Assurance of Energy Efficiency for Wireless Sensor Networks through Adjusting Transmitting Range of Nodes with an Adaptive Cellular Learning Automaton based Protocol *(LMNNACLA)*

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Abstract—**wireless sensor networks which consist of a large number of sensor nodes that are close to each other, providing the energy of its nodes through battery. But because of high number of nodes and inaccessibility of environment; usually replacing or recharging of batteries is impossible and with depletion the battery of one sensor node its lifetime would be finished and with following of this process and dying of some sensor nodes and fault in coverage problem or other network functionalities, the lifetime of network will be ended; so different kinds of energy reduction consumption methods for sensor networks would be depicted. One of principle methods for restricting transmitting energy of nodes is a part of control topology process; which its goal is deleting redundant and unessential topology information and with this approach through controlling radio of nodes that are one of essential energy consumption resources in sensor networks, causes to preserving energy that is a goal.**

In consideration of learning Automata's abilities such as low computational load, adaptability to changes especially topological variations via low environmental feedbacks So; in this paper an adaptive topology control protocol based on irregular cellular learning automata has been proposed; that maps to whole network and in it nodes which have been equipped with automata try to adapt their selected actions to required conditions for creating a connected and energy efficient network, finally select the most proper radio transmission range for themselves and form a proper topology and through this way cause to lower network's energy consumption in its lifetime. The exclusive characteristic of this method is; the high number of transmission ranges that each node can select as transmission radius. Simulation Results show favorable functionality of proposed protocol in comparison with some other similar one from above point of view.

Keywords-Adaptive Protocol; Cellular Learning Automata; Energy Efficiency; Topology Control; Transmitting Rang; Wireless Sensor Networks.

I. INTRODUCTION

Wireless sensor networks are set of large number of sensor nodes that are close to each other that scattered in the environment and each of them autonomously and in cooperation with other nodes; tries to achieve a special goal. Every node in this collection can communicate with others and gives its information to other nodes in order to finally; the under control environment's status be reported to a central point that is sink node. The principal aim in wireless sensor networks is monitoring and controlling variations of climate and physical or chemical changes in an environment of a phenomenon with deterministic region [1,2]. Nevertheless, since nodes work autonomously and without human interference; and also are very small physically, and have some constraints in power processing, memory capacity and power resource and etc; so one of the goals in these networks is to reduce energy consumption in order to prolonging network lifetime.

Between diverse methods that can use for decreasing consumed energy in sensor network, selecting a suitable topology has the most influence on efficiency of network from viewpoints of energy consumption and lifetime. Topology control in sensor networks is the art of coordinating nodes' decisions regarding their transmitting ranges, in order to generate a network with the desired properties (e.g. connectivity), while reducing node energy consumption and/or increasing network capacity [3]. Several topology control protocols have been presented until now in order to allow nodes selecting and setting their transmission ranges. These selections change based on priorities and different conditions such as: less energy consumption, network's sparseness, lower node's degree, fault tolerance and decreasing interference [4].

With consideration to these mentioned constraints for sensors, the aim of many researches is focused on presenting approaches that with simple control methods and with low cost; moreover than responding to requirements; can stand for some constraints such as bandwidth, limited energy, environmental interferences and etc. and can correspond with general conditions based on requirements and available wills such as, transferring high density rich in content information, long lifetime, low cost and etc. Investigations on Learning Automata (L.A) and Wireless sensor networks characteristics have shown that Learning Automata with consideration to properties such as low computing overload, the ability of using in distributed environments with ambiguous information, and the ability of adapting with environmental changes, is a very suitable model for using in sensor networks.

Specially, with consideration to energy restriction in sensor nodes and requiring to reduce transmissions of redundant information; in order to preventing from energy wasting; the tendency of using algorithms; which can work in a distributed manner and with local information has high importance in wireless sensor networks.

Because of this, In this paper a neighbour based topology control protocol, and based on learning Automata has been proposed (LMNNACLA)[i] that in it; a cellular learning automata has been mapped on the network and network nodes which are in the role of network cells with the help of it; and with the passing of time will select the best transmission range, according to conditions for themselves. In previous presented methods the number of transmission ranges that each node could have been selected was limited and few; but in this proposed method some efforts has been done to give nodes more optional selections which are close to each other; as transmission ranges.

The rest of this paper is organized as follows. Section2 is an introduction of topology control and related works to it. Learning automata as a basic learning strategy used in the proposed method; will be briefly discussed in section 3. In Section4 the problem statement is defined. In section 5 the proposed method is presented. Simulation results have been shown in section 6. Section 7 is the conclusion.

II. TOPOLOGY CONTROL

A. *Review of topology control*

The goal of topology control mechanisms is to dynamically change the nodes' transmitting range [18] and for getting into it, control the radio power level of nodes to achieve a connected and of course optimum topology; so that can maintain some properties of the communication graph, while reducing the consumed energy by node's transceivers, and also; can control the energy consumption since transceivers of nodes are one of primary sources of energy consumption in Wireless sensor networks.

These mechanisms themselves; regarding to essence of the network and information that each node can obtain is divided into two categories that are: homogeneous and nonhomogeneous topology control [3,4]. In homogeneous topology control, all nodes of the network use the same transmission range *r*; but this kind of topology is not suitable enough from points of efficiency, lifetime and strong connectivity. However; in nonhomogeneous topology control, nodes are allowed to choose different transmitting ranges and independently choose their transmitting range in order to besides preserving local connectivity, be having less interference too, and depending on the type of information that is used to construct the topology, is classified into three categories [3], which are location-based and direction-based approaches and Third of them is, neighbour-based techniques that nodes have access to a minimal amount of information regarding their neighbours, such as their I.D number.

B. *Related Works On neighbour based topology control*

Kneigh[ii] and XTC[iii] protocols are two distributed topology control protocols from type of nonhomogeneous topology control protocols and neighbour based [15,16].

The goal of Kneigh protocol is to keep at least *k* nearer neighbours to each node. From other topology control protocols can refer to RAA_2L that in it every node selects one from two level transmission ranges R_s or R_w somehow (R_w<R_s)[6]. If node with R_w transmission range can communicate with R_s transmission range neighbours (either directly or through a whisperer range neighbor); then node selects R_w transmission range; else selects R_s transmission range. In RAA_3L transmission ranges is extending to three levels that every node selects one from three transmission ranges R_s or R_w or R_t that it's relation are like:(R_w<R_t<R_s).

Also, in [5] a topology control protocol based on irregular cellular learning automata (CLATC)[iv] has been proposed that in it an irregular cellular learning automaton is mapped to network. But, each node in the network has its own individual learning automata and in cooperation with *LA*s of its neighbor nodes, tries to choose the most suitable transmission range from three available ranges for itself; in consideration to other nodes' transmission ranges; which has better correspondence to network conditions.

III. LEARNING AUTOMATA

Learning automata (L.A) is an abstract model [7,8,17] which randomly selects one action out of its finite set of actions and performs it on a random environment. Environment then evaluates the selected action and responses to the automata with a reinforcement signal. Based on selected action, and received signal, the automata updates its internal state and selects its next action. Figure 1 depicts the relationship between an automata and its environment.

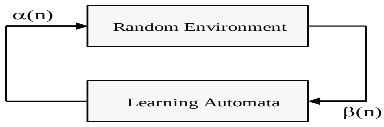

Figure 1. Relationship between learning automata and its environment.

Environment can be defined by the triple $E=\{\alpha,\beta,c\}$ where $\alpha=\{\alpha_1,\alpha_2,\ldots,\alpha_r\}$ represents a finite input set, $\beta=\{\beta_1,\beta_2,\ldots,\beta_r\}$ represents the output set, and $c=\{c_1,c_2,\ldots,c_r\}$ is a set of penalty probabilities, where each element c_i of c corresponds to one input of action α_i. An environment in which β can take only binary values 0 or 1 is referred to as P-model environment. A further generalization of the environment allows finite output sets with more than two elements that take values in the interval [0, 1]. Such an environment is referred to as Q-model. Finally, when the output of the environment is a continuous random variable which assumes values in the interval [0, 1]; it is referred to as an S-model. Learning automata are classified into fixed-structure stochastic, and variable-structure stochastic. In the following, we consider only variable-structure automata.

A variable-structure automaton is defined by the quadruple $\{\alpha,\beta,p,T\}$ in which $\alpha=\{\alpha_1,\alpha_2,\cdots,\alpha_r\}$ represents the action set of the automata, $\beta=\{\beta_1,\beta_2,\cdots,\beta_r\}$ represents the input set, $p=\{p_1,p_2,\cdots,p_r\}$ represents the action probability set, and finally $p(n+1)=T[\alpha(n),\beta(n),p(n)]$ represents the learning algorithm. This automaton operates as follows. Based on the action probability set *p*, automaton randomly selects an action α_i, and performs it on the environment. After receiving the environment's reinforcement signal, automaton updates its action probability set based on equations (1) for favorable responses, and equations (2) for unfavorable ones.

$$
\begin{aligned}
p_i(n+1) &= p_i(n)+a.(1-p_i(n)) \\
p_j(n+1) &= p_j(n)-a.p_j(n) \qquad \forall j \quad j\neq i
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
p_i(n+1) &= (1-b).p_i(n) \\
p_j(n+1) &= \frac{b}{r-1}+(1-b)p_j(n) \qquad \forall j \quad j\neq i
\end{aligned}
\tag{2}
$$

In these two above equations, *a* and *b* are reward and penalty parameters respectively. For *a* = *b*, learning algorithm is called L_{R-P} [v]. For b<<*a* it is called $L_{R\varepsilon P}$ [vi]. Similarly, for *b = 0* the algorithm is called L_{R-I} [vii][9]. One types of learning automata is cellular learning automata (CLA) that in is a CA in which an LA (or multiple LA) is assigned to its every cell [8,9,19,20]. The LA residing in a particular cell determines its state on the basis of its action probability vector; and there is a rule that CLA operates under it. The rule of CLA and state of neighboring cells of any particular cell determine the reinforcement signal to the LA residing in that cell.

IV. PROBLEM STATEMENT

In this paper assumes that every sensor node can choose a proper and deterministic value from the transmission ranges between [R_w,R_s]; or in other words between the low power transmission radius is termed the whisperer radius(R_w) and the high power transmission radius(R_s) is termed the shouter radius; and there is a medium power transmission radius between [R_w,R_s] which is called the speaker radius(R_t) that its value is proportional to network density and defined with it[10].What is being obvious from the above, is that; the R_w transmission radius is lower than two other transmission radiuses and R_s transmission radius is higher than the two others(R_w<R_t<R_s). The value of R_w transmission radius is equal to 0.8*R_t, and the value of R_s transmission radius is equal to 1.25*R_t. In this model we convert the transmission range to *n* different values; that the difference of each value with its previous value is equal to difference of each value with the next value of itself and is called Ainc or Adec and is defined as follows: Ainc= Adec =(R_s - R_w) /n=C*R_t

In this relation *C* is a constant coefficient and is equal to C=0.45/n.

V. THE PROPOSED METHOD

This proposed control topology protocol that is neighbor based and is performing based on cellular learning automata, has two phases as describing below: Learning and selecting the best radio range. The considerable problem is selecting the most suitable transmission radius from transmission ranges between [R_w,R_s] for each node; somehow the required conditions for network connectivity to be conserved.

A. Learning phase

At the first of this stage; a cellular learning automata has been mapped to the network; somehow each node in the network plays role of a cell which is equipped with a L.A. and two distinguished neighbor nodes in the network which their basis are on distance and response to transmitted Hello messages from each other; have the role of two neighboring cells.

Assigned automata to cells in irregular cellular learning automata update synchronously and in discrete periods of time. In each period all automata select one of their actions. Transmission radio range of all nodes; initially; is equal to each other and is R_t which is proportional to network density. Learning automata of each cell that is one node here; is helping to it in choosing the most suitable radio range, finally. Each Learning automata has three actions:α1 , α2, α3 for choosing, that orderly are describing as follows: Increasing the radio range of each node with a constant value which is Ainc, Decreasing the radio range of each node with a constant value which is Adec, Not to change the nodes' radio range. Initially supposed that; the selection probability of all actions is equal to each other. In other words, is according to below relation (3) that in it, *m* is the number of learning automata actions: $\forall i \quad i \le m \quad P_i = \frac{1}{m}$ (3)

α1: (New isensorRadius) = (isensorRadius +Ainc)
α2:(New isensorRadius) = (isensorRadius – Adec)
α3: (last isensorRadius) = (isensorRadius + 0.0)

At first, all nodes randomly and simultaneously select one of L.A actions and then with affecting that selected actions on nodes' radio range and updating them, start broadcasting Hello messages that contain I.D number of node to all surrounding sensor nodes. After passing a little time, every node based on the number of received responses to sent signals by itself that indicates the number of one node's neighbors (N_{ack}) or the same one node's degree achieves the number of its neighbors and forms a neighbor table for itself which involves ID number of neighbor nodes based on selection of its own learning automata. After that; each node in consideration to its neighbors and according to the neighbor table that are formed based on above mentioned method, and the number of received responses, achieve the number of neighbors and also the sum of neighbors of its own neighbors, and at last each node can calculate average number of neighbors for itself; which is called N_{avg} and based on it; reward or penalty is given to selected action and reinforcement signal is being formed. In fact, because giving reward or penalty to one automaton's action; is depending on selected action of other neighbor's automata and their updated transmission radio range; so the whole mapped automata to network would be taken as cellular learning automata.

For this purpose, the achieved average value of each Hello message transmitter node or N_{avg} compares with minimum threshold (T_l) and maximum threshold (T_h) values that has been achieved from [11] and is necessary to guarantee optimal connectivity. So, the environment response to the selected action of each learning automata in one cell which is the same as reinforcement signal (B_i) is calculating as follows:

$$B_{i=}\begin{cases} 0:\ \text{if}\ \ 0 <= |\, N_{avg} - T_l \,| <= 1 : \text{favorable response} \\ \\ 1: \text{if}\ (N_{avg} - T_l) < 0 \ \text{or}\ |\, N_{avg} - T_l \,| > 1 : \text{unfavorable response} \end{cases}$$

If B_i produced value would be equal to 0; reward is giving to performed action which has caused this result, and its probability changes according to relation (1). But, if B_i produced value would be equal to 1; penalty should be given to performed action which has caused this result and its probability changes according to relation (2). The reward coefficient (a) and penalty parameter (b) is supposed to be constant and for calculating the consumed energy for transmitting and receiving packets to neighbour nodes, the proposed method in reference [12] has been used.

B. Selecting the best radio range phase

Each node will continue the learning phase and updating the radio range according to the selection that has been done (with aiding of learning automata); until one of below conditions is happening:

- One of actions' probabilities would be higher than threshold.
- If the number of learning iterations and updating the radio range arrives to a predefined threshold.

In each of above happened conditions, the node in each cell will choose the action, which the mapped probability to it has been more than the other actions; and then will set its radio range according to that selected action.

VI. EXPERIMENTAL RESULTS

To evaluate the performance; CLATC, RAA_2L, RAA_3L protocols [6] and homogeneous case [10] which have been simulated in N.S2 simulator and the achieved results from the proposed method (LMNNACLA) in the presented simulator in [13] have been compared to each other from two points of view that are: mean transmission radius range, and mean of residual energy, for the most suitable achieved values for *n* from experiments which with taking consideration into correspondence with conditions and taking precision metric for nodes' selected transmission radius, have been equal to 45 and 100, and the *a* parameter value is assumed equal to 0.3 and the initial value for parameter *b* equal to 0.1. In simulation, nodes have been distributed in a region of 1250*1250 square meters. The number of sensor nodes is ranging from 200 to 600 nodes; and also it is assumed that nodes have the same initial energy. Every node has transmission range between $[R_w, R_s]$. The medium transmission radius; R_t; which is proportional to network density; is assumed for 200 nodes equal to 109 meter, for 300 nodes equal to 86 meter, for 400 nodes equal to 74 meter, for 500 nodes equal to 67 meter and for 600 nodes equal to 60 meter. The R_w, R_s transmissions radius are defined according to R_t. The energy model in these simulations is what that has been expressed in [12]. However as experiments have shown too, the cost and consumed energy for learning automata's computations, in against of the output result that it achieves; is so low. Achieved results are averaged over running of the above protocols for 100 random different network configurations.

A. Experiment 1

The goal of this experiment is determining the number of proper sub ranges; or in other words; is determining better values for *n*, in concern with the number of learning algorithm iterations running for network. Learning times for automata is limited to maximum 50 times; As this number of learning times; would be necessary for comparison with other protocols Whatever the higher value for *n* to be selected; the transmission range would be divided into more sub ranges and it causes to more selections as radio range to be given to every node, and the amount precision of each node in selection would be increased. Meanwhile $(R_s\text{-}R_w/n)$ as a coefficient; which is the same as *C* has direct effect on selected actions of learning automata(increment and decrement). In this experiment the proposed protocol (LMNNACLA) has been investigated for different values of *n* equal to 1, 15,30,45,60,100,500,1000,5000 from two points of view that are: mean transmission radius, and the mean residual energy for number of nodes in the network equal to 300, and maximum times of learning equal to 50 times. Results have shown that for the number of learning times which is equal to 50, the most suitable value of *n* occurs in mid ranges between 15 to 100, that with consideration to taking precision metric for nodes' selected transmission radius, the *n* value in experiments has been assumed equal to 45 and 100; however the *n* value equal to 15 was proper too; but we have left it for the reason of requiring to higher precision.

As a result, with increasing the number of selected sub ranges; in other words *n*; we should also increase the number of learning times too; so that can get to desired conclusion; but this task is being along with more energy consumption.

Figure 2. Average transmission radius of network nodes for proposed protocol for 300 nodes and maximum learning times equal to 50 in different *n* numbers.

Figure 3. Average residual energy of network nodes for proposed protocol for 300 nodes and maximum learning times equal to 50 in different *n* numbers.

B. Experiment 2

The goal of this experiment is considering the average transmission range of network sensors for RAA_2L, RAA_3L, HOM protocols and the proposed protocol (LMNNACLA). Whatever a node's selected transmissions radius would be lower, its consumed energy would be lower too, and according to decreasing the number of neighbours, congestion happening probability will be lower too. Figure 2 shows sensor nodes' mean transmission radius for above presented protocols in different networks of different sizes. As it has shown; the proposed protocol has an approximately optimized functionality from this point into others. The HOM case has the most average transmissions radius and this is because of that all nodes in it have the same transmissions radius equal to R_t. RAA_3L protocol has less average transmissions radius than RAA_2L, because in RAA_3L every node can choose its own transmissions radius from three available transmissions ranges; while in RAA_2L protocol every node chooses its own transmissions radius from two available transmissions ranges.

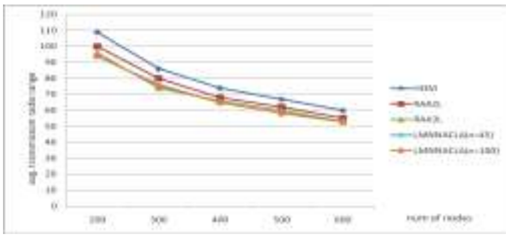

Figure 4. Average transmission radius of network's nodes for RAA_2L, RAA_3L, HOM and proposed protocols in different network sizes.

C. Experiment 3

In this experiment the average residual energy of each nodes in the network for CLATC, RAA_2L, RAA_3L protocols and the proposed protocol (LMNNACLA) has been investigated. Average residual energy of network's nodes for different networks of different sizes is being observed in figure4. As it has shown average residual energy of sensor nodes with all protocols is very high and near to initial energy of nodes, which is one joule. In spite of; the consumed energy of proposed protocol is approximately many times more than RAA_2L, RAA_3L protocols (because of existence of learning phase in the proposed protocol), but; this consumed energy in comparison with total energy of every node is so low. Residual energy increment with increasing the number of sensor nodes in network is because of transmission range decrement in networks with higher density. With consideration to indications; can deduce that evaluated protocols without consuming much more energy; give a proper topology.

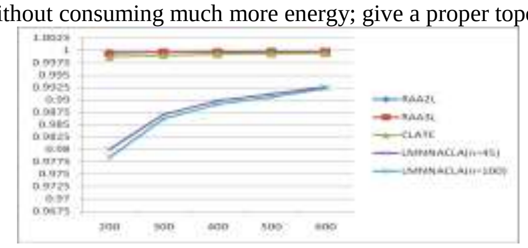

Figure 5. Average residual energy of network's nodes for CLATC, RAA_2L, RAA_3L, HOM and proposed protocols in different network sizes.

VII. CONCLUSION

In this paper a neighbour based topology control protocol and based on cellular learning automata proposed, which in it, in spite of that; nodes with using of learning automata and with negligible energy consumption, select proper transmission radius according to required conditions for preserving connectivity for themselves, But in against, they get to an adequate topology that as possible as will have the lowest energy consumption for communication between nodes in the network's life time, if a balance between required precise for values which we want to take as transmission ranges with learning times and energy consumption; would be taken. Also, the proposed protocol, LMNNACLA, with two different number of sub ranges; has been simulated, and has been compared with other similar protocols. The results of comparisons have expressed the desired functionality of this proposed protocol into other protocols.

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REFERENCES

[1] Akyildiz I. F., Su W., Sankarasubramaniam Y. and Cayircl E., ***"A survey on sensor networks"***, in: Proceedings of the IEEE Communication Magazine, Vol. 40, pp. 102-114, August 2002.

[2] Ilyas M. and Mahgoub I., ***"Handbook of Sensor Networks: Compact Wireless and Wired Sensing Systems"***, in: Proceedings of the CRC Press, London, Washington, D.C., 2005.

[3] Santi P., "Topology Control in Wireless Ad Hoc and Sensor Networks", Wiley, 2005.

[4] Santi P., "***Topology Control in Wireless Ad Hoc and Sensor Networks***", ACM Computer Survey, Vol. 37, No. 2, pp. 164-194, 2005.

[5] Abolhassani, S., Esnaashari, M. and Meybodi, M. R., "***A Cellular Learning Automata based Topology Control Protocol for Sensor Networks***", Proceedings of 14th Annual CSI Computer Conference of Iran, Amirkabir University of Technology, Tehran, Iran, March 10-11, 2009.

[6] Venuturumilli A. and Minai A. A., *"**Obtaining Robust Wireless Sensor Networks Through Self-Organization of Heterogeneous connectivity**"*, in: Proceedings of the 2006 International Conference on Complex Systems (ICCS'06), Boston, MA, June 2006.

[7] Narendra K. S. and Thathachar M. A. L, ***"Learning Automata: An Introduction"***, Englewood Cliffs, NJ: Prentice Hall, 1989.

[8] Beigy H. and Meybodi M. R., ***"A Mathematical Framework for Cellular Learning Automata"***, Advances on Complex Systems, Vol. 7, No. 3, pp. 1-25, 2004.

[9] Thathachar M. A. L. and Sastry P. S., ***"Varieties of Learning Automata: An Overview"***, IEEE Transaction on Systems, Man, and Cybernetics-Part B: Cybernetics, Vol. 32, No. 6, PP. 711-722, 2002.

[10] Stauffer D. and Aharony A., ***"Introduction to Percolation Theory"***, London: Taylor & Francis, 1994.

[11] L. Kleinrock and J. A. Silvester, "**Optimum transmission radii in packet radio networks or why six is a magic number**," in National Telecommunications Conference. Birmingham, Alabama: IEEE, Dec. 1978, pp. 4.3.1–4.3.5.

[12] Heinzelman, W., Chandrakasan, A. and Balakrishnan, H., "**Energy-Efficient Communication Protocol for Wireless Microsensor Networks**,"in HICSS 2000.

[13] http://www.djstein.com/projects/index.html.

[14] M. Meybodi and S. M. Abolhasani "***Usage of Learning Automata for Routing, Fault Tolerance and Topology Control in Wireless Sensor Network.***" Vol. Master of Science Tehran Amirkabir University of Technology (Polytechnic), 2008.

[15] Wattenhofer R. and Zollinger A., *"**XTC: a practical topology control algorithm for ad-hoc networks**"*. in: Proceedings of the 18th International Parallel and Distributed Processing Symposium, pp. 2-16, 26-30 April 2004.

[16] Blough D., Leoncini M., Resta G. and Santi P., ***"The k-neighbors protocol for symmetric topology control in ad hoc networks"***, in: Proceedings of the ACM MobiHoc 03, pp. 141–152, 2003.

[17] K. Najim and A. S. Poznyak, "***Learning Automata: Theory and Application***", Tarrytown, NY: Elsevier Science Ltd., 1994.

[18] Mo Li, Baijian Yang "***A Survey on Topology issues in Wireless Sensor Network***", In Proceedings of the 2006 International Conference on Wireless Networks (ICWN), Las Vegas, Nevada, USA, June 2006.

[19] H. Beigy, and M. R. Meybodi, , "Open Synchronous Cellular Learning Automata", Journal of Computer Science and Engineering, vol. 1, no. 4 (b), pp. 39-51, 2003.

[20] R. Rastegar, M. Rahmati and M. R. Meybodi, "A Clustering Algorithm Using Cellular Learning Automata Based Evolutionary Algorithm", Adaptive and Natural Computing Algorithms, Springer Verlag, pp.144-150, 2005.

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[i] Local Mean Neighbor of Neighbors Algorithm based on Cellular Learning Automata(LMNNACLA)
[ii] *k*-neighbors
[iii] Extreme Topology Control
[iv] Cellular Learning Automata Topology Control
[v] Linear Reward Penalty
[vi] Linear Reward Epsilon Penalty
[vii] Linear Reward Inaction