Advances and Applications in Mathematical Sciences
Volume 17, Issue 1, November 2017, Pages 129-145

MONKEY KING ALGORITHM FOR SOLVING MINIMUM ENERGY BROADCAST IN WIRELESS SENSOR NETWORK

T. KALAIPRIYAN[1], D. RAJAGURU[2], J. AMUDHAVEL[3], T. VENGATTARAMAN[4] and P. SUJATHA[5]

[1,4,5]Department of Computer Science
Pondicherry University
Puducherry, India
E-mail: kalaip27@gmail.com
vengattaraman.t@gmail.com
spothula@gmail.com

[2]Department of Information Technology
PKIET, Karaikal
Puducherry, India
E-mail: raja.guru42@gmail.com

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

Abstract

This paper describes Monkey King Evolution algorithm for solving minimum energy broadcast in wireless sensor networks. The wireless sensor networks is one of the most attracted to researchers is minimization of energy consumption. In this proposed work the main objective of the minimum energy broadcast (MEB) problem is to minimize the overall power consumption. A monkey king algorithm is used to solve the MEB problem for minimizing energy consumption. The Monkey king algorithm is a very effective, simple and easy to reconstruct the broadcast network efficiently. The proposed methodology is measured using four performance metrics for solving minimum energy broadcast problem. The performance of Monkey King

2010 Mathematics Subject Classification: 68N13, 97N50.
Keywords: monkey king evolution algorithm, evolutionary algorithm, minimum energy broadcast, wireless sensor network, optimization problem.
Received March 10, 2017; Accepted July 20, 2017

Evolution algorithm in solving minimum energy broadcast for wireless sensor network was evaluated.

1. Introduction

Energy efficiency is one of the main issues in wireless networks, due to the gradually increasing in the usage of sensor devices with low amount of battery power. The recent research focuses on how to manage communication tasks with low amount of energy. The reducing of energy should not affect the performance of the devices and system. Mostly the existing techniques focus on tuning the transmission ranges of nodes, in order to reduce the cost of energy. However, if fixed power is used for nodes transmission it makes to calculate the consumption of energy and the number of transmissions. The existing broadcasting protocols with few transmissions per node are used for radio networks with known network topology. Here, we discuss the issues in unknown radio networks, which don't have any knowledge of the design of the network. Nature inspired algorithms is used for handling complex problems and many biological based systems have developed with appealing and high level of efficiency in evolutionary objectives such as reproduction. Many algorithms is developed and applied in many issue, based on the Darwinian evolution of biological systems genetic algorithms were developed and based on the swarm behaviour of birds and fish used for developing particle swarm optimization [7], the echolocation behaviour of micro bats is implemented for bat algorithm and flashing light patterns is used for developing firefly algorithm [1, 7, 8]. All these algorithms are incorporated to a wide range of applications. Bio-inspired algorithm to solve scheduling algorithm is used [25].

Bio-inspired systems can be designed by hardware or software for achieving easy configuration of the system, in order to achieve quick processing of information, and to solve complex problems by providing quick solution. Most species of animals showcase their own characteristics and social behaviours. In some species, there is a leader or superiority individual that leads and organizes all group members [3]. In this evolutionary algorithm technique, each Monkey King particle migrates to a little (small) group of monkeys, in order to achieve exploitation. The exploration process carried by more particles in the population, after each particles exploitation process of Monkey King algorithm. Then according to it a randomly select process of particles using the formula R∗*PopSize* from the population is generated. This process helps to change their labels and made them as a new Monkey King Particles [4].

2. Literature Study

Meng, Zhenyu and Jeng-Shyang Pan discusses about the variety of Optimization algorithms for handling complex problems in huge number of areas. In this work, the working process about a new memetic evolutionary algorithm were described, known as Monkey King Evolutionary (MKE) Algorithm, for carrying global optimization process. Then the analysis of three updates methods for the proposed algorithm is identified [1]. Then a problem is used for understanding the capacity of the proposed scheme. Here algorithm is implemented to handle less amount of gasoline consumption optimization for navigation of vehicle. Yu-zhong, L. I. represents improvised version of MKGA and it contains three key operators: 1) pre-processing according to the requirements, 2) MK is used for injecting bid and swapping recombination, 3) for saving strategy Monkey-king elite operator is used. The taken experimental results illustrate that improved version of MKGA surpasses the SGA in size of population and computation [2]. It has the ability to solve efficiently and generates better result for the complex problems. Li, Shuangchen, Ying Yan and Yufang Lin discuss about a short-term load forecasting method depends on the combination of monkey-king genetic algorithm (MK) and wavelet neural network (WNN). The selections of parameters of WNN are artificially or derived through experiments. To achieve the target by solving hard problems, a WNN parameters optimizing method with monkey-king genetic algorithm (MKWNN) was generated. The simulation results displays that the proposed algorithm contains adaptability and high forecasting accuracy [3].

Zhang, Jinhui et al. explains about the fault diagnosis of using support vector machine (SVM), choosing of SVM parameters are achieved either artificially or obtained through experiment. Monkey-King genetic algorithm (MKSVM) is to solve the complex problems by tuning the SVM parameters. The optimized parameters are used in designed model, and the dominance of SVM in processing finite samples is completely used in the process. The experimental result display the proposed method can reach higher diagnosis accuracy it identifies optimum value accurately in a distributed environment [4]. The objective of the paper to find diagnosis the fault can be achieved by the proposed algorithm in an efficient way. Singh, Alok and Wilson Naik Bhukya provides a better study about the nature of a wireless ad hoc network with a specified sink node that has to broadcasting message to all other connected nodes in the connected network. The minimum energy broadcast (MEB) problem defines a broadcast scheme for the wireless network with low energy consumption [5]. The MEB problem is *NP*-Hard. This hybrid approach to the MEB problem is integrated with a genetic algorithm and the local search heuristic is used to identify the nodes which consume high level of energy in the network. The experimental results are compared to the proposed hybrid technique against the best heuristic methods to known for this problem and the results are outperform other results of other algorithms. Karmakar, Sushanta, et al. study case in which a bound k is mentioned and a transmission of node at most k times during the broadcasting protocol. Initially, the approach focuses on unfamiliar algorithms for k-shot broadcasting, where each node decides when to carry the data transmission, by neglecting the prior history of the transmission. The lower bound contains $\Omega\left(\frac{n^2}{k}\right)$ defines as the broadcasting time of k-shot broadcasting algorithm, and (b) an unfamiliar broadcasting protocol gain a matching upper bound, namely $O\left(\frac{n^2}{k}\right)$, for every $K \leq \sqrt{n}$ and an upper bound of $O(n^{3/2})$ for every $K > \sqrt{n}$. The observation of the proposed scheme of adaptive broadcasting protocols shows the time of about the nodes, so that it can decide when to initiate the transmission. This process is based on the available information, namely the transmission history of the node [5].

3. Problem Statement

3.1. Minimum Energy Broadcast Problem

In wireless sensor networks (WSN), the most important and popular technique is broadcasting. This broadcasting technique is used to allow all nodes to spilt the data efficiently with all other nodes connected in the networks. Due to inadequate energy resources, to construct the broadcast trees with essential aspect of energy efficiency. For example in a sample network a group of nodes let us consider one node is going to assign as source node, the work of MEB is to minimize the overall power consumption when the nodes connected together in the network and also they communicate with other nodes remaining connected in the network. In this individuality, the connected nodes have the capacity to correct their transmission power [17]. Consequently, each node connected in the network they assigned a transmission range and every node connected in the network receives a message inside in range. The main aim is to allocate ranges in a way the overall energy consumed is minimized.

The graphical theoretical terms are used to state MEB problem. A directed complete graph $G = (N, E)$, where N represents the set of nodes (i.e., the workstation of the wireless network) and E represents the set of edges. To establish a secured link from node i to j the power P is required to given as P_{ij} where $(i, j) \in E$. In wireless networks the broadcasting property, the two nodes x and y directly transmitted node x to node y are equipped with omnidirectional antennae. Connected wireless networks each other node i such that $P_{xi} \leq P_{xy}$ will also be reached by the signal transmitted by node x. The minimum energy broadcast (MEB) problem is mainly used to find a routing tree broadcast with minimum power transmission such that a source node $S \in N$. The remaining nodes of N have to broadcast a message either indirectly or directly through intermediate nodes. In a tree a directed edge of starting nodes are responsible for transmitted broadcast message to the same edge of the terminal node. The energy transmission required by node x and it is determined by required power is to transmit to the farthest child node of x in that tree [5]. The transmission energy essential by leaf nodes is zero, because leaf nodes are not relay messages to any other node. The broadcast tree is computed, the overall energy transmission is required by each parent node in that tree. The minimum energy broadcast problem (MEB) is discovering a tree rooted at S in the network with required minimum total energy. It is calculated as,

$$TTP_{Sol_i} = \sum_{P \in N} (p, q) \in E_{Sol_i} \max d(p, q)^{\alpha}. \tag{1}$$

The proposed algorithm produces for each iteration are generated minimum energy broadcast trees, which is called as solution [13]. The solution Sol_i generated for each solution as the total transmission power is TTP_{Sol_i}, where i represents the solution index number, α represents a constant and it referred to the path loss exponent, ie., the range between 2 and 4, d represents distance between nodes, $d(p, q)$ here p and called as nodes. The node p and node q receives a transmission from the signal power at q differs as $d(p, q)^{\alpha}$ where the Euclidean distance between two nodes p and q, the coordinates of node p represent as (x_p, y_p) and the coordinates of node q represent as (x_q, y_q). The optimal solution or near optimal solution is one, which contains minimum total transmission power $(TTP)_{Sol}$.

$$d(p, q)^{\alpha} = \left([(x_p - x_q)^2 + (y_p - y_q)^2]^{\frac{1}{2}}\right)^{\alpha}. \tag{2}$$

4. Monkey King Evolution Algorithm

The Monkey King Evolution (MKE) algorithm is inspired by the famous chinese mythological novel by Monkey Kings action. The novel relates to the adventure travel of the priest in search of Buddhist sutras with three disciples [2]. Monkey king is the greates disciple of the three. Each monkey king are capable to mold the small monkeys to acquire knowledge about the circumstances and report the feedback to the Monkey king. The local and global search behaviour of Monkey King is illustrated in Figure 1.

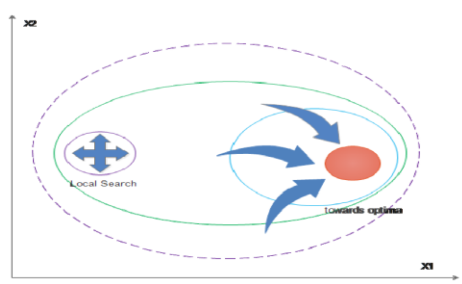

Figure 1. Search behaviour of particles in MKE.

All the small monkeys do the process of exploration and monkey king acquire the optimal solution from these locations [3]. In MKE, the number of small monkeys transfer into the monkey king is $C * D$, where C and D are the constant value and number of dimensions. Larger the area of exploitation, the value of C should be larger and it increases the computational complexity. Usually $C = 3$ is the better selection for lower dimensions. The small monkey particles search with the range of $X_{MK,G}$ using the Equation (3) and the value is updated in $X_{MK,G+1}$.

$$X_j \to X_j \pm 0.2 * rand(\ ) * X_j,\ j \in D. \tag{3}$$

$$X_{MK,\,G+1} = opt_{i \in C \times D}\{X_{sm}(1), \ldots, X_{sm}(i), \ldots, X_{sm}(C \times D)\} \tag{4}$$

X_{sm} denotes the i^{th} small monkey particles of $C * D$ monkey groups. The update of monkey king evolution is done by using Equation (4) for the G^{th} particle.

$$X_{k,G+1} = X_{k,\,p\,best} + F * rand(\ ) * (X_{gbest} - X_{k,G}). \tag{5}$$

For normal particle, the process of exploration of the solution was carried out by the small monkeys using Equation (5). $X_{k,\,pbest}$ denotes the k^{th} overall population with F fluctuation coefficient of the direction vector. The pseudo code and the flow of MKE algorithm is shown in Figures 2 and 3.

```
Algorithm: Monkey King Evolution Algorithm
Initialize the searching space R(r1, r2, ...., rd) and fitness function f(X).
While t <MaxIT do
    If t =1 then
        Generate the population Pi=(Pi,1, Pi,2, ..., Pi,d)^T randomly and initialize Monkey King individual
        Set the Flag for Monkey King Particle
    End if
    If t > 1 then
        For each i =1: N where N ∈ Pop do
            If label_i== 1 then
                Use Eq. (2) and Eq. (3) to search in solution space.
            label_i=0
            Else
                Use Eq. (1) for searching in solution space.
            End if
            Generate new Monkey King particle and set the flag.
        End for
    End if
    Calculate the fitness using fitness function (f), Update Ppbest.
    Update optimal value in Pgbest.
End while
Output: The global Xgbest and f(Xgbest).
```

Figure 2. Pseudo Code of MKE algorithm.

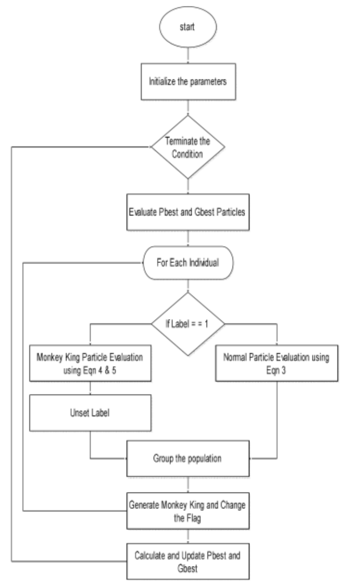

Figure 3. Flowchart of MKE algorithm.

5. Experimental Results

The proposed methodology for solving Minimum Energy broadcasting optimization problem in Wireless Sensor Networks (WSN) has been implemented in MATLAB 8.3 with a system configuration of Intel Core i7 Processor with 3.4GHz speed and 8GB RAM. Efficiency of our proposed algorithm is tested in terms of Best energy optimized value, Found, convergence rate and excess ratio. Random permutation is used for population initialization. The proposed algorithm is compared with other two existing approaches such as Ant Colony Optimization (ACO) [23] and Particle Swarm Optimization (PSO) [14].

Table 1. Parameter Settings.

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

5.1. Performance Metrics

Best: Best value is defined as the amount of energy used for broadcasting the data to all the nodes in the data instance by the proposed algorithm.

$$Best = \min \{f(P_i) \forall i \in N\}.$$

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

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

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

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

where, R is the total number of runs.

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

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

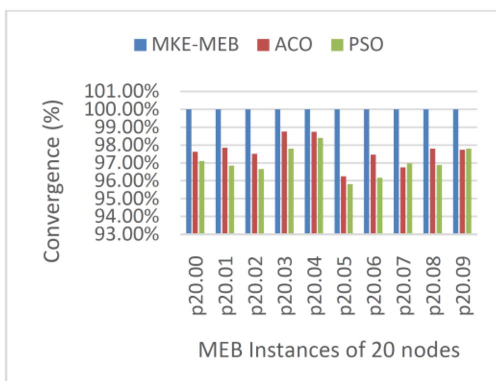

Figure 4. Convergence Rate of MKE-MEB vs ACO Vs PSO for 20 node instances.

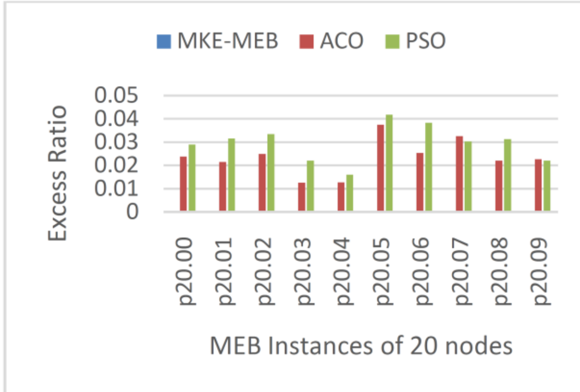

Figure 5. Excess Ratio of MKE-MEB vs ACO Vs PSO for 20 node instances.

Table 2. Best and Found results of MKE-MEB vs ACO Vs PSO for 20 node instances.

		MKE-MEB		ACO		PSO	
Instances	Optimum	Best	Found	Best	Found	Best	Found
p20.00	4072	4072	20/20	4169	15/20	4190	12/20
	50.81	50.81		29.81		70.81	
p20.01	4469	4469	20/20	4565	14/20	4609	11/20
	05.52	05.52		23.52		92.52	
p20.02	3351	3351	20/20	3434	17/20	3463	14/20
	02.42	02.42		67.42		05.42	
p20.03	4883	4883	20/20	4944	20/20	4990	12/20
	44.9	44.9		57.9		87.9	
p20.04	5161	5161	20/20	5226	18/20	5243	16/20
	17.75	17.75		45.75		93.75	
p20.05	3008	3008	20/20	3121	18/70	3134	14/20
	69.14	69.14		45.14		59.14	
p20.06	2505	2505	20/20	2569	15/20	2601	15/20

	53.15	53.15		00.15		46.15	
p20.07	3474	3474	20/20	3587	20/20	3579	14/20
	54.08	54.08		49.08		61.08	
p20.08	3907	3907	20/20	3993	14/20	4029	12/20
	95.34	95.34		91.34		87.34	
p20.09	4476	4476	20/20	4577	13/20	4575	13/20
	59.11	59.11		77.11		21.11	

Table 3. Convergence and Excess Rate of MKE-MEB vs ACO Vs PSO for 20 node instances.

	MKE-MEB		ACO		PSO	
Instances	Conv.	Excess	Conv.	Excess	Conv.	Excess
p20.00	100%	0	97.62%	0.0238	97.10%	0.0290
p20.01	100%	0	97.85%	0.0215	96.85%	0.0315
p20.02	100%	0	97.50%	0.0250	96.66%	0.0334
p20.03	100%	0	98.75%	0.0125	97.80%	0.0220
p20.04	100%	0	98.74%	0.0126	98.40%	0.0160
p20.05	100%	0	96.25%	0.0375	95.82%	0.0418
p20.06	100%	0	97.47%	0.0253	96.17%	0.0383
p20.07	100%	0	96.75%	0.0325	96.98%	0.0302
p20.08	100%	0	97.80%	0.0220	96.88%	0.0312
p20.09	100%	0	97.74%	0.0226	97.80%	0.0220

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

		MKE-MEB		ACO		PSO	
Instances	Optimum	Best	Found	Best	Found	Best	Found
p50.00	3990	4057	18/20	4141	16/20	4216	15/20
	74.64	10.64		71.64		40.64	
p50.01	3735	3875	15/20	3882	16/20	3936	14/20
	65.15	50.15		82.15		33.15	
p50.02	3936	4108	17/20	4072	17/20	4175	16/20
	41.09	31.09		65.09		77.09	
p50.03	3168	3314	19/20	3325	18/20	3412	16/20
	01.09	00.09		48.09		38.09	
p50.04	3257	3436	16/20	3404	15/20	3462	17/20
	74.22	13.22		89.22		06.22	
p50.05	3822	3961	15/20	4004	13/20	4047	15/20
	35.9	27.9		23.9		60.9	
p50.06	3844	3971	13/20	4015	10/20	4033	12/20
	38.46	07.46		19.46		38.46	
p50.07	4018	4201	19/20	4147	16/20	4197	17/20
	36.85	13.85		89.85		49.85	
p50.08	3344	3502	16/20	3491	15/20	3580	12/20
	18.45	66.45		83.45		96.45	
p50.09	3467	3590	17/20	3639	17/20	3673	15/20
	32.05	52.05		65.05		23.05	

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

	MKE-MEB		ACO		PSO	
Instances	Conv.	Excess	Conv.	Excess	Conv.	Excess
p50.00	98.34%	0.0166	96.22%	0.0378	94.35%	0.0565
p50.01	96.26%	0.0374	96.06%	0.0394	94.63%	0.0537
p50.02	95.63%	0.0437	96.54%	0.0346	93.92%	0.0608
p50.03	95.39%	0.0461	95.03%	0.0497	92.29%	0.0771
p50.04	94.52%	0.0548	95.48%	0.0452	93.73%	0.0627
p50.05	96.37%	0.0363	95.24%	0.0476	94.11%	0.0589
p50.06	96.70%	0.0330	95.56%	0.0444	95.08%	0.0492
p50.07	95.45%	0.0455	96.78%	0.0322	95.54%	0.0446
p50.08	95.26%	0.0474	95.58%	0.0442	92.92%	0.0708
p50.09	96.45%	0.0355	95.03%	0.0497	94.06%	0.0594

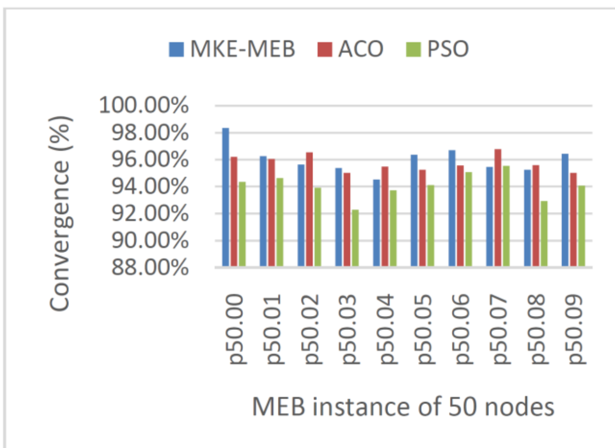

Figure 6. Convergence Rate of MKE-MEB vs ACO Vs PSO for 50 node instances.

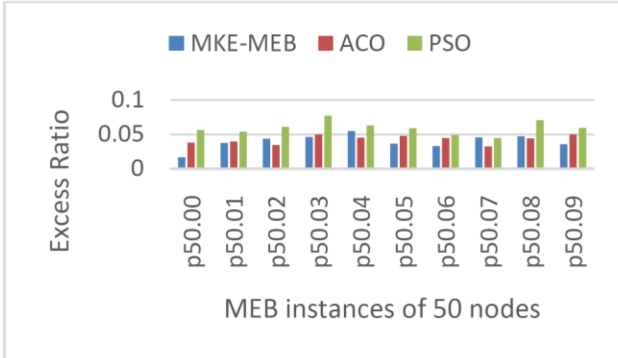

Figure 7. Excess Rate of MKE-MEB vs ACO Vs PSO for 50 node instances.

Tables 2 and 3 show the experimental results of 20 node data instances of Minimum energy broadcasting data set. Table 2 consists of the minimum energy consumed value obtained by our proposed algorithm and the results of existing approaches ACO and PSO are also listed [17]. Along with that this table also consists Found performance metrics for same data instances. Table 3 consists of the convergence rate and excess ratio of all three algorithms. The results are discussed in Figures 4 and 5. Figures 4 and 5 show the comparison status of Convergence rate and Excess rate of 20 nodes data instances of MEB respectively. From Figure 4 can observed that, the proposed algorithm performance on convergence towards optimal solutions when compared to other existing algorithms. From Figure 5, on comparing the results of excess rate the proposed algorithm attains optimal results in all instances of 20 nodes MEB.

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 6 and 7.

Figures 6 and 7 compare the Convergence rate and Excess ratio of 50 nodes data instances of MEB respectively. From Figure 6 it can be perceived that the Flower Pollination algorithm on MEB performs better on convergence towards optimal solution when compared with ACO and PSO.

From Figure 7, the excess ratio of proposed algorithm is minimal when compared to all other existing algorithms in six data instances out of 10 instances in 50 nodes dataset.

6. Conclusion

In this presented work, the author has presented Monkey King Evolution algorithm for finding minimum energy broadcast problem in the wireless sensor network. The effectiveness of the Monkey King Evolution algorithm on solving minimum energy broadcast is measured using performance metrics. The performance with respect to best value, found, excess, and convergence ratio is measured. The computational results shows the superiority of the Monkey King Evolution algorithm over other competitor algorithm.

References

[1] Meng, Zhenyu and Jeng-Shyang Pan, Monkey king evolution: a new memetic evolutionary algorithm and its application in vehicle fuel consumption optimization, Knowledge-Based Systems 97 (2016), 144-157.

[2] L. I. Yu-zhong, Improved Monkey-king Genetic Algorithm for Solving Large Winner Determination in Combinatorial Auction, Computer Knowledge and Technology 1 (2012), 030.

[3] Li, Shuangchen, Ying Yan and Yufang Lin, Short-Term Load Forecasting Based on Wavelet Neural Network and Monkey-King Genetic Algorithm, Computational Intelligence and Software Engineering, 2009. CiSE 2009 International Conference on. IEEE, 2009.

[4] Zhang, Jinhui, Ying Yan and Yufang Lin, Research on Fault Diagnosis Based on SVM and Monkey-King Genetic Algorithm, Computational Intelligence and Software Engineering, 2009, CiSE 2009, International Conference on IEEE, 2009.

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

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

[7] Goyal, Sonia and Manjeet Singh Patterh, Flower pollination algorithm based localization of wireless sensor network, Recent Advances in Engineering and Computational Sciences (RAECS), 2015 2nd International Conference on IEEE, 2015.

[8] A. Kumar, Khosla, J. Saini and S. Singh, Meta heuristic range based localization algorithm for wireless sensor network, International conference on Digital Object Identified 10.1109/icl, 2012.

[9] Askarzadeh and Alireza, A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm, Computers and Structures 169 (2016), 1-12.

[10] M. H. Moradi and M. Abedini, A combination of genetic and particle swarm optimization for optimal DG location and sizing in distribution system, Int J Electr Power Energy Syst 34 (2012), 66-74.

[11] R. V. Kulkarni and G. K. Venayagamoorthy, Bioinspired Algorithms for Autonomous Deployment and Localization of Sensor Nodes, IEEE transactions on systems, man and cybernetics-PART C: Applications and Reviews 40(6) (2010), 663-675.

[12] X. Ren, C. Gao and Y. Xi, A node localization algorithm based on simple particle swarm optimization in wireless sensor networks, Journal of Computational Information Systems 22 (2013), 9203-9210.

[13] Q. Shi, C. He, H. Chen and L. Jiang, Distributed Wireless Sensor Network Localization Via Sequential Greedy Optimization Algorithm, IEEE Transactions on Signal Processing 58(6) (2010), 3328-3340.

[14] M. Vecchio, R. L. Valcarce and F. Marcelloni, Solving the Node Localization Problem in WSNs by a Two-objective Evolutionary Algorithm and Local Descent, chez Third World Congress on Nature and Biologically Inspired Computing, 2011.

[15] Moussa and N. El-Sheimy, Localization of Wireless Sensor Network Using Bees Optimization Algorithm, IEEE, 2011.

[16] D. Manjarres, M. Vecchio and R. Lopez-Valcarce, A novel heuristic approach for distance- and connectivity-based multihop node localization in wireless sensor networks, Springer, 2012.

[17] C. Cao, Q. Ni and X. Yin, Comparison of Particle Swarm Optimization Algorithms in Wireless Sensor Network Node Localization, chez IEEE International Conference on Systems, Man,

[18] R. Kennedy, Eberhart, Particles warm optimization, Proceedings of IEEE International Conference on Neural Networks 4(2) (1995), 1942-1948.

[19] R. C. Eberhart, J. Kennedy, A new optimizer using particles warm theory, in: Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya Japan (1) October (1995).

[20] Y. Shi and R. Eberhart, A modified particles warm optimizer, in: Proceedings of the1998 IEEE International Conferencen Evolutionary Computation Proceedings, 1998 and IEEE World Congress on Computational Intelligence, 1998.

[21] R. C. Eberhart and Y. Shi, Comparing inertia weights and constriction factors in particles warm optimization, in: Proceeding soft he 2000 Congress on Evolutionary Computation, 2000, vol.1, IEEE, 2000.

[22] M. Clerc and J. Kennedy, The particles warm explosion, stability, and convergence in amulti dimensional complex space, IEEET Trans. Evol. Comput. 6(1) (2002), 58-73.

[23] 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.

[24] J. Kennedy and R. Eberhart, Particle swarm optimization. In: 1995 Proceedings of IEEE international conference on neural networks; 1995.

[25] M. Rajeswari, J. Amudhavel, Sujatha Pothula and P. Dhavachelvan, Directed Bee Colony Optimization Algorithm to Solve the Nurse Rostering Problem, Computational Intelligence and Neuroscience, vol. 2017, Article ID 6563498, 26 pages, 2017. doi:10.1155/2017/6563498.