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Global Levy Flight of Cuckoo Search with Particle Swarm Optimization for Effective Cluster Head Selection in Wireless Sensor Network

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ABSTRACT

The advent of sensors that are light in weight, small-sized, low power and are enabled by wireless network has led to growth of Wireless Sensor Networks (WSNs) in multiple areas of applications. The key problems faced in WSNs are decreased network lifetime and time delay in transmission of data. Several key issues in the WSN design can be addressed using the Multi-Objective Optimization (MOO) Algorithms. The selection of the Cluster Head is a NP Hard optimization problem in nature. The CH selection is also challenging as the sensor nodes are organized in clusters. Through partitioning of network, the consumption of energy was improved and through evolutionary protocols for the selection of optimized CHs, the position information and residual energy are considered by the WSNs. There is a need for MOO vision for tackling this issue. Because of its ease of implementation, highly efficient solution, quick convergence and the capability of avoiding the local optima, for such NP hard problem the Particle Swarm Optimization (PSO) is the significant effective algorithms that have been inspired by nature. Another algorithm is the Cuckoo Search (CS) algorithm. The Global Levy Flight of CS with PSO is proposed to get improved network performance incorporating balanced energy dissipation and results in the formation of optimum number of clusters and minimal energy consumption.

Keywords: Multi-Objective Optimization Algorithms, Cluster Head selection, Particle Swarm Optimization (PSO), Cuckoo Search (CS) and global levy flights of cuckoo search.

1 INTRODUCTION

A Wireless Sensor Network (WSN) is a distributed network and it comprises a large number of compact, low-cost, low-power, multifunctional sensor nodes that communicate wirelessly over short distances. The limitation in the energy nodes, hence their computing, communication and capacity to store are the disadvantages of WSN.

The lifetime of network is increased by retaining methodologies like density control techniques, multi-hop communication, energy aware techniques and in-network processing. The WSNs is an important feature to reduce and the protect energy. The sensor network model consumes a novel measurement to its model through clustering and classification systems.

Multi-Objective Optimization (MOO) algorithms solves a diverse Multi-Objective Optimization Problems (MOPs) and treated various purposes concurrently with respect to a set of limitations (Adnan & Razzaque, 2014). There may not be just one single global solution that is optimal and also the best with regard to all of the objectives as, multiple objectives cannot be achieving their corresponding optima simultaneously. Nonetheless, a Pareto-Optimal or non-dominated solutions set exist that spawn a set of Pareto optimal results or objective vectors referred to as Pareto front/ frontier (PF) or Pareto boundary/curve/surface. Particularly, the specific sets of solutions generate the PF wherein, without giving up the other objectives improvisation of multiple objectives is not possible. Also known as the Pareto-efficient set or praetor Set (PS) this set of Pareto optimal or non-dominated solutions formulate the center point of individual attention and is mapped to the Pareto Function in the objective function space.

In both Network literature and data processing, clustering has been extensively researched. This also

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aids in enhancing the network lifetime which facilitates the assessment of the sensor network quality. The researchers have extensively studies the maximizing of the ad hoc network's static network lifespan.' The amount of time till the battery depletion causes the first node failure' is referred to as one of the definitions of network lifetime. Some other definitions state the time during which a fraction of the nodes collapse. In clustering, the nodes in a WSN are grouped into clusters and a cluster Head is chosen (CH). This cluster heads gathers the data from the source in its group. The collated data is then sent to the sink node or to the base station. The sensors in a cluster are directly connected to their cluster head. There are several benefits presented by clustering that include grouping sensors and conserving energy. The benefits of clustering are abridged as follows: Send the gathered data to the base station decrease the amount of nodes that send the data, enhance power conservation, permit scalability by enhancing the nodes and allow the network resources to be used better.

The CH is yielded by the optimal fit of the search procedure, and its responsibility is to transfer the collected information to the base station. That is why; the first nodes to be used in communication are the least energy nodes. The inefficiencies that exist in the dissipation of energy are ruled out by periodic search. The goal is efficiently managing the power that is consumed between the sensor nodes based on the residual energy and for prolonging the network lifespan. The efficiency of the suggested method can be shown when the results that have been obtained are compared with the traditional methods.

The main benefits of clustering are: It decreases the distance between the nodes to transfer a data. The dismissed data is restricted through data aggregation at the CHs. It saves energy and uses the bandwidth efficiently. The clustering problem occurred are: how many SNs is considered in a single cluster. The CH Selection method in an individual cluster. Network Heterogeneity regarding network energy which can act like CH and simple node as a cluster member only.

Numerous clustering methods available are: Low Energy Adaptive Clustering Hierarchy (LEACH) protocol, Threshold-Sensitive Energy-Efficient Sensor Network (TEEN) protocol, Geographic Adaptive Fidelity (GAF) protocol, Periodic, Event-driven and Query-based (PEQ) routing protocol, Clustering Periodic, Event-driven and Query-based (CPEQ) protocol, Energy Efficient Inter-cluster Communication based (ICE) algorithm, Clustering Method for Energy Efficient Routing (CMEER), Distributed Energy Efficient Hierarchical Clustering (DWEHC), Position-based Aggregator Node Election (PANEL), Passive Clustering (PC), Hybrid Energy-Efficient Distributed Clustering (HEED) and Energy Efficient Hierarchical Clustering (EEHC).

Almost all of the aspects of humans as well as work are covered by optimization. Practically speaking, as the resources are less in number, it is very important to optimize. There is some amount of modeling, data analysis, mathematical optimization and computer simulations that are involved in most research activities. This area of applied science deals with determining the valued of the associated variables that would output the least or the greatest values corresponding to multiple objective function or single objective function (Fei, Li, Yang, Xing, Chen & Hanzo, 2017). In the recent past, for solving the MOPs, biometric heuristics or meta heuristic based techniques have been applied predominantly. The reason for this is, they have the ability to arrive at near optimal solutions for problems that have non-differential nonlinear objective functions.

It is extremely challenging to discover optimal solutions for several problems. Looking for every possible solution or combination is not possible due to the complexity of the problems (Ghodrati & Lotfi, 2012). Nonetheless, the complexity prompts the utilization of approximation algorithms for determining approximate solutions has become extremely popular in the recent past .Of these, the popular one is the meta heuristics and this results in meta heuristic optimization which is a new branch of optimization. A majority of these have been motivated by nature, like the Genetic Algorithm (GA), Artificial Bee Colony (ABC), Harmony search (Haklı &Uğuz (2014), Ant Colony Optimization (ACO), Imperialist Competitive Algorithm (ICA) etc.

The most straightforward algorithm is the Particle Swarm Optimization or the PSO. The initialization of particles having velocity vectors and random position takes place first. For each function the evaluation of the fitness function is done. It is updated when good over optimal individual fitness. This is followed by the updating of the best global fitness. After this, for each particle a new velocity as well as position is obtained and this cycle keeps repeating for a certain number of iterations of till the convergence crosses a particular threshold. The PSO and the cuckoo search (CS) are the meta heuristic algorithms (Nandy, Yang, Sarkar & Das, 2015) that have been inspired by the birds. Ensuring that the entire search area is enveloped is the important characteristic of the levy flight. This is because of the heavy tailed feature of the levy distribution.

CS algorithm is based on the cuckoo's behavior of obligatory brood parasitism (Dhivya, Sundarambal & Vincent, 2011) and Levy Flights which follows the random walk with distribution of the step sizes. CS is general and strong when compared to other metaheuristic algorithms. CS effortlessly adapts to investigate the multi-objective optimization with various constraints. Global levy flight on cuckoo search is proposed where once the PSO is iterated for efficient cluster head selection in WSN. Study of relevant literature is discussed in section 2; techniques and methodology are studied in section 3; and section 4 explains the results and its explanation in detail and section 5 concludes the work.

2 LITERATURE SURVEY

A tutorial and survey of (Fei, Li, Yang, Xing, Chen & Hanzo, 2017) recent research and development efforts addressing this issue by using the technique of Multi-Objective Optimization (MOO). First step is providing an overview of the chief objectives of optimization that are employed in the wireless sensor networks. The next step is the explanation of the various techniques that are used in MOO- the family of mathematical programming based scalarization techniques, the family of heuristics/Meta-heuristics based optimization algorithms, and several other advanced optimization methods. The next stages involve abridging the research on MOO done of late, in the perspective of wireless sensor networks that may enable the researchers to appreciate the literature that they reference. The final stage was to discuss the issues that needed to be dealt with in future studies.

PSO-ECHS was suggested (Kumar, Mohanraj & Goudar, 2014) that has its basis on the Particle Swarm Optimization; It is a Cluster Head Selection heuristic that is extremely energy efficient. An effective approach of particle encoding and fitness function was used for developing this algorithm. Several parameters such as sink distance, sensor nodes' residual energy and intra-cluster distance were considered for the energy efficiency of the suggested PSO concept. Cluster formation was also presented wherein the non CH sensor nodes joined their cluster heads on the basis of a derived weight function. This algorithm has been tested by applying it widely across several WSN scenarios, differing number of sensor nodes as well as the cluster heads. The efficacy of the suggested algorithm has been shown by comparing the outcomes with those of the existing algorithms.

A new clustering technique that is on the basis of brood parasitism of few birds that belong to the cuckoo species was suggested by Kumar et al (Karthikeyan & Venkatalakshmi, 2012). This would enhance the network lifespan when compared to the basic LEACH protocol. It was shown by the outcomes of simulation that when such bio inspired computations were appended to the already existing protocol patterns, there was an enhanced efficiency of the network.

In the sensor network, the Cuckoo Search which is a meta-heuristic optimization technique has been employed for data aggregation. As per (Palaiah, Prabhu, Agrawal & Natarajan, 2016), the nodes that have the minimal energy are formulated as subsidiary clusters to sense the data and the nodes having high energy as the CH which communicates with the base station. Enhanced network performance can be obtained by the suggested cuckoo search which can result in balanced energy dissipation and also leads to optimal clusters as well as reduced power consumption. Simulation results demonstrate the efficacy of the scheme when compared to the conventional techniques.

One of the challenges to be tackled in the present days regarding the WSNs is the efficient consumption of energy. When the nodes have been clustered in an organized manner, the lifespan of the networks gets prolonged. The incorporation of the cuckoo search in the PSO was suggested by (Rao, Jana, & Banka, 2017) so that clustering could be done considering the energy efficiency and the outcomes were compared with the CS algorithm. The total communication distance was decreased by means of efficient clustering of the WSN. It also increased the likelihood of a node with superior energy to function as the cluster head. Compared to the LEACH, SEP and the cuckoo search algorithms, the lifetime is improvised by the suggested algorithm.

Levy flight forms the basis of cuckoo search algorithm which enables the location of efficient cluster heads. The local search can be considerably hastened using the Levy flight which also guarantees the optimal covering of the output domain .The benefits of this algorithm are its simplicity, efficiency and its ease of implementation. In a relative learning of the suggested CS algorithm (Solaiman, 2016) based on K-means and Levy Flight have been discussed and the efficacy of this scheme has been shown in the clustering of web documents from the obtained results.

There are some issues with the PSO algorithm, despite the fact that it is both simple and efficient. As a result of premature convergence, there is a possibility that it can get trapped in local minima. Its global search ability is also restricted. These disadvantages can be overcome by combining the PSO with the Levy flight in (Yang & Deb, 2013). Levy flight is a arbitrary walk determining step size through Levy distribution. In case of the Levy flight, a much effective search occurs as the particle jumps longer distances. The suggested approach defined a threshold value for every particle and in case there was no improvement in the particle self-solution when the current iteration ended, this threshold was enhanced .In case the threshold is exceeded by the particle; it is re-dispersed in the search space by employing the Levy flight technique. Hence, the global search ability as well as the avoidance of the local minima are both assured using basic PSO distribution. The suggested way termed as Levy flight particle swarm optimization (LFPSO); its performance as well as accuracy is observed on familiar unimodal and multimodal benchmark functions. It has been experimentally demonstrated that LFPSO is better than the state-of-the-art PSO or SPSO and the several other variations of the PSO as far as the strength and the quality of the solution are considered. After having statistically compared the results, a considerable difference has been noticed between the SPSO and the LFPSO techniques and also, the outcomes of the suggested scheme have been weighed against those of a popular and contemporary population based optimization approaches.

A comparative study of the Genetic Algorithm (GA), particle Swarm Algorithm (PSO) and the Cuckoo Search (CS) was made by (Yang & Deb, 2010), for clustering. CS has been employed with Levy Flight whose heavy tail property has been exploited in this case. On three of the standard benchmark datasets, these algorithms have been used and also applied on one real time multi spectral satellite data set. Various techniques have been employed to tabulate and analyze the results. It has been finally concluded that given a set of parameters, the CS is efficient for most of the data sets and also that an important role is played by the Levy flight.

A combination of CS and PSO were presented by (Ghodrati & Lotfi, 2012) for dealing the optimization issues. The birds of the cuckoo species lay their eggs in the nests of other host birds and if these are determined by the host birds, their either discard the eggs or abandon the nests. The cuckoo birds move to a place wherein the chances of their eggs being discovered by the hosts are less (Srivastav & Agrawal, 2017). Levy flight is used by the birds to experience new places in the standard cuckoo search. In the suggested hybrid approach, the cuckoo birds are aware of the positions of one another and for reaching better solutions; they employ the swarm intelligence in the PSO. Along with standard benchmark functions, experimental outcomes have been noted and the promising futures of these algorithms have been demonstrated by the results.

It is confirmed by the optimization that every network link is symmetrical and energy efficient. Most network features are additive in behavior due to NP hard optimization. Based on nature-inspired ideas, several optimization algorithms have been established. Evolutionary Algorithms (EAs) and swarm optimization algorithms are its two classification types. All species examines a valuable adaptations in all altering environment in natural evolution.

Genetic Algorithm (GA), and Differential Evolution (DE) is an example of EA. PSO, Ant Colony Optimization (ACO), and Bee Colony Optimization (BCO) are comprised in swarm optimization. This work proposed PSO and CS with levy flight. PSO is a population-based search technique in which the position of particles varies with time. CS algorithm depends on the obligate brood parasitic behavior of some cuckoo species with the Levy flight behavior of some birds and fruit flies.

3 METHODOLOGY

THIS section explains on PSO, cuckoo search with levy flight at detail.

3.1 Particle Swarm Optimization (PSO)

A strong stochastic nonlinear optimization method on the basis of motion and swarm intelligence. The communal activity of a swarm of birds which is a group was the motivation for the PSO. Through an adjacent bird to the food source, the birds search for food randomly. The local search techniques are combined along with the global search techniques and for locating the best position has been obtained so far, the social interaction within the swarm is used. The chief concept of the PSO is obtaining several particles moving in the search space that intend to achieve best solutions by talking to the neighbors.

The particle swarm optimization is a population based technique that can improvise the outcomes iteratively. This is done when the solutions are brought closer to the optimal solution. Every particle travels with the velocity v_i at every iteration and in the end all of the particles combine at an optimal solution (Cheng, Wang, Wu & Han, 2015). Initially, there are *n* particles that are formed and these are arbitrarily dispersed in the search space. By considering the classes individually, every particle's fitness is evaluated. The particles move single step to the appropriate particle and to its own best position with a velocity as in equation (1):

$$pbest(i,t) = \arg\min_{k=1,...,t} [f(p_i(k))],\ \mathrm{i} \in \{1,2,....,\mathrm{N}_p\}$$
$$gbest(t) = \arg\min_{\substack{i=1,....,N_p \\ k=1,...,t}} [f(p_i(k))] \tag{1}$$

where *i*- particle index, N_p - total number of particles, t - current iteration number, f - fitness function, and P - position. The velocity V and position P of particles are updated by the equations (2):

$$V_i(t+1) = wV_i(t) + c_1r_1(pbest(i,t) - P_i(t)) + c_2r_2(\mathrm{g}best(t) - P_i(t))$$
$$P_i(t+1) = P_i(t) + V_i(t+1) \tag{2}$$

where V- velocity, ω- inertia weight, r_1 and r_2 - uniformly distributed random variables within range [0, 1], and c_1 and c_2 - positive constant parameters called "acceleration coefficients." After calculating every particle's fitness, the personal best position and the global best position are determined and till the stopping conditions is met, this process is iterated .For a given data set, the best position is the cluster centre.

3.2 Levy flight of Cuckoo Search (CS)

An optimization algorithm formulated by (Yang & Deb, 2010) is the CS. CS algorithm is based on the interesting breeding behaviour such as brood parasitism of definite species of cuckoos. The eggs of this bird are laid in the other birds' nests. Where the optimal solution is searched for in multi-dimensional space, the cuckoo search has been performed for maximization problem. Here the fitness or the quality of a solution is proportional to the objective function's value. The CS is similar to the hill climbing algorithm (Tian, 2017). There are 3 idealized rules on which the CS is based:

1. Laying one egg at a time, a cuckoo bird drops the eggs in a nest that has been arbitrarily chosen.
2. The nests that have the highest quality eggs are carried over to the subsequent generation.
3. The eggs laid by the cuckoo are found by the host with a probability and the number of nests of the hosts is fixed.

The manner that is employed by the animals in nature to look for food is either random or quasi random. As the next move depends on the current state or location and also the likelihood of transition to the next location, the foraging route that is chosen by an animal is an arbitrary walk. The probability that can be mathematically modeled determines the direction that it chooses implicitly. For instance, it has been shown by different studies that the typical traits of Levy flights have been shown by the flight behavior of several animals as well as insects. Light is related to Levy flights. This behavior is functional to optimization and optimal search, and primary results demonstrates its capable proficiency.

Levy flight is random walks where the steps-lengths are defined, which have a certain probability distribution and the direction is random. In Levy's flight the resulting movement depends on the existing position as in equation (3):

$$X_i(t+1) = X_i(t) + \alpha \oplus Levy(\lambda) \tag{3}$$

where α > 0 is the step size, generally it is taken as one. ⊕ - entry-wise multiplication i.e. Exclusive OR operation. The random step size follows a levy distribution as in equation (4):

$$Levy \sim u = t^{-\lambda}(1 < \lambda \leq 3) \tag{4}$$

On generating initial population, iteration process starts where cuckoo is randomly selected using Levy flight. The nests are randomly chosen and the quality of cuckoos egg is evaluated. If any best solution is obtained, its replaces the old solution and the solutions are ranked to find the current best solution.

3.3 Proposed Global Levy with PSO

Step 1: Initialization: Begin the search by selecting the number of sensor nodes, cuckoo nests, eggs in nests to start the search. There are multiple eggs in every nest that represent a solution set. The location of the base station, the energy of the nodes and the location is initialized**.**

Step 2: Formation of Clusters using Cuckoo Search: random walk is used for the selection of the best egg. Step size and Levy angle is restructured. The nests are simplified.

$$f(df_i) = \sum_{i=1}^{n-1}(100 * d_i) \tag{5}$$

Step 3: Communication to the Base Station: The cuckoo finds the optimal route through least levy angle and random walk. Cuckoo navigates from a source node (Cluster) to the base station by travelling over neighbor clusters.

Algorithm for Global Levy with PSO

Step 1: Set the parameter and initialize the Population
Step 2: Initial fitness value of population is calculated
Step 3: Process PSO based search mode for 20 iteration

A. Initialization of PSO

For each particle $i = 1, 2, \ldots\ldots\ldots N_p$, do

Initialize the particle's position with a uniformly distribution as $P_i(0) \sim U(LB,\ UB)$, where LB and UB represent the lower and upper bounds of the search space

Initialize $pbest$ to its initial position: $(i, 0) = (0)$

Initialize $gbest$ to the minimal value of the swarm: $(0) = \text{argmin}[P(0)]$

Initialize velocity: $Vi \sim (-|\text{UB} - \text{LB}|, |\text{UB} - \text{LB}|)$

B. Repeat until a termination criteria is met

For each particle $i = 1, 2, \ldots\ldots\ldots N_p$, do

Pick random numbers: $r1, r2 \sim (0,1)$

Update particle's velocity

Update particle's position

If $[(t)] < [pbest(i, t)]$, do

(i) Update the best known position of particle i: $(i, t) = Pi(t)$

(ii) If $[(t)] < [gbest(t)]$, update the swarm's best known position: $gbest(t) = Pi(t)$

$t \leftarrow (t + 1)$;

C. Output the best found global solution.

Step 4: Global solution of PSO is taken as initial population of CS

Step 5: Process of Cuckoo Search

Begin

Objective function $f(x)=(x_1,\ldots,x_d)^T$

Generate initial population of "n" nests x_i (i=1, 2, ….., n)

While (t<MaxGeneration) or (stop criterion)

Get a cuckoo from the global solution by Levy Flights

Evaluate its quality/fitness F_i

Choose a nest among n (say j) randomly

if $(F_i > F_j)$

Replace j by the new solution;end

A fraction (p_a) of worse nests are abandoned and new ones are built; Keep the best solutions (or nests with quality solutions); Rank the solutions and find the current best

End while

Post process results and visualization

End

Step 6: Best Optimal solution is obtained

4 RESULTS AND DISCUSSION

TABLE 1 shows the parameters of cuckoo search. Table 2 to 5 and Figure 1 to 4proves the number of clusters formed, average end to end delay, average packet loss rate and percentage of nodes alive respectively.

Table 1. Parameter of PSO and Cuckoo Search

Population Size for PSO	60
C1, C2 for PSO	1, 1
Maximum Number of Generations	300
Sensor deployment area	100m * 100m
Base Station location	(50m, 150m)
Number of nodes	100 – 600
Number of nests for CS	100
Number of eggs in a nest for CS	1 – 3
Data packet size	100 bytes
Number of rounds	0-800

Initialize and execute the PSO for 20 iteration then the cuckoo search with Global levy flight run to obtain an optimal solution. Then CS is initiated where the initial population for CS is obtained from the global best positions of the PSO. The levy flight is initialized and the algorithm iterates to obtain optimal solution. The Maximum Number of Generations (300) denote the max iteration the CS algorithm is subjected to and number of rounds (0-800) here denotes the cycle of data transfer happening in the WSN network.

Table 2. Number of Clusters formed for Global Levy with PSO

Number of nodes	PSO	Global Levy with PSO
100	12	14
200	19	23
300	31	36
400	36	40
500	36	45
600	44	51

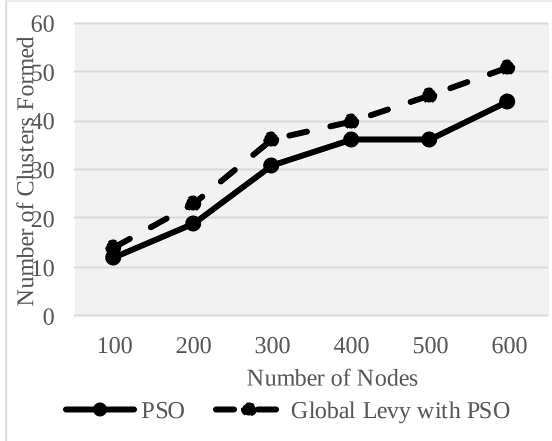

Figure 1. Number of Clusters formed for Global Levy with PSO

From Table 2 and Figure 1 it is observed that the number of clusters formed for Global Levy with PSO performs better by 15.38%, by 19.05%, by 14.93%, by 10.53%, by 22.22% and by 14.74% than PSO at number of nodes 100, 200, 300, 400, 500 and 600 respectively. Table 2 shows that as the number of nodes in the network increases the number of clusters in the network also increases. Since clustering the sensor nodes can significantly increase the energy efficiency and scalability of the network, this proposed method proves the better CH selection to achieve longevity in WSN. The increase in clusters improves the longevity in the network.

Table 3. Average End to End Delay (sec) for Global Levy with PSO

Number of nodes	PSO	Global Levy with PSO
100	0.00172	0.00146
200	0.00178	0.0015
300	0.01746	0.01453
400	0.029	0.02414
500	0.0583	0.05724
600	0.0658	0.05511

From Table 3 and Figure 2 it is observed that Average End to End Delay for Global Levy with PSO performs better by lowering delay by 16.35%, by 17.07%, by 18.32%, by 18.29%, by 1.83% and by 17.68% than PSO at number of nodes 100, 200, 300, 400, 500 and 600 respectively. The transmission distance increases as the number of nodes in the network increases and hence the end to end delay also increases when data get transmitted through more number of nodes. However, even though the nodes increased in the network the end to end delay in the Global Levy with PSO showed considerable improvement compared to other methods.

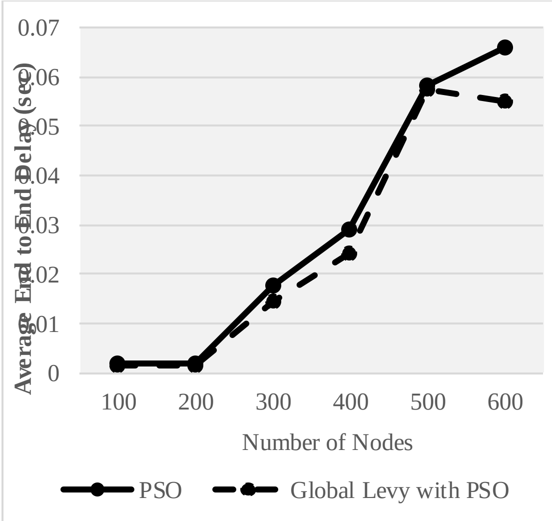

Figure 2. Average End to End Delay (sec) for Global Levy with PSO

Table 4. Average Packet Loss Rate (%) for Global Levy with PSO

Number of nodes	PSO	Global Levy with PSO
100	9.25	8.96
200	14.4	13.81
300	14.75	13.68
400	21.94	20
500	29.26	27.94
600	33.35	29.76

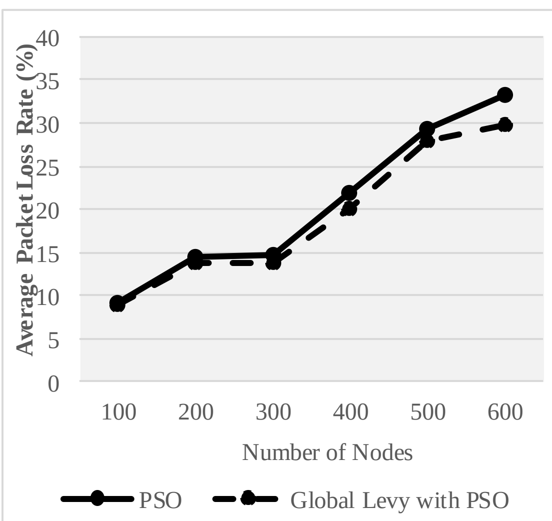

Figure 3. Average Packet Loss Rate (%) for Global Levy with PSO

From Table 4 and Figure 3 it is observed that Average packet loss rate for Global Levy with PSO performs better lowering the packet loss rate by 3.19%, by 4.18%, by 7.53%, by 9.25%, by 4.62% and by 11.38% than PSO at number of nodes 100, 200, 300, 400, 500 and 600 respectively. Packet loss ratio presents the number of data not delivered to the base station. The proposed method evidently showed that the number of packet drop during transmission decreased and hence higher data delivery rate is proved.

From Table 5 and Figure 4 it is observed that percentage of nodes alive for Global Levy with PSO performs equal, better by 6.2%, by 6.4%, by 10.4%, by 31.6%, by 108.43% and by 128.21% than PSO at number of nodes 100, 200, 300, 400, 500, 600 and 700 respectively. The proposed global Levy with PSO provides better node level energy management as shown in figure 4. As the number of rounds for transmission of data in the network increases, the energy consumption in the nodes as time goes by also increases and hence it can be observed that the nodes alive in the network also decreases due energy dissipation.

Table 5. Percentage of Nodes Alive for Global Levy with PSO

Number of rounds	PSO	Global Levy with PSO
0	100	100
100	100	100
200	94	100
300	91	97
400	82	91
500	64	88
600	19	64
700	7	32
800	0	11

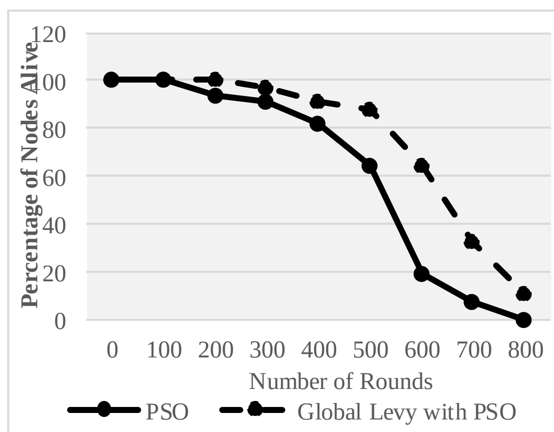

Figure 4. Percentage of Nodes Alive for Global Levy with PSO

5 CONCLUSION

ENERGY is an inadequate resource in WSN. A sensor consists of inadequate power source. Its working condition depends on its battery. Proposed work includes the modeling of a multi-objective problem. While dealing with the MOO optimization, the meta heuristic algorithms demonstrate their benefits. All these basic components are combined effectively in the cuckoo search and using one or some of these components, this is potentially better. In the proposed method, a limit value is stated, and if the particles are not enhanced the self-solutions of existing iteration, then this limit is maximized. When the limit value is overdone by a particle, then it is rearranged with Levy flight algorithm. To avoid the local minima issue and to enhance a global search competence are confirmed through this distribution. Global Levy flights ensure the good diversity of the solutions. Results illustrate that the number of clusters formed for Global Levy flight with PSO performs better by 15.38%, by 19.05%, by 14.93%, by 10.53%, by 22.22% and y 14.74% than PSO at number of nodes 100, 200, 300, 400, 500 and 600 respectively. Also average end to end delay, average packet loss rate, number of nodes alive is better for global levy flight with PSO than the PSO algorithm.

Future research directions on MOO conceived for WSNs include multi-hop transmissions, the deployment of nodes in highly dynamic scenarios, secure multipath routing protocols and solving optimization problems in 3D networks, Cognitive Ratio (CR)-WSNs and smart grid. Future investigation with different meta-heuristic algorithms can be carried out to check the efficacy.

6 DISCLOSURE STATEMENT

NO potential conflict of interest was reported by the authors.

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