Chapter

On the Efficacy of Particle Swarm Optimization for Gateway Placement in LoRaWAN Networks

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Abstract

The efficacy of the Particle Swarm Optimization (PSO) in determining the optimal locations for gateways in LoRaWAN networks is investigated. A modified PSO approach, which introduces gateway distancing measures during the initialization phase and flight time, is proposed. For the ease of comparisons and the understanding of the behavior of the algorithms under study, a square LoRaWAN area is used for simulations. Optimization results on a LoRaWAN script, implemented in NS-3, show that the modified PSO converges faster and achieves better results than the traditional PSO, as the number of gateways increases. Results further show that the modified PSO approach achieves similar performance to a deterministic approach, in which gateways are uniformly distributed in the network. This shows that for swarm intelligence techniques such as PSO to be used for gateway placement in LoRaWAN networks, gateway distancing mechanisms must be incorporated in the optimization process. These results further show that these techniques can be easily deployed in geometrically more complex LoRaWAN figures such as rectangular, triangular, circular and trapezoidal shapes. It is generally difficult to figure out a deterministic gateway placement mechanism for such shapes. As part of future work, more realistic LoRaWAN networks will be developed by using real geographical information of an area.

Keywords: Internet of Things, Particle Swarm Optimization, Networks, Simulation, LoRaWAN

1. Introduction

As more and more devices are being embedded with networking capabilities, the Internet of Things (IoT) paradigm is becoming more entrenched in the society. IoT devices communicate with other devices on the Internet seamlessly. To date, IoT has found ample applications in diverse areas such as health, agriculture, safety and security, smart homes, smart water management, smart grids, fleet management and traffic monitoring.

With the accelerated adoption of 5G, companies' plans to invest in IoT solutions will increase even more rapidly. The recent fourth annual Global IoT Executive Survey [1] shows that the number of IoT devices will increase from 8 billion in 2019 to more than 41 billion IoT devices by 2027. Furthermore, the IoT market is geared to grow to over $ 2.4 trillion annually by 2027.

IoT connectivity was primarily based on short range wireless technologies such as Bluetooth mesh networking, Wi-Fi (IEEE 802.11 standard) and Zigbee (IEEE 802.15.4 standard). The trend is, however, shifting toward Low-Power Wide Area Networks (LPWANs), which provide low power, low data rate and long range wireless transmission in the unlicensed frequency bands, configured in a star topology network [2–4]. Interest in LPWANs is further fueled by low deployment costs, large coverage, and the absense of competitors from cellular technologies in the IoT arena [3]. Examples of LPWAN technologies include Sigfox, Narrowband-IoT (NB-IoT) and Long-Range Wide Area Networks (LoRaWAN) [5].

The LoRaWAN technology currently enjoys greater popularity because it is supported by the LoRa Alliance, which is a non-profit association of more than 500 member companies [6]. It is for this reason that this work focuses on this technology. The LoRaWAN network is a star-of-stars topology, where messages are relayed between end devices (EDs) and the central network server (NS) through gateways (GWs). Gateways are linked to the network server through standard IP connections. They act as transparent bridges by converting RF packets to IP packets and vice versa [7].

Although gateways in LoRaWAN networks can cover large areas of end devices, coverage problems still arise when the areas are too big. In such cases, the need to deploy multiple gateways arises [8, 9]. In [8] the impact of redundant packet reception at multiple gateways on data reliability in the LoRaWAN architecture studied, while in [9], an adaptive algorithm for spreading factor selection in LoRaWAN networks with multiple gateways is proposed. In the latter, the maximum number of number of gateways was four and their locations were fixed deterministically.

This work builds on those earlier works by investigating the efficacy of Particle Swarm Optimization (PSO) for gateway placement in a LoRaWAN network. It draws its the motivation from recent studies on PSO based placement of Master Nodes (MNs) in smart water metering networks (SWMNs) [10, 11]. In these networks, Wi-Fi links were used to create a mesh network for the transmission of readings from Smart Meters to Master Nodes. The need to extend PSO approach to LoRaWAN arises naturally because of the advantages of this technology and its growing popularity in the IoT community.

This work adopts a square area, where EDs are deployed randomly and gateways are deployed by using three approaches: 1) the optimal approach based on the standard PSO; 2) the optimal approach based on the PSO algorithm that incorporates gateway distancing mechanisms to prevent gateway interference; 3) and the deterministic approach, where the area is broken down into a number of equally-sized sub-areas, according to the number of gateways and having one gateway deployed at the centre of each sub-area. The LoRaWAN scripts have been implemented using the LoRaWAN NS-3 [12] module [13]. For the PSO approaches, the optimiser which operates at a higher level, invokes the LoRaWAN script, on every function evaluation to calculate the Packet Delivery Ratio for the gateway position configuration created by the algorithm at that moment.

The rest of this Chapter is organized as follows. Section 2 briefly describes the LoRaWAN technology. An overview of Particle Swarm Optimization (PSO) is given in Section 3. Section 4 presents the distancing mechanisms that have been added to standard PSO in order to enhance the spreading of the gateways in the network. Section 5 presents the experimental setup, the results and discussions, and Secton 6 concludes the Chapter.

2. Overview of the LoRaWAN technology

This section gives a brief overview of the aspects of LoRa and LoRaWAN technologies, that are relevant to this study.

2.1 LoRa

LoRa (Long Range) [6] is a physical layer LPWAN technique, developed by Cycleo in France and acquired by Semtech [14]. This technique uses the chirp spread spectrum (CSS) technology, which spreads a narrow-band signal over a wider channel bandwidth. This process greatly enhances the signal's robustness to interference thereby creating long range, low data rate communication over the license-free sub-1GHz Industrial Scientific Medical (ISM) radio bands. The transmission range in LoRa depends on various parameters: bandwidth, coding rate, transmission power, carrier frequency, and six spreading factors (SF), ranging from 7 to 12. These SFs are known to be quasi-orthogonal because they enable simultaneous receptions of packets with different SFs. Another important characteristic is that the increase in SF is accompanied by the signal's resilience to noise, at the expense of data throughput.

2.2 LoRaWAN

LoRaWAN is an upper layer technique that relies on the physical layer LoRa technique. While the LoRa technology is proprietary, LoRaWAN is an open standard, developed and supported by the LoRa Alliance [6]. It is an ALOHA-based protocol which organizes networks in a star-of-stars topology, with the following major components:

1. *End devices (EDs)*, which generate uplink data and send it to the network server through the gateway through a single-hop LoRa communication. EDs also receive downlink traffic from the gateways.

2. *Gateways (GW)*, which serve as link between the EDs and the network servers by using and IP backbone. They collect data sent by EDs and forward it to network servers. They also relay packets sent by the network servers to the EDs.

3. *Network Server (NS)*, which serves as the central coordinator and controller of the LoRaWAN network.

The LoRaWAN standard defines three types of EDs, namely Class A, Class B, and Class C. Class A is the default class which must be supported by all LoRaWAN EDs. In this class, communication is always initiated by the ED and is fully asynchronous. Uplink transmission is followed by two short downlink windows, to cater for bi-directional communication and/or the transmission of network control commands. In addition to all the components of Class A, Class B EDs provide regular receive windows for potential downlink traffic. In Class C, the EDs remain in continuous receive mode thereby reducing latency on the downlink path.

The LoRaWAN standard also supports an Adaptive Data Rate (ADR) scheme, which enables the NS to maximize both battery battery life of the EDs and overall network capacity, by setting the data rate (DR) and RF output power for each ED individually. When radio conditions are bad, data rate is lowered by increasing th SF, leading to low coverage. Conversely, when radio conditions are good, data rate is increased by lowering the SF or by reducing the transmit power of a node in order to maximize the battery lifetime and optimize overall network capacity. LoRaWAN also suffers from collisions of packets at the gateways [9, 15–17]. This happens when two or more signals arrive at the the gateway in same time duration. These collisions lower the data rates drastically.

Furthermore, this standard also faces the problem of network coverage when the network area is very large. In this case, one GW cannot cater for all the EDs in the area. As a result, there is a need for multiple gateways. To ensure that the network is optimally covered, there is a need for sufficient inter-gateway distance. The work in [9] implemented a maximum of 4 gateways in a 16 km $\times$ 16 km square area, in which the gateways are located at the centres of the four quadrants. The results of this work show that higher packet delivery rates are achieved with 4 GWs as the network coverage area increases. In [8], the impact of redundant packet reception at multiple gateways on data reliability is studied. This work models the Average Successful Transmission Probability (ASTP) as a function of end device density, gateway density, and traffic intensity thereby providing useful insights into the deployment of multiple gateways in LoRaWANs.

Since this work focuses on the determining the effectiveness of Particle Swarm Optimization (PSO) for the placement of multiple gateways, the next section presents an overview of the standard PSO algorithm.

3. The standard particle swarm optimization algorithm

Introduced by Kennedy and Eberhart in 1995, the Particle Swarm Optimization (PSO) draws inspiration from the social behavior of animals living in swarms, such as flocks of birds [18]. PSO is initialized with a population of N particles that are generated randomly in a pre-determined search space S of D dimensions. Each particle denotes a candidate solution to a problem and is characterized by three main parameters: its *current position*, *current velocity* and the *best position* ever found by the particle during the search process. The particles fly in the search space in order to find the optimal solution. The trajectory of a particle is influenced by the particle's own experience as well as it's neighboring particles. The velocity of the i-th particle is updated at every iteration by using

$$v_i(t) = \omega * v_i(t-1) + c_1 r_1 \left(p_i^b - x_i(t)\right) + c_2 r_2 \left(g^b - x_i(t)\right), \tag{1}$$

where $i = 1, 2, \dots, N$; c_1 and c_2 are constants denoting cognitive and social parameters respectively.

The values of c_1 and c_2 are chosen in the range $[0.5, 2.5]$. They are applied to cater for the influence of the particle's historical best position p_i^b and the swarm's best position g^b respectively. Parameters r_1 and r_2 are random numbers uniformly distributed within $[0, 1]$, while ω denotes the inertia weight; it helps to dampen the velocities of the particles to assist in the convergence to the optimum point at the end of the optimization iteration.

In order to keep the particle's velocity bounded, a further arbitrary parameter $V_m = (v_{m1}, v_{m2} \dots v_{mD}) \in S$, was defined. Whenever, a vector element, exceeds the corresponding element of V_m, the element is reset to its upper limit. Once the velocity has been updated by using Eq. (1), the position of each particle is updated at each iteration by using

$$x_i(t+1) = x_i(t) + v_i(t+1). \tag{2}$$

In terms of implementation, the PSO algorithm goes through the following steps:

1. *Initialization*: It begins by initiliazing N, c_1, c_2, ω, and G, which denotes the maximum number of iterations. Then the initial population of N particles is generated with random values from the search space and initial velocities for each particle are set to 0. The fitness function values for all N particles are evaluated based on their initial positions. The initial positions of each particle are set as the personal best positions for the respective particles, and the overall best position found so far is set as best solution for the swarm.

2. *Flight time*: Once the initialization process is done, the algorithm goes into the iterative process. At each iteration, the particle positions in the search space are updated using Eqs. (1) and (2); fitness function values of all particles are updated based on their new positions. If necessary, personal best and global best values are updated accordingly.

3. *Termination*: This iterative process is terminated once G iterations are completed. At this point, the best solution for the swarm becomes the optimal solution for the optimization run.

The next section discusses the gateway distancing measures that have been incorporated in the standard PSO algorithm in order to spread out the locations of gateways in the LoRaWAN network.

4. Gateway distancing measures in PSO

This section presents the gateway distancing measures that were incorporated in the PSO algorithm. Properly distanced GWs will help to ensure that the network coverage is high, thereby increasing the packet delivery rate (PDR). Before presenting these measures, the GW placement optimization problem has to be presented.

4.1 The GW placement optimization problem

The GW placement optimization problem adopts the approach used in the Master Node optimization problem in [10, 11]. A LoRaWAN network is assummed to contain n_{ed} EDs in a rectangular area defined by $L \times M$, where L and M are in kilometers. The number of GWs in the network is denoted by n_{gw}. The location of each GW is defined by the x and y coordinates. As a result, the number of variable parameters in the vector of GW coordinates that depicts the locations of all the n_{gw} GWs is $2 * n_{gw}$. In PSO terminology, this vector is called a particle. For instance, for a LoRaWAN network with 4 GWs, the number of parameters in the particle will be 8. The aim of the optimization process is to obtain the particle that achieves the highest packet delivery ratio (PDR), where PDR is defined by

$$PDR = P_r/P_s, \tag{3}$$

where P_r is the number of packets received at the NS, excluding duplicate packets, while P_s denotes the number of packets sent by by the EDs. The location information for the $2 * n_{gw}$ GWs can be encoded in a particle by using

$$\mathbf{p} = (p_0, p_1 \cdots p_{D-1}), \tag{4}$$

where p_0 and p_1 are the coordinates of the first GW; p_2 and p_3 are the coordinates of the second GW; p_D and p_{D-1} are the coordinates of the final GW; $D = 2 * n_{gw}$. If the standard PSO is used, each even-indexed element of the particle is defined within $[0, L]$, while each odd-indexed element is defined within $[0, M]$, denoting the x and y-cordinates respectively. When GW distancing measures are employed, this process is modified as explained in the next subsection.

4.2 The PSO algorithm with GW distancing measures

GW distancing measures can be applied during the initialization process as well as during flight time. During initialization, the initial GW positions can be set in such a way that they are sufficiently far away from each other. During the iterative process, only those particles that depict sufficient average inter-gateway distance are evaluated. Next, the two techniques that would address GW distancing requirements will be presented.

4.2.1 GW distancing during initialization

This technique aims at initiliazing the locatons for the respective GWs to some equal but distinct sub-areas of the LoRaWAN. The lengths of the sides of each of those sub-areas be denoted by ΔL and ΔM can be defined by

$$\Delta L = L/\sqrt{n_{gw}} \tag{5}$$

and

$$\Delta M = M/\sqrt{n_{gw}}. \tag{6}$$

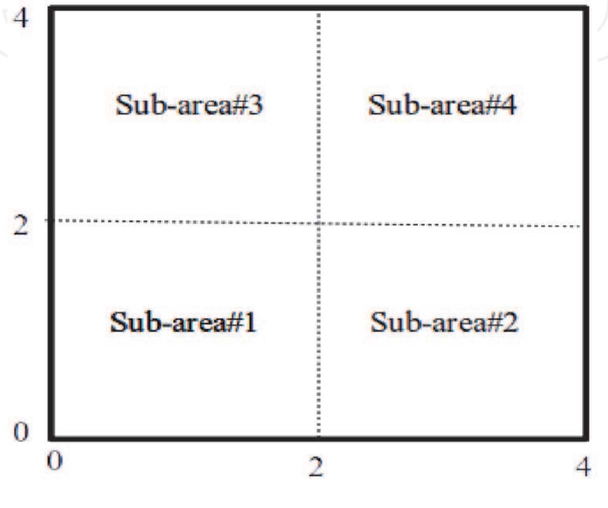

Figure 1.
Illustration of the sub-areas used in the GW initialization process.

For instance, if 4 GWs are initialized in a square LoRaWAN area of sides 4 km by 4 km, $L = M = 4km$, ΔL and ΔM would both be equal to 2 km as illustrated in **Figure 1**. Each GW will be initialized in the distinct sub-area such that the coordinates for the four GWs will be initialized as follows: for GW1, $x \in [0, 2]$ and $y \in [0, 2]$; for GW2, $x \in [0, 2]$ and $y \in [2, 4]$; for GW3, $x \in [0, 2]$ and $y \in [2, 4]$; and for GW4, $x \in [2, 4]$ and $y \in [2, 4]$.

For some LoRaWAN network areas and designated number of GWs, it will not be possible to fit all the GWs into the network by using the aforementioned approach. In such cases, the extra GWs can be randomly initialized with coordinates drawn from the entire area. The number of extra GWs n_{egw} can be determined by using

$$n_{egw} = n_{gw} - (M/\Delta M * L/\Delta L) \tag{7}$$

4.2.2 GW distancing during flight time

The parameter that governs GW distancing during flight time is the average inter-gateway distance d_k, which is defined for each particle k in the swarm by using

$$d_k = \frac{1}{n_e} \sum_{i=0}^{n_{gw}} \sum_{j=i+1}^{n_{gw}} \sqrt{\left(p_{k,2i} - p_{k,2j}\right)^2 + \left(p_{k,2i+1} - p_{k,2j+1}\right)^2}, \tag{8}$$

where n_e is the number of edges among the GWs, which is defined by

$$n_e = \frac{n_{gw}\left(n_{gw} - 1\right)}{2}. \tag{9}$$

After the initialization process, the initial average inter-gateway distance d_k^{init} is calculated for all particles by using Eqs. (8) and (9). During flight time, an inter-gateway distance d_k^{flight} is calculated after every particle position update using the same equations. Fitness function evaluation for the particle k is triggered by using the probabilty pr which is defined by

$$pr = \begin{cases} \dfrac{d_k^{flight}}{d_k^{init}}, & \text{if } d_k^{flight} \le d_k^{init} \\ 1, & \text{otherwise} \end{cases} \tag{10}$$

The decision on whether to evaluate particle k or not is governed by the following rule: if $rand() < pr$, then evaluate particle k, else try to get new position for the particle and test the rule again. The parameter $rand()$ is a random number in the range $[0.0, 1.0]$. This process will continue until the rule fires.

Algorithm 1 shows the modified PSO algorithm, with the GW distancing measures highlighted in blue color. On lines 15 and 30, the LoRaWAN script is invoked and the PDR value emanating from that process is construed as the fitness function value, $F(x_k)$, for each particle k.

Algorithm 1: PSO with GW Distancing Measures

Input: N, c_1, c_2, ω, G, L, M, and n_{gw};
Output: $g^b, F(g^b)$;
Calclulate ΔL and ΔM by using Eq. 5 and 6;
Calculate n_{egw} by using Eq. 7;
for $k \leftarrow 0, N-1$ **do**
    $i = 0$;
    for $l \leftarrow 0, L/\Delta L$ **do**
        for $m \leftarrow 0, M/\Delta M$ **do**
            $p_{k,i} = random(l * \Delta L, (l+1) * \Delta L)$;
            $p_{k,i+1} = random(m * \Delta M, (m+1) * \Delta M)$;
    if $n_{egw} > 0$ **then**
        Initialize the extra GWs randomly in $[0, L]$ and $[0, M]$ respectively;
    Calculate d_k^{init} by using Eq. 8 and Eq. 9;
$F(g^b) \leftarrow 0$ **for** $k \leftarrow 1, N$ **do**
    Invoke the LoRaWAN script with GW locations from particle k;
    Compute the fitness function value, $F(x_k)$;
    $p_k^b \leftarrow x_i$;
    $F(p_k^b) \leftarrow F(x_k)$;
    if $F(x_k) > F(g^b)$ **then**
        $g^b \leftarrow x_k$;
        $F(g^b) \leftarrow F(x_k)$;
$t \leftarrow 0$;
while $t \leq G$ **do**
    for $k \leftarrow 1, N$ **do**
        $pr = 0$;
        while $pr \leq rand()$ **do**
            (1) Update v_k and x_k by using Eq. 1 and Eq. 2;
            (2) Calculate d_k^{flight} by using Eq. 8 and 9;
            (3) Calculate pr using Eq. 10;
        Invoke the LoRaWAN script with GW locations from particle k;
        Compute the fitness function value, $F(x_k)$;
        if $F(x_k) > F(p_k^b)$ **then**
            $p_k^b \leftarrow x_k$;
            $F(p_k^b) \leftarrow F(x_k)$;
        if $F(x_k) > F(g^b)$ **then**
            $g^b \leftarrow x_k$;
            $F(g^b) \leftarrow F(x_k)$;
    $t \leftarrow t + 1$;

5. Simulation environment, results and discussions

Since the goal of this work is to determine the efficacy of PSO in GW placement in LoRaWAN networks, the standard PSO and the modified PSO (with distancing measures) are compared with a deterministic approach. For brevity, the standard PSO, will be referred to as PSO, while the modified PSO will be refered to as PSODIST. For purposes of ease of comparison and discussion of the ensuing results, a square LoRaWAN area is adopted. Parameters L and M are both set to 50 km and 50 km respectively. The number of GWs n_{gw} is varied by using 4, 9, 25, and 49, which are all square numbers. This caters for the ease of deployment in the deterministic approach, which uniformly distributes the GWs as illustrated in **Figure 1** for 4 GWs. The expectation is that such a deterministic approach will yield the best result for the square LoRaWAN network area. If a PSO based approach can achieve similar results to the deterministic approach, the effectiveness of the PSO approach for GW placement will be proved.

5.1 The LoRaWAN script and simulation parameters

The LoRaWAN script is implemented in the NS-3 LoRaWAN module [13]. In order to reduce the simulation time for the LoRaWAN script during the optimization process, the number of EDs, n_{ed} is set 400. These EDs are set up randomly in the LoRaWAN area and the resulting text file is saved on the system. The ED locations are loaded to the simulation together with the GW locations on every LoRaWAN script invocation.

With the introduction of multiple GWs, a single packet may find its way to the Network Server (NS) through two or more GWs. In order to remove such packets from the number of unique packets received at the NS, some modifications were made to the LoRaWAN module. The default LoRa physical layer parameters in [13] were used in the simulations. The rest of the parameters in the LoRaWAN script are shown in **Table 1**. For the PSO algorithms, parameters are set as follows:$N = 20$, $c_1 = 1.5$, $c_2 = 1.5$, $\omega = 0.7$, and $G = 50$. They are all within the ranges that are commonly used in literature.

The basic C++ PSO code used in this study have been downloaded from [19]. The PSODIST code was developed by incorporating the GW distancing measures, explained in Section 4, in the basic PSO code. A personal computer with an Intel® Core™ i7-7500U CPU @ 2.70GHz $\times$ 4 processor with 8 GB RAM, running on Ubuntu 18.04.5 LTS, was used in this study. Ten optimization runs were conducted for each specific number of GWs for the PSO and PSODIST approaches. The LoRaWAN script was seeded with the same values, in order to ensure that the same simulation conditions prevail in all the optimization runs.

5.2 The efficacy of GW distancing measures

In this subsection, the efficacy of the GW distancing measures in the PSODIST algorithm is investigated by examining the mechanics of PSODIST against the basic PSO approach. **Figures 2–5** show the evolution of the optimization process for PSO and PSODIST approaches for the best optimization runs for 4, 9, 25, and 49 GWs. In the case of 4 GWs, in **Figure 2**, the difference in the evolution of the PDR value between the two approaches is very minimal. In fact, contrary to expectation, the PSODIST approach starts from a worse off position at around 36% while PSO starts from 38%. The GW distancing process during the initialization process does not help simply because the partitions in which the GWs are initialized are too big. The flight time GW distancing process helps to push PSODIST barely above the PSO. It can, therefore, be observed that GW distancing measures do not improve the performance of PSO when the number of GWs is low.

Parameter	Value
Spreading factors	7, 8, 9, 10, 11 and 12
GW height	20 m
ED height	2 m
Packet generation rate	12 packets/h
Simulation time	3000 s

Table 1.
LoRaWAN simulation parameters.

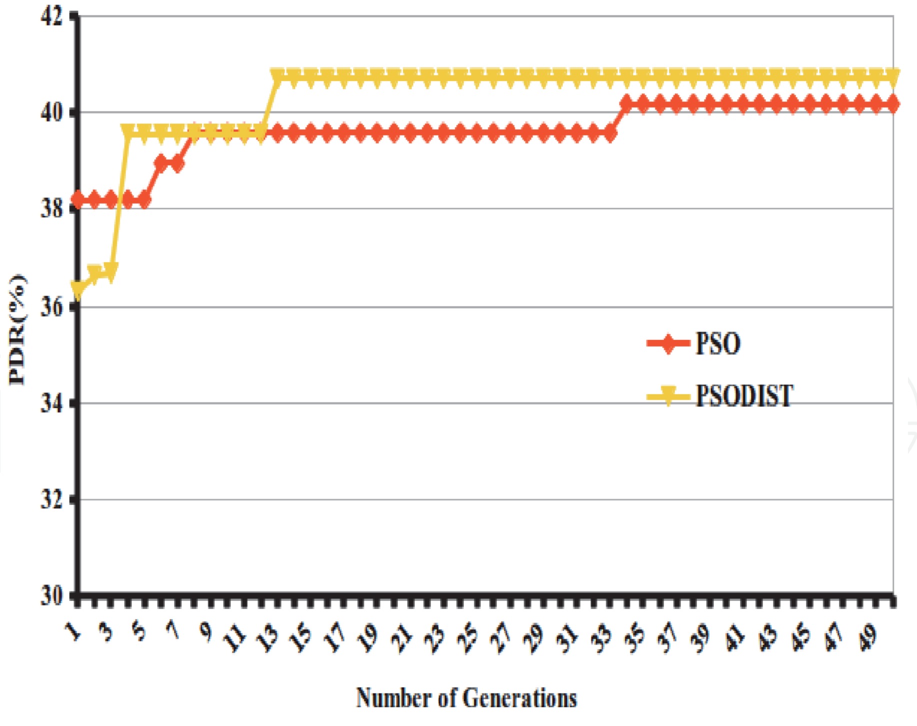

Figure 2.
PDR values of the best particle in the PSO swarms as the number of generations increases, with the number of GWs set to 4.

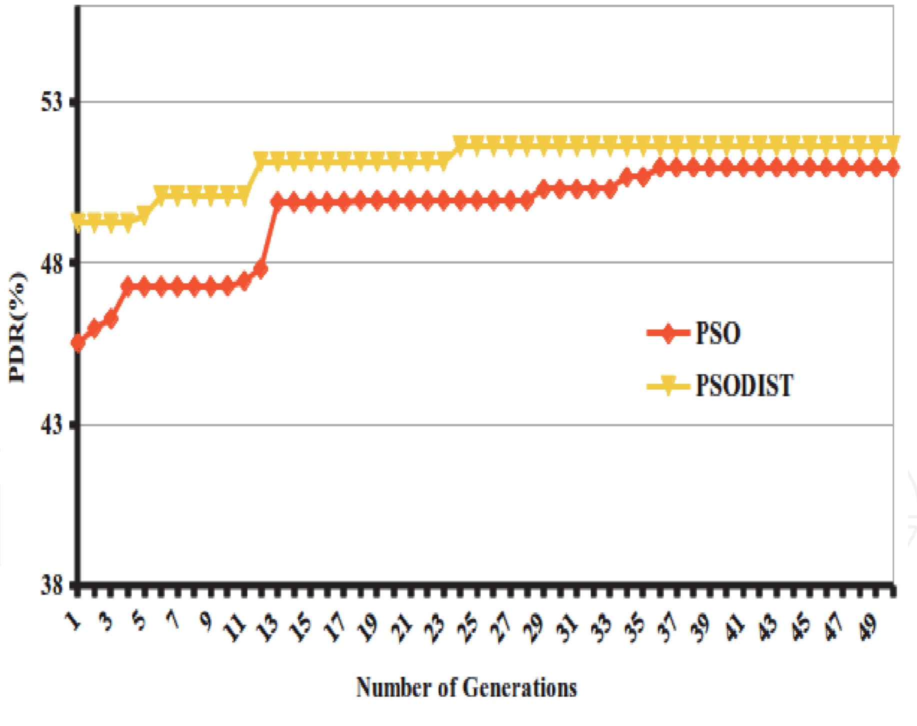

Figure 3.
PDR values of the best particle in the PSO swarms as the number of generations increases, with the number of GWs set to 9.

In the case of 9 GWs, as shown in **Figure 3**, PSODIST starts with a PDR of 49.2% while PSO starts with 45.5%. The trend becomes even more prominent as the number of GWs increases (see **Figures 4** and **5**). At 25 GWs, PSO and PSODIST register initial PDR values of 47.4% and 52.3% respectively, while at 49 GWs, the initial PDR values are 47% and 49.9% respectively. This shows that the benefits of GW distancing measures in the initializition process are only realized as the number

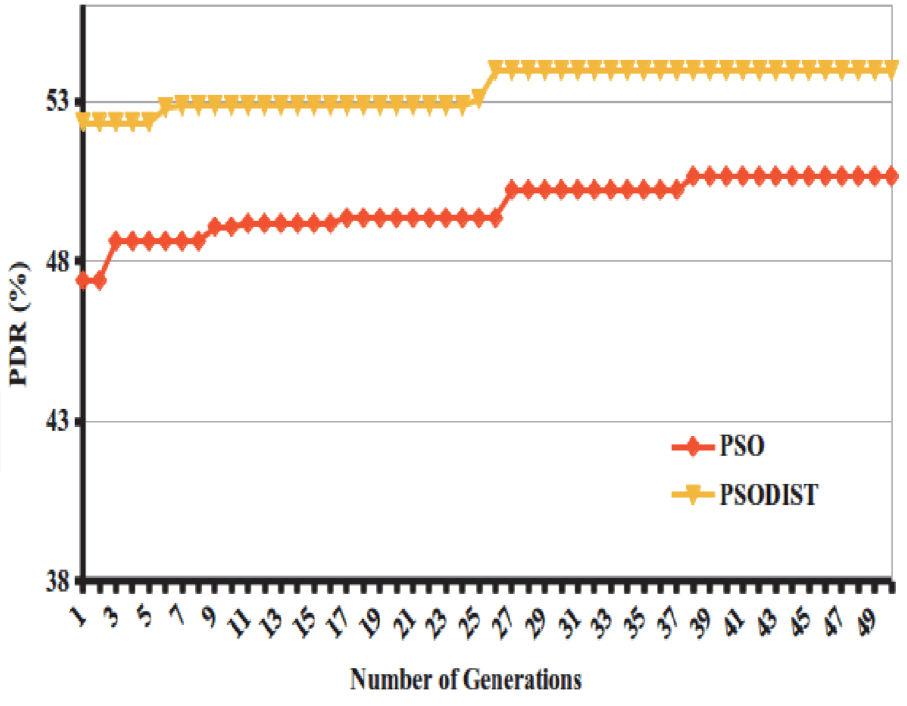

Figure 4.
PDR values of the best particle in the PSO swarms as the number of generations increases, with the number of GWs set to 25.

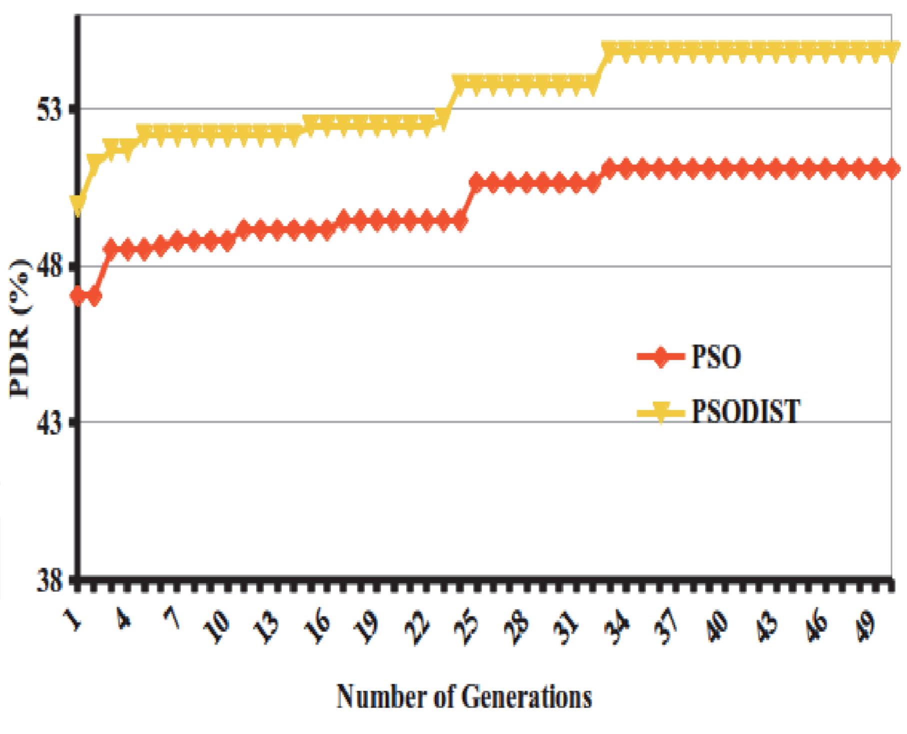

Figure 5.
PDR values of the best particle in the PSO swarms as the number of generations increases, with the number of GWs set to 40.

of GWs increases. This is due to the reduction in the sizes of the partitions in which the GWs are initialized.

As the number of GWs increases, the flight time GW distancing process seems to be more effective than in the case of 4 GWs. **Figure 3** shows that at 9 GWs, PSODIST converges to a PDR value of 51.63% at the 24th generation, while PSO converges to 50.98% at the 38th generation. In the case of 25 GWs, as shown in **Figure 4**, PSODIST converges to a PDR value of 53.95% at the 27th generation, while PSO converges to 50.65% at the 38th generation. When 49 GWs are used, as shown in **Figure 5**, PSODIST converges to a PDR value of 54.8% at the 34th generation, while PSO converges to 51.1% at the 37th generation. These results show that the basic PSO suffers from delayed convergence as well as suboptimal convergence because the initial positions of the GWs are not properly distanced. It can, therefore, be concluded that GW distancing measures improve the performance of PSO when the number of GWs is increased.

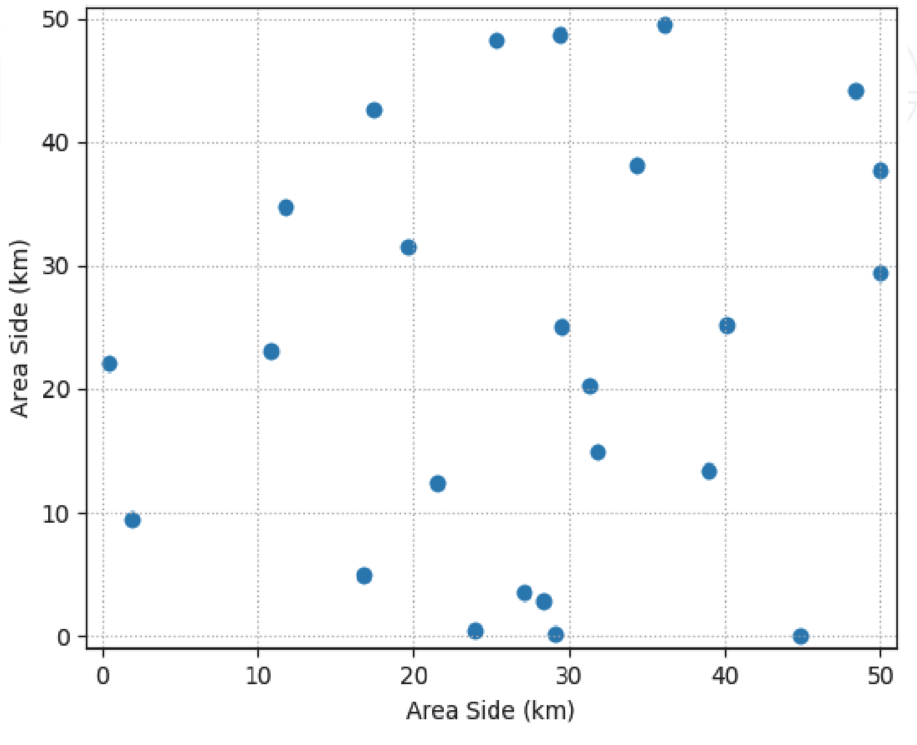

Figure 6.
Locations of 25 GWs in the 50 km × 50 km area, as depicted by the best particle in the PSO swarm.

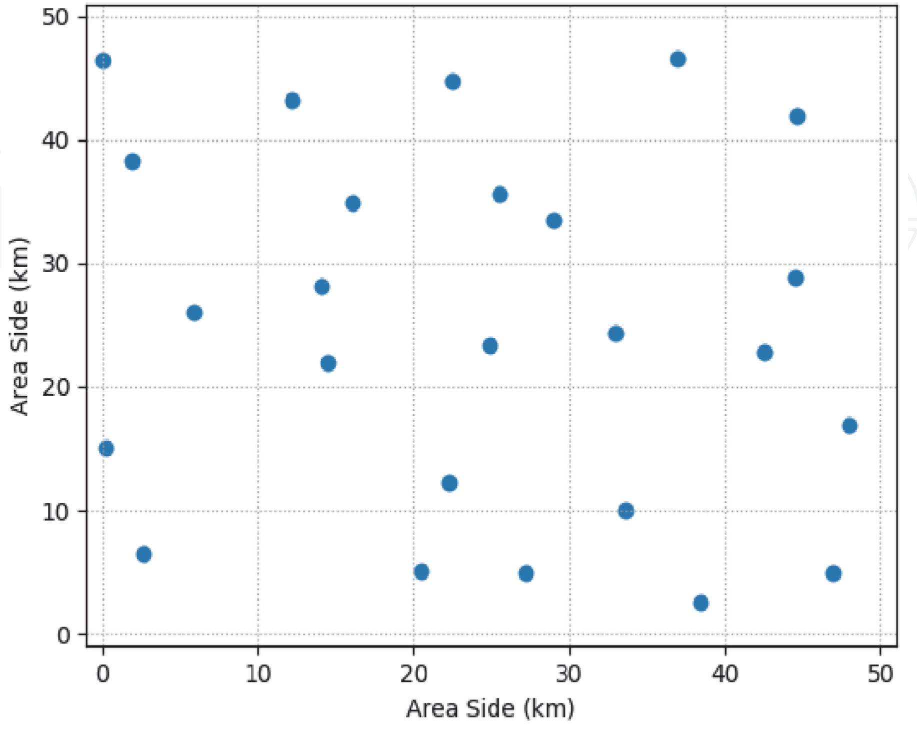

Figure 7.
Locations of 25 GWs in the 50 km × 50 km area, as depicted by the best particle in the PSODIST swarm.

Figures 6–9 illustrate the spread of the GW locations in the LoRaWAN area. From these graphical presentations, it is easy to see that the PSODIST achieves a better GW spread than PSO. In the PSO approach, there are some sections where the GWs are too crowded. For instance, in **Figure 6**, the subarea bounded by coordinates (20, 0), (20, 10, 30, 10, 30, 0), has four GWs, while in the north-western corner, there are no GWs in a subarea that is 2.5 times the former. In **Figure 8**, a similar trend is observed as there are even up 6 GWs in the central

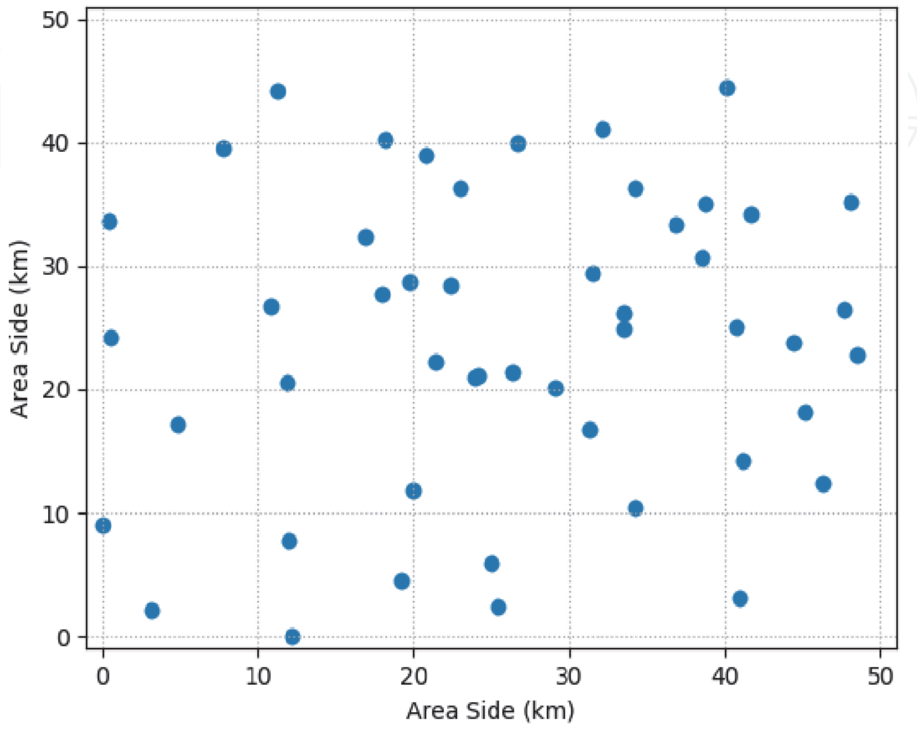

Figure 8.
Locations of 49 GWs in the 50 km × 50 km area, as depicted by the best particle in the PSO swarm.

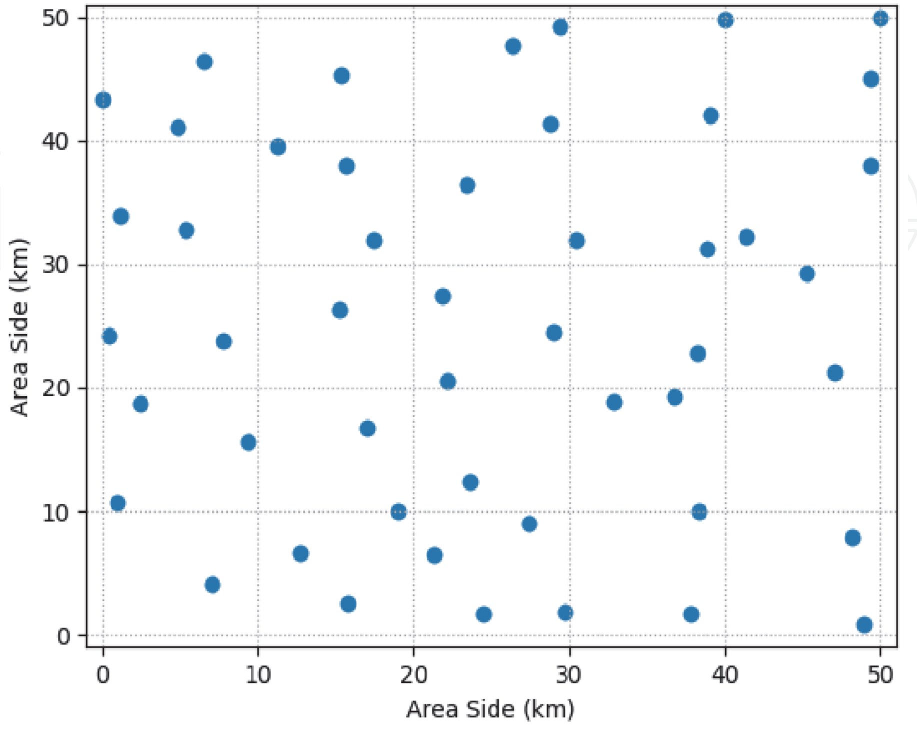

Figure 9.
Locations of 49 GWs in the 50 km × 50 km area, as depicted by the best particle in the PSODIST swarm.

10 km x 10 km subarea. The EDs in the subareas with little GW coverage suffer from GW reachability issues. On the other hand, subareas with many GWs also suffer from increased downlink traffic interference. Both of these conditions lead to the reduction of PDR.

5.3 Benchmarking PDR performance of PSO with the deterministic approach

A separate simulation exercise was conducted using the deterministic approach for benchmarking purposes. Ten simulation runs were also conducted for 4, 9, 25, and 49 GWs. **Table 2** shows the minimum, mean and maximum PDR values from the two PSO approaches along with the deterministic approach. Results depicting the best performing approach are shown in bold text. For 4 GWs, there is no significant difference among the three approaches as best minimum value of 39.8% is from PSO. On the other hand, the deterministic approach and PSODIST achieve the best mean and maximum values of 40.23% and 40.70% respectively. With 9 GWs, PSODIST seems to have an upper hand in the sense that it achieves the best minimum and mean values of 51.28% and 51.51% respectively, while the deterministic approach gets the best maximum value of 52.38%. At 25 GWs, all the best

No. of GWs	Deterministic			PSO			PSODIST		
	Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
4	38.66	**40.23**	42.68	**39.58**	40.06	40.58	39.55	40.17	**40.70**
9	48.15	49.95	**52.38**	48.28	49.81	50.98	**51.28**	**51.51**	51.63
25	49.70	51.78	53.28	50.65	51.50	52.15	**53.50**	**53.74**	**53.95**
49	**54.25**	**55.29**	**57.18**	50.43	50.81	51.10	53.50	54.33	54.80

Table 2.
Benchmarking of PSO approaches with the deterministic approach.

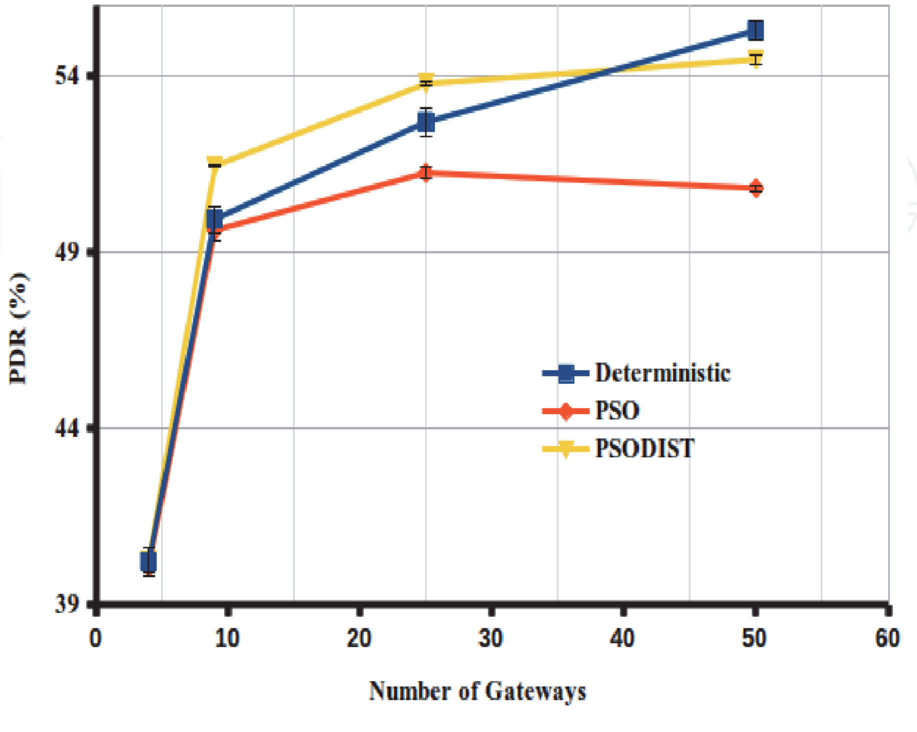

Figure 10.
A comparison of the PDR values for the three approaches when the number of GWs is set to 4, 9, 25 and 50.

values come from PSODIST, while at 50GWs, they all come from the deterministic approach. The basic PSO seems not to compete well with the other two approaches.

Figure 10 illustrates the same results from a graphical perspective, where the performance of PSODIST compares fairly well with the deterministic approach. It even outperforms the deterministic approach at 25 GWs. This clearly shows that when PSO approach is used for GW placement in LoRaWAN networks, there is a need for GW distancing mechanisms in order to prevent GWs from accumulating in some specific zones thereby jeopardizing performance in terms of PDR.

6. Conclusions

This Chapter investigated the efficacy of using Particle Swarm Optimization (PSO) in determining the optimal locations for gateways in large LoRaWAN networks. The coordinates of the gateways are coded into a vector, which denotes particle in PSO terminology. Gateway distancing measures have been proposed for the initiliazation and flight time phases of the PSO in order to spread out the gateways in the network. This process created a modified PSO algorithm, herein refered to as PSODIST. During initialization, the LoRaWAN area is broken down into a number of subareas and each gateway is initiliazed in a specific area. If there are some extra gateways, which cannot fit in the subareas, such gateways are initialized randomly within the entire area. During flight time, only new particle positions, that exhibit a sufficiently high inter-gateway distance, are evaluated. Optimization experiments are conducted to verify the effectiveness of the PSODIST approach. The LoRaWAN script, used in the optimization process, is implemented in NS-3 [12] using the recently proposed LoRaWAN module [13]. The function evaluation routines in the PSO algorithms invoke the LoRaWAN script and the resulting packet delivery rate (PDR) is retained as the fitness for the respective particle.

The mechanics of the optimization process show that there is no difference between PSODIST and PSO when the number of gateways is small. Nevertheless, as the number of gateways increases, the impact of distancing measures becomes evident; PSODIST yields better optimization rates as well as much faster convergence than PSO. The much more even spread of the gateway locations determined by PSODIST has also been demonstrated graphically. The results from the PSO approaches have been further compared with the deterministic approach which arranges the gateways uniformly over the LoRaWAN area. PSODIST yields similar PDR values as the deterministic approach in the 50 km $\times$ 50 km LoRaWAN area. Unlike the deterministic approach, which relies on square numbers and square areas for uniform coverage, PSODIST can work well for any number of GWs. It is, therefore, possible to get optimal performance at a lower number of GWs, in between square numbers. Furthermore, PSODIST is not shape-dependent. It can, therefore, be deployed easily in geometrically more complex LoRaWAN figures such as rectangular, triangular, circular and trapezoidal shapes. The development of more realistic LoRaWAN network by using real geographical information of an area will be considered in future.

Abbreviations

IoT	Internet of Things
NB	Narrowband
LoRaWAN	Long Range Wide Area Network

LPWAN	Low-Power Wide Area Networks
LoRa	Long Range
PSO	Particle Swarm Optimization
ED	End Devices
GW	Gateway
GW	Network Server
SWMN	Smart Water Metering Network
SWMN	Chirp Spread Spectrum
SF	Spreading Factor
PDR	Packet Delivery Ratio

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