Journal of Robotics and Control (JRC)
Volume 3, Issue 4, July 2022
ISSN: 2715-5072, DOI: 10.18196/jrc.v3i4.15539

Survey Paper Artificial and Computational Intelligence in the Internet of Things and Wireless Sensor Network

Galang P. N. Hakim [1*], Diah Septiyana [2], Iswanto Suwarno [3]
[1] Department of Electrical Engineering, Universitas Mercu Buana, Jakarta, Indonesia
[2] Department of Industrial Engineering, Universitas Muhammadiyah Tangerang, Tangerang, Indonesia
[3] Department of Electrical Engineering, Universitas Muhammadiyah Yogyakarta, Yogyakarta, Indonesia
Email: [1] galang.persada@mercubuana.ac.id, [2] dee.septie@gmail.com, [3] iswanto_te@umy.ac.id
*Corresponding Author

Abstract—**In this modern age, Internet of Things (IoT) and Wireless Sensor Network (WSN) as its derivatives have become one of the most popular and important technological advancements. In IoT, all things and services in the real world are digitalized and it continues to grow exponentially every year. This growth in number of IoT device in the end has created a tremendous amount of data and new data services such as big data systems. These new technologies can be managed to produce additional value to the existing business model. It also can provide a forecasting service and is capable to produce decision-making support using computational intelligence methods. In this survey paper, we provide detailed research activities concerning Computational Intelligence methods application in IoT WSN. To build a good understanding, in this paper we also present various challenges and issues for Computational Intelligence in IoT WSN. In the last presentation, we discuss the future direction of Computational Intelligence applications in IoT WSN such as Self-Organizing Network (dynamic network) concept.**

Keywords—IoT; WSN; Computational Intelligence; Artificial Intelligence; Dynamic Network

I. INTRODUCTION

In this modern age, IoT (Internet of Things) has become one of the most many popular and important technological advancements. IoT is a concept which aims to expand the benefits of continuously connectivity of connected internet [1]. IoT provides capabilities for data sharing, monitoring, remote control, and so on [2], including monitoring and controlling "things" in the real world [3]. IoT are include such as foodstuffs, collectibles, electronics, including living things, and etc. All of those, are connected to the IoT using local and global networks, and represented through embedded sensors that are always active [4]. The IoT refers to objects that can be uniquely identified as virtual representations of a physical form in an Internet-based structure [5]. IoT produces an interaction between machines to machines that connected automatically without human intervention anywhere and anytime. The Internet provides a medium between the two machine interactions, while humans only serve as a regulator and supervisor of the work of the tool directly. IoT can be applied to many things from ATMs (Automatic Teller Machine) [6], Street lightning [7], smart homes [8], smart cities [9], and more [10], [11]. The application above shows us that IoT has a lot of potential applications (see figure 1 below).

IoT also gives birth to new technologies such as WSN (Wireless Sensor Network) [12] and Drone [13]. Even though IoT can be used as a single node, such as in health care applications to monitor patient heart rate, blood pressure, body temperature, and others [14], IoT can also be used as a network to expand the IoT application coverage such as forest fire drone monitoring [15] and others [16]. This IoT is called a Wireless Sensor Network.

As defined by ITU-T WSN is a network that is composed of interconnected sensor nodes exchanging information (sensed data) using wireless communication [17]. This WSN is particularly interesting because of its usefulness to monitor its surrounding (environment) using sensors and send its data monitoring using wireless communication [18]. A few main advantages of WSN would be its ability to reduce infrastructure deployment costs and extend its coverage by using ad-hoc wireless communication methods [19]. An ad-hoc wireless communication method is wireless communication that uses node to node for its communication system [20]. This communication method was used in WSN so it can deliver its data monitoring from the farthest node (remote location) to the nearest node with the server (sink node), without using any other wireless infrastructure [21].

Computational Intelligence is a method to construct an intelligent system [22] using a respected algorithm. We can also say that Computational Intelligence is a part of artificial intelligence, wherein problem-solving, they use an innovative approach to adapt its intelligent behavior in complex and ever-changing environments. Computational Intelligence can also be used to resolve problems and issues in IoT WSN applications. This can be achieved by building the computational model for every problem based on collected data or processes running in the IoT WSN network. Therefore, to build a good IoT WSN application, an innovative way such as Computational Intelligence is an inevitability to manage and serve as their application backbone.

In this paper, the author tries to present IoT-WSN applications and how Computational Intelligence can be served as their backbone. The author then raises issues and challenges that may be faced and can be raised as material for further research. The schematic of the paper is explained as follows: Section I describes the needs of IoT-WSN and its relationship with artificial intelligence. Section II presented IoT-WSN. Section III presented artificial intelligence. Section IV presented about artificial intelligence application in IoT WSN. Section V presented challenges and issues regarding IoT-WSN and artificial intelligence. Section VI describes future research that possible to do. Section VII conclusion of our survey paper result.

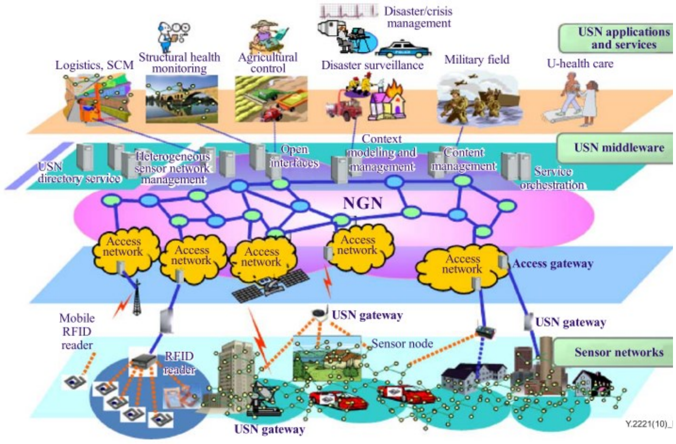

Fig. 1. IoT WSN Use Cases [17]

II. IoT WSN Architecture

There are 2 distinct architectures in IoT WSN, the first was node architecture and the second was system architecture. The first architecture presented us with mostly hardware configuration while the second architecture presented us with system configuration.

A. IoT WSN Node Architecture

Usually, in IoT nodes, there are 4 main basic components such Energy module, Controller module, Sensor module, and communication module [23]. Furthermore, as defined in ITU for next-generation networks, aside from 4 main components. Every WSN node can be added with an additional module such as an actuator (see Fig. 2) [24].

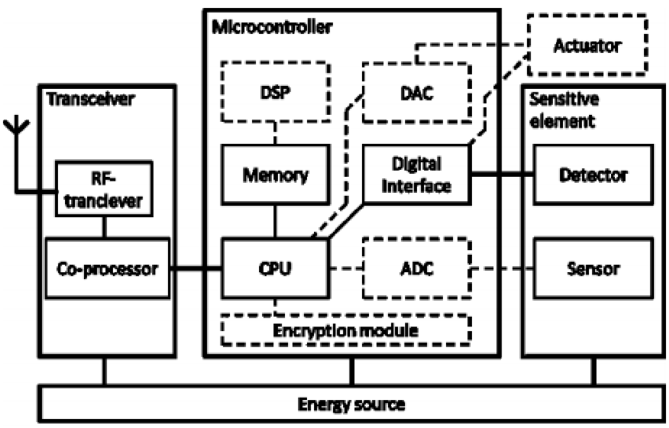

Fig. 2. IoT WSN node Architecture [24].

- The sensitive element usually contains a sensor module that is capable of sensing its environment, whether to see the temperature and humidity [25], light [26], soil moisture [27], and many others [28], [29]. An analog sensor would require an analog-to-digital converter (ADC) feature to format its monitoring data before it can be processed further. Nevertheless, in digital sensors, every monitoring data can process directly [30]. Sometimes sensor is also not enough to provide all the data that the user needs in the complex environment or complex application. Therefore, in some complex applications, some researcher also adds detector such as a camera that acts as an image detector [31], or motion detector [32], or even a tool for object recognition [33].
- The Processing unit usually uses a low-power microcontroller that had CPU, Memory, ADC, DAC, and digital I/O as their minimum feature (such as ATMega328P) [34]. This microcontroller usually needs an additional module to enhance its capabilities to handle more complex functions, such as the digital signal processing (DSP) function (TMS320) [35] and encryption function (FPGA) [36]. In the light of IoT's complex functions such as video recognition, voice recognition, and image recognition, there is the need for faster but still cheaper processing hardware such as SBC (Single Board Computer) raspberry pi [48],[49] or orange pi [39].
- A lot of IoT devices are designed to support mobile applications. Therefore, a lot of IoT devices needed radio transceiver capabilities. Fortunately because of the booming of IoT (Internet of Things) recently, the trend has arisen for a microcontroller that has wireless capabilities [40]. This trend was then answered by Espressif by releasing the ESP microcontroller family. ESP microcontroller families are popular because of the simple and low cost that has WiFi [41] and also Bluetooth [42] radio transceivers all in one SOC (System On Chip) microcontroller. Unfortunately because WiFi and Bluetooth of intended for small range, therefore a new radio transceiver intended for low power and long-range communication LPWAN (Low Power Wide Area Network) has been developed such as LoRa [43], NB-IoT [44], and sigfox [45].
- Meanwhile to power up the WSN node, an energy source for the WSN node usually comes from a battery [46]. Batteries are more preferred in WSN due to their high energy density such as NiMH 60-80 Wh/kg and lithium rechargeable batteries 120-140 Wh/kg [47]. Furthermore, it is very economical for using rechargeable batteries in WSN, because NiMH batteries are rated for 300-500 rechargeable cycles while lithium batteries are rated for 500-1000 rechargeable cycles before the batteries are broken. To highlight this problem, and because super capacitor characteristic offers more than half a million rechargeable cycles and a 10-year operational lifetime, some researchers propose to replace the battery as energy storage and replace it with a supercapacitor to enhance WSN node life [48] as its power source. However, this power source is a stored type, which means once its stored energy is depleted the IoT node will turn off. To combat these issues, several researchers propose a low-energy harvester that uses solar cells [49], electrochemical reaction [50], vibration [51], temperature [52], and many

others [53] to generate small electricity but enough for IoT operation power.

B. IoT WSN System Generic Architecture

There are several proposed architecture layer that has been used in IoT system, such as the basic model and also the general model that negotiates the needs of researcher and industry [54]. Yang et al propose 3 basic IoT architecture layers that contain a perception layer for collecting and capturing information, a network layer which is an IoT infrastructure to provide common service, and an application layer that provides specific services to users through the analyzed and processed perception data [55]. However khan stated that IoT development depends on the technological progress and design of various new IoT applications and business models, hence Khan proposes 5 architecture layers [56] that can be seen in Fig. 3, such as:

- The perception Layer is also defined as the hardware Layer. This layer consists of physical objects and sensor devices. This layer also deals with the identification and collection of objects specific information by the sensor or by the reader device. Depending on the sensors type, the information can vary such as location [57], temperature [58], orientation [59], motion [60], vibration [61], acceleration [62], humidity [63], etc. The information that has been collected is then passed to the Network layer for its secure transmission line to the information processing system.
- The Network Layer can also be called a Transmission Layer. This layer securely exchanges the information from sensor devices to the information processing system. The network layer can be composed of single node IoT to multiple IoT devices. The transmission medium can be wireless or wired and technology can be fiber optic [64], 5G [65], WiFi [66], Bluetooth [67], LoRa [68], Sigfox [69], NB-IoT [70]. In WSN where coverage is important, since a single node cannot service a wide area, therefore it needs multiple nodes to service it. To transfer the data collected from the faraway node to the gateway, an ad-hoc hop-to-hop data transfer [71] was done using available radio transceiver technologies. The Network layer then transfers the exchange data (information) from the Perception layer to the Middleware layer.
- The Middleware Layer has the responsibility to manage the service and database relation. This layer receives the exchange data (information) from the Network layer and pool it in the database. This layer performs information processing and ubiquitous computation and an takes automatic decisions based on the results. This layer uses a software system that designed to be the intermediary between IoT node and applications [72].
- The Application Layer provides global management of the application based on information processed in the Middleware layer. The example of applications layer such as smart health [73], smart farming [74], smart home [75], smart city [76], intelligent transportation [77], and many others.
- The Business Layer provides management of the overall IoT system including the applications and services. This layer also builds business models, flowcharts, graphs, and many others based on the data received from the Application layer. The success of IoT application depends on good business models. Therefore, based on results analysis, this layer has important task which is to determine future actions of business strategies (decision making) [78].

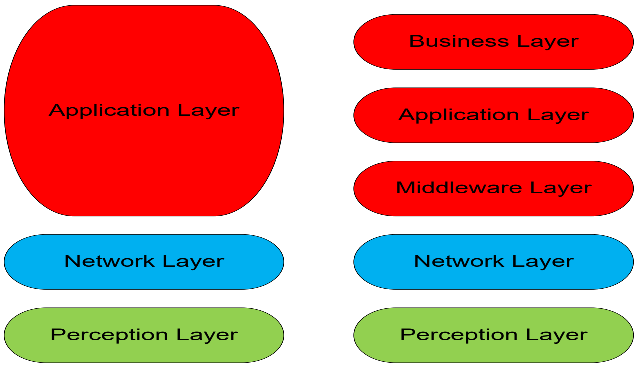

Fig. 3. IoT WSN System Generic Architecture. left proposed by Yang et al [55], right proposed by Khan et al [56].

We can summarize and write IoT WSN Architecture in Table 1.

TABLE I. IOT WSN ARCHITECTURE

IoT WSN Architecture		
Node	Sensitive Element	Detector [79], Sensor [80]
	Processing Unit	Microcontroller [81], SBC (Single Board Computer) [82].
	Transceiver	LoRa [83], Bluetooth [67], WiFi [84], SigFox [85], NB-IoT [86].
	Energy Source	Battery [87], Super Capacitor [88], Energy harvester [89].
System	Perception Layer	Location [57], temperature [58], orientation [59], motion [60], vibration [61], acceleration [62], humidity [63]
	Network Layer	Fiber Optic [64], 5G [65], WiFi [66], Bluetooth [67], LoRa [68], Sigfox [69], etc [70].
	Middleware Layer	Software Bridging [72]
	Application Layer	Smart Health [73], [90], Smart Farming [74], Smart Home [75], Smart City [76], Intelligent Transportation [77].
	Business Layer	Business Models, Decision Making [78]

III. ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

Computational Intelligence is an innovative approach to constructing an intelligent system [103] so it can adapt its intelligent behavior in complex and ever-changing environments. Artificial Intelligence, on the other hand, tries the study the intelligent behavior demonstrated by machines to mimic the natural intelligence of human beings. We could summarize that CI is more like a sub-branch of AI that emphasizes the design, application, and development of its linguistically motivated computational models. There is a lot of computational intelligence method, it can be seen in Fig. 4. In this paper, we present a few of the popular Computational Intelligence that has been used to solve IoT WSN problem such as fuzzy and neural network.

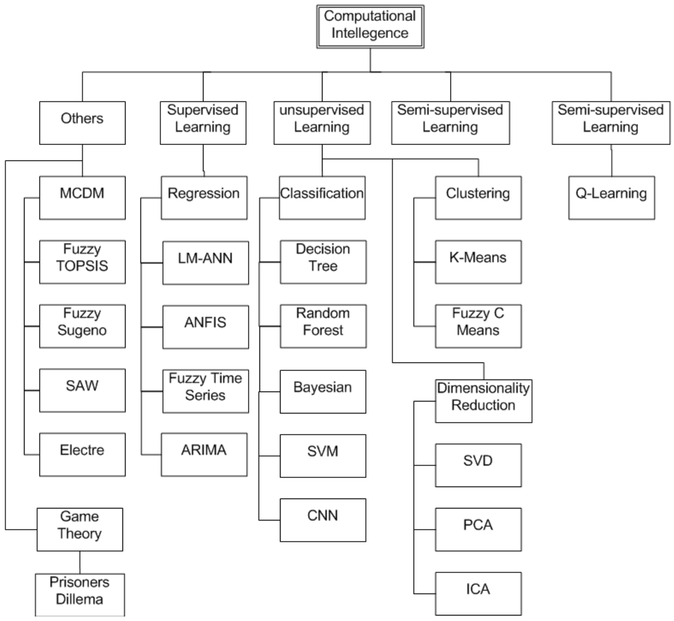

Fig. 4. Computational Intelligence Hierarchy

A. Fuzzy System

In 1975, Zadeh has develop the foundation fuzzy. This was developed from Linguistic Variable and its Application to Approximate Reasoning [91]. Using those foundations, the fuzzy rule then developed to model the qualitative aspects of human expertise (reasoning based on experience) [92] and solve the problem. In conclusion we can use the fuzzy rule based on the reasoning for solving a real-world problem. Even though the fuzzy is usually used for control, such as robot movement [93], [94], speed [95], and other factors [96]–[98]. However, a fuzzy system can be used for anything. Recently several fuzzy algorithms have been developed to solve real-world problems such as follow.

1) Fuzzy Sugeno

Fuzzy Sugeno was developed by Takagi and Sugeno in 1985 [99]. This mathematical model was used to present fuzzy implications and reasoning to control industrial processes or real-world system control [100]–[102]. Fuzzy Sugeno architecture can be seen in Fig. 5. A fuzzy Sugeno algorithm can be presented as follow.

For step one, which is fuzzification each output is denote by O_i^1, which contribute to raise the degree of membership.

$$O_i^1 = \mu A_i(x) \text{ and } O_i^1 = \mu B_i(x), \qquad i = 1,2 \tag{1}$$

Where i is every node in Fuzzy ANFIS architecture, x is the input to node i, A, B is the linguistic label (such as small, large, etc.).

In this step, every type of membership function can be used. However, generalized bell type were used to provide maximum equal to 1 and minimum equal to 0 outputs. Therefore, we can obtain:

$$\mu Ai(x) = \frac{1}{1 + \left(\frac{x - c_i}{a_i}\right)^{2*b_i}} \tag{2}$$

where a, b, c is the parameter set.

The second step is contributed to the firing strength of fuzzy inference using multiplication of the two input signals. Every node represents the.

$$O_i^2 = \mu A_i(x)\, \mu B_i(x), \qquad i = 1,2 \tag{3}$$

For the next step, normalization then applied for each firing of fuzzy inference.

$$O_i^3 = \overline{W_i} = \frac{W_i}{W1 + W2}, \qquad i = 1,2 \tag{4}$$

Where W is the firing strength of the node and $\overline{W_i}$ is the normalized firing strength of the node.

The next step contributed to the calculation of the output based on the parameters of the rule consequent.

$$O_i^4 = \overline{W_i}\,.F_i = \overline{W_i}\,.(P_i x + Q_i x + R_i x), \qquad i = 1,2 \tag{5}$$

Where P, Q, R is the parameter set.

Finally, the last step computes the overall output as the summation of all input signals.

$$O_i^5 = Overall\ Output = \sum_{k=0}^{n} \overline{W_i}\, F_i = \frac{\sum_{k=0}^{n} W_i F_i}{\sum_{k=0}^{n} W_i} \tag{6}$$

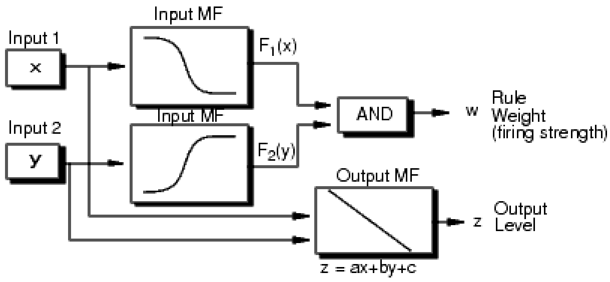

Fig. 5. Fuzzy Sugeno Architecture [103].

2) Adaptive Neuro Fuzzy Inference System (ANFIS)

Adaptive Neuro Fuzzy Inference System (ANFIS) was developed by Jang Jyh Shing Roger in 1993, based on the if-then rules of fuzzy Takagi Sugeno [104]. With the ANFIS method, the fuzzy inference system can adapt naturally based on its training data (training data). ANFIS is composed of artificial neural network method that based on the Takagi - Sugeno fuzzy inference system. Since this method integrates both methods from neural networks and fuzzy logic methods, it has the potential to capture the advantage of both in one framework. This inference system works according to a set of fuzzy IF-THEN rules that can learn to estimate nonlinear functions. Therefore, ANFIS is considered a Universal Estimator (universal assessor). ANFIS architecture based on Jang's research composed of five stages, as shown in the Fig. 6. The square shapes show adaptive nodes, while the circular shapes are the fixed nodes (see Fig. 6).

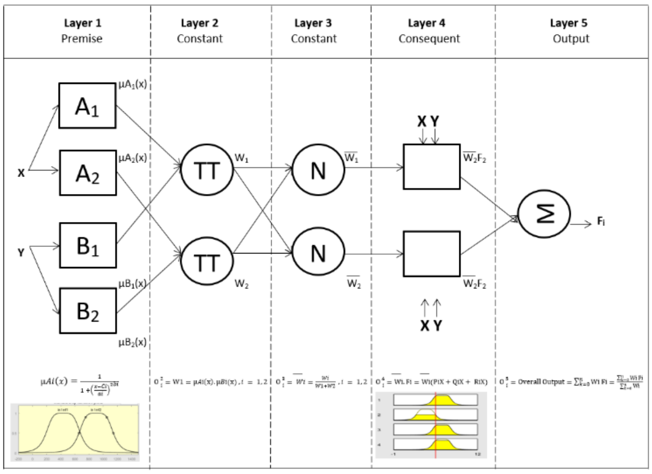

Fig. 6. ANFIS Architecture is based on Takagi-Sugeno fuzzy inference system by Jang [105].

ANFIS uses a fuzzy Sugeno algorithm as a basic algorithm, therefore ANFIS are using equations 1-5 as a basic algorithm. Then Jang uses gradient descent and chain rule so that its parameter can be optimized. ANFIS learns from chain rule and gradient descent, we need to know the error rate for data training for each node output. We can assume i-th position node outputs define O_i, the data training sets has P number of input, and the error function can be calculate as:

$$E_p = \sum_{m=1}^{\#L} (T_{mp} - \mathrm{O}_{mp}^{L})^2 \tag{7}$$

Where E_p is the error measure which the sum of squared errors, T_{mp} is the m component from the P output target vector and $\mathrm{O}\,{}_{mp}^{L}$ is the m component from the actual output vector that has been deliver by the P input vector.

Hence, the error rate can be calculated as:

$$\frac{\partial E_p}{\partial \mathrm{O}\,{}_{i\,p}^{k}} = \sum_{m=1}^{\#k+1} \frac{\partial E_p}{\partial \mathrm{O}\,{}_{m\,p}^{k+1}} \frac{\partial \mathrm{O}\,{}_{m\,p}^{k+1}}{\partial \mathrm{O}\,{}_{i\,p}^{k}} \tag{8}$$

where $1 \leq k \leq L-1$ is the error rate of an internal node. it is expressed as the linear combination error rate of nodes in the next step. Therefore, for all $1 \leq k \leq L$ and $1 \leq i \leq \#(k)$, we can find $\frac{\partial Ep}{\partial \mathrm{O}_{i\,p}^{k}}$, using mathematical equations (7) and 8). Thus, we have α as a parameter of the adaptive network.

$$\frac{\partial E}{\partial \alpha} = \sum_{O*\epsilon S} \frac{\partial Ep}{\partial \mathrm{O}*} \frac{\partial \mathrm{O}*}{\partial \alpha} \tag{9}$$

Where S is shows the set of nodes whose output depends on α.

Derivative for overall error measurement E concerning α is

$$\frac{\partial E}{\partial \alpha} = \sum\nolimits_{p=1}^{p} \frac{\partial Ep}{\partial \alpha} \tag{10}$$

Therefore, we can write the updated mathematical equations for generic parameter α as follows:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{11}$$

Where η is a learning rate.

The learning rate can be written as

$$\eta = \frac{k}{\sqrt{\sum_{\alpha} (\frac{\partial E}{\partial \alpha})^2}} \tag{12}$$

Where k is the step size or length of each gradient transition in the parametric space.

B. NN (Neural Network)

NN (Neural Network) is a computational intelligence inspired by the brain biological neural networks that mimic brain behavior from living things. NN methods have been used to solve many problems, from motor control [106], human detection [107], forecasting [108], [109], and many more. The system will do its job by considering previously accepted examples (called data training) [110]. Currently, there is a lot of NN variation that has been developed to solve a lot of problems such as LMANN [111], CNN [112], GNN [113], BNN [114], and many more. In this subsection, we would like to present a few methods use in ANN to solve a real-world problem.

1) ANN (Artificial Neural Network)

ANN is based on a combination of connected units or nodes called artificial neurons. This neuron is modeled based on neurons in the biological brain. Each connection, like a synapse in the biological brain, can send signals to other neurons. The artificial neuron that receives the signal will process it and then can signal the next neurons connected to it. An ANN consists of processing elements called neurons, which are connected to other processing elements by rules and weights. This network element products and biases are added and then passed through an activation function to produce an output [115]. One layer ANN network can be written with a simple equation:

$$a_i = f_i(IW_i p b_i) \tag{13}$$

Where W is Scalar weight, P is Scalar input, B is Scalar bias and f is Transfer Function.

Recently several ANN optimization algorithms have been produced to solve real-world problems such as Levenberg Marquardt.

2) Levenberg Marquardt ANN

For the network to be able approximate any function with a finite number of discontinuities, multiple layers can be built so that the network can act as a general function approximator. These multiple layers are called feedforward networks. This network is trained by initiating weight and bias and also need an examples of good network behavior (network inputs p and target outputs). During training, the weights and biases of the network are iteratively adapted to minimize the error of network performance function (mean square error). To adjust weights and biases, the gradient of the performance function was used to determine how to adjust the weights to minimize error performance, which is called backpropagation (performing computations backward through the network). Conventional back propagation neural network uses first order steepest descent based on calculation of the gradient of the total squared error for each layer.

$$E(n) = \frac{1}{2}\sum_{k=1}^{m} e_k^2(n);\ e_k(n) = d_k(n) - y_k(n) \quad (14)$$

Where n is a training epoch, m is number of outputs, d is desired (target) output, y is actual ANN output, and E is mean-squared error surface.

The weight update can be written as:

$$W(n+1) = W(n) + \Delta W(n) \quad (15)$$

Thus,

$$\Delta W(n) = -\eta \frac{\partial E(n)}{\partial W(n)} = -\eta\, \nabla E(n) \quad (16)$$

Where W is weight update and η is a training rate.

An algorithm that uses simple steepest descent minimization based on first order minimization is slow due to the computation of error serially on a layer-by-layer basis [116]. Therefore, to avoid oscillation around a local minimum and increase the speed of training the weight update is compute using composed techniques such as adaptive learning rate η* and momentum term α.

$$\Delta W(n) = -\eta * \nabla E(n) + \alpha \Delta W(n-1) \quad (17)$$

The momentum method meant to found some curvature information about the error surface by averaging the gradient locally. Another algorithm for minimization of error E(n) is based on optimization method that use a second order derivative of performance index or cost function J(w).

$$\mathrm{J}(\mathrm{W}_{n+1}) = \mathrm{J}(\mathrm{W}) + \Delta\mathrm{W}\nabla\mathrm{J}(\mathrm{w}) + \frac{1}{2}\Delta\mathrm{W}\nabla^2\mathrm{J}(\mathrm{w}) + \cdots \quad (18)$$

Where

$$\frac{\partial E(n)}{\partial\big(W(n)\big)} = \nabla J(w) = g \quad (19)$$

Which is the gradient of performance index, and

$$\frac{\partial^2 E(n)}{\partial^2\big(W(n)\big)} = \nabla^2 J(w) = H \quad (20)$$

This algorithm was designed to approximate second-order training velocity without the need to calculate the Hessian matrix (36). When the performance function is the sum of squares (as in training feed-forward networks) thus the hessian matrix can be written as:

$$H(n) = J^T(n)\, J(n) \quad (20)$$

The gradient can be written as

$$g(n) = J^T(n)\, E(n) \quad (20)$$

Where J is the Jacobian matrix that contains the first derivatives of the network errors concerning the weights and biases. This Jacobian matrix can be calculated through a standard backpropagation method that is much simple than calculate the Hessian matrix. The LM-ANN (Levenberg-Marquardt Artificial Neural Network) algorithm uses this approximation to the Hessian matrix [35] in the following Newton-like update formula.

$$W(n+1) = W(n) - [J(n)^T J(n) + \mu I]^{-1} J^T(n)\, E(n) \quad (20)$$

Where μ is a non-negative scalar, that controls both magnitude and direction and I is an identity matrix.

When the scalar μ is zero, which is Newton's method. However, when μ is large, this becomes a gradient descent with a small step size. Newton's method is known to be faster and more accurate in achieving an error minimum, so this aim is to shift towards newton's method as faster as possible. Thus, μ is decreased after each time successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function then will always be reduced at each loop of the algorithm, thus making this algorithm to be the fastest method for training medium sized feed forward neural networks (up to several hundredweights) [117], [118].

IV. Computational Intelligence in IoT WSN Functionality

Based on research conducted by Alfuqaha there is 6 IoT element functionality [54], such identification, sensing, communication, processing, service, and semantic. The computational intelligence can be applied in IoT WSN functionality as the example below:

A. Identification

This element is important in IoT because it serves as an IoT node identifier. If an IoT node is connected to the internet and we would like to process the specific data from a specific node, we cannot mistake it for another node. therefore, the node must be recognized and identified as the correct node. there are 2 main categories for identification which are naming and addressing. Naming means the object ID has the meaning of the name of the object such as "object 1" while address means the address where the object is in the communication network where the IoT device is used. The example IoT node naming for identification such as electronic product codes (EPC) [119], Radio Frequency Identification (RFID) [120]–[123], Finger Print [124], ubiquitous code (uCode) [125], [126]. The example IoT node addressing for identification such as IPv4 [127], [128], and IPv6 [129]–[132].

Besides identification naming and addressing, there are also identification methods proposed by other researchers such as DCNI (Dynamic Critical Node Identification) [133], Fog Computing and blockchain [134], [135], SEI (Specific Emitter Identification) using neural network method to identified IoT node using raw IQ (in-phase and quadrature) stream [136], blind IoT Node identification using neural network multilayer perceptron-based models [137], Fuzzy Sugeno to identify faulty IoT node [138], Trust Based Neighbor Identification using Fuzzy Topsis and AHP to minimize security risk [139], and many others.

B. Sensing

Sensing functionality in IoT serves to collect data through the IoT WSN node. usually sensing are done using direct measurement such as humidity sensor [140], [141], temperature sensor [142]–[144], gas sensor [145]–[147], piezoelectric [148], and many other [149]–[151]. However there are several indirect sensing such as the use of GPS to measure distance traveled [152], speed [153], tracking current location [154], [155], and also a camera for video [156] or picture sensing [157]–[159]. This indirect sensing sometimes needs to be done because of sensor limitations. Other methods proposed by researchers are using computational intelligence (machine learning) to enhance recognition such as CNN (Convolutional Neural Network) [160]–[163], SVM (support vector machine) [164]–[166], Naïve Bayes [167], and KNN [168].

C. Communication

Communication functionality in IoT WSN has a purpose which is to connect between nodes in the WSN network and also the gateway to the internet network. With this function, IoT nodes can communicate with each other so that the data that has been captured and collected can be transmitted and sent to the IoT WSN gateway by using hop-to-hop communication. Communication technology that used in IoT include Wi-Fi [169]–[171], Bluetooth [172]–[174], NB-IoT [175]–[177], 5G [178]–[180], Sigfox [181], [182], LoRa [183]–[185], VSAT [186]–[188], fiber optic [64], [189], [190] and more.

However, IoT WSN communication suffers several communication issues. This issue occurs repeatedly such as delay [191]–[193], interference [194]–[196], packet loss [197] and more [198], [199]. Therefore, to build a good IoT WSN problem, we must minimize communication problems and improve its communication (data transmission) over long-range coverage of the IoT WSN network. To do this several researchers propose a computational intelligence to provide optimized and good path routing [200], minimize power consumption (increase network lifetime) [201], [202], and increase IoT WSN Quality of service [203]. Some researchers propose to solve the problem directly which optimizes the network performance. The Computational Intelligence method to perform this feat includes DPSO (discrete particle swarm optimization) and GA (genetic algorithm) [204], chicken swarm-based genetic algorithm [205], Fuzzy System [206]–[209], CNN [210], ACO (Ant Colony Optimization) [211] and FFA (FireFly Algorithm) [212]. However, some researchers hope to use indirect methods to solve IoT WSN communication problems such as environmental modeling for wireless data transmission (radio propagation modeling) [213], [214]. The Computational Intelligence method to perform this feat including ANFIS [105], CNN [215], Random Forest [216], PSO (Particle Swarm Optimization) [217], Markov Chain [218], and more.

D. Processing

This element function works as an IoT processing unit (the brain of IoT). This element is in charge of processing the data that has been collected inside the IoT. Data will be processed to produce information following the services requested by the user. There are several processing elements in IoT. The first element would be processing data from analog to digital which is inside the IoT node. the second processing would be cloud computing technology. Cloud provides facilities for IoT objects to transmit, collected, and store data to the cloud. Cloud also serves to provide facilities for big data so that data can be calculate and processed in real-time.

E. Service

Based on research conducted by Gigli and Koo [219], services in IoT are categorized into 4 classes as

- Identity-related services, these services work for applications that relate to objects in the virtual world, to identify or as object identifiers. An example of application identity-related services such as logistics or shipping.
- Information aggregation services, the information aggregation service is useful for collecting rough data on the results of sensor acquisition, where this raw data needs to be reprocessed so that it can be delivered in form of IoT applications that contain specific services. An example of an information aggregation service is a smart grid and health care.
- Collaborative-aware, collaborative-aware services function as a service that uses the data obtained and has been stored as material for the decision-making process. Example of collaborative awareness is the smart home, smart building, and industrial automation.
- Ubiquitous, for ubiquitous services, it is used to provide collaborative-aware services whenever needed for anyone and anywhere. An example of Ubiquitous service is smart cities.

F. Semantic

This service can extract knowledge to provide the needed services. Knowledge extraction that occurs in this service includes the use of modeling resources and information. This service also includes analyzing data and using it to make the right decisions to provide the right services and as required. Therefore, in other words, semantics is the most important and it was a backbone of IoT because it can classify the needs according to the right resources [220]. This semantic serviceability is supported by semantic web technology, including Resource Description Framework (RDF) and Web Ontology Language (OWL).

Processing, service, and semantic functionality act as one unit functionality. Processing functionalities are driven by service functionality, and in terms of the information, age services are useless and cannot be separated from computational intelligence. This is because computational intelligence will provide data processing depending on the service desired by the user and then semantics will display the data exactly as the user intended. An example of this would be the manufacturing process proposed by Syafrudin et al. IoT node has generated sensor data such as accelerometer, humidity, temperature, and gyroscope from a real-time manufacturing process. Then Outlier detection and Random Forest classification were used to erase outlier data sensor and serve as fault detection during the manufacturing process. The semantic result was IoT-based sensors and the proposed big data processing system makes it very efficient to monitor the manufacturing process [221]. Another example was proposed by Yu et al. The processing is use LSTM (long short-term memory) deep learning network methods to process all IoT data and provide semantic services such as New York City temperature forecasting [222]. Besides those two computational intelligence methods, there are a lot of other methods to process and provide semantic services such as KNN [223], DTMC (Discrete-time Markov chain) [224], SNN [225], CNN [226], Random Tree [227], and more. We can summarize Computational Intelligence in IoT WSN Functionality in Table 2.

TABLE II. COMPUTATIONAL INTELLIGENCE IN IOT WSN FUNCTIONALITY

Functionality	Computational Intelligence
Identification	NN [136], NN MLP [137], Fuzzy Sugeno [138], Fuzzy Topsis & AHP [139]
Sensing	CNN [160]–[163], SVM [164]–[166], Naïve Bayes [167], KNN [168].
Communication	PSO [217], DPSO [204], GA [204], Fuzzy [206]–[209], CNN [210] [215], ACO [211], FFA [212], ANFIS [105], Random Forest [216], Markov Chain [218].
Processing	Random Forest [221], LSTM [222], KNN [223], DTMC [224], SNN [225], CNN [226], Random Tree [227].
Service	
Semantic	

V. CHALLENGES & ISSUE FOR COMPUTATIONAL INTELLIGENCE IN IOT WSN

Computational Intelligence has taken IoT applications to go the next level, which is close to the AI-Driven IoT application. However, many problems are not solved easily for IoT WSN applications. Hence, in this section, we would like to explain the challenges of computational intelligence and its relationship with IoT WSN.

A. Optimum Computational Intelligence method for Optimum IoT application

Computational Intelligence is not omnipotent for every IoT application. An example of this can be seen in IoT WSN path loss modeling for radio propagation and data transmission. In some of the research, BPNN (Back Propagation Neural Network) has obtain the highest accuracy with a minor difference (0.14 and 0.35) compared to SVR (Support Vector Regression) and RF [228], while others researcher has state that ANN (Artificial Neural Network) and RF have remarkably identical performance [229]. Even though BPNN and ANN already demonstrate well in the path loss model, however, there are a lot of researchers who use ANFIS for path loss modeling [230], [231]. Although ANFIS was another variation of ANN besides BPNN, ANFIS optimized fuzzy with neural network [104]. With this combination design, it makes ANFIS likeable because of its transparency in associations to reach the optimal predicted path loss model [232]. The example above indicate that we cannot easily accept that there is some Computational Intelligence method that has performed above other methods. Thus, every computational intelligence method that has been applied in IoT applications needs to be investigated its performance properly.

B. Computational Intelligence with optimizing Low Power Consumption versus Computational Intelligence with optimizing Quality of Service

IoT-WSN has allowed us to provide and collect data from the environment or our real-world using sensors embedded in the IoT-WSN node. this process requires a very low power consumption. However, in IoT WSN applications there are also data collection processes that require a lot of power consumption. This data collection process such as voice, image, and video recognition requires a certain Computational Intelligence (algorithm) for detection and recognition [233]. This detection and recognition process has high computational power consumption [234]. If this IoT WSN node is connected using a cable such as ATM [235], it will have unlimited supply power and there will be no issue with this. However, for IoT WSN which is a mobile application, a high computational power consumption means a drawback for the IoT-WSN node. Researchers have realized that this mobile IoT suffers from small and limited energy [236]. This small energy capacity has limited IoT-WSN node capability to operate on mobile and for a long time [237]. Therefore, to prolong IoT-WSN nodal life, few researchers propose an efficient Computational Intelligence method such as HOG-LX that propose for image and motion detection [238].

Another process that takes a huge power consumption besides the data collection process, would be the communication process. This communication process takes huge power that cause by separated IoT WSN node placement to serve a huge coverage area. This separated IoT WSN node always communicate with each other and provides data hop-to-hop transmission from the faraway node to the close node with the gateway. Therefore to prolong IoT WSN lifetime several researchers propose an efficient power routing communication or energy management communication such as LEACH [239], [240], MUSTER [241], PDORP [242], and many others [243]–[247]. However, efficient power routing communication is also not enough. The researcher also intends to maximize the satisfaction of the services for the IoT WSN application [248], which is QoS (Quality of Service). Therefore, energy optimization and QoS maximization Computational Intelligence is still one of the biggest issues in IoT WSN applications.

C. Computational Intelligence for Optimum Accuracy Forecasting and Decision Making

IoT platform application has created additional value for the digital economy in this information age. Furthermore, IoT platform applications that were once considered small and quirky now have become essential in every Business model. Companies that deploy IoT platform business models continue to surprise and challenge conventional method to create more value. Their company has also been among the first to understand and try harness data-centric strategies, and many have moved to the front of a wide range of disruptive technologies, from cloud to IoT Computational Intelligence. This has created the need for highly accurate forecasting and decision-making Computational Intelligence.

There is a lot of forecasting and decision-making Computational Intelligence such as FTS (Fuzzy time Series), ARIMA, ANN, AHP [249], SAW, ANFIS [250], and many others. However, many researchers still develop and propose a new Computational Intelligence method that can increase forecasting accuracy and decision making. many researchers propose to optimize Computational Intelligence using other Computational Intelligence methods. This example can be seen in Zhang et al research. In those research, Zhang et al propose to combine DBN (Deep Belief Network) with R-LSTM-NN (Recurrent LSTM Neural Network) to provide semantic service which predicts the fire hazard values or other various problems that are gathered from cities using IoT nodes in smart cities application [251]. Another example can also be seen in Deng et al research. Deng et al propose to combine FTS with PSO to obtain higher forecasting accuracy Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) [252]. Therefore, there is the need to optimize or combine Computational Intelligence in IoT WSN applications to provide higher accuracy and achieve higher decision-making conclusions.

D. Computational Intelligence for Security Anomaly Detection

IoT WSN application has a very wide coverage area service. With the growing in the number of IoT connected devices and additional services, it will make security management become a drawback in terms of size, cost, and power. This, in turn, makes IoT more vulnerable to security attacks, and ultimately causing enormous financial and also reputational losses. It is very urgent and also very challenging to provide Computational Intelligence for security. Even though there are several Computational Intelligence security before such as Text-CNN [162], SDRK[253], and others however these are not omnipotent algorithms to detect and overcome the cyberattack.

VI. Future Trend for Computational Intelligence in IoT WSN

IoT WSN is a mobile application that serves a huge coverage area. With that huge coverage, a lot of things can happen, from dead nodes to obstacles due to natural events. This event can cause degradation in IoT WSN application or worse missing node or network. Fortunately, this missing node can be recovered using a self-maintenance mechanism [254]. This mechanism changes the static network to become a dynamic network in configuration [255]. This kind of network is called SON (self-organizing network) model. SON is defined in 3GPP, which is a standardization for mobile communication network (cellular network) features. This standardization reconfigures the radio base station to achieve an optimized network by itself (automatically) [256], [257]. This SON model can be applied in any type of network, especially IoT WSN networks that use Computational Intelligence methods to reconfigure its parameter.

VII. Conclusion

This paper surveys various aspects of IoT WSN technologies. This paper also surveys Computational Intelligence and its relationship with IoT WSN technologies. It provides detailed research activities concerning how Computational Intelligence methods in IoT WSN can raise the level close to the AI-Driven IoT application. To build a good understanding of application Computational Intelligence methods in IoT WSN, in this paper we also present various challenges (issues). In the last of our presentation, we discuss the future direction of Computational Intelligence methods in IoT WSN, that introduce the dynamic network concept.

References

[1] R. P. Wibisono, N. A. Suwastika, S. Prabowo, and T. D. Santoso, "Automation canal intake control system using fuzzy logic and Internet of Things (IoT)," *2018 6th Int. Conf. Inf. Commun. Technol. ICoICT 2018*, 2018, doi: 10.1109/ICoICT.2018.8528756.

[2] T. Sultana, A. Almogren, M. Akbar, M. Zuair, I. Ullah, and N. Javaid, "Data sharing system integrating access control mechanism using blockchain-based smart contracts for IoT devices," *Appl. Sci.*, 2020, doi: 10.3390/app10020488.

[3] S. B. Saraf and D. H. Gawali, "IoT based smart irrigation monitoring and controlling system," *RTEICT 2017 - 2nd IEEE Int. Conf. Recent Trends Electron. Inf. Commun. Technol. Proc.*, 2017, doi: 10.1109/RTEICT.2017.8256711.

[4] D. Ardiansyah, A. S. M. Huda, E. T. Tosida, and A. T. Bon, "Wireless sensor networks for soil nutrition to increase agricultural productivity," *Proc. Int. Conf. Ind. Eng. Oper. Manag.*, 2020.

[5] M. Nitti, V. Pilloni, G. Colistra, and L. Atzori, "The Virtual Object as a Major Element of the Internet of Things: A Survey," *IEEE Commun. Surv. Tutorials*, 2016, doi: 10.1109/COMST.2015.2498304.

[6] V. Jacintha, J. Nagarajan, K. T. Yogesh, S. Tamilarasu, and S. Yuvaraj, "An IOT Based ATM Surveillance System," *2017 IEEE Int. Conf. Comput. Intell. Comput. Res. ICCIC 2017*, 2018, doi: 10.1109/ICCIC.2017.8524485.

[7] Y. Wang, Y. Cui, F. Chen, and R. Ren, "An 'illumination moving with the vehicle' intelligent control system of road tunnel lighting," *Sustain.*, 2020, doi: 10.3390/SU12187314.

[8] Y. Dong and Y. D. Yao, "Secure mmWave-Radar-Based Speaker Verification for IoT Smart Home," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2020.3023101.

[9] R. O. Andrade, S. G. Yoo, L. Tello-Oquendo, and I. Ortiz-Garces, "A Comprehensive Study of the IoT Cybersecurity in Smart Cities," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.3046442.

[10] M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A Survey on the Role of IoT in Agriculture for the Implementation of Smart Farming," *IEEE Access*. 2019, doi: 10.1109/ACCESS.2019.2949703.

[11] Y. Song, F. R. Yu, L. Zhou, X. Yang, and Z. He, "Applications of the Internet of Things (IoT) in Smart Logistics: A Comprehensive Survey," *IEEE Internet of Things Journal*. 2021, doi: 10.1109/JIOT.2020.3034385.

[12] J. Huang, L. Xu, C. C. Xing, and Q. Duan, "A Novel Bioinspired Multiobjective Optimization Algorithm for Designing Wireless Sensor Networks in the Internet of Things," *Journal of Sensors*. 2015, doi: 10.1155/2015/192194.

[13] F. Qi, W. Li, P. Yu, L. Feng, and F. Zhou, "Deep learning-based BackCom multiple beamforming for 6G UAV IoT networks," *Eurasip J. Wirel. Commun. Netw.*, 2021, doi: 10.1186/s13638-021-01932-4.

[14] R. Priambodo and T. M. Kadarina, "Monitoring Self-isolation Patient of COVID-19 with Internet of Things," *2020 IEEE Int. Conf. Commun. Networks Satell. Comnetsat 2020 - Proc.*, 2020, doi: 10.1109/Comnetsat50391.2020.9328953.

[15] A. Tehseen, N. A. Zafar, T. Ali, F. Jameel, and E. H. Alkhammash, "Formal modeling of iot and drone-based forest fire detection and counteraction system," *Electron.*, 2022, doi: 10.3390/electronics11010128.

[16] I. Novkovic *et al.*, "Gis-based forest fire susceptibility zonation with iot sensor network support, case study—nature park Golija, Serbia," *Sensors*, 2021, doi: 10.3390/s21196520.

[17] ITU-T, "Recommendation ITU-T Y.2221: Requirements for Support of Ubiquitous Sensor Network (USN) Applications and Services in the NGN Environment." p. 32, 2010.

[18] N. Sharmin, A. Karmaker, W. L. Lambert, M. S. Alam, and M. S. T. S. A. Shawkat, "Minimizing the energy hole problem in wireless sensor networks: A wedge merging approach," *Sensors (Switzerland)*, 2020, doi: 10.3390/s20010277.

[19] J. Chen, S. Li, S. H. G. Chan, and J. He, "WIANI: Wireless infrastructure and Ad-hoc network integration," *IEEE Int. Conf. Commun.*, 2005, doi: 10.1109/icc.2005.1495092.

[20] S. Aluvala, K. Raja Sekhar, and D. Vodnala, "A novel technique for node authentication in mobile ad hoc networks," *Perspect. Sci.*, 2016, doi: 10.1016/j.pisc.2016.06.057.

[21] M. F. Othman and K. Shazali, "Wireless sensor network applications: A study in environment monitoring system," *Procedia Eng.*, vol. 41, pp. 1204–1210, 2012, doi: 10.1016/j.proeng.2012.07.302.

[22] J.-S. R. Jang, C.-T. Sun, and E. Mizutani, *Neuro-Fuzzy and Soft Computing-A Computational Approach to Learning and Machine Intelligence*. Prentice Hall, 1997.

[23] M. Chetto and A. Queudet, *Harnessing Ambient Energy for Embedded Systems*. Elsevier Ltd, 2016.

[24] ITU-T, "Applications of Wireless Sensor Networks in Next Generation Networks," *Series T.2000: Next Generation Networks*, no. February. pp. 1–94, 2014.

[25] Y. Wang and Z. Chi, "System of wireless temperature and humidity monitoring based on Arduino Uno platform," *Proc. - 2016 6th Int. Conf. Instrum. Meas. Comput. Commun. Control. IMCCC 2016*, 2016, doi: 10.1109/IMCCC.2016.89.

[26] V. Singhvi, A. Krause, C. Guestrin, J. H. Garrett, and H. Scott Matthews, "Intelligent light control using sensor networks," *SenSys 2005 - Proc. 3rd Int. Conf. Embed. Networked Sens. Syst.*, 2005, doi: 10.1145/1098918.1098942.

[27] I. Mat, M. R. M. Kassim, and A. N. Harun, "Precision agriculture applications using wireless moisture sensor network," *2015 IEEE 12th Malaysia Int. Conf. Commun. MICC 2015*, 2016, doi: 10.1109/MICC.2015.7725400.

[28] Y. Li, Z. Wang, and Y. Song, "Wireless sensor network design for wildfire monitoring," *Proc. World Congr. Intell. Control Autom.*, 2006, doi: 10.1109/WCICA.2006.1712372.

[29] T. Dinh Le and D. H. Tan, "Design and deploy a wireless sensor network for precision agriculture," *Proc. 2015 2nd Natl. Found. Sci. Technol. Dev. Conf. Inf. Comput. Sci. NICS 2015*, 2015, doi: 10.1109/NICS.2015.7302210.

[30] R. A. Siddiqui, R. I. Grosvenor, and P. W. Prickett, "DsPIC-based advanced data acquisition system for Monitoring, Control and Security Applications," *Proc. 2015 12th Int. Bhurban Conf. Appl. Sci. Technol. IBCAST 2015*, 2015, doi: 10.1109/IBCAST.2015.7058519.

[31] M. Ben-Ezra, A. Zomet, and S. K. Nayar, "Video super-resolution using controlled subpixel detector shifts," *IEEE Trans. Pattern Anal. Mach. Intell.*, 2005, doi: 10.1109/TPAMI.2005.129.

[32] S. R. Das, S. Chita, N. Peterson, B. A. Shirazi, and M. Bhadkamkar, "Home automation and security for mobile devices," in *2011 IEEE International Conference on Pervasive Computing and Communications Workshops, PERCOM Workshops 2011*, 2011, doi: 10.1109/PERCOMW.2011.5766856.

[33] X. Xiang, M. Zhai, N. Lv, and A. El Saddik, "Vehicle counting based on vehicle detection and tracking from aerial videos," *Sensors (Switzerland)*, 2018, doi: 10.3390/s18082560.

[34] Atmel, "ATmega328P," *AVR Microcontrollers*. 2016.

[35] A. Das and T. Yaswanth, "A low-cost, portable alternative for a digital Lock-In Amplifier using TMS320C5535 DSP," *12th IEEE Int. Conf. Electron. Energy, Environ. Commun. Comput. Control (E3-C3), INDICON 2015*, 2016, doi: 10.1109/INDICON.2015.7443743.

[36] M. I. Soliman and G. Y. Abozaid, "FPGA implementation and performance evaluation of a high throughput crypto coprocessor," *J. Parallel Distrib. Comput.*, 2011, doi: 10.1016/j.jpdc.2011.04.006.

[37] M. Rivai, D. Hutabarat, and Z. M. Jauhar Nafis, "2D mapping using omni-directional mobile robot equipped with LiDAR," *Telkomnika (Telecommunication Comput. Electron. Control.*, 2020, doi: 10.12928/TELKOMNIKA.v18i3.14872.

[38] A. Alexan, A. Alexan, and O. Stefan, "SoC based IoT sensor network hub for activity recognition using ML.net framework," in *2020 IEEE 26th International Symposium for Design and Technology in Electronic Packaging, SIITME 2020 - Conference Proceedings*, 2020, doi: 10.1109/SIITME50350.2020.9292278.

[39] R. C. Lunardi, R. A. Michelin, C. V. Neu, and A. F. Zorzo, "Distributed access control on IoT ledger-based architecture," in *IEEE/IFIP Network Operations and Management Symposium: Cognitive Management in a Cyber World, NOMS 2018*, 2018, doi: 10.1109/NOMS.2018.8406154.

[40] M. Mehta, "ESP8266 : A Breakthrough in Wireless Sensor Networks and Internet of Things," *Int. J. Electron. Commun. Eng. Technol.*, 2015.

[41] Espressif Systems, "ESP8266EX." Espressif Systems, 2020.

[42] Espressif, "ESP32 Series Datasheet," *Espr. Syst.*, 2019.

[43] A. M. Baharudin and W. Yan, "Long-range wireless sensor networks for geo-location tracking: Design and evaluation," *Proc. - 2016 Int. Electron. Symp. IES 2016*, 2017, doi: 10.1109/ELECSYM.2016.7860979.

[44] C. B. Mwakwata, H. Malik, M. M. Alam, Y. Le Moullec, S. Parand, and S. Mumtaz, "Narrowband internet of things (NB-IoT): From physical (PHY) and media access control (MAC) layers perspectives," *Sensors (Switzerland)*, 2019, doi: 10.3390/s19112613.

[45] A. Lavric, A. I. Petrariu, and V. Popa, "Long Range SigFox Communication Protocol Scalability Analysis under Large-Scale, High-Density Conditions," *IEEE Access*, 2019, doi: 10.1109/ACCESS.2019.2903157.

[46] M. T. Penella, J. Albesa, and M. Gasulla, "Powering wireless sensor nodes: Primary batteries versus energy harvesting," *2009 IEEE Intrumentation Meas. Technol. Conf. I2MTC 2009*, 2009, doi: 10.1109/IMTC.2009.5168715.

[47] F. Engmann, F. A. Katsriku, J. D. Abdulai, K. S. Adu-Manu, and F. K. Banaseka, "Prolonging the Lifetime of Wireless Sensor Networks: A Review of Current Techniques," *Wireless Communications and Mobile Computing*. 2018, doi: 10.1155/2018/8035065.

[48] F. I. Simjee and P. H. Chou, "Efficient charging of supercapacitors for extended lifetime of wireless sensor nodes," *IEEE Trans. Power Electron.*, 2008, doi: 10.1109/TPEL.2008.921078.

[49] S. N. R. Kantareddy *et al.*, "Perovskite PV-Powered RFID: Enabling Low-Cost Self-Powered IoT Sensors," *IEEE Sens. J.*, 2020, doi: 10.1109/JSEN.2019.2939293.

[50] E. O. De La Rosa *et al.*, "Plant microbial fuel cells-based energy harvester system for self-powered IoT applications," *Sensors (Switzerland)*, 2019, doi: 10.3390/s19061378.

[51] S. Patra, "Notice of Removal: Design and Development of Magnetostrictive Low Power DC Generator and Vibration Sensor," *IEEE Sensors Journal*. 2020, doi: 10.1109/JSEN.2020.2976541.

[52] S. Patra *et al.*, "Self- operating Flyback Converter for Boosting Ultralow Voltage of Thermoelectric Power Generator for IoT Applications," *IEEE Trans. Ind. Electron.*, 2021, doi: 10.1109/TIE.2021.3135613.

[53] M. Cai and W. H. Liao, "High-Power Density Inertial Energy Harvester without Additional Proof Mass for Wearables," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2020.3003262.

[54] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications," *IEEE Commun. Surv. Tutorials*, 2015, doi: 10.1109/COMST.2015.2444095.

[55] Z. Yang, Y. Yue, Y. Yang, Y. Peng, X. Wang, and W. Liu, "Study and application on the architecture and key technologies for IOT," *2011 Int. Conf. Multimed. Technol. ICMT 2011*, 2011, doi: 10.1109/ICMT.2011.6002149.

[56] R. Khan, S. U. Khan, R. Zaheer, and S. Khan, "Future internet: The internet of things architecture, possible applications and key challenges," *Proc. - 10th Int. Conf. Front. Inf. Technol. FIT 2012*, 2012, doi: 10.1109/FIT.2012.53.

[57] H. Zou, Y. Zhou, J. Yang, and C. J. Spanos, "Unsupervised WiFi-Enabled IoT Device-User Association for Personalized Location-Based Service," *IEEE Internet Things J.*, 2019, doi: 10.1109/JIOT.2018.2868648.

[58] P. Narczyk and W. A. Pleskacz, "Analog Frontend for Reliable

Human Body Temperature Measurement for IoT Devices," *Electron.*, 2022, doi: 10.3390/electronics11030434.

[59] A. Pandey, R. Vamsi, and S. Kumar, "Handling Device Heterogeneity and Orientation Using Multistage Regression for GMM Based Localization in IoT Networks," *IEEE Access*, 2019, doi: 10.1109/ACCESS.2019.2945539.

[60] Y. Koyasako, T. Suzuki, T. Yamada, T. Shimada, and T. Yoshida, "Demonstration of Real-Time Motion Control Method for Access Edge Computing in PONs," *IEEE Access*, 2022, doi: 10.1109/ACCESS.2021.3136876.

[61] Q. Meng and S. Zhu, "Developing iot sensing system for construction-induced vibration monitoring and impact assessment," *Sensors (Switzerland)*, 2020, doi: 10.3390/s20216120.

[62] D. Moreno, X. Fan, F. Niklaus, and L. Guillermo Villanueva, "Proof of Concept of a Graphene-Based Resonant Accelerometer," in *Proceedings of the IEEE International Conference on Micro Electro Mechanical Systems (MEMS)*, 2021, doi: 10.1109/MEMS51782.2021.9375187.

[63] F. Hashim, R. Mohamad, M. Kassim, S. I. Suliman, N. M. Anas, and A. Z. A. Bakar, "Implementation of embedded real-time monitoring temperature and humidity system," *Indones. J. Electr. Eng. Comput. Sci.*, 2019, doi: 10.11591/ijeecs.v16.i1.pp184-190.

[64] C. A. R. Díaz *et al.*, "Iotof: A long-reach fully passive low-rate upstream phy for iot over fiber," *Electron.*, 2019, doi: 10.3390/electronics8030359.

[65] B. Seok, J. C. S. Sicato, T. Erzhena, C. Xuan, Y. Pan, and J. H. Park, "Secure D2D communication for 5G IoT network based on lightweight cryptography," *Appl. Sci.*, 2020, doi: 10.3390/app10010217.

[66] S. R. Pokhrel, H. L. Vu, and A. L. Cricenti, "Adaptive Admission Control for IoT Applications in Home WiFi Networks," *IEEE Trans. Mob. Comput.*, 2020, doi: 10.1109/TMC.2019.2935719.

[67] S. R. Hussain, S. Mehnaz, S. Nirjon, and E. Bertino, "Secure Seamless Bluetooth Low Energy Connection Migration for Unmodified IoT Devices," *IEEE Trans. Mob. Comput.*, 2018, doi: 10.1109/TMC.2017.2739742.

[68] L. Leonardi, F. Battaglia, and L. Lo Bello, "RT-LoRa: A Medium Access Strategy to Support Real-Time Flows Over LoRa-Based Networks for Industrial IoT Applications," *IEEE Internet Things J.*, 2019, doi: 10.1109/JIOT.2019.2942776.

[69] B. Vejlgaard, M. Lauridsen, H. Nguyen, I. Z. Kovacs, P. Mogensen, and M. Sorensen, "Coverage and Capacity Analysis of Sigfox, LoRa, GPRS, and NB-IoT," in *IEEE Vehicular Technology Conference*, 2017, doi: 10.1109/VTCSpring.2017.8108666.

[70] H. A. H. Alobaidy, J. S. Mandeep, R. Nordin, N. F. Abdullah, C. G. Wei, and M. L. S. Soon, "Real-World Evaluation of Power Consumption and Performance of NB-IoT in Malaysia," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2021.3131160.

[71] A. Shahraki, A. Taherkordi, O. Haugen, and F. Eliassen, "A Survey and Future Directions on Clustering: From WSNs to IoT and Modern Networking Paradigms," *IEEE Trans. Netw. Serv. Manag.*, 2021, doi: 10.1109/TNSM.2020.3035315.

[72] C. Xie, B. Yu, Z. Zeng, Y. Yang, and Q. Liu, "Multilayer Internet-of-Things Middleware Based on Knowledge Graph," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2020.3019707.

[73] L. Liu, J. Xu, Y. Huan, Z. Zou, S. C. Yeh, and L. R. Zheng, "A Smart Dental Health-IoT Platform Based on Intelligent Hardware, Deep Learning, and Mobile Terminal," *IEEE J. Biomed. Heal. Informatics*, 2020, doi: 10.1109/JBHI.2019.2919916.

[74] E. Navarro, N. Costa, and A. Pereira, "A systematic review of iot solutions for smart farming," *Sensors (Switzerland)*. 2020, doi: 10.3390/s20154231.

[75] T. Y. Kim, S. H. Bae, and Y. E. An, "Design of Smart Home Implementation within IoT Natural Language Interface," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.2992512.

[76] Y. C. Hsiao, M. H. Wu, and S. C. Li, "Elevated performance of the smart city-a case study of the iot by innovation mode," *IEEE Trans. Eng. Manag.*, 2021, doi: 10.1109/TEM.2019.2908962.

[77] Y. M. Tashtoush *et al.*, "Agile Approaches for Cybersecurity Systems, IoT and Intelligent Transportation," *IEEE Access*, 2022, doi: 10.1109/ACCESS.2021.3136861.

[78] G. Suciu, I. Hussain, A. Badicu, L. Necula, and T. Ușurelu, "IoT services applied at the smart cities level," in *Advances in Intelligent Systems and Computing*, 2020, doi: 10.1007/978-3-030-45691-7_42.

[79] C. T. Chiang, Y. K. Lu, and L. T. Lin, "A CMOS fish spoilage detector for IoT applications of fish markets," *IEEE Sens. J.*, 2018, doi: 10.1109/JSEN.2017.2770222.

[80] S. L. Ullo and G. R. Sinha, "Advances in IoT and Smart Sensors for Remote Sensing and Agriculture Applications," *Remote Sens.*, 2021, doi: 10.3390/rs13132585.

[81] Z. Wu, K. Qiu, and J. Zhang, "A smart microcontroller architecture for the internet of things," *Sensors (Switzerland)*, 2020, doi: 10.3390/s20071821.

[82] D. Fernández-Cerero, J. Y. Fernández-Rodríguez, J. A. Álvarez-García, L. M. Soria-Morillo, and A. Fernández-Montes, "Single-board-computer clusters for cloudlet computing in internet of things," *Sensors (Switzerland)*, 2019, doi: 10.3390/s19133026.

[83] F. Pereira, S. I. Lopes, N. B. Carvalho, and A. Curado, "RNProbe: A lora-enabled IoT edge device for integrated radon risk management," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.3036980.

[84] J. Yang, H. Zou, H. Jiang, and L. Xie, "Device-Free Occupant Activity Sensing Using WiFi-Enabled IoT Devices for Smart Homes," *IEEE Internet Things J.*, 2018, doi: 10.1109/JIOT.2018.2849655.

[85] K. Mekki, E. Bajic, F. Chaxel, and F. Meyer, "Overview of Cellular LPWAN Technologies for IoT Deployment: Sigfox, LoRaWAN, and NB-IoT," in *2018 IEEE International Conference on Pervasive Computing and Communications Workshops, PerCom Workshops 2018*, 2018, doi: 10.1109/PERCOMW.2018.8480255.

[86] S. Popli, R. K. Jha, and S. Jain, "A Survey on Energy Efficient Narrowband Internet of Things (NBIoT): Architecture, Application and Challenges," *IEEE Access*. 2019, doi: 10.1109/ACCESS.2018.2881533.

[87] P. K. R. Maddikunta, G. Srivastava, T. R. Gadekallu, N. Deepa, and P. Boopathy, "Predictive model for battery life in IoT networks," *IET Intell. Transp. Syst.*, 2020, doi: 10.1049/iet-its.2020.0009.

[88] M. G. Vidrascu and P. M. Svasta, "Maintenance-free IOT gateway design for bee hive monitoring," in *2017 IEEE 23rd International Symposium for Design and Technology in Electronic Packaging, SIITME 2017 - Proceedings*, 2017, doi: 10.1109/SIITME.2017.8259886.

[89] M. DInh, N. Ha-Van, N. T. Tung, and M. Thuy Le, "Dual-Polarized Wide-Angle Energy Harvester for Self-Powered IoT Devices," *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3098983.

[90] A. H. Sodhro and N. Zahid, "Ai-enabled framework for fog computing driven E-healthcare applications," *Sensors*, 2021, doi: 10.3390/s21238039.

[91] L. A. Zadeh, "The Concept of a Linguistic Variable and its Application to Approximate Reasoning," *Inf. Sci. (Ny).*, vol. 8, no. 3, pp. 199–249, 1975.

[92] N. Yusof, N. Bahiah, M. Shahizan, and Y. Chun, "A Concise Fuzzy Rule Base to Reason Student Performance Based on Rough-Fuzzy Approach," in *Fuzzy Inference System - Theory and Applications*, 2012.

[93] Iswanto and I. Ahmad, "Second-order integral fuzzy logic control based rocket tracking control," *J. Robot. Control*, vol. 2, no. 6, pp. 594–604, 2021, doi: 10.18196/jrc.26142.

[94] A. Adriansyah, Y. Gunardi, B. Badaruddin, and E. Ihsanto, "Goal-seeking Behavior-based Mobile Robot Using Particle Swarm Fuzzy Controller," *TELKOMNIKA (Telecommunication Comput. Electron. Control.*, vol. 13, no. 2, 2015, doi: 10.12928/telkomnika.v13i2.1111.

[95] R. Kristiyono and W. Wiyono, "Autotuning Fuzzy PID Controller for Speed Control of BLDC Motor," *J. Robot. Control*, vol. 2, no. 5, pp. 400–407, 2021, doi: 10.18196/jrc.25114.

[96] B. AlKhlidi, A. T. Abdulsadda, and A. Al Bakri, "Optimal Robotic Path Planning Using Intlligents Search Algorithms," *J. Robot. Control*, vol. 2, no. 6, pp. 519–526, 2021, doi: 10.18196/26132.

[97] Z. Lin, C. Cui, and G. Wu, "Dynamic modeling and torque feedforward based optimal fuzzy pd control of a high-speed parallel manipulator," *J. Robot. Control*, vol. 2, no. 6, pp. 527–538, 2021, doi: 10.18196/jrc.26133.

[98] S. Sahloul, D. Ben Halima Abid, and C. Rekik, "An hybridization of global-local methods for autonomous mobile robot navigation in partially-known environments," *J. Robot. Control*, vol. 2, no. 4, pp.

221–233, 2021, doi: 10.18196/jrc.2483.

[99] T. Tagaki and M. Sugeno, "Fuzzy Identification of System and its Application to Modeling and Control," *IEEE Trans. Syst. Man Cybern.*, vol. 15, no. 1, pp. 116–132, 1985.

[100] C. H. Chiu and Y. F. Peng, "Design of Takagi-Sugeno fuzzy control scheme for real world system control," *Sustain.*, 2019, doi: 10.3390/su11143855.

[101] X. Tang, D. Ning, H. Du, W. Li, Y. Gao, and W. Wen, "A takagi-sugeno fuzzy model-based control strategy for variable stiffness and variable damping suspension," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.2983998.

[102] X. Tang, D. Ning, H. Du, W. Li, and W. Wen, "Takagi-Sugeno Fuzzy Model-Based Semi-Active Control for the Seat Suspension with an Electrorheological Damper," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.2995214.

[103] The MathWorks Inc., "Mamdani and Sugeno Fuzzy Inference Systems," *Matlab R2020a, https://au.mathworks.com/help/fuzzy/types-of-fuzzy-inference-systems.html*, 2020. .

[104] J. S. R. Jang, "ANFIS: Adaptive-Network-Based Fuzzy Inference System," *IEEE Trans. Syst. Man Cybern.*, vol. 23, no. 3, pp. 665–685, 1993, doi: 10.1109/21.256541.

[105] G. P. N. Hakim *et al.*, "Near Ground Pathloss Propagation Model Using Adaptive Neuro Fuzzy Inference System for Wireless Sensor Network Communication in Forest, Jungle, and Open Dirt Road Environments," *Sensors*, vol. 2022, p. 3267, 2022, doi: 10.3390/s22093267.

[106] C. Ben Jabeur and H. Seddik, "Optimized Neural Networks-PID Controller with Wind Rejection Strategy for a Quad-Rotor," *J. Robot. Control*, vol. 3, no. 1, pp. 62–72, 2022, doi: 10.18196/jrc.v3i1.11660.

[107] W. Rahmaniar and A. Hernawan, "Real-Time Human Detection Using Deep Learning on Embedded Platforms: A Review," *J. Robot. Control*, vol. 2, no. 6, pp. 462–468, 2021, doi: 10.18196/jrc.26123.

[108] D. O. Oyewola, A. F. Augustine, E. G. Dada, and A. Ibrahim, "Predicting impact of COVID-19 on crude oil price image with directed acyclic graph deep convolutional neural network," *J. Robot. Control*, vol. 2, no. 2, pp. 103–109, 2021, doi: 10.18196/jrc.2261.

[109] Z. Dzulfikri, S. T. Nuryanti, and Y. Erdani, "Design and implementation of artificial neural networks to predict wind directions on controlling yaw of wind turbine prototype," *J. Robot. Control*, vol. 1, no. 1, pp. 20–26, 2020, doi: 10.18196/jrc.1105.

[110] S. Sinha, U. Srivastava, V. Dhiman, P. S. Akhilan, and S. Mishra, "Performance assessment of deep learning procedures: Sequential and ResNet on malaria dataset," *J. Robot. Control*, vol. 2, no. 1, pp. 12–18, 2021, doi: 10.18196/jrc.2145.

[111] P. T. T. Ngo *et al.*, "A novel hybrid swarm optimized multilayer neural network for spatial prediction of flash floods in tropical areas using sentinel-1 SAR imagery and geospatial data," *Sensors (Switzerland)*, 2018, doi: 10.3390/s18113704.

[112] J. Gu *et al.*, "Recent advances in convolutional neural networks," *Pattern Recognit.*, 2018, doi: 10.1016/j.patcog.2017.10.013.

[113] Z. Wu, S. Pan, F. Chen, G. Long, C. Zhang, and P. S. Yu, "A Comprehensive Survey on Graph Neural Networks," *IEEE Trans. Neural Networks Learn. Syst.*, 2021, doi: 10.1109/TNNLS.2020.2978386.

[114] T. Geng *et al.*, "O3BNN-R: An Out-of-Order Architecture for High-Performance and Regularized BNN Inference," *IEEE Trans. Parallel Distrib. Syst.*, 2021, doi: 10.1109/TPDS.2020.3013637.

[115] Z. E. Mohamed, "Using the artificial neural networks for prediction and validating solar radiation," *J. Egypt. Math. Soc.*, 2019, doi: 10.1186/s42787-019-0043-8.

[116] S. Mammadli, "Financial time series prediction using artificial neural network based on Levenberg-Marquardt algorithm," *Procedia Comput. Sci.*, 2017, doi: 10.1016/j.procs.2017.11.285.

[117] M. T. Hagan and M. B. Menhaj, "Training Feedforward Networks with the Marquardt Algorithm," *IEEE Trans. Neural Networks*, 1994, doi: 10.1109/72.329697.

[118] S. Roweis, "Levenberg-Marquardt Optimization," *Notes, Univ. Toronto*, 1996.

[119] S. A. Bkheet and J. I. Agbinya, "A Review of Identity Methods of Internet of Things (IOT)," *Adv. Internet Things*, 2021, doi: 10.4236/ait.2021.114011.

[120] J. Yu *et al.*, "Stabilizing Frame Slotted Aloha-Based IoT Systems: A Geometric Ergodicity Perspective," *IEEE Journal on Selected Areas in Communications*. 2021, doi: 10.1109/JSAC.2020.3018795.

[121] J. Grosinger, W. Pachler, and W. Bosch, "Tag Size Matters: Miniaturized RFID Tags to Connect Smart Objects to the Internet," *IEEE Microw. Mag.*, 2018, doi: 10.1109/MMM.2018.2844029.

[122] I. Farris, A. Lera, A. Molinaro, and S. Pizzi, "A CoAP-compliant solution for efficient inclusion of RFID in the Internet of Things," in *2014 IEEE Global Communications Conference, GLOBECOM 2014*, 2014, doi: 10.1109/GLOCOM.2014.7037231.

[123] M. C. Chung, G. M. Lee, N. Crespi, and C. C. Tseng, "RFID object tracking with IP compatibility for the Internet of Things," in *Proceedings - 2012 IEEE Int. Conf. on Green Computing and Communications, GreenCom 2012, Conf. on Internet of Things, iThings 2012 and Conf. on Cyber, Physical and Social Computing, CPSCom 2012*, 2012, doi: 10.1109/GreenCom.2012.30.

[124] H. Ning, X. Liu, X. Ye, J. He, W. Zhang, and M. Daneshmand, "Edge Computing-Based ID and nID Combined Identification and Resolution Scheme in IoT," *IEEE Internet Things J.*, 2019, doi: 10.1109/JIOT.2019.2911564.

[125] N. Koshizuka and K. Sakamura, "Ubiquitous ID: Standards for ubiquitous computing and the internet of things," *IEEE Pervasive Comput.*, 2010, doi: 10.1109/MPRV.2010.87.

[126] C. Ruiz, S. Pan, A. Bannis, M. P. Chang, H. Y. Noh, and P. Zhang, "IDIoT: Towards ubiquitous identification of iot devices through visual and inertial orientation matching during human activity," in *Proceedings - 5th ACM/IEEE Conference on Internet of Things Design and Implementation, IoTDI 2020*, 2020, doi: 10.1109/IoTDI49375.2020.00012.

[127] R. Perdisci, T. Papastergiou, O. Alrawi, and M. Antonakakis, "IoTFinder: Efficient Large-Scale Identification of IoT Devices via Passive DNS Traffic Analysis," in *Proceedings - 5th IEEE European Symposium on Security and Privacy, Euro S and P 2020*, 2020, doi: 10.1109/EuroSP48549.2020.00037.

[128] O. Kleine, "CoAP endpoint identification - A protocol extension for crowd sensing in the mobile internet," in *Proceedings - 2014 IEEE International Conference on Internet of Things, iThings 2014, 2014 IEEE International Conference on Green Computing and Communications, GreenCom 2014 and 2014 IEEE International Conference on Cyber-Physical-Social Computing, CPS 20*, 2014, doi: 10.1109/iThings.2014.65.

[129] A. J. Jara, P. Moreno-Sanchez, A. F. Skarmeta, S. Varakliotis, and P. Kirstein, "IPv6 addressing proxy: Mapping native addressing from legacy technologies and devices to the internet of things (IPv6)," *Sensors (Switzerland)*, 2013, doi: 10.3390/s130506687.

[130] J.-H. Lee, "IPv6 Address Configuration for Privacy Protection in the IoT," *J. Secur. Eng.*, 2015, doi: 10.14257/jse.2015.06.02.

[131] J. D. Kim, M. Ko, and J. M. Chung, "Physical Identification Based Trust Path Routing Against Sybil Attacks on RPL in IoT Networks," *IEEE Wirel. Commun. Lett.*, 2022, doi: 10.1109/LWC.2022.3157831.

[132] F. Samad, A. Abbasi, Z. A. Memon, A. Aziz, and A. Rahman, "The Future of Internet: IPv6 Fulfilling the Routing Needs in Internet of Things," *Int. J. Futur. Gener. Commun. Netw.*, 2018, doi: 10.14257/ijfgcn.2018.11.1.02.

[133] Z. Niu, Q. Li, C. Ma, H. Li, H. Shan, and F. Yang, "Identification of critical nodes for enhanced network defense in MANET-IoT networks," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.3029736.

[134] S. Shukla, S. Thakur, S. Hussain, J. G. Breslin, and S. M. Jameel, "Identification and Authentication in Healthcare Internet-of-Things Using Integrated Fog Computing Based Blockchain Model," *Internet of Things (Netherlands)*, 2021, doi: 10.1016/j.iot.2021.100422.

[135] S. Joshi *et al.*, "Unified Authentication and Access Control for Future Mobile Communication-Based Lightweight IoT Systems Using Blockchain," *Wirel. Commun. Mob. Comput.*, 2021, doi: 10.1155/2021/8621230.

[136] J. M. McGinthy, L. J. Wong, and A. J. Michaels, "Groundwork for Neural Network-Based Specific Emitter Identification Authentication for IoT," *IEEE Internet Things J.*, 2019, doi: 10.1109/JIOT.2019.2908759.

[137] A. Mukherjee, S. Misra, N. S. Raghuwanshi, and S. Mitra, "Blind entity identification for agricultural IoT deployments," *IEEE Internet Things J.*, 2019, doi: 10.1109/JIOT.2018.2879454.

[138] D. Ganesh Kumar, N. Insozhan, and V. Parthasarathy, "Recognition of faulty node detection using fuzzy logic in iot," *Int. J. Sci. Technol. Res.*, 2019.

[139] A. K. Gautam and R. Kumar, "A Trust Based Neighbor Identification Using MCDM Model in Wireless Sensor Networks," *Recent Adv. Comput. Sci. Commun.*, 2019, doi: 10.2174/2666255813666190923101045.

[140] Y. J. Jeong, K. E. An, S. W. Lee, and D. Seo, "Improved durability of soil humidity sensor for agricultural IoT environments," in *2018 IEEE International Conference on Consumer Electronics, ICCE 2018*, 2018, doi: 10.1109/ICCE.2018.8326223.

[141] S. Zeb, A. Habib, Y. Amin, H. Tenhunen, and J. Loo, "Green electronic based chipless humidity sensor for IoT applications," in *IEEE Green Technologies Conference*, 2018, doi: 10.1109/GreenTech.2018.00039.

[142] J. Ramírez-Faz, L. M. Fernández-Ahumada, E. Fernández-Ahumada, and R. López-Luque, "Monitoring of temperature in retail refrigerated cabinets applying iot over open-source hardware and software," *Sensors (Switzerland)*, 2020, doi: 10.3390/s20030846.

[143] M. Bhattacharjee, F. Nikbakhtnasrabadi, and R. Dahiya, "Printed Chipless Antenna as Flexible Temperature Sensor," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2021.3051467.

[144] G. Liu *et al.*, "A flexible temperature sensor based on reduced graphene oxide for robot skin used in internet of things," *Sensors (Switzerland)*, 2018, doi: 10.3390/s18051400.

[145] K. Keshamoni and S. Hemanth, "Smart gas level monitoring, booking & gas leakage detector over iot," in *Proceedings - 7th IEEE International Advanced Computing Conference, IACC 2017*, 2017, doi: 10.1109/IACC.2017.0078.

[146] R. Firdaus, M. A. Murti, and I. Alinursafa, "Air quality monitoring system based internet of things (IoT) using LPWAN LoRa," in *Proceedings - 2019 IEEE International Conference on Internet of Things and Intelligence System, IoTaIS 2019*, 2019, doi: 10.1109/IoTaIS47347.2019.8980437.

[147] H. P. L. De Medeiros and G. Girao, "An IoT-based Air Quality Monitoring Platform," in *2020 IEEE International Smart Cities Conference, ISC2 2020*, 2020, doi: 10.1109/ISC251055.2020.9239070.

[148] C. Maraveas and T. Bartzanas, "Sensors for structural health monitoring of agricultural structures," *Sensors (Switzerland)*. 2021, doi: 10.3390/s21010314.

[149] W. K. Phua *et al.*, "Ain-based mems (Micro-electro-mechanical system) hydrophone sensors for iot water leakage detection system," *Water (Switzerland)*, 2020, doi: 10.3390/w12112966.

[150] F. Jan, N. Min-Allah, and D. Düştegör, "Iot based smart water quality monitoring: Recent techniques, trends and challenges for domestic applications," *Water (Switzerland)*. 2021, doi: 10.3390/w13131729.

[151] R. La Rosa, C. Dehollain, A. Burg, M. Costanza, and P. Livreri, "An energy-autonomous wireless sensor with simultaneous energy harvesting and ambient light sensing," *IEEE Sens. J.*, 2021, doi: 10.1109/JSEN.2021.3068134.

[152] W. N. W. Muhamad, S. A. Bin Razali, N. A. Wahab, M. M. Azreen, S. S. Sarnin, and N. F. Naim, "Smart Bike Monitoring System for Cyclist via Internet of Things (IoT)," in *2020 IEEE 5th International Symposium on Telecommunication Technologies, ISTT 2020 - Proceedings*, 2020, doi: 10.1109/ISTT50966.2020.9279377.

[153] T. Lee and M. Tso, "A universal sensor data platform modelled for realtime asset condition surveillance and big data analytics for railway systems: Developing a 'Smart Railway' mastermind for the betterment of reliability, availability, maintainbility and safety of railway s," in *Proceedings of IEEE Sensors*, 2017, doi: 10.1109/ICSENS.2016.7808734.

[154] N. Patil and B. Iyer, "Health monitoring and tracking system for soldiers using Internet of Things(IoT)," in *Proceeding - IEEE International Conference on Computing, Communication and Automation, ICCCA 2017*, 2017, doi: 10.1109/CCAA.2017.8230007.

[155] S. M. C. Porto, F. Valenti, G. Castagnolo, and G. Cascone, "A Low Power GPS-based device to develop KDE analyses for managing herd in extensive livestock systems," in *2021 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2021 - Proceedings*, 2021, doi: 10.1109/MetroAgriFor52389.2021.9628711.

[156] S. S. N. Perala, I. Galanis, and I. Anagnostopoulos, "Fog Computing and Efficient Resource Management in the era of Internet-of-Video Things (IoVT)," in *Proceedings - IEEE International Symposium on Circuits and Systems*, 2018, doi: 10.1109/ISCAS.2018.8351341.

[157] S. Ravikumar and D. Kavitha, "IoT based home monitoring system with secure data storage by Keccak–Chaotic sequence in cloud server," *J. Ambient Intell. Humaniz. Comput.*, 2021, doi: 10.1007/s12652-020-02424-x.

[158] P. Meda, M. Kumar, and R. Parupalli, "Mobile augmented reality application for Telugu language learning," in *Proceedings of the 2014 IEEE International Conference on MOOCs, Innovation and Technology in Education, IEEE MITE 2014*, 2015, doi: 10.1109/MITE.2014.7020267.

[159] A. Tagami and Z. Shen, "LESAR: Localization System for Environmental Sensors using Augmented Reality," in *Proceedings - 2020 IEEE 44th Annual Computers, Software, and Applications Conference, COMPSAC 2020*, 2020, doi: 10.1109/COMPSAC48688.2020.00-16.

[160] T. Okawara, M. Yoshida, H. Nagahara, and Y. Yagi, "Action recognition from a single coded image," in *IEEE International Conference on Computational Photography, ICCP 2020*, 2020, doi: 10.1109/ICCP48838.2020.9105176.

[161] Shin, W. Paik, B. Kim, and S. Hwang, "An IoT platform with monitoring robot applying CNN-based context-aware learning," *Sensors (Switzerland)*, 2019, doi: 10.3390/s19112525.

[162] M. Zhong, Y. Zhou, and G. Chen, "Sequential model based intrusion detection system for iot servers using deep learning methods," *Sensors (Switzerland)*, 2021, doi: 10.3390/s21041113.

[163] A. Ullah, K. Muhammad, W. Ding, V. Palade, I. U. Haq, and S. W. Baik, "Efficient activity recognition using lightweight CNN and DS-GRU network for surveillance applications," *Appl. Soft Comput.*, 2021, doi: 10.1016/j.asoc.2021.107102.

[164] X. Xu, Y. Zhang, M. Tang, H. Gu, S. Yan, and J. Yang, "Emotion recognition based on double tree complex wavelet transform and machine learning in internet of things," *IEEE Access*, 2019, doi: 10.1109/ACCESS.2019.2948884.

[165] A. Ismail, S. Abdlerazek, and I. M. El-Henawy, "Development of smart healthcare system based on speech recognition using support vector machine and dynamic time warping," *Sustain.*, 2020, doi: 10.3390/su12062403.

[166] Z. Lv, L. Qiao, J. Li, and H. Song, "Deep-Learning-Enabled Security Issues in the Internet of Things," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2020.3007130.

[167] H. Zhang, Z. Fu, and K. I. Shu, "Recognizing Ping-Pong Motions Using Inertial Data Based on Machine Learning Classification Algorithms," *IEEE Access*, 2019, doi: 10.1109/ACCESS.2019.2953772.

[168] G. Nagasubramanian, R. K. Sakthivel, R. Patan, M. Sankayya, M. Daneshmand, and A. H. Gandomi, "Ensemble Classification and IoT-Based Pattern Recognition for Crop Disease Monitoring System," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2021.3072908.

[169] J. Sheth and B. Dezfouli, "Enhancing the Energy-Efficiency and Timeliness of IoT Communication in WiFi Networks," *IEEE Internet Things J.*, 2019, doi: 10.1109/JIOT.2019.2927588.

[170] Y. Zhao *et al.*, "Device-free secure interaction with hand gestures in wifi-enabled iot environment," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2020.3032623.

[171] H. Pirayesh, P. K. Sangdeh, and H. Zeng, "Coexistence of Wi-Fi and IoT Communications in WLANs," *IEEE Internet Things J.*, 2020, doi: 10.1109/JIOT.2020.2986110.

[172] K. H. Chang, "Bluetooth: A viable solution for IoT? [Industry Perspectives]," *IEEE Wireless Communications*. 2014, doi: 10.1109/MWC.2014.7000963.

[173] M. Collotta, G. Pau, T. Talty, and O. K. Tonguz, "Bluetooth 5: A Concrete Step Forward toward the IoT," *IEEE Commun. Mag.*, 2018, doi: 10.1109/MCOM.2018.1700053.

[174] Q. Liu, W. Ijntema, A. Drif, P. Pawelczak, M. Zuniga, and K. S. Yildirim, "Perpetual Bluetooth Communications for the IoT," *IEEE Sens. J.*, 2021, doi: 10.1109/JSEN.2020.3012814.

[175] J. Lee and J. Lee, "Prediction-based energy saving mechanism in 3GPP NB-IoT networks," *Sensors (Switzerland)*, 2017, doi: 10.3390/s17092008.

[176] G. Jia, Y. Zhu, Y. Li, Z. Zhu, and L. Zhou, "Analysis of the Effect of

the Reliability of the NB-Iot Network on the Intelligent System," *IEEE Access*, 2019, doi: 10.1109/ACCESS.2019.2932870.

[177] A. Larmo, A. Ratilainen, and J. Saarinen, "Impact of coAP and MQTT on NB-IoT system performance," *Sensors (Switzerland)*, 2019, doi: 10.3390/s19010007.

[178] K. Shafique, B. A. Khawaja, F. Sabir, S. Qazi, and M. Mustaqim, "Internet of things (IoT) for next-generation smart systems: A review of current challenges, future trends and prospects for emerging 5G-IoT Scenarios," *IEEE Access*. 2020, doi: 10.1109/ACCESS.2020.2970118.

[179] A. M. Escolar, J. M. Alcaraz-Calero, P. Salva-Garcia, J. B. Bernabe, and Q. Wang, "Adaptive Network Slicing in Multi-Tenant 5G IoT Networks," *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3051940.

[180] S. Ahmadzadeh, G. Parr, and W. Zhao, "A Review on Communication Aspects of Demand Response Management for Future 5G IoT- Based Smart Grids," *IEEE Access*. 2021, doi: 10.1109/ACCESS.2021.3082430.

[181] C. Gomez, J. C. Veras, R. Vidal, L. Casals, and J. Paradells, "A sigfox energy consumption model," *Sensors (Switzerland)*, 2019, doi: 10.3390/s19030681.

[182] C. Fourtet and B. Ponsard, "An introduction to Sigfox radio system," in *LPWAN Technologies for IoT and M2M Applications*, 2020.

[183] Q. Zhou, K. Zheng, L. Hou, J. Xing, and R. Xu, "Design and implementation of open LORa for IoT," *IEEE Access*, 2019, doi: 10.1109/ACCESS.2019.2930243.

[184] J. L. Gallardo, M. A. Ahmed, and N. Jara, "LoRa IoT-Based Architecture for Advanced Metering Infrastructure in Residential Smart Grid," *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3110873.

[185] M. S. Islam, M. T. Islam, A. F. Almutairi, G. K. Beng, N. Misran, and N. Amin, "Monitoring of the human body signal through the Internet of Things (IoT) based LoRa wireless network system," *Appl. Sci.*, 2019, doi: 10.3390/app9091884.

[186] K. Sohraby, D. Minoli, B. Occhiogrosso, and W. Wang, "A Review of Wireless and Satellite-Based M2M/IoT Services in Support of Smart Grids," *Mob. Networks Appl.*, 2018, doi: 10.1007/s11036-017-0955-1.

[187] J. Wei, J. Han, and S. Cao, "Satellite iot edge intelligent computing: A research on architecture," *Electron.*, 2019, doi: 10.3390/electronics8111247.

[188] R. Ortigueira, J. A. Fraire, A. Becerra, T. Ferrer, and S. Cespedes, "RESS-IoT: A Scalable Energy-Efficient MAC Protocol for Direct-to-Satellite IoT," *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3134246.

[189] N. Chen and M. Okada, "Toward 6G Internet of Things and the Convergence with RoF System," *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2020.3047613.

[190] H. Guo, J. Liu, and H. Qin, "Collaborative Mobile Edge Computation Offloading for IoT over Fiber-Wireless Networks," *IEEE Netw.*, 2018, doi: 10.1109/MNET.2018.1700139.

[191] F. Deng, P. Zuo, K. Wen, X. Wu, and Y. He, "Low Delay Technology Research of Transmission Line Tower Monitoring Network Integrating WSN and RFID," *IEEE Access*, 2019, doi: 10.1109/ACCESS.2019.2933462.

[192] S. Zoppi, A. Van Bemten, H. M. Gursu, M. Vilgelm, J. Guck, and W. Kellerer, "Achieving Hybrid Wired/Wireless Industrial Networks with WDetServ: Reliability-Based Scheduling for Delay Guarantees," *IEEE Trans. Ind. Informatics*, 2018, doi: 10.1109/TII.2018.2803122.

[193] A. Thakkar and K. Kotecha, "Cluster head election for energy and delay constraint applications of wireless sensor network," *IEEE Sens. J.*, 2014, doi: 10.1109/JSEN.2014.2312549.

[194] A. Suzain, R. A. Rashid, M. A. Sarijari, A. S. Abdullah, and O. A. Aziz, "Machine learning based lightweight interference mitigation scheme for wireless sensor network," *Telkomnika (Telecommunication Comput. Electron. Control.*, 2020, doi: 10.12928/TELKOMNIKA.V18I4.14879.

[195] X. Chang *et al.*, "Accuracy-aware interference modeling and measurement in wireless sensor networks," *IEEE Trans. Mob. Comput.*, 2016, doi: 10.1109/TMC.2015.2416182.

[196] G. D. O'Mahony, J. T. Curran, P. J. Harris, and C. C. Murphy, "Interference and intrusion in wireless sensor networks," *IEEE Aerosp. Electron. Syst. Mag.*, 2020, doi: 10.1109/MAES.2020.2970262.

[197] V. Seedha Devi, T. Ravi, and S. B. Priya, "Cluster Based Data Aggregation Scheme for Latency and Packet Loss Reduction in WSN," *Comput. Commun.*, 2020, doi: 10.1016/j.comcom.2019.10.003.

[198] O. J. Pandey and R. M. Hegde, "Low-Latency and Energy-Balanced Data Transmission over Cognitive Small World WSN," *IEEE Trans. Veh. Technol.*, 2018, doi: 10.1109/TVT.2018.2839562.

[199] M. U. Rehman, I. Uddin, M. Adnan, A. Tariq, and S. Malik, "VTA-SMAC: Variable Traffic-Adaptive Duty Cycled Sensor MAC Protocol to Enhance Overall QoS of S-MAC Protocol," *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3061357.

[200] S. Govindaraj and S. N. Deepa, "Network Energy Optimization of IOTs in Wireless Sensor Networks Using Capsule Neural Network Learning Model," *Wirel. Pers. Commun.*, 2020, doi: 10.1007/s11277-020-07688-2.

[201] B. A. Muzakkari, M. A. Mohamed, M. F. A. Kadir, and M. Mamat, "Queue and Priority-Aware Adaptive Duty Cycle Scheme for Energy Efficient Wireless Sensor Networks," *IEEE Access*, 2020, doi: 10.1109/ACCESS.2020.2968121.

[202] G. Samara and M. Aljaidi, "Efficient energy, cost reduction, and QoS based routing protocol for wireless sensor networks," *Int. J. Electr. Comput. Eng.*, 2019, doi: 10.11591/ijece.v9i1.pp496-504.

[203] W. A. Jabbar, W. K. Saad, and M. Ismail, "MEQSA-OLSRv2: A multicriteria-based hybrid multipath protocol for energy-efficient and QoS-aware data routing in MANET-WSN convergence scenarios of IoT," *IEEE Access*, 2018, doi: 10.1109/ACCESS.2018.2882853.

[204] W. Twayej, M. Khan, and H. S. Al-Raweshidy, "Network Performance Evaluation of M2M with Self Organizing Cluster Head to Sink Mapping," *IEEE Sens. J.*, 2017, doi: 10.1109/JSEN.2017.2711660.

[205] N. Ajmi, A. Helali, P. Lorenz, and R. Mghaieth, "MWCSGA-Multi weight chicken swarm based genetic algorithm for energy efficient clustered wireless sensor network," *Sensors (Switzerland)*, 2021, doi: 10.3390/s21030791.

[206] A. Hamzah, M. Shurman, O. Al-Jarrah, and E. Taqieddin, "Energy-efficient fuzzy-logic-based clustering technique for hierarchical routing protocols in wireless sensor networks," *Sensors (Switzerland)*, 2019, doi: 10.3390/s19030561.

[207] I. S. Alshawi, L. Yan, W. Pan, and B. Luo, "Lifetime enhancement in wireless sensor networks using fuzzy approach and a-star algorithm," *IEEE Sens. J.*, 2012, doi: 10.1109/JSEN.2012.2207950.

[208] S. Ahmed, S. Gupta, A. Suri, and S. Sharma, "Adaptive energy efficient fuzzy: An adaptive and energy efficient fuzzy clustering algorithm for wireless sensor network-based landslide detection system," *IET Networks*, 2021, doi: 10.1049/ntw2.12004.

[209] A. Panchal and R. K. Singh, "EHCR-FCM: Energy Efficient Hierarchical Clustering and Routing using Fuzzy C-Means for Wireless Sensor Networks," *Telecommun. Syst.*, 2021, doi: 10.1007/s11235-020-00712-7.

[210] O. Singh, M. Yadav, P. Yadav, V. Rishiwal, D. S. Jat, and P. Thakur, "QoS-Attentive Learning-based Routing for Scalable WSNs," in *ACM International Conference Proceeding Series*, 2021, doi: 10.1145/3484824.3484906.

[211] A. M. Shamsan Saleh, B. M. Ali, M. F. A. Rasid, and A. Ismail, "A self-optimizing scheme for energy balanced routing in wireless sensor networks using sensorAnt," *Sensors (Switzerland)*, 2012, doi: 10.3390/s120811307.

[212] R. Sinde, S. Kaijage, and K. Njau, "Cluster based wireless sensor network for forests environmental monitoring," *Int. J. Adv. Technol. Eng. Explor.*, 2020, doi: 10.19101/IJATEE.2019.650083.

[213] R. Levie, C. Yapar, G. Kutyniok, and G. Caire, "RadioUNet: Fast Radio Map Estimation with Convolutional Neural Networks," *IEEE Trans. Wirel. Commun.*, 2021, doi: 10.1109/TWC.2021.3054977.

[214] U. Masood, H. Farooq, A. Imran, and A. Abu-Dayya, "Interpretable AI-based Large-scale 3D Pathloss Prediction Model for enabling Emerging Self-Driving Networks," *IEEE Trans. Mob. Comput.*, 2022, doi: 10.1109/TMC.2022.3147191.

[215] S. P. Sotiroudis, P. Sarigiannidis, S. K. Goudos, and K. Siakavara, "Fusing Diverse Input Modalities for Path Loss Prediction: A Deep Learning Approach," *IEEE Access*, 2021, doi:

10.1109/ACCESS.2021.3059589.

[216] A. M. Aldosary, S. A. Aldossari, K. C. Chen, E. M. Mohamed, and A. Al-Saman, “Predictive wireless channel modeling of mmwave bands using machine learning,” *Electron.*, 2021, doi: 10.3390/electronics10243114.

[217] H. M. Jawad *et al.*, “Accurate Empirical Path-Loss Model Based on Particle Swarm Optimization for Wireless Sensor Networks in Smart Agriculture,” *IEEE Sens. J.*, 2020, doi: 10.1109/JSEN.2019.2940186.

[218] X. Lv, J. Li, X. Jia, and B. Yang, “Modeling for train-ground communication channel based on WSN,” in *Proceedings of the 2015 27th Chinese Control and Decision Conference, CCDC 2015*, 2015, doi: 10.1109/CCDC.2015.7162859.

[219] M. Gigli and S. Koo, “Internet of Things: Services and Applications Categorization,” *Adv. Internet Things*, 2011, doi: 10.4236/ait.2011.12004.

[220] L. Atzori, A. Iera, and G. Morabito, “The Internet of Things: A survey,” *Comput. Networks*, 2010, doi: 10.1016/j.comnet.2010.05.010.

[221] M. Syafrudin, G. Alfian, N. L. Fitriyani, and J. Rhee, “Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing,” *Sensors (Switzerland)*, 2018, doi: 10.3390/s18092946.

[222] M. Yu, F. Xu, W. Hu, J. Sun, and G. Cervone, “Using Long Short-Term Memory (LSTM) and Internet of Things (IoT) for Localized Surface Temperature Forecasting in an Urban Environment,” *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3116809.

[223] A. Srinivasan, “IoT Cloud Based Real Time Automobile Monitoring System,” in *2018 3rd IEEE International Conference on Intelligent Transportation Engineering, ICITE 2018*, 2018, doi: 10.1109/ICITE.2018.8492706.

[224] O. M. Bushnaq, A. Chaaban, and T. Y. Al-Naffouri, “The Role of UAV-IoT Networks in Future Wildfire Detection,” *IEEE Internet Things J.*, 2021, doi: 10.1109/JIOT.2021.3077593.

[225] M. R. Azghadi *et al.*, “Hardware Implementation of Deep Network Accelerators towards Healthcare and Biomedical Applications,” *IEEE Trans. Biomed. Circuits Syst.*, 2020, doi: 10.1109/TBCAS.2020.3036081.

[226] S. Vimal, Y. Harold Robinson, S. Kadry, H. V. Long, and Y. Nam, “IoT based smart health monitoring with CNN using edge computing,” *J. Internet Technol.*, 2021.

[227] R. Ferdousi, M. A. Hossain, and A. El Saddik, “Early-Stage Risk Prediction of Non-Communicable Disease Using Machine Learning in Health CPS,” *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3094063.

[228] Y. Zhang, J. Wen, G. Yang, Z. He, and J. Wang, “Path loss prediction based on machine learning: Principle, method, and data expansion,” *Appl. Sci.*, vol. 9, no. 9, 2019, doi: 10.3390/app9091908.

[229] S. P. Sotiroudis, S. K. Goudos, and K. Siakavara, “Neural Networks and Random Forests: A Comparison Regarding Prediction of Propagation Path Loss for NB-IoT Networks,” *2019 8th Int. Conf. Mod. Circuits Syst. Technol. MOCAST 2019*, 2019, doi: 10.1109/MOCAST.2019.8741751.

[230] N. Faruk *et al.*, “Path Loss Predictions in the VHF and UHF Bands within Urban Environments: Experimental Investigation of Empirical, Heuristics and Geospatial Models,” *IEEE Access*, vol. 7, pp. 77293–77307, 2019, doi: 10.1109/ACCESS.2019.2921411.

[231] S. K. Gharghan, R. Nordin, A. M. Jawad, H. M. Jawad, and M. Ismail, “Adaptive Neural Fuzzy Inference System for Accurate Localization of Wireless Sensor Network in Outdoor and Indoor Cycling Applications,” *IEEE Access*, 2018, doi: 10.1109/ACCESS.2018.2853996.

[232] H. A. O. Cruz, R. N. A. Nascimento, J. P. L. Araujo, E. G. Pelaes, and G. P. S. Cavalcante, “Methodologies for path loss prediction in LTE-1.8 GHz networks using neuro-fuzzy and ANN,” *SBMO/IEEE MTT-S Int. Microw. Optoelectron. Conf. IMOC 2017*, 2017, doi: 10.1109/IMOC.2017.8121127.

[233] A. Agrawal, R. Raj, and S. Porwal, “Vision-based multimodal human-computer interaction using hand and head gestures,” in *2013 IEEE Conference on Information and Communication Technologies, ICT 2013*, 2013, doi: 10.1109/CICT.2013.6558300.

[234] P. Akpojotor, A. Adetunmbi, B. Alese, and A. Oluwatope, “Automatic license plate recognition on microprocessors and custom computing platforms: A review,” *IET Image Processing*. 2021, doi: 10.1049/ipr2.12262.

[235] A. Shalaby, R. Gad, E. E. D. Hemdan, and N. El-Fishawy, “An efficient multi-factor authentication scheme based CNNs for securing ATMs over cognitive-IoT,” *PeerJ Comput. Sci.*, 2021, doi: 10.7717/peerj-cs.381.

[236] T. C. Hung and H. H. Trung, “Energy savings in applications for wireless sensor networks time critical requirements,” *Int. J. Comput. Networks Commun.*, vol. 8, no. 4, pp. 47–58, 2016, doi: 10.5121/ijcnc.2016.8403.

[237] X. Liu and J. Wu, “A method for energy balance and data transmission optimal routing in wireless sensor networks,” *Sensors (Switzerland)*, vol. 19, no. 13, pp. 1–14, 2019, doi: 10.3390/s19133017.

[238] V. S. Chua *et al.*, “Visual IoT: Ultra-Low-Power Processing Architectures and Implications,” *IEEE Micro*, 2017, doi: 10.1109/MM.2017.4241343.

[239] G. S. Arumugam and T. Ponnuchamy, “EE-LEACH: development of energy-efficient LEACH Protocol for data gathering in WSN,” *Eurasip J. Wirel. Commun. Netw.*, 2015, doi: 10.1186/s13638-015-0306-5.

[240] A. Wahab, F. A. Mustika, R. B. Bahaweres, D. Setiawan, and M. Alaydrus, “Energy efficiency and loss of transmission data on Wireless Sensor Network with obstacle,” *2016 10th Int. Conf. Telecommun. Syst. Serv. Appl.*, 2016.

[241] L. Mottola and G. Pietro Picco, “MUSTER: Adaptive energy-aware multisink routing in wireless sensor networks,” *IEEE Trans. Mob. Comput.*, 2011, doi: 10.1109/TMC.2010.250.

[242] G. S. Brar, S. Rani, V. Chopra, R. Malhotra, H. Song, and S. H. Ahmed, “Energy efficient direction-based PDORP routing protocol for WSN,” *IEEE Access*, 2016, doi: 10.1109/ACCESS.2016.2576475.

[243] W. Guo, W. Zhang, and G. Lu, “PEGASIS protocol in wireless sensor network based on an improved ant colony algorithm,” *2nd Int. Work. Educ. Technol. Comput. Sci. ETCS 2010*, 2010, doi: 10.1109/ETCS.2010.285.

[244] S. Misra and P. Dias Thomasinous, “A simple, least-time, and energy-efficient routing protocol with one-level data aggregation for wireless sensor networks,” *J. Syst. Softw.*, 2010, doi: 10.1016/j.jss.2009.12.021.

[245] S. R. Heikalabad, M. K. Mirnia, N. Rahmani, S. Ebadi, A. H. Navin, and M. Golsorkhtabar, “REACH: The new routing algorithm based on energy aware clustering hierarchical for lifetime increasing in wireless sensor networks,” *ICEIE 2010 - 2010 Int. Conf. Electron. Inf. Eng. Proc.*, 2010, doi: 10.1109/ICEIE.2010.5559783.

[246] O. Younis and S. Fahmy, “HEED: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks,” *IEEE Trans. Mob. Comput.*, 2004, doi: 10.1109/TMC.2004.41.

[247] R. Bria, A. Wahab, and M. Alaydrus, “Energy Efficiency Analysis of TEEN Routing Protocol with Isolated Nodes,” *Proc. 2019 4th Int. Conf. Informatics Comput. ICIC 2019*, 2019, doi: 10.1109/ICIC47613.2019.8985668.

[248] S. R. Nabavi, N. Osati Eraghi, and J. Akbari Torkestani, “Intelligent Optimization of QoS in Wireless Sensor Networks Using Multiobjective Grey Wolf Optimization Algorithm,” *Wirel. Commun. Mob. Comput.*, 2022, doi: 10.1155/2022/5385502.

[249] G. Liang, D. Niu, and Y. Liang, “Sustainability evaluation of renewable energy incubators using interval type-II fuzzy AHP-TOPSIS with MEA-MLSSVM,” *Sustain.*, 2021, doi: 10.3390/su13041796.

[250] I. Halkijevic, Z. Vukovic, and D. Vouk, “Indicators and a Neuro-Fuzzy Based Model for the Evaluation of Water Supply Sustainability,” *Water Resour. Manag.*, 2017, doi: 10.1007/s11269-017-1695-5.

[251] Y. Zhang, P. Geng, C. B. Sivaparthipan, and B. A. Muthu, “Big data and artificial intelligence based early risk warning system of fire hazard for smart cities,” *Sustain. Energy Technol. Assessments*, 2021, doi: 10.1016/j.seta.2020.100986.

[252] W. Deng, G. Wang, X. Zhang, J. Xu, and G. Li, “A multi-granularity combined prediction model based on fuzzy trend forecasting and particle swarm techniques,” *Neurocomputing*, 2016, doi: 10.1016/j.neucom.2015.09.040.

[253] N. Ravi and S. Mercy Shalinie, “Semisupervised-Learning-Based

Security to Detect and Mitigate Intrusions in IoT Network," *IEEE Internet Things J.*, 2020, doi: 10.1109/JIOT.2020.2993410.

[254] W. Elsayed, M. Elhoseny, S. Sabbeh, and A. Riad, "Self-maintenance model for Wireless Sensor Networks," *Comput. Electr. Eng.*, 2018, doi: 10.1016/j.compeleceng.2017.12.022.

[255] S. Cui, Y. Cao, G. Sun, and S. Bin, "A new energy-aware wireless sensor network evolution model based on complex network," *Eurasip J. Wirel. Commun. Netw.*, 2018, doi: 10.1186/s13638-018-1240-0.

[256] L. Jorguseski, A. Pais, F. Gunnarsson, A. Centonza, and C. Willcock, "Self-organizing networks in 3GPP: Standardization and future trends," *IEEE Commun. Mag.*, 2014, doi: 10.1109/MCOM.2014.6979983.

[257] H. Fourati, R. Maaloul, L. Chaari, and M. Jmaiel, "Comprehensive survey on self-organizing cellular network approaches applied to 5G networks," *Comput. Networks*, vol. 199, 2021, doi: 10.1016/j.comnet.2021.108435.