offset [29].

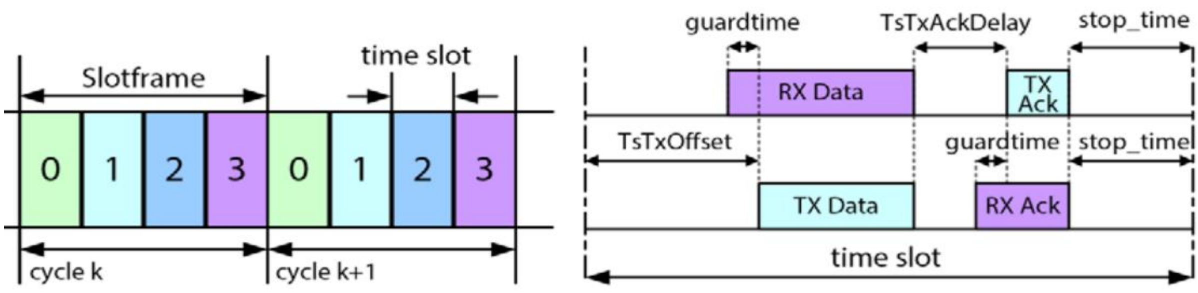


Figure 4: TSCH Timeslot (right) Slot-frame (left).

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

For this method to function, nodes must never be out of sync for longer than Guard-Times. But, due to dissimilarities in temperature, supply voltage, manufacturing, clocks of various nodes typically pulse at a slightly various frequency, obtained in 'clock-drift. For this reason, it is necessary to re-synchronize the nodes at regular intervals. Every node has a relationship with a time source neighbour in order to achieve this, with whom it must maintain synchronization across time. A node can re-synchronize in one of two methods, called Frame-depend on synchronization and ACK-based synchronization [30].

Every time a node gets a data packet from its time source neighbour, it records the precise moment the reception began. This is known as frame-based synchronization. Then, it adjusts the start and end times of its slots such that they coincide with those of its time source (because Ts-Tx-Offset is already known). Similar to this, every time a node sends a datagram to its nearby time source in ACK-based synchronization and places the timestamp that was retrieved in the acknowledgment field. The value is used to adjust the timekeeping mechanism of the sending node once again. Re-synchronization frequency is affected by both Guard-Time and clock drift. The less frequently nodes need to re-synchronize, the larger the guard duration or the smaller the drift rate [31].

6. Ensemble Methods

To improve their generalization ability and robustness, ensemble methods of machine learning aggregate predictions from several base learners. Machine learning has a bright future in ensemble learning owing to computational, representational, and statistical characteristics. With adequate data, different classifiers can be found statistically using sampling distributions. Therefore, ensemble learning has the potential to mitigate dangers like making the wrong choice, achieving locally optimal results, and the algorithmic dependence on input parameters. Based on the ensemble generation structure of the base-learning algorithms, independent and independent & dependent ensemble methods are the two main kinds of ensemble methods. The output of a base learner can have an impact on the creation of later classifiers in dependent techniques, whereas the outcomes of the basic learners are obtained independently and combined using a specific technique. Algorithms like Adaptive Boosting and Boosting are prominent illustrations of dependent ensemble approaches, Random Subspace and Bagging. Approaches are common instances of autonomous ensemble techniques. (Figure 5 shows the flowchart for putting ensemble learning into practice) [32].

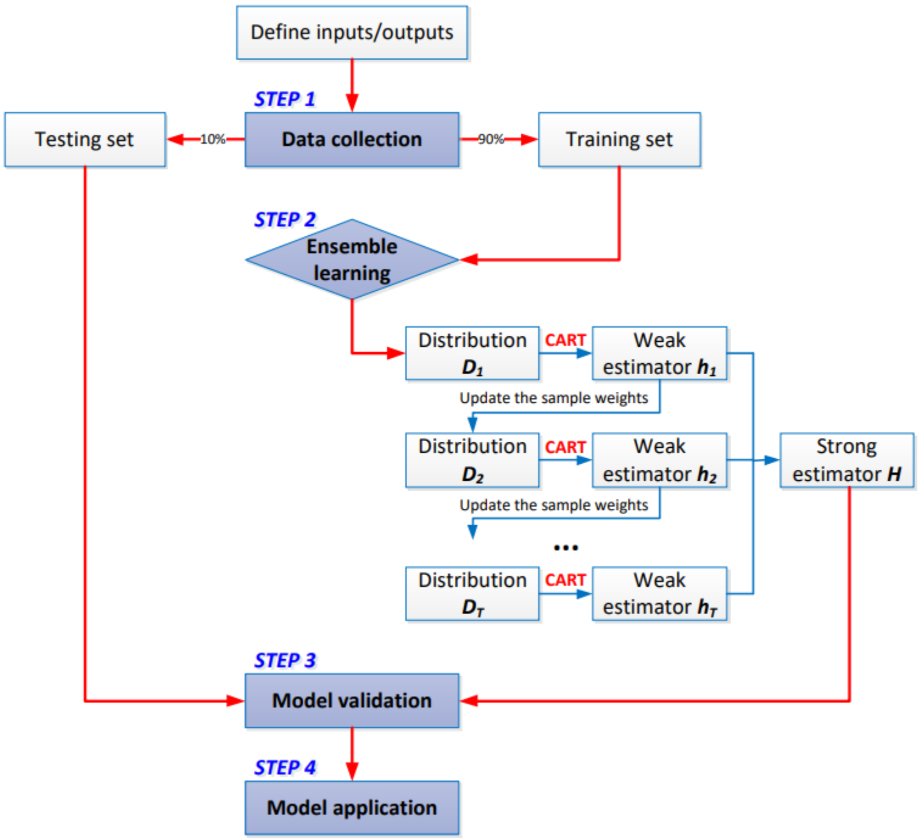


Figure 5: Flowchart for putting ensemble learning into practice.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

7. Stochastic Diffusion Search

Initially, the SDS was proposed in 1989. It serves as the global search and optimization algorithm with a population of multiple agents, which is a novel kind of distributed computation that relies on cooperation amongst relatively simple entities. Its computational foundations come from Geoff Hinton's fascination with 3D object mapping. The SDS algorithm starts a search with the generation of a population and then iteratively refines the population through two stages: they are the diffusion & test phases. In the former, the SDS will do an assessment of the agent hypothesis that yields the Boolean value 1 to determine if the hypothesis was successful. Once this agent activity has been identified, successful hypothesis diffusion for the possibly sound solutions is discovered among the population. This means that every agent has the capacity to bring in a second agent to communicate with him. Once the agents have evaluated their hypothesis, they can choose from a variety of communication [33].

8. Adaptive Boosting Algorithm

A classifier is built using the boosting algorithm called Adaptive Boosting. The purpose of a classifier, in data mining, is to make predictions about the type of data given certain inputs. An ensemble learning method called the boosting algorithm runs various learning algorithms and combines them. (See Figure 6). An ensemble of weak learners can be combined using a boosting algorithm to produce a single robust learner. A less accurate classifier is a weak learner. Algorithm of decision stump, which is essentially a one-step decision tree, is the most effective example of a bad algorithm. Adaptive boosting is the ideal algorithm of supervised learning since it works in iterations and trains the weaker learners with the labelled data during each iteration. Adaptive boosting is a simplistic algorithm that can be easily implemented.

After the user specifies the number of iterations, Adaptive Boosting reevaluates the top learners and adjusts their weights accordingly. As a result, Adaptive boosting is an extremely sophisticated approach to auto-tuning a classifier. Adaptive boosting can encompass the majority of learning algorithms, and is flexible in its data handling capabilities, making it adaptable, flexible, and beautiful [34, 35].

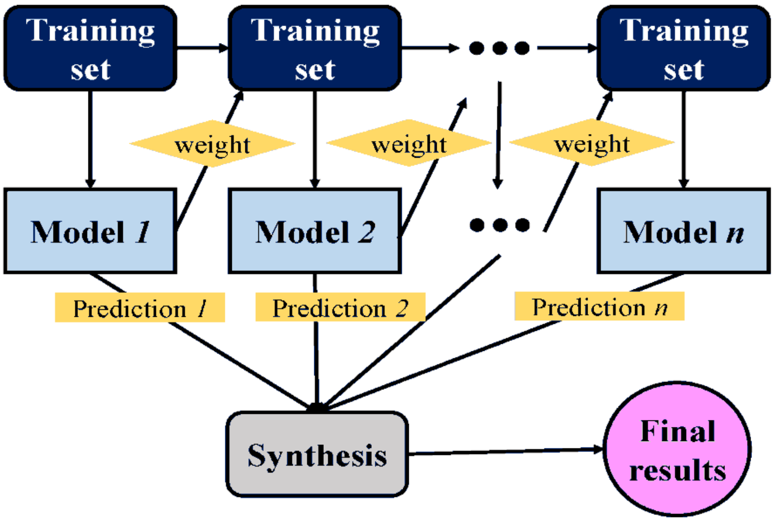


Figure 6: AdaBoost Algorithm.

9. Naïve Bayes

Based on Bayes' theorem, the naive Bayes algorithm is a statistical method. The algorithm is based on the class conditional independence presumption, which states that the value of a property on a certain class is not dependent on the values of other attributes. The assumption makes the necessary computational effort simpler. It has a great predictive performance despite its low complexity, high computing efficiency, and good performance in making predictions. Data mining applications are just one of the many classification tasks for which the naive Bayes algorithm is frequently used. The method achieves results in classification problems that are competitive with those of well-known classification approaches like decision trees and neural networks. The conditional probability and maximum likelihood occurrence were the foundations of the first Nave Bayesian method. (Figure 7 offers NB flowchart) [36, 37].

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

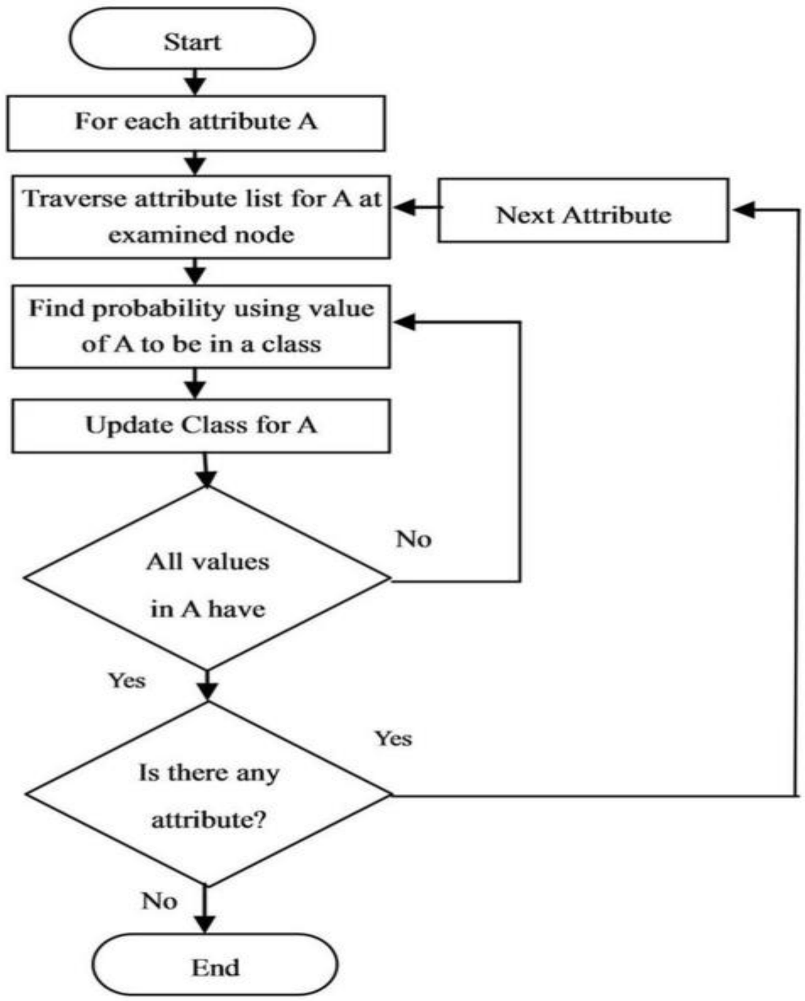
$$(X=x|C=c) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \quad (1)$$

Where :

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_I \quad (2)$$

$$\sigma = [\frac{1}{n-1} \sum_{i=1}^{n} (xi - \mu)^2]^{0.5} \quad (3)$$

Where n is the number of instances, x_i is a specific value of the x variable for the i^{th} instance.



10. Results and Discussion

This section describe the results of data reduction in the sensor node (GW), also determine the performance of TSCH, and describe the results of the performance data mining algorithms.

10.1 Results in Gateway

The proposed compression approach based on the HOSD technique in [25] is evaluated in the sensor node and contrasted with the AVMDA [38], PFF [39], and ATP [40] techniques. After data compression/aggregation, we use the remaining fraction of corona data to measure efficiency and effectiveness. The proportion of leftover data after applying data compression/ aggregation by each IoT sensor node using various approaches is shown in (Figure 8) (ATP, PFF, and AVMDA). The outcomes show that the AVMDA compression techniques can reduce the residual data by up to 75%, when aggregation is used, the ATP technique reduces the leftover data to a maximum of 65%, and PFF can cut down on the remaining data by as much as 70%. While HOSD will reduce the remaining data to a maximum of 80% when applied.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

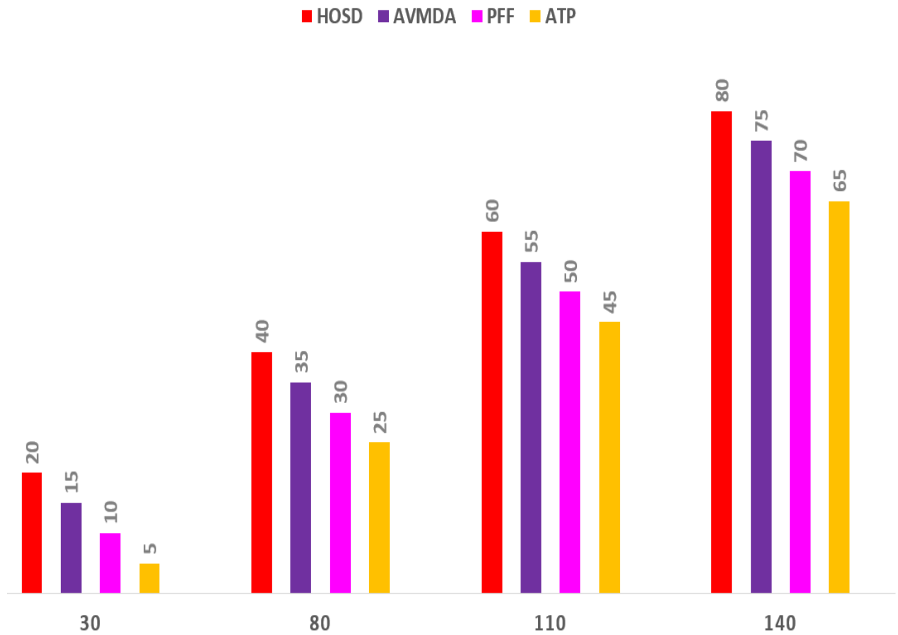


Figure 8: Rates of Data Reduction.

10.2 Impact of channels number on network of TSCH

In this sub-section, we examine the several TSCH performance measures, namely, the average delay, the likelihood of retransmission, reliability, consumption of energy, and throughput depending on the total number of connected devices and the availability of individual channels. This analysis's goal is to determine how the quantity of dedicated channels affects the TSCH network's performance.

Average delays are shown to decrease when the quantity of specialized channels is increased in (Figure 9). This reduction can be attributed to the absence of a waiting period during broadcast over a dedicated channel. Additionally, lowering the likelihood of retransmission is accomplished by multiplying the number of individual channels, which in turn reduces collisions. As a result, the device is in the back off condition for a shorter period of time, which decreases the delay.

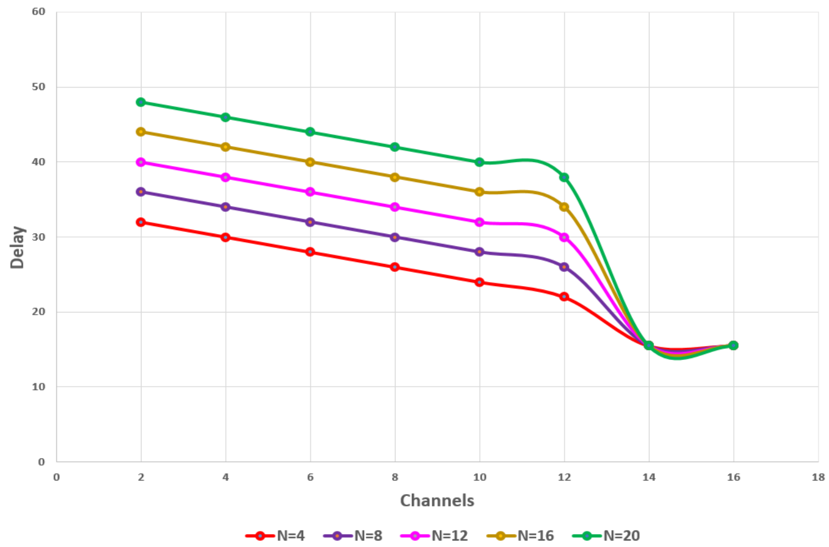


Figure 9: Average Delays.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

(Figure 10) shows how the likelihood of retransmission due to collisions or transmission faults varies with the all channels that are dedicated. Regardless of network size, we observe that the chance of retransmission lowers as the number of dedicated channels increases. By boosting the number of specialized channels, increased likelihood of data packet transmission across a secure channel, it implies that when fewer nodes compete to send data packets on a shared network, collisions become less common. As a result, the likelihood of retransmission is diminished.

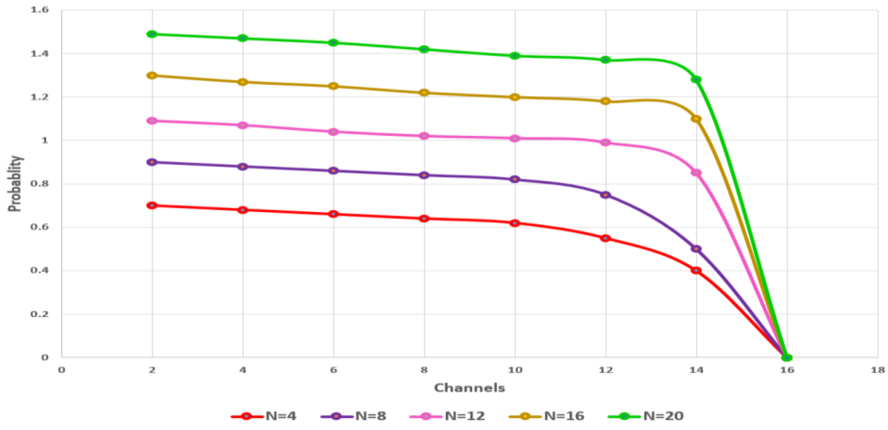


Figure 10: Likelihood of Retransmission.

It is clear from (Figure 11) that the throughput grows proportionally with the number of dedicated channels, independent of the overall size of the network. When the number of devices exceeds the number of available channels, we also find that (up to 5 channels), Throughput is maximized with a smaller number of devices compared to a larger or constant number of devices. In fact, there is more competition for the transmission channel when there are more devices. The channel is not utilized for successful broadcast as a result, and the likelihood of retransmission rises. However, the opposite impact is seen when there are more specialized channels than devices. And because there are fewer collisions, the bandwidth is used more effectively.

As shown in (Figure 12), the energy usage rises as the number of specialized channels grows. Because the odds of transmission improve and the odds of collision decrease, this is exactly what happens. The device uses more energy since it spends more time in the reception and transmission stages. According to (Figure 13), the reliability rises as the number of dedicated channels grows, it doesn't matter how many gadgets are connected. When the number of retransmissions attempts above the maximum retry limit value, the likelihood that the data packets would be rejected decreases. This makes the network even more reliable.

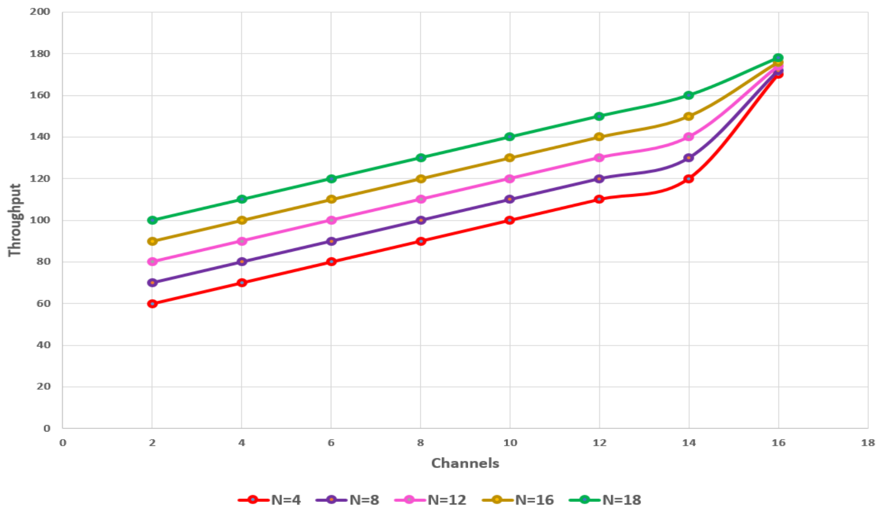


Figure 11: Throughput vs. Channels.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

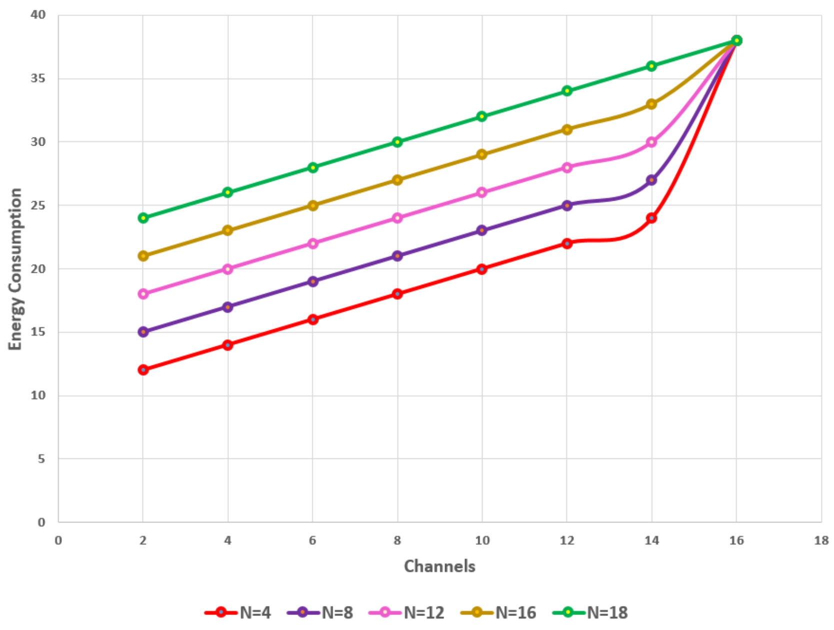


Figure 12: Energy Consumption vs. Channels.

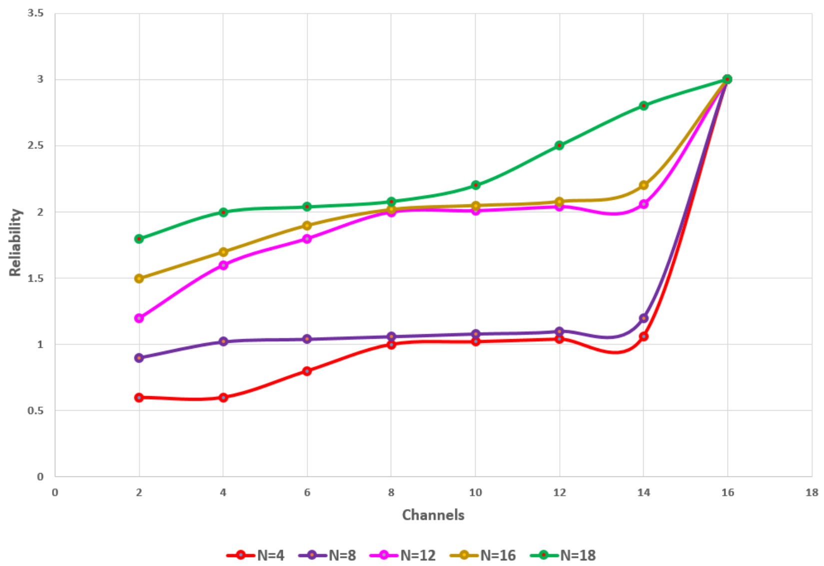


Figure 13: Reliability.

10.3 Performance of Data Mining Algorithms

Using the corona large dataset, the suggested SDS-Adaptive Boosting was tested and compared to previously used classifiers such as CART, Naïve Bayes, Random Forest, Bagging, Adaptive Boosting and GA Adaptive Boosting. The factors of SDS are number of search agents (90), maximum iterations (500), and diffusions values (5). Tables 1, 2, 3, 4 and (Figures 14, 15, 16, and 17) show the accuracy, balance accuracy, precision, and recall of CART, Bagging, Naïve Bayes, Random Forest, Adaptive Boosting and GA-Adaptive Boosting, respectively. Tables and

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

figures show that SDS-Ada-Boost outperforms naïve bays, Adaptive Boosting, CART, GA-Adaptive Boosting, and random forest bagging on the various performance indicators.

It is offer from Table 2 and Table 3 that the accuracy and balance accuracy of SDS-AdaBoost achieves better by 11.21%, by 10.01%, by 9.15%, by 8.11%, by 3.22% and by 1.17% than CART, NB, RF, AdaBoost, Bagging, and GA-AdaBoost, consciously, for 45k events/second. The accuracy of SDS-AdaBoost performs better by 12.44%, by 12.11%, by 9.07%, by 7.9%, by 6.13% and by 3.99% than CART, NB, RF, AdaBoost, Bagging, and GA-AdaBoost, consciously for 47k events/second.

It is observed from Table 4 that the precision of SDS-AdaBoost achieves better by 24.33%, by 22.88%, by 23.84%, by 22.99%, by 11.9%, and by 8.33% than CART, NB, RF, AdaBoost, Bagging, and GA-AdaBoost, consciously, for 45k events/second. The precision of S by 24.01%, by 19.44%, by 17.99%, by 15.33%, and by 11.22% than CART, NB, RF, AdaBoost, Bagging, and GA-AdaBoost, consciously, for 45k events/second, for 47 k events/seconds.

It is observed from Table 5 that the average recall of SDS-AdaBoost performs better by 17.83%, by 15.79%, by 13.78%, by 12.9%, by 5.88%, and by 3.53% than CART, NB, RF, AdaBoost, Bagging, and GA-AdaBoost, consciously, for 45k events/seconds. The average recall of SDS-AdaBoost performs better by 19.39%, by 18.84%, by 15.6%, by 13.49%, by 9.22%, and by 5.13% than CART, NB, RF, AdaBoost, Bagging, and GA-AdaBoost, consciously, for 47k events/seconds.

Table 1: Accuracy of Algorithms.

Algorithm	45 events/ second	47 events/ second
Adaptive Boosting	70	70
Naïve Bayes	68	66
Random Forest	68.5	66.8
GA-Adaptive Boosting	73	71
Bagging	69	67
CART	69.5	67.9
SAS-Adaptive Boosting	77	75.7

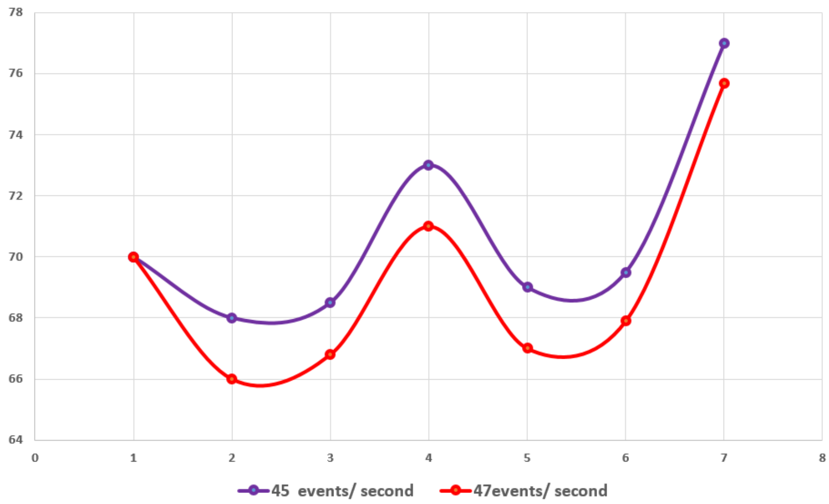


Figure 14: Accuracy of Algorithms.

Table 2: Balance Accuracy of Algorithms.

Algorithm	45 events/ second	47 events/ second
Adaptive Boosting	72	70
Naïve Bayes	70	68

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

Random Forest	70.5	69.8
GA-Adaptive Boosting	75	73.2
Bagging	71	69.4
CART	71.5	69.9
SAS-Adaptive Boosting	79	77

Table 3: Precision of Algorithms.

Algorithm	45 events/ second	47events/ second
Adaptive Boosting	77	75
Naïve Bayes	75	73
Random Forest	67.5	65.8
GA-Adaptive Boosting	80	78
Bagging	76	74
CART	76.9	75.9
SAS-Adaptive Boosting	84.2	82.2

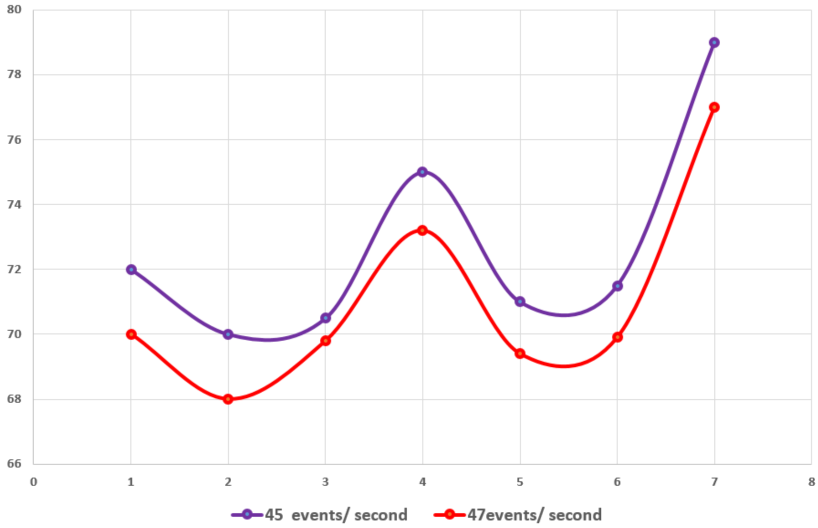


Figure 15: Balance Accuracy of Algorithms.

Table 5: Recall of Algorithms.

Algorithm	45 events/ second	47 events/ second
Adaptive Boosting	75	73.1
Naïve Bayes	74	72.2
Random Forest	65.6	63.8
GA-Adaptive Boosting	78	76.9
Bagging	74.1	73.2
CART	74.7	72.4
SAS-Adaptive Boosting	82	79.1

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

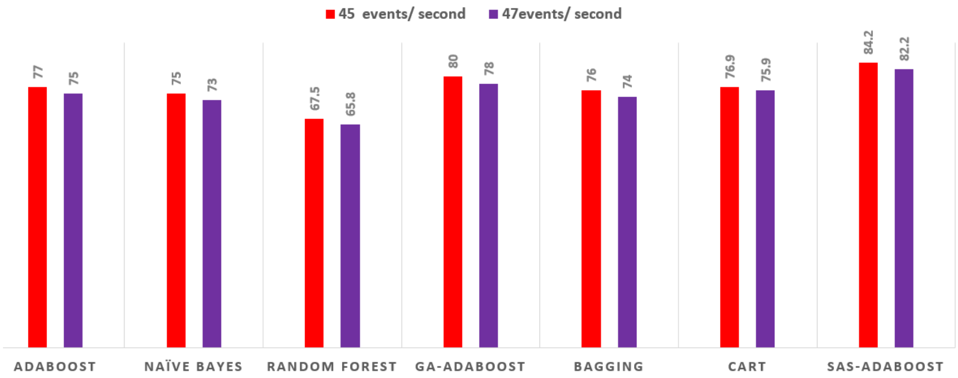


Figure 16: Precision of Algorithms.

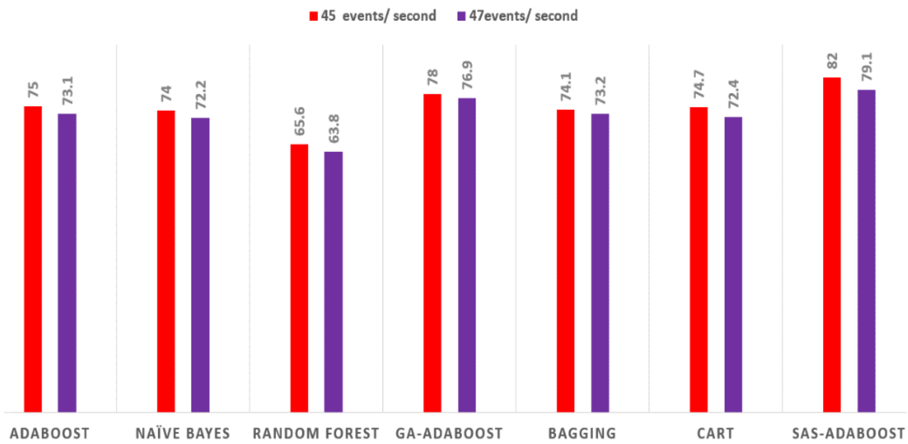


Figure 17: Recall of Algorithms.

11. Conclusions

The WSN-based-IoT is a brand-new internet paradigm that is based on the discovery that there are many more things connected to the internet than there are people. Classifying data helps cut down on unnecessary processing in the IoT, making it run more efficiently. The outcomes demonstrated that SDS-Adaptive Boosting performs more accurately than the NB, Bagging, GA-Adaptive Boosting, Random Forest, and Adaptive Boosting for the 45 & 47 events/seconds. One of the most crucial factors influencing the longevity of a wireless sensor network is the sensor node's battery. The performance metrics, called: energy consumed, average access delay, throughput, and reliability. We have examined the effects of the number of channels on the functionality of the network of TSCH. Important benefits of dedicated channels have been demonstrated. There is conclusive evidence that more dedicated channels result in better network performance. This is accomplished by lowering the likelihood of retransmission, which leads to increase the throughput and reliability to reduce the average access delay. All these enhancements are vital for WSNs to be used in industrial settings. In this paper, the main goal is to take use of the advantage from the integrating of the TSCH, Adaptive Boosting SDS, and spatial data correlation. The future work of this paper is that we suggest using security techniques for building secure healthcare framework based on the WSN and IoTs.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

References

[1] Kuo, Y. W., Li, C. L., Jhang, J. H., & Lin, S. (2018). Design of a wireless sensor network-based IoT platform for wide area and heterogeneous applications. IEEE Sensors Journal, 18(12), 5187-5197.

[2] Maivizhi, R., & Yogesh, P. (2021). Q-learning based routing for in-network aggregation in wireless sensor networks. Wireless Networks, 27(3), 2231-2250.

[3] Ramezanifar, H., Ghazvini, M., & Shojaei, M. (2021). A new data aggregation approach for WSNs based on open pits mining. Wireless Networks, 27(1), 41-53.

[4] Idrees, A. K., & Al-Qurabat, A. K. M. (2021). Energy-efficient data transmission and aggregation protocol in periodic sensor networks based fog computing. Journal of Network and Systems Management, 29(1), 1-24.

[5] Younan, M., Houssein, E. H., Elhoseny, M., & Ali, A. E. M. (2021). Performance analysis for similarity data fusion model for enabling time series indexing in internet of things applications. PeerJ Computer Science, 7, e500.

[6] Jarah, N. B. (2020). Technique Pair of node to provide Power in WSNs. Karbala International Journal of Modern Science, 6(2), 2.

[7] Xu, G., Shi, Y., Sun, X., & Shen, W. (2019). Internet of things in marine environment monitoring: A review. Sensors, 19(7), 1711.

[8] A.K.M. Al-Qurabat, A.K. Idrees, Data gathering and aggregation with selective transmission technique to optimize the lifetime of Internet of Things networks, Int. J. Commun. Syst. 33 (2020), e4408.

[9] Suganya, E., & Rajan, C. (2020). An AdaBoost-modified classifier using stochastic diffusion search model for data optimization in Internet of Things. Soft Computing, 24(14), 10455-10465.

[10] Sandhu SK, Kumar A (2017) Hybrid meta-heuristics based scheduling technique for cloud computing environment. Int J Adv Res Comput Sci 8(5):1457–1465

[11] M Allayla, N., NazarIbraheem, F., Adnan Jaleel, R.: Enabling imageoptimisation and artificial intelligence technologies forbetter internet of things framework to predict COVID.IET Netw. 1–11 (2022). https://doi.org/10.1049/ntw2.12052M ALLAYLA ET AL. - 11

[12] A. K. M. Al-Qurabat, and A. K. Idrees,“Energy-efficient adaptive distributed data collection method for periodic sensor networks,” International Journal of Internet Technology and Secured Transactions, vol. 8, no. 3, pp. 297-335, 2018.

[13] A. K. Idrees, and A. K. M. Al-Qurabat, “Distributed Adaptive Data Collection Protocol for Improving Lifetime in Periodic Sensor Networks,” IAENG International Journal of Computer Science, vol. 44, no. 3, 2017.

[14] A. K. M. Al-Qurabat, and A. K. Idrees, “Distributed data aggregation and selective forwarding protocol for improving lifetime of wireless sensor networks,” Journal of Engineering and Applied Sciences, vol. 13, pp. 4644–4653, 2018.

[15] N. Mahakalkar, R. Pethe, ‘‘Review of Routing Protocol in a Wireless Sensor Network for an IOT Application,” 2018 3rd International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2018, pp. 21-25, doi: 10.1109/CESYS.2018.8723935

[16] M. Priyanga, S. Leones Sherwin Vimalraj, J. Lydia, ‘‘Energy Aware Multiuser & Multi-hop Hierarchical – Based Routing Protocol for Energy Management in WSN-Assisted IoT,” 2018 3rd International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 2018, pp. 701-705, doi: 10.1109/CESYS.2018.8724073

[17] R. Prakash, P. Kansal, V. K. Kakar, ‘‘Optimized Hybrid Clustered Protocol for IoT Heterogeneous Wireless Sensor Networks,” 2019 IEEE Conference on Information and Communication Technology, Allahabad, India, 2019, pp. 1-6, doi: 10.1109/CICT48419.2019.9066258

[18] Al-Rifaie MM, Joyce D, Shergill S, Bishop M (2015) Investigating stochastic diffusion search in data clustering. In: 2015 SAI intelligent systems conference (IntelliSys). IEEE, pp 187–194

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

[19] Chen J, Hu K, Wang Q, Sun Y, Shi Z, He S (2017) Narrowband internet of things: implementations and applications. IEEE Internet of Things J 4(6):2309–2314

[20] Mahdavinejad MS, Rezvan M, Barekatain M, Adibi P, Barnaghi P, Sheth AP (2018) Machine learning for Internet of Things data analysis: a survey. Digit Commun Netw 4(3):161–175

[21] Darabian H, Dehghantanha A, Hashemi S, Homayoun S, Choo KKR (2019) An opcode-based technique for polymorphic Internet of Things malware detection. Concurr Comput Pract Exp. https:// doi.org/10.1002/cpe.5173

[22] Kaur P, Kumar R, Kumar M (2019) A healthcare monitoring system using random forest and internet of things (IoT). Multimed Tools Appl. https://doi.org/10.1007/s11042-019-7327-8

[23] Alves RCA, Margi CB (2016) IEEE 802.15.4e TSCH mode performance analysis. In: IEEE 13th international conference on mobile ad hoc and sensor systems (MASS), pp 361–362. https://doi.org/ 10.1109/MASS.2016.054.

[24] Sciancalepore S, Vuˇcini´c M, Piro G, Boggia G, Watteyne T (2017) Link-layer security in TSCH networks: effect on slot duration. Trans Emerg Telecommun Technol 28(1):e3089.

[25] Abdulzahra, S. A. (2021). Energy Conservation Approach of Wireless Sensor Networks for IoT Applications. Karbala International Journal of Modern Science, 7(4).

[26] S.A. Abdulzahra, A.K.M. Al-Qurabat, A.K. Idrees, Data reduction based on compression technique for big data in IoT, in: 2020 Int. Conf. Emerg. Smart Comput. Informatics, ESCI, 2020, pp. 103e108, https://doi.org/10.1109/ESCI48226.2020. 9167636.

[27] Suganya, E., & Rajan, C. (2020). An AdaBoost-modified classifier using stochastic diffusion search model for data optimization in Internet of Things. Soft Computing, 24(14), 10455-10465.

[28] Ali, N. G., Abed, S. D., Shaban, F. A. J., Tongkachok, K., Ray, S., & Jaleel, R. A. (2021). Hybrid of K-Means and partitioning around medoids for predicting COVID-19 cases: Iraq case study. Periodicals of Engineering and Natural Sciences (PEN), 9(4), 569-579.

[29] IEEE Standard for Local and Metropolitan Area Networks—Part. 15.4: Low-Rate Wireless Personal Area Networks (LR-WPANs) Amendament1: MAC Sublayer, IEEE Standard 802.15.4e, Apr. 2012.

[30] Vogli, E., Ribezzo, G., Grieco, L. A., & Boggia, G. (2015, March). Fast join and synchronization schema in the IEEE 802.15. 4e MAC. In 2015 IEEE Wireless Communications and Networking Conference Workshops (WCNCW) (pp. 85-90). IEEE.

[31] Val, I., Arriola, A., Cruces, C., Torrego, R., Gomez, E., & Arizkorreta, X. (2015, May). Time-synchronized Wireless Sensor Network for structural health monitoring applications in railway environments. In 2015 IEEE World Conference on Factory Communication Systems (WFCS) (pp. 1-9). IEEE.

[32] Zhu, D., Bendlin, R., Akoum, S., Ghosh, A., & Heath, R. W. (2019). Directional frame timing synchronization in wideband millimeter-wave systems with low-resolution ADCs. IEEE Transactions on Wireless Communications, 18(11), 5350-5366.

[33] Feng, D. C., Liu, Z. T., Wang, X. D., Jiang, Z. M., & Liang, S. X. (2020). Failure mode classification and bearing capacity prediction for reinforced concrete columns based on ensemble machine learning algorithm. Advanced Engineering Informatics, 45, 101126.

[34] Al-Rifaie, M. M., & Bishop, J. M. (2013). Stochastic diffusion search review. Paladyn, Journal of Behavioral Robotics, 4(3), 155-173.

[35] Abed, A. S., Hassan, H. F., Aldulaimi, M. H., Zahra, M. M. A., & Jaleel, R. A. (2022, April). An Effective Framework for Enhancing Performance of Internet of Things using Ant Colony Meta-Heuristic and Machine Learning Algorithms. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 2498-2502). IEEE.

[36] Mosa, A. M., Hamed, E. A., Hussein, Z., & Jaleel, R. A. (2022, April). Improved Smart Forecasting Model to Combat Coronavirus using Machine Learning. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 1953-1957). IEEE.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023

[37] Fadhil, Z. M., & Jaleel, R. A. (2022, April). Multiple Efficient Data Mining Algorithms with Genetic Selection for Prediction of SARS-CoV2. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 2016-2020). IEEE.

[38] Harb, H., Makhoul, A., Laiymani, D., Bazzi, O., & Jaber, A. (2015). An analysis of variance-based methods for data aggregation in periodic sensor networks. In Transactions on large-scale data-and knowledge-centered systems XXII (pp. 165-183). Springer, Berlin, Heidelberg.

[39] Bahi, J. M., Makhoul, A., & Medlej, M. (2014). A two tiers data aggregation scheme for periodic sensor networks. Adhoc & Sensor Wireless Networks, 21(1).

[40] Harb, H., Makhoul, A., Couturier, R., & Medlej, M. (2015, June). ATP: An aggregation and transmission protocol for conserving energy in periodic sensor networks. In 2015 IEEE 24th International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (pp. 134-139). IEEE.

[41] Al Basheer, O., "On Some Novel Simplex Linear Codes Defined over the Algebraic Ring F2+vF2 ", Neoma Journal of Mathematics and Computer Science, 2023.

DOI: https://doi.org/10.54216/FPA.130104
Received: March 17, 2023 Revised: June 17, 2023 Accepted: August 14, 2023