Computers and Electrical Engineering 64 (2017) 537–551

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Flexible online multi-objective optimization framework for ISA100.11a standard in beacon-enabled CSMA/CA mode[☆]

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ARTICLE INFO

Article history:
Received 11 October 2016
Revised 24 February 2017
Accepted 24 February 2017
Available online 17 March 2017

Keywords:
Industrial wireless sensor networks (IWSNs)
Multi-objective optimization
Online optimization
Quality of service (*QoS*)
Genetic algorithms (GAs)

ABSTRACT

Maintaining high quality of service (*QoS*) for sensor nodes is important in industrial wireless sensor networks (IWSNs). Wide range of factors severely affects *QoS;* however more research is still needed. In this article, a flexible online multi-objective optimization framework (FOMOF) in carrier sense multiple access with collision avoidance (CSMA/CA) mode is proposed. Nodes are predominantly grouped based on their *QoS* requirements and then optimized in online mode using a constrained genetic based multi-objective approach. FOMOF to maintain a minimum desired *QoS* of the pre-determined groups with maximum number of nodes. Furthermore, the packet delivery ratio (*PDR*) obtained in FOMOF was higher than the one obtained by ISA100.11a standard. Accordingly, the grouping strategy enhanced the number of nodes by 12.5% with End-to-End delay reduction of 16.36% for 27 nodes.

1. Introduction

ISA100.11a is an open-standard wireless mesh networking technology that aims at robust the industrial automation marketplace to offer highly secured and reliable wireless operations for alerting, monitoring, and controlling industrial applications guided by *QoS* [1]. ISA100.11a marks a wider status of process control compared to wireless highway addressable remote transducer (WirelessHART) which is the *de facto* standard for IWSNs [2]. ISA100.11a application provides not only a native protocol but also allows tunnelling for existing wired networks [3] such as Fieldbus Foundation, HART, Modbus [4], the common industrial protocol (CIP) [5], wireless networks including WirelessHART, and Wi-Fi [6]. In IWSNs, exceeding the maximum delivery delay and the minimum *PDR* boundaries are considered to be the most important *QoS* measures. Often, the automation applications for different traffic types lead to system instability, which results in failure, material and economic losses in addition to a possible risk to human safety [7]. Thus, differentiation of the traffic types is prerequisite to obtain required *QoS* [7]. Some of the sensor nodes that are deployed in IWSN can generate more vital data than others. These vital data are transmitted to the sink node with a high delivery ratio. Based on the data delivery, the network must provide different *QoS* classes consistent with sensor nodes. This differentiation of *QoS* values for each group requires maximization of the number of nodes in the network controlled by the medium access control (MAC) layer, which in turn is

☆ Reviews processed and recommended for publication to the Editor-in-Chief by Associate Editor Dr. R. Varatharajan.
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http://dx.doi.org/10.1016/j.compeleceng.2017.02.024
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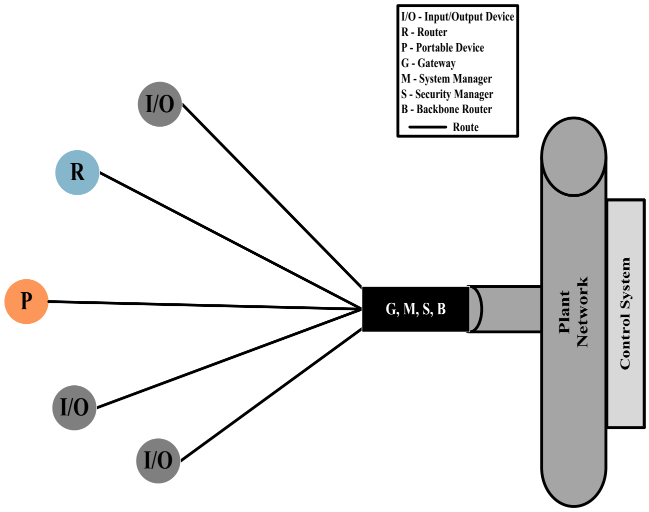

Fig. 1. A typical ISA100.11a standard compliant network in a star topology.

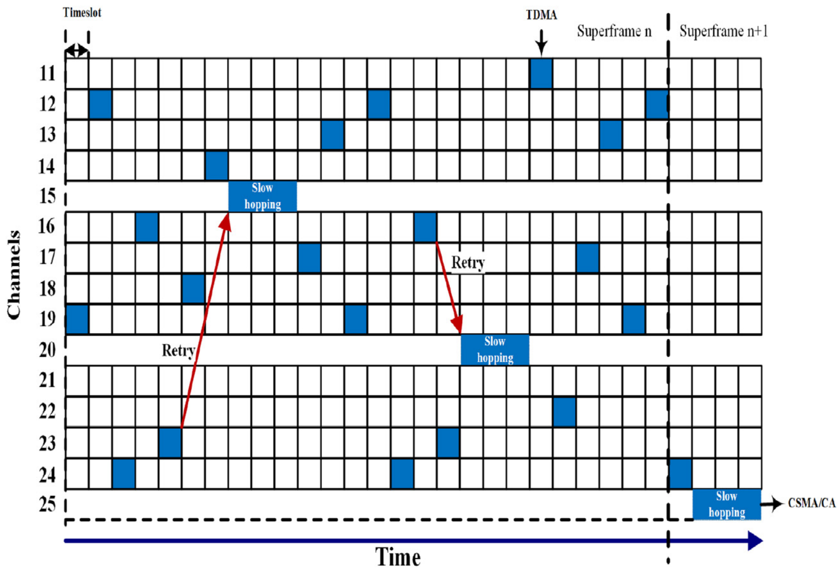

Fig. 2. Hybrid channel hopping mechanism.

responsible for enhanced *QoS* and excellent network performance [8]. Certainly, the contention-based MAC protocols possess a broad range of applications in IWSNs [9].

To render deterministic services, ISA100.11a has adopted the time division multiple access (TDMA) scheme in the MAC layer. However, ISA100.11a considers the CSMA-CA mechanism with priorities for retransmission from the downfall on dedicated links, random data, and network configuration [10]. ISA100.11a supports mesh and start topology. There is more complexity of ISA100.11a standard in mesh topology compared with the star topology, therefore it is a great challenge to implement ISA100.11a in mesh topology. Also, implementing a poor mesh topology may not out-perform a good-designed system in a star topology [11]. Fig. 1 depicts a typical ISA100.11a compliant network in a simple star topology where the Data Link (DL) Subnet, the System Manager (SM), and the Backbone Network (BN) are the basic section of the system. The DL subnet consists of Input/Output (I/O), routing (R), and portable (P) devices; the SM consists of a system manager (M) and a security manager (S); and the backbone network (BN) includes backbone routers (B) and gateways (G). The physical layer of ISA100.11a devices uses IEEE802.15.4-2006 radio transceiver hardware. It employs only 16 channels (from 11 to 26) within a 2.4 GHz-frequency band with operational maximum data rate of 250 kbps and channel hopping of three modes (slotted, slow, and hybrid). Fig. 2 illustrates the hybrid channel hopping pattern in ISA100.11a where the time axis is divided into timeslots with equal durations of 10 or 12 ms in one subnet (composed of units of $\approx 0.95\,\mu s$). In this mode, if transmission attempt fails in a dedicated timeslot, the next slow hopping period can be used for retransmission attempts.

The timeslots are present in a superframe, which is repeatable with cyclic timeslots at a repetition period and universal attributes. Fig. 2 shows, timeslots of two superframes and their retransmission attempts to transmit on different channels during the successive slow hopping period. ISA100.11a uses five predefined channel hopping patterns to provide a specific sequence of communication channels among groups of devices. Continuous control loops in the process industries are based on a fixed-period computation of control outputs on either repeating rates of 4 Hz (0.25 s), 1 Hz (1 s), or multiples of 4 s or 5 s. Process monitoring is typically maps the same 4 Hz rate [12].

Meeting high QoS of IWSN implies performing an optimization of different parameters in the network. Theoretically, there are two main categories of optimization approaches: analytical and heuristic. The analytical based optimization suffers from finding an accurate mathematical model for the system. Alternatively, the heuristic searching is limited to finding an accurate formula for the objective function. Genetic Algorithm (GA) is the most common heuristic optimization approach because it can avoid the local minima during parallel execution. Furthermore, GA can be applied to any continuous or discrete problem via the analytical or numerical definition of the fitness function. The drawbacks of the GA can be overcome by activating the optimizer to operate in online mode. Online mode can be updated continuously alongside with the performance measures of the system to determine the value of the fitness function [13]. Despite many dedicated efforts, the problem of maximizing the number of nodes in the network remains a challenge.

ISA100.11a system configuration can yield the lowest possible latency across the physical layer. It is architecturally very simple but is limited to the range of a single hop [12]. Owing to its speedy responses, a star-based ISA100.11a network with one gateway and different types of sensor nodes is considered for several time-critical industrial applications [14]. In this work, the sensor nodes are classified into groups, where each group has different *QoS* requirement. An online optimization framework of CSMA/CA for dealing with shared timeslot of ISA100.11a has been implemented to enhance the network performance from a real-time perspective, with maximization the number of nodes in the network without influencing the minimum Packet Delivery Probability (*PDP*), which is presented by *PDR* as a measure of network *QoS*.

This paper is organized as follows. Section 2 critically reviews the existing works and highlights their weaknesses. Section 3 presents the mathematical background and problem formulation. The CSMA/CA mechanism mediated ISA100.11a with genetic design, optimization scheme, and the simulation environment with optimization set up are described in Section 4. The performance analysis is explained in Section 5. Section 6 concludes the paper and the future outlook.

2. Related work

GAs' approach is widely used to solve diverse engineering problems due to its excellent search capacity. Being stochastic search engines, GAs can precisely mimic the selection and evaluation of biological processes. Apart from GAs, several other algorithms such as random search, gradient-based local optimization, simulated annealing and symbolic artificial intelligence are also developed [15]. Amongst all these, GA is the most efficient and distinct one [16]. Several types of research revealed the notable success of GA in wireless sensor networks (WSNs). Generally, GA in WSN is used to achieve better network's energy efficiency by finding the proper cluster heads for data aggregation and choosing the best network path to reduce the hops [17].

A genetic-based scheme for WSNs was introduced by Ferentinos and Tsiligiridis [18] using a fitness function with seven design parameters to evaluate the energy consumption and network connectivity. It considers the sensor nodes status, cluster head selection, and distance as an optimization process to design a reliable an energy efficient WSN. This scheme suffered from placement problem when the optimization process requires controlling multiple conflicting objectives such as decreasing the energy while achieving a robust connectivity with large area coverage. To surmount this problem, a multi-objective GA is developed [19], where a deployed network arrangement is considered for maximizing the area coverage with minimized energy cost and robust connectivity. Later, a genetic-based energy efficient adaptive clustering hierarchy protocol is proposed to improve the lifetime of WSN [20]. This protocol minimizes the energy consumption by recognizing the optimum number of cluster heads and their locations in the network. GA is operated in different phases including two steps of setup and steady state. In the setup step, the base station determines the optimum number of cluster heads and allocating the member nodes belongs to it. In the second step, the sensed data is transferred to the cluster heads, gathered in frames, and transferred to the base station. Despite the computational complexity, this protocol reveals better performance regarding stability, network lifetime, and reliability of clustering.

Another GA is proposed targeting the architecture of energy-efficient coverage-aware (EECA) routing protocol [21], which reduces the network energy consumption by improving the clustering technique. Consequently, turning off some redundant nodes enhances the network coverage and lifetime. Unlike low-energy adoptive clustering hierarchy (LEACH) protocol, EECA used the k-mean method for the homogeneous network to select the cluster head from candidates for the base station (BS). Moreover, a GA is introduced to optimize the coverage issues in WSN [22] by optimizing the operational modes of the sensor nodes for transmitting the signals and improving the field coverage. In the optimization process, a significant number of sensor nodes with low energy consumption are demonstrated compared to fewer sensor nodes with higher energy. However, the network and communication channels appear more congested in the presence of a vast number of sensor nodes, leading to broadcast storm issues in the network.

Group-based optimal retransmission medium access (GORMA) protocol is proposed by Kumaraswamy et al. [23] which combine collision avoidance (CA) with efficient energy (EE) management in WSNs to provide self-governing *QoS* to nodes. In this protocol, nodes operated independently with predefined time and are allowed to transmit each packet within an optimal

Table 1
Various useful notations and terms.

Notation	Meaning
x_i, $i=1, 2 .. N_g$	Number of retransmissions for each group
w_i, $i=1, 2 .. N_g$	Weight assigned to each group
n_i, $i=1, 2 .. N_g$	Number of nodes in each group
PLT_i, $i=1, 2 .. N_g$	PacketLifeTime of nodes for each group
QoS_i, $i=1, 2.. N_g$	*QoS* for each group
N	Total number of nodes in the network
g_i	Group *i*
N_g	Number of assumed groups
t_d	Packet transmission duration
λ	Packet arrival rate
P_S	Probability of success for one transmission
P_f	Probability of failure of one transmission
P_i	Optimized *QoS* level
U_i, $i=1, 2 .. N_g$	Maximum allowed number of nodes in each group
L_i, $i=1, 2 .. N_g$	Minimum allowed number of nodes in each group
T	InterArrivalTime, in which each node sends one packet

number of times in a given period of one-hop *QoS* retransmission for one and two groups in WSNs, where the end-nodes remained without receivers resulting in absent received data. To estimate the probability of maximum packet delivery and minimum energy consumption, a mathematical model is designed using retransmission optimization technique. Simulation results revealed that the energy consumption, *QoS*, and delivery probability with GORMA are better than *QoS*-aware MAC protocol optimal retransmission (QoMoR) and IEEE 802.11b protocols with the same number of retransmissions.

Based on node placement methodology of WSN, Bhondekar et al. [24] developed a GA fitness function using network density, energy consumption, and connectivity. This algorithm optimizes the operational modes of sensor nodes along with the clustering schemes and signal strength. Depending on hierarchical clustering GA, another approach is introduced for WSN to address the active state period length issue [25]. A decrease in the distance between sensor and sink node is found to produce prolonged network lifetime and enhanced network performance. This synergistic combination of clustering method with GA remarkably improved the long-distance communication; hence the long-distance requires more energy than short distance sensor nodes.

A real-time scheduling approach using deadline monotonic arrangement is proposed [26] to inspect the super-frame plan of ISA100.11a. Using this method, more data are sent with enhanced network performance. Later, a new method is designed by Saputra and Isa [27] to achieve enhanced performance by reducing the length of superframe overhead in ISA100.11a. This approach uses the same deadline monotonic scheduling with a fewer number of beacons compared to other schemes. Despite all such developments, optimizing the number of nodes and packet lifetime with improved network performance has been practised for better achievement.

To the best of author's knowledge, this framework is introduced for the first time for a new online tuning-based flexible multi-objective optimization scheduling approach in shared timeslot for WSN with CSMA/CA transmission mode and support of star topology. Without the loss of generality, ISA100.11a standard is considered as a benchmark for building and comparison the framework. The novelty of this framework can be seen in the arrangement of developing user defined grouping variant of the industrial network to accept the optimization solution that supports maximum number of nodes with a minimum level of *QoS* needed. Moreover, the optimization has been performed in an online mode, which overcomes the problem of lacking explicit plant definition.

To achieve an improved performance for industrial IWSNs, a provision of different *QoS* is considered based on the flexible maximization of the supportable number of nodes in the network where different *QoS* requirements for each class can be employed. The flexible maximization within FOMOF enabled the user to choose multiple objectives according to certain constrained GA-based multiobjective optimization approach to accomplish the desired performance.

3. Mathematical background and problem formulation

Table 1 enlists various mathematical symbols with their meaning used in this article.

The statistics of generated packets at the sensor nodes was assumed to follow the Poisson arrival statistics [28]. The probability of arrival for k packets $P[n=k]$ during a time interval of t and packet arrival rate λ yields:

$$P[n = k] = e^{-\lambda t} \frac{(\lambda t)^k}{k!} \tag{1}$$

The probability of successful packets transmission after x trials is given by [29]:

$$P(x_i) = P_f + P_f P_S + P_f^2 P_S + \ldots P_f^{x_i - 1} P_S = P_s \frac{1 - P_f^{x_i}}{1 - P_f} = 1 - P_f^{x_i} \tag{2}$$

The probability of (P_S) is given by:

$$P_S = e^{-2\lambda t_d} \tag{3}$$

Then, the probability of failure (P_f) is obtained from the complementary probability principle:

$$P_f = 1 - e^{-2\lambda t_d} \tag{4}$$

By substituting Eq. (4) in Eq. (2), $P(x_i)$ can be represented as in Eq. (5):

$$P(x_i) = \left(1 - e^{-2\lambda t_d}\right)^{x_i} \tag{5}$$

It is worth noting that based on the network status, the arrival rate (λ) changes where the status is highly dynamic depending on the number of retransmissions (x_i) assigned to each node in addition to the number of nodes existing in each group. By assuming the worst-case scenario, where all nodes in every group tend to send packets in time interval T, the maximum value of λ is:

$$\lambda = \lambda_{max} = \sum_{i=1}^{n} \frac{x_i n_i}{T} \tag{6}$$

Substituting the new value of λ_{max} in Eq. (5), the resulting $P(x_i)$ is:

$$P(x_i) = 1 - (1 - e^{-2\lambda_{max} t_d})^{x_i} \tag{7}$$

In ISA100.11a, the number of retransmissions depends on the PacketLifeTime (*PLTi*). Thus, in order to substitute x_i with *PLTi*, the number of retransmissions (x_i) during the *PLTi* is calculated as follows:

$$x_i \;= \left(\frac{2^{\text{macMaxBE}} - 1}{2}\right) \times \text{BackoffSymbolDuration} = \frac{PLT_i}{Expected\ (x)} \tag{8}$$

by substituting (8) in (7) we get:

$$P(PLT_i) = 1 - (1 - e^{-2\lambda_{max}(t_d)})^{\frac{PLT_i}{Expected(x)}} \tag{9}$$

Eq. (9) is further used to maximize the number of nodes (n_i).

The main aim is to find the required PLT_i that optimizes n_i, which is performed according to a priority measure expressed by weight assigned w_i. In addition, meeting the constraint levels of the QoS_i for each group performs the process. This is a multi-objective optimization constrained problem because it maximizes n_i in each group g_i. However, it can be formulated by designing the following objective function:

$$f(n, w, U) = -\alpha_1 \frac{\sum_{i=1}^{N_g} n_i}{\sum_{i=1}^{N_g} U_i} + \alpha_2 \sqrt{\sum_{i=1}^{N_g} (\bar{n}_i - \bar{w}_i)^2} \tag{10}$$

A normalized number of nodes in each group is written as:

$$\bar{n}_i = \frac{n_i}{\sum_{i=1}^{N_g} n_i} \tag{11}$$

The normalized weight for each group is expressed as:

$$\bar{w}_i = \frac{w_i}{\sum_{i=1}^{N_g} w_i} \tag{12}$$

The objective function in Eq. (10) is a combination of two terms, where the first term maximizes the number of nodes and the second term adds the influence of the weights on the maximization process. Obviously, the percentages for the number of nodes and weights considered in the second term eliminate the influence of the absolute value of the weights or nodes in the weighting process. The two parameters α_1, and α_2 are initialized with ones. Although the objective function is a single objective function, it is important to note that conducting multiobjective optimization is performed through converting it to a single objective optimization. The approach relies on weighting equation of the separate objectives considering the flexibility of the framework by allowing the user to intervene in these weights for controlling the optimization trajectory to reach the desired results.

Considering the following constraints, maximizing the objective function can be performed:

$$\begin{aligned} &U_i = u_i \\ &L_i = l_i, \quad i = 1, 2\ ..N_g \\ &\mathrm{QoS_i} < p_i \end{aligned} \tag{13}$$

where $\mathrm{p_i}$ values are calculated using Eq. (9).

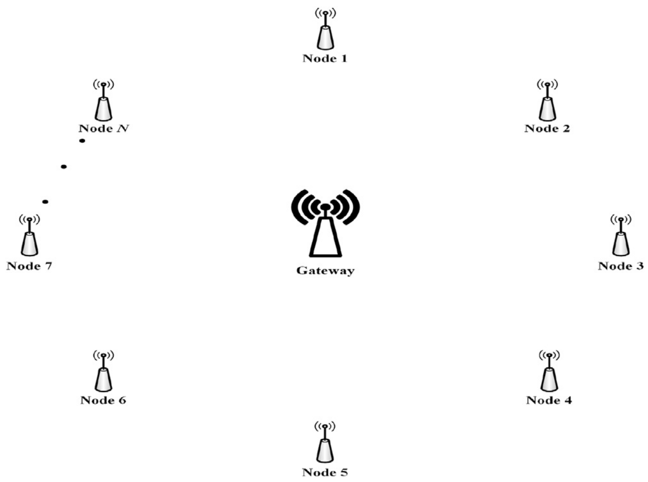

Fig. 3. Star topology of ISA100.11a network.

4. Proposed approach

As mentioned earlier, this paper considers a star network topology of ISA100.11a standard with (N) end-nodes and one gateway as shown in Fig. 3. The gateway receives sensed data from end-nodes in a scenario that all end-nodes are surrounding the gateway with a distance to be aware of all other nodes to avoid the problem of hidden node. The gateway generates only beacon frames for superframe advertisement. End-nodes produce data packets following the Poisson distribution with an inter-arrival rate (λ) and transmit them in a direct channel to the gateway. The superframe and timeslot durations are set to 250 ms and 10 ms, respectively.

The main aim of the proposed approach is to improve the performance of the network in real time perspective. The *PLT* for each group is determined to get the maximum number of nodes in the network without influencing the minimum required packet delivery ratio (*PDR*). The ISA100.11a standard has different data classes, where each class has its specific *QoS* requirements. The flexible maximization renders the supportable number of nodes in the network with different *QoS* requirements for each class involving *PDR* (a measure of QoS). In such network, the sensor nodes are divided into groups ($\mathrm{g}1,\ \mathrm{g}2,\ \ldots,\ \mathrm{g}_i$), where g_i composed of n_i nodes. The user has the flexibility to choose any number of groups ($1 \le i \le N_\mathrm{g}$), the maximum and minimum number of nodes in each group, and each group has its PDR level ($PDR1, PDR2,\ \ldots,\ PDR_{N_\mathrm{g}}$). The aim is to maximize n_i without influencing the *QoS* requirements of the entire network.

This grouping scheme is termed as user defined grouping (UDG) scheme. Fig. 4 displays the proposed FOMOF for ISA100.11a in CSMA/CA mode. The flexibility aspect in the developed FOMOF is achieved by enabling the user to choose between multiple objectives, where a constrained genetic based multi-objective optimization approach is used. Using this optimization, the system accepts three types of input data such as constrained *PDR*, constrained number of nodes (minimum and maximum allowed number of nodes), and the vector of relative weights of the factor of the number of nodes in each group ($w1, w2,\ \ldots,\ w_{N_\mathrm{g}}$).

The objective function is comprised of two terms. The first term represents the number of nodes in each group that needs to be maximized. The second term signifies the difference between the relative weights of the number of nodes in the solution and the one provided by the user that needs to be minimized.

4.1. CSMA/CA mechanism in ISA100.11a

The CSMA/CA mechanism implemented in ISA100.11a is different from the one in IEEE802.15.4 standard. The difference can be attributed to following reasons. Firstly, in ISA100.11a, the clear channel assessment (CCA) is executed only once while executed twice in IEEE802.15.4 standard. Secondly, in ISA100.11a, the number of retransmissions depends on PLT while it depends on a fixed number in IEEE802.15.4. Thirdly, the aUnitBackoffPeriod in ISA100.11a is equal to timeslot duration (TD) while it equals to one-third of TD in IEEE802.15.4 standard. Fourthly, each packet in ISA100.11a standard has a set of priority levels that determines the packet delay time ($\tau[i]$) before performing CCA while it is not implemented in IEE802.15.4. Finally, the MaxLifeTime attribute of ISA100.11a determines the maximum *PLT* in the range of 2–480 s and the default value is set to 30 s [30] while in IEE802.15.4, it is limited to the maximum number of retransmissions. The pseudo code in Algorithm 1 depicts the CSMA/CA mechanism in ISA100.11a [10].

4.2. Genetic design

GA optimization is conducted to obtain the best solution in multi-dimensional space for NP-hard problem. As described in Section 3, the optimization problem has a non-linear nature with a high dynamical aspect and, consequently, it is highly

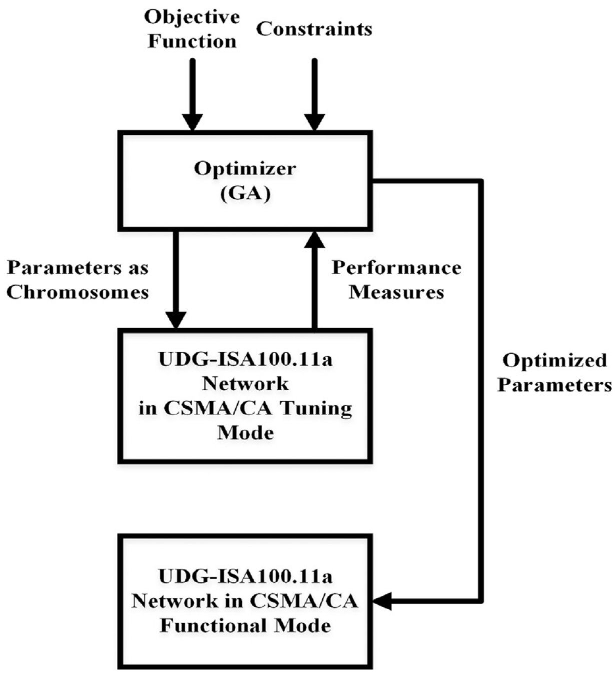

Fig. 4. Design of FOMOF for ISA100.11a in CSMA/CA mode.

Algorithm 1 CSMA/CA with priorities in ISA100.11a.

```
BExp= 0, BackoffCounting= 0
For beginning of each shared timeslot do
        if PacketLifeTime > MaxLifeTime then
                Packet fail to be sent
                Exit this procedure
        End if
        if BackoffCounting > 0 then
              BackoffCounting–
        Else
             Delay for τ[i]
             if CCA – performing returns free then
                   Transmit this packet
                   if the transmission was successful then
                       Exit this procedure
                   End if
             End if
                   ⇒When the CCA returns busy or the transmission fail
             if BExp < MaxBExp then
                   BExp++
             End if
             BackoffCounting=random (0, 2^BExp – 1)
        End if
 End for
```

complicated optimization problem. Adopting genetic optimization is considered due to its parallel nature in execution and the fruitfulness of crossover and mutation for maintaining strong exploration of the solution space as well as obtaining a fast convergence behavior toward the optimal solution. In the applied GA, the chromosome represents a vector of many possible solutions chro $= (PLT1,\ PLT2, \ldots PLT_{N_g}, n1, n2, \ldots n_{N_g})$. The default configuration of the optimization toolbox in MATLAB[1] is used with the exception of adding an integer constraint to the searching space for the number of nodes in the chromosome. Then, a simulation is conducted by combining three groups of wireless nodes $g_1,\ g_2$, and g_3, which contained the number of nodes $n1, n2$, and $n3$, and the packets life times $PLT1$, $PLT2$, and $PLT3$ respectively. These solutions or chromosome values will be used as configurations for the UDG-ISA100.11a system in its online mode to calculate the corresponding fitness values as defined in the Eq. (10) with the corresponding constraints as defined in the Eq. (13). Packets are generated using the Poisson

[1] Crossover factor is 0.8, scale and shrink values for mutation are equal to 1.

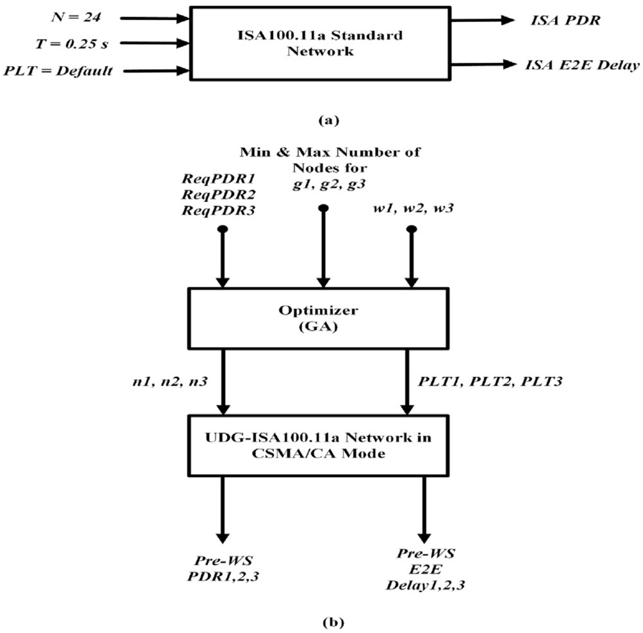

Fig. 5. Feedback mode. (a) ISA100.11a standard network. (b) Optimization scheme in UDG-ISA100.11a mode.

distribution, where each packet is assumed to be transmitted from a subject node to the gateway while the medium remains busy with the transmission process, which may cause collision with other nodes that are trying to simultaneously send packet. To overcome such possible collisions, a prioritized CSMA/CA is adopted in ISA100.11a. Retransmissions are allowed for the nodes according to the optimum solution (*PLT*1, *PLT*2, *PLT*3, *n*1, *n*2, *n*3). It is now customary to authenticate whether the simulation can maintain *QoS* presented by the required *PDRs* (*ReqPDR 1*, *ReqPDR 2*, and *ReqPDR 3*) with an optimum number of nodes n_i and PLT_i for each group. This online optimization method is termed as predefined weighted sum (*Pre-WS*) optimization.

4.3. Pre-WS optimization scheme and simulation setup

The optimization is performed in feedback and feed-forward modes. Fig. 5 illustrates the feedback mode where the original ISA100.11a network, with fixed number of nodes (24), is executed first to obtain PDR for the original ISA100.11a (ISA PDR) level and ISA.100.11a average End-to-End Delay (*ISA E2E Delay*), as depicted in Fig. 5(a). The *ISA PDR* value obtained will be used as a reference in the feedback mode and denoted as *ReqPDR* 1. To determine the other *ReqPDR* levels in g_2(*ReqPDR* 2) and g_3(*ReqPDR* 3), the relation of $\mathrm{ReqPDR_i} = \mathrm{w_i}\ ReqPDR\ 1$ can be applied, where i = 2, 3 are used. These three required *PDRs* are used in tuning mode of optimization framework to get the optimum n_i and corresponding PLT_i. These optimum values are then used as inputs in the UDG-ISA100.11a mode to obtain the simulated PDR ($Pre-WS\ PDR_i$) and E2E Delay for each group ($Pre-E2E\ Delay_i$), which represent the performance evaluation measures. Fig. 5(b) describes the optimization in the UDG-ISA100.11a mode. Then the total number of nodes resulted from the optimization framework is used as an input in ISA100.11a standard network and a comparison is made with the results obtained from the optimization in UDG-ISA100.11a mode ($Pre-WS\ PDR_i$ and $Pre-WS\ E2E\ Delay_i$). The performance is evaluated as a function of the offered load in the network, which is generated by the application layers of all nodes normalized to 250 kbps. The offered load is calculated using the following relation:

$$\text{Offered Load} = \frac{\mathrm{N} * \lambda * \mathrm{t_d}}{\mathrm{SD} + \mathrm{BD}} \tag{14}$$

where N presents the total number of nodes in the network, λ is the packet inter arrival rate, t_d is the packet transmission time, *SD* and *BD* are superframe and beacon frame duration, respectively.

In feed-forward mode, *ReqPDR*1 is assigned to a certain value; the values of *ReqPDR*2 and *ReqPDR*3 are obtained using the relation $ReqPDR_i = wi\ ReqPDR1$. Also, assigning weights and maximum and minimum number of nodes in each group performs the optimization in the UDG- ISA100.11a tuning mode to get the optimum n_i and required PLT_i. Then, these optimum values areused as inputs for UDG-ISA100.11a network in functional mode to obtain the $Pre-WS\ PDR_i$ and $Pre-E2E\ Delay_{gi}$ for each group, as described in Fig. 6(a). For comparison, the total number of nodes obtained from the optimization (*N*) is used as an input in the original ISA100.11a standard to get the *ISA PDR* and *ISA E2E Delay* as depicted in Fig. 6(b).

The performance is evaluated as a function of the number of nodes in the network. Packets are generated in a Poisson distribution with InterArrivalTime intervals (*T*) ranged from 5 s to 0.25 s in the feedback mode, while it is constant

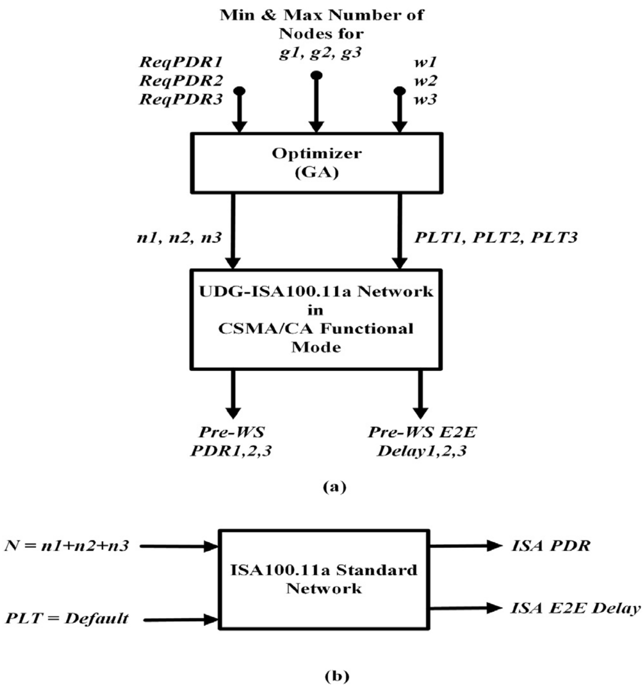

Fig. 6. Feed-forward mode. (a) Optimization in UDG-ISA100.11a mode. (b) ISA100.11a standard network.

Table 2
Optimization and simulation parameters.

Parameter	Value	Parameter	Value
Max PacketLifeTime (Max*PLT*)	30 s	Backoff symbol duration	0.01 s
InterArrivalTime interval (*T*)	5 - 0.25 s	CCA duration	0.000128 s
Alert Priority Levels	16	ACK packet size	18 Bytes
Number of groups (N_g)	3	Packet Size	127 Bytes
Number of Packet Priority Levels	16	Data Rate	250 kbps
Weights (wi)	0 – 1	Simulation time	50 s
Population Size	50	macMinBE	3
Number of Generations	60	macMaxBE	5
Superframe Duration (SD)	0.25 s	Timeslot Duration (TD)	0.01 s

at 0.25 s in the feed-forward mode. The results for longer simulation time are identical as long as the network is stationary. The CSMA/CA parameters are set to their default values in ISA100.11a standard (macMinBE = 3, macMaxBE = 5, MaxPacketLifeTime = 30 s). Packet size is set to the maximum size (127 Bytes) with the maximum payload of 96 Bytes. Simulation duration is set to 50 s. The performance metrics to be obtained are *PDR* and average *E2E Delay*.

The optimization and simulation parameters are listed in Table 2.

5. Performance analysis

The system performance is evaluated using *PDR*, which represents the *QoS* level, and average *E2E Delay*. The evaluation of *PDR* is carried out by Eq. (14):

$$PDR = Number\ of\ received\ packets / Number\ of\ generated\ packets \tag{15}$$

The *E2E Delay* is the time duration starting from the packet generation at the ISA100.11a application layer to its reception by the gateway. The average *E2E Delay* can be calculated by averaging all *E2E* time delays. The optimization approach is validated via three experiments where one experiment is in feedback mode and the other two experiments are in the feed-forward mode.

5.1. Feedback mode experiment

In this mode, the standard ISA100.11a network is run with 100% offered load (24 nodes) with InterArrivalTime equals to the norm superframe duration of 0.25 s and the default MaxPacketLifeTime of 30 s. The value of achieved *PDR* is

Table 3
Experimental results from the feedback mode with variant offered load.

Pre-WS PDR 1	Pre-WS PDR 2	Pre-WS PDR 3	Pre-WS PDR	ISA PDR	Pre-WS E2E Delay (s)	ISA E2E Delay (s)	PLT_1 (s)	PLT_2 (s)	PLT_3 (s)	Offered Load (%)
1.00	1.00	1.00	1.00	1.00	0.030	0.300	2.260	7.256	14.474	5
1.00	1.00	1.00	1.00	1.00	0.040	0.400	2.260	7.256	14.474	10
1.00	0.99	1.00	0.99	0.99	0.091	0.091	4.951	13.388	27.810	20
0.93	0.96	0.94	0.94	0.94	1.318	1.615	4.951	13.388	27.810	40
0.73	0.64	0.64	0.66	0.66	6.227	6.668	4.951	13.388	27.810	60
0.61	0.47	0.50	0.52	0.51	8.420	9.655	10.249	15.646	15.575	80
0.48	0.41	0.38	0.42	0.41	9.067	10.841	10.249	15.646	15.575	100

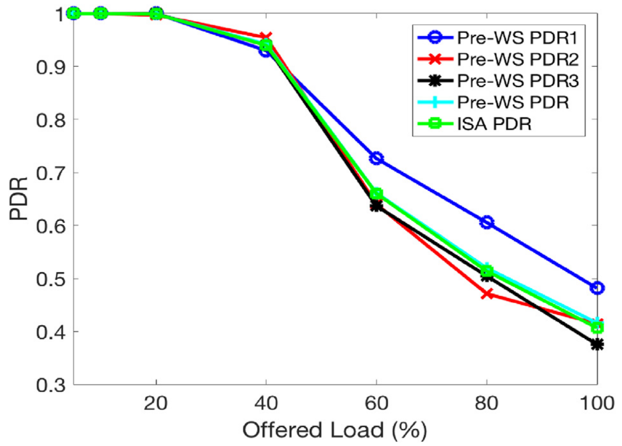

Fig. 7. PDR as a function of the offered load in feedback mode.

ISA PDR = 0.4583, and *ISA E2E Delay* is 9.9148 s. The resultant *ISA PDR* is set as the *ReqPDR*1 ≈ 0.46. The *ReqPDR*2 and *ReqPDR*3 are calculated using $ReqPDR_i = wi\ ReqPDR1$, which produces *ReqPDR*2 value ≈ 0.41 and *ReqPDR*3 value ≈ 0.36. A higher weight is assigned to the lower *ReqPDR*, which is $ReqPDR_3$ ($w1 = 0.7818$, $w2 = 0.8909$, $w3 = 1$). The constraints of minimum and maximum number of nodes in each group are set to 3, 7, 8, and 10, 15, 20, respectively. These parameters are set as inputs for the optimization framework in UDG-ISA100.11a tuning mode, and results from the optimization are set as inputs for UDG-ISA100.11a network in functional mode. The results obtained are $n1 = 7$, $n2 = 9$ and $n3 = 11$ nodes in addition to the $Pre-E2E\ Delay_{gi}$ for each group. To compare these results with the original ISA100.11a network, the total number of nodes in all groups (27) is assigned as an input to the ISA100.11a standard network with the default *PLT* of 30 s. These simulations are repeated with different offered load in the network as outlined in Table 3.

Thus, with online optimization in tuning and functional UDG-ISA100.11a mode, the number of nodes is maximized up to 27 nodes compared to 24 nodes with the original ISA100.11a standard network. The system responded effectively to the weight ratios. Besides, the presence of two constraints on the number of nodes has made the system more flexible in reaching any arrangement regardless of the *ReqPDR* level.

Fig. 7 displays the offered load dependent variation in *PDR* percentage in maintaining the system $ReqPDR_i$ levels. $Pre-WS\ PDR_i$ are found to be higher than $ReqPDR_i$ in all groups even with 100% of the offered load. Furthermore, the $Pre-WS\ PDR$ followed the ISA PDR in all environments with the same number of nodes. The $Pre-WS\ PDR$ is calculated via Eq. (16):

$$Pre-WS\ PDR = \frac{n1*(Pre-WS\ PDR1) + n2*(Pre-WS\ PDR2) + n3*(Pre-WS\ PDR3)}{n1 + n2 + n3} \tag{16}$$

The data in Table 3 provides enough guidelines to show the results obtained from optimization with UDG-ISA100.11a network and from the original ISA100.11a network.

The numerical results in Table 3 are shown graphically in Figs. 7 and 8. in addition to other results. Fig. 8 shows the offered load dependent variation in E2E Delay in maintaining the system $ReqPDR_i$ levels. The maximum values of $Pre-WS\ E2E\ Delay_i$ for all groups and $Pre-WS\ E2E\ Delay$ are lower than *ISA E2E Delay*. The group with less number of nodes, low weight, and high *ReqPDR* level (g1) produced shorter *E2E Delay* compared to the other groups as well as *ISA E2E Delay*. The $Pre-WS\ E2E\ Delay$ is calculated via Eq. (17):

$$Pre-WS\ E2E\ Delay = \frac{n1*(Pre-WS\ E2E\ Delay\ 1) + n2*(Pre-WS\ E2E\ Delay\ 2) + n3*(Pre-WS\ E2E\ Delay\ 3)}{n1 + n2 + n3} \tag{17}$$

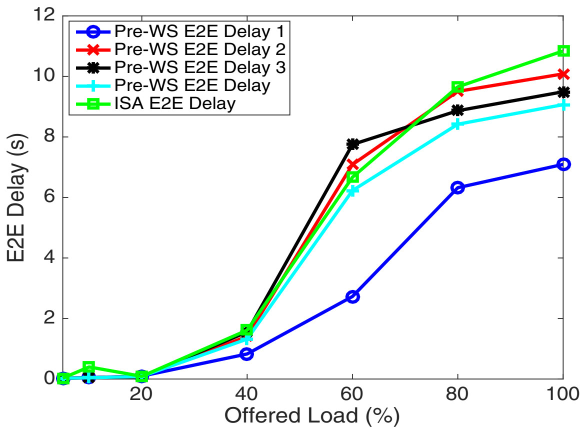

Fig. 8. E2E Delay as a function of the offered load in feedback mode.

Table 4
Experimental results for the first feed-forward scenario.

Pre-WS PDR 1	Pre-WS PDR 2	Pre-WS PDR 3	Pre-WS PDR	ISA PDR	ISA E2E Delay (s)	Pre-WS E2E Delay 1 (s)	Pre-WS E2E Delay 2 (s)	Pre-WS E2E Delay 3 (s)	n_1	n_2	n_3
0.977	0.985	0.998	0.987	0.982	0.486	0.428	0.521	0.592	3	3	3
0.822	0.932	0.885	0.880	0.880	2.854	3.416	1.615	3.652	4	4	4
0.716	0.739	0.721	0.725	0.708	5.860	3.366	4.073	5.408	5	5	5
0.610	0.607	0.654	0.624	0.620	6.204	1.972	4.548	4.531	6	6	6
0.524	0.523	0.551	0.533	0.527	8.594	7.457	8.413	7.839	7	7	7
0.417	0.429	0.401	0.416	0.406	10.841	10.655	9.126	10.955	9	9	9
0.300	0.300	0.317	0.306	0.305	13.535	10.594	12.531	11.643	12	12	12

5.2. Feed-forward mode experiments

Table 4 enlists the results for the first experiment in feed-forward mode. In this experiment, equal weights ($w1 = w2 = w3 = 1$) and equal levels of *ReqPDR* 1, 2, 3 are assigned to all groups. The *ReqPDR* is reduced gradually from 90% to 30% at 10% for each step. This increases the number of nodes in each group from 3 to 12 with around 1–3 nodes in each time. Experimental results revealed good response of the system by maintaining the optimum number of nodes with respect to the *ReqPDR* 1, 2, 3 level. Thus, the system provides the best arrangement of *PLT*1, 2, 3 to maintain the *ReqPDR* 1, 2, 3 and optimum number of nodes in each group. The InterArrivalTime is kept constant (0.25 s) and the constraint of minimum and maximum number of nodes in each group is 2 and 15, respectively. For each experiment the result of the tuning UDG-ISA100.11a optimization is used for assigning the *PLT*1, 2, 3 and n1, n2, and n3 of the actual execution of the three-group network in UDG-ISA100.11a functional mode. This produces *Pre – WS PDR* 1, 2, 3 as well as the *Pre – WS E2E Delay* 1, 2, 3 for the three groups. These results are compared with the original ISA100.11a network results for the same total number of nodes ($N = n1 + n2 + n3$) with the default maximum PLT (30 s). Results in Table 4 clearly show that the system can provide same number of nodes in each group while maintaining the *Pre – WS PDR* 1, 2, 3 levels for all three groups based on the *ReqPDR* 1, 2, 3.

Fig. 9 shows the dependency of the total number of nodes on *PDR* variation in the presence of good tracking of the *Pre – WS PDR* to the *ISA PDR* of the original ISA100.11a standard. It can be also noted that the dependency is exponential and follows Poisson statistical approach. Fig. 10 displays the relationship between the numbers of nodes on *Pre – WS E2E Delay* 1, 2, 3 for all groups and *ISA E2E Delay*. The *Pre-WS E2E Delay* is found to be shorter than the *ISA E2E Delay* for original ISA100.11a standard for the same number of nodes. Furthermore, the relationship between the *E2E delay* and the total number of nodes is not linear; however, it looks logarithmic relation, which under first order approximation by Taylor's series seems to a linear relation. The results are in agreement with Rezha and Shin [30].

In the other feed-forward mode experiment, the following optimizer inputs in tuning mode are set: The InterArrivalTime is fixed at 0.25 s, and the weights for g1, g2, and g3 are assigned to 0.24, 0.33, and 0.43, respectively. The minimum and maximum allowed number of nodes in g1, g2, and g3 are 2, 2, 3 and 10, 20, 30, respectively. The optimization outputs are $n1$, $n2$, and $n3$ and PLT1, PLT2, and PLT3, which are assigned as inputs for UDG-ISA100.11a network in functional mode. This will generate *Pre – WS PDR* 1, 2, 3 and *Pre – WS E2E Delay* 1, 2, 3 for each group. The results of the proposed scheme are compared with the original ISA100.11a standard network. Where, the total number of nodes are N = $n1 + n2 + n3$, and the default maximum PLT (30 s) are assigned as inputs for the original ISA100.11a standard network with the same InterArrival-Time of 0.25 s. The output presented by ISA PDR is compared with *Pre – WS PDR* 1, 2, 3 and *Pre – WS PDR*. In addition, the

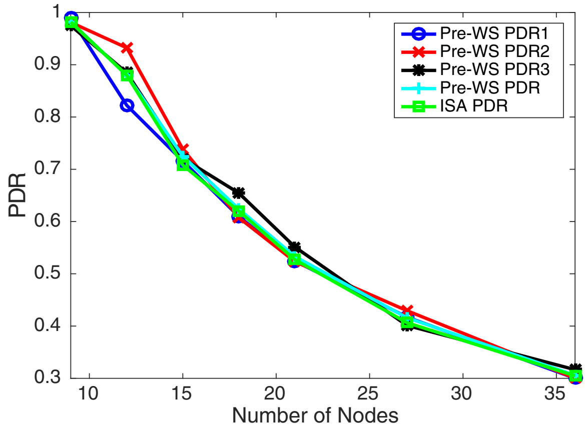

Fig. 9. Number of nodes dependent PDR variation for the first feed-forward mode experiment.

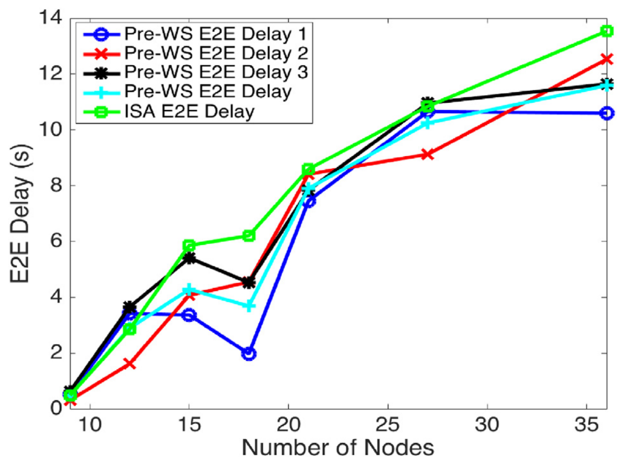

Fig. 10. Number of nodes dependent variation in *E2E Delay* for first feed-forward mode experiment.

Table 5
Requested *PDR* levels in the second feed-forward mode and experimental results.

Req PDR 1	Req PDR 2	Req PDR 3	Pre-WS PDR 1	Pre-WS PDR 2	Pre-WS PDR 3	ISA PDR	Pre-WS E2E Delay (s)	ISA E2E Delay (s)	n_1	n_2	n_3
0.90	0.80	0.70	0.9915	0.9765	0.9807	0.9859	0.4845	0.4875	2	3	4
0.80	0.70	0.60	0.8467	0.7875	0.7334	0.7724	3.8029	3.9588	3	5	6
0.70	0.60	0.50	0.7216	0.6681	0.5442	0.6023	5.2378	6.4817	4	6	8
0.60	0.50	0.40	0.6203	0.5368	0.4159	0.4964	8.5330	9.0783	5	7	10
0.50	0.40	0.30	0.5024	0.4174	0.3012	0.3742	9.0180	11.6380	7	10	12

ISA E2E Delay is compared with the *Pre – WS E2E Delay* 1, 2, 3 for the three groups. Table 5 shows the *ReqPDR* 1, 2, 3 in the second feed-forward mode experiment and the achieved results.

The results in Table 5 demonstrate that the system maintained the *Pre – WS PDR* 1, 2, 3 levels for all groups compared to *ReqPDR* 1, 2, 3 where the optimized number of nodes follows the following pattern $n1 < n2 < n3$. This is attributed to the assignment of the lowest weight to *ReqPDR 1*, and the highest for *ReqPDR*3. Besides, the highest weight is assigned to the g3 having lowest *ReqPDR3*. Fig. 11 shows the *Pre – WS PDR* always exceeds *ISA PDR* which suggests that the model used in this work satisfies the standard and beyond, and depicts the excellent tracking of *Pre – WS* PDR to the *ISA PDR* for the original ISA100.11a network. Besides, *Pre – WS PDR* 1, *Pre – WS PDR* 2 are higher, and *Pre-WS PDR* 3 is lower than the *ISA PDR* of the original ISA100.11a standard network. This is due to the allocation of a low level to *ReqPDR 3* and high weight w3 to g3, which produced more number of nodes in this group. Fig. 12 demonstrates the good performance regarding real-time aspect, where the *Pre – WS E2E Delay* in UDG-ISA100.11a mode is lower than the *ISA E2E Delay* for the original ISA100.11a standard. Furthermore, the *Pre – WS E2E Delay* 1 is observed to be lower than the one for g2, with g2 lower than g3.

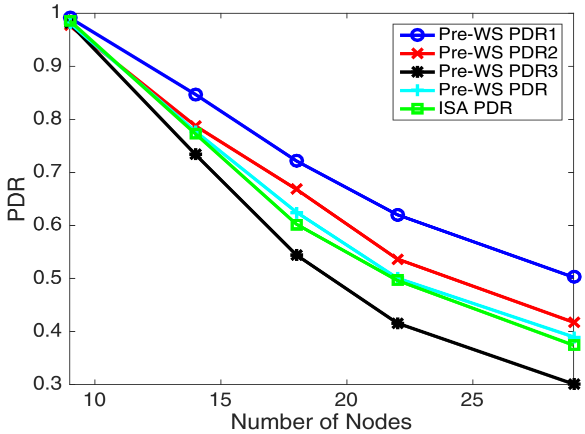

Fig. 11. Number of nodes dependent variation in *PDR* percentage for second feed-forward mode experiment.

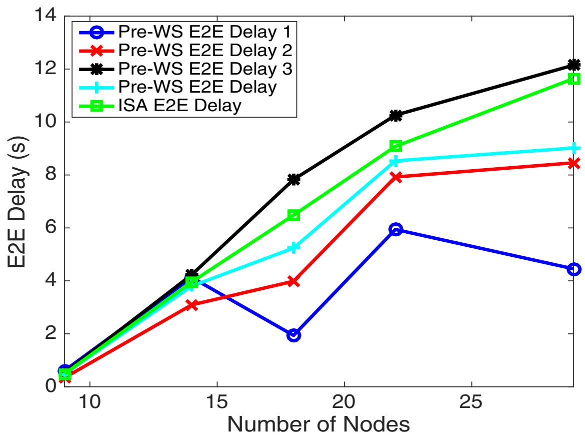

Fig. 12. Number of nodes dependent variation in *E2E Delay* for second feed-forward mode experiment.

The significant of the number of nodes in a workable system can be understood from the fact that these nodes are either primarily set without grouping as in ISA100.11a standard or subjected to a grouping protocol as in the current work. Under the assumption of grouping, the number of groups plays an important role. There is a consensus that the number of groups is taken at three. The grouping process is normally accompanied with assigning a certain *ReqPDR* 1, 2, 3 levels where, logically, have to be different levels. Consequently, the weight for each level becomes necessary in addition to the constraints of maximum and minimum number of nodes to allow the system a flexible level of choice. Within the frame of these three constraints, the system may or may not find an answer; however, if a solution is satisfied, it indicates the occurrence of optimization solution under those conditions.

6. Conclusion and future work

A flexible online optimization framework is carried out using sharing timeslot of ISA100.11a and was conducted by the multi-objective genetic-based constrained optimization. A MATLAB simulation model is introduced for online tuning of the beacon-enabled CSMA/CA mediated ISA100.11a standard and the proposed UDG-ISA100.11a scheme. A UDG-ISA100.11a is developed assuming that nodes are grouped with an assigned level of *QoS*. The user is granted high flexibility to achieve a required *QoS* level with desired number of nodes. The required flexibility cannot be completed without setting a number of constraints to represent the desired range of number of nodes and *QoS* levels. The objective function is formulated to maintain a high number of node and the least difference from the desired weighting ratio in the groups. The simulation model is experimentally validated in feedback and feed-forward modes. The results revealed that a good tracking to the desired level of *QoS* with less average *E2E Delay* and a maximum number of nodes has been achieved. Another result has shown that the highest number of total nodes in the network enhanced the delay of packet delivery. It is established that all *QoS* relevant number of nodes in the system can be arranged to attain the desired *QoS*. Consequently, it is important in future to develop a model by considering TDMA – a subpart in ISA100.11a standard, which can automatically map a fewer portion of allowable requirements for an optimal set of parameters and constraints.

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