MCRO-ECP: Mutation Chemical Reaction Optimization based Energy Efficient Clustering Protocol for Wireless Sensor Networks

Ravuri Daniel[1*] and Kuda Nageswara Rao[2]
[1] Department of Computer Science, Faculty of Technology, Debre Tabor University, Ethiopia
[danielravuri@gmail.com]
[2] Department of Computer Science & Systems Engineering, Andhra University College of Engineering (A), Andhra University, Visakhapatnam, India
[knraoauce@andhrauniversity.edu.in]
*Corresponding author: Ravuri Daniel

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Abstract

Wireless sensor networks encounter energy saving as a major issue as the sensor nodes having no rechargeable batteries and also the resources are limited. Clustering of sensors play a pivotal role in energy saving of the deployed sensor nodes. However, in the cluster based wireless sensor network, the cluster heads tend to consume more energy for additional functions such as reception of data, aggregation and transmission of the received data to the base station. So, careful selection of cluster head and formation of cluster plays vital role in energy conservation and enhancement of lifetime of the wireless sensor networks. This study proposes a new mutation chemical reaction optimization (MCRO) which is an algorithm based energy efficient clustering protocol termed as MCRO-ECP, for wireless sensor networks. The proposed protocol is extensively developed with effective methods such as potential energy function and molecular structure encoding for cluster head selection and cluster formation. While developing potential functions for energy conservation, the following parameters are taken into account: neighbor node distance, base station distance, ratio of energy, intra-cluster distance, and CH node degree to make the MCRO-ECP protocol to be potential energy conserver. The proposed protocol is studied extensively and tested elaborately on NS2.35 Simulator under various senarios like varying the number of sensor nodes and CHs. A comparative study between the simulation results derived from the proposed MCRO-ECP protocol and the results of the already existing protocol, shows that MCRO-ECP protocol produces significantly better results in energy conservation, increase network life time, packets received by the BS and the convergence rate.

Keywords: Clustering, Wireless sensor network, Chemical reaction optimization, Mutation, Energy efficient.

1. Introduction

The recent progress in Information Tech (IT) and Integrated Circuits (IC) fields has led to the development of low cost and compact sensor nodes. An integral of Internet of everything (IoE) is Wireless sensor network (WSN) and it enables data sharing amongst billions of devices, with higher user control. WSN comprises of large number of sensor nodes arranged on ad-hoc basis for observation and interaction with the physical world. Every sensor node comprises of four components: sensors, microcontrollers, power suppliers and transreceivers. The prime function of the sensors present in the sensing unit it to measure and caluculate the physical parameters from the real worls such as temperature, pressure, humidity, vibration, acoustic, infrared signals and vehicular movements, etc.,. The value mesured by the sensing unit is received and processed by the processing unit and then it is sent to the base station (BS) through either single-hop or multi-hop communication. WSNs are popularly used in tracking and monitoring applications that are usually deployed in areas like milatry surveillance, disaster management, agriculture, healthcare, automation industry, inventory control, etc., where the intervention of humans is not very feasible. The major challenge encountered in WSN design is utilization of energy, bandwidth and memory. To replace or recharge the batteries of the sensors becomes almost impossible because of the remoteness of the location. Also the cost of transmission almost exceeds the costs of the sensing and processing units in WSNs. Therefore, an effective protocol with an energy effecient data transmission needs to be developed to send data from sensor nodes to the respective BS to enhance the lifetime of the network. Extensive studies are carried out in clustering, as it is well known for optimization of energy conservation in wireless sensor networks [1,2,3,4]. In the process of optimization the organising of sensor nodes into groups are called as clusters. In the cluster a head is selected which is referred as the clusted head (CH) and other snesor nodes are referred as cluster members (CM). The typical clustering architecture of WSNs is shown in **Fig. 1**. The two types of traffic in clustering are intra-cluster and inter-cluster. Intra-cluster traffic is the data transmission that happens within the cluster and Inter-cluster traffic is the data transmission that happens amongst the cluster. The role of the members in a cluster (CM) is to measure the real world parameters and send the measured values to their resapective CH. Once the CH receives the data, it aggregates (evades redundant data) and transmits the data aggregated to the BS either directly or through CHs which get as intermediate. The entire process is systematic in which the cluster members transmit data to the CH and the CH transmits to the BS.

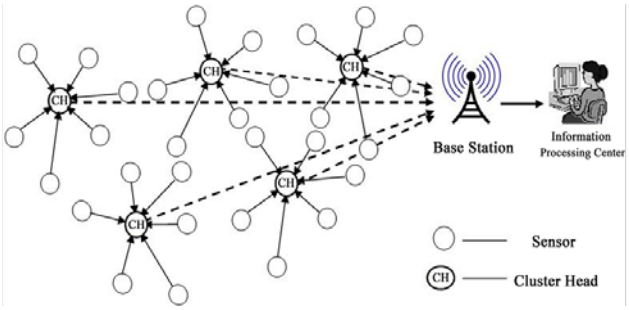

Fig. 1. Architecture of clustering in wireless sensor network.

Difficulty arises in choosing the CH which becoms an NP-hard problem, as the selection of 'm' CHs among 'n' sensor nodes provides ${}^{n}C_{m}$ possibilities. Also the computational complexity

differs exponentially for the large scale networks. Likewise, during cluster formation, in a given 'n' sensor nodes and 'm' CHs, if each sensor node has 'p' CHs as average in the communication range, then the valid number of assignments are p^n. The computational complexity changes exponentially, even here. Classical approaches are found wanting in resolving such type of situations.Various optimization approaches have been used to solve clustering problems in wireless sensor networks. Evolutionary algorithms, inspired by the biological evolution and social behaviour of organisms are the most powerful among optimization techniques. Genetic algorithms (GA) [5, 6] were developed based on the natural process of evolution. Particle swarm optimization (PSO) [7] was inspired by the social behavior of bird flocking. Ant colony optimization (ACO) [8] resembles PSO based on the capability of ants to find the shortest route between their nest and a food source. Artificial bee colony [9] was inspired by the echolocation behaviour of bees. Harmony search [10] was based on the natural musical performance of a musician searching for an optimal state of harmony. A recent study, new chemical reaction inspired evolutionary algorithm named “chemical reaction optimization (CRO)” [11] was sighted in literture. CRO is a low latency algorithm that represents the interaction of molecules in chemical reactions in order to reach a low energy stable state.

In wireless sensor networks, very few instances have been sighted using CRO, however, an effective version of CRO is the real-coded chemical reaction optimization (RCCRO) [12], which can process a large set of concurrent problems. HP-CRO [13], an algorithm based on PSO and CRO, produces more distinguished results compared to RCCRO. However, orthogonal chemical reaction optimization (OCRO) [14] algorithms have proved to be the best when compared with RCCRO and HP-CRO. OCRO is efficient in solving high-dimension functions but found wanting in respect of low-dimensional functions. Mutation chemical reaction optimization (MCRO) algorithm [15] was observed to be efficient in solving both the high and low dimensional functions. The convergence rate of MCRO is very high when compared with the traditional versions of CRO.

The proposed algorithm is based on a recently developed process for chemical reaction optimization (CRO) and two alteration operators like turning operator and mutation operator. Three types of mutation operators like uniform, nonuniform, and polynomial [16] were combined with chemical reaction optimization and turning operator to find the most appropriate framework. The best solution among these three options was selected to be a mutation chemical reaction optimization algorithm for global optimization. The current proposition is an energy efficient clustering based on mutation chemical reaction optimization (MCRO) algorithm termed MCRO-ECP. The proposed protocol combines CRO with a turning operator and a mutation operator. This meathod provides a solution to estimate the combined performance of the three types of mutation operators. (uniform, non-uniform and polynomial). The proposed MCRO-ECP could be a better choice for such NP-hard problems as it is convenient for implementation, high in quality of solution, feasible to escape from the local optima and quick in convergence.

This study proposes a new protocol with a combination of two phases, selection of the cluster head (CH) amongst the nodes and formation of the cluster using a single algorithm MCRO. This proposal is novel and almost first of its kind in WSNs. The first phase efficiently selects the optimum number of CHs and an effective location among the normal sensor nodes. Once the selection of optimal CHs is done the second phase progresses where the organization of cluster takes place. After the selection of optimal CHs, in the second phase– the cluster formation, member sensor nodes get assigned to the CHs based on the derived linear programming model as a cost function. MCRO-ECP is designed with potential molecular

structure encoding schemes. Potential energy functions are developed considering parameters as those of neighbour node distance, base station distance, energy ratio, intra-cluster distance and CH node for energy efficy. The protocol is tested NS 2.35 realistic platform extensively to demonstrate its superiority over other existing algorithms. The features of MCRO-ECP are listed below.

- Adoption of Linear programming models for selection of CHs and cluster formation.
- Introduction of a new protocol that combines CRO with a turning operator and a mutation operator. This Enabling quick convergence and capability to break out from the local optima resulting in efficient data transmission and enhanced network lifetime.

The paper is presented in four sections. Section 2-agives review of related work. Section 3-the proposed approach of MCRO-ECP. Section 4-simulation results discussion. Section- 5 is conclusions and recommendations.

2. Related Work

In the recent years extensive studies have been carried out in the development of clustering protocols. for WSNs. This section details clustering protocols based on brute force and nature inspired approaches.

2.1 Brute Force Approaches

LEACH[17] is a popular distributed clustering protocol in which the CH gets elected on the basis of probability. The lacuna of this algorithm is that there is a chance of a CH with very low energy level to get elected, therefore the CHs will die quickly which will further degrade the performance of the network. Many improvements to LEACH [18, 19] and hierarchical protocols [20, 21] have been proposed, with emphasis on improved network life. Such improvements were found to be unsuitable for large size networks. Likewise LDC [22] and GLBCA [23] have also proved to be unsuitable in view of improper clusterformation and high execution times respectively.

2.2 Nature Inspired Approaches

Large number of clustering protocols are developed and proposed based on nature inspired approaches. Centralized leach (LEACH - C)[24] is developed and implemented with simulated annealing meathod. LEACH-C performs better than LEACH. Tillett et al., [25] have proposed a PSO approach to select the optimal location of CHs. However, it completely ignores the distance to the base station. Enan et al., [26] have presented an energy-aware evolutionary routing protocol (EAERP) for dynamic clustering. Even here possibilities of a node with low energy getting nominated exist. P.C.Srinivas Rao et al., [27] have proposed a PSO based cluster head selection protocol, which also does not consider residual energy levels of the sensor nodes during cluster formation. Latiff et al., [28] proposed an energy based CH selection using PSO-C by using diferent parameters such as ratio of total initial energy and average intra-cluster distance of all nodes to the total current energy of the all CHs. The main drawback of this algorithm is that, it assigns the non-cluster head nodes to the adjacent CH in the cluster formation phase, resulting in decreased network lifetime. Base station distance (which plays a very important role in reducing energy consumption, is not factored) in direct communication of CHs to BS. Buddha and Lobiyal [29] proposed a energy aware cluster head selection protocol using PSO which completely ignores the cluster arrangement stage. In [30],

the proposed evolutionary method for load balanced algorithm. The limitation of this protocol is selected the cluster heads randomly, which causes energy inefficiency of the network. Kuila P. et.al [31], proposed differential evolution protocol for clustering in WSNs. Here too the base station distance is ignored in cluster formation and the CHs are selected randomly, which may lead to energy depletion. P.C.Srinivasa Rao et al., [32] proposed an energy efficient clustering protocol based on chemical reaction optimization approach.

3. Proposed Approach: MCRO-ECP

First time in WSN, a mutation chemical reaction optimization (MCRO) based cluster head selection and cluster formation is proposed. The operation is divided into two sections the setup phase and the steady state phase. Each round of communication commences with a setup phase (when the clusters are organized by MCRO), followed by a steady state phase (when CMs and CHs communicate) using TDMA protocol. Aggregated packets at the level of CH are routed through intermediate CHs to the BS using CSMA/CA protocol.

A mutation chemical reaction optimization (MCRO), which uses CRO and two adjustment operators, turning operator and mutation operator, generates various molecular structures to produce high quality results and accelerate convergence. Details of turning operator and the mutation operator are detailed as follws.

3.1 Turning Operator

Turning operator is a new operator that is merged into a sub algorithm named neighborhood search operator. Neighborhood search operator is used in three types of elementary reactions:

1. Intermolecular ineffective collision,
2. On-wall ineffective collision, and
3. Decomposition

to transform the molecular structure from the neighborhood of the operand [33]. The new molecular structures of the solution are calculated as Equation (1) and turning operator is generated once for an objective function (f_i) by using Equation (2). This new operator can improve the optimal quality and reliability of the algorithm:

$$nS=(pS+r)*s)*T(f_i) \quad (1)$$

where, nS is new Structure, pS is previous Structure, r is Random Gaussian, s is the stepSize, and T is the turning Operator.

$$T(f_i) = \{\text{random interval } [1, e^{-300}]\}\ ,\ (1 \le i \le 23) \quad (2)$$

3.2 Mutation Operator

Mutation operator is migrated into MCRO to improve solution diversity and accelerate convergence by generating various molecular structures. These structures are generated by using the processing mutation formula. This action increases the chance of finding the global optimal solution and avoids being trapped into a local optimal solution; therefore,-accelerates convergence. In our research, the best mutation operator that matches our algorithm was selected the mutation operators (uniform, nonuniform, and polynomial). Uniform and non-uniform mutations are presented in basic GAs and their extending development of algorithm [5]. Polynomial mutation is a popular one that was first introduced in non-dominated sorting genetic algorithm (NSGA) and NSGA-II [6]. Uniform, non-uniform, and polynomial mutations are calculated as equation (3), (4), and (5), respectively. Input data for mutation operator algorithm is a set of molecular structures presented as $\upsilon = \{\upsilon_1, \upsilon_2, \ldots, \upsilon_v\}$, where v is the number of moles, υ_i is a member of υ, $1 \le i \le v$. Likewise output data is a set

of molecular structures presented as ύ. The variable names such as υ and ύ maybe present differently when they appear in other algorithms such as $temp_{\upsilon}$, $temp_{\acute{\upsilon}}$, $temp_{\upsilon 1}$, and $temp_{\upsilon 2}$:

$$u'_i = [(r[0-1] - 0.5) \times p) + u_i \tag{3}$$

$$u'_i = [(ul - u_i) * (1.0 \times r[0-1]^{1.0\text{-FE/FE Limit})^{p}}] + u_i \tag{4}$$

where,

p is perturbation,

$$ul = \begin{cases} U, r\,[0\text{-}1] < 0.5 \\ L, r\,[0\text{-}1] \geq 0.5 \end{cases}$$

$$u'_i = u'_i + \Delta q^2 \times \Delta q \begin{cases} (2.0 \times r + (1.0\text{-}2.0?) \times (1.0\text{-}\Delta 1)^{D}) (1.0/(D+1.0)) & r:[0\text{-}1]<0.5 \\ 1.0\text{-}(2.0\times(1.0\text{-}r)+2.0\times(r\text{-}0.5)\times(1.0\text{-}\Delta 2)^{(D+1.0)}) (1.0/(D+1.0)) & r:[0\text{-}1]\geq 0.5 \end{cases} \tag{5}$$

where, $\Delta 1 = \frac{u'_i - L}{d(U \text{ and } L)}$, $\Delta 2 = \frac{U - u'_i}{d(U \text{ and } L)}$, r is the random number, U is the upper bound, and L is the lower bound.

Mutation operator is applied at the initilization stages of the applied algorithm. During the iteration phase, the mutation operator is applied to process all types of basic reactions such as, on-wall ineffecient collision, intermolecular ineffective collision, decomposition and synthesis to bring about a changed molecular structure.

Mutation is a principal component to improve the performance of MCRO, as it can spread the search space by randomly sampling new points. Furthermore this mutation operator algorithm increases the chance of generating more powerful result not less than twice of original CRO for every basic reaction. There are the four elementary reactions's explained in **algorithm-1**. The proposed algorithm, MCRO for CH selection and cluster formation approaches are as shown in algorithm-1.

Algorithm 1: **A MCRO based energy efficient CH selection and cluster formation**

Input: (1) Number of sensor nodes: S = {s_1, s_2, s_3,...,s_n}.
(2) Predefined population, PopSize of Molecules: M.
(3) Number of characteristics of a Molecule: Dim = m.

Output: Optimal cluster heads CH = {CH_1, CH_2, CH_3,…..,CH_m}.

//Initialization phase

Step 1: Assign parameter value to PopSize, InitialKE, StepSize, buffer, KELossRate, On-wallColl, DecThres, SynThres, the set of molecules in this Container are molecules 1, 2, . . , PopSize.

Step 2: for each of the molecule **do**

2.1 Assign a random solution to the molecular structure $\upsilon_i = [v_{i,1}(t), v_{i,2}(t), \ldots\ldots, v_{i,D}(t)]$, $1 \leq i \leq M$, $1 \leq v_{i,d}(t) \leq n$, $1 \leq d \leq Dim = m$, number of CHs are supposed to be selected.

2.2 Calculate the potential energy (PE) by f(υ) and evaluate objective functions.

2.2.1 if f=0 then f(υ) uses Equation 13 for CHs selection

2.2.2 if f=1 then f(υ) uses Equation 19 for cluster formation

//where, f is a selection approach, f=0 for cluster heads (CHs) selection and f=1 for cluster formation

2.3 Assign the Kinetic energy (KE) with InitialKEy

end for

Step 3: Let the central energy buffer, *buffer* and assign *Initial energy of buffer* =0

// Iterations phase

Step 4: w*hile* t =1 to T_r ***do*** // T_r is the maximum number of iterations, the stopping criteria.

Step 5: ***if*** (T_R % R_{MR} ==0)

Step 6: Select a molecule υ randomly from container
Step 7: ***if*** (XHits[υ]-YHits[υ])>α) ***then***
//MCRO based decompose module
Step 7.1: Decompose (M, buffer) into M and M', success and buffer
Step 7.2: Obtain υ_1 and υ_2 from υ
Step 7.3: Obtain $\acute{\upsilon}_1$ = neighbor(υ_1) and $\acute{\upsilon}_2$ = neighbor(υ_2) with turning operator
Step 7.4: Calculate $PE_{\acute{\upsilon}1}$ and $PE_{\acute{\upsilon}2}$
Step 7.5: $temp1 = PE_{\upsilon} + KE_{\upsilon} - PE'_{\upsilon 1} - PE'_{\upsilon 2}$
Step 7.6: success = TRUE
Step 7.7: **if** $PE_{\upsilon} + KE_{\upsilon} \geq PE_{\acute{\upsilon}1} + PE_{\acute{\upsilon}2}$ then
Step 7.8: Get k randomly in interval [0, 1]
Step 7.9: $KE_{\acute{\upsilon}1} = temp_1 \times k$ and $KE_{\acute{\upsilon}2} = temp1 \times (1 - k)$
Step 7.10: Create new molecules M'
Step 7.11: **else if** $temp_1 + buffer \geq 0$ **then**
Step 7.12: Get r_1, r_2, r_3, and r_4 randomly in interval [0, 1]
Step 4.13: $KE_{\acute{\upsilon}1} = (temp_1 + buffer) \times r_1 \times r_2$
Step 7.14: $KE_{\acute{\upsilon}2} = (temp_1 + buffer - KE_{\acute{\upsilon}1}) \times r_3 \times r_4$
Step 7.15: Update $buffer = temp_1 + buffer - KE_{\acute{\upsilon}1} - KE_{\acute{\upsilon}2}$
Step 7.16: Create new molecules M'
Step 7.17: end if
Step 7.18: **else**
Step 7.19: success = FALSE
Step 7.20: end if
Step 7.21: **If** success = TRUE
Step 7.22: **do** Mutation of $\acute{\upsilon}_1$ to temp$\acute{\upsilon}_1$ and $\acute{\upsilon}_2$ to temp$\acute{\upsilon}_2$
Step 7.23: Calculate the $tempPE_1$ by f(temp$\acute{\upsilon}_1$) and $tempPE_2$ by f(temp$\acute{\upsilon}_2$)
Step 7.24: **If** $tempPE_1$ better than $PE_{\acute{\upsilon}1}$ **then**
Step 7.25: Replace $\acute{\upsilon}_1$ with temp$\acute{\upsilon}_1$ and $PE_{\acute{\upsilon}1}$ with $tempPE_1$
Step 7.26: **If** $tempPE_1$ better than $PE_{\acute{\upsilon}2}$ **then**
Step 7.27: Replace $\acute{\upsilon}_2$ with temp$\acute{\upsilon}_2$ and PE$\acute{\upsilon}_2$ with $tempPE_2$
Step 7.28: Assign $\acute{\upsilon}_1$, $PE_{\acute{\upsilon}1}$, $KE_{\acute{\upsilon}1}$ to the profile of M
Step 7.29: Assign $\acute{\upsilon}_2$, $PE_{\acute{\upsilon}2}$, $KE_{\acute{\upsilon}2}$ to the profile of M'
Step 7.30: end if
// End of *decompose module*
Step 8: ***else***
// MCRO based on-wall ineffective collision module
Step 8.1: on-wall ineffective collision (M, buffer) into M'
Step 8.2: Obtain $\acute{\upsilon} = Neighbor(\upsilon)$ with turning operator
Step 8.3: Calculate $PE_{\acute{\upsilon}}$ by $f(\acute{\upsilon})$
Step 8.4: **if** $PE_{\upsilon} + KE_{\upsilon} \geq PE_{\acute{\upsilon}}$ **then**
Step 8.5: Get r random interval [$KELossRate$, 1]
Step 8.6: $KE_{\acute{\upsilon}} = (PE_{\upsilon} + KE_{\upsilon} - PE_{\acute{\upsilon}}) \times r$
Step 8.7: Update buffer = buffer − $KE_{\acute{\upsilon}}$
Step 8.8: **do** Mutation of υ to tempυ
Step 8.9: Calculate the tempPE by f(tempυ)
Step 8.10: **if** tempPE better **than** $PE_{\acute{\upsilon}}$ **then**
Step 8.11: Replace $\acute{\upsilon}$ with tempυ and $PE_{\acute{\upsilon}}$ with tempPE
Step 8.12: Update the profile of M by $\upsilon = \acute{\upsilon}$, $PE_{\upsilon} = PE_{\acute{\upsilon}}$ and $KE_{\upsilon} = KE_{\acute{\upsilon}}$
Step 8.13: end if
// end of *on-wall ineffective collision module*
Step 9: ***else***
Step 10: Select two random molecules say M_1 and M_2 from *Pop*
Step 11: ***if*** ($KE\upsilon_1 \leq \beta$ and $KE\upsilon_2 \leq \beta$) ***then***

*// **MCRO based synthesis module***
Step 11.1: Synthesis (M_1, M_2) into M'
// satisfies the energy conservation condition
Step 11.2: Obtain $ύ_1$ from $υ_1$ and $ύ_2 = υ_2$
Step 11.3: Calculate $PE_{ύ1}$
Step 11.4: **if** $PE_{υ1} + PE_{ύ2} + KE_{υ1} + KE_{ύ2} \geq PE_{ύ1}$ **then**
Step 11.5: success = TRUE
Step 11.6: $KE_{υ'1} = PE_{υ1} + PE_{υ2} + KE_{υ1} + KE_{υ2} - PE_{ύ1}$
Step 11.7: **do** Mutation of $υ_1$ to $tempυ_1$
Step 11.8: Calculate the tempPE by $f(tempυ'_1)$
Step 11.9: **If** tempPE better than $PE_{ύ1}$ **then**
Step 11.10: Replace $ύ_1$ with $tempυ_1$ and $PE_{ύ1}$ with tempPE
Step 11.11: Calculate the $tempPE_1$ by $f(tempυ_1)$ and $tempPE_2$ by $f(tempυ_2)$
Step 11.12: Assign $ύ_1$, $PEυ'_1$, and $KEυ'_1$ to the profile of M_1
Step 11.13: **else**
Step 11.14: success = FALSE
Step 11.15: end if
// end of s*ynthesis module*
Step 12: *end if*
Step 13: ***else***
*// **MCRO based inter-molecular ineffective collision module***
Step 13.1: Inter-molecular ineffective collision (M_1, M_2) into M_1' and M_2'
Step 13.2: Obtain $ύ_1 = Neighbor(υ_1)$ and $ύ_2 = Neighbor(υ_2)$ with turning operator
Step 13.3: Calculate $PE_{ύ1}$ and $PE_{ύ2}$
Step 13.4: $temp2 = (PE_{ύ1} + PE_{ύ2} + KE_{ύ1} + KE_{ύ2}) - (PE_{ύ1} + PE_{ύ2})$
Step 13.5: **if** $PE_{ύ1} + PE_{ύ2} + KE_{ύ1} + KE_{ύ2} \geq PE_{ύ1} + PE_{ύ2}$ **then**
Step 13.6: Get p randomly in interval [0, 1]
Step 13.7: $KE_{ύ1} = temp_2 \times p$ and $KE_{ύ2} = temp_2 \times (1 - p)$
Step 13.8: end if
Step 13.9: **do** Mutation of $υ_1$ to $tempυ_1$ and $υ_2$ to $tempυ_2$
Step 13.10: Calculate the $tempPE_1$ by $f(tempυ_1)$ and $tempPE_2$ by $f(tempυ_2)$
Step 13.11: **If** $tempPE_1$ better **than** $PE_{ύ1}$ **then**
Step 13.12: Replace $ύ_1$ with $tempυ_1$ and $PE_{ύ1}$ with $tempPE_1$
Step 13.13: **If** $tempPE_2$ better **than** $PE_{ύ2}$ **then**
Step 13.14: Replace $ύ_2$ with $tempυ_2$ and PE $ύ_2$ with $tempPE_2$
Step 13.15: Update the profile of M_1 by $υ_1 = ύ_1$, $PE_{ύ1} = PE_{ύ1}$ and $KE_{ύ1} = KE_{ύ1}$
Step 13.16: Update the profile of M_2 by $υ_2 = ύ_2$, $PEύ_2 = PEύ_2$ and $KEύ_2 = KEύ_2$
// end of *inter-molecular ineffective collision module*
Step 14: Find for any new optimal minimum value
Step 15: *end while*
Step 16: Stop

3.3 MCRO based Cluster Head Selection

The Proposed protocol is designed with a molecular structure and a new energy function that could effectively and efficiently aid in calling out the CH and built potential clusters.

A) Problem Formulation for CH Selection

The proposed protocol is developed with an objective to perform optimal CH selection which would aid to enhance the network life span. To accomplish the objectivethe intra-cluster distance, minimum distance of base stationand maximum residual energy of the nodes are taken into account. Let us consider the function of minimum distance between the sensor nodes as f_1. To optimize the CH selection the f_1 is to be minimized. Let f_2 be the function of

minimum base station distance and f_3 be the function be the function of energy ratio, i.e., the ratio of the energy consumed by the sensor nodes and the remaining energy of the sensor nodes. This ratio should be minimized to acheive optimal CH selection. All the three objectives could be accomplished, if the function range is maintained between 0 and 1, which would result in optimal CH selection. The linear programming design of the optimal CH selection problem is given below:

$$\text{Minimize } F = f_1 \times \alpha_1 + f_2 \times \alpha_2 + f_3 \times \alpha_3 \quad \text{Subject to}$$

$$d(s_i, CH_j) \le d_{max}, \forall s_i \in S, \text{ and } CH_j \in C \tag{6}$$

$$E_{CH_j} > T_h, 1 \le j \le m \tag{7}$$

$$\alpha_1 + \alpha_2 + \alpha_3 = 1,\ \alpha_1, \alpha_2, \text{ and } \alpha_3 \in (0,1) \tag{8}$$

The constraint (6) depicts that the communication range of the sensor node S_i with CH_j is maximum. The constraint (7) states that the energy of CH_j nodes must be greater than the threshold energy T_h. In the constraint (8), α_1, α_2 and α_3 are the control parameters of the function f_1, f_2 and f_3 respectively. It also ensures that those values must not be of 0 or 100 % weight.

B) Potential Energy Function for CH Selection

The derivation of proposed potential energy function depends on the given parameters:

a) Neighbour node distance: We need to select the CHs such that distance from its neighbour nodes is minimal. In the intra-cluster communication process, sensor nodes consume some energy to communicate data to the CHs. If we reduce the neighbour node distance, energy of the intra-cluster communication also reduces.

$$\text{Objective 1: Minimize } f_1 = \sum_{j=1}^{m} \frac{1}{n_j} \left(\sum_{i=1}^{l_j} d(CH_j, s_i) \right) \tag{10}$$

b) The distance of Base Station: It is the distance between a cluster head CH_j and the base station (BS). BS distance has a major role in the selection of energy efficient CHs.

$$\text{Objective 2: Minimize } f_2 = \sum_{j=1}^{m} \frac{1}{m} (d(CH_j, BS)) \tag{11}$$

c) Energy ratio: It is the ratio of the energy consumed by the CHs and the residual energy of the CHs. When a CH consumes minimal energy during sensing, aggregating and transmitting then the residual energy if the CH will be higher therefore the CH will have lower energy ratio. Lower the CH energy ratio the greater is the chance of optimal selection of CHs.

$$\text{Objective 3: Minimize } f_3 = \sum_{j=1}^{m} \frac{E_C(CH_j)}{E_R(CH_j)} \tag{12}$$

It is recommended to minimize the linear combination of all the above three functions together instead of minimizing each function seperately. MCRO-ECP adopts the following potential energy function.

$$\text{Potential energy function } F = f_1 \times \alpha_1 + f_2 \times \alpha_2 + f_3 \times \alpha_3 \tag{13}$$

where, $\alpha_1 + \alpha_2 + \alpha_3 = 1$, $\alpha_2 \ge (\alpha_1 + \alpha_3)$, also $0 < f_1,\ f_2,\ f_3 < 1$

The prime objective of the proposal is to minimize the potential energy function. The lower the value of *PE*, the better is the stability of the molecule, i.e., the better is the CH selection.

3.4 Proposed MCRO based Cluster Formation

After the selection of optimal CHs, with the derived potential energy function, the cluster formation algorithm is runned at the BS for the optimal assignment of the non-cluster head sensor nodes to the CHs.

A) Linear Programming Model for Cluster Formation

In the proposed cluster formation problem, the central objective is to increase the life time of the network by decreasing the energy consumption of the network. Let g_1 be the function of a sensor node to the CH that would maximize the residual energy which would result in optimal cluster formation. Let g_2 be the function to minimize the distance between a sensor node and CH and CH and BS. These two objectives function values are normalised between the range of 0 and 1 thus the lenier combinations of these two functions is minimized in an effecient manner. Let a_{ij} be a Boolean variable defined by

$$a_{ij} = \begin{cases} 1 \text{ if } S_i \text{ is assigned to } CH_j, \forall_i, j: 1 \le i \le n, 1 \le j \le m \\ 0 \text{ otherwise} \end{cases}$$

$$\text{Minimize } G = g_1 \times \beta_1 + g_2 \times \beta_2 \text{ subject to}$$

$$d(s_i, CH_j) \times a_{ij} \le d_{max}, \forall s_i \in S \text{ and } CH_j \in C \quad (14)$$

$$\sum_{j=1}^{m} a_{ij} = 1 \quad (15)$$

The constraint (14) denotes that when the sensor node s_i is in the maximum communication range it can be assignes to the CH_j and constraint (15) denotes that the degree of CH_j and s_i can be assigned to only one CH_j.

B) Potential Energy Function for Cluster Formation

The potential energy derivation of function depends on the following parameters:

a) Intra-cluster distance: During the intra-cluster communication process, sensor nodes consume energy to transmit data to the CHs. So, when the distance in the intra-cluster is minimized it results in decreased energy consumption. To acheive this the CHs are selected with minimal distance from it's neighbour nodes.

$$\text{Objective 1: Minimize } g_1 = \sum_{j=1}^{m} \left(\sum_{i=1}^{l_j} d(s_i, CH_j) \right) \quad (17)$$

b) CH node degree: A sensor node s_i should be paired with a CH_j which has lower node degree rather than any other CH in the communication range of the sensor node.

$$\text{Objective 2: Minimize } g_2 = \frac{1}{\text{node degree}(CH_j)} \quad (18)$$

The weight summation approach is utilized to minimize the energy consumptions of the two objective functions together instead of minimizing the functions seperately as these two are weably conflicting each other which is tackeled by a unique optimal solution. Therefore the following potential energy function is utilized.

$$\text{Potential energy function: } G = g_1 \times \beta_1 + g_2 \times \beta_2 \quad (19)$$

where, $\beta_1 + \beta_2 = 1$

The objective is to minimize the potential energy consumption. The lower the value of PE, better is the stability of the molecule, i.e., optimal assignment of non-CH sensor nodes to CHs.

4. Simulation Results and Performance Analysis

The experimental simulation and performance analysis of proposed protocol, MCRO-ECP are discussed in this section. The energy model used in proposed work is described in [17]. All sensors are deployed randomly in the target area and can calculate distance to other sensors based on RSSI model[34]. The sensor nodes therefore do not require global position system. The sensors are taken into consideration to be stationary after operation and sensors are able to operate in CH and sensor node mode. All the sensors sense the data periodically and the assumption is that, they have data to communicate to cluster head or base station. The sensing and data transmission distances are in a circular field in which all the sensor nodes are uniform and pocess equal ability for implementation and communication. The communication links become wireless and symmetric and become established between the nodes when they are in the range of each other for communication. Life span of the network can be described in many ways [35].

The performance of the proposed protocol was investigated against the well known clustering protocols PSO-C [28], LDC [22], GLBCA [23], GALBCA [30], DECA [31] and CRO-ECA [32]. In order to provide a fair comparison, all the competent protocols along with the proposed protocol were implemented under the NS2.35 simulator. Detailed configuration of the wireless sensor network and the performance of the proposed protocol as against to existing protocols under varied performance metrics are disccused in the following sections.

4.1 Simulation Setup

In our experiment,variable number of sensor nodes 200, 400, 600, 800, and 1000 were deployed randomly in the area of 400 × 400 m^2. The cluster heads (CHs) were selected randomly as 10% of sensor nodes and base station was placed in the corner of the field, (0,0). The values used in the first order radio model [17] are described in **Table 1**. The initial energy (E_{init}) of a node is set to 2 joules, circuite energy (E_{elec}) is 50 nano joules per bit, amplification of the free space energy (ε_{fs}) is set to 10 pJ/bit/m^2, amplification of the multipath transmission energy (ε_{mp}) is 0.0013 pJ/bit/m^4, maximum threshold distance (d_{max}) is 120 metres, minimum threshold distance (d_0) is 87.7 metres, packet length is 512 bytes, and message size is 500 bits.

Table 1. Simulation setup of proposed MCRO-ECP.

Parameter	Value
Sensor field area	400×400 m^2
Position of base station	(0, 0)
Number of sensors	200, 400, 600,800, 1000
Number of CHs	10% of sensor nodes
Initial energy of sensor, E_{init}	2 Joules
Circuite energy, E_{elec}	50 nJ/bit
Amplification of the free space energy , ε_{fs}	10p J/bit/ m^2
Amplification of the multipath Transmission energy ε_{mp}	0.0013 pJ/bit/m^4
Maximum threshold distance, d_{max}	120 mts
Minimum threshold distance , d_0	87.7 mts
Packet length	512 bytes
Message size	500 bits

4.2 Simulation Parameters

The following performance metrics were considered for performance evaluation of the MCRO-ECP.

A. Energy Consumption: The amount of energy consumed in joules in the network over a number of rounds, in each of which the energy utilised by the CHs for data collection, aggregation and transmission to the BS is calculated.

B. Network Lifetime: The life time of the network is defined here as the as death of first node (FND). The increase in the lifetime of the network proportionately enhances the performance of the network.

C. Packets received by BS: The total number of packets received by the BS over the span of network lifetime.

D. Convergence rate: To converge the global optimal solution, an algorithm performs certain number of rounds called as convergence rate.

A) Performance of Energy Consumption

The total energy consumption of the network over number of rounds, in each round, CHs collect data, aggregate and route it to the BS. The unit measurement of energy consumption is joules. In the proposed protocol the performance of the energy consumption is tested under different scenarios by changing the number of sensor nodes and cluster heads. Here, the proposed protocol results are shown in conditions of the total energy consumption of the networks of 400 sensor nodes with 40CHs. **Fig. 2** shows the comparitive results of the proposed protocol with the standard protocols. The proposed protocol outperforms the existing protocols on total energy consumption which is mesuered in joules. MCRO-ECP outperforms PSO-C by 27.1 %, LDC by 23.5 %, GLBCA by 20.6 %, GALBCA by 16.20 % DECA by 11.8 % , and CRO-ECA by 7%.

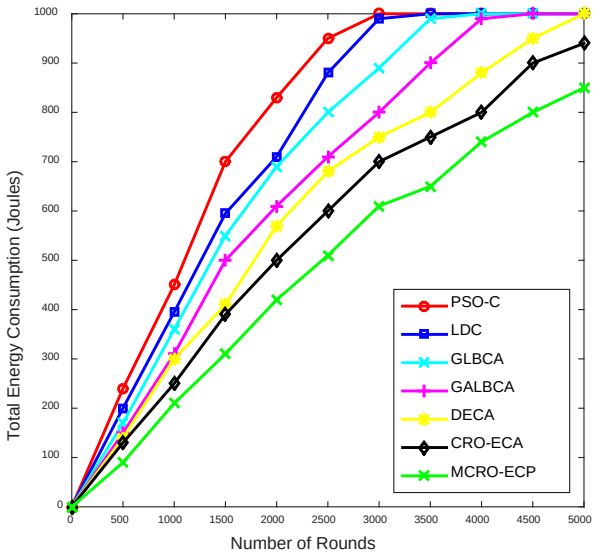

Fig. 2. Performance analysis of energy consumption in 400 sensor nodes and 40 cluster heads wireless sensor network.

B) Analysis of Performance of Network Lifetime

The life time of the network can be defined as the as death of first node (FND). As lifetime increases the network performance gets better. **Fig. 3** shows the FND data of MCRO-ECP

outperforms than CRO-ECA by 4.6%, DECA by 9.6%, GALBCA by 13.2%, GLBCA by 19.3%, LDC by 20.1%, and PSO-C by 30.04%.

C) Analysis of Performance of Packets Receipt by BS

The total number of packets transmitted to the BS in a span of network lifetime is another metric. The unit measurement of packets received by BS is packets/second. **Fig. 4** shows the performance of packets received by base station which is measured by number of packets recieved by BS per second. MCRO-ECP outperforms than CRO-ECA by 4.8%, DECA by 10.4%, GALBCA by 13.2%, GLBCA by 18%, LDC by 20.4%, and PSO-C by 23.4%.

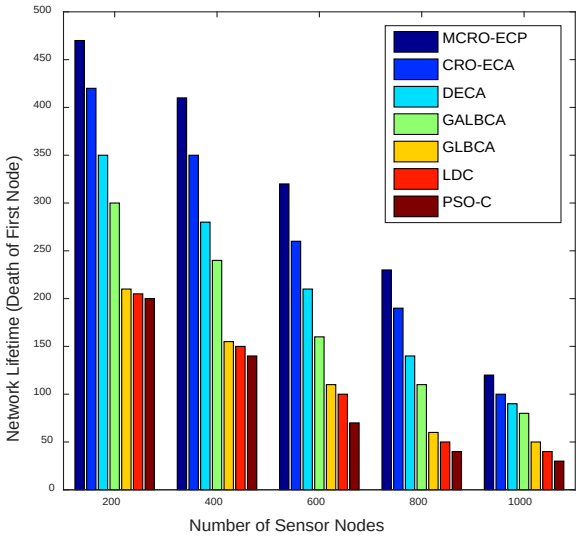

Fig. 3. Performance analysis of network lifetime in 400 sensor nodes and 40 cluster heads wireless sensor network.

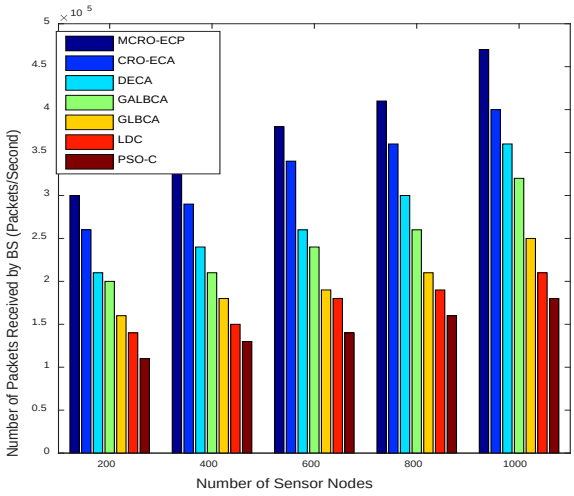

Fig. 4. Performance analysis of packets receipt by base station in 400 sensor nodes and 40 cluster heads wireless sensor network.

D) Performance Analysis in terms of Convergence Rate

To converge the global optimal solution, an algorithm performs certain number of rounds

called as convergence rate. Mutation chemical reaction algorithm is belong to iterative method. As iterative method, a fundamental question is their convergence rates, how fast does an MCRO converge to the optimum per generation?. Convergence rate measures the rate of the fitness change per round. The convergence rate of proposed protocol, MCRO-ECP was extensively tested. **Fig. 5** proves better quality of solution provided by MCRO-ECP compared to other existing methods such as PSO-C, GALBCA, DECA and CRO-ECA protocols. Following the theoretical and experimental chemical kinetics, the faster convergence with enhanced quality of solution of MCRO-ECP is proven. According to the NFL (No Free Lunch) theorem, meta-heuristic is neither superior nor inferior to others. If a problem matches to a particular meta-heuristic then it out performs, i.e., MCRO-ECP out performs all other existing protocols.

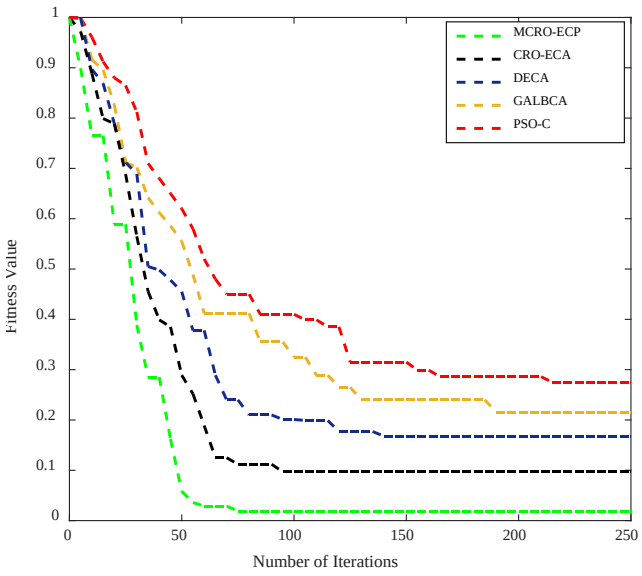

Fig. 5. Convergence rate analysis in 400 sensor nodes and 40 cluster heads wireless sensor network.

5. Conclusion

In this study, linear programming models have been designed and formulated for two optimization problems, i.e., CH selection and cluster formation. The proposed protocol has been presented for the same, based on a novel MCRO technique using efficient molecular structure representations and potential energy functions. For the selection of optimal CH, the neighbour node distance, base station distance and residual energy of sensor nodes are used as key parameters. For cluster formation, intra communication distance and CH node degree were the chosen parameters. In the communication phase, TDMA was used for intra node communication and direct communication was used for inter node communication. Simulation results along with peer comparisons have been presented. The proposed protocol is tested extensively under different conditions as such varying the number of sensor nodes and the number of cluster heads. The experimental results have shown that the proposed MCRO-ECP protocol performs and produced better output, in terms of total energy consumption, network lifetime, number of data packets received by the base station and convergence rate, than the already existing protocols. Development of improved clustering and routing protocols adopting meta-heuristic approaches is the aim in the future.

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Ravuri Daniel, research scholar in the Department of Computer Science and Engineering, JNTUK-Kakinada, Indian. His interest of research includes wireless sensor networks, computer networks, IoT and nature inspired optimization techniques.

Dr.Kuda Nageswara Rao, Professor, Head of the department of Computer Science & Systems Engineering, Andhra University College of Engineering (A), Andhra University, Visakhapatnam, India. His research interests includes Computer Networks, IoT, TCP/IP, Internet Technologies, Wireless and Wireless Sensor Networks. Life member in ISPS and ISTE, member in IETE, ISCA, CSI etc.,