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Resolving the Optimization Problems Of Multi Communication Gateway for Remote Embedded Web Server using PSO

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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 and embedded Web Server, introduces PSO and discusses its suitability for WSN applications. It also presents a brief review of how PSO solve these issues.*

Keywords: *clustering, data-aggregation , embedded web server, , RSA, Optimal coverage problem, PSO, Wireless sensor networks.*

I. INTRODUCTION

The embedded Web server is designed and built as an expansion module for one of the nodes in the wireless sensor network (WSN)[1]. To establish two way communication to the authorized Internet users with the sensor network is allowed by it. By using available hardware resources it implement an interface to the WSN node and serve dynamic HTML pages to the remote user. WSNs along with embedded web server have many challenges, mainly caused by communication failures, storage space and computational constraints , restricted power supply, data aggregation and fusion, energy aware routing, task scheduling, security, optimal deployment , localization, flexibility, autonomous activities, strength against topology changes ,state changes, Fault tolerance, scalability, production cost, operating environment, hardware constraints, transmission media, power consumption are the important factors that is to be consider in the design process of sensor networks. PSO [2][3][4] produces better results in complicated and multi peak problems with few parameters to adjust giving fast as well as accurate computation results which lead to be a popular optimization technique in swarm intelligence field [5].

II. LITERATURE REVIEW

In networks, the communication between a client and a server might be interrupted since the server itself is offline or unreachable as a result of catastrophic network failures is the problem of Reliable Server Assignment in WSN. A novel simulation optimization approach is developed based on Monte Carlo(MC) simulation and embedded into Particle Swarm Optimization (PSO) to solve the RSA problem[6].

The particle swarm algorithm [7] adjusts the trajectories of a population of “particles” through a problem space on the basis of information about each particle's previous best performance and the best previous performance of its neighbours. Previous versions of the particle swarm have operated in continuous space, where trajectories are defined by J. Kennedy et. al as changes in position on some number of dimensions. In the binary version, trajectories are changes in the probability that a coordinate will take on a zero or one value.

The DSC problem is to divide the sensor nodes into different disjoint sets and schedule them to work one by one in order to save energy while at the same time meets the surveillance requirement, e.g., the full coverage.The binary particle swarm optimization (BPSO) approach to solve the disjoint set covers (DSC) problem in the wireless sensor networks (WSN)[8]. As per Zhi-Hui Zhan et. al, the objective of DSC is to maximal the number of disjoint sets. As different disjoint sets form and work successively, only the sensors from the current set are responsible for monitoring the area, while nodes from other sets are sleeping to save energy. Therefore the DSC is a fundamental problem in the WSN and is significant for the network lifetime. In the literature, BPSO has been successfully applied to solve the optimal coverage problem (OCP) which is to find a subset of sensors with the minimal number of sensors to fully monitor the area. Here the BPSO approach is extended by finding the minimal number of sensors for the OCP to fully monitor the area, mark these sensors as unavailable and repeatedly find another subset of sensors in the remained WSN for the OCP.

Various efforts of maximizing the network life time are spontaneously under work. To maximize the network lifetime by minimizing the number of active CHs and to maximize the network scalability by using two-hop communication between the sensor nodes and their respective CHs , a novel centralized PSO protocol for Hierarchical Clustering (PSO-HC) in WSNs suggested by R. S. Elhabyan et al[9]. Extensive simulations show that PSO-HC outperforms the well-known cluster-based sensor network protocols in terms of average consumed energy and throughput.

In the case of wireless sensor network under attacks but also able to ensure secure communications and efficient and reliable coverage is a major problem. The sensor network coverage optimization process is vulnerable to be attacked or invaded. Through the combination of trust management model and heuristic optimization Particle Swarm Optimization and Cuckoo Search, Zuo Chen et al proposed a sensor network security coverage method based on trust management of intrusion tolerance. This method evaluate the trust value of the nodes through their behavior at first, and then adjust the perception radius and decision-making radius. Finally, combine PSO and CS serial optimization in order to achieve the intrusion tolerance for efficient adaptive coverage.

Industrial Wireless Sensor Networks (IWSNs), a novel technique in the field of industrial control, can greatly reduce the cost of measurement and control, as well as improve productive efficiency. IWSNs has high requirements for reliability, especially for large-scale industry application affected by node placement problem in IWSNs. Considering the reliability requirements, the setup cost and energy balance in IWSNs, the node placement model of IWSNs is proposed by Ling Wang et al which is an adaptive mutation probability binary Particle Swarm Optimization algorithm (AMPBPSO). Experimental results show that AMPBPSO is effective for the optimal node placement in IWSNs[11].

To reduce the number of hops between a sensor and its sink node realted to the issues like memory and energy constraints , solutions have been proposed by H. Safa *et. al.* on different levels including the topological level where multiple sinks can be used in the network[12].

One of challenging issues for task allocation problem in wireless sensor networks (WSNs) is distributing sensing tasks rationally among sensor nodes to reduce overall power consumption and ensure these tasks finished before deadlines. The soft real-time fault-tolerant task allocation algorithm (FTAOA) for WSNs in using primary/backup (P/B) technique to support fault tolerance mechanism[13]. In the proposed algorithm, the construction process of discrete particle swarm optimization (DPSO) is achieved through adopting a binary matrix encoding form, minimizing tasks execution time, saving node energy cost, balancing network load, and defining a fitness function for improving scheduling effectiveness and system reliability.

III. METHODOLOGY OF WORK

1. Social Behaviour Simulation :

Simulations of various interpretations of the movement of organisms in a bird flock or fish school. Notably, Reynolds and Heppner and Grenander [14] presented simulations of bird flocking. Reynolds was surprised by the aesthetics of bird flocking choreography, and Heppner, was interested in discovering the underlying rules that enabled large numbers of birds to flock synchronously, often changing direction suddenly, scattering and regrouping, etc. Both of these scientists had the insight that local processes, the synchrony of flocking behavior was thought to be a function of birds' efforts to maintain an optimum distance between themselves and their neighbors. Social sharing of information among conspeciates offers an evolutionary advantage: this hypothesis was fundamental to the development of particle swarm optimization. Birds and fish adjust their physical movement to avoid prechtors, seek food and mates, optimize environmental parameters such as temperature, etc. Humans; adjust not only physical movement but cognitive or experiential variables as well. Two individuals can hold identical attitudes and beliefs without banging together, but two birds cannot occupy the same position in space without colliding. It seems reasonable, in discussing human social behaviour, to map the concept of change into the bird-fish analog of movement. This is consistent with the classic view of qualitative and quantitative change as types of movement. Thus, besides moving through three-dimensional physical space, and avoiding collisions, humans change in abstract multidimensional space, collision-free.

2. Algorithm :

Particle swarm optimization has roots in two main component methodologies. Perhaps more obvious are its ties to artificial life (A-life) in general, and to bird flocking, fish schooling, and swarming theory in particular. It is also related, however, to evolutionary computation, and has ties to both genetic algorithms and evolutionary programming. PSO requires only primitive mathematical operators, and is computationally inexpensive in terms of both memory requirements and speed. Early testing has found the implementation to be effective with several kinds of problems. [14]. It consists of a swarm of *s* candidate solutions called particles, which explore an *n*-dimensional hyperspace in search of the global solution whre *n* is the number of optimal parameters. A particle *i* occupies position *Xid* and velocity *Vid* in the *d*th dimension of the hyperspace, 1 · *i* · *s* and 1 · *d* · *n*.

Each particle is evaluated through an objective function *f*(*x*1*; x*2*;… ; xn*), where *f* : R*n* □R. The fitness of a particle close to the global solution is lower 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 (*pbestid*). Besides, *gbestd*, 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[16].

$$Vid(k + 1) = w ¢ Vid(k) + \varphi 1 ¢ r1(k) ¢ (pbestid ¡ Xid) + \varphi 2 ¢ r2(k) ¢ (gbestid ¡ Xid) \quad .....(1)$$
$$Xid(k + 1) = Xid(k) + Vid(k + 1) \quad .....(2)$$

Here, $\varphi 1$ and $\varphi 2$ are constants, and *r*1(*k*) and *r*2(*k*) are random numbers uniformly distributed in [0,1]. 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 resented in [14].

Particle Swarm Optimization has provided optimization in several aspects of data aggregation such as data prediction and Multi source data feature selection, optimal sensor configuration , determination of optimal local thresholds and optimal transmission power allocation. Multi source data consists of many attributes of different types. PSO is used to extract useful features from numerous multi source data. Correlation evaluation method is used to eliminate unrelated and duplicated attributes using an entropy function. Then an improved Back Propagation Neural Network (BPNN) is used for data prediction. Veeramachaneni *et al*. present a binary multi-objective PSO for optimal configuration. Swarm agents are used to evolve the choice of sensors. Each agent evokes PSO to evolve the thresholds and optimum fusion rules for its sensor set. The result represents agents ability to decide an optimal configuration of sensors, their thresholds and the optimal fusion rule. For the distributed detection The combination of Ant Based Control and PSO (*ABC-PSO*) is used by Veeramachaneni et al for the design of threshold and managing the hierarchy of serial sensor networks.

Clustering is an efficient topology control approach for maximizing the lifetime and scalability of Wireless Sensor Networks (WSNs). Many cluster-based routing techniques have been proposed. However, in most of the proposed protocols, the communication between a sensor node and its designated cluster head (CH) is assumed to be single-hop. Multi-hop communication can be used when the communication range of the sensor nodes is limited or the number of sensor nodes is very large in a network. Particle Swarm Optimization (PSO) is a swarm intelligent approach that can be applied for finding fast and efficient solutions of such problems.

3. Formulation

Data clustering with PSO algorithms have recently been shown to produce good results in a wide variety of real-world data. Although the variety of variations in PSO based clustering techniques are proposed in literature achieving better results, suffers with several limitations more specifically when dealing with multidimensional data. This research presents a novel PSO based clustering technique which is a hybrid approach to the multidimensional data clustering problem by predicting the initial cluster center location and number of clusters and optimizing it with one of efficient PSO variant. A hybridized approach involves swarm intelligence inspired algorithm (i.e. BRAPSO) which is a new variant of PSO with Subtractive clustering algorithm that evaluates clustering over multidimensional data[17].

3.1 Module I*: Subtractive Clustering* In this, a problem space is the multidimensional vector space. Each dot represents a dimension vector in the problem space. Hence the entire dataset represents multidimensional space with a large number of dots in the search space . Such multidimensional data points will be served as input to the algorithm. At the initial stage, the Subtractive clustering module is executed to calculate density function value for each data point in the search space. The computational complexity is linearly proportional to the number of data points in the space and independent of the dimensions of the considered problem [2]. Consider a multidimensional space having collection of *n* data points *{x1,…, xn}*. Since each data point is a candidate for cluster centers, a density measure at data point *xi* is calculated by using (1) .

$$Di = \sum_{j=1}^{n} exp\left(-\frac{||xi - xj||^2}{\left(r_a/_2\right)^2}\right)$$

Where, Di - density value of ith data point *xi - ith data point (Primary Gateway)*
xj - jth data point (Secondary Gateway) *ra - neighborhood radius (positive constant)*

3.2 Module II*: Boundary Restricted Adaptive PSO (BRAPSO)* The output from subtractive clustering module i.e. initial cluster center and number of clusters will be given to BRAPSO module as an initial seed. *Module II* starts with basic PSO process, in which the birds in a flock are symbolically represented by particles. These particles are simple agents ―flying‖ through a problem space, represents individual solution to problem. A different problem solution is generated, as a particle updates itself to new location. The fitness function is evaluated for each particle in the swarm and compared with the fitness of its own best previous position i.e. p_{best} and to the fitness of the global best particle amongst all particles in the swarm i.e. g_{best}. Then, the velocities and positions for the *ith* particle are updated by using (3) & (4) .

$$v_{id}{=}w{*}\ v_{id} + c_1 * rand_1 {*}(\ p_{best} - x_{id}\ ){+}\ c_2 * rand_2 * (g_{best} - x_{id}\ ) \quad (3)$$

$$x_{id}{=}\ x_{id}{+}\ v_{id} \quad (4)$$

Where, d - dimension of the problem space rand1, rand2 - random values in the range of (0, 1)
c1, c2 - acceleration coefficients constants w - inertia weight factor

The necessary diversity of the swarm is provided by the inertia weight factor *w*, by changing the momentum of particles to avoid the stagnation of particles at the local optima . The previous work adopted better solutions or swarm crowding near the global solution with small change in the inertia weight.

Since, our data is provided in constant additional mode and it is not in break up mode therefore, Boundary Restricted Adaptive PSO method is more useful to resolve the optimization problem.

IV. CONCLUSION

Serious challenges to the developers of WSNs and embedded server are created by Scale and density of deployment, environmental uncertainties and constraints in energy, memory and computing resources. The various issues such as node deployment; localization, energy aware clustering, and data-aggregation are most often considered as optimization problems. Many analytical methods have suggested. Most analytical methods suffer from slow or lack of convergence to the final solutions. PSO has been a popular technique used to solve optimization problems in WSNs and embedded web server due to its simplicity, high quality of solution, fast convergence and insignificant computational burden as compared to other techniques such as GA. Moreover the PSO can prohibit its use for high-speed real-time applications. 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, localization of nodes, RSA, DSC needs frequent distributed optimization, and fast solutions: Static deployment, localization and clustering are the problems solved using PSO optimization techniques. Thus PSO moderately suits it.

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