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Multi-objective node deployment in WSNs: In search of an optimal trade-off among coverage, lifetime, energy consumption, and connectivity

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ABSTRACT

The increased demand of Wireless Sensor Networks (WSNs) in different areas of application have intensified studies dedicated to the deployment of sensor nodes in recent past. For deployment of sensor nodes some of the key objectives that need to be satisfied are coverage of the area to be monitored, net energy consumed by the WSN, lifetime of the network, and connectivity and number of deployed sensors. In this article the sensor node deployment task has been formulated as a constrained multi-objective optimization (MO) problem where the aim is to find a deployed sensor node arrangement to maximize the area of coverage, minimize the net energy consumption, maximize the network lifetime, and minimize the number of deployed sensor nodes while maintaining connectivity between each sensor node and the sink node for proper data transmission. We assume a tree structure between the deployed nodes and the sink node for data transmission. Our method employs a recently developed and very competitive multi-objective evolutionary algorithm (MOEA) known as MOEA/D-DE that uses a decomposition approach for converting the problem of approximation of the Pareto fronts (PF) into a number of single-objective optimization problems. This algorithm employs differential evolution (DE), one of the most powerful real parameter optimizers in current use, as its search method. The original MOEA/D has been modified by introducing a new fuzzy dominance based decomposition technique. The algorithm introduces a fuzzy Pareto dominance concept to compare two solutions and uses the scalar decomposition method only when one of the solutions fails to dominate the other in terms of a fuzzy dominance level. We have compared the performance of the resulting algorithm, called MOEA/DFD, with the original MOEA/D-DE and another very popular MOEA called Non-dominated Sorting Genetic Algorithm (NSGA-II). The best trade-off solutions from MOEA/DFD based node deployment scheme have also been compared with a few single-objective node deployment schemes based on the original DE, an adaptive DE-variant (JADE), original particle swarm optimization (PSO), and a state-of-the art variant of PSO (Comprehensive Learning PSO). In all the test instances, MOEA/DFD performs better than all other algorithms. Also the proposed multi-objective formulation of the problem adds more flexibility to the decision maker for choosing the necessary threshold of the objectives to be satisfied.

1. Introduction

An ad-hoc Wireless Sensor Network (WSN) consists of a number of sensors spread across a geographical area. Each sensor has wireless communication capability and some level of intelligence for signal processing and networking of the data. The development of WSNs was originally motivated by military applications such as battlefield surveillance. However, they are currently being employed in many industrial and civilian application areas including industrial process monitoring and control, machine health monitoring, environment and habitat monitoring, healthcare applications, home automation, and traffic control (Callaway, 2003; Zhao and Guibas, 2004; Bulusu and Jha, 2005). A few excellent surveys on the present state-of-the-art research on sensor networks can be traced in Al-Karaki and Kamal (2004), Bojkovic and Bakmaz (2008) and Yick et al. (2008).

An important problem of any sensor node design is the deployment of the sensor nodes in the area to be monitored. The number of sensor nodes that can be deployed in an area is a limitation to the designers. Again, there are always some limitations to the payload of the sensor nodes that are generally carried

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and deployed by an aircraft apart from the cost limitation (Liu and Mohaparta, 2007). Sensor nodes usually have limited energy storage and low processing and communication capabilities (Park et al., 2001). So the energy consumed in them must be small enough so that all the deployed nodes can function till a certain time interval. The impossibility of recharging or replacing the node batteries, especially in networks installed in regions of difficult access, imposes a serious constraint for the designers: each node in the network has a limited lifetime, which cannot be extended. The main motive behind the sensor node deployment is the monitoring of the area concerned. Monitoring of the area may be based on uniform event detection or differentiated event detection, where the probability of the appearance of the event in the area concerned varies both geographically and with time. And last but not the least maintaining connectivity among the nodes so that the data collected by any individual sensor node can flow through other nodes to the sink node. Deployment of the sensor nodes satisfying all such objectives together is a challenging problem.

In the past few years researchers attempted to tackle several of the above mentioned objectives through various optimization processes both by mathematical/numerical programming and through evolutionary computing techniques. The objectives were sometimes modeled as a constrained single objective functions, in special cases aggregating several objectives through well chosen weights. But multi-objective approaches has always been a favorable one for tackling all the aspects of sensor node deployment as will be discussed in the later section of this paper. In literature several works are presented to suggest deployment strategies to tackle those problems. Younis and Akkaya (2007) presented a good overview of various strategies for coverage problems. Meguerdichian et al. (2001) have pointed out that the coverage objective is a measure of the Quality of Service (QoS) that is provided by a particular network design. Several researchers (Chakrabarty et al., 2002; Wu et al., 2007) have proven the NP-hardness of various deployment problems. The main focus is often to determine an optimal sensor placement to cover a grid area (sometimes under uncertainty (Wu et al., 2007)) and minimize the cost or prolong the network lifetime (Cardei and Wu, 2005). Another major step in WSN design is to assign energy efficient transmit power levels to sensors to maximize the network lifetime under certain energy constraints (Xue and Ganz, 2006). Some researchers have also worked on probabilistic or distributed event detection (Aitsaadi et al., 2009a, 2009b). Another way of dealing with coverage, connectivity and lifetime maximization is to deploy a densely distributed sensor network randomly in area concerned and to use active and inactive nodes. After certain period of time active and inactive nodes are rearranged to prolong the network lifetime maintaining connectivity and coverage as described in Martins et al. (2007, 2011).

In this work we have considered the deployment of sensor nodes in a given area taking into account all the above mentioned objectives i.e.: (i) minimizing the number of sensor nodes to reduce cost and payload of deployment; (ii) minimizing the net energy consumed by all the nodes in the deployed sensor node arrangement; (iii) maximizing the area covered by the nodes so that any event occurring in the region of interest is easily detected and the data can be sent to the sink node; (iv) maximizing the lifetime of the network. All the nodes deployed have certain limited initial energy. At each time cycle as the nodes transmit the received data to the sink node a certain amount of energy is consumed and the energy remaining in the sensor nodes decreases until it breaks down. Network lifetime can be thought of as the time in which just one node breaks down thus hampering the whole network setup. But still the network can work at a reduced level until all the nodes break down. (v) Maintain connectivity in the deployed node configuration so every node can communicate with the sink node. The communication in the network is often structured as a tree graph, in which there is only a single path between each sensor node and the sink node. The choice of the tree structure is justified by the energy consumption imposed by this topology, which is lower than the consumption in a redundant network. Considering all the objectives in a single problem is surely challenging and demands efficient algorithms. As it is evident, multi-objective approach is always best in those cases dealing with multiple and conflicting objectives. Maximizing coverage means the nodes must be placed far apart from the sink node, which is considered at the center of the area concerned. Again minimizing energy consumption or maximizing network lifetime demands sensor nodes to be placed near the sink node. Thus it is evident that both the objectives are conflicting in nature and thus multi-objective technique is the best way to deal with those problems. Again with increase in node number net energy consumption in the network increases though the energy consumed by each node decreases thus increasing the network lifetime. Connectivity problem is modeled as a constraint by using tree structure of communication.

Motivated by the inherent multi-objective nature of the WSN deployment problems and the overwhelming growth in the field of multi-objective evolutionary algorithms (MOEAs), we started to look for the most recently developed MOEAs that could solve the WSN deployment problem more efficiently as compared to the conventional single-objective approaches. Since differential evolution (DE) (Price et al., 2005; Das and Suganthan, 2011) has emerged as one of the most powerful stochastic real-parameter optimizers of current interest and unlike PSOs and GAs, has not been used extensively in WSN context, we were also looking for the state-of-the-art MO variants of DE, when our search converged to a decomposition-based MOEA, called MOEA/D-DE (Li and Zhang, 2009; Zhang et al., 2009), that ranked first among 13 state-of-the-art MOEAs in the unconstrained MOEA competition held under the IEEE Congress on Evolutionary Computation (CEC) 2009 (Zhang et al., 2008). MOEA/D-DE uses DE as its main search strategy and decomposes an MO problem into a number of scalar optimization subproblems to optimize them simultaneously. Each sub-problem is optimized by only using information from its several neighboring subproblems and this feature considerably reduces the computational complexity of the algorithm.

In this work, we have used a fuzzy dominance concept to synthesis a algorithm based on the decomposition strategy of MOEA/D and call the same MOEA/decomposition with fuzzy dominance (DFD) (Nasir et al., 2011). Net energy consumed by the sensor nodes and the non-coverage of the demand points are modeled as the two objectives with connectivity as the constraint. Our goal is to minimize both the objectives with different number of nodes to study the variation of lifetime and energy with the number of nodes. From the obtained Pareto front we employ a decision-making technique to select a particular node configuration with minimum energy above a defined non-coverage level. With that node configuration we can find the lifetime of each sensor node and thus that of whole WSN setup. For multi-objective approach we have compared the result of our algorithm with that of MOEA/D and NSGA-II. For single objective approaches we have simulated with PSO (Kennedy and Eberhart, 1995), CLPSO (Liang et al., 2006), classical DE (DE/rand/1/bin) (Price et al., 2005) and JADE (Zhang and Sanderson, 2009) with the non-coverage objective modeled as a constraint. We have seen that the MO approach is far better than single-objective ones in minimizing the energy consumed and maximizing network lifetime. Also MOEA/DFD surpasses NSGA-II and MOEA/D in almost all the cases when compared on the basis of the spacing and coverage metrics.