Testing of Emerging Wireless Sensor Networks Using Radar Signals With Machine Learning Algorithms

Shitharth Selvarajan, *Senior Member, IEEE*, Hariprasath Manoharan, Adil O. Khadidos, and Alaa O. Khadidos

***Abstract*—In this article, machine learning methods are used to assess how well wireless sensor networks transmit and receive radar signals. Measurements are done with labeled and unlabeled datasets where output functions are modified in relation to transmitted input in order to test the transceiver of radar signals. The main contribution in the proposed method is to focus on the possibility of choosing a free space model that transmits the radar signals in wireless sensor networks without any interruptions. Hence, for such type of transmissions, reference time period is selected in order to perform radar signal classification, and at the same time, separation of unnecessary interruptions is reduced using clustering procedures. Since the radar signals can be monitored with automatic transmission techniques, the outcomes are combined with supervised, unsupervised, and reinforcement learning models to increase the effect of transmissions. Therefore, the objective functions are designed with three scenarios where reinforcement learning proves to provide adequate connections for radar signals to all wireless sensor networks at reduced error of 0.3%. In addition, with reinforcement learning, the distance of radar signal transmission is maximized to a level greater than 75% at minimized noise ratio of 0.8%.**

***Index Terms*—Errors, free space model, machine learning, radar networks, wireless sensor networks.**

Manuscript received 10 August 2023; revised 10 January 2024 and 16 April 2024; accepted 20 April 2024. Date of publication 1 May 2024; date of current version 27 May 2024. This work was supported by Leeds Beckett University, Leeds, U.K. Recommended by Lead Guest Editor Hossein Fotouhi and Guest Editor Reza Malekian. *(Corresponding author: Shitharth Selvarajan.)*

Shitharth Selvarajan is with the School of Built Environment, Engineering and Computing, Leeds Beckett University, LS1 3HE Leeds, U.K. (e-mail: s.selvarajan@leedsbeckett.ac.uk).

Hariprasath Manoharan is with the Department of Electronics and Communication Engineering, Panimalar Engineering College, Chennai 600123, India (e-mail: hari13prasath@gmail.com).

Adil O. Khadidos is with the Department of Information Technology, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia (e-mail: akhadidos@kau.edu.sa).

Alaa O. Khadidos is with the Department of Information Systems, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah 21589, Saudi Arabia, and also with the Center of Research Excellence in Artificial Intelligence and Data Science, King Abdulaziz University, Jeddah 21589, Saudi Arabia (e-mail: aokhadidos@kau.edu.sa).

Digital Object Identifier 10.1109/JSAS.2024.3395578

List of Notations

Parameters	Implications.
$P_{t,r}$	Transmitted power of radar transmitter and receiver.
d_r	Distance of reference signal.
$d_{r1} + .. + d_{ri}$	Distance of first radar to ith radar.
E_r, E_t	Energy of transmitting and receiving radar signals.
ρ_r, ρ_t	Gain of transmitter and receiver.
$\mathrm{SNR}_{\mathrm{target}}$	Noise ratio of radar receiver.
SNR_{rn}	Noise ratio at threshold level.
rn_1, rn_i, rn_j	Radar node signal distance.
N_u	Total number of unknown nodes.
R_c	Radius of communication link.
P_u	Unidentified position of nodes.
source_n	Radar signal source.
rate_p	Radar path rate.
$\mathrm{position}_{\mathrm{source}}$	Position of initial signal source.
W_n	Wireless nodes for input unit.
y_i, z_i	Radar data point.
d_e	Information that is present in attribute function.
α_i	Target nodes.
O_i	Output values.
C_m	Maximum value of energy functions.
y_1, y_m	First and midpoint of data.
$\gamma_1 + \gamma_2 + .. + \gamma_i$	Clustered data points.
$\omega(y_n)$	Frequency of transmission.
dp_i	Total number of data points.
$\aleph$	Activation function.
x_i	Total functionality patterns.
ϑ_i	Random data sequence.
$x_i' y_i$	Number of connected states in the system.
dis_r	Data reduction on reward functions.
rand_a	Total number of reward values.
$\mathrm{rew}_1 + .. + \mathrm{rew}_i$	Total reward functions.
date_t	Total number of data representations.

I. Introduction

WIRELESS networks must be implemented for the process of producing radar signals, whether they operate in a clustered or nonclustered fashion. When wireless networks are

© 2024 The Authors. This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

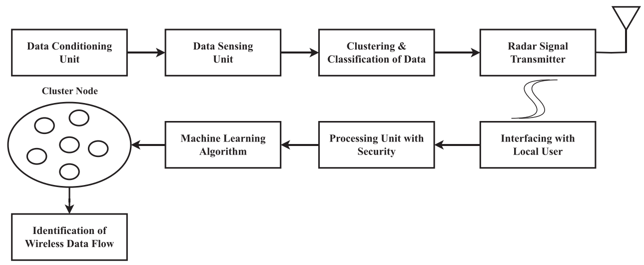


Fig. 1. Block diagram for free space radar systems.

installed, the integrated sensors must work properly to monitor all radar signals, including flow direction, transmission distance, and other factors. Radar signals can also be implemented in numerous applications with low signal strength if they are broadcast over wireless networks since long-range transmission is ensured.

Since radar networks are linked in an ad hoc manner, no infrastructure is needed to transmit signals, allowing for a decentralized method of operation. Since the majority of the data in radar networks are still scattered, the security of transmission is still precarious, and most of the data that are sent over long distances are vulnerable to outside attacks. Machine learning techniques must be used in order to increase operational security because most user data are not properly safeguarded during external attacks. In order to define a set of input radar data functions, the data must also be divided into labeled and unlabeled sets, also known as supervised and unsupervised sets. The proposed method for enhancing the security of radar networks incorporates reinforcement learning in addition to the previously discussed learning techniques.

When machine learning methods are used to create radar networks, there is a chance that dynamic data configuration with feature set-based categorization and grouping will be possible. With special mapping techniques, it is even feasible to pinpoint the location of radar signals, and at the very end, the target of data transfer can be located much more easily. Fig. 1 shows a block diagram of radar wireless sensor networks for security. Fig. 1 shows that the kind of data is determined at the beginning of the data transfer process while both long- and short-distance transmissions are being done. The sensing unit is linked after the data have been transferred in order to identify the various radar signals that are present at the transmitter. The recognized data are then categorized, grouped, and wirelessly transferred in order to interact with the data from the local user. The processing unit uses a combination of machine learning methods to identify the proportion of error in the transmitted signal after matching the data. If faults are found, it means that the security of the radar signals is low. However, in the proposed method, the cluster head adds additional security to all clustered nodes, allowing the data flow to the receiver to be quickly identified.

A. Background and Related Works

The majority of wireless sensor networks apply specific algorithms to increase the quality of improvement, which is expressed in terms of parametric design. This results in greater operating functionality. As a result, this section analyzes the current models that carry out various tasks linked to the operation of wireless sensor networks. In order to comprehend and develop the suggested method, which is based on parametric design measurements with the integration of suitable algorithms, the background works are given the utmost priority. Xie et al. [1] described the development of a minimal security strategy for wireless networks that use a localization strategy to address the main issue of packet arrival time and rate. The high-weight packets cannot be transmitted in the designated sequence despite the fact that the input weights are totally lowered on the assigned network. As a result, a fundamental framework is created for software-defined networks in which the security framework is constructed using a collaborative manner [2], which contrasts with typical operational scenarios. It has been noted that the collaborative approach on wireless sensor networks necessitates the analysis of a greater number of parameters, which makes the operation more difficult. When many network functions are combined, the proposed network architecture is unable to meet the problems at hand. The possibility of each node in wireless sensor networks to be imprisoned must, therefore, be understood [3] in order to offer adequate authentication. When a certain node receives authentication, it remains active until all of the data have been sent. After that, using the node exploration technique, the authentication for the other user must be adjusted in order to prevent packet loss in wireless networks [4]. A multifactor authentication is offered during the node discovery process, allowing the targets to be properly recognized without outside interference.

In addition, surveys are carried out to look at the state of software-defined radio wireless sensor networks in order to analyze the changing user environment [5]. Due to rigid network operations, earlier operational cases are not taken into account during this analysis. However, it is far more challenging to convey information under a centralized method of operation if prior functions are not examined. In addition, if nodes are clustered, a resource-constrained network must be created in which a connection between data and the appropriate application must be made. As a result of this connecting process, the access points' relationships with the central controlling unit—represented by a shared wireless link—remain unchanged. In order to reinforce the database representations, blockchain technology is integrated in addition to strengthening the security of wireless sensor networks. Every time the blockchain method is illustrated, it becomes apparent that some modifications to distributed and transaction blocks are required to display a larger volume of data in sensor networks. The quantity of energy supplied must be less if there are more data present during the visualization process compared with regular operation [6]. As a result, a model of energy consumption is introduced together with the application of radar networks to several clusters. Due to the substantially larger energy requirements of radar signals in wireless sensor networks, a model for the perception of residual energy has been created to deliver transmitted data with little energy. In addition, each node inside the cluster is represented by a cluster head in the low-energy analysis model, ensuring that enough energy is provided to high-operating nodes. Even the distance representation parameter is added to determine effective operations where the ant colony algorithm provides full support.

TABLE I
EXISTING VERSUS PROPOSED

Reference	Methods/Algorithms	Objectives A	B	C	D
[11]	Locomotive source localization	✓		✓	
[12]	Dynamic localization node model		✓		
[13]	Particle swarm optimization based node location		✓		✓
[14]	Optimized hybrid localization	✓	✓		
[15]	Machine learning for smart cities	✓			✓
[16]	Difference transmission algorithms for real-time testing of logistics	✓	✓		
[17]	Reinforce command systems for testing wireless sensor networks		✓	✓	
[18]	Geographic mapping topology for mapping radar signals			✓	✓
[19]	Testing of directional antennas based on range assignments	✓	✓		
[20]	Joint radar communication testing with spectrum sharing techniques		✓	✓	
Proposed	Supervised, Unsupervised and Reinforcement learning algorithms	✓	✓	✓	✓

A: Error localization; B: Range measurements; C: Signal-to-noise ratio D: Classification, clustering and reward functions

When continuous waves are added in representation cases, the distance of radar signals will be maximized by taking into account a concurrent range of vector transformation models. The radar signal increases its corresponding range wireless sensor network operation during the process of distance estimation [7]. But if continuous waves are introduced, the signal must be rebuilt, which necessitates greater Nyquist rate compression and is far more challenging to do. It is also investigated whether changing the Nyquist rate for a radar signal affects its compression characteristics, making it more difficult to reconstruct particular signals while the noise factor is still at a high level [8]. As a result, the gradient technique is integrated for data acquisition while the signal reconstruction approach is interpreted using low-cost sampling. Antinoise representation is significantly harder to achieve at output units even when such cost-effective technologies are used. A learning resource model [9] with topology organization processes must be adopted in order to reduce noise factors in wireless sensor networks. It has been noted that when such networks are organized, a location sensor is positioned in both active and passive modes, allowing the target of a radar signal to be operated in a typical manner using the proper receivers. In addition, all localization methods are grouped together inside a single communication range, where both range-free and range-based parametric operations are recognized in radar signal operations [10]. Table I compares recently published and proposed studies in wireless sensor networks.

B. Research Gap and Motivation

From Table I, it is tacit that some of the relevant methods that contribute to the effect of radar signals are discussed, and solutions are achieved with respect to distance measurements. It is significant that when a wireless sensor network is designed for monitoring and transmission operations, the effective signals must always be analyzed with respect to reference signals by considering time measurements. But in the existing approach, such types of reference signals are not provided; thus, complexity rises in wireless sensor network transmission units, and the aforementioned intricacy is identified as a major gap that needs to be solved with automatic radar signal processing systems. In addition to the identified gap, the following queries must be deciphered for the effective operation of radar signal transmissions with individual wireless network sources.

RG1: Is it possible to transmit radar signals in wireless networks using a free space model at limited power measurements?

RG2: Whether effective transmissions can be achieved at minimized distance and error measurements by using learning algorithms?

RG3: Can localization technique be used for wireless sensor networks to identify unknown nodes at maximized radar path rates?

C. Novelty and Research Merits

The suggested approach relies on unique testing concepts where all developing wireless applications are examined using radar signals, in contrast to previous approaches that test every wireless sensor network application using optimized signals. A radar signal is always required in wireless networks and needs to be applied across various distance measures because all wireless applications have a much greater range and need to monitor all necessary results. The new aspect of the suggested approach is that it uses radar signals to evaluate all wireless sensor networks that are connected to one another for various purposes, enabling current-generation networks to advance by guaranteeing smooth network operations. Furthermore, it is crucial to use machine learning techniques in the testing process for radar signals, ensuring that the required protocols and suitable data formats are followed.

D. Major Contributions

To solve the aforementioned queries that are identified as major gaps in the existing approach, the proposed method introduces a parametric radar design model integrated with three types of machine learning algorithms. Hence, the objectives of radar signal transmissions in wireless sensor networks are as follows:

1) to design a free space model for radar signal transmission are reception by using a time reference period that increases the gain of signal transmissions;
2) to minimize signal-to-noise ratio in radar signals thereby at entire signals are transmitted with appropriate distance in wireless sensor networks;
3) to compare the machine learning algorithms for choosing the best optimization to transmit radar signals with localization and network sources.

II. Proposed System Model

The mathematical representations used to construct the system model for wireless sensor networks allow it to be easily integrated with a variety of machine learning methods that can identify parametric outputs. In addition, if the system model is developed using parametric representations, it will be simple to compare it with different machine learning techniques and see how effective wireless sensor networks are in real time.

A. Free Space Model

Since the wireless sensors in the proposed system are linked to radar networks, the following equation describes the free space model for signal transmission:

$$f_s(\text{receiver}) = \min P_{t,r} \sum_{i=1}^{n} \frac{d_r}{(d_{r1} + \ldots + d_{ri})}. \quad (1)$$

Equation (1) is formulated as a minimization goal that reduces the power of the radar transmitter and receiver.

B. Time Reference

However, the energy given to radar for information processing determines the power of the transmitter and receiver, therefore the following equation is depicted using the following time reference:

$$T_{\text{ref}} = \min \sum_{i=1}^{n} \frac{E_r \rho_r}{E_t \rho_t}. \quad (2)$$

According to (2), the energy transmitted by radar nodes is minimized when the transmitter and receiver are separated by time.

C. Target SNR

However, the signal-to-noise ratio can further cut down on the energy that radar nodes use, so the minimization function for reducing the signal-to-noise ratio is expressed in the following equation:

$$\text{SNR}_{\text{radar}} = \min \sum_{i=1}^{n} \frac{\text{SNR}_{\text{target}}}{\text{SNR}_{rn}} \times 100. \quad (3)$$

According to (3), the overall signal-to-noise ratio will be higher if the threshold level in relation to the noise factor of the receiving nodes is significantly higher.

D. Distance Representations

As shown in the following equation, another method to reduce the signal-to-noise ratio is to minimize the distance between two independent radar nodes:

$$d_{\text{total}} = \min \sum_{i=1}^{n} (rn_1 - rn_i) + (rn_1 - rn_j). \quad (4)$$

Equation (4) states that the chosen location nodes must minimize the radar signal from the true position of the nodes.

E. Wireless Error Measurements

It is necessary to prevent localization error in wireless nodes, which is indicated in the following equation:

$$E_{\text{localization}} = \min \sum_{i=1}^{n} \frac{d_{\text{total}}}{N_u \times R_c}. \quad (5)$$

Equation (5) states that only by reducing the number of unknown nodes is error minimization possible.

F. Wireless Localization

The range measurement for the radar signal, however, varies during the localization process as sensor nodes are present, and it is calculated using the following equation:

$$N_u = \min \sum_{i=1}^{n} (P_u - \text{source}_n). \quad (6)$$

The node minimization problem, where inactive nodes must be deleted from radar networks, is described by (6).

G. Radar Wireless Network Source

The following equation is used to express the parameters of the original source signal:

$$\text{source}_s = \max \sum_{i=1}^{n} \frac{(\text{rate}_{\ p} + \text{position}_{\ \text{source}})}{d_{\text{total}}}. \quad (7)$$

According to (7), the source signal and its corresponding path from the radar must be selected suitably in order to maximize location accuracy.

H. Objective Functions

Equations (8) and (9) are used to generate the established system model's objective functions

$$\text{obj}_1 = \min \sum_{i=1}^{n} \text{SNR}_{\text{radar}}, E_{\text{localization}} \quad (8)$$

$$\text{obj}_2 = \max \sum_{i=1}^{n} \text{source}_s. \quad (9)$$

Equations (8) and (9) define a tri-objective function where noise ratio and localization errors must be decreased for wireless sensor networks in radar processing units. The source signal must be maximized in accordance with minimization when the objective function is combined with machine learning techniques, as mentioned in Section III.

III. Machine Learning Algorithms

It is crucial to transfer more data to end users since the wireless transmission process is connected to computer-aided design. In the suggested method, data-driven recommendations are produced before transmitting a sequence of data, and radar information is transmitted in this way. Therefore, the operation of machine learning is carried out by analyzing all antiquity that is present in radar nodes in order to strengthen the security of wireless sensor networks during data transmission [21]. Further, in wireless sensor networks for radar, the path information can be found by logically identifying it. In addition, machine learning methods are frequently chosen in wireless sensor networks due to their primary benefit of natural processing units, which enable the recognition and classification of projected model radar images for high-security operations. Radar data classification can be done separately because some of the traits are also present in wireless sensor networks with labeled and unlabeled data. In addition, the system model is analyzed using all three types of machine learning algorithms, including supervised, unsupervised, and reinforcement learning models, where necessary operating parameters for wireless sensor networks are specified. In addition, machine learning techniques can further minimize implementation costs and quickly fix automated procedures in the event of node failures. The suggested approach applies a machine learning technique in three steps, including localization, mapping, and positioning of radar signals, where suitable learning models are selected.

A. Supervised Learning Algorithm

Only specific datasets are represented at the input layer of the supervised learning algorithm, which determines the appropriate response at the output layer. The supervised learning algorithm analyzes the training data where only inferred results are provided in wireless sensor networks where both training and testing data are analyzed at the input unit. Since wireless sensor networks are used to transmit the majority of the data, label sets are required to categorize it. As a result, the suggested strategy specifies a distinct label for each type of data, which lowers all process-related empirical and structural hazards. In addition, a radar wireless sensor network must design a generative training set using supervised learning utilizing probability analysis. A supervised learning algorithm can be used with a prediction rule since the main goal of the suggested method is mapping procedures. Other than mapping, the main benefit of supervised learning is that radar data may only be processed by end units if recommendations are made. Speech and picture signals are processed as part of the recommendation-making process stated above. As a result, picture signals are favored for recommendations in radar wireless sensor networks because they allow for a clear view of data transmission. A supervised learning system can then be used to continuously detect radar signals and make correct predictions. The following equation can be used to illustrate the input and functional relationship of the supervised learning algorithm with a particular set of wireless data:

$$x_i = f\left(w_n\right). \tag{10}$$

The supervised learning approach uses two phases to identify unknown inputs since the input units are modeled as wireless nodes with functionality. These processes include classifying active and inactive nodes and performing a deterioration analysis. As a result, using distance representation, two different data points can be separated in classification, as seen below

$$\text{classification}_i = \min \sum_{i=1}^{n} \left(y_i - z_i\right). \tag{11}$$

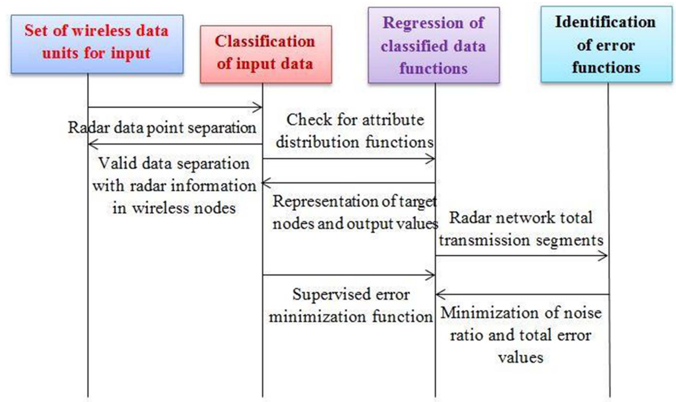


Fig. 2. Supervised learning for wireless sensor networks.

Equation (11) states that when data points differ in radar wireless sensor networks, the quantity of classification is reduced. The following equation can be used to obtain information at the receiver whether a given node has any attributes that are present in wireless sensor networks:

$$A_i = \min \sum_{i=1}^{n} d_e \log\left(d_e\right). \tag{12}$$

Equation (12) indicates that attributes must be minimized to maintain high security in the network; therefore, radar information can be chosen in a random way using the following equation:

$$I_r = 1 - \sum_{i=1}^{n} d_e. \tag{13}$$

Equation (13) states that only when data properties are decreased in the network can the chosen radar data be correctly identified. Therefore, using (14), the following error measurements for supervised learning are calculated:

$$\text{Error}_{\text{ supervised}} = \min \sum_{i=1}^{n} \left(\alpha_i - O_i\right). \tag{14}$$

The block representation of supervised learning is illustrated in Fig. 2.

B. Unsupervised Learning Algorithm

The majority of the data in wireless sensor networks are untagged, meaning that even when radar signals are transmitted, there is no connection made between two different radar datasets. The unsupervised machine learning approach is thus used in these situations where the data are still untagged. In addition, only creative material may be produced using the data included in wireless sensor networks; as a result, the radar data stay unlabeled. Unlabeled data allow the user to assess relevance without relying on outside factors; hence, more time is needed to gather the data. Radar applications perform data clustering and association in two steps, which is where unsupervised machine learning's main advantage lies. Clustering allows for the combination of more data or the combining of duplicate data inside a single network, which enables unsupervised machine learning algorithms to handle more complex operations for a

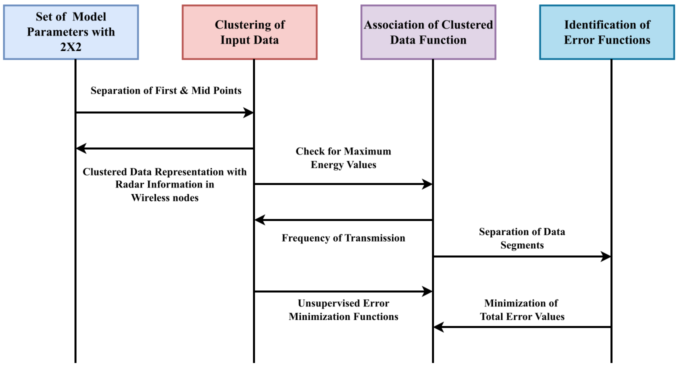


Fig. 3. Unsupervised learning for wireless sensor networks.

given set of data. In addition, all concealed information is found through a search procedure, indicating that exploratory data analysis for radar data occurs during unsupervised machine learning. Unsupervised machine learning also operates based on input weights, where the cluster with more data is prioritized above lesser data types. As a result, during the training phase, substantially less energy will be used for a given set of data if the wireless data representation is constructed as follows:

$$x_i = f\left(\frac{c_m}{1+e^{(y_1-y_m)}}\right). \tag{15}$$

Equation (15) suggests that the first and middle points' functions must have significantly less energy than the data functions present at other representation locations. However, the unsupervised machine learning technique uses clustering, which is defined using the following equation, to create data representations for radar signals:

$$\text{clustering}_i = \min \sum_{i=1}^{n} \gamma_1 + \gamma_2 + .. + \gamma_i. \tag{16}$$

Equation (17) states that clustered data points must be separated with equal distance representations, so in these situations, a neural network is used to create an individual network, which is essential for the majority of the data that lack any labeled sets. Radar signals' transmission frequency plays a crucial role in the case of clustered attribute functions, hence the support vectors are created as follows:

$$\gamma_n(i) = \min \sum_{i=1}^{n} \omega\left(y_n\right)/dp_i. \tag{17}$$

If the frequency of transmission is not matched, then at all data points, error measurements are made with activation functions, and it is represented using the following equation:

$$\text{Error}_{\text{ unsupervised}} = \min \sum_{i=1}^{n} e^{\mathrm{K}/x_i}. \tag{18}$$

Equation (18) states that functionality patterns, whose corresponding activation functions must be recorded in radar systems, minimize errors in unsupervised learning. Fig. 3 shows the block diagrams for the unsupervised machine learning algorithm.

C. Reinforcement Learning Algorithm

Reinforcement learning algorithms are used in wireless sensor applications for radar signals to train the data based on reward functions, with the exception of situations when an outside agent is permitted to interrupt with a signal. The incorporation of trial and error-basis functions is shown during this type of interruption, with the majority of errors occurring as a result of mismatched environmental circumstances. In contrast to supervised and unsupervised machine learning methods, errors are thereby avoided at the beginning of the process before data transmission. Another significant benefit of the reinforcement learning technique in wireless sensor network radar applications is that since all external agents are trained by external agents, additional rewards are added to a particular set of data. However, even after including the data incentives, the application process does not detect duplicated data, resulting in the creation of a distinct learning mechanism. Therefore, users may only decide on security in radar information processing by allowing different nodes to interface with one another. In contrast to other machine learning algorithms, reinforcement learning models decide beforehand what kind of data will be communicated next through the network. The preinteractive decision-making procedure indicated above saves a significant amount of time, thus the remaining time is used for the feedback system. The following is how the reinforcement learning algorithm is represented mathematically:

$$x_i = \vartheta_i + x_i' y_i. \tag{19}$$

According to (19), the construction of a random data sequence must be represented in the reinforcement learning algorithm as an input function where data representations are created in conjunction with the establishment of the sequence. The following equation is used to describe the expected behaviors for random data sequences throughout the reinforcement learning process:

$$A_{\text{expected}} = \min \sum_{i=1}^{n} \text{dis}_{\ r} \times \ \text{rand}_a. \tag{20}$$

Equation (20) states that in wireless sensor networks, the attribute of predicted functions must be lowered with random reward values; if dishonest awards are given out, then appropriate action must be done, and radar signals must be verified. The following equation can be used to investigate the error functions during the testing process:

$$\text{Error}_{\text{reinforcement}} = \min \sum_{i=1}^{n} \frac{\text{rew}_1 + .. + \ \text{rew}_i}{\text{data}_t}. \tag{21}$$

Equation (21) states that the system can only minimize the error function for reinforcement learning if the system avoids using the wrong reward functions. Fig. 4 shows the reinforcement learning algorithm's block representations, and a list of notations with implications are listed in the Nomenclature.

IV. Results

The assimilation results of the suggested system model with machine learning algorithms are assessed in real time with numerous data-gathering mechanisms in the proposed method.

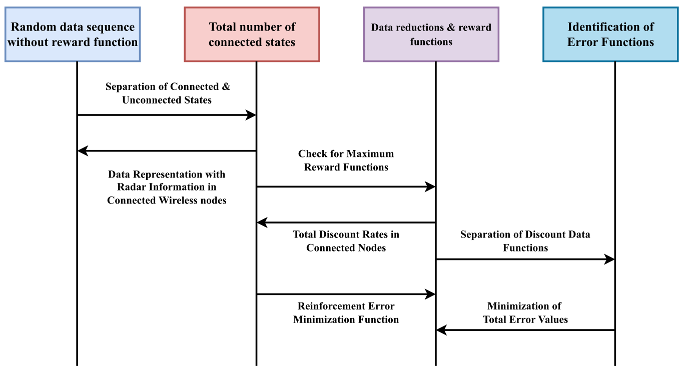


Fig. 4. Reinforcement learning for wireless sensor networks.

TABLE II
SIGNIFICANCE OF SCENARIOS

Scenarios	Need/ Significance
Error localization	To identify node errors after classification and clustering
Radar distance measurements	To transmit the radar data to allocated long distances
Signal-to-noise ratio	To identify and minimize the noise that is present in radar signals

Data from the radar signal are split and made to communicate over vast distances in order to analyze the results in real time. The majority of signals are seen to experience delays and faults during the transmission process, although these problems are quickly fixed. In addition, a random data sequence is created, which connects a greater number of distinct states instantly. In addition, classification and clustering techniques are used in conjunction with machine learning algorithms to further separate the data. In total, 250 nodes are chosen for data transport, scattered across a specific area, and equipped with cluster heads that identify each node's operation during transmission states. Furthermore, replay resources are set aside for data retrieval using a reference time system in the event that any radar data are lost during wireless transmission. The procedure is more complicated since the resources are typically allocated independently, which causes the rotational speed of data functions to be significantly higher. As the security of the suggested solution is maximized, the previously indicated process of allocating different resources is not conducted. The following three scenarios are carried out to investigate the suggested radar processing signals with machine learning algorithms:

1) *Scenario 1*—error localization;
2) *Scenario 2*—radar distance measurements;
3) *Scenario 3*—signal-to-noise ratio.

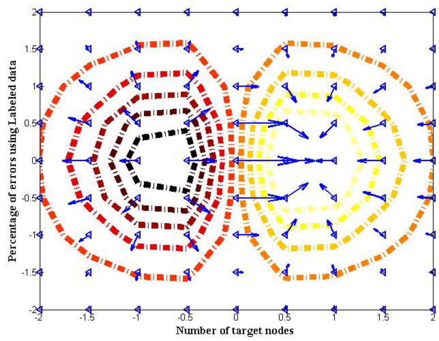
All the aforementioned scenarios are simulated in real time using MATLAB to show the output representations, and comparisons for machine learning algorithms are made to determine the application of radar signals. The importance of considered scenarios is listed in Table II, and a detailed description of all scenarios is as follows. Also, the simulation parameters are indicated in Table III.

Scenario 1: Error localization: Local interface faults will occur whenever a radar signal is relayed over long distances using a machine learning technique, and these errors are tracked in this scenario. The suggested method identifies and reduces mistakes brought on by both labeled and unlabeled datasets. Further, in the free space model, receiver errors are minimized below the threshold value, resulting in fewer reference errors during the period in question. When dealing with labeled data, faults are investigated by locating the target nodes where the output value discrepancy is counted. However, in the case of an unlabeled dataset, specific patterns that are represented in an exponential form are separated to show the activation functions. Thus, labeled data are considered direct representations, whereas unlabeled data are considered indirect representations. In addition, the reward function is distributed at each state with distinct data representations, substantially reducing error. The comparison of transmitted radar signal errors is shown in Fig. 5. Fig. 5 shows that the error function in all three categories of machine learning algorithms is reduced when compared with the current methodology [7]. The number of target nodes is taken into consideration to be 6, 8, 12, 15, and 19, and the error measurements are seen to be 10, 7, 4, and 2 for the present method and 5, 2, 1, 0.7, and 0.3 in the case of the existing methodology [7]. In contrast, error measurements in the unlabeled dataset are substantially greater, with 14, 11, 8, 5, and 3 for the present technique and 7, 3, 2, 1, and 1 for the proposed method, even when activation functions 1, 2, 3, 4, and 5 are taken into account. Although the total number of rewards for transmitting radar signals is 24, 32, 38, 45, and 50, respectively, where errors remain in low-range percentages of 8, 6, 3, and 1, with 1, 1, 0.8, 0.3, and 0.1 for existing and projected models, both the proposed and existing approaches have errors minimized after providing appropriate reward functions. Therefore, error localization is only reduced if the suggested method integrates a reinforcement learning model.

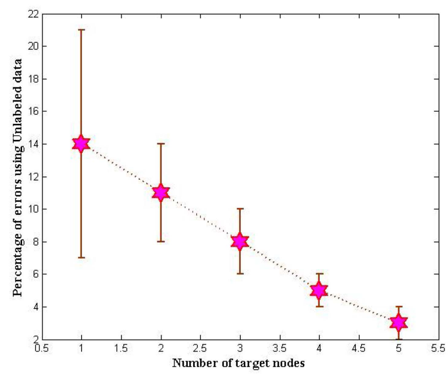
TABLE III
SIMULATION ENVIRONMENTS

Bounds	Requirement
Operating systems	Windows 8 and above
Platform	MATLAB and machine learning toolbox
Version (MATLAB)	2015 and above
Version (Machine learning tool)	5.7 and above
Applications	Wireless sensor network radar signal transmission and reception
Implemented data sets	Number of episodes, steps per episode, the learning rate, the discount factor, and the exploration rate
Reinforcement learning data set standards	
Number of episodes	1024
Steps per episode	1000
Learning rate	0.8
Discount factor	0.9
Exploration rate	1

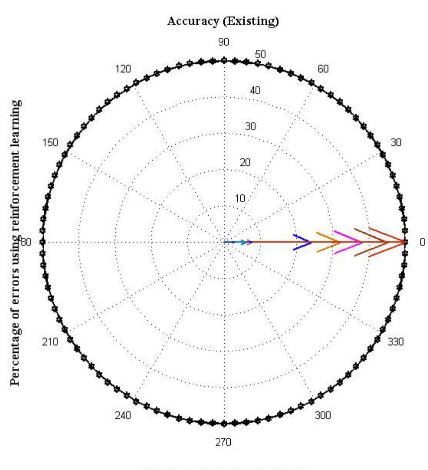
Scenario 2: Radar distance measurements: As specified that radar signals are carried over large distances, it is important to measure how far wireless sensor networks at the specified reference time travelled that distance according to stated input functions. As predefined networks with the same signal information can be used to convey data over medium to long distances,



(a)



(b)



(c)

Fig. 5. Representation of error functions. (a) Supervised. (b) Unsupervised. (c) Reinforcement.

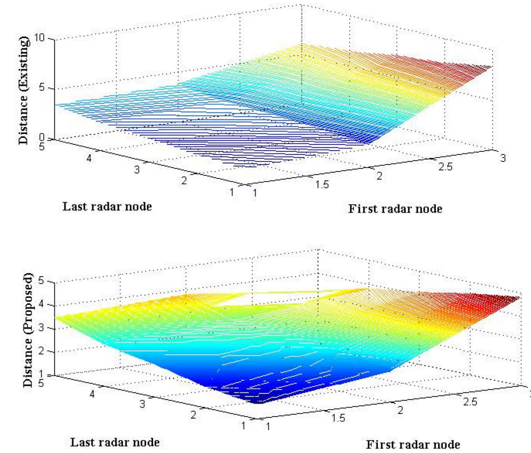


Fig. 6. Radar data separation with distance measurements.

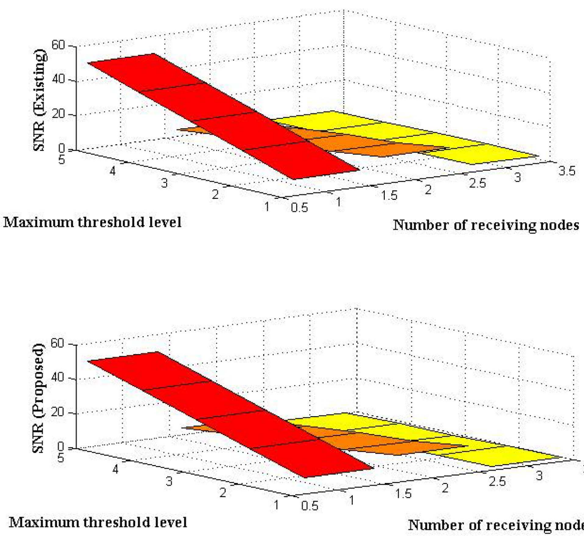


Fig. 7. Signal-to-noise ratio for radar signals.

the suggested technique first performs classification and clustering before moving on to distance measurement. The difference between the first and mid data nodes with the summation of total data functions is represented for distance measurements further in the free space model where two separate radar nodes are taken into account with reference points as i and j. The total number of idle nodes can be identified by separating the total distance from the total radius of communication lines. Distance measurements also show the connection to localization issues since complete separation causes data localization. The results of a simulation for measuring distance are shown in Fig. 6. Fig. 6 shows how the suggested method reduces the distance between two independent radar nodes in comparison with the conventional approach [7]. The simulation tool is connected with independent nodes where the information is not defined to illustrate distance measuring in MATLAB. The distance of the existing approach with idle nodes is 8.4, 7.6, 7.2, 6.5, and 6.1 in this scenario verification. However, using the same first and last node measurements, the proposed method can be able to provide minimized distance measurements as 4.8, 4.5, 4.1, 3.8, and 3.2, respectively. Since only reinforcement learning attributes are connected to distance measurements, the proposed method can achieve high security at minimized distances and, in contrast to supervised and unsupervised algorithms, only reinforcement learning algorithms can produce better observations.

Scenario 3: Signal-to-noise ratio: In the suggested technique, the signal-to-noise ratio is assessed using direct and indirect measurements, with the direct measurement separating the highest noise level, or threshold level, from the goal noise level. As a result, whereas in indirect measurements, the signal-to-noise ratio is detected with distance values, direct measurements can reach a direct signal-to-noise ratio. Radar signal transmission distance can be fully reduced if the signal-to-noise ratio is significantly higher. However, if there is a poor signal-to-noise ratio, the target receiver separation with the highest threshold values must be measured. However, since reference points are taken into account, both measurements will have the same effect on the receiver, and the noise ratio will be minimized at a specific moment. The signal-to-noise ratio of the suggested and existing approaches is shown in Fig. 7. The signal-to-noise ratio at the receiver, which is simulated in Fig. 7, illustrates that the noise ratio is minimized for the proposed method as compared with the existing approach [7]. For the demonstration case, the number of receiving nodes is considered as 10, 20, 30, 40, and 50, and the radar signals are transmitted with the same signal but at different ranges to the receiver. It is observed that when labeled and unlabeled data are represented, the receiving nodes provide a high signal-to-noise ratio, which is beyond the threshold level. Therefore, with the distance range that is measured in scenario 2, the observations are taken and the outcomes show that signal to noise ratio is minimized for proposed method. Hence, direct signal-to-noise ratio measurements are made using a total number of unknown nodes in the system. The measurements indicate that 2.66 dB of signal-to-noise ratio are present in the existing method, but in the proposed method, 0.8 dB is present.

A. Performance Analysis

The performance of the proposed method for radar signal transmissions in wireless sensor networks can be proved with an indication of cost factor. Since the substantial structure that is provided for radar signals must tolerate maximum noise ratio, the built-up structure of transmission units (intermediate channels) can be designed for broad access. Hence, a broadband unit that can be able to reformat necessary information to end users with radar signal processing is considered and total cost is evaluated for complete channel connections. Moreover, the network connectivity can be made in such a way with processing equipment before radar signal transmission is made. Thus, fiber units are considered for wireless sensor networks. In the proposed system, as a free space model is considered, the cost of connected units can be reduced further as radar frequency diversity is provided with a resource localization technique. Fig. 8 indicates the comparative outcomes of the proposed and existing approaches.

From Fig. 8, it is pragmatic that total cost is reduced for proposed method as compared with existing approach. The reductions in cost are provided in terms of reward functions where, with indicated data sequence, the radar signals are transmitted in channels. Due to such types of transmissions, it is possible to reduce data errors; thus, 100% of radar signals are transmitted without any external effect. To prove the possible reductions in cost factor, the best epoch for the reinforcement algorithm is considered as 20, 40, 60, 80, and 100. For the above-mentioned step periods, the total cost for the proposed method is reduced below 400 $, whereas due to the absence of a free space model, the total cost in the case of the existing approach is increased above 600 $. Hence, in real time for radar signal transmissions, it is possible to implement a proposed method for wireless sensor networks at reduced cost with a free space model.

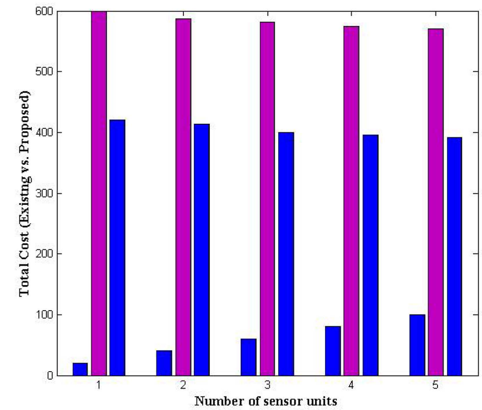


Fig. 8. Comparison of cost with varying sensor units.

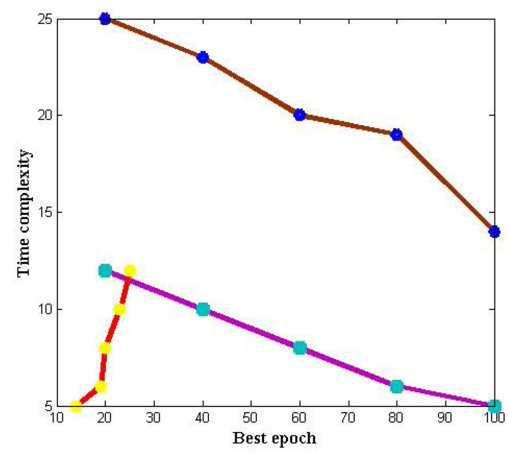


Fig. 9. Time complexities reductions for radar signal transmissions.

B. Time Complexity

The transmission process with individual channels for radar signal transmissions must be executed at reduced complexities where, at a reduced time period, more amount of signals must be transmitted to the indicated distance. Since free space models are used, it is possible to reduce the overall time period to the reference time period, and even the position of nodes can be made constant. Thereafter, the cost can be reduced further. Moreover, the computational complexities in the proposed method are observed not only with respect to algorithmic patterns but also in real time when the signal is transferred toward the destination. With equivalent representations, it is possible to observe the computations by maximizing the step size. Fig. 9 illustrates the computational complexity of the proposed and existing approaches. From Fig. 8, it is realistic that computational complexities are reduced for proposed method as compared with existing approach. The indicated distance in radar signal processing units is reduced, and the network source in considered paths is provided in a free space manner across varying junctions. To prove the outcome of computational complexity, 100 epoch periods are considered where total complexities are reduced below 5 s in the case of the proposed method and complexities are increased to 14 s for the existing approach [7].

V. Conclusion

When operating wireless sensor networks, the effectiveness of machine learning algorithms that use labeled and unlabeled datasets is crucial for enhancing data transmission security. In order to evaluate the impact of machine learning techniques in wireless sensor networks, the proposed method is used to look at the relevant parameters that have been developed as mathematical models. A free space model with an established reference time period serves as the basis for the parameters used to analyze the impact of wireless sensor networks. All vacant node positions are monitored since the signal-to-noise ratio measurements are also done with regard to distance minimization. These measurements enable the recovery of information from vacant nodes, protecting the system from all external threats. In addition, the suggested method is used to examine radar signals, where information is transferred over great distances and requires extremely robust security. In order to examine the error functions, measurements are also done in conjunction with machine learning techniques. Anytime the error functions are displayed, the security of radar signals is minimized, making wireless sensor network nodes vulnerable to many types of attacks. The suggested method uses a step approach to make classification and clustering using incentive functions. When incentive functions are offered, it is possible to transmit a radar signal without any errors. Contrarily, compared with supervised and unsupervised learning algorithms, the reinforcement learning model offers minimal error (less than 1%). The predicted model subsequently validates the current approach at a distance of 3.8 m in real-time execution when compared with error measurement, signal-to-noise ratio, and distance measurements. In terms of overall efficacy, the proposed solution achieves 80% more security than the current system.

Appendix

The flow representations of integrated algorithms are as follows.

Algorithm 1: Supervised learning.

Begin PROCEDURE SL
Given:
w_n : Number of wireless nodes
x_i : Total number of inputs
for i = $\underline{\underline{1:n}}$ **do**
1. $classification_i$ for Classifying the data with radar data points
2. A_i for receiving all attribute information from radar nodes
end for
or
for all $i = \underline{1:n}$ **do**
3. I_r for choosing the valid radar information
4. $Error_{\text{supervised}}$ to find total number of errors
end for
end PROCEDURE

Algorithm 2: Unsupervised learning.

Begin PROCEDURE USL
Given:
Model parameters: [2×2 structure]
Weight functions: [320×358 clusters]
for i = $\underline{\underline{1:n}}$ **do**
1. $clustering_i$ for Clustering the data with radar data points
2. γ_n for setting up frequency in all defined radar nodes
end for
or
for all $i = \underline{1:n}$ **do**
3. $Error_{\text{unsupervised}}$ to find total number of errors
end for
end PROCEDURE

Algorithm 3: Reinforcement Learning.

Begin PROCEDURE RL
Given:
ϑ_i : Random data sequence
y_i : Number of connected states
for i = $\underline{\underline{1:n}}$ **do**
1. A_{expected} for taking appropriate actions
2. dis_{r} for data reductions in reward functions
end for
or
for all $i = \underline{1:n}$ **do**
3. $Error_{\text{reinforcement}}$ to find total number of errors
end for
end PROCEDURE

References

[1] N. Xie, Y. Chen, Z. Li, and D. O. Wu, “Lightweight secure localization approach in wireless sensor networks,” *IEEE Trans. Commun.*, vol. 69, no. 10, pp. 6879–6893, Oct. 2021.
[2] C. Miranda, G. Kaddoum, E. Bou-Harb, S. Garg, and K. Kaur, “A collaborative security framework for software-defined wireless sensor networks,” *IEEE Trans. Inf. Forensics Secur.*, vol. 15, no. 1, pp. 2602–2615, Feb. 2020.
[3] C. Wang, D. Wang, Y. Tu, G. Xu, and H. Wang, “Understanding node capture attacks in user authentication schemes for wireless sensor networks,” *IEEE Trans. Dependable Secure Comput.*, vol. 19, no. 1, pp. 507–523, Jan./Feb. 2022.
[4] F. F. Jurado-Lasso, L. Marchegiani, J. F. Jurado, A. M. Abu-Mahfouz, and X. Fafoutis, “A survey on machine learning software-defined wireless sensor networks (ML-SDWSNs): Current status and major challenges,” *IEEE Access*, vol. 10, pp. 23560–23592, 2022.
[5] S.-J. Hsiao and W.-T. Sung, “Employing blockchain technology to strengthen security of wireless sensor networks,” *IEEE Access*, vol. 9, pp. 72326–72341, 2021.
[6] T. Jiang, W. Zang, C. Zhao, and J. Shi, “An energy consumption optimized clustering algorithm for radar sensor networks based on an ant colony algorithm,” *EURASIP J. Wireless Commun. Netw.*, vol. 2010, pp. 1–7, 2010.
[7] S. Ivanov, V. Kuptsov, V. Badenko, and A. Fedotov, “An elaborated signal model for simultaneous range and vector velocity estimation in FMCW radar,” *Sensors*, vol. 20, no. 20, 2020, Art. no. 5860.
[8] S. Zhu, S. Chen, X. Peng, H. Xiong, and S. Wu, “A signal reconstruction method of wireless sensor network based on compressed sensing,” *EURASIP J. Wireless Commun. Netw.*, vol. 2020, no. 1, 2020, Art. no. 106.

[9] Z. Mathews, L. Quiriconi, C. Schüpbach, and P. Weber, "Learning resource allocation in active-passive radar sensor networks," *Front. Signal Process.*, vol. 2, 2022, Art. no. 822894.
[10] X. Qi et al., "A combined localization algorithm for wireless sensor networks," *Math. Problems Eng.*, vol. 2018, pp. 1–10, 2018.
[11] H. Kabir, J. Kanesan, A. W. Reza, and H. Ramiah, "A mathematical algorithm of locomotive source localization based on hyperbolic technique," *Int. J. Distrib. Sensor Netw.*, vol. 11, no. 10, 2015, Art. no. 384180.
[12] X. Liu et al., "Wireless sensor network dynamic mathematics modeling and node localization," *Wireless Commun. Mobile Comput.*, vol. 2018, pp. 1–8, 2018.
[13] S.-H. Lee, C.-H. Cheng, C.-C. Lin, and Y.-F. Huang, "PSO-based target localization and tracking in wireless sensor networks," *Electronics*, vol. 12, no. 4, 2023, Art. no. 905.
[14] M. W. Khan, N. Salman, and A. H. Kemp, "Optimised hybrid localisation with cooperation in wireless sensor networks," *IET Signal Process.*, vol. 11, no. 3, pp. 341–348, 2017.
[15] H. Sharma, A. Haque, and F. Blaabjerg, "Machine learning in wireless sensor networks for smart cities: A survey," *Electronics*, vol. 10, no. 9, 2021, Art. no. 1012.
[16] J. Wu and X. Ding, "Using wireless sensor network to remote real-time monitoring and tracking of logistics status based on difference transmission algorithm," *J. Sensors*, vol. 2021, pp. 1–10, 2021.
[17] A. Ali, Y. K. Jadoon, S. A. Changazi, and M. Qasim, "Military operations: Wireless sensor networks based applications to reinforce future battlefield command system," in *Proc. IEEE 23rd Int. Multitopic Conf.*, 2020, pp. 1–6.
[18] R. Li, J. Wang, and J. Chen, "Movable platform-based topology detection for a geographic routing wireless sensor network," *Sensors*, vol. 20, no. 13, 2020, Art. no. 3726.
[19] R. George and T. A. J. Mary, "Review on directional antenna for wireless sensor network applications," *IET Commun.*, vol. 14, no. 5, pp. 715–722, 2020.
[20] S. Mazahir, S. Ahmed, and M.-S. Alouini, "A survey on joint communication-radar systems," *Front. Commun. Netw.*, vol. 1, 2021, Art. no. 619483.
[21] R. Ahmad, R. Wazirali, and T. Abu-Ain, "Machine learning for wireless sensor networks security: An overview of challenges and issues," *Sensors*, vol. 22, no. 13, 2022, Art. no. 4730.

Shitharth Selvarajan (Senior Member, IEEE) received the Ph.D. degree from the Department of Computer Science and Engineering, Anna University, Chennai, India, in 2018, and the Postdoctoral degree from The University of Essex, Colchester, U.K., in 2023.

He has worked in various institutions with a teaching experience of seven years. He is currently a Lecturer in cyber security with Leeds Beckett University, Leeds, U.K. He has authored or coauthored more than 85 international journals and 20 international and national conferences, and also four patents in IPR. His current research interests include cyber security, blockchain, critical infrastructure and systems, and network security and ethical hacking.

Dr. Selvarajan is an active Member of IEEE Computer Society and five more professional bodies. He is also a Member of the International Blockchain organization. He is a certified Hyperledger Expert and certified Blockchain Developer. He is an active Researcher, Reviewer, and Editor for many international journals.

Hariprasath Manoharan received the B.E. degree in electronics and communication engineering from Annamalai University, Annamalainagar, India, in 2013, the M.Tech. degree in communication systems from SRM University, Chengalpattu, India, in 2015, and the Ph.D. degree in electronics and communication engineering from Annamalai University, in 2019.

He is currently an Associate Professor with the Department of Electronics and Communication Engineering, Panimalar Engineering College, Chennai, India. He has completed nine years of research experience and teaching experience. He has guided both B.Tech. and M.Tech. students for doing projects in the areas of wireless sensor networks. He has authored or coauthored 92 research articles, which include SCI, SCIE, ESCI, and SCOPUS indexed articles, and has presented articles in six international conferences. He has also authored or coauthored a book titled *Computer Aided State Estimation for Electric Power Networks*, which provides a complete guide to all research scholars in the field of electronics and communication engineering. His research interests include wireless sensor networks, data communications, and testing of communication devices.

Adil O. Khadidos received the B.Sc. degree in computer science from King Abdulaziz University, Jeddah, Saudi Arabia, in 2006, and the M.Sc. degree in Internet software systems from the University of Birmingham, Birmingham, U.K., in 2011, and the Ph.D. degree in computer science from the University of Southampton, Southampton, U.K., in 2017.

He is currently an Associate Professor with the Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia. His research interests include computer swarm robotics, entomology behavior, machine learning, self-distributed systems, and embedded systems.

Alaa O. Khadidos received the B.Sc. degree from King Abdulaziz University, Jeddah, Saudi Arabia, in 2006, the M.Sc. degree from the University of Birmingham, Birmingham, U.K., in 2011, and the Ph.D. degree from the University of Warwick, Coventry, U.K., in 2017, all in computer science.

He is currently an Associate Professor with the Faculty of Computing and Information Systems, King Abdulaziz University. His research interests include computer vision, machine learning, optimization, and medical image analysis.