An Elite Adaptive Niche Evolutionary Algorithm for Duty Clustering Problem in SoWSN

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Abstract. The recent success of emerging low power wireless sensor networks technology has encouraged researchers to create novel duty cycle design algorithm in this area. Since "sensors are constrained in sensing capabilities", duty cycle design plays a crucial role in maximizing the point coverage rate, while most researches for duty cycle design are related to a duty cycle design algorithm. But unfortunately, the ideal duty cycle design requires an exhaustive search over all combinations of the allowed combinations. In this letter, we present a new elite adaptive niche evolutionary algorithm (EANEA) for duty cycle design problem in Service-oriented wireless sensor networks (SoWSN). In order to extend the network life cycle, we designed an objective function for SoWSN. We also give an EANEA which, depending on a powerful niche operator, blends the merits of both elite selection and adaptive adjusting for the channel assignment problem. Simulation results show that the shown algorithm can achieve a higher point coverage rate over genetic quantum algorithm (QGA) and Shuffled Frog-Leaping Algorithm (SFLA). Moreover, the optimization employs an elite selection to initialize the parameters and avoid local optima proficiently.

Keywords- Service-oriented wireless sensor networks (SoWSN); elite adaptive niche evolutionary algorithm (EANEA); duty clustering problem

1. Introduction
The significant advances of efficient software algorithms, micromanufacturing and wireless communications have made it feasible to equip small-size, low energy consumption, low storage, and fast response wireless sensors. [1-2] Service-oriented wireless sensor networks (SoWSN) composed of a group of sensor nodes having limited information acquisition, wireless communication, computation, and storage capabilities. [3-4] Each wireless sensor made up of four components, including the signals sensing component, the microprocessor component, the transceiver component, the data storage component and the small power source component. [5] SoWSN are emerging techniques in many areas such as tracking, military surveillance, medical diagnostic, environmental, commercial management, home automation and many other areas.

Recently, research is focusing on developing novel duty cycle design strategies in order to maximizing the point coverage rate in low power wireless sensor networks. [6] Sensor nodes mainly use tiny sensing
units and they are limited in sensing ability. Since "sensors are restricted in sensing capabilities", duty cycle design plays a crucial role in maximizing the point coverage rate, while most researches for duty cycle design are related to a duty cycle design algorithm. [7-8] The best duty cycle design problem with discrete variables is a NP-hard problem in its exact formulation. [9] While exhaustive exploit is recognized as one possible solution to duty cycle design problem, its computational complexity is too high to be adopted for practical real-time applications. Many randomness had been developed for this NP-hard problem including simulated annealing (SA) and particle swarm optimization (PSO) in heuristic algorithm.

In [10] WSN point coverage rate is studied by according to genetic quantum algorithm (QGA) strategy through a duty cycle design strategy. In their paper they maximize the point coverage rate without considering energy restriction. Nevertheless, the convergence speed is truly low since of the stationary parameters of the method. In [11] the authors present a duty cycle design scheme, the simulated annealing (SA). This paper focused on stochastic optimization the network efficiency with network restraints. However, only the detecting range is considered, and the search is prone to achieve stuck into local ideal and sensitive to initialization. In [12], duty cycle design strategy based on Shuffled Frog-Leaping Algorithm (SFLA) have been presented in order to maximize the point coverage rate in low power wireless sensor networks. This algorithm had proposed to perform well with small number of sensors and targets. However, the rate of convergence could not reach an acceptable point.

Genetic Algorithm (GA) is an adaptive and robust optimization and search approach which borrows the ideas of natural selection and survival of the fittest from natural evolution. Their robustness of explore in large exploit spaces and their domain independent nature motivated their applications in many fields. Recently, since the computation abilities of computers have become enormously enhanced, gas have been widely utilized in various areas of engineering.

Research on merging elite theory and "immune theory" has being carried out because the late 1990s and then new niche theory strategies are being researched. Niche theory has also been successfully applied in a lot of stochastic optimization applications. Based on the above studies, an elite adaptive niche evolutionary algorithm (EANEA) of SoWSN depending on elite theory is represented in this chapter. Hence, in this paper, an elite adaptive niche evolutionary algorithm (EANEA) in SoWSN is suggested to maximize the point coverage rate to meet the network efficiency. To speed up the convergence rate, the elite operator and adaptive operator operators are included while forming the individuals. The strategy mixes the merits of elite selection and an adaptive adjusting, and niche operator. This method can not only improve the global explore capability with elite selection, but also enhance the global explore capacity with adaptive adjusting. An adaptive adjusting approach is used to achieve better experiments and at the same time, avoid local optima.

The results are conducted based on EANEA, and the results are comparatively evaluated against the genetic quantum algorithm (QGA) and Shuffled Frog-Leaping Algorithm (SFLA). Simulation results demonstrate that the presented EANEA develops a good choice for achieving a higher point coverage rate over other QGA and SFLA schemes for SoWSN. EANEA has improved its performance for optimizing issues by combining the adaptive adjusting method and the improved optimizing helps to avoid local optima.

In this study, we employ the EANEA to a duty cycle design problem of SoWSN through simulations that seek to maximize the point coverage rate. In this study, an elite operator to genetic-based algorithms is proposed. To avoid premature convergence adaptive and niche operators are also applied. On the one hand, we show that an adaptive operator according to Boolean region can be naturally integrated with EANEA so that feasible solutions are completely searched. On the other hand, through the niche operation, the EANEA can overcome the premature issues of conventional GA. With these new operations, EANEA becomes a suitable global optimizing method to find best solutions without getting stuck in local optima. As in the duty cycle design problem, the novel operations of the EANEA is capable to create a feasible solution for SoWSN in a computationally acceptable time.
2. System Model

In this section, we have established an energy-efficient duty cycle system model under the constraints of the sensing radius and sensor battery energy. For example, there are $p$ sensor nodes and $q$ objects to be monitored in a sensor network, and the monitoring relationship between them can be expressed as the matrix $M$ in formula (1).

\[
H = \begin{bmatrix}
h_{1,1} & h_{1,2} & \cdots & h_{1,Q-1} & h_{1,Q} \\
h_{2,1} & h_{2,2} & \cdots & h_{2,Q-1} & h_{2,Q} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
h_{p-1,1} & h_{p-1,2} & \cdots & h_{p-1,Q-1} & h_{p-1,Q} \\
h_{p,1} & h_{p,2} & \cdots & h_{p,Q-1} & h_{p,Q}
\end{bmatrix} \quad \left(h_{p,q} \in \{0, 1\}\right) \tag{1}
\]

The relationship between the $p$-th sensor and the $q$-th monitored target is represented by $h_{p,q}$. When the $q$-th target can be monitored by the $p$-th sensor, $h_{p,q} = 1$, otherwise $h_{p,q} = 0$.

Because the battery power carried inside each sensor is limited, one sensor can work at most $L$ rounds, so the maximum working time in a SoWSN with $P$ sensor nodes is $PL$ rounds. The duty cycle matrix can be represented by the matrix $N$ in equation (2).

\[
K = \begin{bmatrix}
k_{1,1} & k_{1,2} & \cdots & k_{1,P-1} & k_{1,P} \\
k_{2,1} & k_{2,2} & \cdots & k_{2,P-1} & k_{2,P} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
k_{p-1,1} & k_{p-1,2} & \cdots & k_{p-1,P-1} & k_{p-1,P} \\
k_{p,1} & k_{p,2} & \cdots & k_{p,P-1} & k_{p,P}
\end{bmatrix} \quad \left(k_{i,j} \in \{0, 1\}\right) \tag{2}
\]

In the matrix $N$, $n_{ip}$ represents the duty cycle situation of the $p$-th sensor in the $i$-th round. When $k_{i,p} = 1$, it means that the $p$-th sensor is in the open working state in the $i$-th round. Otherwise $k_{i,p} = 0$.

Whether the $q$-th target can be monitored by the $p$-th sensor node in each round can be represented by the matrix $KH$

\[
KH = \begin{bmatrix}
\sum_{p=1}^{P} k_{1,p} h_{p,1} & \sum_{p=1}^{P} k_{1,p} h_{p,2} & \cdots & \sum_{p=1}^{P} k_{1,p} h_{p,Q-1} & \sum_{p=1}^{P} k_{1,p} h_{p,Q} \\
\sum_{p=1}^{P} k_{2,p} h_{p,1} & \sum_{p=1}^{P} k_{2,p} h_{p,2} & \cdots & \sum_{p=1}^{P} k_{2,p} h_{p,Q-1} & \sum_{p=1}^{P} k_{2,p} h_{p,Q} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\sum_{p=1}^{P} k_{p-1,p} h_{p,1} & \sum_{p=1}^{P} k_{p-1,p} h_{p,2} & \cdots & \sum_{p=1}^{P} k_{p-1,p} h_{p,Q-1} & \sum_{p=1}^{P} k_{p-1,p} h_{p,Q} \\
\sum_{p=1}^{P} k_{p,p} h_{p,1} & \sum_{p=1}^{P} k_{p,p} h_{p,2} & \cdots & \sum_{p=1}^{P} k_{p,p} h_{p,Q-1} & \sum_{p=1}^{P} k_{p,p} h_{p,Q}
\end{bmatrix} \tag{3}
\]

If any value of 0 appears in a row, it means that there are individual targets among the $q$ targets in this round that are not detected by other sensors, and the full coverage of $q$ targets cannot be completed. Then
the lifetime of the wireless sensor network can be expressed as the number of rows in this row minus one. Therefore, the mathematical model of the duty cycle problem is as follows:

Objective: \[ f(L) = row\_zero(HK) - 1 \] (4)

subject to: \[ \sum_{i=1}^{HK} k_{i,p} \leq L, p = 1 \ldots P \] (5)

The constraint condition of formula (5) indicates that the battery power of each sensor can only support \( L \) rounds of work at most.

3. An Eana For Duty Clustering Problem In Sowsn

EANA produces new individuals through randomly combining the good features of existing individuals. EANA iteratively searches for an optimum individual by based on genetic operations. The different steps of the EANA process are as follows. The flowchart of the represented stochastic optimization operation is presented as follows. A) initialize the individuals of EANA. B) select individuals to create novel mating pool. C) perform crossover and mutation for all individuals. D) evaluate all objective values for all individuals. E) Let novel individuals compete in order to determine superiority. Go to step 2 and repeat this loop until the termination conditions are achieved. The essential components of EANA are described as follows.

3.1 Solution Coding

In this section, the presented individual representation will be discussed. The solution to the duty cycle design problem is known as an individual. Each individual represents a prospective solution to the duty cycle design problem. Each individual is coded as a Boolean string via the survival of the string stationary by its objective value to maximize the point coverage rate. The Boolean encoding scheme actually exerts a restriction on individuals so that they can reflect the duty cycle methods. In EANA, every variable is encoded to an individual. We employ a variable as an individual to imply a solution to the duty cycle design problem. Each solution is characterized by an individual and every individual contains some genes. The coding we implemented is the Boolean gene model, in which a gene represents a sensor node is active or not. Each gene in the individual represents the duty cycle method for the duty cycle design problem.

3.2 Iteration of Initial Community

Unlike other genetic methods, EANA settle a community of solutions that competes for surviving at any evolutionary iteration. In EANA, a community pool of individuals has to be installed, and it can be randomly set initially.

EANA solves the stochastic optimization problem based on a fixed number of solutions (called the group size). Generally, with a very small group only a reduced para graph of the explore region is explored, thus improving the risk of prematurely converging to a local extreme. A number of individuals are created in each generation of group. For ensuring the global convergence, a novel generation method of the children is proposed. Before starting the EANA, the group's individuals had their genes randomly generated from a random number generator based on a uniform distribution. Starting with an initial pool of community constructed randomly, the individuals in the current community have a certain chance to reproduce their children. The maintenance individual is randomly developed using the community size. Usually, a simple EANA is mainly composed of three operations: selection, crossover, and mutation. The community is improved using these EANA operations. While EANA exploit the optimum solutions for improvement according to objective functions, they also explore the search space according to the probabilities of mutation and selection.

3.3 Selection

A particular group of individuals is chosen from the community to be parents. Selection is a genetic operation that chooses an individual from the current iteration’s community in order to include in the next
iteration’s mating pool. For the better objective value, the corresponding individuals will be picked for the mating pool for the process of crossover. The individuals that have higher objective values will have a higher chance to be picked. In general, individuals with a high objective value ought to be picked and at the same time individuals with a low objective value ought to be discarded. A value-based roulette wheel schema is used for selection. To maintain diversity and avoid settling to local optima, some individuals with objective values are randomly selected by roulette wheel. In result, the probability of premature convergence decreases relatively and the preservation of individual is improved. It is worth noting that only individual individuals can be selected for crossover. The possibility of an individual being picked is using the objective value. Repeat these steps until no more selections are demanded for the upcoming iteration. And the new community in the next iteration is produced by selecting the superior members in the children or parent community of the current iteration. This is the selection procedure. This can ensure the continuous development of the personal community. After many iterations, the process of discussion simulates the extinction of individuals who are more suitable for the environment and those who are least suitable for them.

3.4 Crossover
After selecting the variables from the current iteration community, the next step is to generate a second iteration community of solutions from those chosen through stochastic operations: crossover and mutation. The crossover operator is the most important section in EANEA. This operation exchanges the individual variable of two picked individuals starting from a random index. The genes of both parents are exchanged to produce the next generation. A number of variations on crossover operations are frequently used, such as 1-point, 2-points, and uniform crossover. In EANEA, the objective value based single-point binary crossover is modified to meet the proposed representation, which is defined as next. Two positions in the two individuals are selected at random. The crossover operation causes random swapping of two portions of individuals. The crossover possibility is how often a crossover will be performed; the probability is defined to 0.9 in EANEA. After the crossover is performed, the novel individuals are added to the new group set.

3.5 Mutation
To maintain diversity and avoid premature convergence, mutation is utilized to the newly developed group. With mutation operator, a new generation of EANEA is achieved. In the shown mutation process, a number of genes are randomly picked among the newly produced group. The mutation operator randomly alters some values in an individual with a possibility fixed by the mutation rate. Mutation operation is done by randomly selecting any individual with a prespecified possibility. New individuals are also produced by randomly changing a few genes of an existing individual. Mutation is placed by stochastically selecting individuals from the community with a small mutation probability, then randomly selecting a gene or some bits of the selected individual and inverting its value from 1 to 0 or from 0 to 1. Sometimes a mutation on an unfit individual may create a very meet individual. Mutation occurs during evolution based on the probability defined by the mutation possibility. The mutation probability should typically be set to a fairly low value. Each individual had a given probability of being mutated, for the EANEA this possibility is set to 0.05. In EANEA, preserving the diversity is important.

3.6 Evaluation
The objective value is the only information that APCEA employs while investigate for possible solutions. In the give context, the objective value of a solution variable depends on the point coverage rate. Here, the objective value is the point coverage rate of the duty cycle method. In this way, the higher the objective value, the better the individual is. During each iteration, the individuals are evaluated, using some measures of objective function. The objective function is used to evaluate the quality of the individuals in the community. The EANEA evaluates the objective value of every individual with respect to objective functions such as the point coverage rate in the duty cycle design problem. In this paper, builds the mechanism for evaluating the objective value of every individual (possible solution to the
problem) and, therefore, serves as the fitness function of the suggested EANEA method. The objective value is evaluated based on the objective function according to their point coverage rate. As the objective is to decrease the point coverage rate, then the lowest value in (4) corresponds to the best individual. In EANEA, from iteration to iteration, the ideal individual is always preserved in a procedure called elitism. It is an operation that leaves only some individual candidates with the highest objective value among the individuals and deletes the other individuals.

Termination is a criterion by which the EANEA decides whether to continue investigate or to stop the exploit. The cycle is carried out by repeating each of the aforementioned processes to generate the fittest individuals. The cycle is repeated until a predetermined number of times or a solution with a predefined objective value threshold is achieved. When the objective value reaches a particular threshold, EANEA will terminate based on the number of iterations. After various generations, the algorithms converge to the ideal individual, which represents the optimum solution.

4. Simulation and Discussion

In this section, we will test the performance of the represented EANEA method with the QGA and SFLA method for duty cycle design in SoWSN. To validate and test the performance of the represented EANEA technique to the duty cycle design problem in SOWSN, simulations are executed. The objective value of randomness has been computed according to formula (2) in paragraph ii. In simulation, all sensors are initially investigated uniformly distributed in the monitoring region. The sensing range is 500m for all the sensors. For comparison, we also test QGA, and the SFLA. The stop condition being stationary by the number of iterations, equivalent to 100. EANEA is used and a community of 40 individuals is employed at every iteration. If not particularly stated, all results for EANEA use the same parameters settings as the community size 40, the interval for the mutation rate 0.05.

![Figure 1. The network lifetime.](image)

Figure 1 (a) to Figure 1 (b) reveal the of the network lifetime of the duty cycle design depending on the EANEA, QGA and SFLA with 80 sensors and 30 targets, 100 sensors and 40 targets. Only the global optimal solution at each iteration is recorded. For all strategies, we conducted 100 independent simulations. As the figures shows, it can be obviously obtained that EANEA can gain even better solutions than QGA and SFLA. In Figure 1 the network lifetime of EANEA method is 4.01% and 5.21% longer than that of QGA and SFLA respectively. In Figure 2 the network lifetime of the EANEA method is 5.53% and 9.16% longer than QGA and SFLA respectively.

Compared with QGA and SFLA, the proposed EANEA has a faster convergence speed. The total computation time can dramatically be reduced by employing EANEA. In such a scenario, the aforementioned EANEA is powerful to the SOWSN system, as the computational time of EANEA is all lower than the QGA and SFLA. This indicates that the suggested EANEA employing elite operator and adaptive operator is more powerful for the duty cycle design in the SOWSN system. Additionally, the results identify that EANEA is more robust to duty cycle design than the other randomness. Simulation
results reveal that the suggested EANEA is suitable and can greatly enhance the network lifetime in duty cycle design issues.

5. Conclusion
In this study, we will employ an elite adaptive niche evolutionary algorithm (EANEA) to settle the duty cycle design problem in SoWSN. First, we formulate an objective function to extend the network life cycle under multiple constraints. To show the advantages of EANEA, experiments are conducted for the duty cycle design problem and performance comparisons are made with QGA and SFLA. Simulation experiments present that the proposed EANEA method achieves a higher point coverage rate than QGA and SFLA, and its complexity is much lower than that of previous methods. Adaptive adjusting is used to avoid local optima and enhance upon swarms to duty cycle design issues.

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