Young Scientist- Tomorrow's Science Begins Today
http://eurekajournals.com/Young_Scientist.html
ISSN: 2581-4737

A Hybrid Glowworm Swarm Optimization Using in Smart Sensor Network for Electric Grids

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Abstract

The special features of smart grid technology includes regular metering communication, renewable power incorporation, allotment computerization and whole scrutinizing and organization of complete power grid. Little micro-electrical automatic schemes that are deployed in collecting and broadcasting data from ambience are Wireless Sensor Networks (WSNs). Providing security and energy consumptions are the most emerging issues in Wireless sensor network communication. To enhance the lifespan of a network, energy efficiency should be increased by decreasing energy consumption of the sensor nodes, thus striking a balance in the power consumption of each node. As the primary source of origin of energy consumption of sensor nodes is long distance transmission of data, good impact on energy consumption can be provided through an efficient routing protocol. So as to enhance the lifespan of a network, a number of protocols have been put forth in the form of optimization algorithms. This study involves Glowworm Swarm Optimization (GSO). In GSO, a probabilistic cost is computed by every glowworm in spite of finding its neighboring glowworm that has the enhanced luciferin intensity than others. Based on this probability cost, a glow worm moves towards the chosen glowworm. To enhance GSO performance, the GSO hybrid optimized with Harmony Search (HS) and Tabu Search (TS) local methods are also proposed. Results prove that proposed method achieves better performance.

Keywords: GSO, Harmony Search, Tabu Search, Localization, Luciferin, Wireless Sensor Networks, Electric Grids.

Introduction

WSNs are made up of 100s and 1000s of sensor nodes which are distributed independently in observing physical or ecological considerations including pressure, heat, tremor and movement at various disaster positions such as earthquakes. At least one sensor is present in every node in a SN which is a communication device that resembles a land transient, a small embedded system and a battery for provider of energy (Gong et al, 2018; Elhoseny, Tharwat, Yuan & Hassanien, 2018). Energy plays an important role as the nodes are battery- operated. There are several fields involved such as armed battlefield, fire discovery and erstwhile excessive surroundings. As a result of depletion of power dead nodes are increased and it is quite hard to replace them with new one in remote conditions. So, it is crucial to exploit the duration of sensors by increasing the battery life. (Manjusha and Kannammal, 2014, Janani and Kumar, 2013).

According to standard, the term grid implies an electrical system which supports energy production, broadcast. The technology of power grid is going on huge metamorphosis and one of such recent innovative addition is smart grid. Smart grid is nothing but improvised power grid technology. To deploy Smart grid network, infrastructure of both electrical and broadcasting are inevitable. A smart grid is an improvement of the latest power grid. Based on convention, the power grid bears the power from middle producer to consumers. With the use of modern information technologies, a smart grid can deliver power effectively and can respond to large range of consumers (Fang et al, 2012; Guerrero et al, 2017; Sancho-Asensio et al, 2014).

Two-way communication system is depended upon in WSN with smart grid, where consumers can interact with the network, where both power consumption data and feeding back the energy produced into the grid. As smart grid technology is digital and not electromechanical. In power grid, the daily operation will range from physical apparatus ensures to distant inspecting and prophetic time-oriented preservation by a number of specialized sensors (Robinson & Rajaram, 2016). AMI is used smart grid technology providing easy communication with the consumers and also monitor and control their power consumption. With the use of advanced sensor technologies, consumers can have more advanced home automation tools implemented (Sharma and Pandove, 2017).

When the location of certain fixed or mobile devices remain uncertain, localization becomes important. Then an efficient localization algorithm can conclude the position of individual devices by using all available information for the WSNs. The positioning of mobile robot is another application which has its basis on the signal strength that is received from a set of radio beacons that are located at known locations on the factory floor (Harold Robinson and Rajaram, 2015). If an electrical network has to be fully accountable, a number of monitoring devices have to installed on its nodes and links (to be accurate, the device can be localized anywhere along any link) (Balaji, Golden Julie & Robinson, 2017). Moreover, the message collected by these devices need to be relayed to centralization servers which stored and/or performed computation on these data. Through power lines or wireless medium communication of data can take place. The main aim is in installing just few devices subject to satisfactory monitoring of the network (Poirion et al, 2014). With regards to smart grid applications, the WSNs used have different features when compared to other networks that used for erstwhile nonspecific appliances. Secrecy of data communication is dealt in confidentiality. Authentication is needed to prevent false data from hostile nodes. It assures authenticity of messages. Accessibility implies reliability of military when there is an attack. Integrity refers to messages being received unaffected at the intention. Authorization denotes that only sensor nodes that are authorized can contact and illegal data sharing should be restricted (Chhaya et al, 2017).

The method of optimization is the constraints of a function sought for standards that can maximize or diminish the task. In this, the entire suitable assessments are called sufficient solution and finest assessment is the best resolution. All the mathematical oriented problems are identified using the optimized algorithms. There are various optimization techniques are used in scheduling and resource allotment. This is again a non-deterministic polynomial hard problem. To an extent, these problems can be solved by swarm intelligence algorithms. These types of algorithms are used to improve the scalability, reliability, quality of service and enhanced packet delivery in networks.

The main objectives of the proposed work are

- A hybrid GSO-based dynamic algorithm is proposed to reduce the data traffic and consumption of energy among the sensor nodes.
- Extremely consistent links are proposed for increasing the lifetime of the WSN.
- Significantly improved load balancing technique is proposed to maintain the high link quality among the electric grids in WSN.
- The proposed work is framed to increase the accuracy, reduced computational runtime, increased number of packets and priority packets received; more number of clusters are framed within the WSN environment using electric Grids.

Related Works

In WSN, one of the issues faced in achieving reliable communication is localization. Localization is nothing but estimating a sensor node's position. Extended Kalman Filtering (EKF) is a nonlinear version of Kalman Filtering (KF) which has its own problem of consistency compacts with the case that is the nonlinear stochastic in nature. Efficient localization algorithm was proposed (Chander Janapati et al, 2015) through which sensor nodes approximate their position with elevated precision. This work's purpose is to develop PSO assisted EKF for localization in WSN. For time critical applications, performance evaluation proved that PSO-EKF was better compared to conventional KF.

An Energy Efficient Ant Based Routing (EEABR) Algorithm based on Ant Colony Optimization (ACO) (Camilo, Carreto, Silva & Boavida, 2006) is used for increasing energy as well as life span of WSN. In this algorithm forward ants and backward ants where used to find the path from source to destination through number of intermediate nodes. These intermediate nodes were selected based on the pheromone trail of the node and residual energy of neighbours from current routing table. However, this algorithm is suitable for early period of transmitting packets; this algorithm cannot find the optimal solution because of variation in the collection of pheromone trail.

Multipath Routing Adaptive energy-efficient and lifetime-aware routing protocol (QELAR) (Hu, Fei & Qelar, 2010) routing protocol is used the concept Q-learning method for learning the nodes energy and workload. Based on the learning the work will be efficiently shared among the nodes will improve the energy efficiency by dynamically using routing table. Ant colony optimization router chip (ACORC) (Okdem & Karaboga, 2009) is developed for routing in WSN. It provides the reliable data delivery with presents of fault.

BeeSensor based on the principle of honey-Bees is introduced for swarm intelligent based routing methodology (Saleem, Di Caro & Farooq, 2011). It contains four stages of protocol scouting, foraging, swarming and pocketing. The working principle of Packer is to establish connection between higher layer node and place appropriate forger. Foragers are similar to workers in Bee. It will collect packet from source node to sink node through already established path by Scouts (Forward and Backward). Swarming encapsulate all the foragers into own group. BeeSensor perform better that Swarm.

Fuzzy Ant Colony Optimization Routing (FACOR) algorithm (Amiri et al, 2014) is combined the two principles one is from ant algorithms foraging with fuzzy logic. This algorithm gives better result than AODV for finding optimal path and improved packet delivery ratio.

A distributed modification methodology (Yao & Jiang, 2015) is used for WSN to accomplish localization and position modification of nodes; WSLA+WSRA have to run iteratively in real applications. Through the analysis of experimental results of WSLA, some errors are found and WSRA is eventually proposed, which is based on geographical relationships of neighbours. A nested solution method (Keskin, Altinel, & Aras, 2015) was proposed to demonstrate the location of the sensor networks with improve the efficiency using simulated approaches. HS algorithm (Guo & Mu, 2015) in optimizing WSN node position computation, by minimizing the collision of assortment fault and recovering the location truthfulness node; it also diminish the mathematical convolution, increase speed. A HS-based deployment algorithm (Harold Robinson et al, 2016) is used to help in locating the most favourable number and location of sensor nodes to exploit network coverage and diminish its cost. The appropriate number of sensor nodes is automatically evolved and their optimal locations modified through the capacity of HS. This is possible through the integration of the impression of adjustable duration encoding in every solution vector in representative a changeable quantity of aspirant sensor nodes. The chief elements of new objective function are complex exposure rate, the quantity of sensor nodes and maximum space within sensor nodes which can confirm the choice of most favourable amount of sensor nodes and their locations.

An Improved Harmony-search Energy Efficient Routing Algorithm (Zeng & Dong, 2016) which has its basis on HS algorithm which is a meta-heuristic. Several prime improvements have been proposed to address the WSN routing issues with HS protocol: Primarily, on the basis of features of routing in WSNs, there is enhancement of the encoding of Harmony Memory (HM); next, there is enhancement in the improvisation of New Harmony. Prematurity in generations is reduced by vibrant adjustment for the constraint HM Consideration Rate and confined exploration capability is strengthened. Simultaneously, there is discarding of alteration procedure of HS method in order to build the proposed routing algorithms have less parameter. Finally, the local search ability is improved through the proposition of a successful confined investigate scheme, where the union swiftness and truthfulness of routing method is improved.

Hybrid-Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) (Xu, Ding, Qu & Li, 2018) is used to complete the multi-objective optimization in WSN are effectively optimized through the methodology. Optimal path selection (Vijayalakshmi & Anandan, 2018) is used to enhance the lifespan of the network and its energy efficiency. With poor local optima problems, a number of meta-heuristic techniques, especially PSO have been used effectively. The basis for the proposed technique is PSO and TS algorithms. The impact of heterogeneity of nodes, more energy resources are present in a proportion of inhabitants of sensor nodes (Golden

Julie, Tamil Selvi & Harold Robinson, 2016). Based on the literature shown are about meta-heuristics based routing algorithms for different application improved energy efficiency in different manner.

The basis for Glowworm Swarm Optimization algorithm is that one glowworm gets attracted to another depending upon the concentration of Luciferin. Basically, glowworms interact with one another by releasing luciferin. While they are soaring, they release luciferin, so that brightness can be given out. Through this fluorescent light, they attract the others flying around them. Depending upon the attentiveness of luciferin, the concentration of luminous increases and the glowworm preserve create a centre of attention of related glowworms. By simulation, the features of glowworm swarm optimization algorithm can be formulated: this algorithm's search strategy is several-point corresponding inclusive arbitrarily find based on inhabitants with no progress of mathematical operations. Based on the glowworm's decisions, the exploration gateway is indomitable and most favourable consequence is reached (Zhou, Zhou, Wang & Zhao, 2013). Every solution is called "harmony" and is characterized by a D- dimension authentic vector in the basic HS algorithm. There is haphazard production of preliminary population of harmony vectors and is stored in Harmony Memory (HM). Then invention of a latest contender harmony is prepared from all elucidation sin HM with the exploit of memory thoughtfulness rule, and terrain alteration rule. Ultimately, modernizing of HM was completed as evaluated to inventive harmony (Wu, Qian, Ni & Fan, 2012). Additionally, the search-based algorithms are based on primal shape of tabu search. The supplementary better shapes of tabu search enclose numerous key methodologies that may jointly construct the most excellent results (Orojloo & Haghighat, 2016).

The drawbacks of the existing works are whenever the Wireless sensor network based smart grid applications, conventional methods are used for gathering the global data and obtaining the position of the sensor nodes. The sensor nodes having the reduced memory and watchful usage of resources in an active network topologies in smart grid based surroundings. Hence, the existing methods are unable to optimize the performance of reliable communication in extended behaviour. Also, the proactive neighbour finding methodology is used for dynamic routing in an alternate path. Hence, the existing methods failed to provide the optimized framework for memory exploitation. This increased the packet delay and network overhead in WSN.

The main Contributions of the proposed work are

- Two new heterogeneous algorithms for smart grid in WSNs have been proposed.
- A new generation method of a new harmony for routing optimization in WSNs has been proposed.
- An effective local search strategy is proposed to improve the speed of the proposed routing algorithm.
- Hybrid HS-GSO method is executed. GSO is fewer efficient in preliminary iterations while believing noteworthy space of ultimate optimal solution with holds to preliminary solutions.
- Hybrid TS-GSO algorithm makes full use of the exploration ability of GSO and the exploitation ability.

Hybrid Glowworm Swarm Optimization

Network Formation

GSO algorithm finds its applications in many fields including multimodal function and combination optimization, robotics applications, and WSNs. It is also used widely in certain NP-Hard problems such as Travelling Salesman Problem (TSP) and 0-1 knapsack issues. There are certain disadvantages of GSO algorithm which include reduced precision in later iterations, decreased convergence speed and easy trapping in local optimal solutions (Du, Lei & Wu, 2014). The quality of optimization process can be enhanced by the proposed hybrid HS-GSO- method. As GSO can utilize previous local and global solutions, and HS can acquire preliminary most favourable solutions of the complex problem, hybrid HS-GSO method is executed. GSO is fewer efficient in preliminary iterations while believing noteworthy space of ultimate optimal solution with holds to preliminary solutions. Regarding this, allotment of original iterations to HS methodology acquires position in the proposed hybrid HS-GSO method. This work occupies 20% iteration to HS technique and the enduring to the remaining iterations to hybrid HS-GSO technique to modernize optimal solutions. On the other hand, final iteration in HS is not efficient completely in modernizing optimal solutions. As no sorting is required in GSO method, the optimal solution with elevated speed is achieved in GSO. Consequently, the last iterations are allocated to GSO technique for acquiring the completed optimal solution. In this work, 40% of the iterations are allocated to GSO method (Nazari- Heris, Fakhim-Babaei & Mohammadi-Ivatloo, 2017). Figure 1 demonstrates the wireless sensor network formation with the sensor nodes, sink node is elected using the algorithm and the data can be sending from the source node to the destination node through the active path.

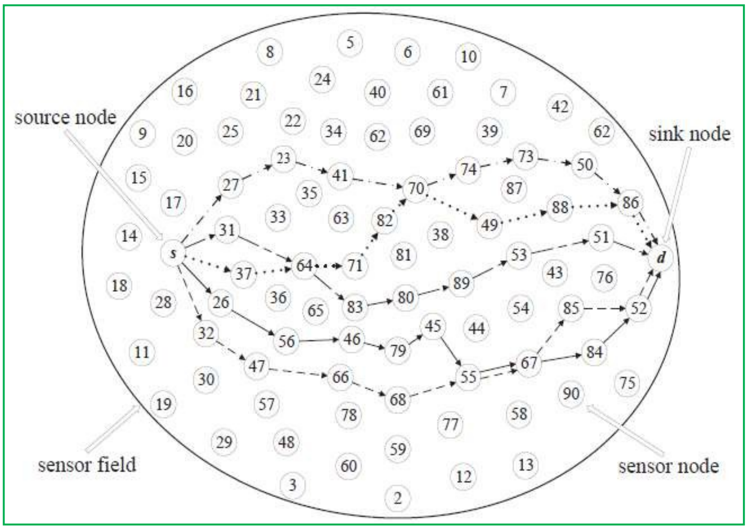

Figure 1.Wireless Sensor Network Formation

The location of the glowworm is computed for updation of luciferin. In this procedure, every glowworm includes the initial luciferin value with the current functional value. Moreover, the small amount of luciferin is deleted from the initial value. The updating value is calculated using the Eq. (1)

$$lu(p + 1) = (1 - \gamma)\, lu_i(p) + \omega\, O(x_i(p + 1)) \tag{1}$$

In this work, some modifications are accomplished in implementing HMCR, PAR, and BW. The modified versions of the mentioned parameters are calculated using the Eqs. (2, 3, 4, 5).

$$PAR(iteration) = PAR_{initial} + \left(PAR_{final} - PAR_{initial}\right)\left(\frac{iteration}{MaxIteration}\right)^{1.25} \tag{2}$$

$$\begin{aligned} HMCR(iteration) \\ &= HMCR_{initial} \\ &+ \left(HMCR_{final} - HMCR_{initial}\right)\left(\frac{iteration}{MaxIteration}\right)^{1.25} \end{aligned} \tag{3}$$

$$BW(iteration) = BW_{initial} + \left(BW_{final} - BW_{initial}\right)\left(\frac{iteration}{MaxIteration}\right)^{0.8} \tag{4}$$

$$V_i^{new} = \begin{cases} V_i(k) \in \{V_i(1), V_i(2), \ldots., \ldots V_i(k)\}, & x_1 > HMCR \\ V_i(k) \in \{V_i^1, V_i^2, \ldots \ldots.., V_i^1\}, & x_2 \leq HMCR \\ x_i(k) + x_3 * BW, & x_3 \leq PAR \end{cases} \tag{5}$$

Algorithm - Proposed Hybrid GSO

Total amount of dimensions = d

Total amount of glowworms = g

Let ss is the size of the step

Let $x_i(p)$*is the position of glowworm it at period* p

deploy_randomly;

for i = 1 to n do

$lu(0) = lu_0$

$ra_m^i(0) = ra_0$

assign MaxIteration as the maximum iteration number

assign $p = 1$;

while $(p \leq MaxIteration)$*do*

{

for every glowworm i do

$lu(p+1) = (1-\gamma)\, lu_i(p) + \omega\, O(x_i(p+1))$

$for\ every\ glowworm\ i\ do$

{

$A_i(p) = \{j: m_{ij}(p) < ra^i\ (p);\ lu_i(p) < lu_j(p)\};$ m

$for\ every\ glowworm\ j \in A_i(p)\ do$

$$pr_{ij}(p) = \frac{lu_j(p) - lu_i(p)}{\sum_{k \in A_i(p)} lu_k(p) - lu_i(p)}$$

$$j = choose\_glowworm(\overrightarrow{pr});$$

$$x_i(p+1) = x_i(p) + s\left(\frac{x_j(p) - x_i(p)}{||x_j(p) - x_i(p)||}\right)$$

$$ra_m^i(p+1) = \min\{ra_s, max\{0, ra_m^i(p) + \beta\left(g_p - |A_i(p)|\right)\}\}$$

}

$p = p + 1;$

}

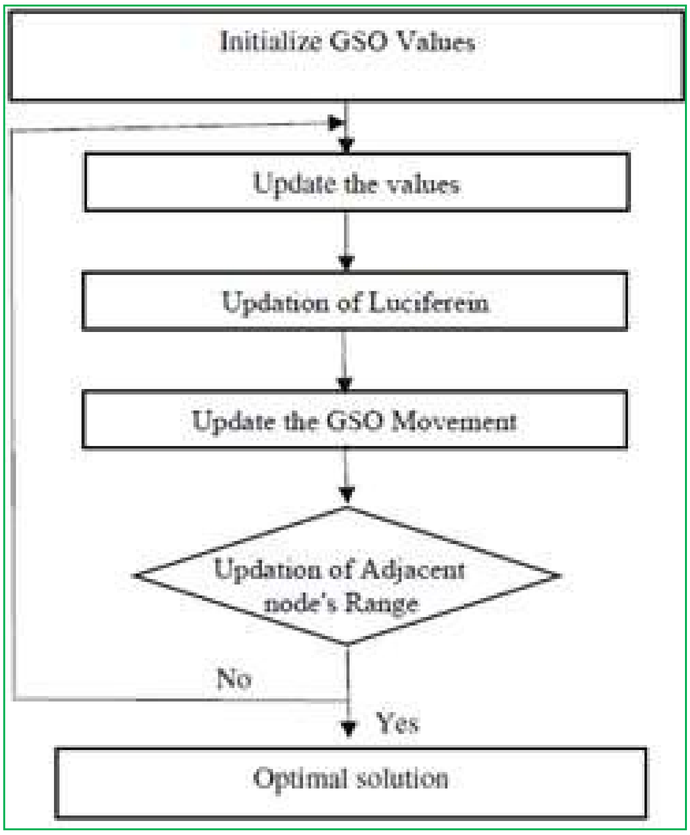

Figure 2.Flow chart for the algorithm

Figure 2 demonstrates the steps are followed in the algorithm. Figure 3 illustrates the Glowworm formation within the radius. Figure 4 demonstrates the flowchart.

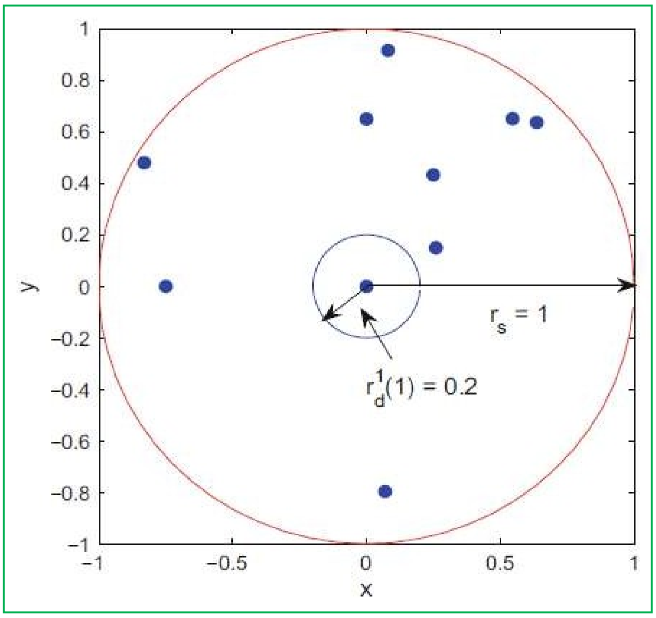

Figure 3.Glowworm formation within the radius

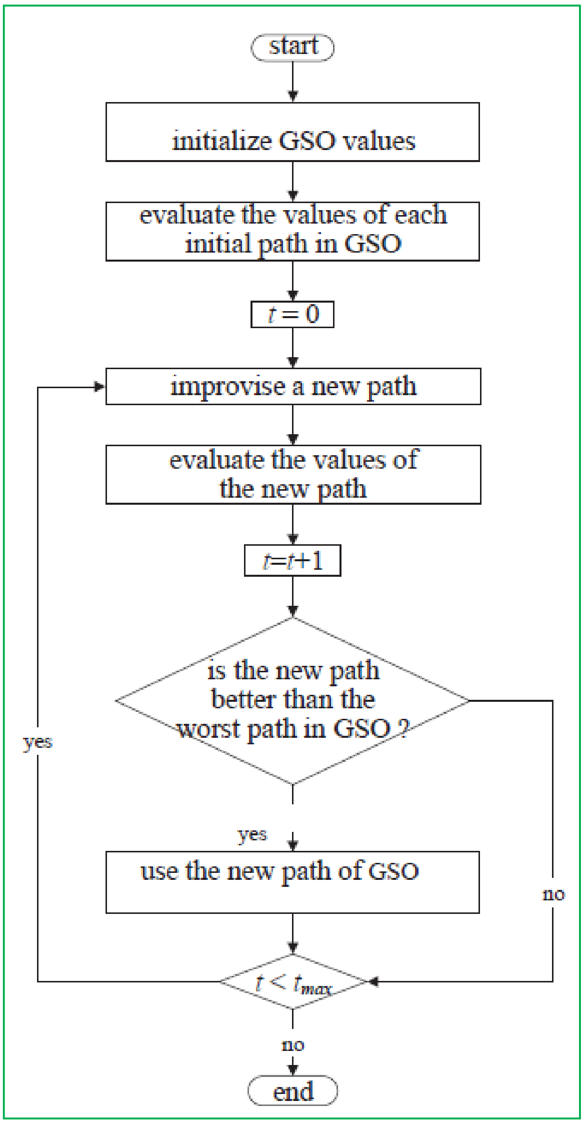

Figure 4.Flowchart for the Hybrid HS-GSO

Optimizing the Transmission Range of the Proposed Method

Combinatorial optimization can be resolved through a local search algorithm, TS. Memory structures such as tabu list or frequency list are used in order to force penetrating progression in covering new searching area and to prevent early conclusion to confined optimal solution. The advantage of TS lies in a strong local searching ability and the ability to jump out local optimum (Fang & Zhang, 2016).

With regards to global search, GSO performs very well but not so proficient with confined exploration; whereas TS achieves fine in confined exploration and not so well in global search. Thus, a combination of both can lead to the formation of a new algorithm which can perform both local and global search in all the iterations, leading to an increase in the probability of finding optimal points. The proposed hybrid TS-GSO algorithm makes full use of the exploration ability of GSO and the exploitation ability of TS and offsets the weaknesses of each other (Zhang & Wu, 2012).

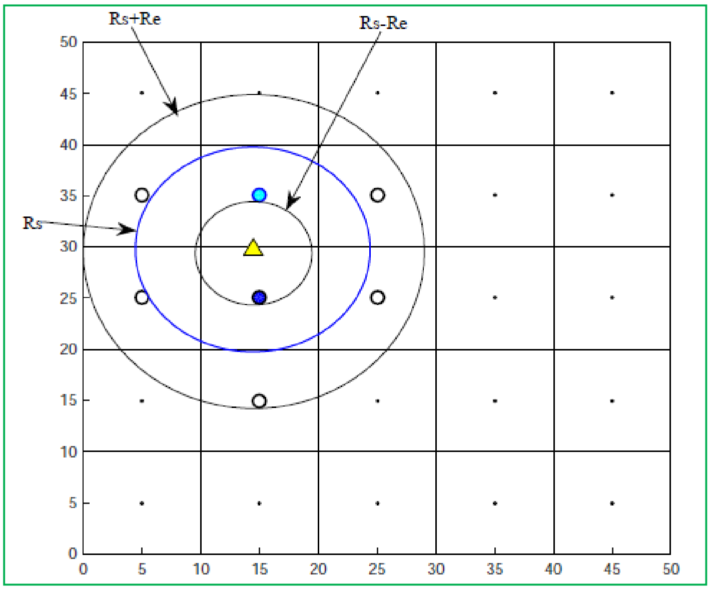

Figure 5.GSO Transmission Range

The updated distinct model of the movement repeatedly acquires to solve the optimization problem. In reality, throughout the movement procedure, every glowworm travels a distance of restricted step size s between neighbours. Therefore, whenever the distance within a glowworm x imminent a neighbour y < s, x selects the location of y and befalls an organizer to y. Figure 5 demonstrates the GSO transmission range.

$$lu(p + 1) = \max \{0, ((1 - \gamma)\ lui(p) + \omega\ O(xi(p + 1)))\} \tag{6}$$

$$pr_j(p) = \frac{lu_j(p)}{\sum_{k\, \epsilon\, A_i(p)} lu_k(p)} \tag{7}$$

$$x_i(p + 1) = x_i(p) + s \left(\frac{x_j(p) - x_i(p)}{||x_j(p) - x_i(p)||} \right) \tag{8}$$

$$ra_m^i(p+1) = \frac{ra_s}{1+\beta\, D_i(p)} \tag{9}$$

$$D_i(p) = \frac{A_i(p)}{\pi\, ra_s^2} \tag{10}$$

$$ra_m^i(p+1) = \alpha + \frac{ra_s - \alpha}{1+\beta\, A_i(p)} \tag{11}$$

$$ra_m^i(p+1) = \begin{cases} ra_m^i(p) + \beta_1 |A_i(p)|, if\, |A_i(p)| \le n_p \\ ra_m^i(p) - \beta_2 |A_i(p)|, if\, |A_i(p)| > n_p \end{cases} \tag{12}$$

β_1 *and* β_2 *are constant parameters*

$$\lim_{p\to\infty} lu_i(p) \le \lim_{p\to\infty} lu^{max}(p) = \left(\frac{\omega}{\gamma}\right) O_{max} \tag{13}$$

Table 1 demonstrates the notations are used in the proposed method and Figure 7 illustrates the proposed TS-GSO method's Flowchart.

Table 1.Notations used in the proposed method

Notations	**Descriptions**
$lu_i(p)$	level of luciferin
p	time period
γ	constant for luciferin decay
ω	constant for luciferin enhancement
$O(x_i(p))$	objective function
i	value of glowworm
j	neighbour for glowworm i
$A_i(p)$	adjacent node finding within time period p
MaxIteration	maximum iteration number
$pr_{ij}(p)$	probability of movement from i to j within the time period p
$m_{ij}(p)$	distance from i to j within the time period p
α	lower bound
β_1	constant parameter 1
β_2	constant parameter 2
$Omax$	maximum value for the objective function
$ra_m^i(p+1)$	neighbour range
$D_i(p)$	Distance for the node i
HMCR	harmony memory considering rate
PAR	pitch adjusting rate
BW	bandwidth

Calculating Node Location and Angle of the sink node

For calculating the converse correlation of the Wireless Sensor Networks, the locations must be measures with the use of the exclusive points. This method is implemented using Monitoring in Figure 6. Monitoring is extremely important where two or more sinks nodes are accessible in WSN.

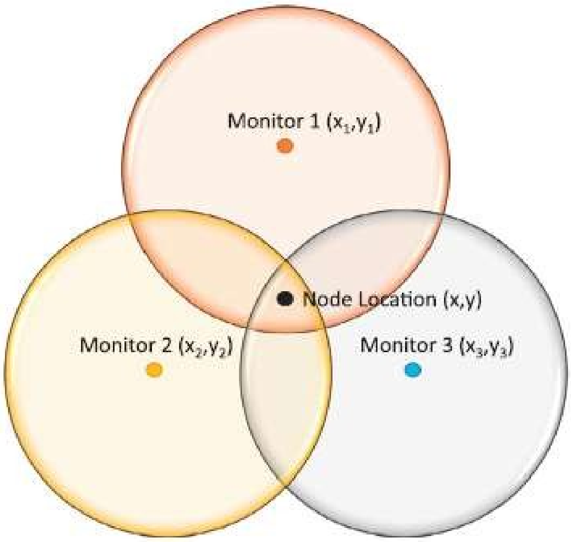

Figure 6.Monitoring of node location

Angle of the sink node is computed where the coordination points can match with the location of the node with particular angle in Figure 7. The particular angle is determined as the Angle of the sink node. It will find the location of the sensor node.

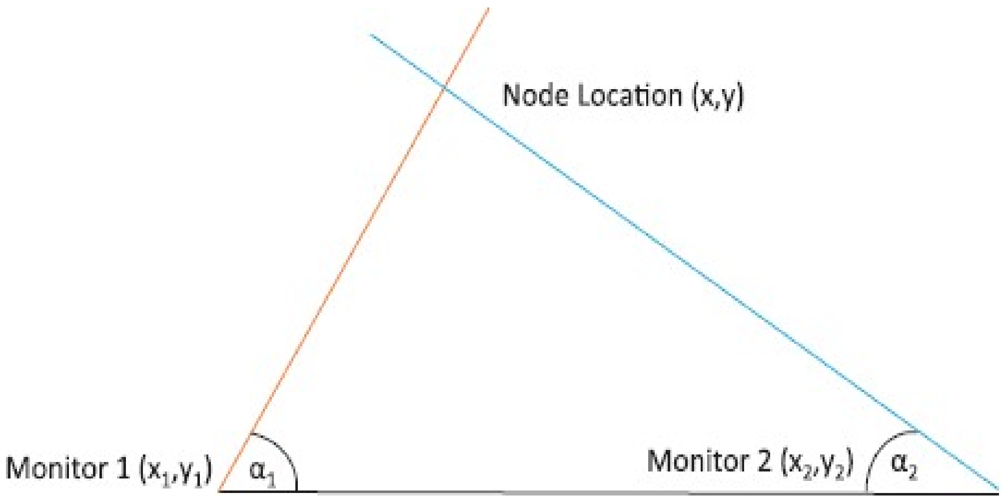

Figure 7.Angle of Sink node

Results and Discussion

Simulation Parameters

The simulation of the WSN is done using NS2. The network is simulated with limited number of nodes from 100 to 1000. The parameters of simulation are displayed in table 2.

Table 2.The parameters for Experimentation

Parameters	Values
Length of the packet	2600 bits
Distribution range	160 m x 160 m
coordination for the sink node	(30, 30)
Total amount of nodes	1000
propagation value	1.52×10^{-10} J/bits/m^2
Type of Mobility	Random Way Model
Type of traffic	Constant Bit Rate
Total number of sensors	265 to 345
Routing Type	Multi-path Routing Model
Type of Modulation	PSK
Sink Model	Poisson
time period for simulation	525 seconds
Bandwidth	30 MHz

The Simulation Results compared the Proposed Work HybridGSO with HSGSO and TSGSO.

Wireless Sensor Network Environment Formation

In the Wireless Sensor Network environment, sensor nodes, fusion centre and standby node are placed in Figure 8. They occupied the specific area of positioning the sensor node. The sensor nodes are positioned at [0.40 m, 0.60 m]. For every anchor node, the fusion centre is used to find the distance of the sensor nodes with constraint. The minimum and the maximum boundary values are initialized to find the position of the sensor nodes.

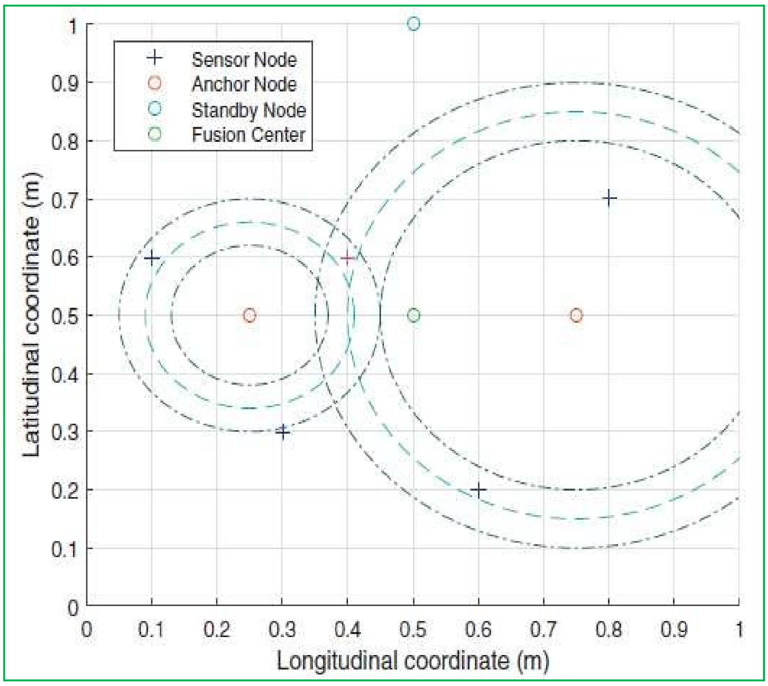

Figure 8.Radius Calculation

The sink nodes are placed in the WSN environment to monitor every node in the network. The data is communicated to the sink node through the fusion centre node to implement the proposed algorithm. The fusion centre is responsible for identify the position of the sensor nodes in the network. The standby node accesses the distance within the sensor node to the sink node. The entire WSN setup is illustrated in Figure 9. Figure 10 illustrates the cluster formation using hybrid GSO.

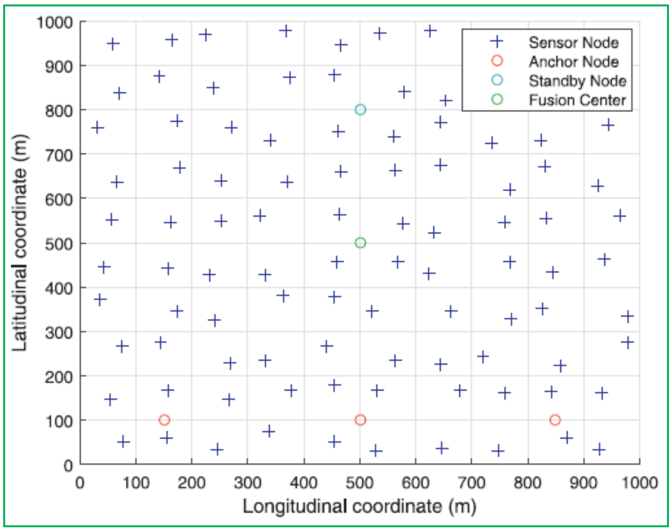

Figure 9.Wireless Sensor Network group formation

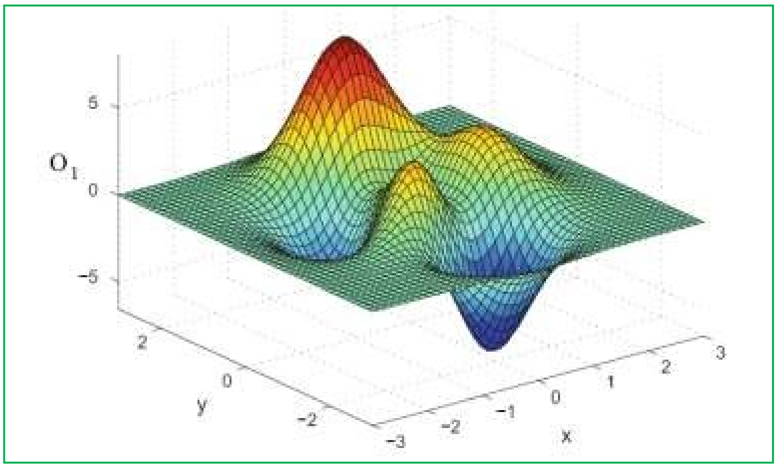

Figure 10.Cluster formation using hybrid GSO

Simulation Results for Sink Node Monitoring

For every simulation stage, we generate the total computational runtime for the whole simulation with the mean calculated time per feature set, per iteration and per node. At last, we separated the whole runtime into the number for node to calculate the runtime of every node. The simulation results are described in Figures (11, 12, 13, 14). The simulation results prove that the 3 sink node monitoring is performed well compared with the 2 sink node monitoring in every stage of the simulation.

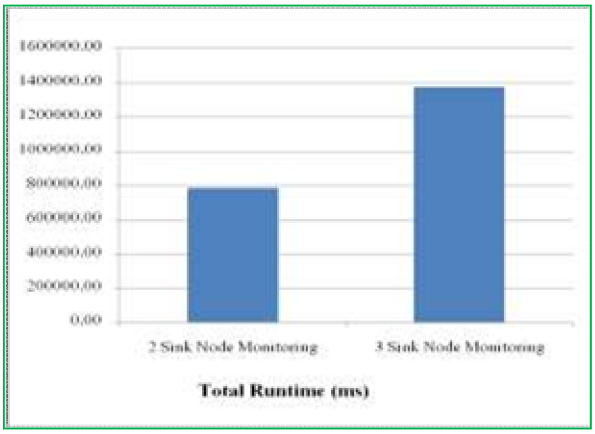

Figure 11.Total Runtime

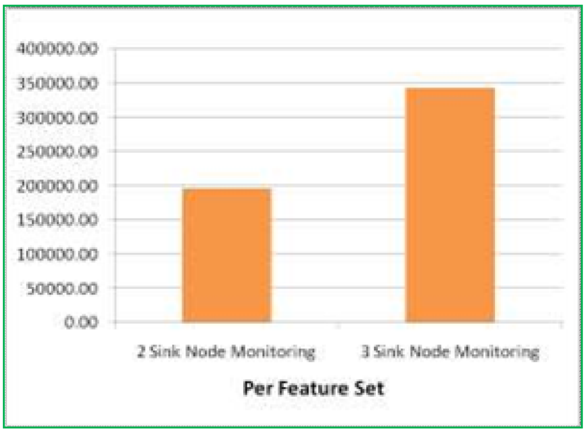

Figure 12.Per Feature Set

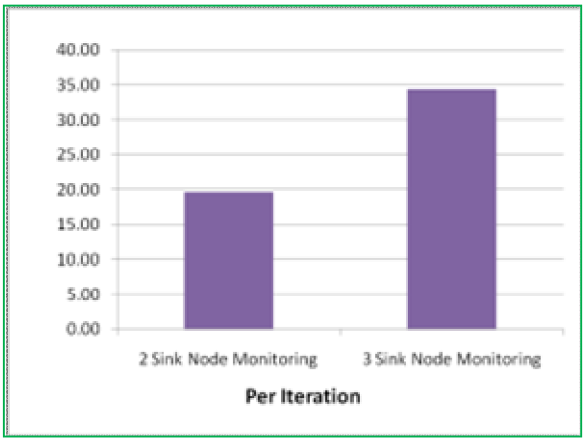

Figure 13.Per Iteration

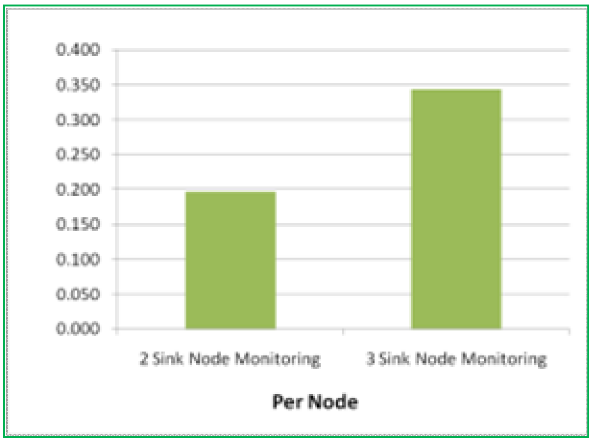

Figure 14.Per Node

Accuracy

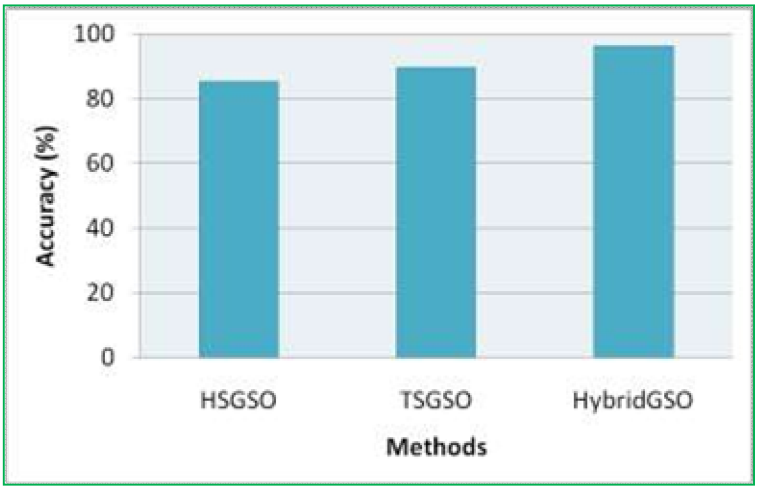

Figure 15.Accuracy (%)

The accuracy is calculated using the how many search parameters are matched with the total amount of search parameters. The position of the sensor node is used for finding the accuracy parameter. The WSN is deployed using the sensor nodes and sink nodes. Figure 15 demonstrates the Accuracy percentage of all the methods used in the simulation. The result suggests that the proposed method has the better Accuracy percentage compared to the related works.

Computation Runtime

For every experiment, the total runtime for the whole simulation is computed using all the input possibility permutations to discover the mean runtime per stages. The experimental result suggests that the computational runtime for the proposed work is reduced while compared to all the related works. Figure 16 illustrates the computational runtime in ms.

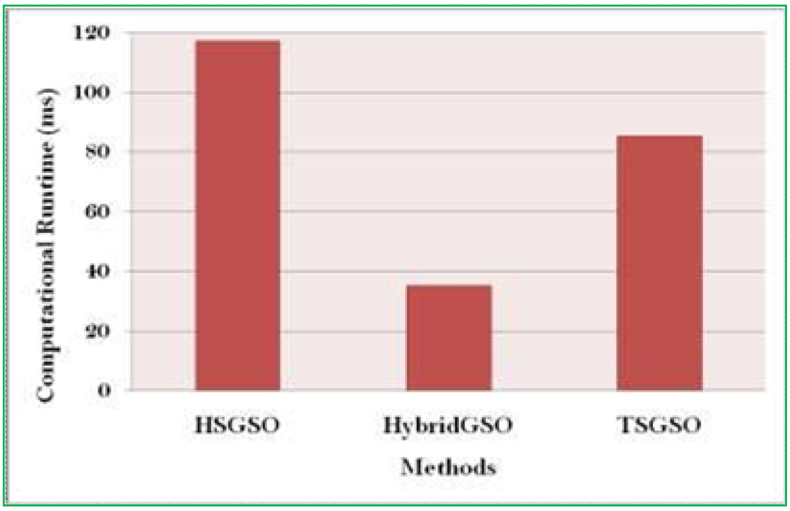

Figure 16.Computation Runtime

Data Packets Received

The number of data packets received at base station is demonstrated in Table 3.

Table 3.Number of Data Packets Received at Base Station for Hybrid GSO

Number of Round	HSGSO	TSGSO	HybridGSO
200	58	62	68
400	54	56	60
600	50	55	60
800	49	53	57
1000	46	50	54
1200	42	45	49
1400	41	44	48
1600	31	33	36
1800	28	30	33
2000	22	24	27

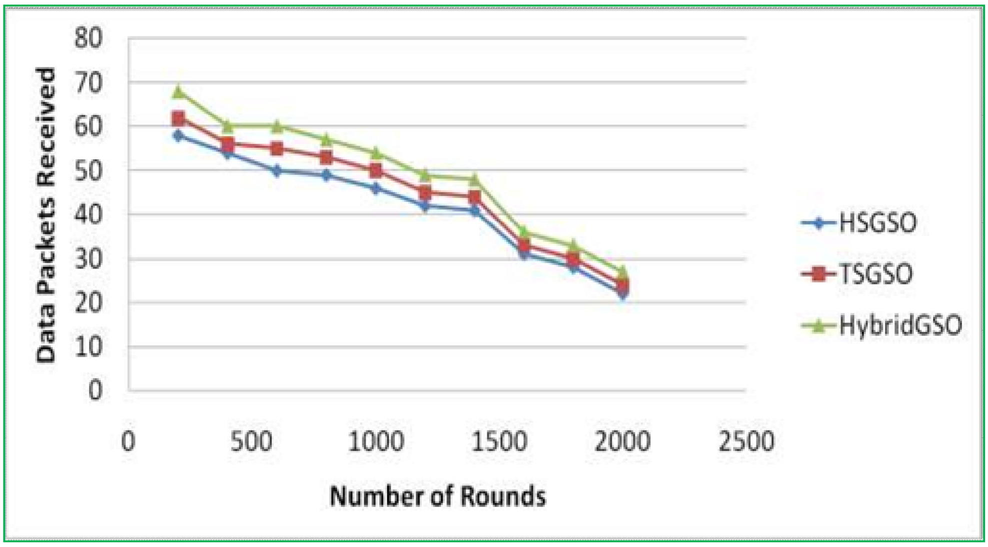

Figure 17.Number of Data Packets Received at Base Station for Hybrid GSO

From the figure 17, it can be observed that the Hybrid GSO has higher number of data packets received at base station averagely by 15.55% for HSGSO and by 2.46% for TSGSO for the different number of rounds.

Number of Priority Packets Received

The number of priority packets received at base station is demonstrated in Table 4.

Table 4.Number of Priority Packets Received at Base Station for Hybrid GSO

Number of Round	HSGSO	TSGSO	Hybrid GSO
200	10	14	18
400	9	13	17
600	8	11	14
800	8	11	14
1000	7	10	12
1200	6	9	11
1400	6	8	11
1600	6	9	11
1800	5	8	11
2000	5	8	10

From the figure 18, it can be observed that the Hybrid GSO method has higher number of priority packets received at base station averagely by 106.35% for HSGSO and by 63.97% for TSGSO for the different number of rounds.

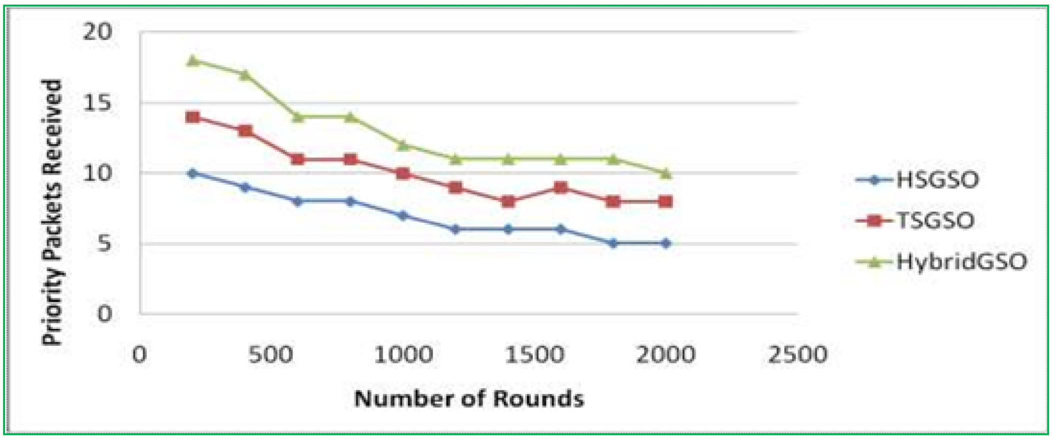

Figure 18.Number of Priority Packets Received at Base Station for Hybrid GSO

Number of Clusters Formed

The number of clusters formed is demonstrated in Table 5.

Table 5.Number of Clusters Formed for Hybrid GSO

Number of Round	HSGSO	TSGSO	Hybrid GSO
200	8	11	14
400	7	10	13
600	6	9	11
800	6	9	11
1000	5	8	11
1200	5	7	10
1400	4	7	10
1600	5	7	9
1800	4	6	8
2000	4	6	8

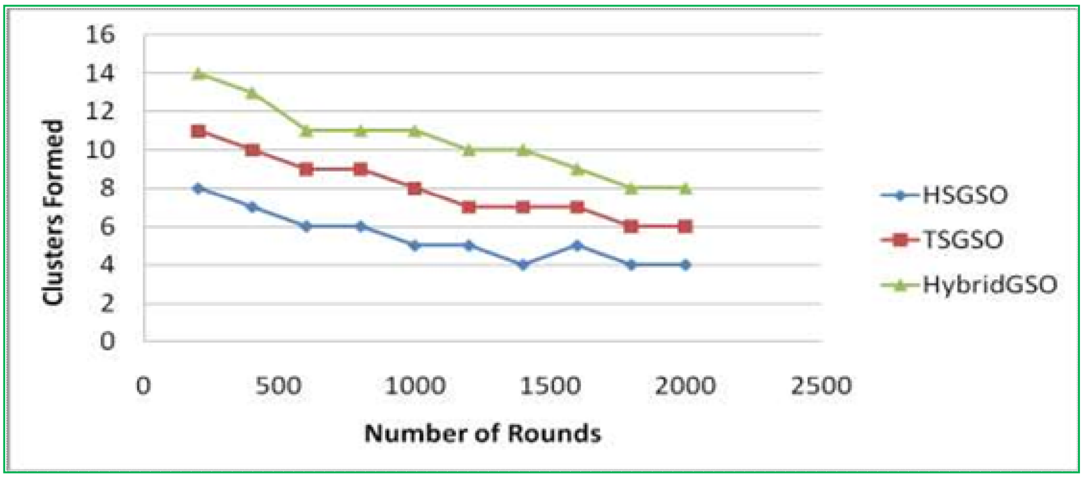

Figure 19.Number of Clusters Formed for Hybrid GSO

From the figure 19, it can be observed that the Hybrid GSO method has higher number of clusters formed averagely by 64.15% for HSGSO and by 13.19% for TSGSO for the different number of rounds.

Conclusion

A complex, hierarchical, heterogeneous network is smart grid. Several applications of smart grid take place through WSN. WSNs play a vital role in energy management in home, business applications and industry. This work involves hybrid GSO (HS-GSO and TS-GSO) algorithm. HS mimics the improvisation process of musicians. Clarification area is searched as a whole in the HS algorithm in finding optimum vector, where the objective function is optimized. The terminology of GSO algorithm is integrated in this hybridization in the HS order, so as to limit the search time for the optimum. TS belong to the category of confined search methodologies. The advantages of mutually GSO and TS are commonly used by this innovative algorithm and this has a quick calculation speed and confined mathematical solution is evaded robustly. Results show that the Hybrid GSO method has superior amount of clusters evaded by 64.15% for HSGSO and by 13.19% for TSGSO for the dissimilar amount of rounds.

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