A Centralised Routing Protocol with a Scheduled Mobile Sink-Based AI for Large Scale I-IoT

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***Abstract*—Extensive efforts have been undertaken to enhance the centralised monitoring-based software defined network (SDN) concept of the large-scale Intelligent-Internet of Things (I-IoT). Furthermore, the number of IoT devices in vast environments is increasing and a scalable routing protocol has therefore become essential. However, due to associated resource restrictions, only very small functions can be configured using IoT nodes, principally those related to the power supply. One solution for increasing network scalability and prolonging the life of the network is to use the mobile sink (MS). However, determining the optimal set of data gathering points (S_{DG}), optimal path, scheduling the entire network with the MS in an energy efficient manner and prolonging the life of the network present huge challenges, particularly in large-scale networks. This paper therefore proposes an energy efficient routing protocol based on artificial intelligence (AI), i.e., particle swarm optimisation (PSO) and genetic algorithm (GA), for large scale I-IoT networks under the SDN and cloud architecture. The basic premise is to exploit cloud resources such as storage and data-centre units by using a centralised SDN controller-based AI to calculate: a load-balanced table of clusters (CT), an optimal S_{DG}, and an optimal path for the MS (MS_{Opath}). Moreover, the proposed new routing technique will prevent significant energy dissipation by the cluster head (CH) and by all nodes in general by scheduling the whole network. Consequently, the SDN controller essentially balances energy consumption by the network during the routing construction process as it considers both the S_{DG} and the movement of the MS. Simulation results demonstrate the effectiveness of the suggested model by improving the network lifespan up to 54%, volume of data aggregated by the MS up to 93% and reducing the delay of the MS_{Opath} by 61% in comparison to other approaches.**

***Index Terms*—IEEE 802.15.4, Hybrid MAC protocol, PAN coordinator, IoT, Sleep mode, Scheduler table (ST).**

I. INTRODUCTION

IN recent years, the Internet-of-Things (IoT) has increasingly played an important role in many everyday applications, such as environmental surveillance, navigation, healthcare, smart homes, smart cities, smart farming, the industrial internet, wearable devices, and education [1], whilst, at the same time, the MS has developed as an indispensable choice for efficient monitoring and balancing of the energy dissipation of such applications [2]–[4]. IoT refers to the connection of many physical things to the internet using settled items with a level of AI [5]. These settled items empower IoT “physical objects to see, hear, think, and perform jobs by communicating in order to share information and coordinate decisions” [6]. In general, Wireless Sensor Networks (WSNs) are considered a resource that enables the accomplishment of IoT [5]. However, the sensors in WSNs are restricted by insufficient battery, radio communication capacities, storage memory, and processing ability. Moreover, the deployment of IoT devices is usually random and unbalanced, taking place within a harsh and large-scale environment, which makes the replacement of any device’s battery a nigh on impossible task [5]. Hence, it is important to design an energy efficient routing protocol-based AI that properly balances the load between the devices and is suitable for both small and large-scale environments, thus improving the lifespan of the entire IoT network.

There is a need to involve intelligence in IoT operations by analysing the data and predicting the optimal routing control, rather than employing the traditional inactive techniques. Furthermore, an I-IoT network should be able to compensate for failure in any part in the network and to control it with a minimum amount of degradation in its performance. The involvement of AI in IoT is essential because it allows the controller, based on the collected information, to automate the network and make smart decisions without human interference. However, one major issue for I-IoT is the lack of a controller and software platform that can support numerous types of AI techniques and integrate them into the network management operation according to requirements. Hence, implementation of I-IoT requires a collaboration procedure across many technologies, such as cloud and SDN, with AI techniques as smart software.

I-IoT control operation techniques should not only perform data collection and analysis of the current situation of the IoT network. They should also be getting smarter so as to make life easier by integrating more than one AI methodology. This will lead to improved operation effectiveness, automated risk management and maintenance as well as the facilitation of the production of the I-IoT protocols. It will also provide the capacity to respond to any potential unplanned network downtime in the future. AI is playing a successful role in improving IoT due to its remarkable intuition capability and capacity for inspecting data, thus allowing for smarter decisions. For example, AI techniques can deliver network automation as well as, earlier patterns prediction and identification with much greater accuracy than the traditional methodologies. In sum, AI is considered as being a step towards a smart life through an intelligent platform that makes automated decisions for applications including air conditions, vehicle handling, coffee machines, TVs, lighting, etc.

Sensors in WSNs detect environmental phenomena and

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the sensed data are then gathered by the sink node across the CHs. Moreover, in clustering two different types of sink node, namely, mobile and static, are considered [7]. The WSN routing algorithms with a static sink suffer from energy hot-spot problems, because the sensor nodes closer to the sink node dissipate more energy than the others [8]. Additionally, the use of a static sink only covers a small-scale network region and thus, mobile sink routing algorithms-based AI for WSN become indispensable for resolving hot-spot problems and extending the life of the network [9]. However, the technique used by a mobile sink to roam across the network to gather data has suffered from delay issues. Consequently, the scheduling of mobile sinks and efficient path determination are perceived as the key research challenges. Furthermore, current routing protocols use the sensor's resources to conduct their computations or to memorise network information. The development and growth of I-IoT, however, is often restricted due to sensor resource constraints.

These challenges can be solved through the employment of smart network supervision using cloud, AI, and SDN. The term cloud refers to a processing service or information from a third party, where through the use of the Internet, the information is controlled remotely from any position. In so doing, the cloud enables companies to save databases or software [10]. SDN technology facilitates centralised network supervision and easier programming by splitting the data plane from the control plane [11]. Intelligent mechanisms, such as neural networks, GA and swarm, are optimisation techniques that require a global view of the entire network. However, centralised network monitoring using the SDN controller and global network optimisation are deemed substantial challenges in IoT, as each device follows an independent routing protocol to transmit their sensed data to other devices or to the sink device [10]. This independent protocol leads to unbalanced cluster construction, which can shorten the lifetime of the entire network.

This paper therefore proposes a load balanced and scheduled protocol, named, optimised mobile sink-based load balancing (OMS-LB) that employs optimisation algorithms for large scale I-IoT networks. The protocol will use the MS to collect data across a large-scale sensing field. The main aims of this study are to provide an energy efficient procedure that will balance the workload of I-IoT devices, while scheduling the MS, which drives the whole I-IoT network into sleep/wakeup mode, as required. Consequently, this procedure will prolong the life of the network and reduce energy dissipation in sensor nodes. The proposed OMS-LB transfers complex protocol computations from the network devices and implements them using the SDN controller, which utilises cloud resources such as data centres and storage in its calculations. The sensed data are gathered using a single MS and then sent to the cloud for further processing. Moreover, the load balanced set of clusters, optimal S_{DG}, and best path of the MS node are all determined by the SDN controller using AI, i.e. PSO and GA, to gather the sensed data from the CHs in the sensing fields. Thereafter, the SDN controller sends the optimal set of clusters, best S_{DG}, optimal path for the MS, and the network scheduling message (NSM) to the MS to be forwarded to the entire network. In sum, this paper provides the following contributions.

- Proposing a construction for the SDN controller-based AI that will implement the routing design through the utilisation of cloud resources. This controller is responsible for the formulation of CT as well as determination of the S_{DG} and the MS_{Opath} using robust AI (see Section 4). Furthermore, the suggested design construction will mitigate the functionality performed by the I-IoT devices.
- Determining the MS_{Opath} using the GA to collect the data from each S_{DG} at a pre-scheduled time.
- Developing an energy efficient joint model, which connects the impact of the MS_{Opath} determination with the cluster formulation process to define an optimised routing protocol suitable for large scale networks.
- Presenting extensive simulation results for both small and large scale I-IoT networks regarding network lifespans, energy dissipation along with the volume of data transmitted to the sink node and the MS_{Opath}, which will validate the proposed OMS-LB.

The remainder of this paper is arranged as follows. Section II briefly reviews studies related to this topic and Section III describes the formulation of the problem presented in this paper. The methodology for the proposed mobile sink-based protocol using optimisation approaches is illustrated in Section IV, with the shortest path determination using a GA also being introduced in this section. In Section V, the obtained simulation results and validation are examined. Finally, Section VI presents a paper conclusion and future work.

II. Related Work

This section is divided into three subsections. Each subsection briefly reviews several energy-efficient algorithms that have been considered for the path determination of the sink nodes and data aggregation algorithms.

A. Mobile sink based routing protocols

To reduce energy consumption, cluster head selection and rotation with sink mobility have been used to balance the energy dissipation among all sensor nodes in the sensing field without any degradation in network performance. This section presents sink node mobility techniques for a large-scale WSN.

Two-Tier Data Dissemination (TTDD) was proposed in [12] for a large-scale WSN. This is a hierarchical data dissemination approach, which delivers the data efficiently to multiple mobile sinks. Moreover, TTDD is a grid-based approach with a static data node. Each sensor node needs to know its coordinates to create proactively a grid around itself, which enable the mobile sink to transfer within the local grid cell and collect data using flooding queries. However, TTDD does not define the optimal path for the mobile sink and it experiences high overheads from having to build a distinct grid for each source node.

Mobile sink improved energy-efficient PEGASIS-based routing protocol (MIEEPB) was offered by [13]. This protocol enhances the lifetime of a WSN by presenting a multi-chain with multi-head concept based on the MS. However, the trajectory, sojourn and sojourn number of the MS are fixed, which means that this protocol suffers from a higher energy dissipation by the CHs when transferring their data to the MS or the sojourn points. Moreover, the impact of this issue increases the larger the scale of the area network.

Virtual Grid-based Dynamic Routes Adjustment (VGDRA) was suggested in [14] to minimise the cost of route reconstruction of the sensor nodes by maintaining the best route to the current position of the MS. VGDRA contains a list of communication instructions that manage the route rebuilding procedure, so that only a restricted number of devices are required to re-adapt their data routes toward the MS.

On the other hand, Tian in [15] proposed the TRAIL protocol. In this protocol, the sink node produces a trail path for its movement throughout the entire network. Furthermore, if the device has a trail path, then it uses the recent one to forward its messages to the sink; otherwise, the device uses a random walk technique to forward its messages to a sensor device that has an updated trail path of the sink node or sends it to the sink node directly.

Yang et al. [16] proposed an environmental sensing platform architecture that includes closed loops of interactions among physical devices and people nodes as well as servers and recommendations on device construction by cognitive computing, namely, people-centric and cognitive Internet of Things (PIoT). An algorithm-based MS to collect on demand user data from smart device-to-device (D2D), is suggested. A case study of a cognitive IoT model for particulate matter PM2.5 exposure in New York City is offered to exemplify the possible application of people-centric measurement model and data analysis.

Tunca in [17] suggested a protocol that employs three kinds of nodes: ring, anchor, and regular nodes. Initially, the speed of the MS was defined as being between 0 and 5 m/s. The ring nodes memorise information regarding the location of the anchor node and they are generally positioned at a defined distance from the centre of the network. The anchor node, on the other hand, is positioned as the closest node to the sink. It needs to be changed when the link quality between it and the sink degrades below some threshold. Furthermore, when a regular node has data to be transferred to a sink node, then it first has to inquire of the ring node the anchor node's location. The regular node can start the transmission of data to the anchor node using geographical routing, once it receives this location.

However, the prevalence of sink nodes in the WSN monitoring area can be classified into four different categories [7]: static sink, mobile sink, multiple mobile sinks and a dual sink where both static and mobile sinks are used. With a static sink, the CH uses single or multi-hop transmission to forward the data to the sink device. However, there is a load balancing problem arising from this technique where, in multi-hop transmission, the CHs closer to the sink device drain more energy than others, leaving many parts of the network disconnected and resulting in network energy holes, called the hot spot problem [7].

On the other hand, a sink node with a mobility feature travels across the sensing field to collect the data from the CHs. Sink mobility can be categorised into three classes: predictable mobility, controllable mobility and random mobility [7], [18]–[20]. The controlled mobile sink was presented in [21]. The authors presented a greedy-based higher residual energy approach, where the sink node transferred to the new position, according to the maximum residual energy in the nodes. The results displayed that the controlled mobile sink is more energy efficient in comparison to the random/uncontrolled sink mobility in a sensor network.

Salarian et al. [22] proposed an energy efficient routing protocol for the WSNs called mTSP which followed the Travel Salesman Problem (TSP) to find the path for the MS. The mobile sink stays at each CH and collects the sensed data using static sensors. In general, mTSP is used when the network has been organised into m clusters and m collecting points. Therefore, mTSP leads to greater energy consumption by both the MS and the CHs. However, mTSP does not combine the effect of the shortest path and load balancing during cluster construction. Furthermore, it does not consider network synchronisation and scheduling, which leads to greater energy depletion across the whole network due to the overheads, and listening and waiting for the MS.

Further models for improving the mobile sink improvements are presented in [23]–[26]. In [26], the authors addressed the issue of using multiple mobile sink nodes to monitor the WSN home environment. The rationale for using multiple mobile sinks, velocity, and their first position were studied. The results showed that network lifespan was improved once the number of sink nodes had been increased up to a definite point. However, this method suffers from high overheads; moreover, once the number of mobile sink nodes passed the definite point, then the performance in terms of network lifespan ceased to increase.

The final category is the dual sink network, where both static and mobile sinks are used [18]. The author proposed a static sink located in the middle of the sensing field. At the early stage of the transmission, this sink sends a "hello" messages to all sensor devices in the network. Thereafter, a MS sends a "hello" message, but only to a subgroup of devices in the network. A compared of simulation results between a static sink, single MS and dual sink networks, showed that the performance of the network using the latter-most was much better than for the other sink mobility approaches.

B. Static sink based routing protocols

Clustering techniques in the WSN environment can be defined as the grouping of sensor nodes into clusters to achieve a high level of energy efficiency, improve network lifespan, and to enhance network scalability. There are many clustering algorithms available in the WSN literature such as low energy adaptive clustering hierarchy (LEACH) [27], [28], stable election protocol (SEP) [29], [30], and other clustering-based optimisation algorithms.

LEACH [27] is a single hop hierarchical, probabilistic, and distributed schem. The measuring unit of the LEACH algorithm is "round". In this algorithm the entire devices have the opportunity to be a CH at each round with a probability "p".

Furthermore, following the selection of an eligible group of CHs, the CHs broadcast an advertisement message to adjacent devices. The non-CH devices select the CH with the strongest signal energy and then join the cluster to which it belongs. Following the cluster construction process, the CHs collect, aggregate and transfer the gathered data to the sink node. A centralised-based LEACH methodology was developed later by Heinzelman et al. [28], wherein the cluster construction process is performed by the sink using information about the residual energy of the devices and their current position, so that devices with a greater amount of remaining energy are more suited to becoming a CH.

SEP [29] is a two levels of heterogeneity routing protocol, which represents an improvement over LEACH in WSN. In SEP, sensor nodes are categorised according to the initial energy into two types, normal nodes and advanced nodes, the latter of which has higher energy than the former. Moreover, as in LEACH, the selection of CHs by cluster heads is accomplished randomly depending on the probability of each node. However, the advanced nodes have higher probability than the normal nodes. An extension of SEP was presented in [30], where the authors proposed a Threshold Stable Election Protocol (TSEP). TSEP is considered a three level of heterogeneity protocol. Based on the initial energy of devices, it categorises them into super devices, normal devices or advanced devices.

An example of a clustering protocol-based optimisation algorithm is the PSO clustering algorithm. PSO is an optimised scheme that based on a preliminary group of random populations, and is inspired by the mutual behaviour of birds when flocking [31]. Alternatively, Latiff et al. [32] offered the PSO-based clustering (PSO-C), which is considered as an energy-aware routing protocol that employs the PSO technique at the base station for cluster construction. PSO-C employs both the remaining energy of the devices, as well as Euclidean distances between the CMs and their CHs during the CH selection process. However, such routing algorithms do not pay any attention to network synchronisation or to balancing the load of the devices among the CHs. Furthermore, they assume that the sink is static, which results in more energy being consumed by the CHs as it sends its data to the sink.

Wasan et al. in [33] presented a self-organizing cluster head to sink algorithm (SOCHSA) that uses the optimisation techniques to improve the network performance. This algorithm works by arranging the machine to machine (M2M) devices in a hierarchical manner and within multi-sinks layers, which helps in providing an efficient routing algorithm that prolong the network lifespan. However, the authors, in this algorithm, did not include the emerging technologies such as the cloud and SDN technologies, as well as the MS for data collection purposes; therefore, this algorithm seems not able to work efficiently and not suitable for large scale IoT network.

C. SDN based routing architecture

SDN that based on the open-flow algorithm for WSN nodes has been proposed by Luo et al. [34]. Following this suggestion, Gante et al. [35] discussed taking a broader approach to the administration of SDN in WSNs. Another improvement is a TinySDN that has been proposed by Oliveira et al. [36], which allows multiple controllers for WSNs. The provided technique comprises two principle devices: the SDN assisted sensor device (switch) and the SDN controller device, with its implementation results being focused on the delay and memory footprint. The authors in the above studies examined the framework and construction of SDN-based WSNs; however, they did not employ the optimisation technique to discover the optimal clustering method, nor did they use the resources of cloud in their construction because they assumed that the SDN controller is executed at the sink node.

In WSN routing techniques, the energy is generally consumed due to the complexity of the network and data transmission. The control functions are placed within the duties of the node, which maximise network complexity and exploit node resources. Additionally, unbalanced cluster formulation is an inherent concern in WSNs, for this causes uneven energy exhaustion amongst CHs in the network, which can significantly reduce network lifespan. Furthermore, nodes in networks with the MS consume most of their resources when they identify the time scheduling and path of the MS. These protocols are thus not suitable for large-scale networks, because of their high use of energy, due to either the unbalanced formulation of the clusters or insufficient synchronisation between the cluster members (CMs), CHs, and the sink(s).

This paper proposes an efficient load-balancing routing protocol, which defines the concept of SDN in a way that reduces the functionality implemented by the nodes and provides an efficient scheduling technique for the MS across the entire network. The SDN controller uses an efficient AI techniques, which schedules the CMs, CHs, and the MS. This scheduling technique allows the nodes to sleep/wake-up, according to the arrival time of the MS, and thus, enhances the lifespan of the entire network.

III. Problem Formulation

The key main goal of this paper is to develop an energy effective routing protocol for large scale I-IoT networks. However, the WSN nodes suffer from sensor resource restrictions in terms of processing units, battery, communication capability and memory. Hence, a clustering technique is used for the data aggregation process to conserve energy. The cluster formulation process begins by electing the set of CHs responsible for collecting the data from the CMs and forwarding them to the sink, which can be either static or mobile. Consequently, the CHs deplete their energy more rapidly than the cluster members due to: the unbalanced cluster formulation that forces one CH to spend more power than others, performing the data aggregation, and sending these data to the sink from a greater distance than the CMs. Furthermore, in a large-scale network, it is practically impossible to cover the entire region using a static sink. Additionally, the use of such a sink in large scale networks leads to high energy exhaustion among the CHs and increases the hot spot problem due to the connection to the sink.

One effective solution to reduce the energy spent by the CHs is to use the MS. However, its execution in the IoT network presents many challenges, such as: determination of the MS's optimal path and optimal S_{DG}, synchronisation between the MS and the CHs, and protocol overheads for route discovery by the CHs when forwarding their data to the sink. In this study, an energy efficient routing protocol for large scale IoT networks-based AI is proposed that considers the above issues, with the aim of reducing the overall energy consumed by the nodes and thus, prolonging the overall network lifespan. The proposed protocol involves using a centralised architecture based on the SDN and cloud technologies to reduce network complexity, thereby effectively mitigating the overheads generated by the nodes in the route identification procedure. Furthermore, the SDN controller uses AI algorithms to define a load balanced set of clusters that considers the impact of the MS_{Opath} during the CH selection process. In addition, the proposed protocol offers a synchronisation technique between the MS and the CHs that allows the latter to sleep whenever possible and thus, reduces the energy consumed by them.

IV. Proposed Scheduling Protocol-Based Optimisation Algorithms

The proposed approach is divided into four related phases: cluster formation, S_{DG} determination, MS_{Opath} identification and network scheduling with the MS. The following assumptions are made prior to the simulation of the proposed protocol:

1) The sensor nodes are identical in terms of having the same computational and sensing capabilities, but differ in that they have two levels of initial energy;
2) Each sensor node has a chance to transmit its location based on the global positioning system (GPS) using long range transmission.
3) A delay tolerance network is assumed, which can tackle the technical concerns in such heterogeneous networks that may be absent due to the continuous connectivity of the network nodes.

A. Network Architecture

The network is designed in such a way as to reduce the average energy consumed by the CMs and CHs. The protocol is implemented using optimisation algorithms and new technologies, including SDN and the cloud. As shown in Figure 1, the proposed OMS-LB architecture can be organised into three main layers: the infrastructure layer, the processing layer and the application layer. The infrastructure layer is comparable to the data-plane layer in the SDN construction and includes two sub-layers: the data collecting sub-layer and the sensing sub-layer. The data are first collected at the sink or gateway and either sent to the cloud to be stored and used by specific applications, or processed and then sent to the SDN controller to make intelligent routing decisions.

The SDN controller is executed over the cloud and has the responsibilities of: cluster construction by applying AI techniques, S_{DG} determination using PSO, MS_{Opath} identification using a GA, and network scheduling. The use of OMS-LB construction has a crucial impact in that it reduces network complexity. Furthermore, the positioning of the SDN controller over the cloud provides vital benefits by employing its resources for the intention of data storage or processing. For instance, the SDN controller uses the data-centre in the cloud as a huge resource for the tasks of computational, such as the implementation of the optimisation algorithms outlined in this paper. Therefore, the development of the OMS-LB provides efficient mapping and fairness in the allocation of CHs as well as the sink nodes, such that there is no congestion at the sink and redundant paths are provided for it in the event of sink node failure.

B. Clusters Formulation

The suggested protocol employs cloud resources using a centralised SDN controller to find an optimal routing protocol for I-IoT networks. This work provides an intelligent energy efficient routing protocol by combining the impact of the moving cost of the MS to collect the data with the cluster formulation process, such that the energy consumed when sending data over the entire network is reduced. The cluster construction is handled by the SDN controller, which constructs the CT by implementing a load-balanced PSO technique. For the first round, the SDN controller builds the CT using only the coordinate information of the device. For subsequent rounds, the SDN controller exploits the collected information related to the remaining energy and distances to choose the best group of CHs, thus constructing the CT. In addition, at each round, the same CT construction process is performed, if a new node is appended to the network, a CH runs out of energy or a current node earns more energy, for instance, employing energy harvesting technology. For this study, heterogeneity of the nodes is assumed, with different energy levels and no more energy is going to be added to any node in the network throughout the implementation process. Thereafter, the SDN controller transmits the CT to the MS, with the former scheduling information about the clusters, the group of CHs and the CMs connected to each CH (see Figure 1). Subsequently, the MS broadcasts the CT to all the devices, and each inspects it to determine whether it is a CM or CH.

As shown in Figure 2, the PSO begins by generating a group of stochastic particles (GSP), with each particle (p) being a D dimension vector inspected by a fitness function. Hence, the perfect solution for PSO is only achieved after a certain number of iterative evolutions. Throughout these, each p in the swarm (set of nominate solutions) follows the global best (G_{best}) and its personal best (P_{best}). The SDN controller, in this work, computes the average energy of all the devices that are alive at each round and memorises those with a level of energy greater than average as candidates to be CHs, in a matrix known as number of CHs (NCH). Moreover, PSO maximises the cost of the following function:

$$cost = \alpha f_1 + \beta f_2 + \tau f_3 + \gamma f_4 \quad (1)$$

$$f_1 = \frac{\sum_{j=1}^{K} Eng_{(CH_{(p,j)})}}{\sum_{i=1}^{N} Eng_{(n_i)}} \quad (2)$$

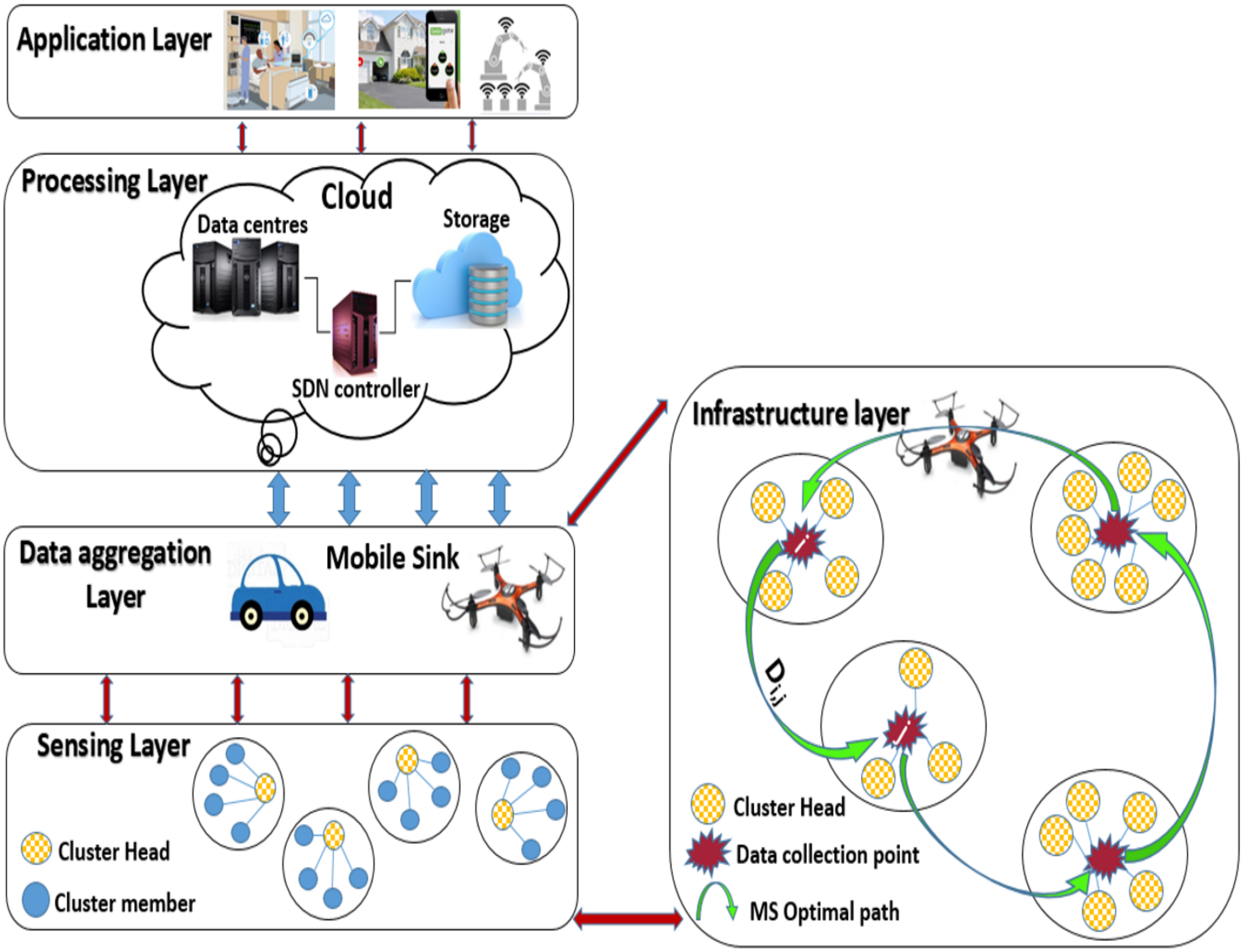

Fig. 1: Routing structure-based SDN and MS

$$f_2 = \sum_{j=1}^{K} \frac{NA_r}{\sum_{i=1}^{NC_{p,j}} dist_{(CH_{(p,j)},n_i)}} \tag{3}$$

$$f_3 = \frac{(LB_{avg})^2}{\delta + \sum_{j=1}^{K} (NC_{(p,j)} - LB_{avg})^2} \tag{4}$$

$$LB_{avg} = \frac{(NA_r - K)}{K} \tag{5}$$

$$f_4 = \frac{S_{DG}}{MS_{Opath}} \tag{6}$$

where, α, β, τ and γ are constants coefficients that employed to weight and balance the influence of each sub-objective [32], i.e. the energy, communication, load balancing and MS_{Opath}, and presented in Table I. The function f_1 identifies the group of CHs with a higher energy percentage. The function f_2 chooses clusters with minimal communication costs between the CH and CMs. The function f_3 selects the set of clusters with a maximum load-balancing rate. The δ, in Equation 4, is a constant that provides a method of escape from the local maximum throughout the progression of the PSO, whilst N, K and NC are the number of network nodes, CHs and CMs, respectively. Furthermore, load balancing in the I-IoT is distinct, whereby there is a uniform distribution of load among the CHs and accordingly, the SDN controller implements a load balancing technique by choosing a well-balanced group of clusters through applying equation 4. The value LB_{avg} is the mean number of CMs belonging to each cluster, and NA_r is the total number of devices alive throughout round r. The function f_4 comprises the minimum movement cost of the MS. The value S_{DG} is the optimal set of the data gathering points discussed in section IV-C, and MS_{Opath} refers to the selection of the optimal path for the MS with minimum distances (see section IV-D). As shown in Figure 2, on determining the routing protocol the cluster formulation in the proposed protocol combines with the impact of the optimal MS movement.

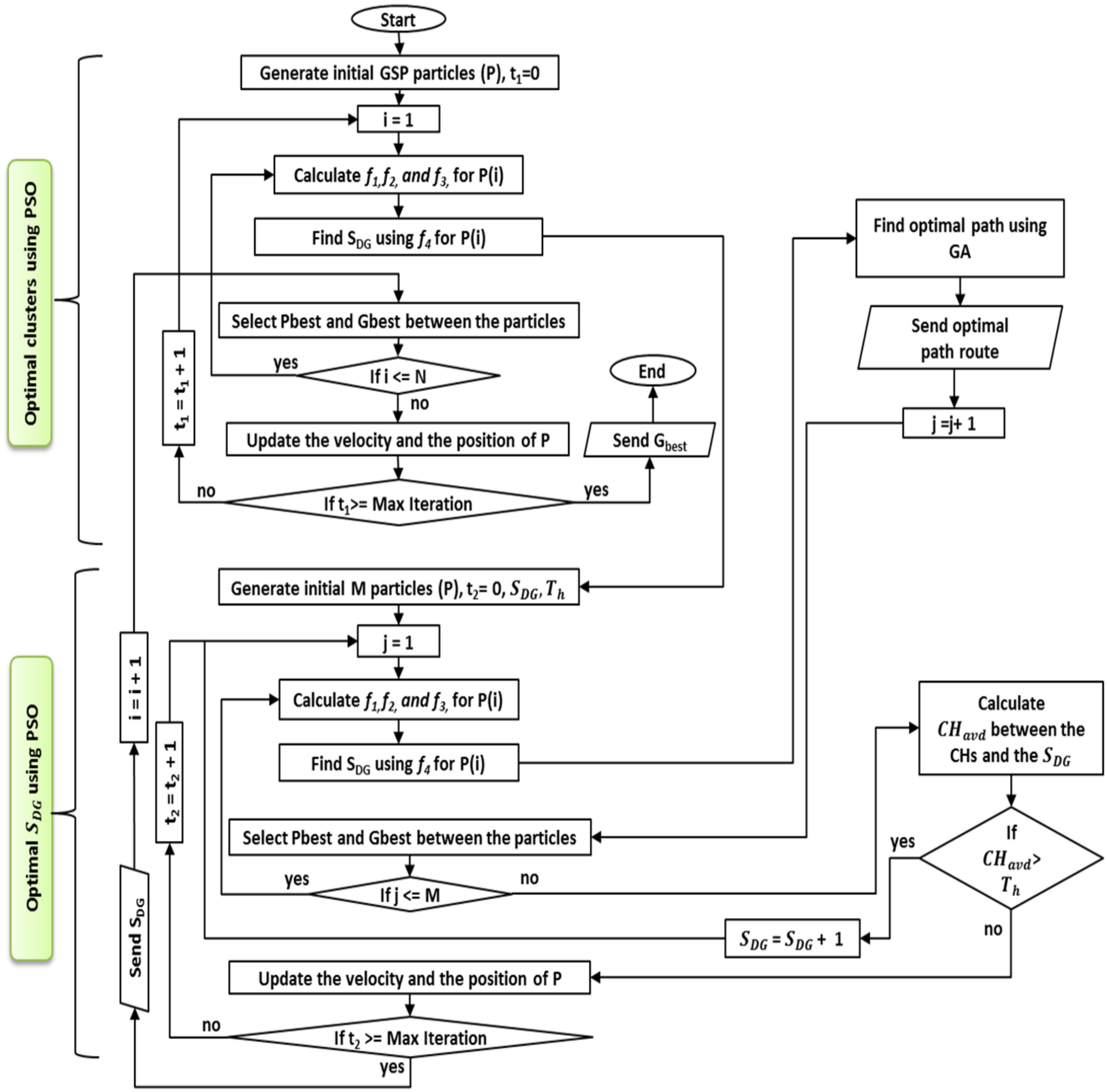

Fig. 2: The flowchart of the $OMS-LB$ cluster formulation based optimisation algorithms

C. Data Aggregation Points

The S_{DG} in the proposed protocol are defined using the PSO algorithm (as shown in Figure 2). Initially, the number of S_{DG} in this work is equal to (DG x K), where DG is the percentage of S_{DG} selected between 0 and 1. Furthermore, the optimal S_{DG} is defined using PSO by maximising the cost of the following fitness functions:

$$cost = \Phi f_{dg1} + \psi f_{dg2} + \mu f_{dg3} \tag{7}$$

$$f_{dg1} = \sum_{i=1}^{S_{DG}} \frac{\sum_{j=1}^{K_i} CHs_{(i,j)}}{S_{DG}} \tag{8}$$

$$f_{dg2} = \sum_{i=1}^{S_{DG}} \frac{K}{\sum_{j=1}^{K_i} dis_{(CH_{p,j}, S_{DGi})}} \tag{9}$$

$$f_{dg3} = \frac{S_{DG}}{optimaldistance} \tag{10}$$

where, Φ, ψ and μ are presented in Table I. The function f_{dg1} selects the S_{DG} that covers the maximum number of CHs. Furthermore, the function f_{dg2} selects the S_{DG} containing the shortest distances between the CHs and their data collection points, whilst the function f_{dg3} selects the S_{DG} with the shortest path for the MS. Moreover, the shortest path found in the last iteration is used in Equation 6 as MS_{Opath}. However, the shortest path is identified using the GA (explained in section IV-D and has the advantages of reducing the delay, which also restricts the energy consumed by the CHs when waiting for the MS. In addition, each CH is connected to the closest S_{DG}, whilst the proposed algorithm has been designed such that the maximum average distance between a CH and the closest S_{DGi} (named as CH_{avd}) is no greater than the threshold (T_h) (see Figure 2). However, if the distance is more than T_h, an extra collection point should be added to the routing design to satisfy a higher level of energy conservation by the CHs.

D. Optimal Mobile Sink Path Determination

One of the problems to be solved, in this subsection, is how to determine the best route (path) for the MS in the search space. Once the SDN controller identifies the optimal S_{DG} using PSO, it executes the GA-based algorithm to evaluate the MS_{Opath}, which passes across all the data aggregation points for S_{DGs} only and collects data from the CHs to the mobile sink using a one-hop transmission. The GA is a heuristic search algorithm based on the principles of natural selection and is used to resolve optimisation problems [37]. It develops finite length strings of alphabet known as chromosomes, which are sets of nominee solutions to the search problem, with these alphabets being also known as genes [38]. The set of chromosomes represents a set of paths, and the genes in each represent the position of S_{DG}, as defined in section IV-C.

The objective function of the GA is based on the shortest path passing through all the S_{DG} positions, one beginning from the position nearest to the start point and returning there without visiting the same node twice (see Figure 1). The process of the GA is described in Figure 2. Once the set of populations is encoded into a set of chromosomes, the fitness function distinguishes good resolutions from bad ones. The process of can be summarised as the following steps:

1) Initialisation: initialising sets of populations for different routes, which are generated randomly as nominee solutions in the search space;
2) Evaluation: evaluating the nominee solutions of parent routes using the fitness function;
3) Selection: selecting two copies of nominee routes with higher fitness values and this is known as survival-of-the-best between the candidate solutions;
4) Recombination: forming a crossover between the selected candidates to create a better solution;
5) Mutation: modifying the route randomly using the GA;
6) Replacement: selecting the best route between the old and that newly generated;
7) Repeat steps 2 to 6 until the optimisation criteria are met.

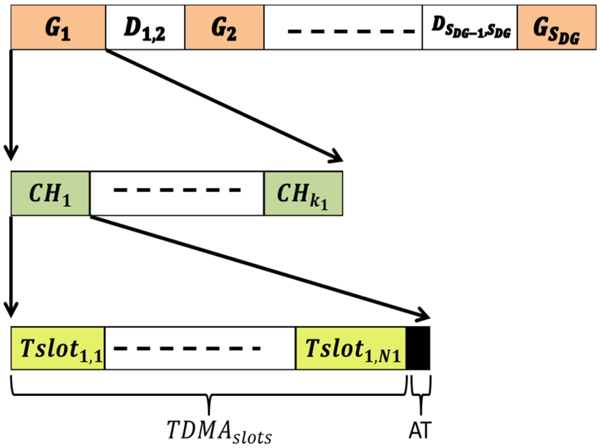

Fig. 3: Network scheduling message

E. Network Scheduling

Network scheduling is one of the key challenges in the design protocols of WSNs. Without it, the devices deplete higher energy when accessing the channel or waiting for a chance to send their data. In this paper, a network scheduling technique arranged by the SDN controller is proposed in the form of a network scheduling message (NSM) shown in figure 3. This message is used to schedule the sleep/wakeup period of the CHs, according to the arrival time of the MS. Furthermore, the data transmission period is also structured by the SDN controller using time division multiple access (TDMA) scheduling. Additionally, regarding the TDMA scheduler, all the CMs send their residual energy, ID, and data to their predetermined CH throughout their definite slot duration and shut down their radio across all others to save energy.

Figure 3 depicts the structure of the proposed scheduling technique, where each device in the network has its own time slot in which to send its data. Furthermore, all the CMs and CHs can turn their radio off to conserve energy, if the MS has not yet arrived; however, according to NSM, the devices can turn their radio on once it has. The total delay in the network, which is equivalent to the time required by the MS to perform one lap, can be calculated according to Figure 3, as follows:

$$Delay = \sum_{i=0}^{S_{DG}} G_i + D_{i,i+1} \tag{11}$$

where, G_i represents the time spent by the MS at S_{DGi} to collect the data from K_i number of CHs, which belong to the aggregating point i. Furthermore, G_i is calculated as follows:

$$G_i = \sum_{j=0}^{K_i} \sum_{L=0}^{N_j} T_{slot(j,L)} + AT_i \tag{12}$$

where, N_j is the number of nodes connected to CH_j and is identified by the SDN controller during the generation of the TDMA schedule. $T_{slot(j,L)}$ represents the time slot used by the device L to send its data to CH_j. The value $D_{i,i+1}$, in Equation 11, considers the delay by the MS in moving from S_{DGi} to S_{DGi+1} (See Figure 1), and is calculated as follows:

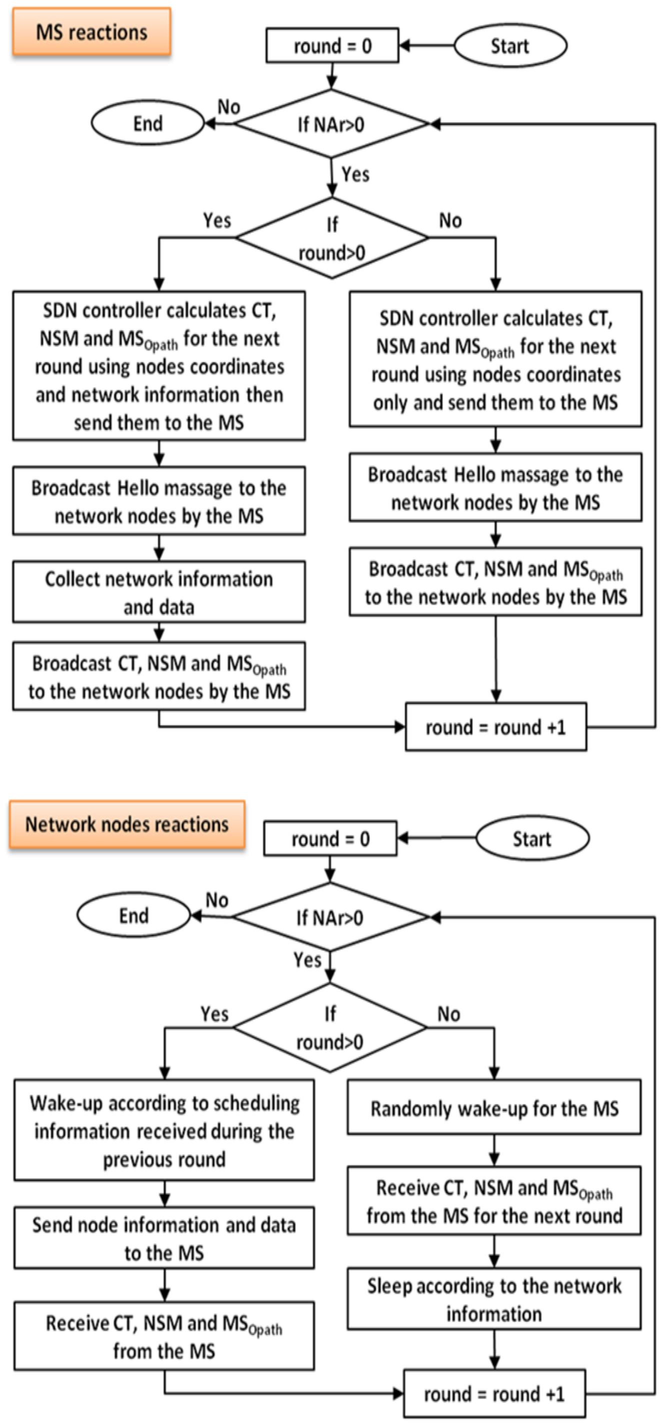

Fig. 4: Reactions that needs to be performed by both the MS and network nodes

$$D_{i,i+1} = \frac{Dis_{i,i+1}}{V_{MS}} \tag{13}$$

where, $Dis_{i,i+1}$ is the Euclidean distance between S_{DGi} and S_{DGi+1}, and V_{MS} is the velocity of the MS.

As shown in figure 4 the overall scheduling process can be divided into two main reactions: those performed by the MS, which are previously provided by the SDN controller, and those that are implemented by the network nodes. According to the round sequence, each of these reactions includes two phases, which are the initial step at round zero and the subsequent rounds. The initial MS reaction is started by the SDN controller that calculates the CT, NSM, TDMA and MSOpath using the node coordinates only and sends this information to the MS, which in turn broadcasts them to the network nodes to be used as scheduling information. In this way, the network nodes will be able to recognise themselves as CHs and CMs in the next round. In addition, according to the MSOpath, CT and the velocity of the MS, they will be able to know the next arrival time of the MS. For the subsequent rounds, the nodes send data to the CHs during their specified TDMA time slot. Moreover, as shown in figure 3, all the other nodes for a particular cluster have to wake-up at the end of the TDMA slots for announcement time (AT) to receive the scheduler information from the MS for the next round, which has been previously prepared by the SDN controller.

F. Radio Model

The first order radio scheme proposed in [28] is employed in this work. Each device can waste its energy in amplification (E_{amp}), reception (E_{RX}), transmission (E_{TX}), and data aggregation (E_{DA}). Additionally, to attain evident levels of Signal-to-Noise Ratio (SNR) in broadcasting a single bit over a distance d, the E_{amp} is expressed by:

$$E_{amp} = \begin{cases} \varepsilon_{FS} d^2 & \text{if } d < d_0 \\ \varepsilon_{TR} d^4 & \text{if } d \geq d_0 \end{cases} \tag{14}$$

Where ε_{FS}, ε_{TR}, and d_0 are stated in Table II. Furthermore, the required energy to receive or send l bits over a distance (d) is given in Equation 15 and 16, respectively:

$$E_{TX}(l,d) = lE_{elec} + lE_{amp} \tag{15}$$

$$E_{RX}(l,d) = lE_{elec} \tag{16}$$

where E_{elec} is the energy depleted in the electronic circuit to transmit or receive a single bit. Moreover, all other radio simulation parameters are given in Table II.

V. Performance Evaluation Results

A. Network Set-up

The proposed network model consists of N stationary I-IoT devices, which are position aware and randomly deployed in a X, Y square metre network field. In this work, there is consideration of the results of two cases aimed at improving the scalability of the proposed protocol, which are: network size 200m x 200m, and network size 700m x 700m. Additionally, the network employs two degrees of device heterogeneity, these being: 50 percent of advanced devices and 50 percent of normal devices. The normal devices have $0.5J$ of initial energy and the advanced ones have $1J$, while the sink device (static or mobile) is presumed to be resource sufficient. The traditional network based static sink device is located at the centre of the network. Besides this, at each round, K is set to

TABLE I: PSO simulation parameters

Parameter	Value	Definition
GSP	40 particles	Swarm size
It_{max}	400	Maximum number of iterations
α	0.2	Energy parameter
$\beta = \psi$	0.3	Distance parameters
τ	0.2	Land balancing parameter
γ	0.3	MS_{Opath} weight parameter
δ	1	Load balancing constant
Φ	0.3	number of CHs covered parameter
μ	0.4	route length parameter

TABLE II: Network parameters used in the simulation

Parameter	Value	Definition
N	200	Number of network devices
E_{elec}	$50nJ/b$	Energy depleted to transmit one bit
ε_{FS}	$10pJ/b/m2$	Amplifier energy for free space
ε_{TR}	$0.0013pJ/bit/m4$	Amplifier energy for multipath space
E_{DA}	$5nJ/bit$	Energy required to aggregate data
d_0	$\sqrt{\frac{\varepsilon_{FS}}{\varepsilon_{TR}}}$	Threshold of the transmission distance
Packet	$4000bit$	Size of data message
V_{MS}	3 m/sec	Velocity of the MS

be 10 percent of all the live devices (NA_r) and the number of S_{DG} is initially set to be 50 percent of K. Moreover, the number of S_{DG} continues to increase until it satisfies the average destination criteria stipulated in function (7). All the relevant simulation parameters are presented in Table I and Table II.

B. Performance Evaluation

Extensive simulations are applied using MATLAB simulator to demonstrate the performance of the presented clustering scheme and the MS_{Opath}-based AI. To improve the efficiency of the presented clustering scheme-based optimisation, the OMS-LB protocol was compared to two well-known clustering-based routing techniques with a static sink: LEACH and PSO-C.

Furthermore, to improve the effectiveness of the proposed OMS-LB, it was first compared with the centralised clustering algorithm-based load balancing without the use of the MS, namely, CLBCA. Then, it was compared to the MIEEPB-based MS and the random move determination for the MS-based load balancing, called RM-LB, using the same proposed clustering algorithm in CLBCA to identify the optimal set of CHs. The RM-LB uses the random wake technique similar to the approach provided by [19] and [20]. Network lifespan is identified as the number of alive devices over time (rounds) from the initiation of the transmitting until the death of the last device in the intended network. Moreover, the network lifespan is categorised into two phases: the stable phase (from the initialisation of transmitting until the death of the first device) and the unstable one (from the death of the first device until that of the last).

Figures 5 and 6 illustrate the network lifespan. It is clear from the figures that the suggested protocol can considerably extend the overall life of the network, essentially the stability

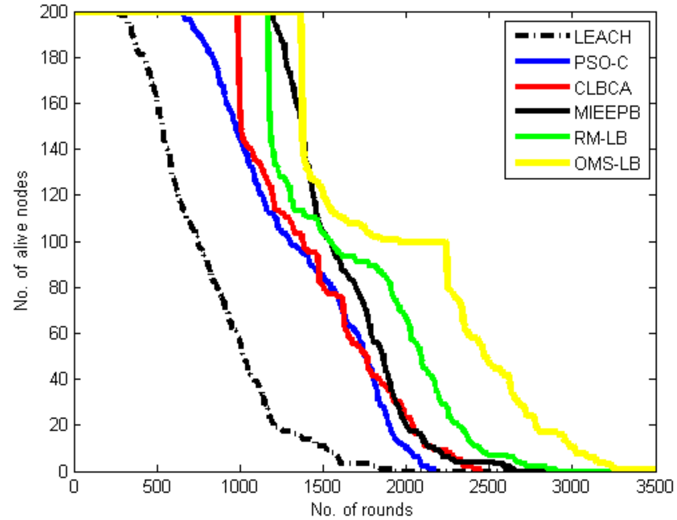

Fig. 5: Network lifespan when the IoT network size = 200 x 200

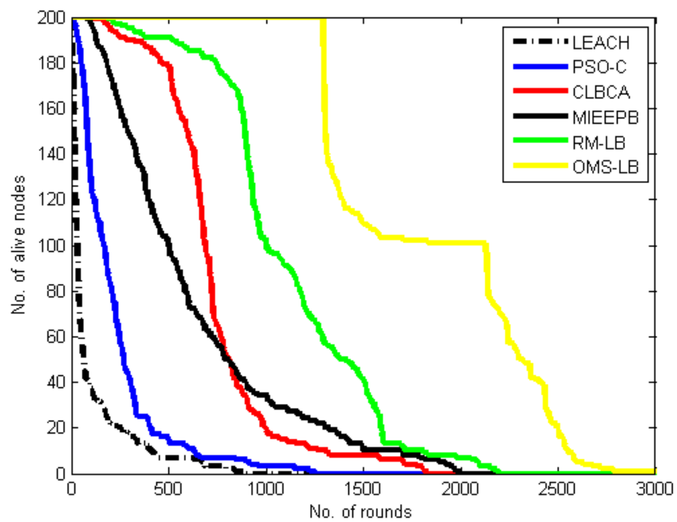

Fig. 6: Network lifespan when the IoT network size = 700 x 700

phase, in comparison to other routing protocols. The improvement in the overall network lifespan and the long stability phase justify the attention of load-balancing, S_{DG}, network scheduling and the MS_{Opath} by the PSO through the cluster construction process. Additionally, the figures show that the death of the first device of the protocol occurs at approximately rounds 1410 and 1280 for Figures 5 and 6, respectively.

The proposed protocol enhances the stability period compared to other protocols, and the curve displays a relatively steep decline. This is the outcome of fair load-balancing and consideration of the optimal route for the MS using the GA. Hence, the entire network has many devices within a small amount of preliminary energy that all give out at the same interval. Figures 5 and 6 show the network lifespan for the first and second cases, respectively. It is obvious from these figures that the presented algorithm exhibits efficient energy

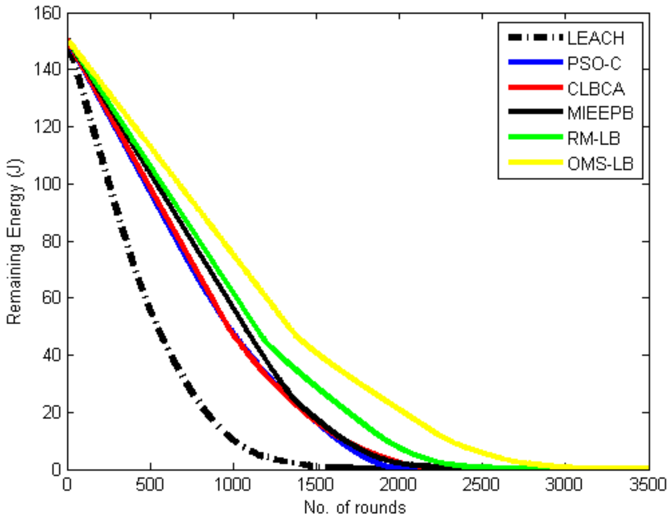

Fig. 7: Remaining energy in joule when the IoT network size = 200m x 200m

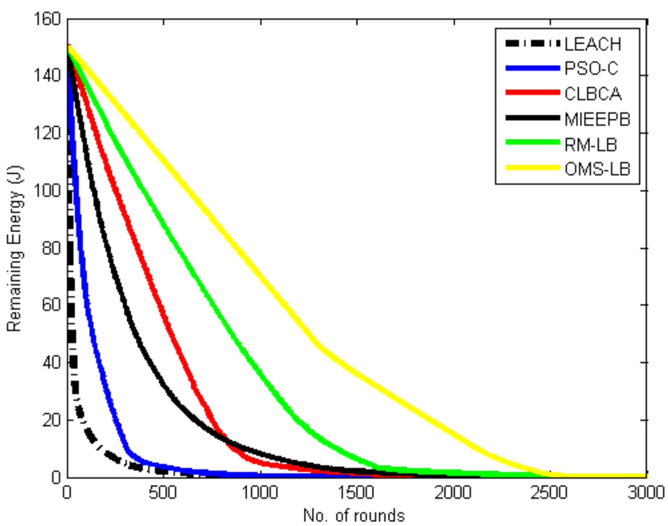

Fig. 8: Remaining energy joule when the IoT network size = 700m x 700m

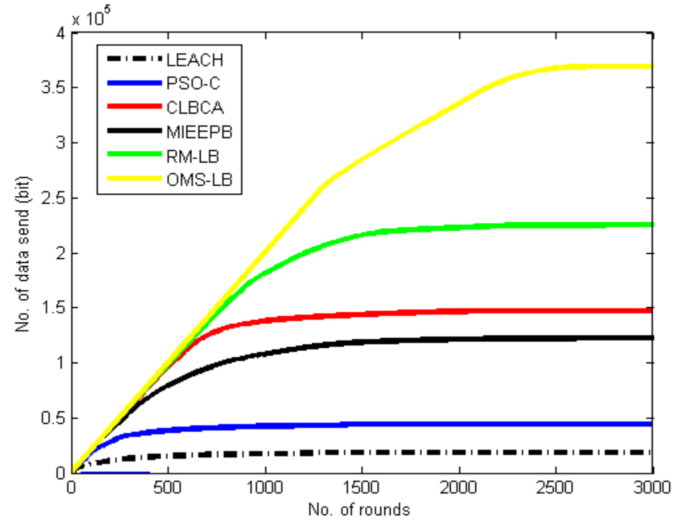

Fig. 9: Volume of data sent when the IoT network size = 200m x 200m

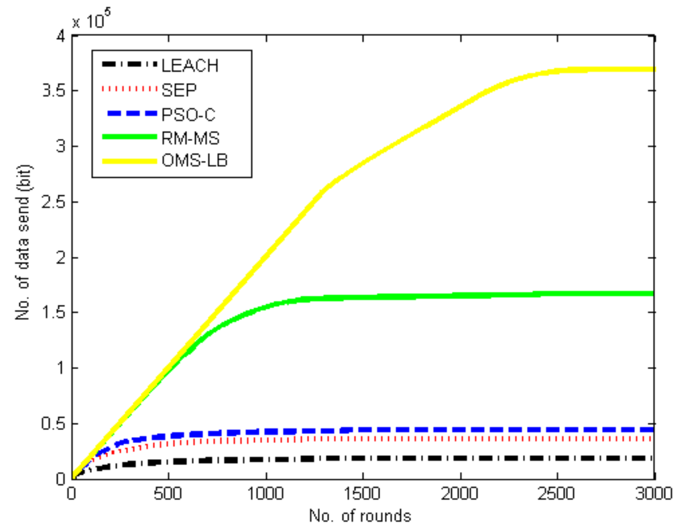

Fig. 10: Volume of data sent when the IoT network size = 700m x 700m

consumption and furthermore, it works more efficiently with a large-scale network than do other protocols. The MIEEPB routing protocol uses the MS, under the assumption that the path of the MS and the number and positions of the data collection points are constant. As a consequence, the nodes will spend more energy in sending their data, especially in large scale networks. Additionally, the overall performance indicates that, compared to RM-LB, MIEEPB, CLBCA and PSO-C, the OMS-LB protocol prolonged the life of the network in the first case, by 15%, 19% 25% and 37% percent, respectively, and in the second case, by 23%, 31%, 38% and 54%.

Figures 7 and 8 display the residual energy of the I-IoT nodes with the simulation rounds for the first and the second case. All the protocols start with the same level of initial energy. However, the OMS-LB protocol has more residual energy than the existing protocols in both cases. This is because, firstly, the OMS-LB efficiently disseminate energy consumption among all the devices throughout each round in contrast to other protocols; hence, the entire network remains alive for an extended time. Such efficient distribution is due to the fair load balancing technique executed by the SDN controller through the cluster formulation process using Equations 1 and 7. Secondly, the determination and customisation of the MS_{Opath} using AI algorithms improves data gathering across the network field and ensures that the nodes save their energy for future transmission and control duties.

Fairness in energy dissipation through the network field means that the OMS-LB sends substantially more packets to the base station than other protocols, as displayed in Figures 9 and 10. The overall throughput of the I-IoT devices is enhanced by approximately 62%, 33%, 28%, 20% and 15%, respectively in comparison to LEACH, PSO-C, CLBCA,

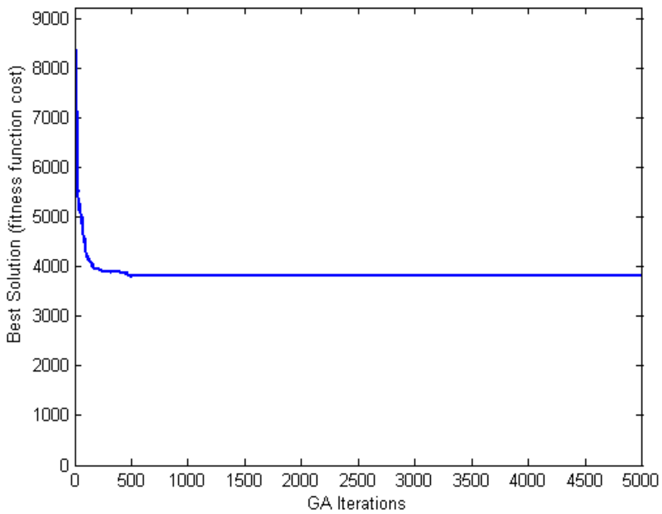

Fig. 11: Convergence cost of GA fitness function to find MS_{Opath}

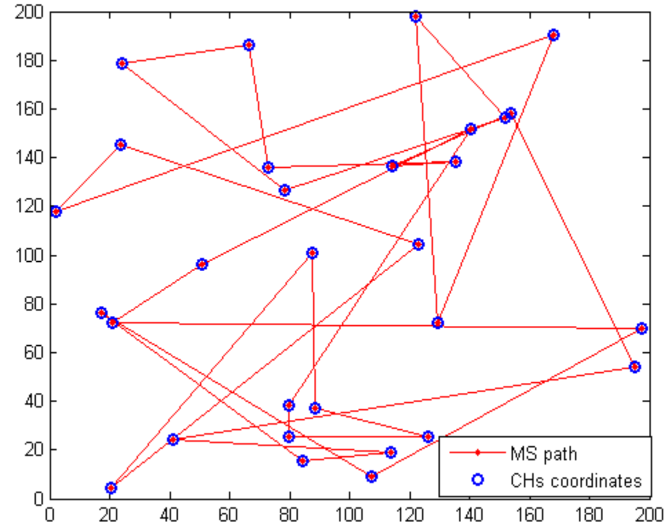

Fig. 13: MS path in meter using RM-LB, the MS pass through each CH in a random movement over $200m \times 200m$ geographical area

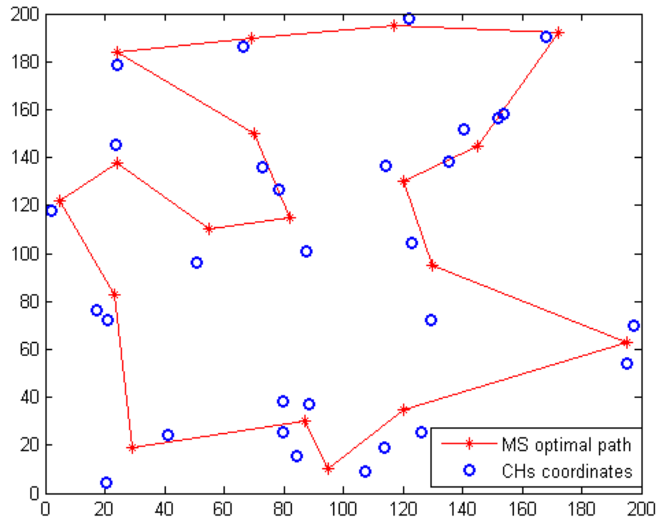

Fig. 12: MS_{Opath} in meter using OMS-LB, the MS pass through the S_{DG} not the CHs over $200m \times 200m$ geographical area

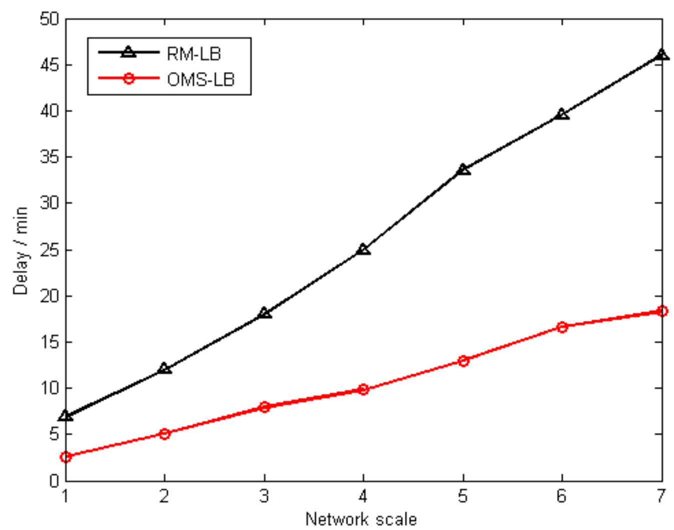

Fig. 14: The route delay with network scale when the MS velocity =3m/sec

MIEEPB and RM-LB for the first case and by approximately 93%, 86%, 62%, 69% and 44% for the second case with a large scale network. The OMS-LB routing protocol reduces the number of hops from the sensor nodes to the CH node and from the CHs to the S_{DG} using the PSO. This reduction in hop count will minimise the energy wasting in relay nodes. Furthermore, the proposed algorithm schedules the entire network with the aid of the GA, which allows most of the sensor nodes and the CHs to conserve energy by turning their radio off. Consequently, the volume of data sent increases as the lifespan of the network increases.

Figure 11 illustrates the convergence process of the GA-based MS_{Opath} after a few iterations when reaching the optimal solution. The figure shows how quickly the proposed approach converges to the MS_{Opath} when the sensing field has the maximum number of S_{DG}. Figure 12 displays the optimum mobile sink path in red for the proposed OMS-LB, indicating where the MS visits the S_{DG} not the the CHs to collect the data from the cluster heads. Therefore, this figure gives a clear indication of the optimum path, which passes through the minimum number of S_{DG} in the sensing area. Figure 13 shows the MS random path for the RM-LB, which visits each CH to collect the data from the CHs. Therefore, the route length of the RM-LB is longer than that of the proposed OMS-LB.

Figure 14 compares OMS-LB and RM-LB in terms of the delay. The network scales (1, 2, 3, 4, 5, 6 and 7) refer to the network fields (100m x 100m, 200m x 200m, 300m x 300m, 400m x 400m, 500m x 500m, 600m x 600m and 700m x 700m), respectively. It is clear from the figure that the MS delay using the proposed OMS-LB has been reduced in comparison to the RM-LB. This reduction is the result of using AI, i.e., the PSO to identify the optimal set of S_{DG} and GA during the path determination process, whereas the RM-LB chooses the CHs positions as a collection points and move randomly to collect the data, which causes more delay and a longer MS path.

VI. Conclusion and Future work

This paper has presented a flexible and scalable intelligent routing protocol-based mobile sink path administration for large scale I-IoT networks, known as OMS-LB. The OMS-LB comprises a centralised network construction that integrates the SDN concept in IoT, exploits the huge resources of the cloud to minimise network complexity, and employs AI to specify the best group of clusters and the MS_{Opath} for collecting the data from the I-IoT network. Moreover, the SDN controller employs a framework that considers the impact of MS movement during the cluster construction process. This framework uses GA and PSO algorithms to construct the optimal S_{DG} and MS_{Opath} and thus, reduce the energy consumed by the CHs and prolong the life of the network. Furthermore, this framework ensures the proposed protocol is highly flexible and will work successfully with both large and small-scale networks. Moreover, the SDN controller uses a cost-effective load-balancing scheme with the PSO to launch a well-balanced group of clusters that encompasses the entire network. The results for the case of the large-scale network show that, compared to RM-LB, MIEEPB, CLBCA, PSO-C and LEACH, the proposed OMS-LB protocol increases the number of packets sent to the MS by factors of 54%, 86%, 88% and 93%, respectively as well as increasing the lifespan of the network by up to 36%, 54%, 62% and 66%, respectively.

One further research direction that can deliver energy efficiency within a large-scale network, is the association of network function vertualisation (NFV), multiple MS and SDN controllers. However, the involvement of such technologies in the networks will be accompanied by a number of issues, which accordingly, will open up many other research inquires. Examples of these are: distinguishing the paths and synchronisation of the multiple MSs as well as quantifying the optimal number, position and distribution of the controllers. The involvement of SDN technology can significantly reduce the energy depleted by the nodes due to processing and aggregation. In particular, more research in the future is essential to evaluate the trade-off between the processes implemented by the SDN controller and the nodes. Finally, investigation of SDN impact on I-IoT networks needs to be evaluated more in the future using different types of controllers, such as Floodlight and NOX.

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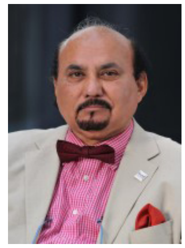

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