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Adaptive Genetic Algorithm-Based Network Lifetime Maximization of Wireless Sensor Networks

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***Abstract*:-When designing or developing the topology or structure of wireless sensor networks, it is of great importance considering prolonging the network lifetime. Energy crisis in the context of high cost, limited availability, inconvenience factors makes the research on wireless sensor networks (WSNs) an interesting one. In the quest to mitigate the effect in WSNs, considering the position of the source node, sink node and energy consumption on data transmission and receiving, the paper proposes the adaptive genetic algorithm-based optimization technique to balance the energy in the network system, hence prolonging the network lifetime. Simulation results demonstrate a significant additional two and quarter hour (135mintes) longer lifetime of the nodes.**

Index terms: Adaptive Genetic Algorithm (AGA), Network Lifetime, WSN, Energy.

I. INTRODUCTION

Energy is a great parameter to consider in the world of wireless networks. To monitor an area or an entity marked to be hazardous or unsafe for human being there is need for a well-planned network of sensors to obtain the data remotely. The sensors are networked and connected wirelessly. The activities of the nodes are proportional to the energy consumption of the node. The distance of the nodes from source to the sink is also a factor that drains the energy of the cell. The entire network lifetime is determined by the rate of energy dissipation and consumption. Genetic algorithm is an evolutional search optimization that mimics the chromosomes in a cell formation. The conventional GA suffers slow convergence as a result of ordinary mutation and crossover inherent formation; hence more energy will be dissipated. The adaptive genetic algorithm will be sensitive to the weighty indicators in other to arrive at the focal point in time thereby saving significant time and reasonable amount of energy. For smooth and reliable data collection from any network, the consistency of the network operation in a given area should be paramount.

II. RELATED WORKS

Reducing energy consumption and increasing network lifetime have featured frequently in wireless sensor network research. The authors of [1] proposed a low-complexity near-optimal genetic algorithm for analyzing the joint links cheduling and routing strategies for the sake of maximizing the traffic delivery from a source node to a specific destination node with in a given delay-deadline in the context of wireless meshnet works. By contrast, in [2] a low-complexity genetic algorithm was advocated for jointly optimizing the channel assignment, power control and routing operations for the sake of throughput maximization in cognitive radio based wireless mesh networks. Even though both [1] and [2] proposed genetic algorithms for solving complex cross-layer operation problems at a reduced complexity, neither the energy efficiency nor the network lifetime were considered in the context of the low-complexity routing optimization of WSNs.The authors of [3] and [4] investigated beneficial uplink scheduling and transmit power control techniques for maximizing the network lifetime of battery driven machine to machine devices deployed in long-term evolution networks, where both an optimal solution as well as a low-complexity suboptimal solution were presented. To elaboratea little further, the suboptimal solution was capable of accomplishing a near-optimal network lifetime performance at asignificantly reduced complexity than the optimal one.

In [5] the authors considered an optimal routing algorithm as well as a reduced-complexity near-optimal routing optimization algorithm designed for maximizing the network lifetime, while guaranteeing the end-to-end delivery-success probability of WSNs. However, they did not take the inter-nodeinterference into account. Similarly, the authors of [6] presented a utility-based nonlinear optimization problem formulation for the sake of network lifetime maximization and proposed a fully distributed routing algorithm for solving the optimization problem, which can of course only provide a near-optimal solution compared to a centralized technique. Nonetheless, the authors of [7] succeeded in conceiving a distributed algorithm for maximizing the network lifetime, which was capable of approaching the performance of the optimal solution at alower computational complexity. But again, in [7] the impact of the inter-node interference as well as that of the network size was not considered. The authors of [8] proposed atree-cluster-based data-collection algorithm for WSNs in conjunction with a mobile sink, where the traffic load ofthe entire network was balanced, since the sink node wasable to move around the network for a certain period inorder to collect data and avoid the utilization of the samehot-spots in order to prolong the network lifetime. Similarly, in [9] theauthors advocated a low-complexity genetic algorithm forachieving both an enhanced coverage and an improved NL for multi-hop mobile WSNs, but their objective function was to minimize the energy dissipation, which also improved the network lifetime. However, as discussed in [10], even though energy conservation isbeneficial in terms of extending the network lifetime, it has subtle differences with respect to the network lifetime maximization. This difference is mainly due to the network topologies, which is strictly dependent on the type of the applications considered. For example, for the point to point communication of a single source and a single destination, the network lifetime is fully dependent on the source node, assuming that the destination node is plugged into the mainspower source. Hence, for this specific scenario, minimizing the energy consumption only at the source node is adequate for maximizing the network lifetime. However, in certain topologies minimizing energy dissipation of each individual sensor node may not be sufficient for maximizing the network lifetime. Therefore, only minimizing the energy dissipation of each node in the network may not be feasible for maximizing the network lifetime. However, the network lifetime may be extended with the aid of an energy minimization approach depending on the applications and the network topology considered.

Shi *et al.* in [11] proposed a low-complexity genetic algorithm for jointly optimizing the power control, the scheduling and the routing to maximize the end-to-end throughput in cognitive radio networks. Moreover, Gu *et al.* [16] studied the options for beneficial base station placement for extending the network lifetime based on a specific problem formulation, given the flow routing and energy conservation constraints. Hence, the authors of [12] developed a heuristic algorithm for solving the network lifetime maximization problem at a reduced complexity, but at the cost of a small reduction in network lifetime compared to the optimal NL solution. A multi-objective routing optimization approach was proposed in [13] for extending the lifetime of disaster response networks, where a low-complexity genetic algorithm was utilized for analyzing the trade-off between the energy dissipation and the packet delivery delay. Similarly, the authors of [14] formulated the maximum-network lifetime routing challenge as a linear programming problem, where the optimal network lifetime was obtained and compared to the near-optimal network lifetime acquired by the proposed routing algorithm. However, the goal in [15] was to only find the specific flow that maximizes the network lifetime relying on the flow conservation constraint.The paper considered the position of the source node and destination node with respect to the process to be monitored or sensed. The papers suggested optimal distance between nodes and also with the system.

III. ENERGY SIGNAL MODEL

The signal distributions are proportional to the distance between the receivers and the transmitter. The WSNs are mostly powered by tiny dc battery cells which drain faster if the signal has to travel a long distance before hitting its target. In equation (1) and (2) expresses the relationship.

$$E_{T,x}(l,d) = \begin{cases} l \times E_{diss} + l \times E_{Fs} \times d^2 ; if\ d < do; \\ l \times E_{diss} + l \times E_{Tr} \times d^4 ; if\ d > do; \end{cases} \quad (1)$$

$$E_{R,x} = l \times E_{diss} \quad (2)$$

where $\boldsymbol{E_{T,x}}$ is the transmission energy, $\boldsymbol{E_{R,x}}$ is the energy used in reception, $\boldsymbol{d}$ is the distance between two nodes or between a node and the sink, $\boldsymbol{E_{diss}}$ is the energy dissipated per bit to run the transmitter or the receiver circuit,$\boldsymbol{E_{Fs}}$ and $\boldsymbol{E_{Tr}}$ depend on the transmitter amplifier model, $\boldsymbol{do}$ is threshold transmission distance .$\boldsymbol{l}$ is the length of the data transmitted.

The network lifetime is defined as the time elapsing from initial deployment to the instant of the probability of connectivity reaching the prescribed threshold. In this work, the lifetime of the network is defined as the length of time from the network deployment until thefirst relay node runs out of its energy. Lifetime is expressedin terms of seconds in this paper and for a singlenode it can be evaluated by the following equation:

$$L = \frac{e_{initial}}{e_{total}} \quad (4)$$

where $e_{initial}$ is initial energy of a sensor node, e_{total} is total energy spent in the process of data transmission and reception.

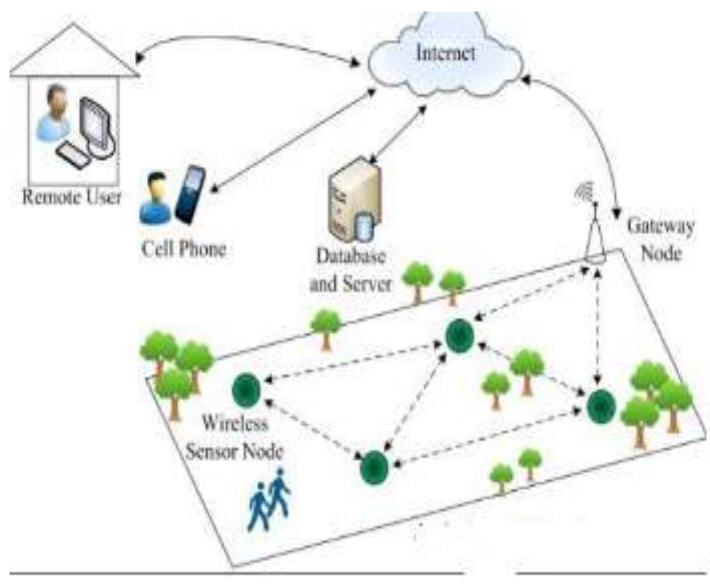

Fig 1: WSNs distributions

To minimize the energy loss from the wireless sensor networks the distance was a great factor and adaptive genetic algorithm was deployed to optimize the energy routing and protocol.

IV. ADAPTIVE GENETIC ALGORITHM

The adaptive genetic algorithm is used here majorly in the learning operation. The senor node output is analyzed and classified to indicate the weighty and interested insight from the environment. The base station houses the operation and maintenance of the wireless sensor networks. Adaptive genetic algorithm is also flexible with the distance between the nodes and even with the distribution center (base station). The energy savings are significant in the wireless sensor network as the adaptive genetic algorithm is deployed.

V. RESULTS AND ANALYSIS

The simulation results indicate that energy is saved with the adaptive genetic algorithm deployed in the wireless sensor networks. As approximately two hour and fifteen minutes live activities was recorded without performance shed. In fig 2 the downward drop of the average energy consumed by the nodes showed the robustness of the algorithm.

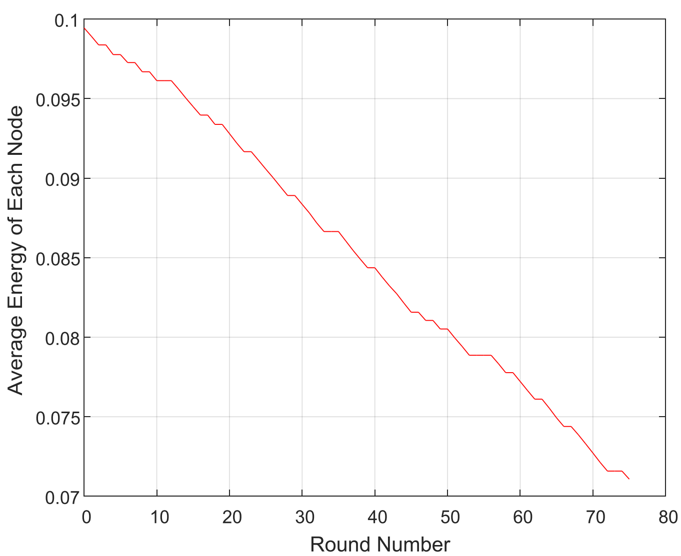

Fig 2: Energy consumption per node against the cluster

VI. CONCLUSION

It was observed that the conventional genetic algorithm and other optimization techniques could not perform as much as the adaptive genetic algorithm in energy minimization without compromising quality of sensing, transmitting and receiving. The AGA deployed in this work showed seamless capacity for energy management. In this paper, the area of other dynamic environmental factors was not covered hence the authors recommend that part for further research.

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