Wireless Sensor Network Deployment Performance based on FOA, PSO and TPSMA

Nurhidayah Kamal Akbar, *Member, IEEE*, Husna Zainol Abidin,*Member, IEEE*, and Ahmad Ihsan Mohd Yassin, *SeniorMember, IEEE*

***Abstract*—One of the crucial challenges in deploying a Wireless Sensor Network (WSN) is the position of the sensor nodes. It may create coverage holes as the sensor nodes become redundantfor each distribution. These coverage holes emerge when some of the poinst in terrain area is not covered by any sensor nodes. Hence, sensor nodefull connectivity may not be achieved andenergy consumption will be increased in sensing and communicating due to the distance between the sensor nodes. This paper compares the random deployment with other two algorithms known as Fruit Fly Optimization (FOA) and Particles Swarm Optimization (PSO) Territorial Predator Scent Marking Algorithm (TPSMA) to solve the coverage hole problem. The performance of these algorithms are compared in terms of coverage, connectivity and energy consumption. A performance study was carried out using MATLAB and Network Simulator 2 (NS2) on Linux platform. Based on the simulation work that have been done, it can beenseen that FOA outperforms PSO, TPSMA and random deployment.**

***Index Terms*—Wireless sensor network, Deployment, Fruit fly Optimization Algorithm, Particle Swarm Optimization, Territorial Predator Scent Marking Algorithm, Coverage, Connectivity and Energy consumption.**

I. INTRODUCTION

One of the main supporting technologies in Internet of Things (IoT) is Wireless Sensor Networks (WSN)[1]. In WSN it is very difficult to get 100% sensing coverage. Coverage problem or also known as coverage holes [2] always happen when one or more regions in a terrain area that iscovered by any sensor nodes in the field. It may appear due to many reasons and anywhere in the field of WSN. Coverage problemsnormally occur when random sensor nodes deployment takes place. Therefore in order to maximize the coverage rate, an effective mechanism is needed in deploying the sensor nodes.

WSN application can be categorized into two parts known as monitoring and tracking[3]. Monitoring is used to check and observe the event while tracking is used to update about the changes that occur in the event such as the number of persons, animals or cars. Each application has different Quality of Service (QoS) metrics depending on their requirements.

There are two ways to locate the sensor nodes in Region of Interest (RoI). The first way is call to random deployment and the second way is deterministic deployment [4][5]. Random deployment is where nodes are randomly deployed in RoI while deterministic deployment is where the location of each sensor nodes is predefined in order to achieve one or more objective function.

This paper compares three deployment algorithmsknown as Fruit fly Optimization Algorithm (FOA) and Particles Swarm Optimization (PSO) through simulation study. PSO is an effective, simple and computationally efficient optimization algorithm [6]. It has many throughput and efficiency rather than other mathematical and heuristic approaches [7]. These features make PSO suitable to be used for mobile sensor nodes redeployment while TPSMA was chosen for comparison as it represents the same network scenario. FOA is simpler and have less parameter. FOA commonly used in several application such as numerical optimization problems and neural network parameter [8].The remainder of this paper is organized as follows. Section II summarizes the related work. Section III elaborates the three algorithms while Section IV dwells on the simulation model and results. Finally Section V contains the conclusion and future work.

II. RELATED WORK

In recent years, many researchers have attemptedseveral methods in order to improve the coverage of WSNs.Researchers in[9] used Harmony Search Algorithm (HSA) to improve WSN coverage and connectivity. HSA reduces the number of sensor nodes deployed. It can be seen that theaverage coverage ratio had improved by 16.95% compared to existing algorithms.

FOA was proposed in [1] where the sensor nodes are using osphresis which is the scent of smell to find food. The highest smell concentration will become the position and then the fruit fly will move to the position according to their sensitive vision. The performance of FOA was compared with classic PSO [10] and novel Glow-worm Swarm Optimization (GSO).It shows that FOA can give higher coverage rate than others.

This manuscript is submitted on 18th December 2018 and accepted on 14th March 2019. N. K. Akbar is Master student at Faculty of Electrical Engineering, UniversitiTeknologi MARA (UiTM) (e-mail: hidayahakbar91@gmail.com).

H. Z. Abidin is a Senior lecturer at the Faculty of Electrical Engineering, UniversitiTeknologi MARA (UiTM) (e-mail: husnaza@salam.uitm.edu.my).

A. I. M. Yassin is a Senior lecturer at the Faculty of Electrical Engineering, UniversitiTeknologi MARA (UiTM) (e-mail: ihsan.yassin@gmail.com).

PSO is a social behavior of a flock of birds [6]. It starts with a random deployment in adimension area. It will find the global best where each sensor nodes or also known as particles will find its own best location and from all the particles it will find the best among the best to move to its new location rather than other sensor nodes. The simulation shows that it can achieve a good coverage rate.

GSO was proposed by Liao et al.[11]where each sensor node is considered as an individual glowworm. Each glowworm emitting a luminant substance called luciferin. The intensity of luciferin depends on the distance between sensor nodes and its neighbors. If the neighbor has the lowest intensity of luciferin among other glowworms then the sensor nodes will move towards it. When this happens the coverage of dimension area will be maximized. From the simulation results it can be seen that GSO based deployment can provide good coverage with limited movement.

Mishra et al. [12]introduced the use of different energy levels of active nodes in dimension area. This method is used to prolong the sensor nodes lifetime and provide 100% connectivity where the communication range is less than sensing range.

Three algorithms were used in [13] to solve the coverage holes problem in RoI. The algorithms are Artificial Immune System (AIS), Normalized Genetic Algorithm (NGA) and PSO. AIS is used to find the best antibody in population and NGA uses the best genetic in population to take place.Meanwhile, PSO is used to find the best particle swarm that can be moved to the coverage holes. Results show that the AIS and NGA outperform PSO in terms of coverage rate and the mobility cost.

In[14], Artificial Fish Swarm Algorithm (AFSA) and Particle Swarm Algorithm (PSA) were combined to improve the coverage. AFSA was used to search satisfactory solution domain and PSA was used to adjust position and direction of sensor nodes in WSN. This algorithm can eliminate coverage overlay and holes. It proves that this proposed algorithm can improve the coverage rate from the results. The new improved algorithm was used to compare between the classical AFSA and PSA.

Paper [15]introduced a novel sensor deployment scheme based on the Social Spider Optimization (SSO) algorithm in order to increase coverage for WSN. This algorithm divides their individual simulated social spiders habit, labour and cooperation effort depending on different gender. Males can be classified into two types which are dominant members (D) and non dominant (ND). D will perform mating operation while ND is needed to protect the food for the population. After mating with a femaleit will create a new spider. If the newly formed spider weight is greater than the lightest spider in the previous population then the old spider will be replaced by the new one. If not the newly performed spider will be abandoned and the spider population remains the same.From the results it shows that SSO algorithm is more effective than Genetic Algorithm (GA) and PSO algorithm and Virtual Force Algorithm (VFA) in redeployment method.

Work in[16]used Quasi-random method of low-discrepancy in order to increase the coverage and the lifetime of the network. There are three types of quasi-random deployment by Monte Carlo Simulation which is Halton, Sobol and Faure Sequence. Halton sequence can be obtained by reversing the binary digits sequence to deploy the sensor nodes, but SobolSequnceuses a base of 2 to form finer identical partitions and then reorders the coordinates in each dimension. Faure sequence is analogous to the Halton sequence. It uses identical prime number as the base for each of the mechanism of the vector. From the results, the quasi-reandom deployment is better than random deployment. This novel deployment can reduce the energy consumption and increase the lifespan of the network.

Reference [17] used a new localization algorithm named as Localization Algorithm Based on Anchor Optimization (LA-BAO). This algorithm uses a virtual force theory, where each sensor node will use repulsive and attractive in order to redeploy sensor nodes that had been distributed randomly in order to get good coverage and it uses DV-Hop algorithm to locate the unknown nodes. Simulation results show that this algorithm can increase the coverage rate of the anchor nodes and improve the location accuracy of the unknown nodes.

Paper[18] used a Territorial Predator Scent Marking Algorithm (TPSMA). This algorithm is inspired by a territorial predator in order to marking their territory using scent. The scent matching allows the animal to distinguish their area depend on recognizing their smell through sniffing. Sensor nodes position will be based on their marked territories. From the result it shows that TPSMA performs better than GA interms of coverage and moving distance.

III. METHODOLOGY

A. *Fruit Fly Optimization Algorithm (FOA)*

Fruit Fly Optimization Algorithm (FOA) [1]imitates the behaviour of a fruit fly group insearching for food. Fruit fly is popular than other species in terms of smell and vision. There are two stages for a fruit fly in finding food. In the first stage, the fruit fly will use osphresis organ to smell the food. During the second stage, it will fly towards the food by using its vision. The flow chart shown in Fig.1 depicts the process of FOA.

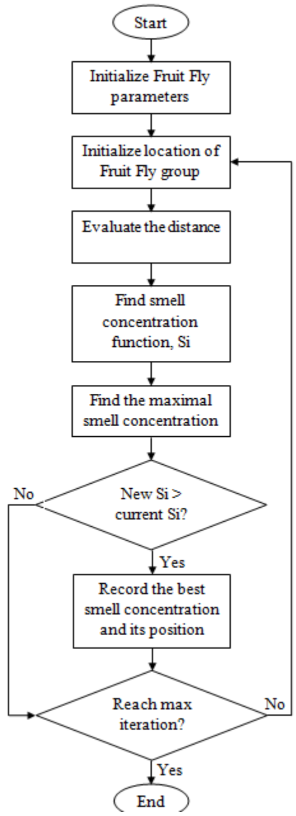

Fig. 1.Flow chart of Fruit Fly Optimization Algorithm (FOA)

The process started with the initialization of all parameters that include the size of the group, maximum iteration and the initial position of the fruit fly.Each of the fruit fly will be given a random number of direction and distance in order to find the food using osphresis.

$$\begin{cases} X_i = X\_axis + RandValue \\ Y_i = Y\_axis + RandValue \end{cases} \tag{1}$$

The distance between the food and the origin is determined by using equation (2).

$$Dist_i = \sqrt{{X_i}^2 + {Y_i}^2} \tag{2}$$

The smell concentration judgement value is calculated using equation (3) which will be substituted into smell concentration function as shown in equation (4).

$$S_i = {}^{1}/_{Dist_i} \tag{3}$$

$$Smell_i = Function \tag{4}$$

Fruit fly that gives maximal smell concentration value in fruit fly group is then obtained by using equation (5).

$$[bestSmell\ bestIndex] = max(Smell) \tag{5}$$

The best smell concentration and its position are recorded and all fruit flies will fly to the position depending on their sensitive vision.

$$Smellbest = bestSmell \tag{6}$$

$$X_{axis} = X(bestIndex) \quad Y_{axis} = Y(bestIndex) \tag{7}$$

B. *Particle Swarm Optimization (PSO)*

Particle Swarm Optimization (PSO) was inspired by Kennedy and Eberhart [9]. The idea of PSO came from natural bird flocking and fish schooling. Each particle has its own best position where it is known as individual best *(ibest)* and this result will be recorded during execution. Then from the ibest value the particle will be compare among each other to find the best position among them to be announcing as global best *(gbest)*. The PSO steps are shown in Fig.2.

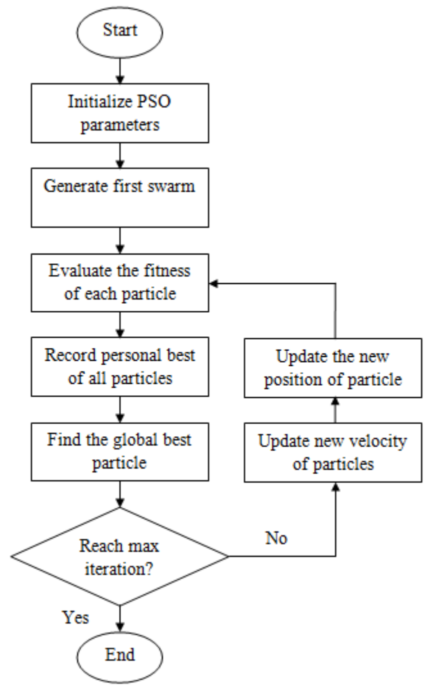

Fig. 2.Flow chart of Particle Swarm Optimization (PSO)

PSO is started with the initialization of all parameters. Each sensor node fitness function is evaluated as follows:

$$fitness = \sum_{i=1}^{N} x^2 \tag{8}$$

Personal best fitness of all sensor nodes in terrain area are then recorded and the global best sensor nodes are determined in order to move to coverage hole. Sensor node that has the global best value will be moved to the new position.If the stop condition is not met, the new velocity of particle will be updated based on equation (9).

$$v_i(t+1) = \omega(t+1)v_i(t) + 2rand_1\left(pos_{ibest} - pos_i(t)\right) + 2rand_2\left(pos_{gbest} - pos_i(t)\right) \quad (9)$$

$$pos_i(t+1) = pos_i(t) + v_i(t+1) \quad (10)$$

If the next global best value is better than previous the sensor nodes will move to the new position.

C. *Territorial Predator Scent Marking Algorithm (TPSMA)*

TPSMA was inspired by the territorial predator behaviour in order to mark their territory[18]. Tiger and bears is one of the territorial predators. It defend it certain areas from others based on certain factors such as food resources. Territorial predators always mark their territory area based on scent mark. Scent is usually mark based on urination, rubbing parts of their body like leg and chin, defecation, scratches and destruction of plants. Tiger usually use urinating to mark their territory while, cat rub their face and flanks against objects. Scent mark allows the animal to distinguish from intruders by using sniffing.

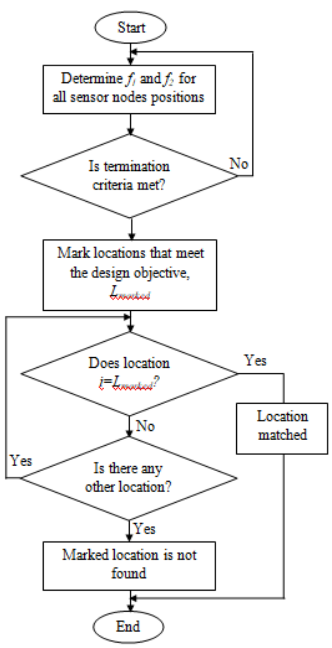

Fig. 3.Flow chart of Territorial Predator Scent Marking Algorithm (TPSMA)

TPSMA is use to move the sensor nodes to the certain are inorder to give maximum coverage in terrain area. Equation (11) and (12) is an objective function of TPSMA.

$$NCovered_p = \begin{cases} 1 & d(s_i, m_p) \le R_s \\ 0 & otherwise \end{cases} \quad (11)$$

Where $NCovered_p$represents coverage for each monitoring point and $d(s_i, m_p)$ represents distance between monitoring point and sensor nodes *i.*

$$f_2 = NCovered = \sum_{p \in M} NCovered_p \quad (12)$$

The objective function of TPSMA, f_2 represents the sum of all coverage for each monitoring point.

IV. Performance Study

A. *Simulation Model*

Four sets of simulation study were carried out to observe the coverage rate, average connectivity and energy consumption. The simulation work has been done using MATLAB R2014a and Network Simulator-2 (NS-2) on Ubuntu Linux 16.04.

1) *Experiment 1*

Experiment 1 is focusing on evaluating the coveragerate of the WSN.The simulation parameters are tabulated in Table I. The coverage rate for each distributed sensor nodeis determined using equation (13)[19].

TABLE I
SIMULATION PARAMETERS

Symbol	Parameter	Value
N	Number of sensor nodes	10, 15, 20, 25, 30, 35, 40, 45, 50
A	Area size	50 m×50 m
R_s	Sensing range	5 m
R_c	Communication range	10m

$$Coverage\ rate = \frac{mp - b}{mp} \quad (13)$$

where *b* represents the number of monitoring point without sensor nodes and *mp* represents the number of monitoring points in terrain area.

2) *Experiment 2*

Experiment 2 evaluates the connectivity ratio with the simulation parameters listed in Table II. The connectivity ratio is obtained by using equation (14) as stated in[19]

TABLE II
SIMULATION PARAMETERS

Symbol	Parameter	Value
N	Number of sensor nodes	30
A	Area size	50 m × 50 m
R_s	Sensing range	5m
R_c	Communication range	5m, 10m, 15m, 20m,

$$Connectivity\ ratio = \frac{N_{base}}{N} \quad (14)$$

Where N represents number of sensor nodes in network and N_{base} represents number of sensor nodes that connected to the base station [20].

3) Experiment 3

This simulation was carried out to determine the average connectivity ratio of WSN for different number of sensor nodes. The simulation parameters for Experiment 3 is tabulated in Table I.

4) Experiment 4

This experiment was conducted to evaluate the energy consumption for each algorithm where the simulation parameters are listed in Table III. The remaining energy can be calculated based on equation (15). This simulation is performed in 700 seconds simulation.

TABLE III
SIMULATION PARAMETERS

Symbol	Parameter	Value
N	Number of sensor nodes	40
A	Area size	50 m ×50 m
R_s	Sensing range	5m
R_c	Communication range	10m
E_{total}	Initial energy	100 Joules

$$E = E_{total} - E_r - E_t - E_i \tag{15}$$

E is average energy that remaining in sensor nodes. E_r is an energy use for receiving session, E_c is an energy use for transmit and E_i is an energy that use when sensor nods in idle state.

B. Results

Fig. 4 shows the coverage rate of each algorithm obtained from the Experiment 1. Forthe number of sensor nodes from 10 to 15 random deployment,the coverage rate is between 36% to 48% which is better than other algorithms. As the number of sensor nodes increase, FOA starts to increase the coverage rate value. From the results below it shows that FOA can give better coverage rate than PSO and TPSMA because the coverage rate for FOA reach 97% where the sensor nodes almost covers the coverage hole in the terrain area. This is due to FOA that selected the best smell among sensor nodes and then moved to the new location. The sensor nodes among the selected sensor nodes will attract and repel each other in order to avoid redundant among sensor nodes.

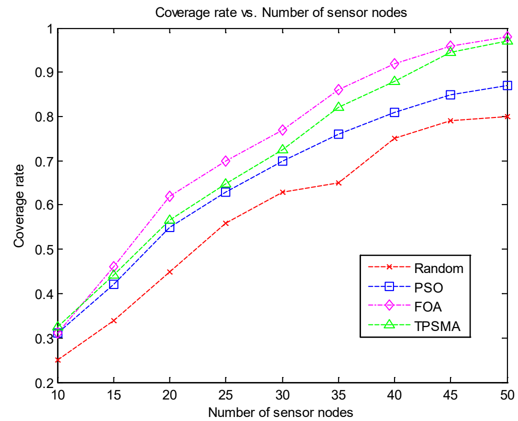

Fig. 4.Comparison between PSO and FOA interms of coverage rate versus number of sensor nodes.

Fig. 5 shows an average connectivity ratio as the number of communication range is increased obtained from the Experiment 2 forthe $R_c$values of5m, 10m, 15m and 20m respectively. From the figure 5,it can be seen that whenR_c is 5m, the connectivity ratio for random deployment is around 0.3 but as the number of R_c increased, the TPSMA deployment almost achieve full connectivity while FOA increase rapidly when R_c equal to 5m until 20m. It shows thatTPSMA can give better connectivity ratio which is 100% as compared to FOA and PSO deployment where it can give more than 90% connectivity when the communication range reach 20m.This is because after the sensor nodes can reach maximum coverage it can communicate easily with other sensor nodes in R_c.

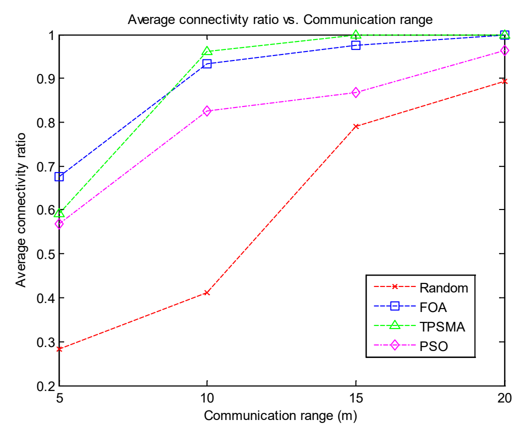

Fig. 5.Average connectivity ratio vs. Communication range.

Fig. 6depicts an average connectivity as the number of sensor nodes increase as produced from the Experiment 3. The results showthat TPSMA, FOA and PSO perform better than random deployment. Random deployment cannot connect with other sensorsbecause it creates redundancy and hence it becomes the limitation for the sensor nodes to communicate with others.TPSMA and FOA can outperform PSO because it can communicate with other sensor nodes and sends the data to the base station easily as it can give almost full coverage rather than PSO where only the best sensor nodes will move to the new location.

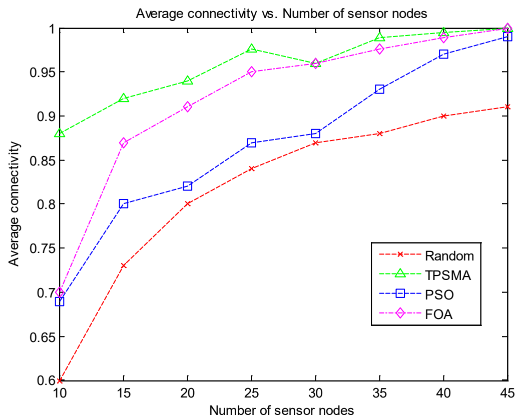

Fig. 6.Average connectivity vs. number of sensor nodes.

Fig. 7shows the energy consumed by WSN deployed using PSO and FOA which the results from Experiment 4. The figure clearly indicates that the FOA consumes less energy as compared to PSO. Hence, the algorithm is able toprolong the network lifetime. From the figure,it can be seen that at 100 second, FOA, TPSMA and PSO do not have a significant difference but when the time reached 700 secondsand PSO cannot maintain the energy and decreases while FOA is still at 97 Joules. This is due to the PSO not being able to give full coverage rate and connectivity that consequently will consume more energy in sensing and communication with other sensor nodes in order to send the data to the base station. Thus, it can be saidthat FOA can provide better energy consumption rather than TPSMA and PSO.

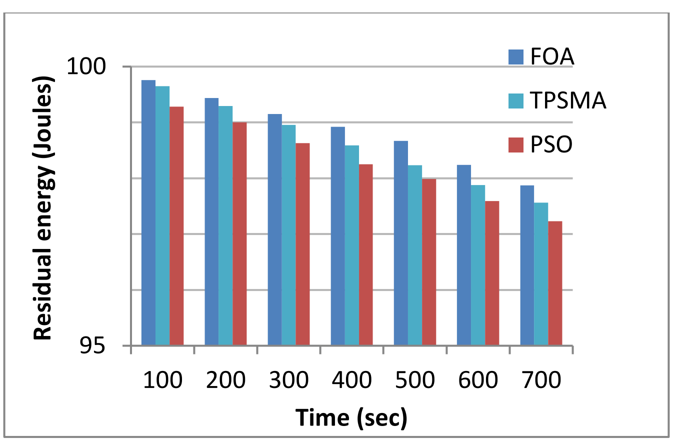

Fig. 7. Comparison residual energy in FOA and PSO.

V. Conclusion And Future Work

The used of FOA, TPSMA and PSO to improve coverage, connectivity and energy consumption in WSN through optimized sensor nodes deployment has been studied. The resultsshow that FOA effectively gives better coverage as compared to TPSMA and PSO and traditional random deployment. It is due to the best smell concentration detected and the selected sensor nodes will move to the new location. The sensor nodes among the new locations will repel and attract each other in order to avoid redundancy amongthemselves rather than the PSO where only the selected sensor nodes move towards the new locations while others remain the same. FOA and TPSMA is also able to maintain the connectivity and increase the value when the numbers of communication range increase rather than PSO and random deployment where it can achieve0.9645 and 0.8932 when the *Rc* is 20m. For the first hundred second FOA may use more energy in order to move among sensor nodes in order to avoid redundancy but after that FOA only needed to use little energy as the sensor nodes are near to each other rather than TPSMA and PSO where it needed more energy because the sensor nodes are far away and sometimes there are still coverage holes and are needed to find another path in order to sense and communicate and send data to the base station. As far as the energy consumption is concerned PSO usesmore energy to transmit, sense and process the data than FOA and TPSMA. For future research work, it is recommended that further investigation could be made for FOA, TPSMA and PSO sensor nodes deployment in 3 dimension terrain area.

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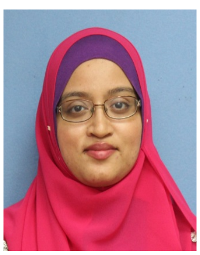
Nurhidayah Kamal Akbarwas born in AlorSetar, Kedah in 1991. She received a Dip. In Electronics Engineering Technology from Japan-Malaysian Technical Institute, Malaysia in 2012. She obtained her B.Eng. in Electronics Engineering from UniversitiTeknologiMARA, Malaysia, in 2017.She is pursuing a Master of Science in the Faculty of Electrical Engineering, UniversitiTeknologi MARA. Her research interest is in Wireless Sensor Network.



Husna Zainol Abidinreceivedher B.Eng. degree in Electrical Engineering from the University of Wollongong, Australia in 2001. She obtained her MEng and PhD from the UniversitiTenaga Nasional, Malaysia in 2006 and 2015 respectively.

She is currently a Senior Lecturer in the Faculty of Electrical Engineering, UniversitiTeknologi MARA. Her research interest includes the wireless networking, teletraffic monitoring, Internet of Things and Artificial Intelligence.Dr Husna is also a member of IEEE and a Chartered Engineer from the Institution of Engineering and Technology, UK.

Ahmad Ihsan Mohd Yassinreceivedhis B.Eng. degree in Electrical Engineering from the Universiti Tun Hussein Onn Malaysia. He obtained his MEng and PhD from the UniversitiTeknologi MARA, Malaysia.

He is currently a Senior Lecturer in the Faculty of Electrical Engineering, UniversitiTeknologi MARA. His research interest includesneural network, deep learning, system identification, optimization and blockchain technology. Dr Ihsan is also a senior member of IEEE, a Professional Engineer of the Board of Engineers Malaysia and a Chartered Engineer from the Institution of Engineering and Technology.