Task Allocation for Wireless Sensor Network to Improve Energy Consumption and Network Lifetime using Modified Binary Particle Swarm Optimization

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Abstract- *A wireless sensor network (WSN) is a system of spatially distributed sensor nodes that collect important information in the target environment. The execution of several computationally intense in-network processing tasks are required in wireless sensor network (WSN).Here task allocation is an essential one to allocate the work load of task among nodes in an efficient manner.Modified Binary particle swam optimization(MBPSO) is proposed to search for the best task allocation solution for WSN.In order to maximize measurement information MBPO based node selection is proposed. Study is proposed to run a simulation in such a way that network load is shared in a time effective manner.*

I. INTRODUCTION

A wireless sensor network (WSN) is a system of spatially distributed sensor nodes that collect important information in the target environment. WSNs have been envisioned for a wide range of applications, such as battlefield intelligence, environmental tracking, and emergency response. Each sensor node has limited computation capacity, power supply and communication capability. In a wireless sensor network (WSN), the usage of resources is usually highly related to the execution of tasks which consume a certain amount of computing and communication bandwidth. Parallel processing among sensors is a promising solution to provide the demanded computation capacity in WSNs, and task allocation and scheduling play an essential role in parallel processing

II. BACKGROUND

In [1] shows the feasibility of the proposed MBPSO-based approach for task allocation problem in WSN. The paper MBPSO-based approach also outperforms the approaches based on genetic algorithm and BPSO in the comparative analysis.

In[2] The results show that the proposed method obtains a set of optimal allocations with increased level of performance over the other PSO methods.

In [3] this study, a modified version of binary particle swarm optimization (MBPSO), which adopts a different transfer function and a new position updating procedure with mutation, is proposed for the task allocation problem to obtain the best solution. Each particle in MBPSO is encoded to represent a complete potential solution for task allocation.

In [4] Energy consumption is currently a key issue in research for future sensor networks. This study presents a novel approach to sensor network routing based on energy consumption. The unique routing algorithm uses swarm intelligence, which is computationally efficient.

In[5] results show that the system nodes selection mechanism is significantly better than the classical branch and bound algorithm, and satisfies the needs of large-scale network nodes selection

III. METHODOLOGY

Modified binary particle swarm optimization, MBPSO

In basic BPSO, along with the iterations, the random walk slows down the convergence speed of the algorithm. In addition, it is easy to fall into local optimum. Therefore, a modified version of BPSO is proposed.

Velocity and position updating for MBPSO In BPSO, a particle represents possible solutions.The fitness of particles reflects their performance.

The two basic equations which govern the working of PSO are that of velocity vector and position vector given by:

$$\alpha_1 = (MAXITE - ITE)/MAXITE, MAXITE$$

Represents the maximum number of iterations and ITE represents the current iteration number.

$$\alpha_2 = (d_{\max} - d_{gi})/d_{\max},$$

d_{max} represents the maximum distance between two points in the solution space

- The first part of Equation (1) represents the inertia of the previous velocity;
- The second part is the cognition part and it tells us about the personal experience of the particle;
- The third part represents the cooperation among particles and is named as the social component [11].
- Acceleration constants $c_1; c_2$ and inertia weight w [12] are the predefined by the user and $r_1; r_2$ are the uniformly generated random numbers in the range of [0; 1].

The proposed the velocity vector is generated by using Equation (1).

$$v_{id} = \alpha * \alpha_1 * \alpha_2 * \alpha_3 * (p_{gd} - p_{id}) \quad (3)$$

And d_{gi} represents the distance between the global best particle and the *i*th particle.

The maximum distance $d_{\max}$ between two points in the solution space $(a; b)$ is computed as

$$d_{\max} = \sqrt{\sum_{i=1}^{D} (b_i - a_i)^2}$$

where $a = (a1; a2; : : : ; aD)$, $b = (b1; b2; : : : ; bD)$.

The distance between two particles *xp* and *xq* can be calculated as follows:

$$d_{pq} = \sqrt{\sum_{i=1}^{D} (x_{pi} - x_{qi})^2},$$

D represents the dimension of swarm particle.

$$\alpha_3 = f(P_g)/f(X_i),$$

where f(Pg) is a fitness function value of the global best particle Pg, f(Xi) is a fitness function value of the ith particle Xi.

The four parameters , 1, 2, 3 help in controlling the velocity of the swarm particles. Unlike the usual velocity equation of the basic PSO (given by Equation (1)) the proposed velocity vector do not make use of inertia weight and acceleration constants and is more or less adaptive in nature. From the velocity Equation (3), we can easily see that in the beginning the velocity is large therefore the particles move rapidly but during the subsequent generations the velocity decreases and the particles slow down as they reach towards the optimum solution.

Mutation operation for MBPSO

In order to solve the problem of local optimum. The mutationoperation is introduced into MBPSO. When the evolution of the population is stagnation, and stagnation number reaches a certain threshold, the algorithm performs mutation operation. Mutation operation can increase the diversity of the population .The mutation operation is expressed as:

$$x_{i,d}^{t} = \begin{cases} 1 - x_{i,d}^{t} & if\ rand() < p_m and\ N > \lambda \\ x_{i,d}^{t} & else \end{cases}$$

Where N is the number of stagnation, λ is the threshold, p_m is the mutation rate.

IV. EXPERIMENT AND RESULT ANALYSIS

As the hierarchical network topology has been widely used in WSNs, a multi-agent-based architecture for WSN. Due to the topological, spatial and deployment conditions, a WSN is always divided into several regions, each of which is divided into several clusters as well. Moreover, clusters may contain smaller clusters, for example, node 1 is the head of a 1st level cluster, which includes node 2 and node 3, and these two nodes are the heads of 2nd level clusters. Each cluster consists of a cluster agent (CA) and several member agents. In user requests are sent to the WSN through external networks, such as the Internet and satellites. The architecture is based on a three layer hierarchy of software agents. Generally, a user request is always transformed to an initial task, which is decomposable. Then, the initial task is decomposed into several smaller tasks with the same functionality. Acting as a high energy “gateway”, a sink agent is responsible for ensuring the interaction between the external network and the WSN. In addition, it also processes the final data obtained from the regional agents. At the regional layer, a regional agent manages a part of all the sensor agents, and performs local task allocation and data processing. Finally, a cluster agent collects the data from the agents in the cluster and performs some in-network operations, while simple agents usually implement some simple procedures, such as data sensing and local computing.

V. RESULT & ANALYSIS

Let us consider a task allocation problem with 128 tasks and 16 sensor nodes, the internal energy consumption of sensor nodes is the consumption cost of executing 100 estimated runtimes, which is between 0.2 and 1.5 s with a normal distribution whose center point is 1, while communication consumption of WSN is represented as a m × m matrix which is between 3 and 7 with a normal distribution whose center point is 5. We assume that every task can be equally accomplished by any sensor, regardless of its position. Then we perform the MPSO algorithm with each test data for five times and take the best solution. After a lot of tries, MPSO can get satisfied solution in short time (10 s level) when parameters are set in this way: the number of iterations is 1,000, the population size is 100, the threshold of particle diversity is 0.2, and the threshold of population diversity is 0.4.

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AUTOMATIC INPUT VALIDATION

Switch "OnOff_graph_fg_mean" is active, but "num_trials" == 1.  In other words, you have chosen to graph the mean function value per iteration over

Since "OnOff_swarm_trajectory," "OnOff_phase_plot," or "OnOff_graph_x" is active, "OnOff_xhist" has been activated automatically so that "xhist" wil

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USER INPUT VALIDATION

Local Best (Lbest) PSO
35 iterations maximum
Position clamping inactive.
Velocity reset inactive.
Velocities clamped to 50% of the range on each dimension.
History, "ghist," of global bests active.
History, "lhist," of local bests active.
History, "phist," of personal bests active.
History, "fhist," of all function values active.
History, "xhist," of all positions active.
History, "vhist," of all velocities active.
1 trial(s)
3 particles
Inertia weight linearly varied from 0.9 to 0.4 per grouping.
Cognitive acceleration coefficient, c1: 1.49618
Social acceleration coefficient,    c2: 1.49618
Ackley: 2 dimensions
Symmetric Initialization: [-30,30]
Threshold required for success: 5e-005
"OnOff_Terminate_Upon_Success" inactive.

Are the displayed settings as you intended (Y or N)?
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Fig 1 User Input

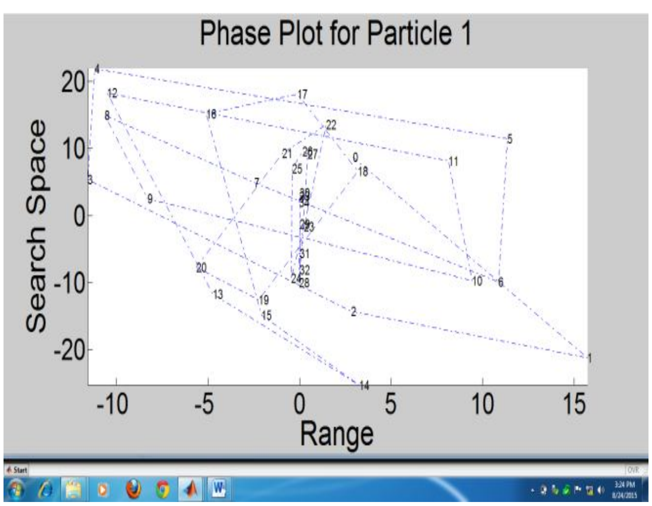

Fig 2 Phase Plot For Particle1

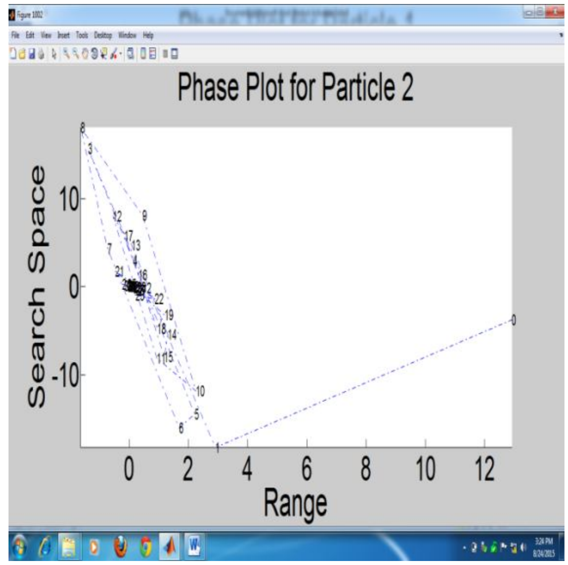

Fig 3 Phase plot for particle 2

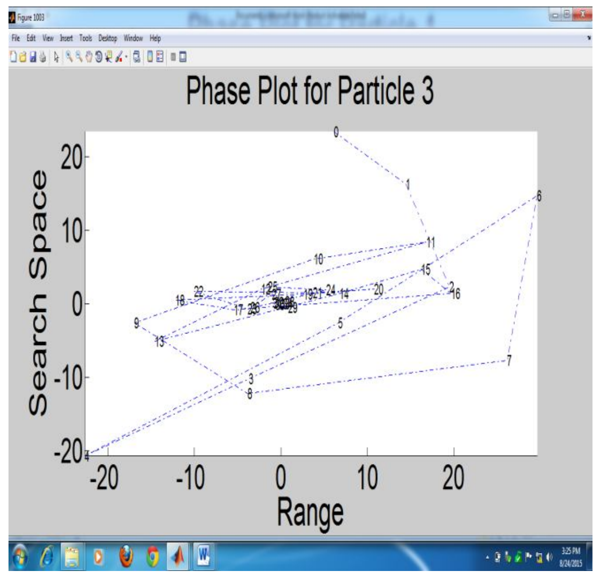

Fig 4 Phase plot for particle 3

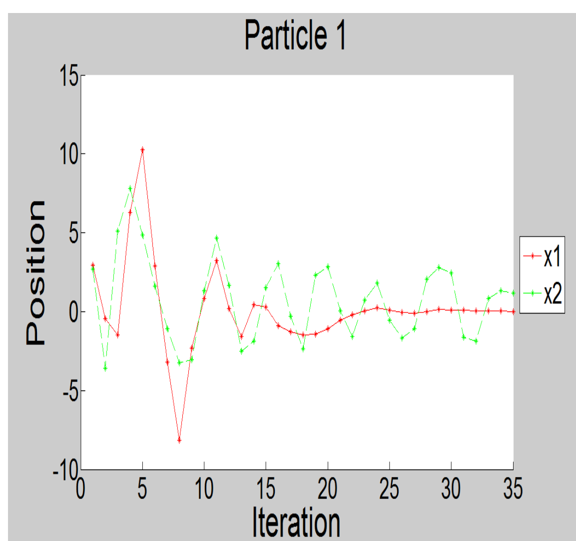

Fig 5 Position particle 1 in various iteration

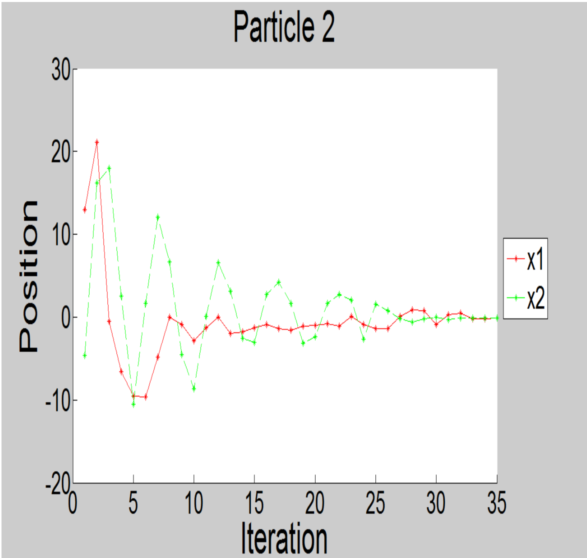

Fig 6 Position particle 2 in various iteration

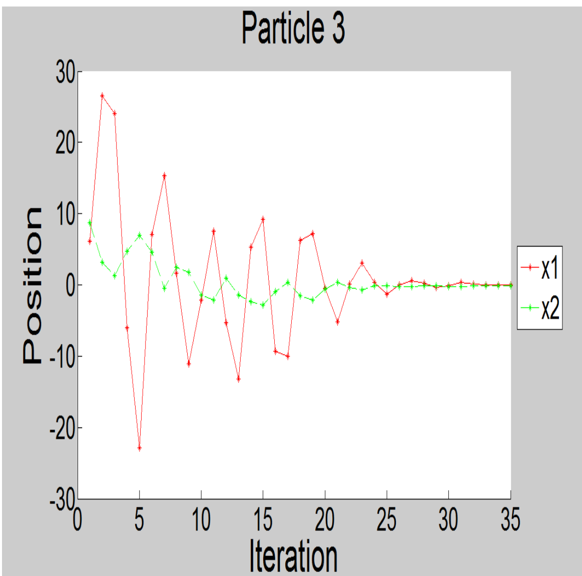

Fig 7 Position Particle 3 in various iteration

VI. CONCLUSION

In this work, a task allocation approach based on MBPSO is proposed to search for the best task allocation solution for WSN.The BPSO is modified with a different transfer function and a new position update.

A MBPO based nodes selection algorithm was proposed to maximize measurement information for the objective function. According to the characteristics of the particles and the decision variables, we design a new particle coding method, and the v-shaped transfer function was used to improve the convergence speed. in addition, the mutation operation was used to avoid local optimum, nonlinear decreasing inertia weight to balance the global search ability and local search ability. The simulation results show that the proposed node selection mechanism can find high quality solution in a relatively short period of time.

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