Elite Adaptive Parallel Evolutionary Algorithm for Sensor Nodes Clustering Optimization in High Density Sensor Network

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Abstract. Minimizing the communication energy consumption has always been a key aspect of the research of High Density Sensor Network (HDSN). HDSN is a group of small devices with restricted battery capacities. Accordingly, the objective of the clustering technique is to design a best set of sensor nodes clustering result for the combination that minimize the communication energy consumption. The ideal clustering problem with discrete variables is a np-hard problem in its accurate formulation. In this study, an improved elite adaptive parallel evolutionary algorithm (EAPEA) is proposed to lower the communication energy consumption in HDSN. The suggested algorithm is tested by a fitness function, and new adaptive operator and elite operator have been designed to speed up the convergence rate. The EAPEA merges the merits of the adaptive adjusting and elite selection. By the mechanism of adaptive adjusting, its overall exploit capacity is fully applied for finding the overall optimal solution. EAPEA simultaneously develop a large number of results to explore the explore area and to avoid local optima. A convergence analysis is carried out, and extensive experiments are carried out that compare EAPEA with two other heuristics. Our experimental simulations denote that the presented EAPEA technique, when used into HDSN, is competent to offer better performance and a low communication energy consumption compared to two other heuristics.

Keywords. Sensor network, Evolutionary algorithm, Clustering

1. Introduction

The rapid progress in the research and development of efficient software algorithms, nano-systems technologies and wireless technology have made it feasible to equip inexpensive small, numerous, vulnerable, and networked tiny nodes \cite{[1],[2][3]}. High Density Sensor Network (HDSN) made up of some sensor nodes having sensing, wireless communication, computing, and self-organizing capabilities \cite{[4],[5][6]}. HDSN have been widely studied and usefully employed in many important areas such as medical diagnostic, military affairs, home automation, preventing forest fire loss, building monitoring and control, traffic control, etc \cite{[7],[8]}

Recently clustering has been receiving a lot of attention for wide applications of HDSN. Because sensors are constrained in battery capacities, it is very important and necessary to explore new energy efficient clustering algorithms. Accordingly, minimizing the communication energy consumption under the battery capacities is a NP-hard problem. Nevertheless, as exhaustive explore are desired in
every combination, the computational complexity is too high to be practical. The problem is an
optimizing issue, and several heuristics is researched to gain low communication energy consumption.
In [8], Particle Swarm Optimization (PSO) has been researched. The method solves the problem based
on a hybrid heuristic approach. However, for PSO, the algorithm cannot always get the ideal solution.
In [9] the authors present another heuristic clustering scheme, the Simulated Annealing (SA). Their
method not only reduces energy consumption significantly but also decreases the computational
complexity. The SA is simple and fast but it generally yields a higher communication energy
consumption than PSO. In [10] clustering technique for the problem in WSNs to minimize the
communication energy is investigated using Quantum Genetic Algorithm (QGA). QGA can obtain
lower energy consumption than SA. However, the rate of convergence could not reach an acceptable
point.

The evolutionary algorithm (EA) is a stochastic explore method inspired from the principles of
biological evolution observed in nature. Recently, it has been suggested that the evolutionary
algorithms that maintain the optimal discovered solution either before or after the selection procedure
asymptotically converge to the global best. Evolutionary algorithms have been utilized widely in the
stochastic optimization issues.

Adaptive theory and elite theory have recently inspired researchers in numerous domains of
artificial intelligence. In this chapter, we present a novel clustering method using an elite adaptive
parallel evolutionary algorithm (EAPEA). We then propose a detailed algorithm design of EAPEA for
clustering in HDSN. We propose a novel framework that mixes the merits of adaptive adjusting and
elite selection while adjusting the contention for the parallel operator. EAPEA has global explore
ability, fast search speed and strong robust. In addition, parallel search technique is used to avoid local
optima.

Simulations are conducted by using the EAPEA and the clustering methods using SA and QGA.
Results show that the represented EAPEA strategy outperforms the conventional SA and QGA
schemes with lower communication energy consumption and faster convergence speed.

2. System Model

This section describes the model of energy efficient clustering in HDSN with respect to the
communication energy consumption. Communication energy consumption consists of transmitting
energy consumption and receiving energy consumption, which can be shown as formula (1).

\[ \text{Energy}_{\text{sum}}^{i} = \text{Energy}_{\text{send}}^{i} + \text{Energy}_{\text{receive}}^{i} \]  

(1)

In (1), \( \text{Energy}_{\text{sum}}^{i} \) is the communication energy consumption of the \( i \)-th sensor, \( \text{Energy}_{\text{send}}^{i} \) is the
transmission energy consumption of the \( i \)-th sensor node and the \( \text{Energy}_{\text{receive}}^{i} \) is the receiving energy
consumption of the \( i \)-th sensor node.

The energy consumption of the whole sensor network after clustering is shown as formula (2).

\[ E_{\text{sum}} = \sum_{i=1}^{I} \text{Energy}_{\text{sum}}^{i} \]  

(2)

In (2), \( E_{\text{sum}} \) is the energy consumption of the whole sensor network, and \( I \) is the number of sensor
nodes in the network.

The transmission and reception energy consumption of wireless sensor network can be shown in
formula (3) and (4) respectively.

\[ \text{Energy}_{\text{send}}^{i}(k,h) = E_{\text{elec}}^{i} \cdot k + E_{\text{amp}}^{i} \cdot k \cdot h^{n} \]  

(3)

In (3), \( \text{Energy}_{\text{send}}^{i}(k,h) \) is the transmission energy consumption of the \( i \)-th sensor node with
distance \( h \) and transmitted data \( k \) bits. \( E_{\text{amp}}^{i} \) is the power amplification, \( E_{\text{elec}}^{i} \) is the parameter of
electronics energy and \( n \) is the propagation coefficient.
In (4), $Energy_{\text{receive}}^{i} (k) = E_{\text{elec}} \cdot k$

3. Sensor Nodes Clustering Optimization in HDSN based on EAPEA

We use the EAPEA to explore for optimal solutions in order to achieve ideal performance. We describe the algorithm with a new adaptive mechanism. To avoid premature convergence elite and parallel procedures are also used. Firstly, the EAPEA performs parallel explore, thus minimizing the communication energy consumption for the clustering problem. Secondly, through the adaptive procedure, it is more powerful for operations with dynamic parameters than conventional evolutionary algorithm. These features increase the probability of finding the optimum or close-to-optimal solution in the clustering problem. EAPEA iteratively searches for an ideal chromosome by using heuristic procedures.

3.1. Representation of chromosomes

In this section, the sensor nodes clustering encoding technique is firstly introduced to the representation of chromosomes. The successful procedure of EAPEA depends a lot on the coding method used to represent the sensor nodes clustering. EAPEA uses binary coded vectors called chromosomes. So, a chromosome is a candidate solution made up of a set of sensor nodes clustering. In EAPEA, a sensor node should be suggested by a Boolean code. If the code is 1, the sensor node on the position is the cluster head. If the code is 0, the sensor node on the position is the member node. The proportion of cluster head is fixed. Member nodes are only clustered with the nearest cluster head node. Therefore, a possible solution can be suggested as a Boolean vector. Each chromosome is a vector where the length of the vector demonstrates the number of sensor nodes. In this way, the potential solutions of the explore space are encoded as Boolean vectors. Each chromosome made up of $I$ elements, where $I$ is the number of sensor nodes in the network. Binary coding has various effectiveness over other representation and is, therefore, selected for the cluster heads expression in this paper. In the population, every chromosome contains exactly same elements.

3.2. Generating feasible solutions

The EAPEA solves the optimizing problem by keeping a population consists of several subpopulations. Different subpopulations evolve in parallel. The EAPEA does not work on a single population but on several subpopulations with vectors that undergoes an evolutionary process starting through the initial population. A number of initial feasible solutions are produced and the optimization tries to update the solutions until the best solution is obtained. In the beginning of the investigate procedure of the EAPEA, an initial set of solutions, referred to the initial population, is created randomly. A random number generator is utilized to create the initial population comprising a certain number of chromosomes. To promote the heuristic diversity, in our algorithm, the related sensor nodes clustering is randomly generated for each chromosome in the initial population. In nature, the random creation of new stochastic information may lead to the capacity to survive. This procedure will be used repeatedly many times unless the chromosome becomes feasible before that. And then, the EAPEA carries out the procedure of selection, crossover, and mutation to evolve into a high-performance set of chromosomes. The EAPEA is a particular class of evolutionary algorithms and the population composed of a large number of chromosomes is improved through these procedures. The population is divided into several subpopulations. These heuristic procedures are utilized to generate the novel generations from the previous one.

3.3. Selection and crossover

In EAPEA, pairs of elements are chosen to develop descendants. The choice of parents is fixed by random and selective methods. The EAPEA adopts a roulette wheel selection strategy to select the
parents. Two parents are picked according to the roulette wheel rule. Roulette wheel selection describes the chance of reproduction to most chromosomes in the population, while selecting two chromosomes through the optimal fitness assigns more opportunities to the better chromosomes. It begins its procedures as selecting two chromosomes from the population using roulette wheel selection after initialization. The number of chosen chromosomes is the same as that of the initial population. Once a pair of chromosomes is selected, and its corresponding restriction is determined, this pair of chromosomes is replaced by using a random pair of chromosomes that is chosen from all possible pairs that suit the restriction.

Crossover procedure swaps some paragraph of stochastic bit vector within parents. The crossover procedures are employed on two picked parents to exchange their parts to create offspring. The crossover procedure, the two parents are picked randomly. A typical crossover procedure splits two solutions at a randomly picked crossover point and exchanges parts between them. Crossover causes a structured yet randomized exchange of heuristic material between solutions. When the cluster head percentage is not correct, it needs to be corrected. In this way, the selected solutions are combined by partly mixing their characteristics to develop two novel solutions. The crossover rate in EAPEA is 0.95. The crossover procedure is the major facility to search the search region to locate good solutions.

3.4. Adaptive Mutation
To maintain diversity and avoid premature convergence, mutation is employed to the newly developed population. By mutation procedure, the child gains novel characteristic. Mutation procedure is an inversion of some bits from whole binary vector at very low rate. In optimizing according to EAPEA, the mutation procedure is an auxiliary procedure in the course of crossover. Each chromosome had a given possibility of being mutated, for the EAPEA this probability is adaptively adjusted. Population diversity is needed because mutation is the method by which novel candidate solutions are generated. Moreover, mutation procedure leads the exploit to obtain out of a local optimal.

3.5. Fitness calculation and Elite Preservation
In the EAPEA process, the fitness value measures the quality of chromosomes. The impact of chromosomes on the fitness value is fixed by the communication energy consumption. The clustering problem is associated with a fitness value, and a lower fitness value refers to a better solution. In this work, the fitness value of chromosome is calculated by (2). The communication energy consumption as the fitness function is evaluated for every chromosome. In our tailored EAPEA, the smaller the value of the fitness function is, the better the chromosome is. In EAPEA, the explore procedure is performed by using an elite preservation method. With the elitist technique, the chromosomes via the better fitness value are selected to reproduce the new generations.

If the termination criteria is satisfied, the cycled process of EAPEA is terminated. Thereafter crossover and mutation on the population are carried out and such procedures are repeated until a predefined minimum number of generations are produced. The convergence criteria is the genetic evolution reaches a predefined minimum number of generations. The earlier process are repeated for many generations, then the evolution procedure converges to a chromosome that has the highest fitness value, and the ideal or near-optimal solution to the problem can be acquired. After several generations, the algorithms converge to the ideal chromosome, which represents the best solution.

4. Simulation and Results
In this section, we compare the suggested EAPEA method via the SA and QGA method for clustering in HDSN. To validate and test the performance of the shown EAPEA technique to the clustering problem in HDSN, simulations are executed. The platform utilized for experiments is a Pentium i7 9700F machine with 8 GB RAM and MATLAB is employed as programming language. In such situations, the fitness function (2) is employed to evaluate the communication energy consumption. In experimental, all sensors are uniformly placed in the simulation area.
In order to present the EAPEA algorithm’s capabilities, we compare it against the SA and the QGA. All the runs of the EAPEA, SA and QGA algorithms were terminated after 150 generations. The range of the parameters of EAPEA, SA and QGA by the optimizing are presented as follows. The population size was set to 100. According to recommendations, the crossover possibility of EAPEA is picked as 0.95, the mutation chance of EAPEA is chosen as 0.08. In SA, The initial temperature is 400 °C, and the annealing coefficient is 0.98.

Fig. 1 to fig. 2 give out the communication energy consumption of the proposed EAPEA, SA and QGA scheme with 250 and 350 sensor nodes. The percentage of cluster heads is 14%. For every approach, we only select the best solution at each generation from the current population. All the results are averaged over 20 runs. It can be seen that the EAPEA method outperforms the SA and QGA method in both scenarios, which validates the advantages of EAPEA. The EAPEA method achieves 105.50J network communication energy consumption with 250 sensor nodes and 152.71J communication energy consumption with 350 sensor nodes. In comparison, QGA cannot achieve its optimal value and the communication energy consumption found by the QGA are 121.78J and 169.10J respectively. After 150 generations, the best result of SA are 135.34J and 180.61J, respectively.

Fig.1 and fig.2 also presents the convergence of EAPEA, SA and QGA during the generations. In the beginning, all the randomness have suggested good simulations. It is clear that the EAPEA then achieves better convergence rate than the SA and QGA. Meanwhile, SA and QGA have various local optima and very slow convergence. More specifically, the convergence speed of EAPEA is much faster than that of SA and QGA for 250 and 350 sensor nodes.

Finally, the computation time for EAPEA, SA and QGA are almost identical. The computation time for EAPEA, SA and QGA are 5.32s, 5.61s and 6.21s respectively for 250 sensor nodes. The computation time for SA and QGA desired slightly more time than the EAPEA, and EAPEA identifies a lower communication energy consumption than SA and QGA. For a large number of sensors, the entire simulation time will be longer. The computation time for EAPEA, SA and QGA are 7.14s, 7.85s and 7.92s respectively for 350 sensor nodes. Simulations reveal the superior performance of the represented EAPEA in both the communication energy consumption as well as fast convergence.

5. Conclusion
The new contribution of our study is that we describe an elite adaptive parallel evolutionary algorithm (EAPEA) for clustering problem in HDSN, which has not been considered previously. To demonstrate the capability of the EAPEA and the usefulness of the new adaptive operator and elite operator, the shown algorithm is tested by a fitness function. Simulations are carried out with EAPEA, SA and QGA. Results show that the communication energy consumption of the suggested EAPEA method decreased compared to the other two methods which means that the represented method reduces the communication energy consumption.

![Figure 1. Communication energy with 250 sensors with 14% cluster head nodes](image1)

![Figure 2. Communication energy with 350 sensors with 14% cluster head nodes](image2)
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References
[1] Zheng M, Chen S, Liang W and Song M 2019 NSAC: A Novel Clustering Protocol in Cognitive Radio Sensor Networks for Internet of Things. IEEE Internet of Things Journal 6 pp 5864-5865.

[2] Shivappa N and Manvi S S 2019 Fuzzy-based cluster head selection and cluster formation in wireless sensor networks. IET Networks 8 pp 390-397.

[3] Zhang H, Zhou X, Wang Z, Yan H and Sun J 2019 Adaptive Consensus-Based Distributed Target Tracking With Dynamic Cluster in Sensor Networks. IEEE Transactions on Cybernetics 49 pp 1580-1591.

[4] Neamatollahi P, Naghibzadeh M, Abrishami S and Yaghmaee M 2018 Distributed Clustering-Task Scheduling for Wireless Sensor Networks Using Dynamic Hyper Round Policy. IEEE Transactions on Mobile Computing 17 pp 334-347.

[5] Bahbahani M S and Alsusa E 2018 A Cooperative Clustering Protocol With Duty Cycling for Energy Harvesting Enabled Wireless Sensor Networks. IEEE Transactions on Wireless Communications 17 pp 101-111.

[6] Sun P, Wu L, Wang Z, Xiao M and Wang Z 2018 Sparsest Random Sampling for Cluster-Based Compressive Data Gathering in Wireless Sensor Networks. IEEE Access 6 pp 36383-36394.

[7] Pachlor R and Shrimankar D 2018 LAR-CH: A Cluster-Head Rotation Approach for Sensor Networks. IEEE Sensors Journal 18 pp 9821-9828.

[8] Kaur T and Kumar D 2018 Particle Swarm Optimization-Based Unequal and Fault Tolerant Clustering Protocol for Wireless Sensor Networks. IEEE Sensors Journal 18 pp 4614-4622.

[9] Ateş E, Kalayci T E and Uğur A 2017 Area-priority-based sensor deployment optimisation with priority estimation using K-means. IET Communications 11 pp 1082-1090.

[10] Li B, Zhou Z, Zou W and Li D 2012 Quantum Memetic Evolutionary Algorithm-Based Low-Complexity Signal Detection for Underwater Acoustic Sensor Networks. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 42 pp 626-640.