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Survey on Task Allocation using Particle Swarm Optimization in Wireless Sensor Network

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ABSTRACT: Wireless sensor networks (WSNs) are networks of autonomous nodes used for monitoring an environment. Developers of WSNs face challenges that arise from communication link failures, memory and computational constraints, and limited energy. Many issues in WSNs are formulated as multidimensional optimization problems, and approached through bio-inspired techniques. Particle swarm optimization (PSO) is a simple, effective and computationally efficient optimization algorithm. It has been applied to address WSN issues such as optimal deployment, node localization, clustering and data-aggregation. This paper outlines issues in WSNs, introduces PSO and discusses its suitability for WSN applications. It also presents a brief survey of how PSO is tailored to address these issues.

KEYWORDS: clustering, data-aggregation, localization, optimal deployment, PSO, Wireless sensor networks.

I.INTRODUCTION

Wireless sensor networks (WSNs) are an emerging technology [1] that has potential applications in surveillance, environment and habitat monitoring, structural monitoring, healthcare, and disaster management [2]. A WSN monitors an environment by sensing its physical properties. It is a network of tiny, inexpensive autonomous nodes that can acquire process and transmit sensory data over wireless medium. One or more powerful base stations serve as the final destination of the data. The properties of WSNs that pose technical challenges include dense ad-hoc deployment, dynamic topology, spatial distribution and constrains in bandwidth, memory, computational resources and energy. WSN issues such as node deployment, localization, energy-aware clustering and data-aggregation are often formulated as optimization problems. Particle swarm optimization adopts traditional heuristic method to search for the solution step by step. However, the drawback of traditional heuristic method is that they may be easily stuck in local optimum and have limited ability for complex problems with high solution space. So, the bio-inspired stochastic intelligent optimization algorithms are then adopted to find the global optimum with high convergence rates.

Traditional analytical optimization techniques require enormous computational efforts, which grow exponentially as the problem size increases. An optimization method that requires moderate memory and computational resources and yet produces good results is desirable, especially for implementation on an individual sensor node. Bio-inspired optimization methods are computationally efficient alternatives to analytical methods. Particle swarm optimization (PSO) is a popular multidimensional optimization technique [3]. Ease of implementation, high quality of solutions, computational efficiency and speed of convergence are strengths of PSO. Literature is replete with applications of PSO in WSNs. The objective of this paper is to give a flavor of PSO to researchers in WSN, and to give a qualitative treatment of optimization problems in WSNs to PSO researchers in order to promote PSO in WSN applications. The Particle swarm optimization algorithms are discussed in the following section.

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II.THE PSO ALGORITHM

PSO models social behavior of a flock of birds [3]. It consists of a swarm of s candidate solutions called particles, which explore an n-dimensional hyperspace in search of the global solution (n represents the number of optimal parameters to be determined). A particle i occupies position X_{id} and velocity V_{id} in the d^{th} dimension of the hyperspace, $1 \cdot i \cdot s$ and $1 \cdot d \cdot n$. Each particle is evaluated through an objective function $f(x_1; x_2; \ldots ; x_n)$, where $f : R^n \rightarrow R$. The cost (fitness) of a particle close to the global solution is lower (higher) than that of a particle that is farther. PSO thrives to minimize (maximize) the cost (fitness) function. In the global-best version of PSO, the position where the particle i has its lowest cost is stored as ($pbest_{id}$). Besides, $gbest_d$, the position of the best particle. In each iteration k, velocity V and position X are updated using (1) and (2). The update process is iteratively repeated until either an acceptable $gbest$ is achieved or a fixed number of iterations $k_{\max}$ is reached.

$$V_{id}(k+1) = w \text{ ¢ } V_{id}(k) + \varphi_1 \text{ ¢ } r_1(k) \text{ ¢ } (pbest_{id} \text{ ¡ } X_{id}) + \varphi_2 \text{ ¢ } r_2(k) \text{ ¢ } (gbest_d \text{ ¡ } X_{id}) \quad (1)$$

$$X_{id}(k+1) = X_{id}(k) + V_{id}(k+1) \quad (2)$$

Here, φ_1 and φ_2 are constants, and $r_1(k)$ and $r_2(k)$ are random numbers uniformly distributed in [0,1]. This is the basic "textbook" information about PSO. Popular themes of PSO research are: choice of parameters and their ranges, iterative adaption of parameters, particle interaction topologies, convergence acceleration, adaption to discrete, binary and integer domains, and hybridization with other algorithms. The state-of-the art in PSO is presented in [4].

III.TASK ALLOCATION PROTOCOLS

V. Tsiatsis et al [5] explore the network level architecture of distributed sensor systems that perform in-network processing. A system with heterogeneous nodes is proposed that organizes into a hierarchical structure dictated by the computational capabilities. The presence of high-performance nodes amongst a sea of resource-constrained nodes exposes new tradeoffs for the efficient implementation of network-wide applications. The experiments show that even for a low relative density of resource-constrained nodes to high-performance nodes there are certain gains in performance for a heterogeneous and hierarchical network over a homogeneous one. The introduction of hierarchy enables partitioning of the application into sub-tasks that can be mapped onto the heterogeneous nodes in the network in multiple ways. The tradeoffs between the execution time of the application, accuracy of the output produced is analyzed and the overall energy consumption of the network for the different mapping of the sub-tasks onto the heterogeneous nodes. The performance is evaluated and energy consumption of a typical sensor network application of target tracking via beam forming and line of bearing (LOB) calculations on the different nodes. The experiments also include the study of the overall performance and energy consumption of the LOB calculation using two different types of resource constrained sensor nodes (MICA and MICA2 nodes) and show how these metrics are affected by changes in the node architecture and operation. The results indicate that when using MICA motes as resource-constrained nodes, 85% of the time on average the hierarchical network outperforms a homogeneous network for approximately the same energy budget. When using MICA2 motes as resource-constrained nodes, 54% of the time the hierarchical network performs better than a homogeneous network with approximately the same energy budget.

S. Abdelhak et al [6] proposed EBSEL, an energy-balancing task scheduling and allocation heuristic whose main purpose is to extend the network's lifetime, through energy balancing. Balancing the energy consumption among the nodes can help avoid the disintegration of the network where some nodes die unnecessarily, while others still have high energy reserve. EBSEL was extensively simulated on random task graphs and on a task graph of a real-world application. Compared to related work, EBSEL achieved more than 50% increase in lifetime and up to 5% energy savings per iteration.

L. Chen et al [7] introduced the improved C-MEANS algorithm to cluster nodes to decrease the number of bidders, and at

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the same time, the LMS algorithm is adopted to predict the bid value of the nodes. The simulation results show that the energy consumption and traffic flow are reduced, and the bid value more accurately reflects the status of the node when allocated tasks, which increased the complete rate of network tasks.

W. Xiao et al [8] considered a task allocation problem for real-time WSN which aims to conserve as much energy as possible while keeping the latency experienced by the network within a specified value. A novel prediction based MinMin heuristic (P-MinMin) search algorithm is proposed. Simulation results show that the proposed algorithm outperforms existing task allocation algorithms in terms of energy consumption and the capability in meeting real-time requirements demanded by WSN applications.

Y. Yu and V. K. Prasanna [9] proposed an energy-balanced allocation of a real-time application onto a single-hop cluster of homogeneous sensor nodes connected with multiple wireless channels. An epoch-based application consisting of a set of communicating tasks is considered. Each sensor node is equipped with discrete dynamic voltage scaling (DVS). The time and energy costs of both computation and communication activities are considered. Both an Integer Linear Programming (ILP) formulation and a polynomial time 3-phase heuristic are proposed. The simulation results show that for small scale problems (with $\leq$ 10 tasks), up to 5x lifetime improvement is achieved by the ILP-based approach, compared with the baseline where no DVS is used. Also, the 3-phase heuristic achieves up to 63% of the system lifetime obtained by the ILP-based approach. For large scale problems (with 60-100 tasks), up to 3.5x lifetime improvement can be achieved by the 3-phase heuristic. It also incorporate techniques for exploring the energy-latency tradeoffs of communication activities (such as modulation scaling), which leads to 10x lifetime improvement in the simulations. Simulations were further conducted for two real world problems - LU factorization and Fast Fourier Transformation (FFT). Compared with the baseline where neither DVS nor modulation scaling is used, it observed up to 8x lifetime improvement for the LU factorization algorithm and up to 9x improvement for FFT.

Y. Tian and E. Ekici [10] presented an application-independent task mapping and scheduling solution in multihop homogeneous WSNs, multihop task mapping and scheduling (MTMS) that provides real-time guarantees. Using the proposed application model, the multihop channel model, and the communication scheduling algorithm, computation tasks and associated communication events are scheduled simultaneously. The dynamic voltage scaling (DVS) algorithm is presented to further optimize energy consumption. Simulation results show significant performance improvements compared with existing mechanisms in terms of minimizing energy consumption subject to delay constraints.

W. Guo et al [11] presented a self-adapted task scheduling strategy for WSNs. First, a multi-agent-based architecture for WSNs is proposed and a mathematical model of dynamic alliance is constructed for the task allocation problem. Then an effective discrete particle swarm optimization (PSO) algorithm for the dynamic alliance (DPSO-DA) with a well-designed particle position code and fitness function is proposed. A mutation operator which can effectively improve the algorithm's ability of global search and population diversity is also introduced in this algorithm. Finally, the simulation results show that the proposed solution can achieve significant better performance than other algorithms.

Y. Jin et al [12] proposed an adaptive intelligent task mapping together with a scheduling scheme based on a genetic algorithm to provide real-time guarantees. This solution enables efficient parallel processing in a way that only possible node collaborations with cost-effective communications are considered. Furthermore, in order to alleviate the power scarcity of MHWN, a hybrid fitness function is derived and embedded in the algorithm to extend the overall network lifetime via workload balancing among the collaborative nodes, while still ensuring the arbitrary application deadlines. Simulation results show significant performance improvement in various testing environments over existing mechanisms.

M. Naeem et al [13] applied the binary particle swarm optimization to the problem of selecting sensors from a set of sensors for the purpose of minimizing the error in parameter estimation. The motivation of selecting sensors rather than utilizing all sensors includes computational efficiency of parameter estimation and also the efficiency of energy consumption of sensor operations. The computational complexity of finding an optimal subset through exhaustive search can grow exponentially with the number of sensors. If and are large, then it is not practical to solve this problem by evaluating all possible subsets of sensors. In addition to applying the general binary particle swarm optimization (BPSO) to the sensor selection problem, a specific improvement is presented to this population-based heuristic algorithm, namely, it uses cyclical shifts to construct the members of the initial population, with the intention of reducing the average convergence time (the number of iterations until reaching an acceptable solution). The proposed BPSO for the sensor selection problem is computationally efficient, and its performance is verified through simulation results.

Aziz et al in [14] proposed the objective of the centralized, off-line PSO-Voronoi algorithm to minimize the area of coverage holes. The strategy is based on the principle that if each point in the region-of-interest (ROI) is covered by a sensor, then the whole ROI is covered. Assessment of coverage involves sampling the ROI through grid scan. PSO-Voronoi circumvents this by Voronoi polygons around the sensors. PSO particles are sensors positions. For each particle, a set of Voronoi polygons are determined, and the vertexes of the polygons are treated as sample points. The cost function is the number of vertexes that are uncovered by sensors. PSO-Voronoi achieves close to ideal coverage but ignores the time complexity of determining Voronoi polygons.

Hu et al. [15] have proposed PSO-Traffic for topological planning for a real world traffic surveillance application. The study uses a large number of camera loaded nodes, some of which require larger transmission radii facilitated by expensive high-power transmitters. The objective is to determine the nodes with high power transmitters such that the highest possible connectivity is achieved at the lowest possible hardware expense. PSO-Traffic is binary PSO in which the particles represent sequences of sensors. PSO seeks to minimize a multi-objective fitness parameter LDC = a.L + b.D + c.C, where L is the transmission hop of the signal, D is the increase in conflict and C is the cost of the extra high power transmitters. Constants a, b and c define the relative weights of L, D and C respectively. L and D are computed from the scaled length and the scaled degree, concepts from the small world phenomenon. This algorithm has resulted in symmetric distribution of high power transmitters, improved network performance and a saving in system cost.

Li et al. [16] have proposed a mixture of stationary and mobile nodes and particle swarm genetic optimization (PSGO) as a remedy to coverage holes. The PSGO hybrid is employed to determine redeployment positions of mobile nodes in order to improve average node density. PSGO maximizes quality-of-service, defined as the ratio of the area covered to the total area of the ROI, QoS = Sc/S, which should be ideally equal to unity. PSGO borrows the mutation and selection operations from GA. In each iteration, PSGO discards some worst particles and generates an equal number of new particles at random locations. Besides, it moves a few particles randomly. The paper reports as high as 6% increase in QoS with 5 out of 100 static nodes replaced by mobile nodes. Mobile nodes can be repositioned using PSGO dynamically as the network topology changes. But, it necessitates mechanisms for obstacle avoidance and location awareness.

Wang et al. [17] have proposed a virtual force co-evolutionary PSO (VFCPSO) for dynamic deployment of nodes for enhanced coverage. Virtual force based dynamic deployment involves iteratively moving a sensor based on virtual attractive or repulsive forces from other nodes, obstacles in the field and the areas that need higher coverage probability. Virtual force vectors depend on the distance between nodes and whatever attract or repulse them, and their relative directions. A sensor's new positions are computed in such a way that it moves in the direction of the virtual force by a step size proportional to its magnitude.

Hong et al. [18] have PSO Multi-Base for optimal positioning of multiple base stations in a two tier WSN. The two tier network consists of nodes that can communicate only with the application nodes they are assigned to. Application nodes possess long-range transmitters, high-speed processors, and abundant energy. The PSO Multi-Base method aims at determining positions of base stations so that the total of distances of application nodes to their nearest base stations is minimal. This deployment requires minimum transmission power and, assures maximum network life.

Gopakumar et al. [19] have proposed PSO-Loc for localization of n target nodes out of m nodes based on the a priori information of locations of m ¡ n beacons. The base station runs a 2n-dimensional PSO (x and y coordinates of n nodes) to minimize the localization error. Here, (x; y) is an estimate of the target node location, (xi; yi) is the location of beacon node i, and M ¸ 3 is the number of beacons in the neighborhood of the target node. Estimated distance from beacon is simulated as the actual distance corrupted by an additive Gaussian white noise. The variance of noise influences the localization accuracy. The approach does not take into account the issues of flip ambiguity and localization of the nodes that do not have at least three beacons in their neighborhood. The scheme works well only if either beacons have sufficient range, or there exist a large number of beacons. Moreover, the base station requires range estimates of all target nodes from all beacons in their neighborhoods. This requires a lot of communication that may lead to congestions, delays and exhaustion of energy. In addition, the proposed scheme has a limited scalability because the PSO dimensionality is twice the number of target nodes.

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IV.CONCLUSION

Scale and density of deployment, environmental uncertainties and constraints in energy, memory, bandwidth and computing resources pose serious challenges to the developers of WSNs. Issues of node deployment; localization, energy-aware clustering, and data-aggregation are often formulated as optimization problems. Most analytical methods suffer from slow or lack of convergence to the final solutions. This calls for fast optimization algorithms that produce quality solutions utilizing fewer resources. PSO has been a popular technique used to solve optimization problems in WSNs due to its simplicity, high quality of solution, fast convergence and insignificant computational burden. However, iterative nature of PSO can prohibit its use for high-speed real-time applications, especially if optimization needs to be carried out frequently. PSO requires large amounts of memory, which may limit its implementation to resource-rich base stations. Literature has abundant successful WSN applications that exploit advantages of PSO. Data-aggregation needs frequent distributed optimization, and fast solutions: Thus PSO moderately suits it. Static deployment, localization and clustering are the problems solved just once on a base station: Thus PSO highly suits them.

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