Received July 21, 2017, accepted August 2, 2017, date of publication August 11, 2017, date of current version September 6, 2017.

Digital Object Identifier 10.1109/ACCESS.2017.2737951

A New Intelligent Approach for Optimizing 6LoWPAN MAC Layer Parameters

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The work of B. R. Al-Kaseem was supported by the Iraqi Ministry of Higher Education and Scientific Research.

ABSTRACT Fairness, low latency, and high throughput with low energy consumption are desired attributes for medium access control (MAC) protocols. The IEEE 802.15.4 standard defines the MAC and physical layers standard for IPv6 over low power personal area network (6LoWPAN). When a non-appropriate parameter setting is used, the default MAC parameters generate excessive collisions, packet losses, and high latency under high traffic when a large number of 6LoWPAN nodes being deployed. A search of the literature revealed few studies that investigate the impact of optimizing these parameters to achieve high throughput with minimum latency. This paper proposes a new intelligent approach to selecting the optimal 6LoWPAN MAC layer parameters set; the introduced mechanism depends on artificial neural networks, genetic algorithm, or particles swarm optimization to select and validate the optimized MAC parameters. The obtained simulation results showed that utilizing the optimal MAC parameters improved 6LoWPAN network throughput by 52–63% and reduced the end-to-end delay by 54–65% in which the enhancement percentage depends on the number of deployed sensor nodes in the network.

INDEX TERMS 6LoWPAN, artificial neural network, genetic algorithm, particle swarm optimization, MAC parameters.

I. INTRODUCTION

There are many different trends that need to be taken into account when considering the development of the Internet-of-Things (IoT) [1], which include the IEEE 802.15.4 compliant protocols [2], future Internet [3], and Machine-to-Machine (M2M) networks [4]. Nowadays, the IEEE 802.15.4 is a common standard used by the Low power Wireless Personal Area Network (LoWPAN) devices for lower protocol layers. However, problems emerge when presenting the upper layers of the protocol stack. To address this, ZigBee Alliance [5], an industrial group, developed the ZigBee protocol in 2003 as an IEEE 802.15.4 compliant protocol and specified the vertical upper layers of the protocol stack. The ZigBee protocol has suffered from many limitations including the dependency on a single wireless link and application profile, along with scalability and Internet integration. The term future Internet was introduced in [6] and [7] to depict the Internet architecture and protocols research in the next 20 coming years. There are several European projects targeting future Internet research (i.e., EU 4WARD [8]), but are not focusing on embedded Internet devices and LoWPANs. Internet integration was not considered in traditional LoWPAN, because it was thought to be completely isolated. However, the EU SENSEI project [9] has focused on the integration of embedded devices with IPv6 over Low power Personal Area Network (6LoWPAN) functionality in the current and future global Internet. M2M networks are cognitive systems that have the ability to communicate with each other without human intervention [10]. The traditional M2M devices include cellular modems along with an Internet based back end system for IP communications. Recently, the M2M gateway has been used to bridge local embedded networked device with IP based networks. 6LoWPAN can be connected to the Internet via M2M gateway and encouraged both the research community and industry to become involved with the IoT revolution [11].

The IEEE 802.15.4 standard defines the Medium Access Control (MAC) and Physical (PHY) layers characteristics for low-data rate and low-power wireless devices [12]. Internet Engineering Task Force (IETF) working group introduced the 6LoWPAN [13] in order to adopt the implementation of Internet protocols over wireless embedded devices that are characterized by limited memory size, being power constrained, and having relaxed throughput. The 6LoWPAN protocol stack is similar to the TCP/IP stack. However, there are a few differences between them because of the large size of IPv6 packet compared to the IEEE 802.15.4 packet. Accordingly, the IETF working group added an extra layer to 6LoWPAN protocol stack, which is called the adaptation layer. This layer is responsible for header compression, fragmentation and reassembly of an IPv6 packet when it is sent or received over the IEEE 802.15.4 standard.

Wireless M2M sensor networks are usually composed of hundreds to thousands of energy constrained and short range communication devices. These limitations affect the selection of one protocol stack over the others. In fact, the increasing interest in M2M sensor networks has led to the development of a range of different communication protocols, but their diversity has limited the integration of different networks. Regarding the MAC and PHY layers, a widely used solution has been offered by the IEEE 802.15.4 standard and the IPv6 because the IP layer will cope the isolated network integration problems. This paper focuses on optimizing the MAC layer parameters of the 6LoWPAN protocol stack based on the specifications released by IETF working group [13].

Any MAC protocol for M2M sensor network should ensure prudent energy consumption in all M2M nodes in order to prolong the network lifetime. This paper motivated from the work developed by Zayani *et al.* [14] which is an enhance work inspired from the work presented by Park *et al.* [15]. In both works [14] and [15], the analytical model for the main characteristics of IEEE 802.15.4 standard was studied and verified using Markov chain model and Monte-Carlo simulation. The level of contention at the MAC layer influences the network throughput and end-to-end delay. In addition, the performance indicators at MAC and PHY layers showed that the selection of appropriate MAC parameters led to minimize the energy consumption, enhance reliability and reduce the end-to-end delay. The core contribution of the proposed approach is to select the optimal MAC layer parameters, the selection was carried out by using a) artificial neural networks; b) intelligent optimizer scheme. Moreover, the results are validated using Generic Algorithm (GA) and Particle Swarm Optimisation (PSO) to verify the selected MAC layer parameters sets.

The rest of this paper is organized as follows. Section II reviews the relevant recent works of the literature. Section III gives an overview of the basic soft-computing techniques. The methodology and proposed approach are illustrated in Section IV. In Section V, the interactions between MAC parameters are studied, in addition to the numerical evaluations of the proposed approach. Finally, Section VI concludes this paper.

II. RELATED WORKS

The IEEE 802.15.4 MAC layer standard of 6LoWPAN has received much attention, with a focus on its performance in terms of successful packet reception probability, packet delay, throughput, and energy consumption. Nowadays, IEEE 802.15.4 standard is a key technology for the development of M2M and IoT. Consequently, many works in the literature are generally verified by simulation tools such as MATLAB, NS-2, NS-3, OPNET, or OMNET. These studies have studied the performance of Carrier Sense Multiple Access/Collision Avoidance (CSMA/CA) mechanism of the IEEE 802.15.4 standard and proposed different algorithms either to enhance the end-to-end delay or improve the energy consumption. The energy consumption and end-to-end delay in WSN are affected by a variety of MAC parameters and the challenge of optimizing WSN networks in terms of a low-energy consumption with minimum latency has been a difficult problem need to be addressed by research community.

Ergen *et al.* [16] presented a novel approach for minimizing the energy consumption of un-slotted IEEE 802.15.4 MAC protocols using optimisation techniques. The objective function was related to the total energy consumption in the transmit, receive, listen, and sleep states, in addition to the delay and reliability of the packet delivery. While the decision variables were the sleep and wake time of the receivers. Storing light look-up tables in the receiver nodes represented the optimal solution and made it easy to implement on existing IEEE 802.15.4 hardware platforms.

Fischione *et al.* [17] conducted an analysis of un-slotted IEEE 802.15.4 MAC, the expressions of which were represented as a function of sleep time, listening time, traffic rate and MAC parameters. The analytical results were then used to optimize the duty cycle of the nodes and MAC protocol parameters. The authors reported that significant reduction of sensor node energy consumption compared to existing solutions was achieved.

Marco *et al.* [18] provided an analysis of the fundamental MAC and routing protocols for Low-power and Lossy Networks (LLNs): IEEE 802.15.4 MAC and IETF IPv6 Routing Protocol for Low-power and lossy networks (RPL). The characterisation of their cross layer interactions was presented in the form of a mathematical description, with a protocol selection mechanism being implemented to select the appropriate routing metric and MAC parameters for given specific performance constraints. Both the analytical and experimental results showed that the behaviour of the MAC protocol affected the performance of the routing protocol and vice versa, unless these two were carefully optimized together.

Wallace *et al.* [19] proposed a fuzzy CSMA/CA MAC protocol with two separate fuzzy logic controllers. The first controller was used to optimize the MAC parameters and sleeping schedule duty-cycle, whilst the second controller was aimed at optimizing the size of the contention window using three performance metrics as inputs. These two fuzzy logic controllers were deployed to ensure maximum power efficiency achievement while utilizing the optimized parameters in sensor network.

Liu and Li [20] proposed a Collision-Aware Backoff algorithm (CABEB) to improve the performance of a slotted

CSMA/CA for the IEEE 802.15.4 standard. The CABEB algorithm provided dynamic selection of a backoff period depending on the current collision probability of the network. The proposed approach was able to configure the MAC layer parameters autonomously based on the available channel state information. The analytical results were based on Markov chain modelling, while the simulation results were based on OMNET++ simulation software. The obtained results showed that the CABEB algorithm performed better that the default IEEE 802.15.4 standard and the knowledge-based exponential backoff algorithm.

Abdeddaim *et al.* [21] applied models that led to the idle sensing access method of IEEE 802.11 to the slotted CSMA/CA of IEEE 802.15.4 standard. They were taking into account the central role of the coordinator as well as the burst nature of the traffic. The contention window was adjusted depending on optimal values to achieve high throughput along with low duty cycles and minimum energy consumption in sensor nodes.

Pinto *et al.* [22] proposed a Genetic Machine Learning Algorithm (GMLA) for Wireless Sensor Network (WSN) data fusion applications, with the aim of improving communication efficiency. Random topologies were used in the simulation and GMLA presented almost 13% of gain over IEEE 802.15.4 in 1,000 simulation rounds.

Brienza *et al.* [23] compared off-line computation, model-based adaptation, and measurement-based adaptation by simulation in to select the optimal MAC parameter setting to provide reliability with minimum energy consumption with the IEEE 802.15.4 standard. The adaptive algorithms performed well compared to other models, that were unsuitable in practical scenarios, where the transmission errors could not be neglected.

Li and Sikdar [24] developed a queueing model to evaluate the delay of a class of discrete-time, throughput-optimal MAC protocols. Then, the queuing model was used to derive the optimal parameter settings for the MAC protocol. The parameters selection and the delay model were validated using simulation tools. Their approach addressed the problem of selecting parameters that minimize the average packet delay.

Elshaikh *et al.* [25] focused on optimizing WSN protocols using the Ichi Taguchi (Taguchi) optimization method. That is, the energy consumed by sensor nodes were optimized using the Taguchi method to predict network topology design parameters. The simulation results were obtained using an OMNET++ simulator, with the results showing the impact of the network protocols on energy consumption.

Francesco *et al.* [26] proposed the Adaptive Access Parameters Tuning (ADAPT) algorithm for dynamically adjusting the MAC parameters, based on the desired level of reliability and actual operating conditions experienced by the sensor nodes. The simulation results showed that the ADAPT algorithm was able to provide the desired reliability with a very low energy expenditure, even under operating conditions that dynamically change with time during network operation.

Park *et al.* [27] proposed an adaptive tuning mechanism for IEEE 802.15.4 MAC layer parameters. their proposed protocol was adjusted dynamically to minimize the sensor node energy consumption using a constrained optimisation scheme that run on each device in the network.

Akbar *et al.* [28] proposed a Tele-Medicine Protocol (TMP) based on beacon-enabled IEEE 802.15.4 standard. The TMP optimized the sensor node duty-cycle and tuning MAC layer parameters to conserve sensor node energy.

As seen in the above literature review, many studies have shown that IEEE 802.15.4 may suffer from severe limitations in terms of network reliability and energy efficiency, if non-appropriate parameter settings are used. Many efforts have been made regarding MAC layer's parameters selection in terms of achieving better power consumption and overcoming delay constraints: optimized proposals for beaconless-enabled IEEE 802.15.4 standard conducted in [16]–[18]. Alternatively, the beacon-enabled IEEE 802.15.4 standard proposals conducted in [19]–[28]. Most of the aforementioned proposals tried to optimize the sensor node duty-cycle and tuning MAC parameter settings for minimizing sensor node energy expenditure. However, less attention has been paid to optimizing these parameters and selecting the exact optimal set that provide high reliability with minimum energy consumption. This issue is solved in this paper by proposing an intelligent scheme for optimal MAC parameters set evaluation. The evaluation technique is based on Artificial Neural Network (ANN) and optimisation techniques to achieve high throughput with minimum delay. Also, a comparison between Genetic Algorithm (GA) and Particles Swarm Optimisation (PSO) was conducted to choose the best intelligent optimizer that provides the optimal set for 6LoWPAN MAC layer parameters.

To the best of our knowledge, there are several important areas where this work makes several noteworthy original contributions. This paper contributes to existing knowledge of 6LoWPAN MAC layer optimisation by:

1) Predicting the 6LoWPAN network behaviour using ANN with exhaustive search to select optimal ANN topology and LevenbergMarquardt (LM) learning algorithm. The trained neural network is ease the understanding of MAC layer parameters using non-parametric model while most of statistical methods in the literature are parametric model that need higher background of statistic;
2) Introducing an intelligent optimizer for 6LoWPAN network to maximize the reliability and minimize the end-to-end delay with relative to MAC parameters set. Two evolutionary algorithms (EA) are used to find the optimal MAC parameter set: PSO and GA. Both EA algorithms are compared in terms of effectiveness (finding the true global optimal solution) and computational efficiency. The performance comparison of the GA and PSO is conducted using MATLAB 2017a;

3) Providing comprehensive comparisons between the default MAC parameters setting suggested by the standard and the optimal parameters settings achieved from the proposed approach in this paper.

III. SOFT-COMPUTING TECHNIQUES

Soft-Computing (SC) is one of the possible ways for building intelligent and wiser machines. It aims to model and provide solutions for existing problems that are not modelled or not easy to modelled mathematically. Accordingly, SC will achieve a robust, tractable and low-cost solution from uncertainty and approximate reasoning [29]. The techniques of SC are nowadays being used successfully in many applications and three of them are used in the proposed approach to determine the optimal MAC layer parameters for 6LoWPAN networks, these techniques are:

A. ARTIFICIAL NEURAL NETWORKS

Artificial Neural Networks (ANN) are a family of models inspired by biological neural networks, which can be viewed as a network of simple processing elements called *neurons*. These neurons work in harmony to provide the solution for scientific problems, such as pattern recognition or data classification, through a learning process. In general, they are composed of three layers, which are an input layer, some hidden layers and an output layer. The pool of neurons or simple processing elements communicate by sending signals to each other over a large number of weighted connections. These connections have numeric weights that can be tuned based on experience, making the ANN adaptive to inputs and capable of learning system behaviour [30].

ANN are typically organized in layers, these being composed of a number of interconnected neurons, which contain an activation function. The input data are presented to the ANN via the input layer, which is linked to one or more hidden layers for actual data processing through a system of weighted connections. The hidden layers are then linked to an output layer where the predicted output is found. The predicted output can be found by minimizing the error between the ANN output(s) and the actual output(s).

The most efficient and accurate learning process in ANN is the Feed-Forward (FF) and the selection of proper ANN topology depends on the number of neurons in the input, hidden and output layers. Moreover, there are two main approaches to make the topology selection: a) evolutionary algorithms (EAs), such as a GA or PSO; and b) exhaustive search, which is based on the neurons prediction number in each layer. This paper is based on exhaustive search method in order to build the optimal ANN topology.

B. GENETIC ALGORITHM

A Genetic Algorithm (GA) is a method for solving both constrained and unconstrained optimisation problems based on a natural selection process. It evolves a set of individuals, also called chromosomes, which constitutes the generational population and produces a new population. These individuals are developed according to selection rules and other genetic operators, such as mutation and crossover, with each individual receiving a measure of fitness. The selection rules focus on the individuals that have high fitness. Mutation and crossover provide an attempt to simulate the natural breeding process that simulates the reproduction process [31].

GA is implemented through the procedure described in Algorithm 1, where *ps*, *ef* and *gn* are the population size, the expected fitness of the returned solution and the maximum number of generations allowed, respectively. The procedures are repeated until the particular fitness is accepted (termination criterion is reached), or the predetermined number of iterations (generations) have been run.

Algorithm 1 Genetic Algorithm

```
Require: population size ps, expected fitness ef,
         generation number gn,
Ensure:  the problem solution
  generation = 0
  population = initial_Population()
  fitness = evaluate(population)
  repeat
     parents = select(population)
     population = mutate(crossover(parents))
     fitness = evaluate(population)
     generation = generation + 1
  until (fitness[i] = ef , 1 ≤ i ≤ ps) or generation ≥ gn
```

C. PARTICLE SWARM OPTIMIZATION

Particle Swarm Optimisation (PSO) is a computational method that tries to solve complicated problems using an iterative approach to optimize a candidate's solution with regard to a given performance. The main steps of the PSO algorithm are described in Algorithm 2, where each particle has a velocity and an adaptive direction that determines its next movement within the search space. The particle is also endowed with a memory that makes it able to remember the best previous position that it passed by [32].

The PSO is formed by a set of particles, each one of which represents a potential solution to the given problem. The particle has a velocity value to indicate how much the data can be changed across position coordinates in n-dimensional search space. The PSO algorithm keeps track of three global variables to reach the target:

1) Target value or condition;
2) Global best value indicates which particle's data is currently closest to the target;
3) Stopping value indicates when the algorithm should stop if the target is not found.

To update the position of each particle i, there is a set of velocities, each of which is the element that promotes the capacity of particle location and can be computed as described in (1), where w is called the inertia weight, r_1 and r_2 are random numbers in the interval [0,1], c_1 and c_2 are

Algorithm 2 Particle Swarm Optimisation Algorithm

for $i = 1$ to n-particles do
  Initialize the information of particle i
  Random initialize position and velocity of particle i
end for
repeat
  for $i = 1$ to n-particles do
    Compute the $Fitness_i$ of particle i
    if $Fitness_i \leq Pbest$ **then**
      Update $Pbest$ using the position of particle i
    end if
    if $Fitness_i \leq Gbest$ **then**
      Update $Gbest$ using the position of particle i
    end if
    Update the velocity of particle i
    Update the position of particle i
  end for
until Stopping condition is true
return $Gbest$ and corresponding position

positive constants, y_{ij} is the best position (*Pbest*) found by the particle i with respect to dimension j, and finally y_j is the best position (*Gbest*) with respect to dimension j. The position of each particle is updated according to the formula in (2).

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1 (y_{ij} - x_{ij}(t)) + c_2 r_2 (y_{ij} - x_{ij}(t)) \tag{1}$$

$$x_{ij}(t+1) = v_{ij}(t+1) + x_{ij}(t) \tag{2}$$

while $x_{ij}(t+1)$ is the current position and $x_{ij}(t)$ is the previous position of the particle.

IV. PROPOSED OPTIMAL MAC PARAMETERS SELECTION

In this section, a brief and clear explanation for the proposed mechanism of optimal MAC parameters selection will be given. As stated earlier, this paper is motivated and based on the mathematical models introduced by Zayani *et al.* [14] that was inspired from Markov chain analytical model developed by Park *et al.* [15].

Low energy consumption is vital in M2M sensor networks and nodes can achieve high throughput by extending the network lifetime or reducing packet drops. Packets are dropped either because the channel is busy or the maximum number of retries limit has been reached. Extension of network lifetime with reduced delay can be achieved by selecting the optimal MAC parameters set as depicted in Fig. 1 and the detailed steps for the proposed optimisation scheme are as follows:

1) Data Collection: complete data sets were collected from the proposed mathematical model in [14] for different network sizes;
2) Data Analyses: collected data were analysed and pre-processed prior to the training stage. The datasets are separated into inputs and outputs, and divided randomly into three subsets: training set (70%), testing set (15%), and validation set (15%);
3) ANN Training: the analysed data (training set) were fed as inputs to the ANN for complete output prediction prior to optimisation stage. The MAC layer parameters set represented by input data while the throughput and latency represented the output of the ANN;
4) Data Post-Processing and Testing: the predicted ANN output was verified with unseen raw data (validation set) to validate ANN training and determine its accuracy using the testing data set;
5) Data Optimisation: once the ANN output was verified, two optimisation techniques (PSO and GA) were run individually to choose the optimal MAC parameters of 6LoWPAN network with different network size. These EAs were compared among each others to give more certainty to the optimal selected parameters of the MAC layer, and which one is more efficient than the other when it being deployed in the developed approach.

The performance of an ANN is dependent on the number of hidden layers and hidden neurons in each layer. The latter determines the neural network architecture design. On one hand, a smaller number of hidden neurons restricts the competence of the ANN to model the problem. Such ANN may not train properly to obtain a reasonable error. On the other hand, a larger number of hidden neuron forces the ANN to memorize the data rather than learning them and may result in high computational time.

The Levenberg Marquardt algorithm (LM) was used to train the ANN. During the training phase, the data set was first tested using a single hidden layer but, unfortunately, the training failed to give a good performance in terms of Mean Square Error (MSE). Multiple ANN layers were studied to determine the best number of neurons in both the first and second hidden layers in a nested loop fashion, as depicted in Fig. 2. Hence, the optimal topology for ANN was selected by conducting an exhaustive search. The number of hidden neurons is determined by altering the number of neurons, starting with a few hidden neurons, and then adding neurons until the computed MSE for the training patterns comes to a minimum. The number of hidden neurons at that point is taken as the optimal. Owing to the random initialisation of the ANN parameters (weights and biases), every selected topology was trained ten times to ensure that the network was not trapped in the local minima. The performance of the network as MSE versus the network architecture for single and double layers are shown in Fig. 3 and Fig. 4, respectively.

The IEEE 802.15.4 [12] is a standard for low-rate, low power, and low-cost Personal Area Networks (PANs). It defines two different channel access methods, namely a beacon-enabled mode and a non-beacon-enabled mode. This paper will focus on the non-beacon-enabled mode only, since it is the channel access mechanism for 6LoWPAN that use un-slotted carrier sense multiple sense/collision avoidance (CSMA/CA).

Fig. 1(b) shows the proposed optimizing scheme for selecting the optimal MAC layer parameter set of a 6LoWPAN

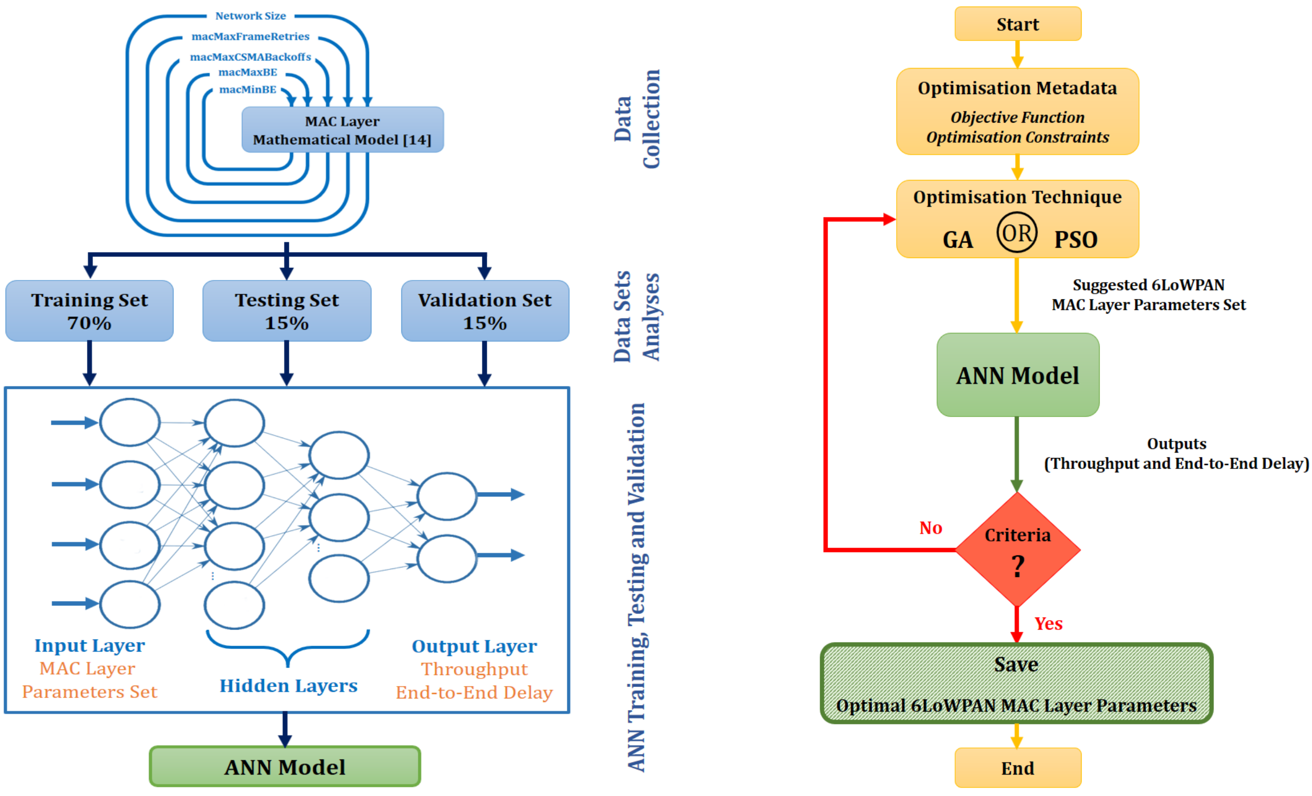


FIGURE 1. **Optimal MAC layer parameters selection scheme. (a) Trained ANN model. (b) MAC layer parameters optimization mechanism.**

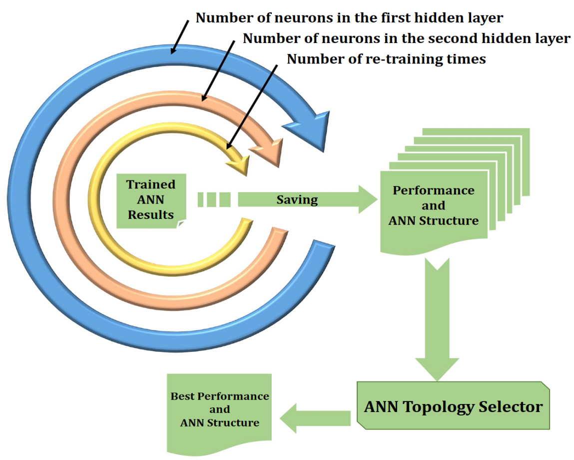


FIGURE 2. **Exhaustive searching scheme of optimal ANN topology selection.**

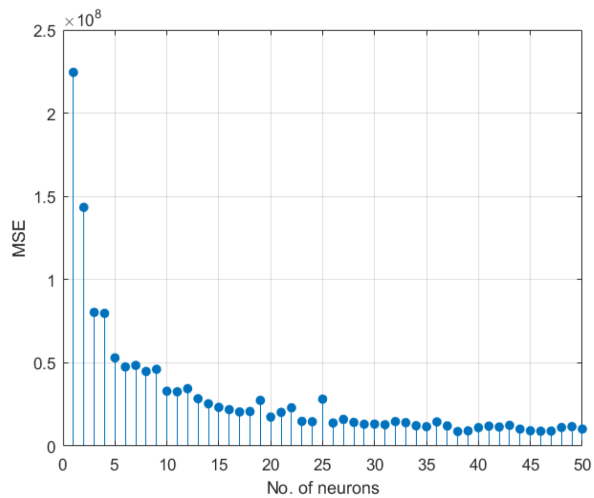


FIGURE 3. **Performance of a single hidden layer ANN.**

network. The optimizer suggested the following input parameters in order to achieve maximum throughput with minimum end-to-end delay:

- Backoff exponent (*BE*) is a random number determines the random backoff interval before sensing the channel. The *macMinBE* and *macMaxBE* represent minimum and maximum BE for the IEEE 802.15.4 MAC layer;
- Maximum CSMA backoff (*macMaxCSMABackoffs*) is the number of times that the node stays in the backoff stage after unsuccessful channel sensing before the packet being dropped;
- Maximum frame retries limit (*macMaxFrameRetries*) is the number of the retransmissions limit when there is no acknowledgement received and the packet will be dropped.

These MAC parameters were fed into the ANN as inputs in addition to the desired network size (number of nodes), while

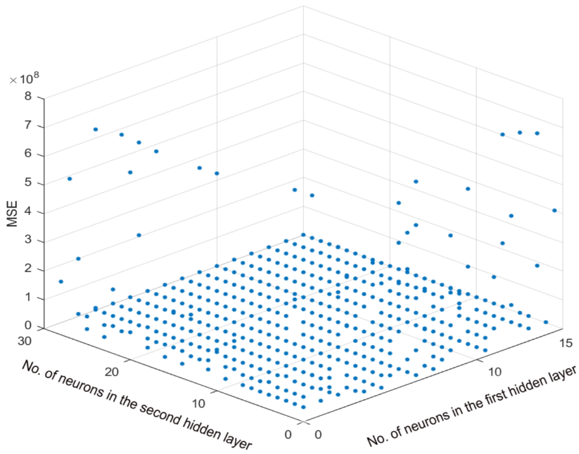


FIGURE 4. Performance of a double hidden layer ANN.

the outputs were throughput and delay. As stated earlier in this subsection, the ANN was trained in order to predict the actual output and to prepare data for the optimisation stage. The objective function attempts to obtain the optimized MAC layer parameters set that gives maximum throughput with minimum delay for a given nodes number.

In this study, a novel optimisation scheme is proposed to select optimal 6LoWPAN MAC layer parameters set for adequate and reliable communication while reducing the energy consumption in 6LoWPAN nodes. A constrained optimisation problem is utilized to evaluate the optimized sets. The objective function ($E_{consumed}$) is related to the total energy consumed by the 6LoWPAN nodes during transmitting and receiving of IPv6 packets over IEEE 802.15.4 standard. The optimisation constraints are given by the channel throughput and mean service time. For a transmitting 6LoWPAN sensor node, the constrained optimisation problem can be expressed as:

$$\min_{M} \tilde{E}_{consumed}(M) \tag{3}$$

$$s.t.\ \tilde{TH}(M) \geq TH_{min} \tag{4}$$

$$s.t.\ \tilde{MST}(M) \leq MST_{max} \tag{5}$$

$$M_0 \leq M \leq M_m \tag{6}$$

where TH is the channel throughput and TH_{min} is the minimum in demand channel throughput. MST is the mean service time for a successful transmitted packet, and MST_{max} is the maximum desired latency at the MAC layer of the 6LoWPAN node. The constrained optimisation variable $M_0 \leq M \leq M_m$ follows the IEEE 802.15.4 default values for the MAC parameters that are given in Table 1. The symbol $\sim$ indicates that the throughput, mean service time, and 6LoWPAN node energy consumption are approximated by the ANN. These approximations enhance the proposed approach accuracy and reduced optimisation computational complexity. The optimal 6LoWPAN MAC layer parameters set represents the solution of the constrained optimisation problem that each 6LoWPAN nodes utilizes to minimize its energy consumption.

TABLE 1. 6LoWPAN MAC layer parameter values.

Parameters	Value Range	Default Value	Optimised Value
macMinBE	0 – 7	3	2
macMaxBE	3 – 8	5	6
macMaxCSMABackoffs	0 – 5	4	3
macMaxFrameRetries	0 – 7	3	0 – 5

The decision variables of the 6LoWPAN optimizer are denoted by the vector $M = (m_0, m_1, m, n)$ and each variable is given in Eq. (7a-d) which are subjected to network throughput and end-to-end delay constraints.

$$m_0 \triangleq macMinBE \tag{7a}$$

$$m_1 \triangleq macMaxBE \tag{7b}$$

$$m \triangleq macMaxCSMABackoffs \tag{7c}$$

$$n \triangleq macMaxFrameRetries \tag{7d}$$

The optimisation problem becomes combinatorial as the decision variables adopts only discrete values. The vector of decision variables M is practical if and only if the network throughput and the end-to-end delay constraints are true. In other words, the optimal solution can be reached by analysing every combination of the vector M elements that leads to minimum objective function. It is obvious that this approach suffers from high computational complexity and time-consuming processes: there are $8 \times 6 \times 7 \times 8 = 2688$ combinations of 6LoWPAN MAC layer parameters that have to be analysed and checked. The scope of this study is to introduce an intelligent algorithm based on ANN to evaluate the objective function of optimizer more quickly, and hence reduce the computational complexity and processing time.

V. PERFORMANCE EVALUATION RESULTS

After investigating the performance of different ANN architectures using an exhaustive search method, the best trained ANN with two hidden layers was reached by 15 neurons in the first and 12 in the second. This ANN topology demonstrated that the MSE is less than 1.29×10^{-22}. Fig. 5 and Fig. 6 show the performance of the network in terms of MSE versus the number of samples in the training and testing phases, respectively. The results of the linear regression of the trained and tested samples are shown in Fig. 7, with their verifying the validity of the trained ANN and its ability to.

MATLAB has been used as a simulator for medium and large scale M2M sensor networks to implement the 6LoWPAN MAC layer represented by the IEEE 802.15.4 standard. A 6LoWPAN network with 50 and 100 M2M sensor nodes are considered, with the impact of each single MAC parameter being evaluated in terms of node throughput. In the conducted simulation scenario, it is assumed that the message generation process is periodic to evaluate saturated and unsaturated traffic. Fig. 8 and Fig. 9 are for 50 and 100 sensor

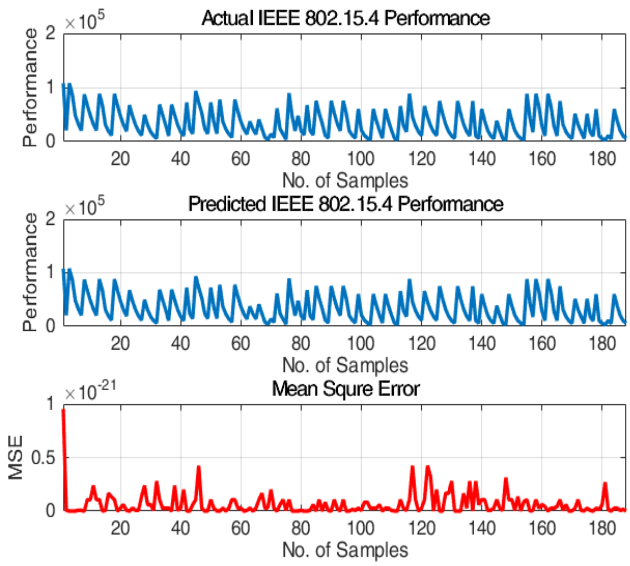


FIGURE 5. Actual and predicted output for training sets.

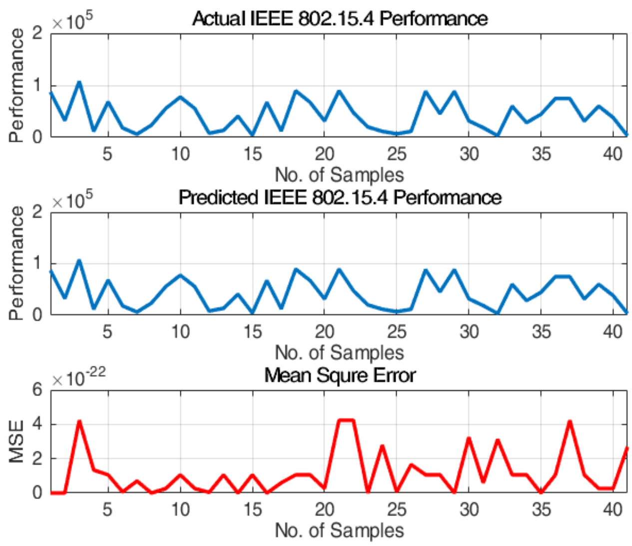


FIGURE 6. Actual and predicted output for testing sets.

nodes, respectively and the MAC parameters observations are:

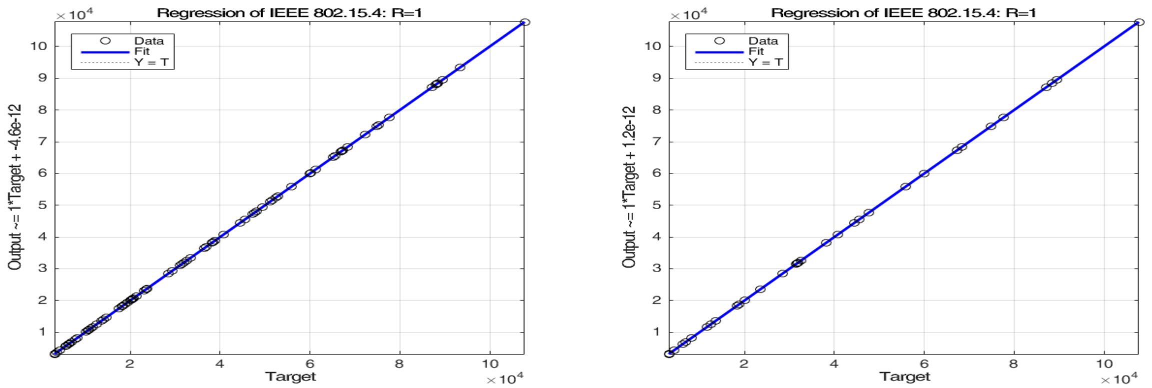
1) Impact of *macBE*:
Fig. 8(a)(b) and Fig. 9(a)(b) show the impact of the *macMinBE* and *macMaxBE* on throughput, respectively. *macMinBE* is in the range between 0 and 7, *macMaxBE* is in the range between 3 and 8, while the other parameters with their default values are shown in Table 1. For a fixed value of *maxMacBE*, the throughput tends to be improved when increasing *minMacBE*, because a larger initial backoff window reduces the collision probability in the first backoff stages;
2) Impact of *macMaxCSMABackoffs*:
Fig. 8(c) and Fig. 9(c) show the impact of *macMaxCSMABackoffs* on network throughput. This parameter is in the range between 0 and 5, whilst the others, are with their default values, as shown in Table 1. When *maxMacCSMABackoffs* value increases, the node's throughput will increase to some extends in medium size network as shown in 8(c), after that the throughput decreased when the traffic increases as multiple nodes try to access the channel many times and collisions occur frequently. Fig. 9(c) shows the impact of *maxMacCSMABackoffs* in large networks, whereby the throughput decreases as its value increases, because nodes have a high probability of sensing the channel and it is busy in dense networks;
3) Impact of *macMaxFrameRetries*:
Fig. 8(d) and Fig. 9(d) show the impact of *macMaxFrameRetries* on network throughput. This parameter is in the interval between 0 and 7, while the others have the default values shown in Table 1. The throughput remains constant for the values equal to or greater than 2 in medium size networks, as shown in Fig. 8(d) and to or greater than 3 in larger networks Fig. 9(d).

Table 1 shows the optimal MAC layer parameter values obtained from the two optimisation techniques (GA and PSO). The input and output sets of the ANN fed back to an optimizer running GA and PSO to predict the input set that provides maximum throughput and minimum delay. The optimizer outputs are the optimal 6LoWPAN MAC parameters given in the last column of Table 1. To summarize, from the above analysis it is concluded that *macMaxCSMABackoffs* and *macMaxFrameRetries* should set to the optimal values (not the default MAC parameters setting suggested by the standard) as the sensor nodes need to adapt optimal *BE* to increase the throughput and minimize the latency.

Rather than setting the default values of the 6LoWPAN MAC layer, the optimized parameters achieve highest throughput and less service delay for a given node number, as shown in Fig. 10 and Fig. 11, respectively. The optimized MAC parameters enhance network throughput by 52 – 63% depending on the 6LoWPAN network size. The range of optimized *macMaxFrameRetries* in Table 1 means that the retransmission would not affect the optimisation process of the other parameters because when the *macMaxFrameRetries* equal to 0 means that 6LoWPAN network runs User Datagram Protocol (UDP) while the *macMaxFrameRetries* has certain value means that 6LoWPAN network runs Transfer Control Protocol (TCP).

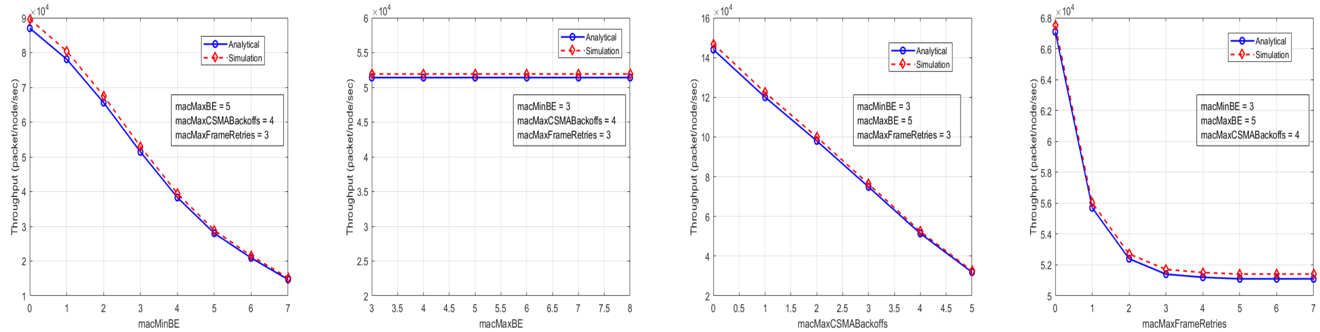
Fig. 12 shows the access channel probability versus different node numbers in 6LoWPAN network. The most obvious finding to emerge from the analysis is that the reduction in access channel probability and mean service time led to enhancement of the network throughput as more packets were successfully delivered to the destination. In addition, This reduction reduces the end-to-end delay by 54 – 65% depending on the 6LoWPAN network size.

Extensive simulations were carried out to find the optimal initial parameters for GA and PSO, like population size,



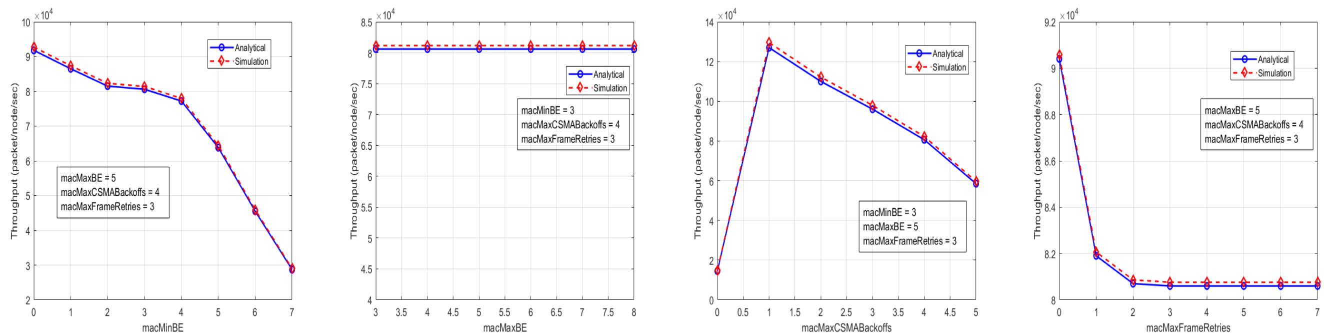
(a) (b)

FIGURE 7. Linear regression of the ANN output. (a) The linear regression of targets vs outputs for training sets. (b) The linear regression of targets vs outputs for testing sets.



(a) (b) (c) (d)

FIGURE 8. The effect of MAC layer parameter for 50-node network size and offered load 1000 packet/node. (a) macMinBE. (b) macMaxBE. (c) macMaxCSMABackoffs. (d) macMaxFrameRetries.



(a) (b) (c) (d)

FIGURE 9. The effect of MAC layer parameter for 100-node network size and offered load 1000 packet/node. (a) macMinBE. (b) macMaxBE. (c) macMaxCSMABackoffs. (d) macMaxFrameRetries.

initial condition, weight, etc. Due to the randomness of the initialisation stage, 10 simulation runs were performed independently of each algorithm. The performance for both GA and PSO are shown in Table 2. Clearly, the performance of the PSO-based optimisation indicates better achievement regarding the convergence speed as well as computation time than with GA.

The 6LoWPAN nodes are generally battery powered, and hence, energy efficiency is one of the key issues of 6LoWPAN network. As the Internet traffic increases, the energy utilisation becomes one of the most important factor that need to be considered in order to improve energy efficiency and reduce energy waste. Fig. 13 shows the total remaining energy versus simulation rounds for a 6LoWPAN network consists

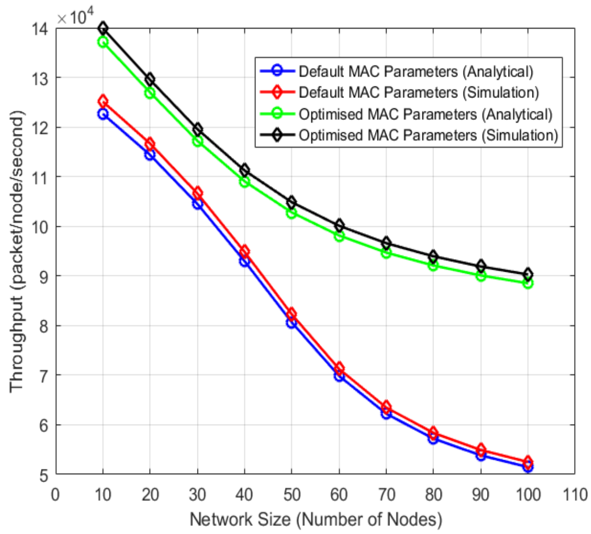


FIGURE 10. Network throughput.

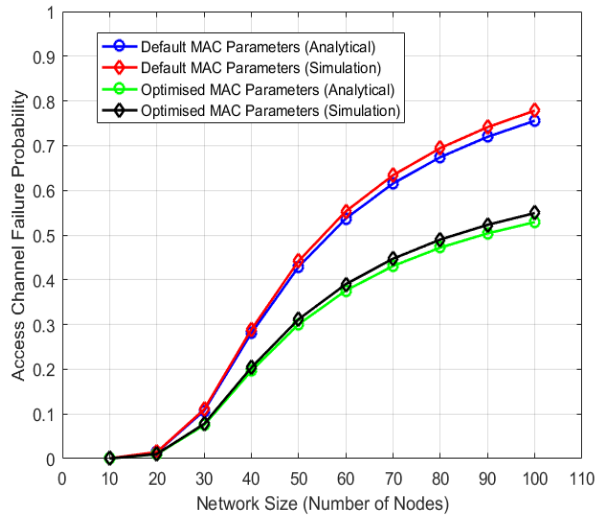


FIGURE 12. Access channel failure probability.

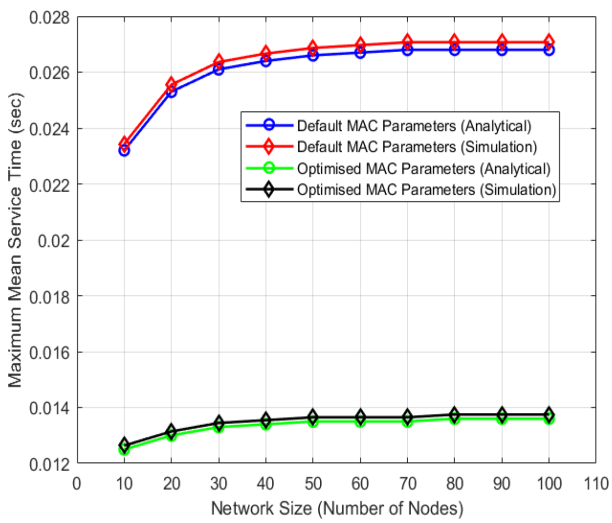


FIGURE 11. Mean service time.

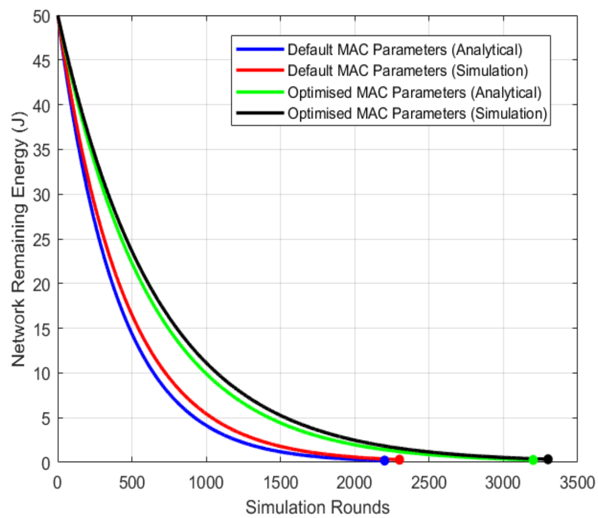


FIGURE 13. Residual network energy.

TABLE 2. GA and PSO execution time.

Algorithm	Total Iterations	Convergence Iterations	Computation Time (sec)
GA	1000	327	72
PSO	1000	85	39

of 100 nodes with 0.5 J per node. Compared with the default MAC layer parameters set, it is obvious that the optimized MAC layer parameters effectively prolong the nodes' operational time and hence, the overall lifetime of the network will be extended. The proposed MAC layer optimisation scheme succeeded in prolonging the 6LoWPAN network lifetime by 40%, whilst enhancing its throughput and reducing the end-to-end delay compared to a traditional 6LoWPAN network with default MAC layer parameters set.

VI. CONCLUSION

In this paper, a simple optimized analytical model for the IEEE 802.15.4 MAC layer standard has been developed, also investigated the MAC parameters effects in medium and large size networks. An ANN has been proposed to find the correlation between the most effective MAC parameters inputs and throughput as output. The various topologies of the ANN were tested by applying one and two hidden layers with different numbers of neurons. Moreover, LM was used as learning algorithm in the feed-forward ANN structure. Moreover, LM was used as learning algorithm in the feed-forward ANN structure. Two optimisation techniques used to optimize the 6LoWPAN MAC layer parameters for a given channel throughput and the number of nodes in the network. GA and PSO algorithms used for deriving the optimal settings of IEEE 802.15.4 MAC layer in 6LoWPAN networks in order to guarantee the reliability requirements of the application with minimum computational complexity and both algorithms performed well.

The obtained results showed that the optimal MAC parameters were feasible for both unsaturated and saturated conditions with or without retransmission option. The obtained results were validated by simulation and showed that the channel throughput can be increased by setting the MAC layer with the optimized parameters for a given number of nodes in the network. Moreover, the optimized MAC parameters showed that the throughput was considerably higher than the network set by the default MAC parameters of IEEE 802.15.4 standard. Hence, the future extension of this paper will be carried out by implementing the optimal parameters in real 6LoWPAN network and validated the simulation results by experimental indoor testbed.

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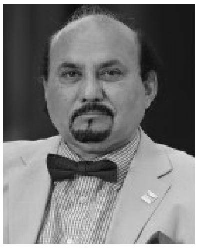

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