Energy Aware Swarm Optimization for Wireless Sensor Network

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Abstract: A Wireless Sensor Networks (WSN) is a distributed network of wireless nodes with built in sensors for measurement of physical parameters like temperature, humidity and so on. WSNs inbuilt characteristics of limited available power source and low complexity processors differentiate such networks from other wireless networks including MANETs. WSN routing is specifically challenging when the node has mobility. The main objective of any WSN routing protocol is to provide effective and efficient communication for the network with minimal power utilization. In this paper, a hybrid Particle Swarm Optimization (PSO) algorithm is proposed based on residual energy for finding optimal number of clusters and cluster head (CH). The suboptimal solutions found during CH become the key nodes for formation of multiple routes between the CH and sink node using Iterative deepening depth-first search approach. Results show improved performance of the network compared to Leach protocol.
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1. Introduction

Wireless sensor networks (WSN) is a collection of nodes formed into a network [1] with each node having processing capability and contain memory, a RF transceiver, has a power source, and accommodates different sensors and actuators. The nodes communicate wirelessly and self-organize after ad hoc deployment. WSN are widely deployed at an increasing pace and is expected that in a decade, WSN access via the Internet is the norm. The new technology has unlimited potential for many application areas including military, environmental, crisis management, medical, transportation, and entertainment.

Multihop routing is an important service needed for WSN. Internet and MANET routing techniques fail to perform well in WSN. Internet routing assumes reliable wired connections and hence there are rare packet errors, but this is not the case with WSN. Though most MANET routing solutions depend on symmetric links between neighbors it is not true for WSN. These differences necessitated the invention and use of new solutions. For WSN, often deployed ad hoc, routing begins with neighbor discovery. Nodes send rounds of messages and construct local neighbor tables which include minimum information about each neighbor's ID and location. The nodes should know their geographic location prior to neighbor discovery. Information in tables should include nodes' remaining energy, delay through that node, and link quality estimate. Once tables exist, most WSN routing algorithms messages are directed from source location to an address based on geographic coordinates, not IDs.

A typical routing algorithm which works similarly is Geographic Forwarding (GF) [2]. In GF, a node knows its location, and a message about it "routing" has the destination address. This node then computes as to which neighbor node makes most progress to the destination by using geometry based distance formula and message is forwarded to the next hop. In GF variants, a node also accounts for delays, link reliability and remaining energy. Another WSN routing paradigm is directed diffusion [3]. This solution integrates routing, queries and data aggregation. A query is disseminated indicating data interest from remote nodes. A node with appropriate requested data replies with an attribute-value pair. This attribute-value pair is attracted to the gradients based requestor, set up and updated during query dissemination and response. Along the way from source to destination data is aggregated to lower communication costs. Data can travel over multiple paths increasing routing robustness. However geographic forwarding and directed diffusion are not effective when the wireless sensor node is mobile.

WSN routing is challenging because of inbuilt characteristics which differentiate it from other wireless networks including MANETs or cellular networks. Following are some of the main characteristics inherent to WSN:

- Sensor nodes are tightly constrained as regards energy, processing, and storage capacities. Hence they require careful resource management. In most application scenarios, WSN nodes are stationary after deployment except for a few mobile nodes.

- In WSNs, sometimes data receipt is more important than learning the IDs of nodes which forwarded the data. Also in contrast to typical communication networks, all sensor network applications require sensed data flow from multiple sources to a specific BS. But this does not prevent data flow in other forms.
- WSN are application specific i.e., design requirements of sensor networks change with application.
- WSN nodes position awareness is important as data collection is generally location based. It is not practical to use Global Positioning System (GPS) hardware for this task.
- Finally, data collected by many WSN sensors is based on common phenomena and so there is the probability that the data is redundant. This factor needs exploitation by routing protocols to improve energy and bandwidth utilization.

The main objective of any routing protocol is to provide effective and efficient communication for the network with minimal energy utilization. Clustering has been widely pursued by the research community in WSN to achieve the network scalability objective. Each cluster has a leader, referred to as the cluster-head (CH). Load balancing is used to allocate traffic amongst different paths to avoid forming congested areas and at the same time allow the energy consumed to be distributed among the entire network [4, 5]. For energy efficient WSN routing protocol, the main objective function would be the energy constraints within the network. Being a NP complete problem, an ideal route can be found using metaheuristic algorithm [6]. This paper explores route optimization technique using an improved Particle Swarm Optimization (PSO), a metaheuristic algorithm known for fast convergence which is critical for a highly mobile WSN. To deal issues like clustering, optimal deployment, data aggregation and node localization, the PSO has been successfully applied [6].

2. Related Works

There are various energy aware algorithms available in literature. Some of the works are reviewed in this section.

Kwon, et al., [7] studied the problem of the lifetime maximization in WSN. The end-to-end transmission success probability constraint with a cross-layer strategy which concerns a combination of physical layer, MAC layer and routing protocol is proposed. The problem considered is divided into sub-problems at every layer. The optimal algorithm along with another substitutive heuristic algorithm involving only less complexity for every sub-problem is also proposed. Using simulations, an exchange relation present between the reliability constraint and the network lifetime maximization is illustrated. The strategy developed by a combination of the proposed algorithm at every layer extensively enhances the lifetime of the network. For various energy consumption models, the effect of the retransmission control on the energy competence was examined. The results obtained by simulating the proposed model reveals that little gain is achieved with low power yield in the multiple retransmissions. Along with the transmission power, the power conversion efficiency of the amplifier maximizes and also when there is short link distance. Therefore, the proposed model is efficient and also reliable.

The data transformed to a sink by intermediate sensors are mostly aggregated in order to decrease the cost. A subset of the sensors called “aggregators” performs this compression. The challenging problem faced is to deploy an appropriate number of aggregators strategically as most of the sensors are equipped with small and unreplenishable energy reserves thereby to reduce the energy consumption during transporting and aggregating the data. Chen et al., [8] initially studied the single-level aggregation and then proposed an Energy-Efficient Protocol for Aggregator Selection (EPAS) protocol. Subsequently, to an aggregation hierarchy is it generalized and further the work was done to extend EPAS to Hierarchical EPAS. For aggregator selection, a fully distributed algorithm was introduced by deriving the optimal number of aggregators. The results obtained by simulation of the proposed algorithm revealed that in WSN, the energy consumption for data collection can be decreased significantly.

Zhang et al., [9] proposed a new online routing scheme named Energy-efficient Beaconless Geographic Routing (EBGR) that facilitates fully stateless, loop-free, without the help of prior neighborhood knowledge the energy-efficient sensor-to-sink routing at only low communication overhead. Initially, in EBGR every node calculates its best next-hop relay position the basis of the energy-optimal forwarding distance, and using the Request-To-Send/Clear-To-Send (RTS/CTS) handshaking mechanism, every forwarder chooses the neighbor closest to its best next-hop relay position as the next-hop relay. Under EBGR, the lower and upper limits on hop count and the upper limit on energy consumption for sensor-to-sink routing are established. To provide energy-efficient routing in the presence of unreliable communication links in lossy sensor networks the EBGR can be capably used. In wireless sensor networks with highly dynamic network topologies, the results obtained from simulation of the proposed scheme reveals the high-throughput over the other existing protocols.

In single-hop sensor networks, the transmissions are performed between every sensor and a fusion center, directly whereas in the multihop sensor networks transmissions are performed between neighboring sensors that is much effective in spectrum and energy. Huang et al., [10] introduced a digital transmission energy planning algorithm along with an analog transmission energy planning algorithm in multihop sensor networks for the purpose of progressive estimation involving the knowledge of a routing tree from every sensors to a destination node. The proposed progressive estimation algorithms including their transmission energy planning within a finite time minimizes the network transmission energy when ensuring any pre-specified estimation performance at the destination node. When the transmission time-bandwidth product available for each link and each observation sample is not too restricted, the digital transmission shows superior performance in transmission energy compared to the analog transmission.

For wireless networks, many power-aware routing approaches are developed considering that the nodes are prepared to give up their power reserves as a whole for the network. But, in many practical utility applications in which the nodes are present in groups, a node is prepared to give up power reserves within the nodes present in its group and not to other nodes in the network. For reduction in power consumption of each group, resources will be shared among other groups also. Consequently, a coalition is created by the groups and through which they are able to route each other's packets also. There are various properties for sharing among groups than sharing among individuals and mutually beneficial sharing between groups and investigate fair. Guha et al., [11] proposed a pareto-efficient condition specifically for group sharing on the basis of max-min fairness named as fair coalition routing. In order to compute the fair coalition routing, distributed algorithms are also proposed. Therefore, beneficial sharing of resources mutually among different groups is achieved by fair coalition routing which is also validated by performing a range of simulations.

The most widespread and lucrative are fixed-power wireless sensor networks. But the tribulations experienced by these networks are energy constraints, RF interference and environmental noise. In order to obtain energy efficiency, reliability and scalability in message delivery, the routing protocols for these networks should prevail over these tribulations. But, the accomplishment of these necessities creates conflicting demands. Loh, et al., [12] proposed a new routing protocol EAR which is able to accomplish efficient, reliable and scalable performance only with a minimized concession of energy efficiency. On the basis of four parameters i.e., a weighted combination of distance traversed, expected path length, energy levels and determination and maintenance of best routes dynamically and the link transmission success history are employed for designing the routing protocol EAR. The proposed method is compared with four existing protocols. The simulation results obtained show that the proposed EAR illustrates superior performance. Hence, the protocol based on a combination of routing parameters is better than the protocols based on only hop-count and energy or those implementing flooding. The better performance of the proposed EAR is demonstrated in terms of packet latency, packet delivery ratio, energy consumption and scalability.

In several wireless sensor applications the Top-k monitoring is an essential component. Minji Wu et al., [13] using the semantics of top-k query proposed FILA, which is an energy-efficient monitoring scheme. The common idea used to suppress unnecessary sensor updates is achieved by installing a filter at each sensor node. For the precision and efficacy of FILA, the basic issues are filter setting and query re-evaluation. In order to handle concurrent sensor updates, a query re-evaluation algorithm is developed. Especially, to decrease the probing cost, optimization schemes are introduced. For the purpose of balancing energy consumption and extending the network's lifetime a skewed filter setting scheme is designed. Eager and lazy are two filter update strategies proposed for supporting various application scenarios. Order-insensitive top-k monitoring, approximate top-k monitoring, and top-k value monitoring are some of the top-k query variants for which the algorithm is extended. Using real data traces, the performance of the proposed FILA is evaluated extensively. The results show that:

1) In terms of both network lifetime and energy consumption, FILA outperforms the existing TAG-based approach and Cache approach constantly.
2) Furthermore to returning the top-k result set, for each of top-k sensor readings FILA is able to achieve a tightly bounded approximation.
3) For the traces evaluated, the overall performance of the lazy filter update scheme is superior to the eager scheme.
4) For the HM sampling scenario, the skewed filter setting is better than the uniform filter setting.

Qing Cao et al., [14] proposed a new multicast protocol called uCast, in sensor networks for energy efficient content distribution. The uCast is designed to sustain several multicast sessions particularly during which the number of destinations is small in a session. Any state information relevant to the ongoing multicast deliveries at intermediate nodes is not retained in uCast. But, using a scoreboard algorithm at intermediate nodes the multicast information in the packet headers and parse these headers are directly encoded. The illustrations in this paper are to handle multiple addressing and unicast routing approaches, uCast is potent and sufficient. uCast is well-organized, robust and scalable in the face of modifications in network topology, such as initiated with the energy conservation protocols. The performance of uCast is evaluated by simulation systematically and compared to other protocols and based on the Berkeley motes platform gathers preliminary data from a running system. Therefore, uCast is efficiently employed in various unicast routing protocols.

3. Methodology

3.1 Particle Swarm Optimization (PSO)

The Particle Swarm Optimization (PSO) algorithm is an adaptive algorithm founded on a psycho-social representation; a population of individuals also referred to as particles, adapting through returning stochastically toward previously successful regions [15, 16]. There are two primary operators in Particle Swarm: Velocity update and Position update. During generation each particle is accelerated toward the particles in the previous best position and the global best position. A new velocity value for each particle is calculated at every iteration and this is based on its current velocity, distance from its previous best position, and distance from its global best position. The value of velocity is then utilized to compute the next position of the particle in search space. This procedure is then iterated a specific number of times, or till a minimum error is noticed [17, 18].

The PSO algorithm can be visualized as follows: The PSO simulates the behaviour of bird flocking randomly searching for food in an area and there is only one piece of food available in the area under search. All birds are ignorant of the location of the food. But the distance to the food through each iteration is calculated. The effective procedure is to follow the bird nearest to the food. PSO learned from the above scene and used it to solve optimization problems. In PSO, each single solution is a "bird" in search space, called "particle". All particles have fitness values evaluated by the fitness function to be optimized, and have velocities which direct the particle flight. The particles fly through the problem space by following current optimum particles.

PSO initializes with a cluster of random particles or solutions and searches for optima through updating of generations. In each iteration, the two "best" values of the particle is updated. The first one is called pbest which is the best solution (fitness) achieved till then. Another "best" value tracked by the particle swarm optimizer is the best value, obtained till then by any particle in the population i.e the global best and is called gbest. Another best value used is ‘lbest’ which is the best value of the particle participating with its topological neighbors.

PSO is computationally economical as it requires only primitive mathematical operators. PSO optimizes clustering in a network because these kinds of networks have limited resources. Particle positions and velocities are generated randomly in the beginning. The algorithm then proceeds iteratively and updates all velocities and positions of all the particles as follows:

$$v_i^d = wv_i^d + c_1 r_1 \left(p_i^d - x_i^d \right) + c_2 r_2 \left(p_g^d - x_i^d \right)$$

$$x_i^d = x_i^d + v_i^d$$

where d is the number of dimensions, i is the size of the population, w is the inertia weight, c_1, c_2 are positive constants called cognitive parameter and social parameter respectively, r1 and r2 are random values in the range [0, 1]. v_i^d is the new velocity of the ith particle computed based on the particle’s previous velocity, distance between the previous best position and current position and distance between the best particle of the swarm. x_i^d calculates the new position of the particle.

In classical PSO, if gbest is far away from the global optimum then the particles tend to get trapped in the local optimum in the gbest region. To avoid this, the particles are moved to a larger search space to fly and pbest position of a paricle is updated based on the pbest position of all the particles in the swarm. This increases the ability to avoid local optimum and improves diversity of the swarm. The updating velocity of the particle is given by:

$$V_i^d = w * v_i^d + c * rand_i^d * \left(pbest_{fi(d)}^d - x_i^d \right)$$

where $f_i = \left[f_i(1), f_i(2), ..., f_i(d) \right]$ refers to the pbest that the particle i used and $pbest_{fi(d)}$ is the dimension of particles pbests. Two particles are selected randomly and the particle’s whose velocity is updated is excluded. The fitness value of the particles pbests are compared and the dimension of the better one is selected to update the velocity [19].

3.2 Proposed Methodology

The proposed methodology is implemented in two steps to modify the existing Leach routing. In the first step, cluster head is selected using PSO and in the second step, multiple routes are selected using sub optimal nodes and iterative deepening depth-first search approach. Figure 1 shows the flowchart of the flow chart of the proposed optimizing of PSO.

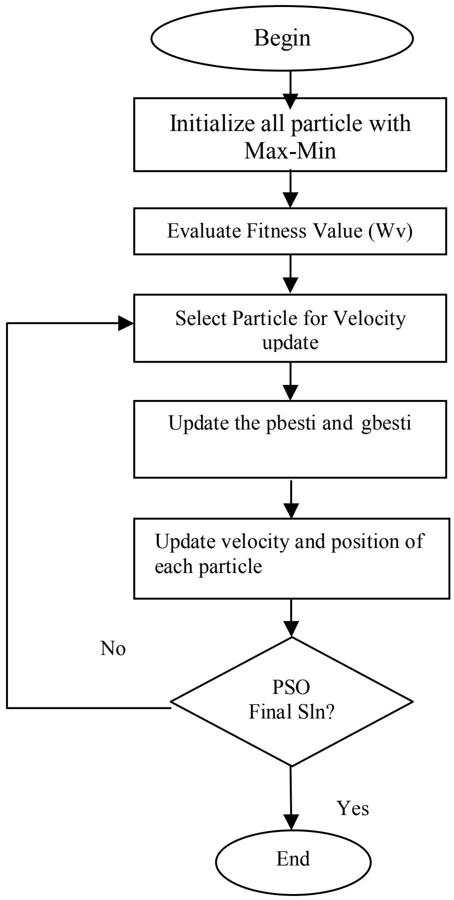

Figure 1: Flowchart of optimizing using Particle Swarm Optimization

A clustering algorithm is used for selection of the CH based on the weight of each node [20]. The weight of the node *v* is given by W_v as follows:

$$W_v = w_1 D_v + w_2 S_v + w_3 M_v + w_4 P_v$$

where D_v=degree of difference,
S_v= sum of distances of the members of the CH
M_v=avg speed
P_v = accumulative time of a node being a CH

The CH chosen has a sum of weights equal to 1 and with minimum weight W_v. Each node has a unique ID which is used to encode the particles and particles have the IDs of all the nodes in the network. The CH algorithm stops when all the nodes are assigned as CHs or members of a CH. Following are the conditions that the algorithm iteratively uses on each node in the particle to check the suitability of a node to be CH or not:

- Is the node a CH
- Is the node member of CH
- Is the number of neighbors less than the maximum neighbors allowed.

The W_v value is used to find the fitness of each particle. Process is continued to maximum number of iterations. On converging of the algorithm, solution for the global best particle is reported.

The clustering algorithm observes the following rules: the Received Signal Strength (RSS) gives the distance of the node from the event; if the RSS is above the threshold value RSS, then the node is located within the event area; residual energy of the neighboring nodes are known. The energy consumption is less when the distance is less, thus CH located nearest to the event requires the least energy for data transmission. The lifetime of the network can be prolonged by minimizing the energy consumption in the cluster. This can be given as follows:

$$\max T_C, \min \sum_{(i,j \in Se)} E_{Se}$$

where E_{Se} is the energy consumption of the cluster and T_C is the working time of the cluster.

Residual energy is taken into consideration during selection of CH. The chance of a node to become CH is high, when it has higher residual energy, more neighbors and strong signal strength. The objective function of the CH is obtained as follows:

$$q_1 = (E_i)^{k_1} * (K_i)^{k_2} * (SE_i)^{k_3}$$

where E_i represents the residual energy, K_i set of neighboring nodes, SE_i signal strength detected and k_1, k_2, k_3 are the weights controlling E_i, K_i and SE_i.
The CH dynamically chooses a route for transmitting data that depends on path metric, such as energy consumption. An energy constraint metric is used while searching for the multiple routes among the CHs and sink node. The Energy Constraint metric computes the inter-flow interference and the variation in the transmission rates and loss ratios of wireless links. The EC metric is designed as follows:

$$IEC_{ij}(c) = ETT_{ij}(c) * |N_i(c) \cup N_j(c)|$$

where $N_i(c)$ is the set of neighbors of node *i*
c is the channel *c*
$|N_i(c) \cup N_j(c)|$ is the total number of nodes that may be interfered with by the transmission activities between Node *i* and Node *j* over channel *c*.
$ETT_{ij}(c)$, the expected transmission time, which computes differences in transmission rates and loss ratios of links.

The EC metric is the combined channel time of all nodes used by the transmissions of the flow at link (*i, j, c*). An important implementation issue of *EC* is the estimation of *Ni*(*c*). When nodes are within each other's interference range, the transmission rate is reduced if both the nodes transmit simultaneously [21].

The Iterative deepening depth-first search approach works as follows: First, a depth-first search to depth one node is performed. Then, discarding the nodes generated in the first search, start over and do a depth-first search to level two. Next, start over again and do a depth-first search to depth three and so on, continuing this process until a goal state is reached. as Iterative deepening depth-first search approach expands all nodes at a given depth before expanding any nodes at a greater depth. It is guaranteed to find a shortest-length solution.

4. Experimental Setup

The proposed method was simulated in OPNET for evaluation. The evaluation setup consists of 18 sensor nodes and one sink spread over an area of 4 sq. Km. The maximum hop count in the setup is 5 hops. Maximum available bandwidth is 11 Mbps and transmission power for each node is 0.005w. Figure 2 shows the simulation environment. The simulations are run for 300 sec.

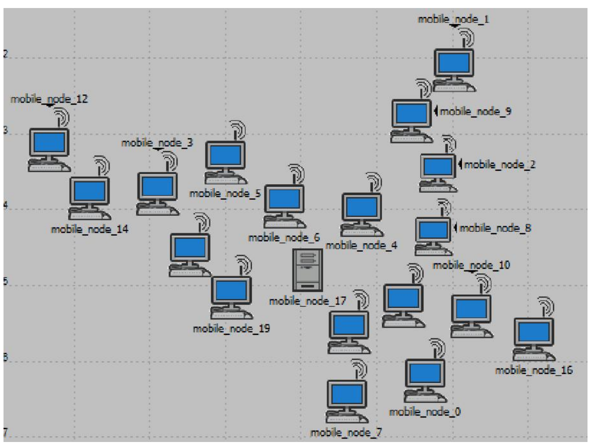

Figure 2: The experimental setup.

Figures 3 to 5 give the simulation results for routing and routing with proposed optimization. Route discovery time, Number of clusters formed and packet delivery ratio are shown respectively.

From Figure 3, it is observed that the route discovery time for the proposed Leach routing is higher than the regular Leach. The discovery time is more as CH dynamically chooses a route for transmitting data that depends on path metric in the proposed Leach and also as multiple routes are selected using sub optimal nodes.

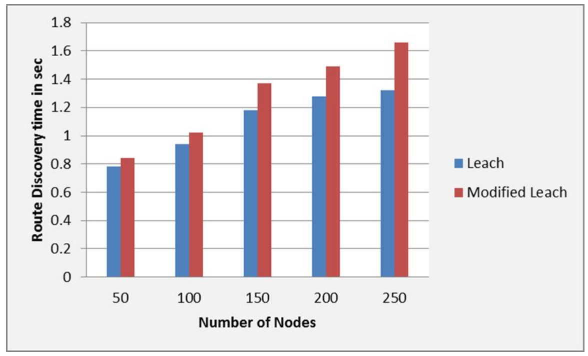

Figure 3: Route discovery time for Leach with and without optimization

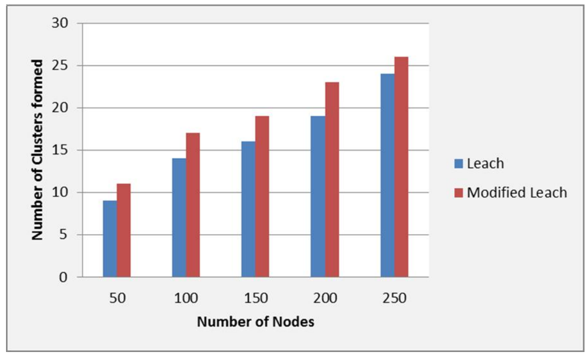

Figure 4: Number of Clusters formed for Leach with and without optimization

The number of clusters formed by the proposed Leach is slightly more than the regular Leach routing.

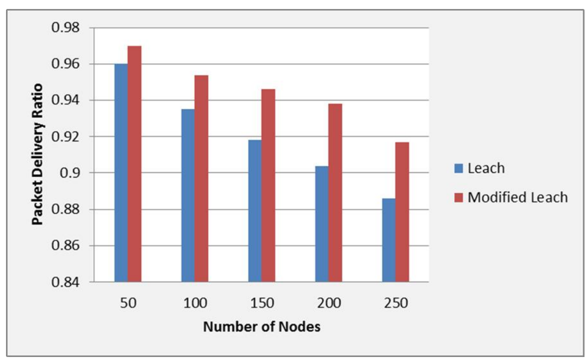

Figure 5: Packet Delivery Ratio for Leach with and without optimization

It is observed from the Figure 5, that the packet delivery ratio improves drastically in routing with proposed optimization. This leads to improvement in the performance of the network. Though the route discovery time and the number of clusters formed is more in the proposed Leach routing, the packet delivery ratio increases in tune of 3.5% for network of more than 200 nodes.

5. Conclusion

The routing protocol of any network aims to provide effective and efficient communication. In WSN, Sensor nodes are tightly constrained as regards energy, processing, and storage capacities, requiring careful resource management. In most application scenarios, WSN nodes are stationary after deployment except for a few mobile nodes. In this paper, a hybrid Particle Swarm Optimization (PSO) algorithm is proposed based on residual energy and multiple routes between the cluster head (CH) and sink node are found based on energy constraint metric. The suboptimal solutions found during CH become the key nodes for formation of multiple routes using Iterative deepening depth-first search approach. The proposed method is evaluated through simulation. The simulation results demonstrate the efficiency of the proposed optimization for finding routes and improving the packet delivery ratio in WSN network.

References

1. J. Hill, R. Szewczyk, A, Woo, S. Hollar, D. Culler, and K. Pister, System Architecture Directions for Networked Sensors, ASPLOS, November 2000.
2. B. Karp, Geographic Routing for Wireless Networks, PhD Dissertation, Harvard University, October 2000.
3. C. Intanagonwiwat, R. Govindan, and D. Estrin, Directed Diffusion: A Scalable Routing and Robust Communication Paradigm for Sensor Networks, Mobicom, August 2000.
4. Jian Tang, Guoliang Xue, and Weiyi Zhang, “Interference-Aware Topology Control and QoS Routing in Multi-Channel Wireless Mesh Networks,” in ACM Mobihoc, 2005.
5. Yaling Yang, Jun Wang, and Robin Kravets, “Interference-aware Load Balancing for Multihop Wireless Networks,” Tech. Rep. UIUCDCS-R-2005-2526, Department of Computer Science, University of Illinois at Urbana-Champaign, 2005.
6. Raghavendra V. Kulkarni, and Ganesh Kumar Venayagamoorthy, Technical Correspondence Particle Swarm Optimization in Wireless-Sensor Networks: A Brief Survey, IEEE Transactions On Systems, Man, And Cybernetics—Part C: Applications And Reviews, Vol. 41, No. 2, March 2011.
7. Hojoong Kwon, Tae Hyun Kim, Sunghyun Choi, and Byeong Gi Lee, A Cross Layer Strategy for Energy-Efficient Reliable Delivery in Wireless Sensor Networks, IEEE Transactions On Wireless Communications, Vol. 5, No. 12, December 2006
8. Yuanzhu Peter Chen, Arthur L. Liestman, and Jiangchuan Liu, A Hierarchical Energy-Efficient Framework for Data Aggregation in Wireless Sensor Networks, IEEE Transactions On Vehicular Technology, Vol. 55, No. 3, May 2006
9. Haibo Zhang and Hong Shen, Energy-Efficient Beaconless Geographic Routing in Wireless Sensor Networks, IEEE Transactions On Parallel And Distributed Systems, Vol. 21, No. 6, June 2010
10. Yi Huang and Yingbo Hua, Energy Planning for Progressive Estimation in Multihop Sensor Networks, IEEE Transactions On Signal Processing, Vol. 57, No. 10, October 2009
11. Ratul K. Guha, Carl A. Gunter, and Saswati Sarkar, Fair Coalitions for Power-Aware Routing in Wireless Networks, IEEE Transactions On Mobile Computing, Vol. 6, No. 2, February 2007
12. Xiaoying Zheng, Chunglae Cho, and Ye Xia, Optimal Swarming for Massive Content Distribution, IEEE Transactions On Parallel And Distributed Systems, Vol. 21, No. 6, June 2010
13. Peter Kok Keong Loh, Hsu Wen Jing, and Yi Pan, Performance Evaluation of Efficient and Reliable Routing Protocols for Fixed-Power Sensor Networks, IEEE Transactions On Wireless Communications, Vol. 8, No. 5, May 2009
14. Minji Wu, Jianliang Xu, Xueyan Tang, and Wang-Chien Lee, Top-k Monitoring in Wireless Sensor Networks, IEEE Transactions On Knowledge And Data Engineering, Vol. 19, No. 7, July 2007
15. Qing Cao, Tian He, and Tarek Abdelzaher, uCast: Unified Connectionless Multicast for Energy Efficient Content Distribution in Sensor Networks, IEEE Transactions On Parallel And Distributed Systems, Vol. 18, No. 2, February 2007
16. Latiff, N.M.A.; Tsimenidis, C.C.; Sharif, B.S.; , "Performance Comparison of Optimization Algorithms for Clustering in Wireless Sensor Networks," Mobile Adhoc and Sensor Systems, 2007. MASS 2007. IEEE Internatonal Conference on , vol., no., pp.1-4, 8-11 Oct. 2007
17. Matthew Settles,” An Introduction to Particle Swarm Optimization”, 2005
18. Eberhart, R. C., Shi, Y.: Particle swarm optimization: Developments, applications and resources, In Proceedings of IEEE International Conference on Evolutionary Computation, vol. 1 (2001), 81-86.
19. S. Agarwal, J. Padhye, V. Padmanabhan, L. Qiu, A. Rao, and B. Zill, “Estimation of Link Interference in Static Multihop Wireless Networks,” in ACM Internet Measurement Conference (IMC), 2005.

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