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Performance Analysis of Swarm Intelligence Techniques to improve lifetime of Wireless Sensor Networks

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Abstract— Wireless Sensor networks (WSNs) is collection of various sensor devices and used to capture the environment conditions. Node deployment, limited energy capacity, location of sensor devices, Quality of Services (QoS) and data aggregation are the critical design challenges in WSNs. To overcome these design challenges in WSNs, many techniques have proposed. Swarm Intelligence (SI) is one of the most appropriate techniques to overcome the design challenges in WSNs.SI shows a current computational and behavioral similarity for taking care of disseminated issues. Initially took its motivation from the biological illustrations gave by social insects like ants, termites, honey bees, wasp and bee. In this paper, implement performance analysis of many SI techniques such that Ant Colony Optimization (ACO), Elephant swarm Optimization (ESO), Hnee based optimization (HBO), Particle Swarm Optimization (PSO) and Modified Artificial Bee Colony (MABC) to improve the WSNs lifespan.

Keywords—Wireless Sensor networks (WSNs), Swarm Intelligence (SI), Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), Modify Artificial Bee Colony (IABC).

I. Introduction

Swarm Intelligence (SI) shows a current computational and behavioral similarity for taking care of issues. It is motivation from the biological illustrations like ants, termites, honey bees and wasp. From an engineering perspective, SI highlights the bottom-up plan of autonomous frameworks that can prove adaptable, dynamic, and scalable practices. The SI techniques incorporate other well-known systems, for example Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Hnee based optimization (HBO), Elephant swarm Optimization (ESO) and Modified Artificial Bee Colony (IABC). ACO is performed to enhance the lifetime of WSNs with energy efficiency. Every wireless sensor nodes are established as a mock ant and automatic routing is performed. The ant indication is introduced at the point when a power saving station from the source to base station is protected. To make enhancement in lifetime of WSNs by optimal path selection based on residual energy. Particle swarm improvement (PSO) approach is SI technique and classification of artificial intelligence (AI). PSO approach begins from the investigation of the nature of predacious birds. According to PSO nature each bird is inattentive as a particle and the enhanced outcome and compares to the location of the particles in the search space [1]. In every phase, the elements are classified as: one is the preeminent location of the neighborhood arrangement and another is the finest location of the comprehensive optimum solution. It provided optimum solution and enhances the WSNs lifespans. Honey bee optimization (HBO) algorithm is utilized viable grouping of nodes based on the distance from the food sources and considers the fitness of the food source which is only the energy accessible in the nodes. HBO based on two classes: utilized foragers and jobless foragers. Scout honey bees respond to search food [2]. Elephant Based Swarm Optimization (EBSO) deals with enhance WSNs lifetime. Elephants are social warm blooded creatures and show propelled knowledge [3-4]. Elephants are frequently found in a "liquid splitting combination" social condition [5]. Elephants portrayed by their great memory, their tendency to exist together and make due inside a cluster [6-8]. Modify Artificial bee colony (MABC) proposed based on the caring foraging manners of honey bees. ABC meta-heuristic technique offered clustering algorithm using effective cluster formation with better cluster head selection. It is more effective based on single objective. It also applied optimal routing to select least hop count from source to destination to save energy and improved lifespan on WSN [9].

The rest of the paper is organized as follows. Section II shows SI techniques for nodes deployment issues of WSNs.

Section III presents SI techniques based on clustering. Section IV shows SI techniques for localization issues. Section V presents SI techniques based on data aggregation in WSNs. SI techniques based on Quality of Services are discussed in Section VI. In addition, comparative performance analysis of various Swarm Intelligence techniques shows in Section VII. Finally the conclusion and future works are presented in Section VIII.

II. Swarm Intelligence techniques for nodes deployment problem of WSNs

WSNs development is a troublesome activity which generally impacts the throughput of WSNs. WSNs design and deployment is located in ideal area, where the sensor nodes could be put. SI techniques are profoundly valuable in tackling the plan and developments issues of WSNs. The systematically deployment of sensor nodes reduced energy consumption, availability and improve scope. In view of the applications, the design and deployment of sensors can be static or dynamic. The topology design will be deterministic if establishment of sensor static, otherwise it is non-deterministic. Both designs are more effective to reduce the energy consumption, in this manner improve the network lifespan. In these sub-sections different types of SI optimization techniques will introduce to resolve the design and deployment problem of WSNs [10-11].

A. A ACO and ABC based optimizations

A hexagonal grid-based and ant colony sensor deployment approach proposed. Hexagonal grid plot and ant colony approach are placed sensor nodes to the suitable places of WSNs. The calculation incorporates both deterministic and self-sorting out arrangements in a bound together structure. Furthermore, it not just ensures the greatest scope of sensor arrangement, yet in addition decreases sensor node moving distance. Easi Design: an enhanced ACO approach for sending in genuine sensor arrange framework. An alteration in the convergence approach and the ant state move governs of the common ACO. Making an allowance for the feasibility issues, we outline the difficulty prevention and the route establishment cost tradeoff systems to guarantee that Easi Design cans effort effectively. It depends on two sorts of useful issues: upgrading the routing hops and avoiding obstacles. Right off the bat gives another pheromone refreshing principle which considers the quantity of sensors as well as the directing expense in the built arrangement. After this outline an impediment location segment to manage the ants to circumvent the obstacles. After the correlations Easi Design accomplishes preferable execution over the traditional ant colony approach [12]. To determine sensor node deployments issue in WSNs an ant colony optimization (ACO) algorithm proposed. It is a proficient deployment plan can decrease the arrangement cost and upgrade the identification capacity of the WSNs. Likewise, it can upgrade the quality of checking in remote sensor and arranges by expanding the coverage area. It gives a characteristic and natural method for investigation of search space for multiple knapsack problems (MKP). The proposed deployment plans to draw out the network lifetime, while guaranteeing complete scope of the network area [13]. Enhanced version of ACO with three classes of ant transitions (ACO-TCAT) is proposed to diminish lesser rate arrangements and narrow the looking scope of the approach. It settles minimum-cost and connectivity guaranteed grid coverage (MCGC) issues for the accomplishment of WSNs. It represents three classes of ant transitions. The decent varieties of modules of ant transitions is connected to minor arrangements and limited the looking scope of the calculation and furthermore enhances the nature of the arrangement space and raise the seeking speed detectably. In addition, it manages diverse sizes of networks. Moreover, the availability of the framework is ensured for various sink areas and the framework cost is reduced [14]. A novel deployment algorithm, ACO-Greedy is proposed. It tackled the issue of grid-based coverage with low-cost and connectivity-guarantee (GCLC). It depends on the ACO with greedy movement approach, which can rapidly entire the full scope, and notably diminish the organization cost. Furthermore, ACO-Greedy can powerfully modify the sensing, detecting and communication range to lighten the energy gap issue and enhance the WSNs lifespan [15]. A novel ant colony optimization (ACO) is proposed for blindness deficiency maintaining a strategic distance in WSNs. In first stage, a non-blind aggregate based association instrument is intended to decrease deployment cost. Second stage, a non-blind load-balancing approach is intended to accomplish stack adjusting on request in the genuine sense. At last, reenactments demonstrate that our discoveries fundamentally beat the best in deployment cost as far as sending overhead [16]. A revised version Ant Colony Optimization based LEACH (RA-LEACH) has been proposed for sensor nodes outline and deployment. Cluster Heads (CHs) played out the accompanying parameters like the proportion of the residual energy at every node with unique energy and the proportion of the distance of the node from the Base Station (BS) with the distance of the most distant node. Based on the demonstration, RA-LEACH shows preferred execution over LEACH as for the quantity of powered nodes and energy utilization [17]. A novel algorithm is mix of ant colony optimization algorithm and local heuristic approach. It illuminates the minimum cost reliability and obliged sensor node deployment issue (MCRC-SDP). In result comes about on 24 issues cases with various operational parameters showed the viability of the proposed approach in discovering brilliant solutions for the issue. Results show that the quality of the acquired solutions by the proposed ACO approach is better than that of solutions got by a Greedy Heuristic [18]. A novel ACO-GD based on ant colony optimization (ACO) algorithm and gradient diffusion (GD). It is a non-uniform gradient diffusion approach and can be utilized to tackle the energy holes issues and expand the network lifetime. The preparatory approach is coordinated with the ACO approach. The result comes about demonstrate that our ACO-GD performs better and effectiveness for cost, arrange lifetime, and quantity of nodes [19]. ABC (Artificial Bee Colony) algorithm is based on efficient deployment and scheduling mechanisms. It solve simple coverage problem [20].

B. Hnee based optimization

HBO approach is utilized to defeat basic coverage issue in WSN [21]. Utilizing a similar approach is provided solution of Q-k coverage issues in WSNs [22]. After solution of coverage issue, it enhanced WSNs lifespan. An artificial honey bee colony approach is introduced [23]. Preceding the premise of probabilistic detection model (PDM) to extend coverage scope and advance dynamic deployment of static and portable WSNs introduced [24]. Subsequently covering objective coverage is the dire requirement for dynamical deployment. This is proficient by discussed probabilistic identification demonstrate through ABC approach [25].

C. PSO based design and deployment

Fuzzy adaptive particle swarm optimization is mix of PSO and fuzzy system. It is progressively modify the latency mass to enhance the throughput of the PSO. Three standard capacities utilized for testing the throughput of the fuzzy adaptive PSO. Comparative performance conducted using simulator for the fuzzy adaptive PSO and PSO with a linearly diminishing latency weight. The outcomes additionally outline that PSO with a fuzzy system tuning its inertia weight enhance performance and improve lifetime of WSNs [26-27]. The cooperative particle swarm optimizer (CPSO) approach is proposed. It is utilizing cooperative behavior to altogether enhance the performance of the existing approach. This is accomplished by utilizing numerous swarms to enhance distinctive parts of the arrangement vector cooperatively. Use of the new PSO approach on a few benchmark advancement issues demonstrates to check change in performance over the conventional PSO [28]. An improved PSO is introduced to solve sensor node deployment issue and enhance WSNs lifetime. The change of PSO is powerful and accomplishes a superior execution than VF algorithm. An adaptive particle swarm optimizer is proposed to enhance the WSNs lifetimes. The adaptive criterion is affixed on singular level. Since the critical constant ϵ is chosen by the accuracy prerequisite to fitness, it is all the more effectively to be chosen for various issues. An enhanced discrete particle swarm optimization (DPSO) is proposed in view of target coverage control technique for WSNs. It is actualized under two procedures: deployment arranging and movement control. Results delineate that in development control, the enhanced DPSO which is anything but difficult to deal with, is of superior which is no not as much as conventional discrete issue solver. The reader arrangement is the primary issue for the most difficult RFID network planning (RNP), and should be sensibly explained to work the huge scale RFID frameworks. An enhanced Particle Swarm Algorithm is proposed (SA-PSO) to take care of this issue, which can limit the position change of unique and new particles in the cycle procedure and quicken the merging velocity of the calculation. SA-PSO approach is better than the traditional algorithm [29]. Particle Swarm Optimization (PSO) approach is proposed to solve deployment issue i.e. suffered from deployment strategy. So locate the position of the node with less number of dead nodes. Another system is recommended in this exploration work which utilizes deployment. It may bring about discovering ideal coverage region for sensors and lessen number of dead nodes [30]. An ABC-PSO vertical handover decision approach is proposed for single and multi-attribute issues and individually with the goals of minimizing the normal aggregate cost and limiting the average quantity of handovers. The proposed algorithm has a lesser add up to cost and average quantity of handovers than the technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach [31].

III. SWARM INTELLIGENCE TECHNIQUES FOR ENERGY EFFICIENT NODE CLUSTERING

Battery limitation is one of the real issues in sensor nodes. Once the WSNs nodes are set in remote areas, revive and change of battery isn't a simple task. Subsequently energy efficiency is one of the vital objectives to enhance the lifetime of WSNs and availability of the sensor networks. Different SI based energy efficient node clustering techniques are used for saving energy of sensor nodes [32].

A. ACO and ABC based clustering optimization

An efficient routing approach is proposed for substantial scale group for WSNs. The approach utilizes two routing levels. In the primary level, cluster members individually send information specifically to their cluster head. In the second level, the cluster heads utilize ant colony optimization (ACO) approach, which is an organically roused worldview for improvement approach, to discover a route to the base station. The delay of the approach is limited by utilizing the ant colony optimization algorithm alongside clustering [33]. A novel energy efficient Ants colony optimization clustering (ACO-C) approach is proposed in WSNs. It used to choose optimal cluster head determination and powerfully transformed the distance between the cluster heads to distribute clusters all through the network. Results demonstrate the adequacy of proposed approach over other clustering protocols for example, LEACH, LEACH-C and PSO-C [34]. An inter-cluster Ant Colony Optimization algorithm (IC-ACO) is proposed based on ACO algorithm. It avoids wastage of redundant data sent by the sensors to base station. It is more energy efficient as compare to existing protocols. An energy efficient and load balanced ant colony optimization based hierarchical data gathering method (ACOHC) is proposed. The cluster head selection is performed using ACO. It reduced data delay and improves WSNs lifetimes. Inter-cluster Ant Colony Optimization algorithm is proposed for transfer data packets in WSNs. It reduced packets wastage during the routing times. In result the inter cluster ACO data aggregation is best as compare to the rendezvous Leach [35]. Improved Artificial bee colony (ABC) meta-heuristic performed balancing with exploitation capabilities and increases the global optima. It performed balancing between exploration and exploitation phases during the search time [36-37].

B. Hnee based clustering optimization

Energy distributed clustering Hnee based clustering is proposed to suitable cluster head selection. Utilizing energy and distance factor cluster head choice performed. It works to enhance WSNs lifetime and efficient energy utilization. As per performance analysis, comes about it is more effective than LEACH and Clustered Multiple Routing (CMR) approach. It additionally maintained a strategic distance from information repetition and work to choose ideal route selection [38]. Unequally Clustered Multiple Routing (UCMR) is proposed utilizing Honey Bee Optimization (HBO). In simulation result demonstrated that energy utilization of node for each round in proposed network is minimum as compare to LEACH, UCR, and UCMR. So this approach is basic and in addition utilizes different parameters, for example, energy, no of neighbour sensor node and position of sensor nodes to choose CH which improve the WSNs lifespan [39]. Honey Bee Optimization is proposed to reduce the energy consumption and find best path from source to destination. It improved network lifetime of WSNs. The proposed approach is to broaden the lifetime of a system and throughput and it conveys preferable performance over existing strategy as far as the energy effectiveness, end to end connectivity and scalability. Cluster formation and selection is performed using biologically inspired artificial bee colony approach. Additionally energy level of nodes is calculated by the intelligent agent and also optimal route is selected by the intelligent agent.

C. PSO based clustering Optimization

Particles swarm optimization (PSO) approach is proposed to cluster head formation and selection. It uses two main slave cluster head to save energy and improve network lifetime. It is shown best result as compared than LEACH. A PSO inspired approach acquainted with resolves clustering and routing issue in WSNs. It is working in two stages: first stage takes a shot at find appropriate cluster head and second stage tackles the issue and inter-cluster communication utilizing the best route selection. It enhanced packets delivery rate at both base station and Cluster head. It likewise enhanced WSNs lifetime and coverage. It connected in GPS for area discovery [40]. Energy efficient PSO based routing algorithm with Mobile Sink (EPMS) is presented for WSNs. Virtual clustering technique merged with PSO approach to enhance the WSNs lifetimes. Cluster head election performed based on left energy and node location information. The controlling procedure of mobile sink node depends on the gathering of information from different cluster heads. According to simulation results it shown better performance as compare to existing routing algorithms for WSNs [41]. Optimized QoS-based Clustering with Multipath Routing Protocol (OQoS-CMRP) is introduced for WSNs to reduce energy consumption in base station coverage area using the modified PSO based clustering approach to formulate and selection suitable cluster head. It avoids energy holes issue. It accomplishes better load balancing by powerfully picking exchange way from subset of best-case ways to transmit information. It provides better performance as compare to EE-LEACH and EPSO-CEO. ABC-PSO vertical handover decision approach is proposed for single and multi-property circumstances respectively, with the objectives of minimizing the normal aggregate cost and minimizing the normal number of handovers.

IV. A SWARM INTELLIGENCE TECHNIQUES FOR LOCALIZATION IN WSNS

Localization is a most significant subject in light of the fact that the area data is ordinarily valuable for routing, organization, deployment, rescue operation and target following [42]. Subsequently, location estimation is a huge specialized challenge for the analysts. What's more, localization is one of the key strategies in WSN. In this paper, examine different localization based SI procedures [43].

A. ACO and ABC based localization in WSNs

A node localization approach is proposed based on mobile beacon. Utilize one mobile beacon is replaced by virtual beacons rather than original condition, decreasing the cost of localization. This work has a smaller amount of virtual beacon points and shorter visiting way length contrasted with Hilbert approach, so sparing energy drops. Acquire the ideal arrangement of virtual beacon points for every node by the ideal sifting strategy, so enhance the localization exactness [44]. A Bees Optimization Algorithm (BOA) is proposed for localizing the nodes of the WSNs. BOA is populace based searching approach that plays out an area look joined with random pursuit. It is enlivened by natural foraging behavior of honey bees. The analysis of the squared range mistake between the node and the stay is utilized as the target capacity to be limited in this work [44]. A novel deployment approach, ACO-Greedy approach is proposed to take care of issue of grid-based coverage with low-cost and connectivity-guarantee (GCLC). It depends on the ACO with greedy migration method, which can rapidly entire the full coverage, and particularly diminish the deployment cost factors. It is likewise changing the detecting/correspondence range to ease the energy holes issue and enhanced the WSNs lifetime [45]. ACO with Mobile Anchor Positioning (ACO-MAP) is introduced for localization in WSNs to solve location exactness of Mobile Anchor Positioning with Mobile Anchor and Neighbor (MAP-M&N). This approach reduces localization error fundamentally by 96.9 % on a normal when contrasted with MAP-M&N approach. Subsequently clearly ACO-MAP developmental approach limits the mistake in limitation much superior to utilizing MAP-M&N approach [46]. Self-adaptive artificial bee colony (SAABC) algorithm proposed to calculate the unknown nodes location. It displayed best result locating performance precision and precision stability than DV-Hop algorithm. It is a more promising locating scheme in WSNs with both random distributing nodes and dynamic topology.

B. PSO based localization in WSNs

Particle swarm search localization approach is exhibited utilizing constraint-based WSNs. In first stage, it characterized constraints domain of an obscure. At that point the locations which satisfy particular criteria are sought out by PSO approach and the looking outcomes inside the constraint domain are noted. Finally, the obscure nodes localization can be gotten by ascertaining the normal recording results. As is appeared in the comparison comes about, CPL has solid robustness, and contrasting and typical plans, for example, least square technique (LS), and CPL's situating accurateness can enhance half when the going fault is 35% [47]. Other ways to implement Particle Swarm Optimization (PSO) way to deal with perform fine tune and get exact estimation of the areas. The proposed approach is partitioned into two stages. At the primary stage an enhanced variant of DV distance composed with multi modification was utilized to give coarse introductory area measurements. It takes care of issue of localization, for example, flip vagueness, aggregate interpretation and error propagation. To assess the execution of the approach, numerical recreations executed and the outcomes were contrasted and comparable separation based techniques, to be specific one-stage simulated annealing (SA), trilateration and simulated annealing (TSA) and semi-definite programming localization (SDP) [48]. Particle swarm optimal is proposed based on quantum to enhance the location accurateness of sensor nodes in WSNs. It has quicker convergence, shorter computation time, and higher clarification exactness. It can finish the optimal situating of WSNs viably and rapidly, and to a great extent enhance the situating exactness of WSNs, which assumes an imperative part in broadening the life time of WSNs [49]. The idea of various relocation variations of Biogeography-Based Optimization (BBO) approach and Particle Swarm Optimization (PSO) for conveyed ideal optimal localization of randomly deployed sensors nodes. Biogeography is aggregate learning of land assignment of natural life forms. PSO models had just quick convergence yet less develop. Opposite side PSO is attainable to take care of multidimensional optimization issue as a result of its brisk convergence and direct request for computing assets. In this work, the underlying pursuit search space is characterized by bounding box strategy and a refinement stage is advanced to rectify the error because of flip uncertainty. Further, the control of iterative mistake propagation and energy utilization is potential and huge bearings [50]. This new calculation utilizes a streamlining approach the conventional PSO for localization, and utilizations a localization approach maximum likelihood estimation (MLE) to keep beginning extent and the region iterative procedure of PSO confinement process. A MLE-PSO indoor restriction calculation in view of Received signal strength indicator (RSSI) is proposed to enhance the limitation exactness and dynamic execution. The proposed MLE-PSO takes full favorable position of the high exactness of MLE while extending mistake is little and in addition the solidness of PSO while running blunder is enormous, so the MLE-PSO calculation displays higher precision contrasted and customary MLE calculation and PSO calculation. At the interim, MLE-PSO calculation needs fewer circumstances of cycles and less populace of molecule swarm, which demonstrates that MLE-PSO has better powerful execution [51].

V. SWARM INTELLIGENCE TECHNIQUES FOR DATA AGGREGATION IN WSNS

Data Aggregation is characterized as the way toward collected the information from various sensor nodes with the objective to dispose of repetitive communication and evaluating the desirable answer about the sensors condition. In this section introduce various SI techniques based on data aggregation in WSNs [52].

A. ACO and ABC based on data aggregation in WSNs and other SI techniques

An ant colony optimization approach is proposed in view of information collection to overthrow existing ant-based data-centric routing algorithms. Trial comes about demonstrate that the proposed calculation performs considerably more adequately than other customary techniques. The proposed approach has brought down directing overhead, transmitting overhead and normal delay. Data Aggregation Ant Colony Algorithms (DAACA) works with three stages: introduction, data communication and procedures on pheromones. In the transmit stage, every sensor node evaluates the rest of the energy and the measure of pheromones of neighbor node to figure the probabilities for powerfully choosing the next sensor node. After specific rounds of transmissions, the pheromones alterations are performed, which take the upsides of both worldwide and neighborhood merits for dissipating or saving pheromones. Four unique pheromones modification techniques are intended to accomplish the global network lifetime, in particular Basic-DAACA, ES-DAACA, MM-DAACA and ACS-DAACA. Contrasted and some other data aggregation approach, DAACA demonstrates higher prevalence by and large level of sensor node, energy efficiency and improve network lifetime. Ant-colony aggregation based on distributed approach is proposed to reduce energy consumption and reduces network traffic by remove information repetition in the message sending process. It gives an inherent method for investigating the look space to streamline settings for optimal data aggregation. It reduces energy consumption and enhance network lifetime in WSNs [53]. Another probabilistic collection convention in view of ACO and Genetic Algorithm (GA) mixture approach is proposed. The Multi-Objective Steiner Tree (MOST) is characterized as the ideal structure for information gathering, which can be investigated and every now and again misused amid the routing procedure. The route choice is powerfully achieved by computing the pheromone and the heuristic. This versatile planning arrangement has the capacity of decreasing the transmission delay and enhancing aggregation probability. Through the reenactment comes about, the proposed convention shows better exhibitions when compared with other existing conventions. An Inter-cluster ACO approach is proposed to lessen the energy utilization issue and furthermore transmits the information in destructive way by utilizing the ACO. Origin CH conveys collected data to sink and cluster heads impart information to the root CH specifically or by implication in view of the created root by ant colony improvement. The similar examination has demonstrated that the proposed ant colony improvement based ILEACH beats over the accessible conventions as far as the different quality measurements [54].

VI. SWARM INTELLIGENCE TECHNIQUES FOR QUALITY OF SERVICES

It Data should be conveyed inside a specific time-frame from the period it is sensed. Something else, the information will be pointless. In any case, it is troublesome in light of the way that the framework topology may change persistently and the open state information for steering is naturally free.

A. ACO and ABC based Quality of Services optimization and other SI techniques

A novel Quality of Service (QoS) routing methodology is proposed in light of Ant Colony Optimization (ACO) to decrease throughout complexity and energy utilization of the QoS routing techniques. ACO approaches utilizing aggregate intelligence of artificial ant. Intelligent agents are exceptionally proper to tackle the combinatorial enhancement issues in a completely dispersed manner. An enhanced version of ACO approach is acquainted with unravels Delay Constraint Maximum Energy Residual Ratio (DCMERR) QoS directing issue of WSNs [55]. An energy-effective QoS routing approach is proposed to speeds up the convergence of ant colony algorithm by using stateless non-deterministic geographic forwarding (SNGF). The pheromone is characterized as a mix of connection load and bandwidth delay, at that point, with a specific end goal to adjust the energy utilization of WSNs. Nodes energy are utilized as the control factor of the ant colony approach [56]. A trust QoS routing approach is introduced in light of the Particle Swarm Optimization (PSO) to discover the route with most maximum residual energy and enhance its throughput. Contrasted with existing routing algorithms in WSNs, this new approach has given best results [57]. A Hybrid Ant Colony Optimization (ACO)/Particle Swarm Optimization (PSO) approach is proposed make more effective the multicast tree. It settles delay, packets loss rate, data transfer capacity, and delay jitter issues. The proposed approach developed the multicast tree designs all the more sensibly to such an extent that the tree designs fulfill the QoS requirements, as well as tries to limit the tree cost [58]. Optimized QoS-based Clustering with Multipath Routing Protocol (OQOS-CMRP) approach is acquaint with improve WSNs performance by applying the Modified Particle Swarm Optimization (PSO)- based clustering approach to from sink node to cluster head to resolve energy holes issues. The Single Sink-All Destination approach is utilized to discover close ideal multi-hop correspondence way from sink to sensors for choosing the next hop neighbor nodes. The Round-robin Paths Selection approach is utilized for exchanging information to sink. It likewise diminishes transmission postponement and correspondence overhead based on guaranteeing the result of the whole system [59].

VII. COMPARATIVE PERFORMANCE ANALYSIS OF VARIOUS SWARM INTELLIGENCE TECHNIQUES

The comparative performance analysis of various swarm intelligence techniques are simulated on network simulator-2 (NS-2). To evaluate performance of various swarm intelligent techniques following parameters are used in Table 1.

Table 1.

Parameter	Value
Channel type	Wireless channel
Antenna	Omni Directional
MAC Protocol	802.11
Radio propagation	Free space
Node Deployment	Random
Node transmission Range	200m
Routing protocol	LEACH,ACO,IABC,PSO,HBO,ESO
Data transfer rate	3MBPS
Packet Size	4000 bits
Message Size	500 bits

Simulation scenario setup implemented using 25,50,75,100,125,150,175,200,225,250,275 and 300 sensor nodes with n-cluster and common nodes (c-nodes). Simulator defined a multi-path route between the sensor nodes and cluster head (CH) and single –hop routing between cluster head and base station (BS) for transmission of data packets. This section analysed comparative performance of LEACH (Low Energy Adaptive Clustering Hierarchy) with ACO, IABC, PSO, HBO and ESO respectively based on end to end delay with n-cluster and the simulated result shown in Table 2. End to end delay means time taken for a packet to be transmitted across a network from source to target. In figure 1 shows that the swarm intelligent approaches are performed better than LEACH.

Next evaluated remaining energy with n-cluster and simulated result shown in Table 3. Remaining energy is also called residual energy. It is remaining energy after completion of each round in the wireless sensor network. Here, we analysed comparative performance of LEACH (Low Energy Adaptive Clustering Hierarchy) with ACO, IABC, PSO, HBO and ESO respectively based on remaining energy with n-cluster and the simulated result shown in Table 3.

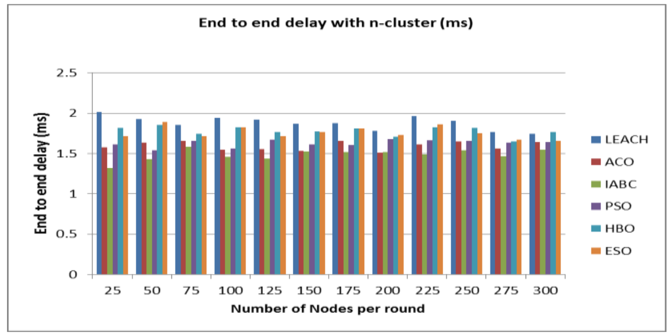

Figure 1 End to end delay with n-cluster

In figure 2 shows that the swarm intelligent approaches perform better than LEACH based on the remaining energy.

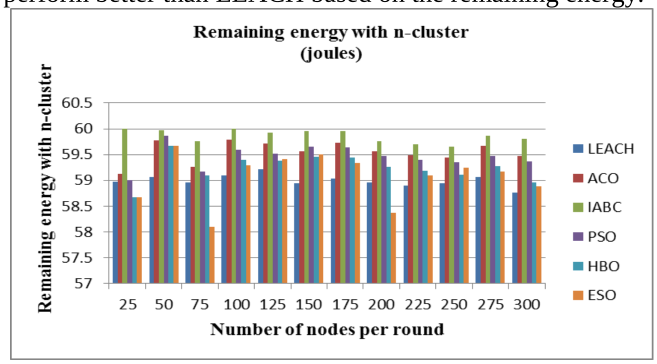

Figure 2 Remaining energy with n-cluster

In this simulation scenario evaluated end to end with common nodes and result shown in Table 4. Here network is established without cluster head. In this paper analysed comparative performance of LEACH (Low Energy Adaptive Clustering Hierarchy) with ACO, IABC, PSO, HBO and ESO respectively based on end to end delay with common-cluster and the simulated result shown in Table 4. End to end delay means time taken for a packet to be transmitted across a network from source to target.
In figure 3 shows that the swarm intelligent approaches perform better than LEACH.

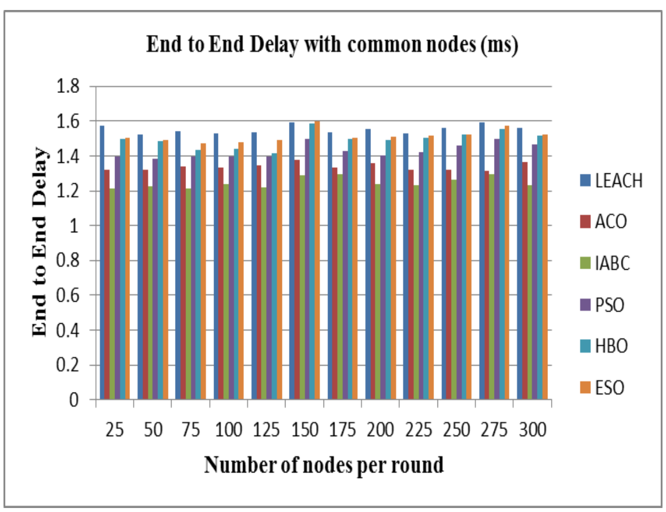

Figure 3 End to End Delay with common nodes

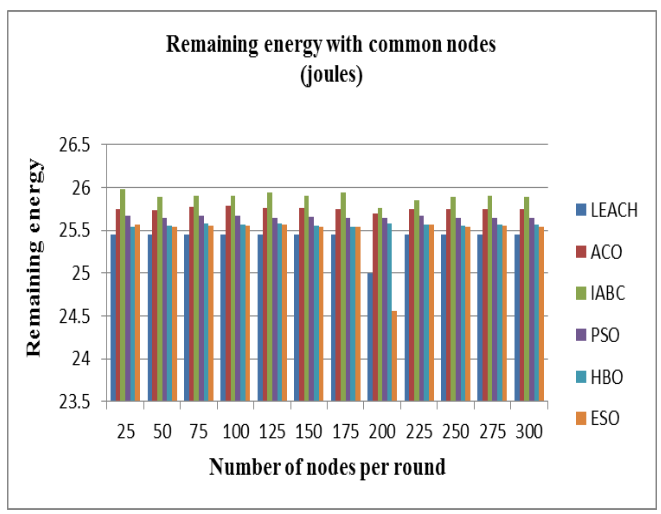

Figure 4 Remaining Energy with common nodes

Here we analysed comparative performance of LEACH (Low Energy Adaptive Clustering Hierarchy) with ACO, ABC, PSO, HBO and ESO respectively based on remaining energy with common nodes and the simulated result shown in Table 5. In figure 4 shows that the swarm intelligent approaches perform better than LEACH based on the remaining energy.

Table 2: End to end delay with n-cluster (ms)

No of Nodes	N-Clusters	LEACH	ACO	IABC	PSO	HBO	ESO
25	10	2.01633	1.57562	1.31633	1.61563	1.81644	1.71693
50	10	1.93042	1.63444	1.43112	1.53896	1.85621	1.88952
75	10	1.85589	1.65419	1.58519	1.65581	1.74582	1.71542
100	10	1.93969	1.54578	1.45896	1.56412	1.82147	1.82475
125	10	1.92144	1.55431	1.43524	1.67124	1.76541	1.71542
150	10	1.86966	1.53426	1.52319	1.61432	1.77605	1.76965
175	10	1.87799	1.65779	1.51790	1.60777	1.81034	1.81234
200	10	1.78418	1.51289	1.51841	1.68123	1.71008	1.73212
225	10	1.96157	1.61267	1.48617	1.66154	1.82617	1.86150
250	10	1.90444	1.64653	1.54053	1.65421	1.81414	1.75421
275	10	1.76874	1.55824	1.46866	1.63214	1.64874	1.66874
300	10	1.74227	1.64321	1.54323	1.64221	1.76742	1.65432

Table 3: Remaining Energy with n-cluster (Joules)

No of Nodes	N-Clusters	LEACH	ACO	ABC	PSO	HBO	ESO
25	10	58.973831	59.125439	59.998768	58.999889	58.6738321	58.673214
50	10	59.071667	59.771611	59.977653	59.871432	59.6717651	59.671660
75	10	58.962524	59.262589	59.762512	59.162565	59.098765	58.098765
100	10	59.093270	59.791110	59.998765	59.593233	59.393254	59.283278
125	10	59.210025	59.719875	59.918762	59.517654	59.387654	59.417654
150	10	58.949929	59.556783	59.947865	59.649920	59.449987	59.499943
175	10	59.035207	59.735342	59.957632	59.635213	59.435257	59.343567
200	10	58.964672	59.564676	59.764453	59.464654	59.267654	58.364621
225	10	58.891848	59.491845	59.691865	59.391854	59.191678	59.089198
250	10	58.946191	59.446659	59.646176	59.346145	59.114667	59.246543
275	10	59.066968	59.674589	59.869874	59.465428	59.276918	59.167541
300	10	58.768335	59.468765	59.798531	59.367653	58.965425	58.881685

Table 4: End to End Delay with common nodes

No of Nodes	C-Nodes	LEACH	ACO	IABC	PSO	HBO	ESO
25	10	1.57544	1.32341	1.21114	1.39871	1.49712	1.50711
50	10	1.52526	1.31776	1.22511	1.38211	1.48266	1.49216
75	10	1.54066	1.34021	1.21566	1.39896	1.43416	1.47111
100	10	1.53041	1.33092	1.23765	1.39713	1.44320	1.48123
125	10	1.53547	1.34654	1.21887	1.39871	1.41234	1.49096
150	10	1.59575	1.37652	1.29121	1.49987	1.58765	1.59659
175	10	1.53309	1.33441	1.29312	1.43123	1.49987	1.50311
200	10	1.55187	1.35678	1.23567	1.40112	1.49156	1.51156
225	10	1.52937	1.31876	1.22897	1.42123	1.50543	1.51564
250	10	1.56146	1.32165	1.26199	1.46111	1.52132	1.52182
275	10	1.59205	1.31211	1.29765	1.49651	1.55234	1.57211
300	10	1.56151	1.36786	1.23342	1.46563	1.51611	1.52189

Table 5: Remaining Energy with common nodes (Joules)

No of Nodes	C-Nodes	LEACH	ACO	ABC	PSO	HBO	ESO
25	10	25.445713	25.747865	25.984577	25.664321	25.545787	25.564573
50	10	25.445706	25.738976	25.894578	25.645111	25.559871	25.539872
75	10	25.445578	25.778652	25.899872	25.667858	25.578976	25.548578
100	10	25.445689	25.786754	25.907865	25.676887	25.564566	25.555689
125	10	25.445686	25.756689	25.945432	25.645673	25.578976	25.568765
150	10	25.445747	25.765876	25.905731	25.655764	25.556412	25.541574
175	10	25.445725	25.745552	25.945711	25.644720	25.546543	25.545725
200	10	24.994028	25.694765	25.764321	25.648769	25.584321	24.556753
225	10	25.445626	25.748724	25.856432	25.666878	25.565627	25.565454
250	10	25.445710	25.745723	25.894543	25.645765	25.554571	25.544578
275	10	25.445642	25.754565	25.904762	25.645621	25.564502	25.554552
300	10	25.445710	25.745564	25.894532	25.644523	25.564554	25.544565

VIII. CONCLUSION AND FUTURE SCOPE

Wireless Sensor networks (WSNs) is collection of various sensor devices to capture the environment conditions. Node deployment, limited energy capacity, location of sensor devices, Quality of Services (QoS) and data aggregation are the critical design challenges in WSNs. To overcome these design challenges in WSNs, many techniques have proposed. Swarm Intelligence (SI) is one of the most appropriate technique to overcome the design challenges in WSNs.SI shows a current computational and behavioural equality for taking care of disseminated issues that initially took its motivation from the biological illustrations gave by social insects like ants, termites, honey bees, wasp. In above sections, we evaluated comparison LEACH with many SI techniques such that Improved Artificial Bee Colony(IABC), Ant Colony Optimization (ACO), Elephant swarm Optimization (ESO), Hnee based optimization (HBO) and Particle Swarm Optimization (PSO) to make network energy efficient and improve the WSNs lifespan. ABC, ACO, HBO, ESO, PSO and LEACH based approaches have applied to resolve the sensor nodes deployment issue and helpful in energy utilization and extend WSNs lifespan. In next section SI techniques are merged with clustering algorithms and gave best results. These SI techniques are more results oriented, when applied on location, data aggregation and Quality of Services Challenges. In future work, these comparative results will more beneficial to select novel technique for WSNs design challenges and extend network lifetime. In this paper analysed comparative performance of LEACH (Low Energy Adaptive Clustering Hierarchy) with ACO, IABC, PSO, HBO and ESO respectively based on remaining energy with n-cluster and the simulated result shown in Table 2. In figure 3 shows that the swarm intelligent approaches perform better than LEACH based on the remaining energy.

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REFERENCES

[1] Hu Yu, Wang Xiaohui, (2011), “PSO-based Energy-balanced Double Cluster-heads Clustering Routing for wireless sensor networks”, In Procedia Engineering, Vol.15, pp. 3073-3077,2011.

[2] Yuce, B., Packianather, M. S., Mastrocinque, E., Pham, D. T., & Lambiase, A., “Honey Bees Inspired Optimization Method: The Bees Algorithm. Insects”, Vol.4, pp. 646–662,2013.

[3] Ado Adamou Abba Ari, BlaiseOmerYenke, NabilaLabraoui, IrepranDamakoa, Abdelhak Gueroui, “A power efficient cluster based routing algorithm for wireless sensor networks: Honey bees swarm intelligence based approach”, Elsevier, Journal of Network and ComputerApplications vol. 69 , pp.77-97,2016.

[4] Wilson, E.O, “Sociobiology: The New Synthesis”. 25th Anniversary Editions. The Belknap Press of Harvard University Press Cambridge, Massachusetts and London, England,2000.

[5] Krebs J. R., Davies N. B, “An Introduction to Behavioral Ecology”,Third Edition. Blackwell Publishing, Oxford, UK 1993.

[6] Elizabeth A. Archie, Cynthia J. Moss and Susan C. Alberts, “The ties that bind: genetic relatedness predicts the fission and fusion of social groups in wild African elephants”, Proc. R. Soc. B 273, pp. 513–522, 2006.

[7] Elizabeth A., Archie, and Patrick I. Chiyo, “Elephant behavior and conservation: social relationships, the effects of poaching, and genetic tools for management”, Molecular Ecology, Vol. 21, pp. 765–778,2012.

[8] Rachael Adams,“Social Behavior and Communication in Elephants- It's true! Elephants don't forget!”, Available at: http://www.wildlifepictures-online.com/elephant.html ,2013.

[9] Mann, P.S. & Singh , “S. Artificial bee colony metaheuristic for energy-efficient clustering and routing in wireless sensor networks”, Soft Computing, Springer Berlin Heidelberg, Vol. 56 ,pp 6699–6712,2017.

[10] Wyatt, T.D, “Pheromones and Animal behavior - Communication by Smell and Taste”, Cambridge University Press. UK,2003.

[11] O. Younis, M. Krunz and S. Ramasubramanian,“Node Clustering in Wireless Sensor Networks: Recent Developments and Deployment Challenges,” IEEE Network, vol.20(3), pp.20-25,2006.

[12] D. Li, W. Liu, and L. Cui,"Easi Design: an improved ant colony algorithm for sensor deployment in real sensor network system," IEEE Globe com, pp.1-5, 2010.

[13] Liao, Wen-Hwa & Kao, Yucheng & Wu, Ru-Ting, "Ant colony optimization based sensor deployment protocol for wireless sensor networks", Expert Syst. Appl., Vol. 38. pp. 6599-6605,2016.

[14] Xuxun, L,"Sensor Deployment of Wireless Sensor Networks Based on Ant Colony Optimization with Three Classes of Ant Transitions," IEEE Communications Letters, Vol. 16, pp.1604-1607,2012.

[15] Liu and D. He, "Ant colony optimization with greedy migration mechanism for nod deployment in wireless sensor networks," Journal of Net- work and Computer Applications, Vol. 39, pp. 310 -318,2014.

[16] G. Huang, D. Chen, and X. Liu , "A node deployment strategy for blindness avoiding in wireless sensor networks,"IEEE Commun. Lett., Vol. 19 , No.6 , pp. 1005-1008,2015.

[17] X. Liu, "A deployment strategy for multiple types of requirements in wireless sensor networks," IEEE Trans. Cybern., Vol. 45, No. 10, pp. 2364-2376, 2015.

[18] K. Sakai, M. T. Sun,W. S.Ku, T. H. Lai, and A.V.Vasilakos, "A framework for the optimal k-Coverage deployment patterns of wireless sensors," IEEE Sensors J., Vol.15, No. 12, pp. 7273-7283,2015.

[19] Shun-Miao Zhang, Degen Huang, Shu-Chuan Chu, Tien-Wen Sung, Tsu-Yang Wu ,"An Adaptive ACO-Based Node Deployment Algorithm in Wireless Sensor Networks," Journal of Internet Technology, Vol. 18, No. 5 , pp. 1193-1202, 2017.

[20] Ghotra, "Optimizing Inter Cluster Ant Colony Optimization Data Aggregation Algorithm with Rendezvous Nodes and Mobile Sink", Wireless Sensor Network,Vol. 9, pp.16-24,2017.

[21] S. Mini, S. K. Udgata, and S. L. Sabat, "Sensor deployment in 3-D terrain using artificial bee colony algorithm," in Proc. Swarm, Evol. Memetic Comput., pp.424-431,2013

[22] S. Mini, S. K. Udgata, and S. L. Sabat,"Artificial bee colony based sensor deployment algorithm for target coverage problem in 3-D terrain,"in Proc. Distrib. Comput. Internet Technol., pp. 313-324, 2011.

[23] S. Mini, Siba K. Udgata, and Samrat L. Sabat, "Sensor Deployment and Scheduling for Target Coverage Problem in Wireless Sensor Networks", IEEE Sensors Journal, Vol.14, No. 3,2014.

[24] M. Chaudhary and A. K. Pujari, "Q-coverage problem in wireless sensor networks", in Proc. Int. Conf. Distrib. Comput. Netw., pp. 325-330,2009.

[25] C. Ozturk, D. Karaboga, and B. Gorkemli, "Probabilistic dynamic deployment of wireless sensor networks by artificial bee colony algorithm," Sensors, Vol. 11,No. 6, pp. 6056-6065,2011.

[26] Yuhui Shi and R. C. Eberhart, "Fuzzy adaptive particle swarm optimization," Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No.01TH8546), Seoul, Vol 1, pp. 101-106,2001.

[27] Eberhart and Yuhui Shi, "Particle swarm optimization: developments, applications and resources," Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No.01TH8546), Seoul, Vol 1, pp. 81-86,2001.

[28] F. van den Bergh and A. P. Engelbrecht, "A Cooperative approach to particle swarm optimization," in IEEE Transactions on Evolutionary Computation, Vol. 8, No. 3, pp. 225-239,2004.

[29] Ming Tao, Shuqiang Huang, Yang Li, Min Yan, Yuyu Zhou, "SA-PSO based optimizing reader deployment in large-scale RFID Systems", In Journal of Network and Computer Applications, Vol. 52, pp. 90-100,2014.

[30] Harjeet Kaur, Dr. Sandeep Kautish, "An Implementation of Wireless Sensor Network Using Voronoi_PSO (Particle Swarm Optimization)", International Journal for Research in Applied Science & Engineering Technology , Vol. 4, No. 11, ,pp. 361-368,2016.

[31] Shidrokh Goudarzi, Wan Haslina Hassan, Mohammad Hossein Anisi, Ahmad Soleymani, Mehdi Sookhak, Muhammad Khurram Khan, Aisha-Hassan Abdalla Hashim, Mahdi Zareei, "ABC-PSO for vertical handover in heterogeneous wireless networks", In Neurocomputing, Vol. 256, pp 63-81,2017.

[32] Ashouri, M., Yousefi, H., Basiri, J., Hemmatyar, A.M.A., Movaghar, "A. PDC: prediction-based data-aware clustering in wireless sensor networks", J. Parallel Distrib. Comput. Vol. 81, pp. 24–35,2015.

[33] Salehpour, A., Mirmobin, B.,Afzali-kusha, A."An Energy Efficient Routing Protocol fo Cluster-based Wireless Sensor Networks Using Ant Colony Optimization", IEEE Proceedings of the 5th International Conference on Innovations in Information Technology, pp. 455459.2015.

[34] Ziyadi, M., Yasami, K.,Abolhassani, B, "Adaptive Clustering for Energy Efficient Wireless Sensor Networks Based on ant Colony Optimization", IEEE Proceedings of the 7th Annual Communication Networks and Services Research Conference, pp. 330-334,2009.

[35] Ghotra, A, "Optimizing Inter Cluster Ant Colony Optimization Data Aggregation Algorithm with Rendezvous Nodes and Mobile Sink", Wireless Sensor Network,Vol. 9, pp.16-24,2017.

[36] Mann, P.S. & Singh, "S. Artificial bee colony metaheuristic for energy-efficient clustering and routing in wireless sensor networks", Soft Computing, Springer Berlin Heidelberg, pp. 6699–6712,2017.

[37] Mann, P & Singh, Satvir, "Improved metaheuristic-based energy-efficient clustering protocol with optimal base station location in wireless sensor networks", Soft Computing, Vol. No.17,2017.

[38] Kiranpreet Kaur, Harjit Singh, "Cluster Head Selection using Honey Bee Optimization in Wireless Sensor Network", International Journal of Advanced Research in Computer and Communication Engineering Vol. 4,No. 5,pp-358-363,2015.

[39] Nisha Rani, D r . J a swinder Singh, "Honey Bee Optimization based Zone Divided Wireless Sensor Network", International Journal of Engineering Research & Technology, Vol. 5, No. 4, pp-73-77,2016.

[40] Riham S.Y. Elhabyan, Mustapha C.E. Yagoub, "Two-tier particle swarm optimization protocol for clustering and routing in wireless sensor network", In Journal of Network and Computer Applications, Vol 52, pp 116-128, 2016.

[41] Jin Wang, Yiquan Cao, Bin Li, Hye-jin Kim, Sungyoung Lee, "Particle swarm optimization based clustering algorithm with mobile sink for WSNs", In Future Generation Computer Systems, Vol. 76 , pp. 452-457,2017.

[42] Weijie Lu and Donglin Bai, "Energy efficient distributed lifetime optimizing scheme for wireless sensor networks," Transactions of Tianjin University Journal, Vol. 22, No. 1, pp. 11-18,2016.

[43] F. Qin, C. Wei, and L. Kezhong, "Node Localization with a Mobile Beacon Based on Ant Colony Algorithm in Wireless Sensor Networks," In Proc. Of Int. Conf. on Communications and Mobile Computing, pp. 303-307.,2010.

[44] A. Moussa, N. El-Sheimy, "Localization of wireless sensor network using bees optimization algorithm", in Proceedings of IEEE International Symposium on Signal Processing and Information Technology, pp.478-481,2010.

[45] X. Liu , D. He, " Ant colony optimization with greedy migration mechanism for node deployment in wireless sensor networks", J. Netw. Comput. Appl.,Vol. 39, pp. 310–318,2014.

[46] S Sivakumar and R Venkatesan, "Error Minimization in Localization of Wireless Sensor Networks using Ant Colony

Optimization", International Journal of Computer Applications Vol. 145, No. 8, pp. 15-21.2016.

[47] Z. Shu-wang, W. Ying-long, G. Qiang and W. Nuo, "Constraint-based sensor network nodes particle swarm search localization algorithm," The 2010 14th International Conference on Computer Supported Cooperative Work in Design, Shanghai, China, pp. 448-451,2010.

[48] P. H. Namin and M. A. Tinati, "Node localization using Particle Swarm Optimization," 2011 Seventh International Conference on Intelligent Sensors, Sensor Networks and Information Processing, Adelaide, pp. 288-293,2011.

[49] Y. Jian-Bin and X. Wen-Bo, "Research on the Node Localization Based on Quantum Particle Swarm Optimal Algorithm for WSNs," 2011 10th International Symposium on Distributed Computing and Applications to Business, Engineering and Science, Wuxi, pp. 309-313,2011.

[50] Dan Li, Xian bin Wen, "An Improved PSO Algorithm for Distributed Localization in Wireless Sensor Networks", International Journal of Distributed Sensor Networks, Vol. 11, pp. 970-272,2015.

[51] C. Zhao and B. Wang, "A MLE-PSO indoor localization algorithm based on RSSI," 36th Chinese Control Conference (CCC), Dalian, pp. 6011-6015,2017.

[52] Wang, Hongpeng & Luo, Neng., "An Improved Ant-Based Algorithm for Data Aggregation in Wireless Sensor Networks", Communications and Mobile Computing, International Conference, Vol 3., pp. 239-243,2014.

[53] M. Xie and H. Shi, "Ant-Colony Optimization Based In-Network Data Aggregation in Wireless Sensor Networks,"12th International Symposium on Pervasive Systems, Algorithms and Networks, San Marcos, pp. 77-83,2012.

[54] Kaur J., Chopra V. ,"Enhanced iLEACH Using ACO Based Intercluster Data Aggregation", In: Behera H., Mohapatra D. (eds) Computational Intelligence in Data Mining—Advances in Intelligent Systems and Computing, Vol 4,No. 11,2016.

[55] Cai W., Jin X., Zhang Y., Chen K., Wang R., "ACO Based QoS Routing Algorithm for Wireless Sensor Networks",In: Ma J., Jin H., Yang L.T., Tsai J.JP. (eds) Ubiquitous Intelligence and Computing. UIC 2006. Lecture Notes in Computer Science, Vol 4159,2006.

[56] Z. Li and Q. Shi, "An QoS Algorithm Based on ACO for Wireless Sensor Network", 2013 IEEE 10th International Conference on High Performance Computing and Communications & 2013 IEEE International Conference on Embedded and Ubiquitous Computing, Zhangjiajie, pp. 1671-1674,2013

[57] J. W. Wang and Y. T. Wei, "PSO-Based Trust QoS Routing Algorithm for Wireless Sensor Networks", Applied Mechanics and Materials, Vol.. 401-403, pp. 1751-1755,2013.

[58] Manoj Kumar Patel, Manas Ranjan Kabat, Chita Ranjan Tripathy (2014), "A hybrid ACO/PSO based algorithm for QoS multicast routing problem", In Ain Shams Engineering Journal, Vol. 5, No. 1, pp. 113-120,2014.

[59] O. Deepa, J. Suguna, "An optimized QoS-based clustering with multipath routing protocol for Wireless Sensor Networks", In Journal of King Saud University - Computer and Information Sciences,2017.

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