Genetic Algorithms for Wireless Sensor Networks

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INTRODUCTION

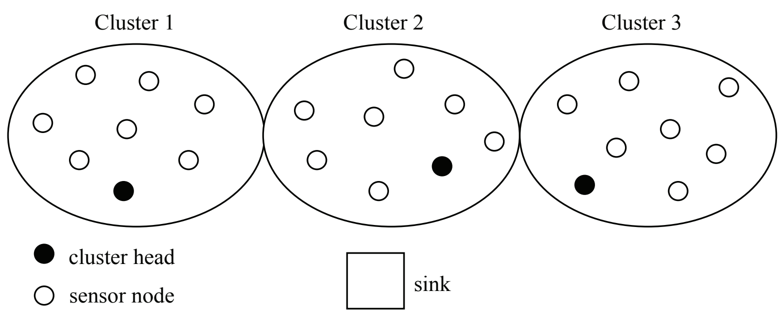
Wireless sensor networks (WSNs) consist of a large number of low-cost and low-power sensor nodes. Some of the applications of sensor networks are environmental observation, monitoring disaster areas and so on. Distributed evolutionary computing is a poweful tool that can be applied to WSNs, because these networks require algorithms that are capable of learning independent of the operation of other nodes and also capable of using local information (Johnson, Teredesai & Saltarelli, 2005). Evolutionary algorithms must be designed for the resource constraints present in WSNs. This article describes how genetic algorithms can be used in WSNs design in order to satisfy energy conservation and connectivity constraints.

BACKGROUND

The recent advances in wireless communications and digital electronics led to the implementation of low power and low cost wireless sensors. A sensor node must have components for sensing, data processing and communication. These devices can be grouped to form a sensor network (Akyildiz, Sankarasubramaniam & Cayirci, 2002) (Callaway 2003). The network protocols, such as formation algorithms, routing and management, must have self-organizing capabilities. In general, sensor networks have some features that differ from traditional wireless networks in some aspects: the number of sensor nodes can be very high; sensor nodes are prone to failures; sensor nodes are densely deployed; the topology of the network can change frequently; sensor nodes are limited in computational capacities, memory and energy.

The major challenge in the design of WSNs is the fact that energy resources are significantly more limited than in wired networks and other types of wireless networks. The battery of the sensors in the network may be difficult to recharge or replace, causing severe limitations in the communication and processing time between all sensors in the network. Thus, the main parameter to optimize for is the network lifetime, or the time until a group of sensors runs out of energy. Another issue in WSN design is the connectivity of the network according to the selected communication protocol. Usually, the protocol follows the cluster-based architecture, where single hop communication occurs between sensors of a cluster and a selected cluster head sensor that collects all information obtained by the other sensors in its cluster. This architecture is shown in Figure 1. Since the purpose of the sensor network is the collection and management of measured data for some particular application, this collection must meet specific requirements depending on the type of data. These requirements are turned into application specific parameters of the network.

Figure 1. Cluster-based sensor network



GENETIC ALGORITHMS FOR WIRELESS SENSOR NETWORKS

A WSN designer who takes into account all the design issues deals with more than one non-linear objective functions or design criteria which should be optimized simultaneously. Therefore, the focus of the problem is how to find many near-optimal non-dominated solutions in a practically acceptable computational time (Jourdan & de Weck, 2004) (Weise, 2006) (Ferentinos & Tsiligiridis, 2007). There are several interesting approaches to tackling such problems, but one of the most powerful heuristics, which is also appropriate to apply in the multi-objective optimization problem, is based on genetic algorithms (GA) (Ferentinos & Tsiligiridis, 2007).

Genetic algorithms have been used in many fields of science to derive solutions for any type of problems (Goldberg 1989) (Weise, 2006). They are particularly useful in applications involving design and optimization, where there are large numbers of variables and where procedural algorithms are either non-existent or extremely complicated (Khana, Liu & Chen, 2006), (Khana, Liu & Chen, 2007). In nature, a species adapts to an environment because the individuals that are the fittest in respect to that environment will have the best chance to reproduce, possibly creating even fitter child. This is the basic idea of genetic evolution. Genetic algorithms start with an initial population of random solution candidates, called individuals or chromosomes. In the case of sensor networks, the individuals are small programs that can be executed on sensor nodes (Wazed, Bari, Jaekel & Bandyopadhyay, 2007).

Each individual may be represented as a simple string or array of genes, which contain a part of the solution. The values of genes are called alleles. As in nature, the population will be refined step by step in a cycle of computing the fitness of its individuals, selecting the best individuals and creating a new generation derived from these. A fitness function is provided to assign the fitness value for each individual, based on how close an individual is to the optimal solution. Two randomly selected individuals, the parents, can exchange genetic information in a process called crossover to produce two new chromosomes know as child. A process called mutation may also be applied to obtain a good solution, after the process of crossover. This process helps to restore any genetic values when the population converges too fast. After the crossover and mutation processes the individuals of the next generation are selected. Some of the poorest individuals of the generation can be replaced by the best individuals from the previous generation. This is called elitism, and ensures that the new generation is at least as fit as the previous generation. The algorithm stops if a predetermined stopping criterion is met (Hussain, Matin & Islam, 2007).

Fitness Function and Specific Parameters for WSNs

The fitness function executed in a sensor node is a weighted function that measures the quality or performance of a solution, in this case a specific sensor network design. This function is maximized by the GA system in the process of evolutionary optimization. A fitness function must include and correctly represent all or at least the most important factors that affect the performance of the system. The major issue in developing a fitness function is the decision on which factors are the most important ones (Ferentinos & Tsiligiridis, 2007) (Gnanapandithan & Natarajan, 2006).

A genetic algorithm must be designed for WSN topologies by optimizing energy-related parameters that affect the battery consumption of the sensors and thus, the lifetime of the network. At the same time, the algorithm has to meet some connectivity constraints and optimize some physical parameters of the WSN implemented by the specific application. The multiple objectives of the optimization problem are blended into a single objective function, the parameters of which are combined to formulate a fitness function that gives a quality measure to each WSN topology. Three sets of parameters dominate the design and the performance of a WSN: the application specific parameters, connectivity parameters and the energy related parameters. Some possible parameters are discussed in (Ferentinos & Tsiligiridis, 2007):

- Operation energy: the energy that a sensor consumes during some specific time of operation. It depends whether the sensor operates as cluster head or as regular sensor.
- Communication energy: the energy consumption due to communication between sensors. It depends on the distances between transmitter and receiver.

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