Advances and Applications in Mathematical Sciences
Volume 17, Issue 1, November 2017, Pages 79-94

ARTIFICIAL IMMUNE OPTIMIZATION ON MINIMUM ENERGY BROADCASTING IN WIRELESS SENSOR NETWORKS

R. S. RAGHAV[1], J. AMUDHAVEL[2] and P. DHAVACHELVAN[3]

[1,3]Department of Computer Science
Pondicherry University
Puducherry, India
E-mail: vpmrags@gmail.com
dhavachelvan@gmail.com

[2]Department of CSE
KL University
Andhra Pradesh, India
E-mail: info.amudhavel@gmail.com

Abstract

The classical problem faced in WSN environment is Minimum energy broadcast problem; in this work we address the issues created by the MEB. Here we used an Artificial Immune System (AIS) to solve the minimum energy broadcast (MEB) problem. In WSN the packet needs to be communicated from the sink node to all other nodes in the network. The algorithm identifies a node which consumes minimum energy for effective communication in the network and to minimize the total energy consumption. The simulation results is carried and compared with other Meta heuristics algorithms. The experimental result of the algorithm outperforms all other approaches and shows the emerged solutions are best.

1. Introduction

In recent years, all-wireless networks have grabbed key attention due to their complex issues faced by the sensor devices. The issues can vary according to the environment and the deployment of the sensor nodes or devices. The minimum energy broadcast is the key issues in wireless

2010 Mathematics Subject Classification: 68N15, 97N50.
Keywords: Artificial Immune System (AIS), Minimum Energy Broadcast (MEB), Wireless Sensor Network (WSN).
Received March 10, 2017; Accepted July 20, 2017

environment; it fails sensor nodes to communicate the message to achieve the target. The Bio inspired algorithm can be incorporated in many fields such as cloud computing, big data analytics etc. [20, 24, 25]. The design of the network is one of the major qualities to describe the strength of the network. Mostly nodes consume some initial energy for data transferring; if the network doesn't have fixed topology the usage of energy will become huge. This kind of network design fails to give throughput and it won't have energy efficiency. Each node in a network has a less amount of energy resource (battery), and each node operates neglected due to insufficiency of the energy. The broadcast communication is an important operation to carry data communication in all-wireless networks. The role of optimization algorithm such as Artificial Bee colony, Particle swarm Optimization and krill herd optimization is used in WSN for solving issues like energy, fault tolerance, coverage [21, 22, 26].

In this work, we implement artificial immune algorithm for figure out minimum energy broadcast problem in WSN. It is inspired from Biological Immune System (BIS) and the algorithm includes automatic learning, automatic-adaption, automatic regulatory, scattered with automatic/non-automatic detection capability. Due to these spectacular qualities AIS are substantially used in inconsistency node identification. The attackers are treated as foreign nodes that need to be detected. Therefore, AIS mostly used for development of an energetic system to find and avoid peculiar and undiscovered anomalies. It can be incorporated use to handle the minimum energy broadcast problem. As disused, broadcast of the data needs to be monitored to have an effective communication in the wireless environment. The algorithm has the ability to solve the minimum energy broadcast (MEB) problem where the packets need to be propagating from the sink node to all other nodes.

2. Literature Study

Vijayalakshmi and Radhakrishnan propose a novel variety of constrained used for carrying multicast routing algorithm. This algorithm is completely based on combination of genetic algorithm. To handle constraints, the incorporation of an artificial immune based method is carried. This method has the ability to removes the complexity faced by penalty factor method. The used artificial immune algorithm mimics the interaction between antigens and antibodies [1]. The proposed algorithm has the characteristics such as (1) Affinity measure method is merged to handle constraints in an effective way. (2) To move the antigens into a proper position Local search heuristic function along with '*m*' (random) point crossover and mutation is incorporated in the algorithm [1]. (3) For moving antibodies to a better position the algorithm infers Clonal selection method forward with operator of heuristic hyper-mutation. The above mentioned factors are integrated with *GA* to Artificial immune Algorithm for handling dynamism.

Tan, Kay Chen, et al. illustrates about an evolutionary artificial immune system for solving problem related to multi-objective optimization. The projected algorithm is the combination of evolutionary algorithms for global search ability and immune learning of artificial immune systems. The clonal choosing method is used as a new selection strategy to manage the equivalence between exploration and exploitation [2]. Gao, Jiaquan and Jun Wang presents a unique weight-based multiobjective artificial immune system (WBMOAIS) and it is depend on opt-aiNET. The projected algorithm is mainly used for solving multi-modal optimization with main factors. (1) The fitness function is declared from a randomly weighted summation of multiple objectives.

The process of evaluation is based on Pareto ranking, where position of fitness and the value should have lower computational complexity, (2) from the memory of the population a set of individuals are selected and indicated as set of exclusive solutions. A local search process is used to simplify the utilization of the search space, and (3) a new truncation algorithm with similar individuals is added to the clonal suppression algorithm and it is used in opt-aiNET (TASI). It also used to remove identical individuals in memory and acquire well-scattered non-dominated solutions [3]. Hernández, Hugo, and Christian Blum discuss about the re-establishment of the MEB issues for an antenna model for sensor networks. The levels of strength of transmission power are chosen from a finite set of possible ones. The variation of ant colony optimization, a current algorithm for the classical MEB problem, is carried for solving more realistic problem version in sensor networks [4].

Arivudainambi and Rekhaintroduce heuristic memetic algorithm to identify the minimum energy broadcast tree in wireless adhoc networks. The simulation outcomes on variety of issues, declare that the proposed algorithm provides a better solution or quality compared with other heuristic algorithms in terms of quality of the solution [5]. The experimental results are evaluated by the memetic algorithm and it generally shows the robustness over other recently proposed algorithms. Singh, Alok, and Wilson Naik Bhukya discuss about a hybrid *GA* for reducing the energy broadcast in wireless sensor network. In a wireless network a specified sink node that has to broadcast messages to all other nodes in the network. The minimum energy broadcast (MEB) problem explores a broadcast scheme for wireless network with low amount of energy consumption. The MEB problem is meant to be *NP*-Hard. The evaluation of results are compared our hybrid approach against the best heuristic approaches known for this problem [6]. The proposed algorithm surpasses all these methods and emerged as the best result.

3. Problem Formulations

The minimum energy broadcast (MEB) issue is used for finding a broadcast design with minimum energy consumption. In the wireless network path with network model, to send packet from source to destination they required power.

$$P = \xi \times d^{\alpha}, \tag{1}$$

where the above equation power threshold represents, and d represents distance from sender node to receiver node. Here constant variable α is used for path loss exponent, this constant depends on communication in the surroundings. The constant variable range usually fix as real number, the real number range between 2 and 4. In the wireless network distance d within the nodes are located can receive the packet form the sender. The power threshold ξ value is establish to 1 without loss of generality, and packet sending from node i to node j they required power can be decreased to equation.

$$P_{ij} = d_{ij}^{\alpha}. \tag{2}$$

The equation i represents node i and j represents node j, where d_{ij} represents the distance between the two nodes of node i and nod j. The overall consumption of power OPC of a broadcast tree in the network $BT = (V, E)$ can be described by

$$OPC = \sum_{i \in V} \max_{\{j \mid e_{ij} \in E\}} d_{ij}^{\alpha}. \tag{3}$$

The network broadcast tree BT, V represents the group of sensor nodes in a tree, E represents a set of supervised edges in the broadcast tree BT, and node i to node j represents the directed edge represents e_{ij}. The transmitted packets from node i can receive standing for node j. The BT represents the path from source node s (specified node) to all other nodes in the sensor V. The main aim of this problem is to reduce the overall consumption of energy in the wireless sensor networks. The overall energy transmission required to broadcast by each node in a directed tree in which all edges point away from the root.

4. Artificial Immune System (AIS)

Artificial Immune Optimization algorithm is inspired from the vertebrate immune process system. The key structure of artificial immune system is based on the contact between the antigen and antibody. The solution representation of artificial immune system is composed of binary representation. Genetic Algorithm operators are used in this artificial immune system in order to generate next generation population. The fitness of an individual is termed as affinity [11]. The proposed method is incorporated with the cloning procedure of Artificial Immune System [12]. The pseudo code of Artificial Immune System is given in detail in Figure 1.

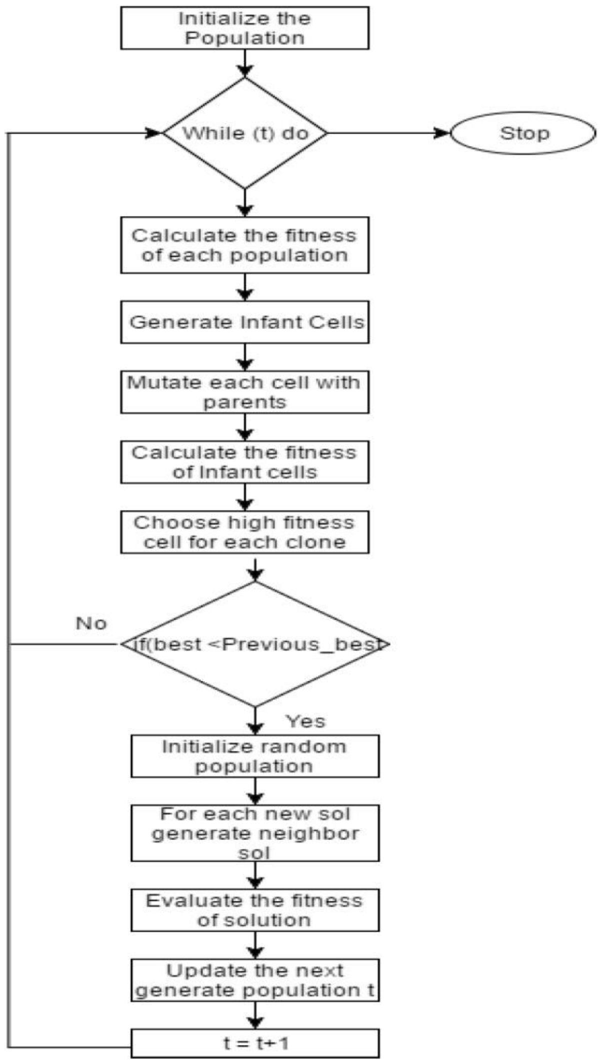

Figure 1. Workflow of Artificial Immune System.

Algorithm 1: Artificial Immune Algorithm

Initialize the parameter for Artificial Immune System
Initialize the population
While (t) do
Calculate the fitness of each population
Generate Infant cells
Mutate each cell with parents
Calculate the fitness of Infant cells
Choose high fitness cell for each clone
If (best <previous_best)
Goto2
Else
Initialize random population
For each new sol generate neighbor sol
Evaluate the fitness of solution
Update the next generate population
t=t+1

5. Experimental Results and Discussions

For solving Minimum Energy broadcasting problem in Wireless Sensor Networks using the proposed algorithm, a simulation setup has been implemented in MATLAB 8.4 with a system configuration of Intel Core i5 Processor with 3.4GHz speed and 8GB RAM. Performance metrics that are used for finding the Efficiency of proposed algorithm is are optimized value, Found, convergence rate and excess ratio. The proposed algorithm is compared with other two existing approaches namely Particle Swarm Optimization [17] and Genetic Algorithm [18]. Parameter settings are as follows:

Table 1. Parameter Settings.

Population size	100
Maximum iterations	500
R	3
C	10
Threshold Value (∂)	0.5

5.1. Performance Metrics

1. Best. Best is minimum energy consumption used by the algorithm for broadcasting the messages to all the nodes in the tree. For each instance the minimal energy is compared with its respective optimal energy consumption value.

$$\text{Best} = \text{Min}\,\{f(P_i) \forall i \in N\}.$$

2. Found. Found is the number of times the algorithm computed the best value out of 20 runs. Euclidian distance is used to compute the solutions are considered which are near to the obtained best energy consumption value.

$$\text{Found} = \frac{\#\,\text{Runs Best value found}}{\#\,\text{of Runs}}.$$

3. Convergence (%). Convergence rate shows the algorithm efficiency towards the tabulated optimum results. It can be given as,

$$\text{Convergence}\,(\%) = 1 - \frac{\text{Best} - \text{Optimum}}{\text{Optimum}} \times 100.$$

4. Excess. Excess ratio is defined as the ratio of result that is deviated from the tabulated optimum value.

$$\text{Excess Ratio} = \left[\frac{\text{Best energy consumptio n}}{\text{Optimal value}} - 1\right]$$

Table 2. Best and Found of AIS-MEB vs PSO Vs GA for 20 node instances.

		AIS-MEB		PSO		GA	
Instances	Optimum	Best	Found	Best	Found	Best	Found
p20.00	4072	4072	20/20	4128	16/20	4179	13/20
	50.81	50.51		09.81		44.81	
p20.01	4469	4469	20/20	4521	15/20	4588	13/20
	05.52	05.52		45.52		62.5	
p20.02	3351	3351	20/20	3412	18/20	3456	15/20
	02.42	02.42		76.42		56.42	
p20.03	4883	4883	20/20	4935	19/20	4975	13/20
	44.9	44.9		35.9		72.9	
p20.04	5161	5161	20/20	5233	17/20	5241	17/20
	17.75	17.75		15.75		88.75	
p20.05	3008	3008	20/20	3079	19/20	3100	15/20
	69.14	69.14		27.14		95.14	
p20.06	2505	2505	20/20	2581	16/20	2586	17/20
	53.15	53.15		88.15		89.15	
p20.07	3474	3474	20/20	3531	18/20	3593	13/20
	54.08	54.08		70.08		86.08	
p20.08	3907	3907	20/20	3968	20/20	4020	13/20
	95.34	95.34		30.34		02.34	
p20.09	4476	4476	20/20	4557	14/20	4604	11/20
	59.11	59.11		74.11		17.11	

Table 3. Convergence and Excess rate of AIS-MEB vs PSO Vs GA for 20 node instances.

	AIS-MEB		PSO		GA	
Instances	Conv.	Excess	Conv.	Excess	Conv.	Excess
p20.00	100.0%	0	98.63%	0.0137	97.37%	0.0263
p20.01	100.0%	0	98.83%	0.0117	97.32%	0.0268
p20.02	100.0%	0	98.16%	0.0184	96.85%	0.0315
p20.03	100.0%	0	98.94%	0.0106	98.11%	0.0189
p20.04	100.0%	0	98.61%	0.0139	98.44%	0.0156
p20.05	100.0%	0	97.65%	0.0235	96.93%	0.0307
p20.06	100.0%	0	96.95%	0.0305	96.75%	0.0325
p20.07	100.0%	0	98.35%	0.0165	96.57%	0.0343
p20.08	100.0%	0	98.46%	0.0154	97.13%	0.0287
p20.09	100.0%	0	98.19%	0.0181	97.15%	0.0285

Tables 2 and 3 show the experimental results of 20 nodes, data instances of Minimum energy broadcasting data set. Table 2 consists of the minimum energy consumed value obtained by AIS on MEB instances and the results of existing approaches PSO GA are also shown. Table 3 consists of the convergence rate and excess ratio of AIS and other two existing approaches GA and PSO [7]. The results are discussed in Figures 2, 3.

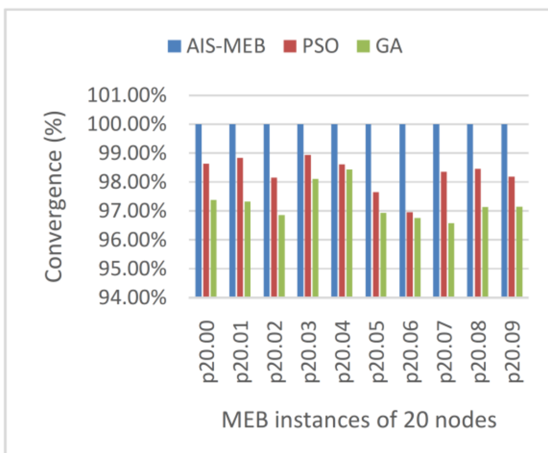

Figure 2. Convergence Rate of AIS-MEB vs PSO Vs GA for 20 node instances.

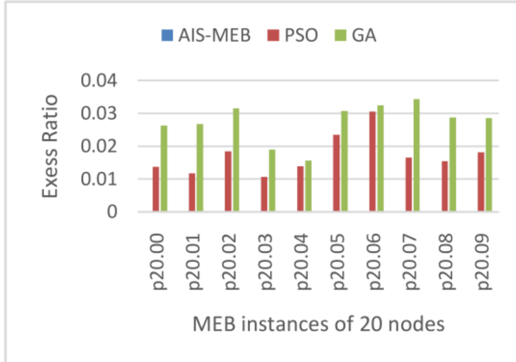

Figure 3. Excess Ratio of AIS-MEB vs PSO Vs GA for 20 node instances.

Figures 2 and 3 show the comparison status of Convergence rate and Excess rate of 20 nodes data instances of MEB respectively. From Figure 1 it can be observed that the proposed algorithm performs well on convergence towards optimal solutions when compared to other existing algorithms. From Figure 2, on comparing the results of excess rate the proposed algorithm attains optimal results in all instances of 20 nodes MEB by attaining all energy levels equal to optimal results tabulated.

Table 4. Best and Found of AIS-MEB vs PSO Vs GA for 50 node instances.

		AIS-MEB		PSO		GA	
Instances	Optimum	Best	Found	Best	Found	Best	Found
p50.00	3990	4115	18/20	4123	15/20	4158	16/20
	74.64	25.64		68.64		00.64	
p50.01	3735	3885	16/20	3914	15/20	3915	15/20
	65.15	65.15		48.15		85.15	
p50.02	3936	4078	18/20	4093	16/20	4123	12/20
	41.09	01.09		78.09		71.09	
p50.03	3168	3292	18/20	3346	17/20	3345	15/20
	01.09	48.09		50.09		44.09	
p50.04	3257	3380	17/20	3407	14/20	3440	13/20
	74.22	74.22		69.22		60.22	
p50.05	3822	3925	15/20	3983	12/20	3982	14/20
	35.9	07.9		78.9		39.9	
p50.06	3844	3949	14/20	3999	11/20	4006	12/20
	38.46	62.46		45.46		62.46	
p50.07	4018	4139	17/20	4176	15/20	4197	14/20
	36.85	89.85		59.85		48.85	
p50.08	3344	3462	18/20	3496	14/20	3509	12/20
	18.45	45.45		62.45		17.45	
p50.09	3467	3567	17/20	3622	15/20	3630	14/20
	32.05	60.05		04.05		96.05	

Table 5. Convergence and Excess rate of AIS-MEB vs PSO Vs GA for 50 node instances.

	AIS-MEB		PSO		GA	
Instances	Conv.	Excess	Conv.	Excess	Conv.	Excess
p50.00	96.88%	0.0312	96.67%	0.0333	95.81%	0.0419
p50.01	95.98%	0.0402	95.21%	0.0479	95.18%	0.0482
p50.02	96.40%	0.0360	96.00%	0.0400	95.24%	0.0476
p50.03	96.07%	0.0393	94.37%	0.0563	94.40%	0.0560
p50.04	96.22%	0.0378	95.40%	0.0460	94.39%	0.0561
p50.05	97.31%	0.0269	95.78%	0.0422	95.81%	0.0419
p50.06	97.26%	0.0274	95.97%	0.0403	95.78%	0.0422
p50.07	96.98%	0.0302	96.06%	0.0394	95.54%	0.0446
p50.08	96.46%	0.0354	95.44%	0.0456	95.07%	0.0493
p50.09	97.11%	0.0289	95.54%	0.0446	95.28%	0.0472

Tables 4 and 5 tabulate the simulation results of 50 node data instances of MEB data set. Table 4 holds the minimum energy consumed value obtained by the proposed algorithm and the results of existing approaches ACO and PSO are also tabulated. The performance metric Found is also tabulated in the same table. Table 5 holds the convergence rate and excess ratio of our proposed algorithm along with existing approaches. The results are discoursed in Figures 4 and 5.

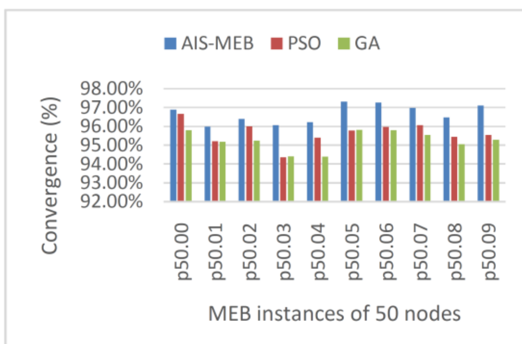

Figure 4. Convergence Rate of AIS-MEB vs PSO Vs GA for 50 node instances.

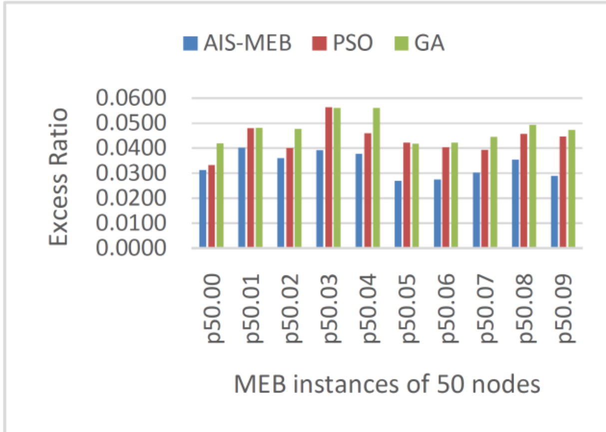

Figure 5. Excess Ratio of AIS-MEB vs PSO Vs GA for 50 node instances.

Figures 4 and 5 compare the Convergence rate and Excess ratio of 50 nodes data instances of MEB respectively. From Figure 4 it can be perceived that the Flower Pollination algorithm on MEB performs better on convergence towards optimal solution when compared with PSO and GA. From Figure 5, the excess ratio of proposed algorithm is minimal when compared to all other existing algorithms in all instances of 50 nodes dataset.

6. Conclusions

The overall energy consumption of WSNs can be obviously decreased through the deployment of nodes of an effective routing design in the network [8, 23]. In this work, we used an algorithm with on Artificial Immune System for solving the minimum energy broadcast problem in WSN environment. Also the algorithm results are compared with other metaheuristic algorithms and the experimental results of the algorithm suppress the outcome of other algorithm, by producing effective outcomes.

Acknowledgements

This work is a part of the Research Projects sponsored by Visvesvaraya Ph.D. Scheme for Electronics & IT, Ministry of Electronics & Information Technology, India, and Reference Nos.: PHD-MLA-4(44)/2015-16, dated August 2015. The authors would like to express their thanks for the financial supports offered by the Sponsored Agency.

References

[1] K. Vijayalakshmi and S. Radhakrishnan, Artificial immune based hybrid GA for QoS based multicast routing in large scale networks (AISMR), Computer Communications 31(17) (2008), 3984-3994.

[2] Tan, Kay Chen, et al., An evolutionary artificial immune system for multi-objective optimization, European Journal of Operational Research 187(2) (2008), 371-392.

[3] Jiaquan Gao and Jun Wang, WBMOAIS: A novel artificial immune system for multiobjective optimization, Computers & Operations Research 37(1) (2010), 50-61.

[4] Hugo Hernández and Christian Blum, Minimum energy broadcasting in wireless sensor networks: An ant colony optimization approach for a realistic antenna model, Applied Soft Computing 11(8) (2011), 5684-5694.

[5] D. Arivudainambi and D. Rekha, Memetic algorithm for minimum energy broadcast problem in wireless ad hoc networks, Swarm and Evolutionary Computation 12 (2013), 57-64.

[6] Alok Singh and Wilson Naik Bhukya, A hybrid genetic algorithm for the minimum energy broadcast problem in wireless ad hoc networks, Applied Soft Computing 11(1) (2011), 667-674.

[7] Hsiao, Ping-Che, Tsung-Che Chiang and Li-Chen Fu, Static and dynamic minimum energy broadcast problem in wireless ad-hoc networks: A PSO-based approach and analysis, Applied Soft Computing 13(12) (2013), 4786-4801.

[8] Zhao Xiulan, Xu Xiulan and Li Keqing, Differential Clustering Route Algorithm Baing on LEACH Protocol, Application Research of Computers 30 (2013), 866-868.

[9] Hu Yifan, Ding Yongs Heng, Ren Li Hong and Hao Kuangrong, An endocrine cooperative particle swarm optimization algorithm for routing recovery problem of wireless sensor networks with multiple mobilesinks, Information Sciences 300 (2015), 100-113.

[10] Hu, Yifan et al., An immune orthogonal learning particle swarm optimisation algorithm for routing recovery of wireless sensor networks with mobile sink, International Journal of Systems Science 45(3) (2014), 337-350.

[11] M. Kumlachew, Gary Woldemariam and G. Yen, Vaccine-Enhanced Artificial Immune System for Multimodal Function Optimization, IEEE Transactions on System, Man, and Cybernetics-Part B: Cybernetics 40(1) (2010), 218-228.

[12] Yongxian Li and Jiazhong Li, Swarm Intelligence Optimization Algorithm Based on Orthogonal Optimization [C], ICCMS, 4 (2010), 12-16. Second International Conference on Computer Modelling and Simulation, Sanya, China.

[13] Čagalj, Mario, Jean-Pierre Hubaux and Christian Enz, Minimum-energy broadcast in all-wireless networks: NP-completeness and distribution issues, Proceedings of the 8th Annual International Conference on Mobile Computing and Networking, ACM, 2002.

[14] Sweidan, I. Husam and Timothy C. Havens, Coverage optimization in a terrain-aware wireless sensor network, Evolutionary Computation (CEC), 2016 IEEE Congress on. IEEE, 2016.

[15] Alok Singh and Wilson Naik Bhukya, A hybrid genetic algorithm for the minimum energy broadcast problem in wireless ad hoc networks, Applied Soft Computing 11(1) (2011), 667-674.

[16] Karmakar, Sushanta, et al., Energy-efficient broadcasting in ad hoc wireless networks, Journal of Discrete Algorithms (2016).

[17] J. Kennedy and R. Eberhart, Particle swarm optimization, In: 1995 Proceedings of IEEE International Conference on Neural Networks; 1995.

[18] J. H. Holland and J. H. Holland, (1992), Adaptation in natural and artificial systems: an introductory analysis with applications to biology, control, and artificial intelligence (No. Sirsi) i9780262581110).

[19] Dorigo, Marco, Vittorio Maniezzo and Alberto Colorni, Ant system: optimization by a colony of cooperating agents, IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 26(1) (1996), 29-41.

[20] R. Raju, et al., A bio inspired Energy-Aware Multi objective Chiropteran Algorithm (EAMOCA) for hybrid cloud computing environment, Green Computing Communication and Electrical Engineering (ICGCCEE), 2014 International Conference on. IEEE, 2014.

[21] J. Amudhavel, et al., A krill herd optimization based fault tolerance strategy in MANETs for dynamic mobility, Circuit, Power and Computing Technologies (ICCPCT), 2015 International Conference on, IEEE, 2015.

[22] J. Amudhavel et al., An robust recursive ant colony optimization strategy in VANET for accident avoidance (RACO-VANET), Circuit, Power and Computing Technologies (ICCPCT), 2015 International Conference on. IEEE, 2015.

[23] D. Saravanan et al., A brief survey on performance analysis and routing strategies on Vanets, Indian Journal of Science and Technology 9(11) (2016).

[24] J. Amudhavel et al., Big Data Scalability, Methods and its Implications: A Survey of Current Practice, Proceedings of the 2015 International Conference on Advanced Research in Computer Science Engineering & Technology (ICARCSET 2015), ACM, 2015.

[25] P. Karthikeyan et al., A comprehensive survey on variants and its extensions of big data in cloud environment, Proceedings of the 2015 International Conference on Advanced Research in Computer Science Engineering & Technology (ICARCSET 2015), ACM, 2015.

[26] J. Amudhavel et al., A fault tolerant distributed self organization in peer to peer (p2p) using krill herd optimization, Proceedings of the 2015 International Conference on Advanced Research in Computer Science Engineering & Technology (ICARCSET 2015). ACM, 2015.