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Meta-Heuristics optimization for mobile sink in WSNs based smart grid

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Abstract

Wireless Sensor Network (WSN) is made up of many battery-powered sensor nodes that are utilized for information gathering and transmission to sink in Smart grid (SG). The harsh channel conditions that characterise SG environment provide an important obstacle to WSN deployment in SG applications. While WSN sensors near the sink convey data to distant sensors, their energy is rapidly exhausted. So, energy holes are known as hotspot problems. In this paper, meta-Heuristics optimization algorithms are used to develop WSN-based SG. Particle swarm optimization, firefly algorithm and imperialist competitive algorithm, which are computationally efficient to handle WSN issues, have been studied. Single and multiple sinks, either static or mobile, offer greater flexibility and adaptability in monitoring and collecting data. Mobility is used to improve overall network coverage, help overcome network failures by moving to cover gaps, enhance connectivity, and even redistribute energy consumption in the network by allowing the workload to be shifted from one sensor to another. Particle Swarm Optimization enables fine-tuning of the resulting density to increase network lifetime and achieve better result. mobility is employed to help hotspot problem by balancing the energy consumption across the network, thereby extending the overall network lifetime with 1.6 months.

Keywords: Meta-heuristic; Particle Swarm Optimization; wireless sensor network; smart grid; mobility

I. Introduction

A wireless sensor network (WSN) is made up of nodes, each of which is linked to a sensor that detects physical or environmental parameters such as temperature, pressure, humidity, and so on. The nodes are connected in smart grid (SG) environments [1]by wireless channels which enable data obtained from monitoring, detecting, and recording the smart grid environments to be sent between them. SG is an electrical network that can intelligently integrate the different associated producers, transmitters, distributors, and consumers to deliver efficient, dependable energy services. Multi-hop communication will be used to transfer the acquired data to the sink. The sensor nodes are operated with limited energy. The energy is the most resource constrain in a WSN, because each node has battery to work independently. Limited energy may induce node isolation, resulting in network separation, often known as the hotspot problem. Mobile sinks that travel between nodes help to avoid node isolation [2]. By collecting data from isolated sensor nodes and decreasing hotspots on WSNs [3], saving network energy helps to enhance the lifetime of networks. Tmote Sky platforms apply a realistic WSN model under SG conditions with high path loss, low signal to noise ratio (SNR), and high bit error rate (BER) values to optimize transmission power level and data packet size[4].

Several WSN problems are expressed as optimization problems utilising artificial intelligence meta-heuristic approaches. Nature-inspired intelligence approaches are unaffected by problem volume or nonlinearity. Particle Swarm Optimization (PSO) is used to handle WSN problems such as optimum deployment and node location [5]. PSO is a popular solution for addressing optimization issues in WSNs. It is frequently utilised due to its simplicity, high-quality replies, quick convergence, and low computing expenses [6]. Another solution for optimization problems that takes inspiration from nature is the firefly algorithm (FA). FA enhances sensor node location information to estimate convergence and accuracy. When interacting in a multi-hop environment, FA requires less location information exchange between the sensor node and the sink node [7]. The imperialist competitive algorithm (ICA)[8] is a complicated problem-solving evolutionary algorithm. To deliver the needed coverage while retaining WSN connectivity [9], ICA has developed a new deployment technique.

This paper's main contributions are summarized concisely as follows:

- Mobile sinks solve hotspot problems in WSN-based SG by roaming the network, allowing sensor nodes to send data over shorter distances, saving energy and, eventually, extending the network's lifetime.

- Employing meta-heuristic algorithms in WSN-based smart grids enables efficient and adaptive solutions to optimization challenges, contributing to the development of reliable and sustainable SG infrastructures.

- SG optimizes network lifetime using realistic channel and energy models (log-normal shadowing, MIP model) for industrial applications and analyzing the effect of mobility or multiple sinks. MIP model enhance network lifetime by energy dissipation models.

This paper is structured as follows. In Section 2, the problem definition is described in more detail. In Section 3, the mathematical programming model for maximizing the network lifetime of WSNs with mobile BS is developed. In Section 4, metaheuristic algorithms have been employed to optimize smart grids. In Section 5, numerical results are discussed. In Section 6, we describe the study's conclusions.

II. Related Work

The lifetime of WSN is extended by optimizing energy consumption, enhancing network efficiency, and prolonging the operational duration of sensor nodes[10]. The applications that tolerate some delay in delivering data to the sink [11] are extended the lifetime of wireless sensor networks (WSNs) by utilizing a mobile sink. hotspot problems can be solved by mobile sink that is travelling the network and allowing sensor nodes to communicate data over shorter distances, therefore reducing energy consumption and, eventually, extending the network's lifetime [6].

The optimization problems in WSNs can be represented using Mixed Integer Programming (MIP), which can be addressed through the General Algebraic Modeling System (GAMS)[12] or meta-heuristic algorithms. There are several studies using GAMS to solve WSN applications. For instance, data packet optimization examines real energy consumption through a MIP framework, which accounts for the entire link layer handshake cycle. Consequently, the maximum allowable packet length is utilized to enhance the network's lifetime [13]. The energy model on the Mica2 motes' energy dissipation characteristics is used to maximize WSN lifetime by varying both transmission power and data packet size. The maximum network lifetime is achieved for the maximum packet size with limited signal range [14]. Metaheuristic algorithms can be challenging due to the complexity and combinatorial nature of the optimization problems. The complexity and scalability of deployments, environmental issues, and constraints on energy, capacity, connections, and processing resources are some of the difficulties that WSN developers must overcome. PSO is a popular approach to solve WSN optimization issues. PSO is ideal for issues that can only be resolved once on a sink, such as permanent installation and position. PSO and LEACH collaborate with each other to improve the number of active nodes in each iteration and packet transmitted to the sink and to find optimum cluster head [15][16]. The firefly localization algorithm is essential for improving the WSN's dependability and performance [17][18]. ICA can balance the energy consumption of various sensor nodes in the network by decreasing network energy consumption and improving network lifetime [7][8].

WSN performance is examined by systematic exploration of the parameter set for various SG environments and combined as MIP optimization model of transmission power level and data packet size in [4]. WSN based-SG model was solved by GAMS, but SG operates within a range of environmental challenges, including extreme weather conditions, temperature fluctuations, electromagnetic interference, and physical obstacles, among others. To guarantee dependable and efficient operation, SG systems must be engineered for lasting and adjusting to these harsh conditions. SG optimization challenges generally involve uncertain variables. Meta-heuristic algorithms may efficiently handle complicated objective functions resulting from SG [19]. Mobility is utilised with WSN based-SG model to increase network lifetime.

III. Problem Definition

WSN, which is deployed for SG applications, is built using Tmote Sky mote platforms [20]. The WSN is represented as a directed graph (G = (V,C), where V is a collection of 81 sensor nodes, including a sink in the center, and C is a collection of arcs signifying wireless connectivity. V that contains every node aside from the sink is referred to as set S. Data is never transmitted over cyclic arcs. Tmote Sky mote platforms used a log-normal shadowing channel model to calculate propagation loss for WSN. The path loss signal receives inside buildings or heavily populated regions over a distance is predicted by the model of radio propagation. As a result of the transmission from node i with power level Pl, the signal-to-noise ratio ($\mathcal{E}$ in dBm) at receiving node j may be computed as follows:

$$\mathcal{E}_{ij}(Pl) = \rho_{tx}^{ant}(Pl) - \left(\beta_0 + 10t\log_{10}\left(\frac{D_{ij}}{D_0}\right) + \delta\right) - \rho_n, \tag{1}$$

Since $\rho_{tx}^{ant}(Pl)$ is the antenna's transmit power at level Pl determined in Table 1, β_0 is path loss reference, t is exponent path loss, The shadowing is handled using the Gaussian random variable δ , ρ_n is the power of noise.

O-QPSK modulation is employed to Tmote Sky motes. After taking account for processing gain costs, the probability that a **Ω**-byte data packet would be successfully received at node j because of node i's transmission at power level Pl is computed as follows:

$$p_{ij}^{suc}(Pl,\Omega) = \left(1 - Q\left(\sqrt{16\mathcal{E}_{ij}(Pl)}\right)\right)^{8\Omega}. \tag{2}$$

and the probability of failure is

$$p_{ij}^{fail}(Pl,\Omega) = 1 - p_{ij}^{suc}(Pl,\Omega)\ . \tag{3}$$

When both packets are successfully received by their intended receivers, a handshake is considered successful. The probability of handshake may be computed as in (4) to guarantee effective communication.

$$p_{ij}^{HS,s}(Pl,Pk) = p_{ij}^{suc}(Pl,M_P) * p_{ji}^{suc}(Pk,M_A) \tag{4}$$

Table 1 Output antenna power ($\rho_{tx}^{ant}(Pl)$ in dBm) for different power level (Pl)

Power Level (Pl)	$\rho_{tx}^{ant}(Pl)$	Power Level (Pl)	$\rho_{tx}^{ant}(Pl)$
3	25.5	19	41.7
7	29.7	23	45.6
11	33.6	27	49.5
15	37.5	31	52.2

The data rate of the Tmote Sky platforms is 250 kbps, with M_P equaling 128 bytes, M_A equaling 12 bytes. The expected sent packets rate is described as $\alpha = 1/\left(p_{ij}^{HS,s}(Pl, Pk)\right)$. These platforms require $P_{rx}^{con} = 69\ mW$ of power to receive data. Energy packet processing, or $E_{PP} = 12.66\ \mu\mathrm{J}$, is a single time calculation for $M_p =$ 120 Bytes. Power consumption transmission $\rho_{tx}^{con}(Pl)$ for power levels (Pl) for the CC2420 radio platform is explained in [20]. The dissipated energy during packet processing and transmission, as well as any retransmissions necessary because of packet failures, is expressed in (5).

$$E_{tx,ij}^{Ds}(Pl, Pk) = E_{PP} + \alpha_{ij}(Pl, Pk) * \left([P_{tx}^{con}(Pl) * T_{tx}(M_P)] + P_{rx}^{con}\left(T_{slt} - T_{tx}(M_P)\right)\right) \tag{5}$$

As a result, the overall receiving node j's dissipated energy for a single slot is calculated as in (6). A timeslot is allocated by time division multiple access (TDMA)-based Medium Access Control (MAC) layer to minimize interference between active links 4.78 milliseconds are used as the slot time (T_{slt}).

$$E_{rx,ji}^{Ds}(Pl, Pk) = E_{PP} + \alpha_{ij}(Pl, Pk) * \begin{bmatrix} p_{ij}^{HS,s} * \left(E_{tx}^{A}(PK, M_A) + P_{rx}^{con}\left(T_{slt} - T_{tx}(M_A)\right)\right) \\ + p_{ij}^{suc}(l, M_P) * p_{ij}^{fail}(k, M_A) * \left(E_{tx}^{A}(PK, M_A) + P_{rx}^{con}\left(T_{slt} - T_{tx}(M_A)\right)\right) \\ + p_{ij}^{fail}(k, M_A) * (P_{rx}^{con}.T_{slt}) \end{bmatrix} \tag{6}$$

Various topologies, such as grid and spiral, are used to construct network topologies. In a grid topology, sensors are placed with a fixed distance between nearby sensors in the same row or the same column [9]. The topology assures complete coverage of the area. In spiral topologies, the network's center is denser, and its edge is sparser. Spiral topology is generated by $Y(\text{i}) = e^{(\text{i}*\text{s})} * \cos(\text{i})$ and $X(\text{i}) = e^{(\text{i}*\text{s})} * \sin(\text{i})$ Where the value of density (i) is computed exactly to fit into the area. scaling factor (s) is tuned with density which is chosen as 0.03.

IV. Proposed Model

Mobility in Wireless Sensor Networks has a major influence on a variety of critical network characteristics. Sensor nodes are reduced lifetime due to WSN battery issues. Sensor nodes can link to any other sensor by tuning its transmission power at a sufficient level to harvest data and transmit it to mobile BS[21]. The network lifetime is extended at the mobile sink through changing its locations (i.e. positions) when gathering information from the sensor nodes. $\lfloor$ represents a list of possible sink positions visited by mobile sink to cover the overall network area. Various areas in $\lfloor$ may see sink positions. Like in past articles, it is anticipated that the sink moves between different locations in a very little period[11]. Therefore, the energy consumption of the mobile sink is neglected. Thus, researchers focus on the energy efficiency of the sensor nodes in the WSN. This article concerns how to incorporate $\lfloor$ (i.e possible sink position) into the MIP model.

The objective function in Mobile model is the sum of overall rounds number from the starting of network operation to the point at which the sink consumes all of battery power travelling by each location $\lfloor$ in (7). Nomenclature is represented in Table 2. The following provides an explanation of the model's constraints:

- Equation (8) depicts the balance for data flow received and sent for all nodes, while the sink is at $\lfloor$.
- Equation (9) illustrates a conflict-free TDMA result is limited to a total bandwidth that is less than or equal to the bandwidth needed for sending and receiving, and all nodes at location $\lfloor$.
- Equation (10) explains overall working time for each sensor includes time spent transmitting, receiving, and acquisiting data, sometimes retransmissions at each location $\lfloor$. Furthermore, interfering flows are also prevented.

- Equation (11) justifies the quantity of energy required for working time by each sensor node for data The transmission, receiving, acquisition, and sleeping ($T_{slp,i} = R_{nd} * T_{nd} - T_{wrk,i}$), that is restricted to the initial battery of each node at location $\mathfrak{l}$.

$$maximize \ \sum_{\mathfrak{l}} R_{nd}^{\mathfrak{l}} \tag{7}$$

$$Subject\ to$$

$$\sum_{i,j\in S} X_{ij}{}^{\mathfrak{l}} - \sum_{i,j\in S} X_{ji}{}^{\mathfrak{l}} = R_{nd}^{\mathfrak{l}} PS_i \quad \forall i \in S \tag{8}$$

$$T_{slt}\left[\sum_{i,j\in S} \alpha_{ij}(Pl,Pk) * X_{ij}{}^{\mathfrak{l}} + \sum_{i,j\in S} \alpha_{ji}(Pl,Pk) * X_{ji}{}^{\mathfrak{l}} + \sum_{i,j\in S} \alpha_{jn}(Pl,Pk) * X_{jn} * In_{jn}(Pl,Pk)\right] \le R_{nd}^{\mathfrak{l}} T_{nd} \tag{9}$$

$$T_{wrk} = T_{slt}\left[\sum_{i,j\in S} \alpha_{ij}(Pl,Pk) * X_{ij}{}^{\mathfrak{l}} + \sum_{i,j\in S} \alpha_{ji}(Pl,Pk) * X_{ji}{}^{\mathfrak{l}}\right] + R_{nd}^{\mathfrak{l}} * T_{DAc} \ \forall i \in S \tag{10}$$

$$\sum_{i,j\in S} E_{tx,ij}^{Ds}\ (Pl,Pk) X_{ij}{}^{\mathfrak{l}} + P_{slp} * T_{slp,i} + \sum_{i,j\in S} E_{rx,ij}^{Ds}\ (Pl,Pk) X_{ji}{}^{\mathfrak{l}} + R_{nd}^{\mathfrak{l}} * E_{DAc} \le \beta \quad \forall i \in S \tag{11}$$

$$R_{nd}^{\mathfrak{l}}, X_{ij}{}^{\mathfrak{l}} \ge 0 \ \forall\ i,j \epsilon S \tag{12}$$

Fig. 1 MIP model for mobile sink

Table 2. NOMENCLATURE

Variable	**Description**
$R_{nd}^{\mathfrak{l}}$	Sum of rounds number at each location $\mathfrak{l}$
T_{nd}	Round time
$X_{ij}{}^{\mathfrak{l}}$	Num of packets sent from node i to node j at each location $\mathfrak{l}$
α_{ji}	Sent packets rate
PS_i	Packet size
β	Battery limit
T_{slt}	Slot time
$T_{wrk,i}$	Working time for each sensor
$T_{slp,i}$	Sleeping time
T_{DAc}	Data acquisition and processing time
$E_{tx,ij}^{Ds}$	Dissipated energy during packet processing and transmission,
$E_{rx,ij}^{Ds}$	overall receiving node j's dissipated energy for a single slot
In_{jn}	Interference function
ρ_{sn}	Average receiver sensitivity
Pl	Power level for transmission
Pk	Power level for Acknowledgment

- Equation 12 is a non-negativity restriction.
- more power level is increased, the more energy is consumed, and the more interference there is, and vice versa. So, the value of the interference function, represented in (13), is unity if transmitter node-i at power level- Pl is interfered by the handshake to the receiver node-j or node-n ACKing at power level- Pk otherwise the

value is zero. Since ρ_{sn} stands for -90dBm[4], the t-mote sky's reception sensitivity.

$$In_{jn}^{i}\,(Pl, Pk) = \begin{cases} 1 & if\ \rho_{rx,ji}^{ant}(Pl) \geq \rho_{sn} \quad or \quad \rho_{rx,ni}^{ant}(Pk) \geq \rho_{sn} \\ 0 & o.w. \end{cases} \tag{13}$$

Each node battery (β) in the network is given a starting energy of 25KJ [13], the equivalent of two AA batteries, at the beginning of operation.

V. Experimental Work

Meta-heuristic algorithms effectively deal with complicated problems in SG to deal with accurate computational complexity and problem handling (i.e. discrete variables, uncertainty, constraints, and so on). The employed meta-heuristic algorithms are Modified Particle Swarm Optimisation, Firefly Algorithm, and Imperialist competitive algorithm. The algorithms are implemented using a mutation operator, which causes the position to be recovered from the local minimum and shifted outside of it. The meta-heuristic parameters are presented in Table 3.

Several models are used for these topologies to guarantee that the maximum power level is used to decrease packet errors. The topologies are applied to the following suggested algorithms PSO, FA and ICA. In a wireless sensor network with a central static sink, the PSO, FA, and ICA were compared. When a sink arrives at a certain location in the mobile instance, it sends a notification message telling sensors where to begin broadcasting aggregated data in accordance with prior topologies. After round trip time, the sink depart towards the next location. Figure 2 depicts network diagram for mobile sink with grid and spiral topologies [6]. For sparse networks, these earlier topologies employ a variety of transmission power levels. The maximum transmission power level is used in both topologies to decrease packet errors and improve network lifetime.

Table 3. Meta-heuristic Parameter settings

	PSO		***FA***		***ICA***	
Population No.	30		30		30	
	$\boldsymbol{C_1}$	0.7	α	0.5	α α	1
	$\boldsymbol{C_2}$	1	β_0	2	β	1.5
	$\boldsymbol{\omega}$	0.2	γ	1	ʓ	0.2
Iterations No.	10		10		10	
Mutation Rate	0.1		0.1		0.1	

A. Modified Particle Swarm Optimisation

PSO is a meta-heuristic technique [18] that is affected by behavior for grouping of fish or birds. They move in groups to avoid collisions while searching for food, water, and shelter with minimum effort. The MPSO algorithm goes through the steps in Alg.1. A particle swarm is randomly initialized. The velocity v_i , location x_i are evaluated as in (14) and (15) to allow each particle i to move over space region a 400 by 400-meter.

$$v_i(t+1) = w(t)v_i(t) + C_1r_1\left(pbest_i - x_i(t)\right) + C_2r_2\left(gbest_i - x_i(t)\right) \quad (14)$$

$$x_i(t+1) = cx_i(t) + dv_i(t+1) \quad (15)$$

Where $C_1$and C_2 define accelerating Factors, r_1 , r_2, c and d are random values.

$$w = \mathrm{r}\, e^{-\frac{\mathrm{gbest}}{\sum_i pbest_i}} \quad (16)$$

The inertia weight (w) is calculated in (16) to compute each particle's velocity based on network lifetime maximization to overcome premature convergence and accomplish exploration and exploitation in search space [22], where r is a random value, pbest for each iteration and gbest for all previous iterations. Two "best" values (pbest and gbest) are determined for each particle to maximize the network lifetime (fitness function), that is calculated in seconds (via $R_{nd} * T_{nd}$). All the pbest values are compared while the particles are attempting to optimize yields a global solution (gbest). Particle position and velocity are being updated. Local Search based on Mutation is applied. the model's goal is to determine where a particle should be placed in order to increase network lifetime with low energy usage or reach the max number of iterations. The objective of WSN optimization [23] is to identify the particles that maximize network lifetime (i.e. optimize the fitness function value). The particle is assessed using Pbest and Gbest for each particle in accordance with the fitness function to obtain the maximum rounds for each update [16].

Alg.1: MPSO

```
Begin:
    Initialize population of particles with random positions and velocities
    Set initial global best position and fitness
    Set parameters: inertia weight (w), accelerating Factors(c1, c2), mutation_rate, max_iter
    For each iteration t = 1 to max_iter do
      For each particle i do
        Update velocity and position of particle i // as Eq.14 , Eq.15
        Evaluate fitness of particle i
        Update pbest:
        If fitness_i < pbest_i then:
          pbest_i = x_i(t + 1)
          Update pbest_fitness_i
        Update global best:
        If fitness_i < gbest_fitness then:
          gbest = x_i(t + 1)
        Update inertia weight (w) // as Eq. 16
      End For
      Apply mutation:
        For each particle:
          If random() < mutation_rate then:
            Mutate particle's position randomly within the search space.
      Update gbest_fitness
    End For
Return gbest
```

B. Firefly algorithm

FA algorithm is a meta-heuristic stimulated by the behavior of fireflies, which attract other fireflies for mating by flashing their lights [17]. FA algorithm is represented by the following steps in Alg.2. Firstly, the firefly is Initialized. After determining the intensity of each firefly (through$R_{nd} * T_{nd}$) to get the fireflies' brightness, attractiveness process moves from the i^{th} firefly to the brighter j^{th} firefly as in (17).

$$x_i(t+1) = x_i(t) + \beta_0 e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha * rand \quad (17)$$

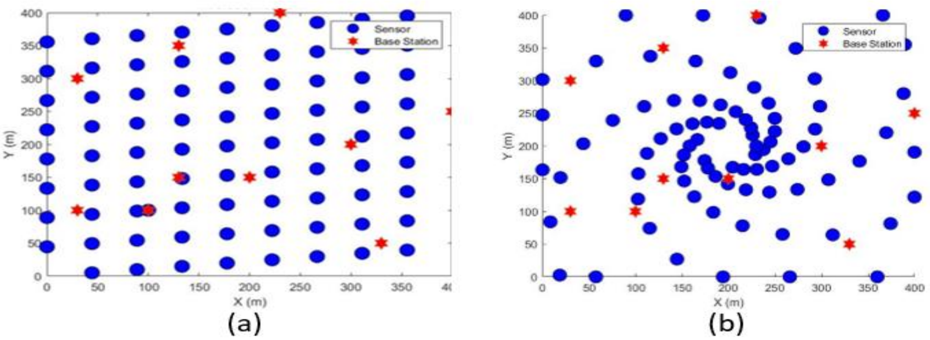

Fig. 2 Network Design for Mobility in (a)Grid and (b)spiral topology

Where r_{ij} is the distance between two nodes x_i and x_j, light intensity β_0 is related to attraction in $r = 0$, Light attraction factor (γ) and $\alpha \in [0,1]$. The attraction of the brightest firefly from the current firefly is used to measure the distance between fireflies. After moving to brighter fireflies, rank the fireflies to get the global best based on fitness function (through $R_{nd} * T_{nd}$). Mutation is applied to inject diversity into the population and help escape local optima. This cycle is repeated until the brightest firefly maximizes network lifetime (the number of rounds) or reaches the max number of iterations. The objective function for nodes with the highest attraction is calculated to maximize rounds[24]. Nodes with the highest fitness (objective) function are selected for sending information and collecting data for transfer to BS.

Alg.2: FA

Begin:

Initialize population of fireflies with random positions and brightness (fitness).
Define parameters: light absorption coefficient(α), attractiveness coefficient(β_0), mutation rate(γ)
For each iteration t = 1 to max_iter do
  For each firefly i:
    For each firefly j (where j != i):
      If the brightness of firefly j > the brightness of firefly I **then:**
        Move firefly i towards firefly j: //as Eq. 17
      Move towards the direction of firefly j to the attractiveness and distance.
      Update the position of firefly i.
  //Apply mutation:
  If random() < gamma **then:**
    Mutate the position of firefly i randomly within the search space.
  Evaluate the brightness (fitness) of the new position.
  Sort fireflies based on brightness (best fireflies come first).
  Update the light intensity of each firefly based on its position in the sorted list.
Return the best firefly found.

C. Imperialist competitive algorithm

ICA is a zone of evolutionary computing based on human sociopolitical progress[8]. The following ICA algorithm steps are represented in Alg.3. Firstly, the empires are initialized with some initial random solutions. Then, the colonies moved toward their relevant imperialist. Based on their authority, each imperialist encloses colonies. The more powerful imperialists will have more colonies than the weaker ones. The positions are exchanged for that imperialist and the colony if there is a colony in an empire with more energy than the imperialist. The network lifetime of the empire is measured by $(R_{nd} * T_{nd})$ then, apply mutation. The weakest colony is picked from the weakest empire and joined one of the stronger empires at the maximum lifetime. the powerless empires are eliminated. This cycle is repeated until there is only one empire, or a predefined finish condition is satisfied. ICA's objective is to direct the search process towards powerful imperialist or optimal locations based on their power[8]. The empire's imperialists ultimately fell and joined the other empires. With the absorption policy, imperialist powers absorb their colonies. Based on their might, the stronger empire will have a better chance of beating the colony.

Alg.3: ICA

Begin:

1. Initialize population of countries (imperialists) and colonies with random positions and fitness
2. **For** each iteration t = 1 to max_iter :
3. Sort countries based on fitness (descending order)
4. **For** each country (imperialist) i in the population:
5. **For** each colony j of imperialist i:
6. **If** fitness of colony j is better than fitness of imperialist i **then:**
7. Replace imperialist i with colony j
8. Set colony j to a random position.
9. //Apply mutation:
10. **For** each country (imperialist) i except the strongest one:
11. Perform mutation on imperialist i:
12. Perturb its position based on a mutation strategy.
13. Evaluate the fitness of the mutated imperialist.
14. Update population based on movements and mutations.
15. **Return** the final country's position found.

VI. Results and Discussion

The performance of the algorithms (PSO, FA, and ICA) in this study computes overall energy consumption and network lifetime based on grid and spiral topologies with static, multiple, and mobile sinks. The multiple sinks were shortening the communication path between them and the various sensor nodes. The mobile sink moved throughout the sensing field and landed at the predetermined rest locations. All three algorithm runs utilize identical communication and coverage parameters. There were 20 simulation runs for each algorithm. The algorithms' performance is evaluated using their average (Avg) and standard deviation (STD) values for maximum network lifetime in months. Table 4 depicts comparison between network lifetime for indoor line-of-sight SG environment with static sink[4]and proposed meta-heuristic algorithms. Meta-heuristic algorithms are employed to compare Avg and STD values for mobile sink or multiple sinks in grid and spiral topologies as shown in Table 5. While MPSO performs similarly to previous work on grid topology, it offers competitive results compared to other algorithms. On spiral topology, ICA gives slightly better performance than FA and PSO.

Table 4 Network lifetime for grid-based WSNs in months.

Algorithm	**Lifetime**
GAMS**[4]**	33.2
Proposed MPSO	33.16172204
Proposed ICA	33.12064162
Proposed FA	29.2533196

Multiple sinks are made up of four static sinks distributed in the center of quarters. Network lifetime values for multiple sinks are better than static sink values in both grid and spiral topology for three meta-heuristic algorithms. Under similar settings, MPSO outperforms FA and ICA in grid topology. ICA outperforms MPSO in spiral topology somewhat. The mobile sink travelled over the sensing field to collect data. On grid topology with Mobile BS, MPSO give better performance than others, but on spiral topology, MPSO slightly surpasses ICA.

Table 5. Network lifetime results for multiple & mobile sinks in months.

Topology	Algorithm		Static	Multiple	Mobile
Grid	MPSO	Avg	**33.16172204**	**33.45587123**	**34.79402953**
		STD	3.626812082	2.626874588	3.394121371
	FA	Avg	29.2533196	30.19767334	30.73254953
		STD	2.574128509	3.614216258	2.731821512
	ICA	Avg	**33.12064162**	33.29254527	34.11945332
		STD	2.914664988	2.854657034	3.867722158
Spiral	PSO	Avg	32.59735638	**33.20810535**	**33.92409235**
		STD	2.250548061	2.429418454	2.594240581
	FA	Avg	29.41216285	29.99273489	30.16231078
		STD	5.181712784	5.022944619	5.153542488
	ICA	Avg	**32.65823237**	**33.285951235**	33.3901109
		STD	2.358645212	2.901161964	2.369255641

VII. Conclusion

A network's lifetime is a key component for a WSN-based SG. Optimizing WSNs for smart grid applications is crucial to maximize network lifetime and handle resource constraints. Optimizing protocols used for sensor communication to minimize energy consumption while maintaining proper data transfer. Optimization algorithms may handle more difficult WSN challenges. Three optimization algorithms (PSO, FA, and ICA) were used to examine the effectiveness of the best methodology. The model is constructed using a path-loss model with log-normal shadowing to investigate the influence of grid or spiral topology deployment, as well as mobile or multiple sinks. The longest network lifetime for a static sink is accomplished using grid mobility. Grid topology is characterized by high coverage and high connectivity. According to the results, the lowest performance improvements are achieved by FA algorithm. MPSO calculated a longer network lifetime than the ICA and FA. The multiple sinks were successful in extending the network lifetime slightly by limiting the impact of the hotspot problem marginally. MPSO enables fine-tuning of to increase network lifetime and achieve better results that is near solution to the previous work. Mobility enables to extend network lifetime and get better results with respect to static model. The hotspot problem was mostly overcomed when the mobile sink went through the sensing field.

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تحسين الشبكة الذكية باستخدام الاستدلال التجريبي للشبكة اللاسلكية بمحطة متنقلة لتجميع البيانات

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تتكون شبكة الاستشعار اللاسلكية من العديد من المستشعرات التي تعمل بالبطارية والتي يتم استخدامها لجمع المعلومات ونقلها للتحكم في الشبكة الذكية . توفر الشبكة اللاسلكية حل للظروف القاسية ،والتي تشكل عقبة مهمة أمام نشرالشبكة اللاسلكية في تطبيقات الشبكة الذكية .في حين أن أجهزة استشعار الشبكة اللاسلكية القريبة من الحوض تنقل البيانات إلى أجهزة استشعار بعيدة، فإن طاقتها تستنفذ بسرعة. لذلك، تُعرف هذه ثقوب الطاقة بمشاكل النقاط الساخنة. في هذا البحث، تم استخدام خوارزميات تحسين الاستدلالات التجريبية لتطوير الشبكة الذكية القائمة على الشبكة اللاسلكية .تمت دراسة تحسين سرب الجسيمات، وخوارزمية اليراع، والخوارزمية التنافسية الإمبريالية، والتي تتميز بالكفاءة الحسابية للتعامل مع مشكلات الشبكة اللاسلكية .توفر المحطات الاساسية الفردية والمتعددة، سواء الثابتة أو المتنقلة، قدرًا أكبر من المرونة والقدرة على التكيف في مراقبة البيانات وجمعها. تُستخدم إمكانية التنقل لتحسين التغطية الشاملة للشبكة، والمساعدة في التغلب على أعطال الشبكة من خلال التحرك لتغطية الفجوات، وتعزيز الاتصال، وحتى إعادة توزيع استهلاك الطاقة في الشبكة من خلال السماح بنقل عبء العمل من مستشعر إلى آخر. يتيح تحسين سرب الجسيمات الضبط الدقيق للكثافة الناتجة لزيادة عمر الشبكة وتحقيق نتيجة أفضل. يتم استخدام التنقل للمساعدة في حل مشكلة النقاط الساخنة من خلال موازنة استهلاك الطاقة عبر الشبكة، وبالتالي إطالة عمر الشبكة الإجمالي بمقدار ١,٦ شهرًا.