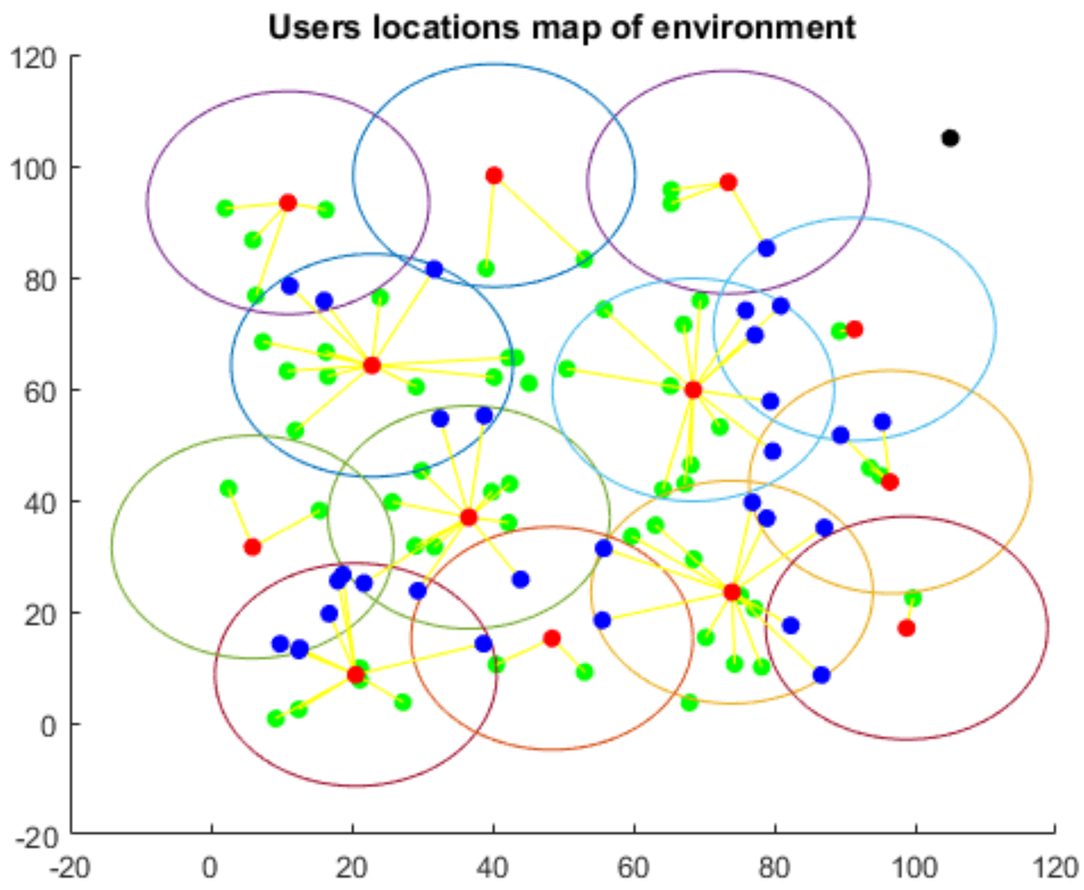
CLUSTERING USING Q-VALUES

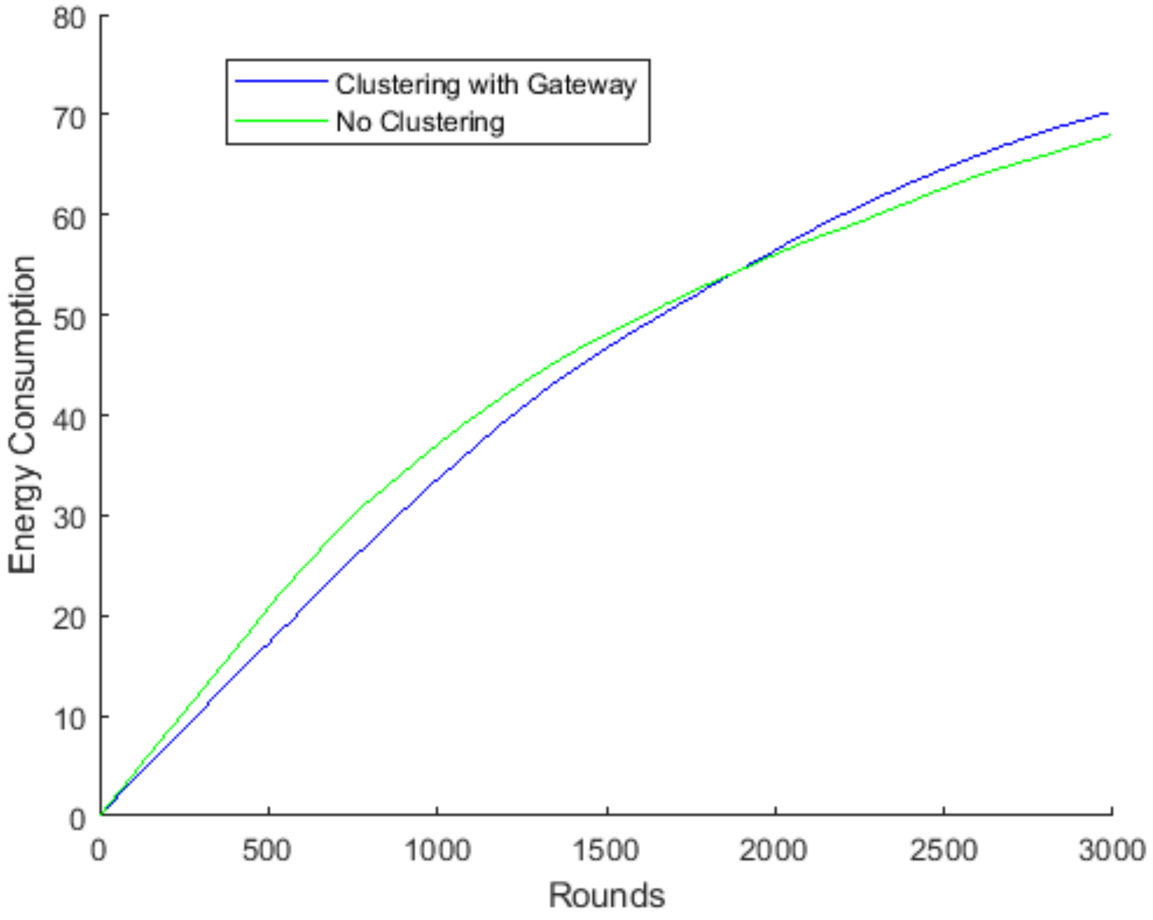
Nodes with max Q-Values are selected as cluster heads

Nodes that falls in the overlapping region of two or more clusters are declared as gateways. They are used for communication between the adjacent clusters.

SIMULATION SCENARIO



SIMULATION RESULTS

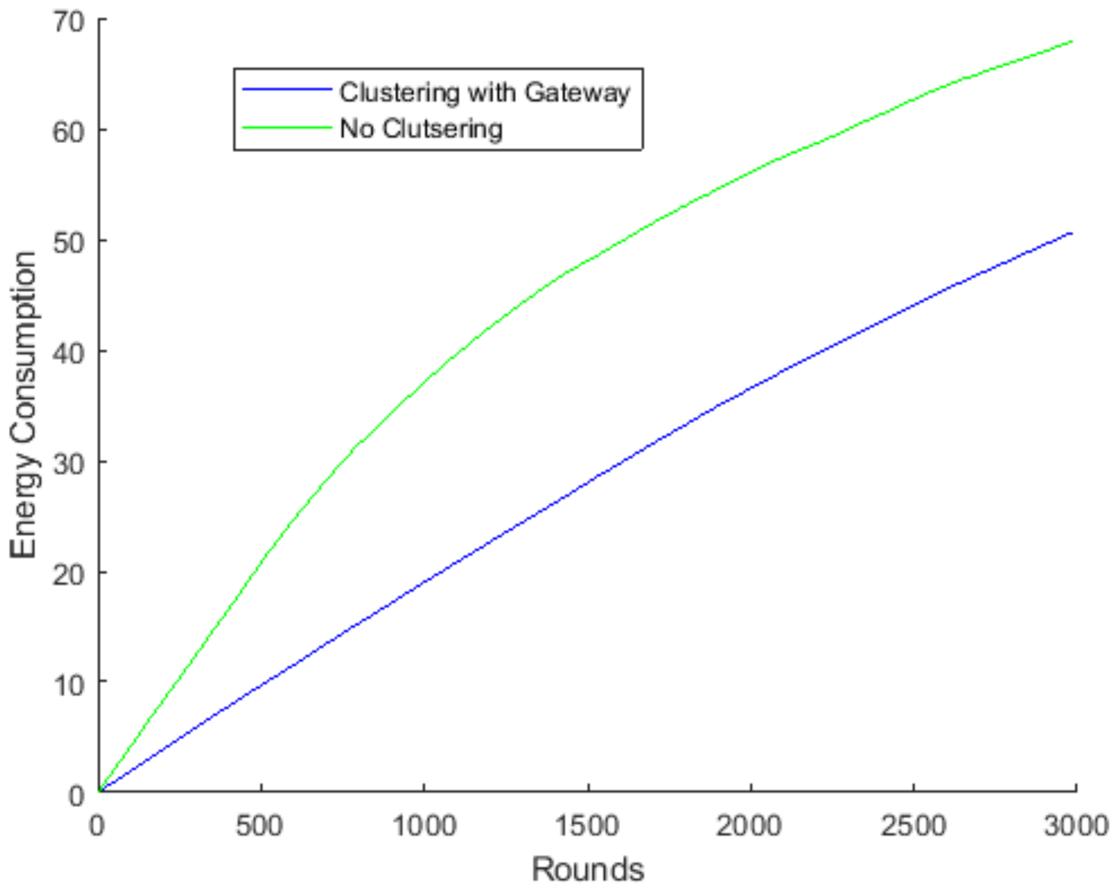


CLUSTERING BASED ON ENERGY

Nodes with max energy are selected as cluster heads

Nodes that falls in the overlapping region of two or more clusters are declared as gateways. They are used for communication between the adjacent clusters.

SIMULATION RESULTS



Article

Self-Learning Power Control in Wireless Sensor Networks

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SELF-LEARNING POWER CONTROL

The scope of this work is to investigate how machine learning may be used to bring wireless nodes to the lowest possible transmission power level and, in turn, to respect the quality requirements of the overall network.

Lowering transmission power has benefits in terms of both energy consumption and interference.

They propose a protocol of transmission power control through a reinforcement learning process that we have set in a multi-agent system.

The agents are independent learners using the same exploration strategy and reward structure, leading to an overall cooperative network.

The simulation results show that the system converges to an equilibrium where each node transmits at the minimum power while respecting high packet reception ratio constraints. Consequently, the system benefits from low energy consumption and packet delay.

A Supervised Learning Approach for Routing Optimizations in Wireless Sensor Networks

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As a case study, they use link quality prediction to demonstrate the effectiveness of their approach.

For this purpose, they propose MetricMap, a link-quality aware collection protocol atop MintRoute that derives link quality information using knowledge acquired from a training phase.

Our approach allows MetricMap to maintain efficient routing in situations where traditional approaches fail.

Evaluation on a 30-node sensor network testbed shows that MetricMap can achieve up to 300% improvement on data delivery rate in a high data-rate application, with no negative impact on other performance metrics, such as data latency.

They approach is based on real-world measurement and provides a new perspective to routing optimizations in wireless sensor networks.

An Improved Ant Colony Algorithm in Wireless Sensor Network Routing

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Abstract—In order to make the energy consumption of network nodes relatively balanced, we apply ant colony optimization algorithm to wireless sensor network routing and improve it. In this paper, we propose a multi-path wireless sensor network routing algorithm based on energy equalization. The algorithm uses forward ants to find the path from the source node to the destination node, and uses backward ants to update the pheromone on the path. In the route selection, we use the energy of the neighboring nodes as the parameter of the heuristic function. At the same time, we construct the fitness function, and take the path length and the node residual energy as its parameters. The simulation results show that the algorithm can not only avoid the problem of local optimal solution, but also prolong the life cycle of the network effectively.

LEACH Robust Routing Approach Applying Machine Learning

Babar Ali[1†], Tariq Mahmood[2††], Muhammad Abbas[3†††], Muzamil Hussain[4††††], Habeeb Ullah[5†††††], Anupam Sarker[6††††††], Asad Khan[7†††††††]

In the proposed approach, the mean method and the minimum distance (MD) method based on LEACH-RP is implemented to solve the issues of data redundancy.

A data fusion algorithm (DF) based on Cyclic Neural Networks(CNN) is implemented on LEACH RP.

The simulation results indicate that the mean method & minimum distance method can effectively resolve the issues of data redundancy caused by a single sensor node in a short time and the data fusion algorithm of the CNN can effectively solve the problem of data redundancy generated by adjacent sensor nodes at the same time.

Routing Protocols Based on Reinforcement Learning for Wireless Sensor Networks: A Comparative Study

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3.2. Multi-agent Reinforcement Learning based Routing Protocol with Quality of Service (QoS) Support for WSN (MRL-QRP)

In this routing protocol [9], QoS routes are cooperatively computed using a distributed value function. Global optimization can be achieved through local information about the network and the exchange of values regarding states with the neighboring nodes. In [9], two things are checked before a node sends any data packet. First, it checks the packet to look up at the QoS requirements. Next, it checks the Q-value table. After that, the packet is transmitted to a neighboring node having the Q-value that is higher than other forwarding nodes.

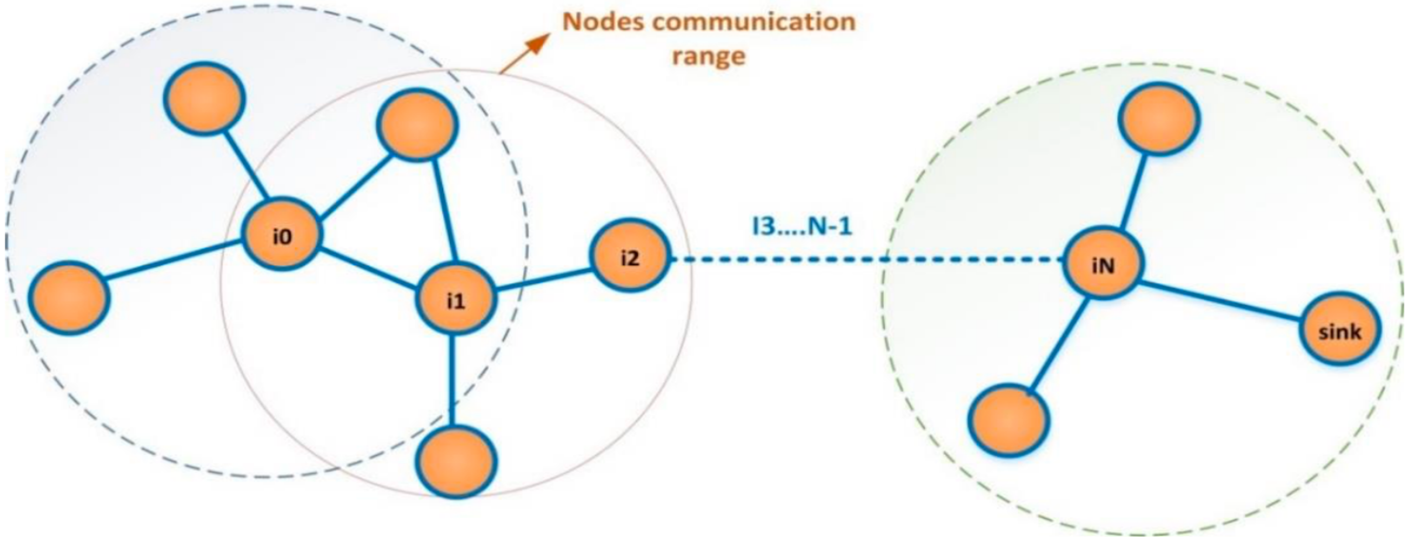

Figure 2. Multi-hop wireless sensor network for MRL-QRP

In Figure 2, a data packet is originated by sensor node i_0. When the learning process is going on, i_0 sends the packet to node i_1 by random selection. After that, i_1 forwards the packet to i_2. This process goes on until node i_n receives the data packet, where node i_N is the last node attached to sink in the routing process.

In [10], it is claimed that MRL-QRP has superiority over a well-established conventional protocol for WSNs, which is ad hoc on demand distance vector (AODV) routing protocol. MRL-QRP [9] performs exceptionally well when the traffic load is heavy. It considers end-to-end delay, PDR, and energy consumption as routing metrics.

3.3. Reinforcement Learning as Adaptive Network Routing of Mobile Agents

In this routing protocol, mobile agents that traverse routing nodes target to quest for the optimal path at each time step for decreasing the service processing time. Movements of the agents are designed in a way so that congestions are avoided. The Q-learning algorithm implemented in this protocol learns policies online. Mobile agents are routed, and changes in the traffic patterns, network load levels, and topologies are promptly dealt with through incorporation into the routing policies. System topology is determined by the agent through network discovery. After that, gained information is stored within the nodes. Q-routing exploits Q-learning and was first proposed by Boyan and Littman [11].

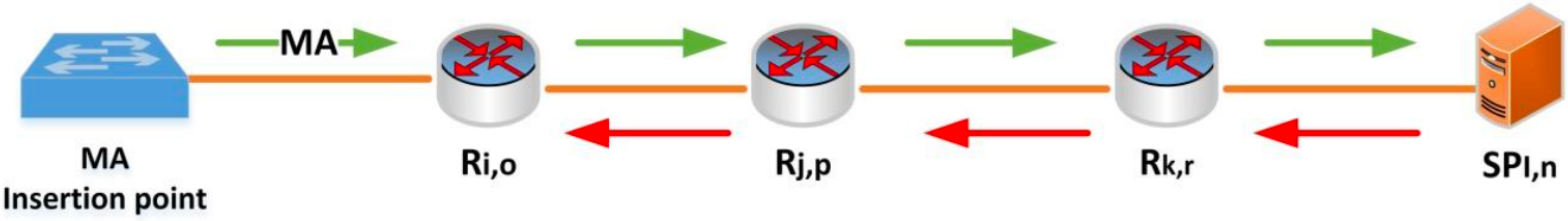

Figure 3. Agent system

Figure 3 presents an agent system used in [8]. *R* denotes the intelligent router nodes in the figure. *MA* stands for mobile agents, and *SP* represents service providers. *R* forwards *MA* from the input link towards next *R* depending on the concrete configuration, and it determines its output link by observing attained Q values. Having received *MA* immediately, *R* sends the reply with predicted route towards previous *R*. The process goes on until the *MA* had found *SP* and *SP* then performs the requested task on behalf of *MA* [8]. The right-ended arrows in Figure 3 represent the movement of *MA*. Movement of replies starting from *SP* is denoted using the left-ended arrows. Each *R* manages its input and output links. The last node in the figure is *SP* that performs the final processing of mobile agents.

The best part of this routing technique is that it can adapt to frequent topology changes and works fine with varying network traffic. Also, accurate measurement of service processing time along a particular route makes the protocol more efficient. In [8], no comparison was shown with the standardized routing protocols to establish the superiority of the proposed routing algorithm. Moreover, average service processing time is high in this routing approach because it has to learn the whole network in order to perform routing. Routing metrics taken under consideration in [8] are PDR and latency.

3.4. Energy-aware QoS Routing using RL (EQR-RL)

In [12], decision on routing relies on resource availability in the network and QoS requirements. For sending a data packet to the sink node, the sending node decides which intermediate node to go for using the routing table. For the ease of explanation, let us consider the node to be i. Node i takes into account some neighboring nodes that have been denoted as s. The nodes in this set s should fulfill the minimum QoS requirements. After this in [12], a node from the set s is chosen with the help of a load balancing algorithm. The proposed algorithm was implemented in a scenario where there were periodic and long lasting transmissions to the sink node. The algorithm in this protocol is also scalable. In [12], to retrieve the information of the neighboring nodes, a node can look up at the header of the data packet obtained by them. The information includes failure of any node, removal of any node from neighborhood, and link quality. Neighbors can have a look at the data packet header to update the routing table when new nodes are added. Also, a neighbor node is excluded from the routing table if there is no response from it.

EQR-RL supports multiple QoS requirements that include latency, geographical distance, and the number of hops for data delivery. Also, it can handle mobility and failure recovery of nodes. EQR-RL supports mobile sink nodes as well. To implement reinforcement learning for any network scenario, a balance between exploration and exploitation strategies are needed. Only exploration will lead to routing overhead, but it is definite that an optimal route will be found. Considering exploitation strategies only will lead to a faster route finding in the network but with a good amount of probability that the route will not be optimal. Authors in [12] consider exploration strategies only. Network scenario in [12] consists of a few mobile nodes. It is claimed that the proposed protocol improves lifetime of the network, PDR and end-to-end delay in comparison to [13], [14] and [9].

3.5. Distributed Adaptive Cooperative Routing Protocol (DACR)

In [15], authors propose a protocol that can ensure QoS requirements by decreasing delay and increasing reliability. Using the AODV protocol, a route from source to destination is established in this discussed protocol. Data transmission is possible either in a direct manner or in a relayed manner. Based on the energy level of the node, one among these two transmission modes is elected. If relayed transmission is chosen, the protocol then considers residual energy, reliability and delay as important criteria.

All routing nodes learn these criteria using lightweight RL. After this, it uses a lexicographic optimization [16] to find the optimal relay. The contribution of this protocol is summarized below:

- No central control is needed for DACR and nodes can be deployed in a distributive way. Global information on channel state condition is also unnecessary for this protocol. That is why DACR has relatively lower network overhead.
- It is also shown that selecting the relay in a proactive way is more efficient in comparison to selecting relays in a reactive manner.
- Finally, the process for finding out routes and relays could save large amount of energy.

In this protocol, the process of discovering routes and relays can save significant amount of energy. One big flaw for this protocol can be it's being too much complex because it uses an RL algorithm and transmission mode selection algorithm in the routing process. It considers energy consumption and network lifetime as routing metrics.

3.7. RL-based Routing Protocol for Multi-hop WSNs

Routing approach proposed in [19] extends Q-routing algorithm [11] for its implication in WSNs. Optimization of network lifetime is achieved by balancing the routing effort within sensor nodes. This routing approach minimizes the control overhead too, and current residual batteries are also taken into account. Routing approach in [19] is designed and implemented for plenary exploration scenarios with a goal to bring satellite and WSN technologies in space. An example scenario for the implementation of this routing technique can be SWIPE project [20]. The main concept lies in deploying hundreds or thousands of small sensor nodes with some of them having abilities for satellite communication. Other which do not have abilities for satellite communication will be responsible for on surface ad hoc network. Retrieved data will be sent to satellite first after processing and earth after that.

Q-routing updates Q value through the following function:

$$Q(s,a) = Q(s,a) + \alpha(R(s,a) + \gamma * max_a\, Q(s',a') - Q(s,a)), \qquad (1)$$

where s is a random state, a is a random action and R is the reward achieved for choosing action s and a. s' and a' are next state and action after s and a. Here, learning rate is denoted as α and it fixes how much the older information will be replaced by the new information. Value of this parameter is: $0 \leq \alpha \leq 1$. 'γ' stands for discount factor. Importance of the future rewards is determined by it. Value of this parameter is $0 \leq \gamma \leq 1$. When a node transmits a packet to the next forwarding node, routing table gets updated. The neighbor node should back acknowledge (ACK) after that to node i. The update process is done through function described in (1). Node i requires the data from neighbor nodes only. As Q function gets updated, an assumption of the overall network is gained if the network topology remains unchanged. The proposed protocol was compared with different versions of Q-routing.