Combining the Social harmony search algorithm and harmony search algorithm based clustering protocol for better optimization in WSN

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Abstract-*In wireless sensor networks many protocols has been proposed and implemented in order to transfer the data from source to sink node with low energy power consumption and prolong their network lifetime. But many of the methods have been failed in prolongation of network lifetime. So in order to overcome the shortcomings of previously proposed protocols, meta-heuristic mehod is adopted in order to optimize different optimization problems,by combining social harmony search algorithm and harmony search algorithm the better optimization and results can be achieved. To improve the performance of the HS algorithm, SHS algorithm uses the principles of the normal distribution and adjusts the value of the decision variables selected from HM.In this Social harmony search the probability of applying PAR is considered 100 percent during all iterations.*

Keywords-Harmony memory considering rule,Metaheuristic, pitch adjusting rule,social harmony search

1. Introduction

Harmony Search (HS) was first developed by Zong Woo Geem et al. in 2001 [21], though it is a relatively new metaheuristic algorithm, its effectiveness and advantages have been demonstrated in various applications.Metaheuristic algoritms are higher-level heuristic algorithms. Here, ‘*meta*-’means ‘higher-level’ or ‘beyond’, so metaheuristic means literally to to find the solution using higher-level techniques through certain error and trial process.The metaheuristic algorithms such as; genetic algorithms simulated annealing, ant colony optimization, particle swarm optimization, bee algorithms, and firefly algorithms [1]. The main reasons that metaheuristic algorithms are popular than traditional optimization methods such as gradient-based methods among researchers are: algorithm simplicity, ease for implementation, and solution diversity [2]

There are two important components in modern metaheuristics, and they are: intensification and diversification, and such terminologies are derived from Tabu search [5]. For an algorithm to be efficient and effective, it must be able to generate a diverse range of solutions including the potentially optimal solutions so as to explore the whole search space effectively, while it intensifies its search around the neigbourhood of an optimal or nearly optimal solution. In order to do so, every part of the search space must be accessible though not necessarily visited during the search.The evolutionary process of solutions in HS algorithm can be summarized as follows:

1.1Initialization

This algorithm produces more number of solution in randomized manner.These solutions are stored in a memory namely Harmony Memory (HM). Harmony Memory Size (HMS) showing the number of solutions is considered low because the HM simulates the short-term memory of musicians. Consider an optimization problem having N number of decision variables and the lower and upper bounds of each decision variable are *LBi* and*UBi* , respectively. Then the HM is filled as follows $x_i^j = LB_i + r * (UB_i – LB_i), 1 \le i \le N$
$j = 1,2,.......HMS$ where $r \sim U(0,1)$.

1.2 Improvisation

HS generates a new solution using its three rules: RS, HMC, and PA rules. Value of each decision variable may be selected either using the HMC rule with probability of HMCR (harmony memory considering rate) or using the RS rule with a probability of (1-HMCR). Then with probability of (HMCR × PAR (pitch adjusting rate)) PA rule is applied to change the values of those decision variables selected using the HMC rule.In HS algorithm it is difficult to balance between global and local search .In HS algorithm the PA rule is not effectively used. Mahdavi et al. [8] proposed a new variant of harmony search, namely Improved Harmony Search (IHS) algorithm. Dynamically increasing pitch adjusting rate and decreasing the bandwidth (Bw), Mahdavi et al. tried to improve HS algorithm performance. The serious drawback of the IHS is in early iterations where the value of PAR is low. Hence, PA rule cannot satisfy the need of the exploration of the algorithm in early iterations and it may result in a premature convergence.

To eliminate this drawback of IHS Taherinejad [9] proposed a new variant of harmony search, namely, the Highly Reliable Harmony Search (HRHS) algorithm. The key difference between the HRHS and the IHS is in the way of adjusting PAR. To eliminate the mentioned drawback of IHS, HRHS dynamically decreases PAR. It means in the early iterations the value of the PAR is high and it is gradually decreased. The drawback of the HRHS algorithm is in final iterations where the value of the PAR is near to zero which may result in stagnation in the algorithm convergence performance. Geem and Sim [10] recently conducted an investigation on parameter-setting-free harmony search algorithm which supports Taherinejad's assertion.

The social HS algorithm adjusts the new harmony according to the following equations:

$$N(x_i', \sigma_i')$$

Where x_i' is selected value for the *ith* decision variable using HMCR *i* σ′ standard deviation of the *ith* decision variable computing using Eq. (2)N(x_i', σ_i') denotes a random number normally distributed with mean value x_i' and variance σ_i'

$$\sigma_i' = \xi \times \sum_{j=1}^{HMS} \frac{\left| x_i' - x_i^j \right|}{HMS - 1}$$

Where *HMS* is the harmony memory size, x_i^j is the value of the *ith* decision variable in the *jth* solution ($1 \le j \le HMS$) and($1 \le i \le N$) andξ a fixed value.

1.3 Analysis of HS Algorithm's rule

The exploration and exploitation components of the algorithm, which are mandatory parts of any metaheuristic algorithm, can be realized and the efficiency of their balancing can be investigated.

2. Comparison of SHS and HS

The key difference between social HS and earlier methods of the HS is in the way of adjusting a new harmony found by the first rule of harmony search (memory consideration). To improve the performance of the HS algorithm and its derivations, social HS algorithm uses the normal distribution for adjusting the new harmony found by the memory consideration rule, then one should check whether the current decision variable value violates the variable bounds or not.

If it does, it should be reset to the previous position. When the harmonies search in the feasible space to find the solution, if any one of them searches into the infeasible region, it will be forced to come back to the previous position to guarantee a feasible solution. The harmony which comes back to the previous position may be closer to the boundary at the next iteration. This allows the harmonies to search to the global minimum with a higher probability.

2.1 Harmony Memory Considering rule

The metaheuristic algorithms is elitism which means employing parts of current best solutions to generate new solutions.Elitism is regarded as explotation component in metaheuristic algoritms.Its major aim is to increase the convergence speed.Using HMC rule the HS algorithm applies elitism to generate new solutions.

This rule, which is applied with HMCR probability, ensures that parts of current best solutions, which are stored in the HM, will be considered as elements of new solution. The high degree of elitism can bring about a premature convergence which leads metaheuristic algorithms to get stuck on local optima. Three concepts tries to escape from this premature convergence.

The first one can be named parallelism; in each generation, utilizing the solutions stored in the HM, in parallel, the HS generates a new solution. It means the elements of each current best solution have a chance to be considered as elements of the new solution. Such a parallelism makes the HS algorithm works better than Genetic Algorithms (GA) [12]. HS algorithm using such a concept (parallelism), which works as a exploration component, can control the amount of HMC rule's elitism better than the one that the crossover procedure does in GA.

To generate values of decision variables of the new solution, the algorithm applies either HMC rule or RS rule. Hence, the possibility of selecting the value of all decision variables just using HMC rule is low; it is not impossible. To select the value of all decision variables just usong HMC rule is very low. RS rule is another one which can help the algorithm to escape from premature convergence due to HMC rule's elitism.

The HS algorithm uses efficient concepts and rules to control the elitism of HMC rule, choosing a high value as probability of applying HMC rule (HMCR=0.95 ~ 0.99), not only doesn't lead to a premature convergence but also increases the convergence speed of the algorithm and can result in better final solutions.

2.2 Random Selecting Rule

RS rule is completely a random rule and works as an exploration component in HS. In fact, it is used to increase the diversity of the new solutions and works as a global search.The RS rule is applied rule in early iterations may be effective due to preventing the algorithm to get stuck on local optima.In final iteration its HMC and PA rules help it to intensify its earch in this region,RS rule may disturb the algorithm's performance. decreasing the probability of applying RS rule during the iterations of the algorithm can bring about better results. Overall, choosing a low value as probability of applying RS rule, *0.01 ~ 0.05*, may be a reasonable choice. The probability of applying HMC rule will be increased which as mentioned earlier result in better performance of the algorithm.

2.3 Pitch Adjusting Rule

The PA rule is one of the most important rules in HS and it is considered as an exploration component in HS.This rule forces the algorithm to add a low fixed value (bw × U(-1, 1)) to the values of those decision variables selected from HM. PA rule is considered as an exploration component, it forces the algorithm to concentrate its search around the current best solutions. PA rule is considered as a local search in the HS. Behind the concept of PA rule is valuable, it may bias the search of the algorithm toward local optima and makes a premature convergence. It means, in early iterations the value of decision variables selected from HM must be changed too much. Vice versa, in final iterations these values must be changed slightly.In this way,PA rule in early iterations will work as a global search and in final iterations will work as a local search.

In HS, if we choose a low fixed value for *bw*, PA rule will bring about a local search and vice versa, if we select a high fixed value for it, PA rule will result in a global search through all iterations. Hence, it can be said that PA rule is suffering from the lack of an efficient balance between exploration and exploitation. In fact, in the early iterations the algorithm should have the high exploration with the low exploitation, and gradually reduce exploration while increasing exploitation simultaneously to create an efficient balance between exploration and exploitation.

3. Results and Discussions

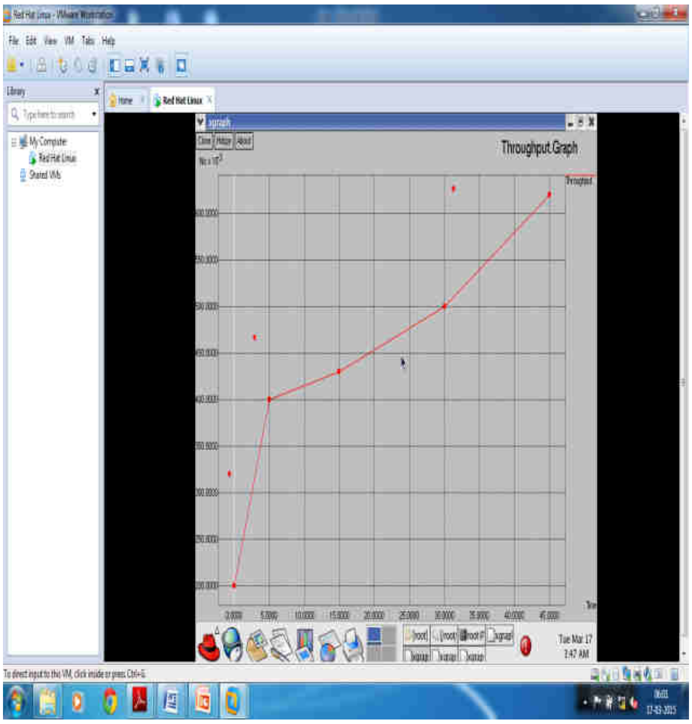

Fig: 1. Throughput

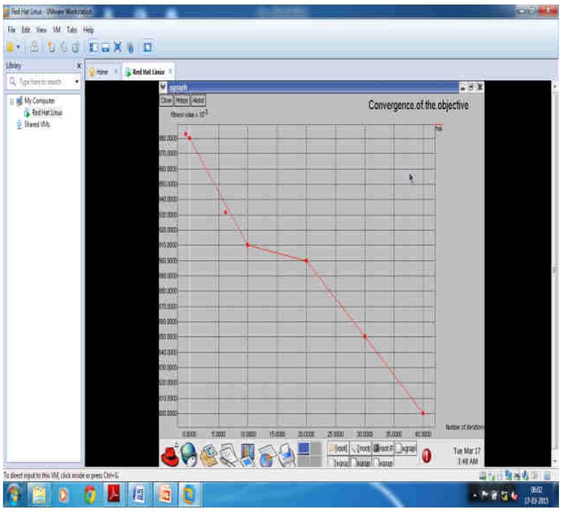

Fig.2 .Convergence of the objective

The above fig.1.and fig.2. for the throughput and convergence of the objective which is obtained for HSA.When HSA is combined with SHSA it will produce still more better results.

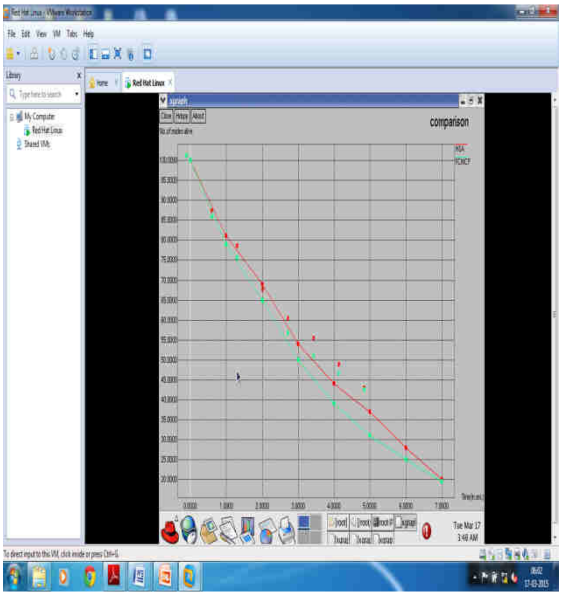

Fig .3 . Comparison graph of HSA and FCMCP

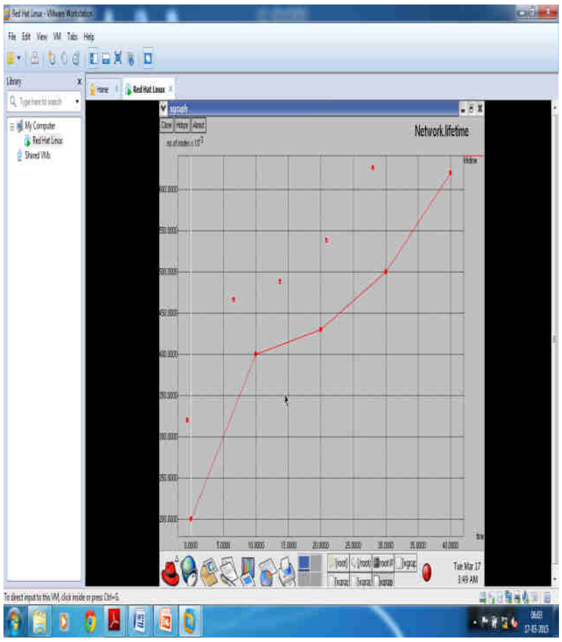

Fig .4 . Network lifetime

The above fig.3.and fig.4. proves that by using the HSA the network lifetime is increased and number of active nodes is also increased.

Conclusion

It maintains a good balance between diversification and intensification in the pitch adjustment section of HS. To achieve this goal a normal distribution rule is employed. Since variance of normal distribution for each decision variable is related to diversity of their previous value sorted in the harmony memory, their diversities are high in early iterations and gradually decrease when the algorithm reaches its final iterations. Hence, it makes global and local search in early and final iterations, respectively. Besides, it shown that applying the PA rule to HMC rule is a great idea, because it helps the algorithm to make a proper balance between its exploration and exploitation. Along with the PA rule, the parallelism and RS rule are other concepts helping the algorithm to control the elitism of the HMC rule. However, RS rule in final iterations may disturb the algorithm performance by changing its convergence trajectory. Hence, if we could remove it in final iterations or using a proper PA rule, which works as a global search in early iterations and local search in final iterations, could cover the role of the RS rule in HS algorithm, we may achieve better results.

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