Computational Intelligence for Wireless Sensor Networks: Applications and Clustering Algorithms

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ABSTRACT

WSN has been directed from military applications to various civil applications. However, many applications are not ready for real world deployment. Most challenging issues are still unresolved. The main challenge facing the operation of WSN is saving energy to prolong the network lifetime. Clustering is an efficient technique used for managing energy consumption. However, clustering is an NP hard optimization problem that can't be solved effectively by traditional methods. Computational Intelligence (CI) paradigms are suitable to adapt for WSN dynamic nature. This paper explores the advantages of CI techniques and how they may be used to solve varies problems associated to WSN. Finally, a short conclusion and future recommendation is being provided.

General Terms:

Wireless Sensor Network, WSN Applications

Keywords:

Wireless Sensor Network, Computational Intelligence, Clustering Algorithms

1. INTRODUCTION

The evolution and advance in micro electro-mechanical systems (MEMS) has led to the development of reliable, low cost, small size micro sensors [1]. Nowadays, hundreds to thousands of these heterogeneous sensors are deployed over a geographic area of interest, and communicate together forming a wireless sensor network. WSNs are deployed in land, underground and underwater [2]. They are designed to work for months and years according to the application. The sensors deployment need not be centralized, or with fixed infrastructure. The wireless sensors (nodes) in the network sense external data from the surrounding environment, process the sensed data locally, and then send the data to a base station for further processing through wireless communication, as shown in Figure 1. The nodes may be deployed uniformly, specifically located or randomly (e.g. dropped by an airplane). They may also be static or mobile. There are two variations of wireless sensor deployment: structured and unstructured. While in Structured WSN the nodes are deployed in a pre-planned manner, the deployment of nodes in unstructured WSN is random. WSN is dynamic in nature; nodes can be added to the network or go out of energy. The dynamic nature of the network adds complexity due to repetitive changes.

This paper is organized as follows: Section 2 describes number of WSN applications. Section 3 briefly explains WSN technology. Section 4 describes the energy consumption problem challenges, then Section 5 explains how clustering algorithms can be used to help solving energy saving problem in WSN. Section 6 gives a brief overview on Computational Intelligence techniques. Section 7 analyzes CI work done in clustering WSN, and finally, Section 8 concludes the work.

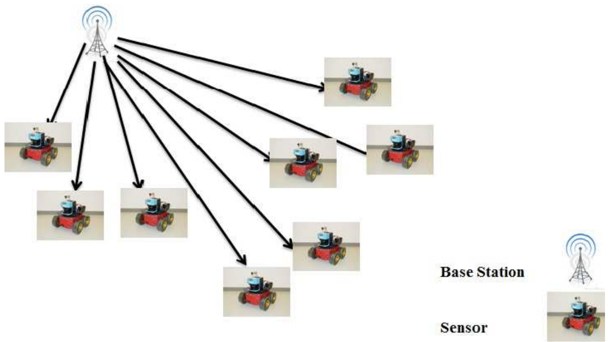

Fig. 1. Example of Wireless Sensor Network

2. APPLICATIONS OF WSN

Authors categorized WSN applications traditionally. In [3], the applications were grouped according to their objectives. With respect to the type of WSN operation, the applications can be classified into two categories: event detection and periodic sensing [4]. In this paper, the applications are categorized according to its current state. Two main categories are proposed [5]:

Deployed: the Deployed category contains the actual applications that are implemented in real-world.

Potential: the second category contains the applications that are not yet mature, and are viewed as vital and promising.

In the following sub-sections, we describe some, but not all, applications and some well-known projects.

2.1 Military Applications

It was the first motivation for development of WSN. In 1980, the Defense Advanced Research Projects Agency (DARPA) adopted the Sensor Information Technology (SENSIT) and National Science Foundation (NSF) Programs explored WSN for more tracking capabilities [6]. Other applications included battle field surveillance, and intrusion detection. The sensors were programmed to collect measurements, communicate with each other, and send notification in case of object movement detection. More recent military projects were the detection of nuclear, chemical and biological toxins as well as calculation of their concentration levels.

2.2 Environmental Applications

As sensors are deployed in a natural hostile area, long term environmental data were gathered either for future research, monitoring, or disaster detection (as fire, flood or earthquake forecast, etc.) [7]. In 1970s, the earliest real world project founded was the Automated Local Evaluation in Real Time, (ALERT). It was designed to detect the existence of flood using sensors that take measurements as: temperature, humidity, rain, and water level. The data was transmitted to a station using Laser technology. In 2002, Intel Research Laboratory and University of California founded the Great Duck Island, North Atlanta, project to monitor the behavior of Petrel bird [5]. There are about hundred well equipped sensors; some of them have cameras for video monitoring. It was not only beneficiary to monitoring, but it also reported the network operation and functionality problems that needed more research.

2.3 Home and Office Buildings

Started in late 1980s, Smart buildings are those equipped with systems that do some intelligent actions, as door opening. Wireless sensors are used to study the effect of wind, monitor the employees and students [2]. In 1990s, research has been adopted to use smart buildings to disabled people. WSN is recently incorporated in smart building for more quality of life. Smart Kindergarten deploys wireless sensors for childhood education and monitoring [8].

2.4 Agriculture Applications

Precision agriculture means applying the right amount of input (water, fertilizer, etc.) at the right location and at the right time to enhance production and improve quality, while protecting the environment [9]. It is accomplished with WSN that monitors parameters as: soil moisture and air temperature, then calculates the amount of water and fertilizers needed. Also, irrigation management, adopted by WSNs, helps farmers to prevent damages to their crops and increasing crop production. WSN is also used to control the green house temperature and humidity levels starting from messaging to using controller [10].

2.5 Health Applications

Health care is considered a potential application of WSN whose research is dominant [11]. Deployed applications are tele-monitoring physiological data, tracking patient locations and patient drug management [12]. WSN will allow the patient to be under constant supervision without hospital admission. Two promising applications are being investigated: glucose level and artificial retina [13]. The diabetic patient can be implanted with glucose meter that monitors the sugar level and alerts the patient in case of serious condition detection. The second project considers implanting a chip of micro-sensors in the human eye to enhance vision. Important functional requirements as reliability, communication, and safety are challenging issues.

2.6 Smart Energy

Energy production and consumption is an extremely critical problem worldwide. Research on producing smart building has gained great interest. The energy improvement solution incorporated the use of wireless sensors for improving home utilities, such as lighting, water and gas [14, 15]. Studies are in-process to design the network to monitor the energy consumption parameters, analyze them and finally regulate consumption. Recent studies are working on controlling the devices automatically. WSN is expected to be the next generation for smart home by improving energy distribution and consumption. In the United States, it is expected that WSN will be able to save about 50 billion dollars yearly and reduce 35 million metric tons of carbon emissions [16].

3. WSN TECHNOLOGY

Wireless sensor is mainly composed of: sensing unit, processing unit, transceiver, and a power supply [3]. The size of the sensors has decreased dramatically to about 1 inch after the development of Micro-Electro-Mechanical System (MEMS). The sensing unit contains at least one sensor that measures data from its surrounding. Different sensing units exist according to the application deployed. The processing unit, with the help of embedded memory, processes the data measured by the sensing unit as well as data gathered from neighbor sensors. The data is sent and received by means of a transceiver. The sensors communicate by laser, infrared, or most commonly radio waves. Each sensor is equipped with a battery that has limited lifetime. The limited-powered sensors are deployed in hostile areas; making recharging or replacing the battery unfeasible [17].
Recently, some sensors are equipped with renewable energy, or energy harvesting module [18, 19]. However, their expensive cost almost ceased their deployment. The death of the node was preferred economically. Any useful or unuseful operation performed by the sensor consumes energy. Useful energy consumed includes sensing, receiving, transmitting, and processing, but idle listening, collision and overhearing is considered as unuseful [1].

4. ENERGY CHALLENGES

Although different challenges face WSN, they all share one main challenge, 'Energy'. WSNs are very sensitive to energy consumption and its performance depends on network lifetime. The death of one node is soon succeeded by the death of others, and node isolation occurs. Therefore, a critical aspect to concern is how to reduce the energy consumption of nodes and prolong the network lifetime [20].
Energy consumption is managed at different levels. For example, in technology level, research is made to produce low duty cycles, minimize delays, handle data redundancy and implement short range transmission. In network layer, energy efficient routing protocols are developed to prolong network lifetime. A detailed taxonomy of the energy conservation schemes is discussed in [21].
There are five types of WSNs: Terrestrial, Underground, Underwater, Multimedia, and Mobile WSNs [2]. Each type has its architecture, characteristics and challenges. Table 1 summarizes the major difference between various types of networks.

5. CLUSTERING ALGORITHMS

Clustering is an efficient technique used in WSN that can be used to solve the energy consumption problem by avoiding long distance communication [22]. The nodes are divided into disjoint groups called 'cluster'. The nodes within each cluster can intercommunicate, or communicate with only one node in the group, named 'Cluster Head' (CH). The CH is responsible for gathering data from all nodes in the group, then sending the data to the base station, directly or using multi-hop, after processing it [23, 24]. Since the energy consumed varies exponentially with the communication distance, sending data to a neighbor node saves more energy than sending to the base station. Figure 2 shows an example of clustered WSN. Clustering technology has many advantages as follows:

Table 1. Wireless Sensor Network Types

Types	Cost	Deployment	Challenges
Terrestrial WSN	inexpensive	structured, unstructured	energy
Underground WSN	expensive	structured structured	energy, signal loss, attenuation
Underwater WSN	expensive	structured, unstructured	energy, bandwidth signal fading
Multimedia WSN	inexpensive	structured, unstructured	energy, high data rate, high bandwidth
Mobile WSN	expensive	initial spreading	Energy, localization, deployment

—minimizes communication overhead

—enhances resource use. For example, non-neighbor clusters can use the same communication frequency.

—scalability; nodes can join or leave the group without affecting the entire network.

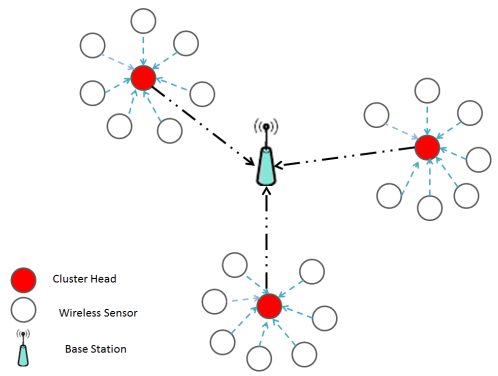

Fig. 2. Clustered WSN

5.1 Traditional Clustering Techniques

Clustering is an NP hard problem that is ineffectively solved by traditional techniques. The dynamic nature of the WSN makes the problem more complex due to repetitive changes in the clusters and CHs which can't be modeled by traditional mathematical methods. Several traditional clustering protocols are implemented. More advanced probabilistic algorithms have been developed. In this section, three famous clustering techniques are mentioned: Low Energy Adaptive Clustering Hierarchy (LEACH), Hybrid Energy-Efficient Distributed clustering (HEED), and Energy Efficient Unequal Clustering (EEUC).

The LEACH protocol [25] simply divides the network into groups each has a CH. LEACH protocol repeats a two-phase round. The CH election is implemented periodically and in a randomized manner during a setup phase. In the steady-state phase, the elected CH gathers the data and sends them to the base station. However, this algorithm does not guarantee good distribution or uniform representation of CH [26]. Moreover, it assumes that the CH consumes the same energy as the member node. This technique is expensive and not applicable to be deployed in large geographic region.

The HEED protocol [27] depends on residual energy in the election of CH. It minimizes the communication overhead with less costly algorithms. This protocol extends the network lifetime and forms compact cluster with better distributed CH. The problem with HEED is that it consumes high energy for local communication and also for communication between CH and base station [27].

EECU algorithm adopts variable cluster size architecture [28]. Based on the fact that CHs placed near the base station will contribute in routing communication more than far CHs. The algorithm distributed smallest clusters to be the nearest to the base station. The CHs are chosen randomly. EECU is not practical for real world because it assumes circular distribution of nodes.

To summarize, traditional clustering algorithms suffer from non-uniformity in clusters and CH distribution [29]. Residual energy is not taken accurately in calculation; and insufficient parameters are used.

6. COMPUTATIONAL INTELLIGENCE

CI is an intelligent computational methodology that uses heuristic algorithms to obtain approximate solutions to NP hard problems efficiently. CI paradigms are suitable to adapt to the dynamic nature of WSN. The next subsections briefly describe some CI paradigms used in clustering WSN.

6.1 Genetic Algorithm

Inspired by Charles Darwin's theory of evolution: 'the survival of the fittest", Genetic Algorithm (GA) was introduced formally by John Holland in 1970s [30]. GA is an adaptive heuristic search algorithm that models biological genetic evolution. It proved to be a robust optimizer that searches among a population of solutions, and showed flexibility in solving dynamic problems. It has been successfully applied to many NP-hard problems. The main challenge in solving a problem with GA is the encoding of the problem into a set of chromosomes; each representing a solution to the problem. The quality of each chromosome is evaluated using a fitness function. Based on their fitness value, crossover and mutation processes are applied on selected chromosomes. The crossover process produces new solutions, called offspring, by concatenating parts of two selected chromosomes. Mutation changes one or more genetic element in the produced offspring to prevent being trapped in local minima. GA algorithm is shown in Figure 1.

6.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) was developed in 1995 by James Kennedy, and Russell Eberhart [32]. PSO is a robust stochastic nonlinear- optimization technique based on movement and intelligence of swarms. It is inspired from social behavior of bird or fish, where a group of birds randomly search for food in an area by following the nearest bird to the food. It combines local search methods with global search methods depending on social interaction between particles to locate the best achieved position so far. PSO and GA are very similar [33]. Both are population based stochastic optimization that starts with a group of a randomly generated population. They have fitness values to evaluate their population, and update the population and search for the optimum with random techniques. However, PSO differs from GA in that there is no crossover and mutation. PSO particles do not die. They update themselves with the internal velocity. Finally, the information sharing mechanism in PSO is significantly different.
Each particle is treated as a point in a multi-dimensional space, and modifies its position influenced by two components: the cognitive component and the social component resulting from

Algorithm 1: Basic steps describing the GA [31]

begin GA
for all N chromosomes
Initialize the population,generation counter
Initialize the GA parameters.
Calculate the **fitness** of each chromosome.
end for
while (the convergence condition is not satisfied) or
(the maximum number of iterations is not reached)
{
for all created N **offsprings**
Probabilistically select a pair of chromosomes
from current population using the **fitness** value.
Produce a new offspring x_i using crossover
and mutation operators,where $i = 1, 2, \ldots$,N.
Evaluate the population.
end for
Replace current population with newly created one.
Update the generation counter.
}
end while
end GA

neighbor communication. The basic PSO equations are shown in Equations 1 and 2. Several enhancements on the standard PSO equation are listed in [34].

$$v_{id}^{new} = v_{id}^{old} + \phi_1 * rand_1 * (p_{id} - x_{id}) + \phi_2 * rand_2 * (p_{gd} - x_{id}) \quad (1)$$

$$x_{id}^{new} = x_{id}^{old} + v_{id}^{new} \quad (2)$$

where v_{id} is the velocity of particle i in dimension d, x_{id} is the position of particle i in dimension d, ϕ_1, ϕ_2 are positive constants, $rand_1, rand_2$ are random numbers, p_{id} is the best position reached so far by the particle, and p_{gd} is the global best position reached by the neighborhood.

Algorithm 2: Basic steps of the PSO algorithm

begin PSO
Randomly initialize the position and velocity of
the particles: $X_i(0)$ and $V_i(0)$
while (While terminating condition is not reached) do
for for i = 1 to number of particles
Evaluate the fitness:= $f(X_i)$
Update p_i and g_i
Update velocity of the particle V_i
Update position of the particle X_i
Evaluate the population fitness
Next for
end while
end PSO

The steps of PSO process is shown in Algorithm 2. The choice of the neighborhood to communicate, named the swarm topology, affects the model used in implementation. In Star topology, all particles in the swarm communicate with each other, while in Ring topology, each particle communicates only with only two neighborhoods. Star typology's fast convergence is misleading in some cases, where premature convergence is reached. The Ring topology is characterized by having slower and less premature convergence and performs better on multimodal problems. Different topologies are proposed and discussed in [35, 36].

6.3 Cuckoo Search

Developed by Yang and Deb in 2009, Cuckoo Search is a new metaheuristic optimization algorithm that is inspired from the behavior of some cuckoo species [37]. The cuckoo lays an egg in a host's nest with risk of surviving. If the egg is discovered by the host, it can either throw the egg away, or abandon the nest and build a completely new nest. This behavior is converted to Algorithm 3.

Algorithm 3: Basic steps describing the CS

begin CS
Objective function $f(x), x = (x_1, x_2, ...x_d)^T$
Generate initial population of n host nests $x_i (i = 1, 2, ..., n)$
while ($t <$ Max Generation) or (stop criterion not met)
Get a cuckoo randomly by random walk,
$x(t + 1) = x(t) + sE_t$
Evaluate its Quality/Fitness F_i.
Choose a nest among n (say,j) randomly
If $(F_i > F_j)$
replace j by the new solution
end if
A fraction (P_a) of the worse nests are abandoned
and new ones are built
Keep the best solutions/nests
Rank the solutions/nests and find the current best
Pass the current best solutions to the next generation
end while
end

s, and P_a (the probability of discovering the egg) have values between zero and 1. E_t is taken from a standard normal distribution with zero mean and unity standard deviation. It can also be taken form Lèvy Flight distribution which is a random walk with step length depending on the current state plus a transition probability [38]. This algorithm is characterized by its simplicity and fast convergence. However, the improper tuning of the CS parameters could result in decrease of the algorithm efficiency. Several improvements are made to the CS algorithm, as in [39, 40, 41].

7. CI AND CLUSTERING IN WSN

Clustering has been successfully applied to manage the WSN energy consumption. Traditional techniques have some limitations. Recently, CI paradigms are used to cluster WSN. This section summarizes the work done by CI paradigms to cluster WSN.

7.1 Clustering Using GA

In [42], authors proposed the use of GAs to solve the optimizing problem for selecting the best number of CHs. The chromosome representation proposed was simply a 9-bit binary representation where the bit value of 1 represents a CH, and a 0 represents an ordinary node. The 9-bit Binary Chromosome representation [42] was given as follows:

1	0	1	1	0	0	1	0	1

The fitness function was defined as given in Equation 3.

$$Fitness = w * (D_T - D_i) + (1 - w) * (N - H_i) \quad (3)$$

where D_T is the total distance from all nodes to sink, D_i is the total distances from regular nodes to their cluster head, N is the total number of nodes, H_i is the number of cluster heads, and w is preset weight. The results showed that the cluster layout depends on the location of the base station (sink). More cluster heads are elected when the base station is around the center of the network. Authors in [43] used the same model as presented in [42], but with different mutation mechanism and sink location. They showed that better fitness value can be reached when CH saturated to 25 percent of the total nodes. However, the choice of CH was not based on its residual energy. This could lead to network disconnection because if the optimal CHs have at least one CH with low energy, it will fade quickly and disconnect part of the network.

In [44], authors improved the previous work of [42], and [43] by adding the residual energy to the fitness function calculation as shown in Equation 4.

$$\begin{aligned} Fitness &= RE + SE + (w * (D_T - D_i)) \\ &+ ((1-w) * (N - H_i)) \end{aligned} \quad (4)$$

RE is the total cluster heads' energy, and SE total energy needed to send data from cluster heads to sink. The results were compared with LEACH showed proper distribution of clusters and significant improvement in the network lifetime [44]. In [45], authors used GA to optimize the clustering problem based on minimizing the energy consumption. In their model, the radio transmission technology was used in their calculations. The Radio Energy Dissipation system of equations is presented in Equation 5.

$$\begin{aligned} TE_{xy} &= E_e + \epsilon_s d_{xy}^2, \quad d < d_o \\ TE_{xy} &= E_e + \epsilon_l d_{xy}^4, \quad d > d_o \\ d_o &= \sqrt{\epsilon_s / \epsilon_l} \end{aligned} \quad (5)$$

where TE_{xy} is the total energy needed to transmit data from a sensor to its CH, d is the distance between the sensor and its CH, d_0 is the threshold distance. Given that:

$$\begin{aligned} E_e &= 50 \\ \epsilon_s &= 10pj/m^2 \\ \epsilon_l &= 0.0013pj/m^4 \end{aligned} \quad (6)$$

The fitness calculation depends on the distance between nodes, CHs and sinks. The GA's outcome was the optimal Cluster Heads. The base station then identifies the cluster members and the transmission schedule. Each CH is assumed to send directly to the sink. Although their algorithm performed better than LEACH, the improvement was not significant. This is because of the complexity of the fitness function. Many parameters have been taken into consideration and each one is assigned a weight that is updated at each generation.

In [46], authors proposed a GA to minimize the communication distance. Moreover, a two-dimensional chromosome representation is used. The chromosome mapped the actual sensor layout of the deployment area. The gene's value of zero indicate non-existing nodes, 1 indicate a sensor node, and 2 two indicate a CH. The algorithm used the result of the LEACH as an initial condition to GA algorithm. The fitness function used is as follows:

$$Fitness = \sum_i \sum_j d_{CH(ij)}^2 + \sum_i d_{SN(i)}^2 \quad (7)$$

where i is the number of CHs , j is the member number in cluster i, d_{CH} is the distance between the sensor and its CH, and

Table 2. Group array and sequence array Chromosome in [47]

Sequence Array	7	4	1	6	8	5	3	2
Group Array	3	1	2	2	0	0	0	0

Table 3. PSO particle structure presented in [29]

Cluster 1				Cluster 2				Cluster 3			
12	8	7	1	4	10	6	11	3	5	9	2
CH	members			CH	members			CH	members		

d_{SN} is the distance between CH and sink. The chromosome is divided into sectors, and crossover is performed by exchanging sectors between parents to ensure that the genes move with their neighbors. The results proved better performance than LEACH. However, the transmitted data size and cluster size is not added to the fitness function.

In [47], authors proposed dividing the network into clusters. But instead of sending the measured data from the node to CH, they used mobile agent with each cluster that migrated through its nodes. The mobile agent collects the data and sends it to the base station.

Authors divided the chromosome into two arrays: group array and sequence array (see Table 2). The group array contains number of members in each cluster. The sequence array identifies the nodes that are belonging to each cluster. Crossover only exchanges the nodes in the same group. The mutation changes the number of nodes in two groups to ensure consistency. They used GA to calculate the optimum number of mobile agents (i.e. clusters) and the cluster layout. The objective criterion selected based on the network latency. The energy condition was not included. Analysis of simulation results showed that the sensor nodes traversed by the mobile agent will result in energy depletion.

7.2 Clustering Using PSO

In [48], authors applied PSO to obtain the optimum cluster layout using a fitness function based on distance calculations (see Equation 8). Residual energy calculations were not included.

$$F = \sum_{j=1}^{k} \sum_{i=1}^{n_j} (d_{ij}^2 + \frac{D_j^2}{n_j}) \quad (8)$$

where d_{ij} is the distance between node i and its cluster head j, D_j is the distance from cluster head j to the base station, and n_j is the number of nodes in the cluster j. Authors applied the PSO algorithm while varying inertia weight, or the acceleration constant. Analysis of the results are discussed in details in [49],[48].

In [29], authors proposed using an improved PSO algorithm to solve the uneven clustering problem. They decided to choose the number of clusters to be 5 percent of the total nodes, and each cluster has the same number of nodes. Their fitness was based on the communication distance. The particle structure used contains the ID of the cluster head followed by the IDs of its members, as shown in Table 3. Moreover, the PSO dynamic inertia weight was modified to include the particles' diversity. The CHs resulted from the PSO algorithm is then checked for their energy level. If their energy level falls below a threshold, they are replaced by the nearest node whose energy is more than the threshold. Compared with LEACH and improved LEACH, the proposed PSO algorithm showed better results. However, the overall nodes' remaining energy and lifetime is not considered.

7.3 Clustering Using CS

In [50], authors proposed the use of an embedded PSO-Cuckoo search algorithm to minimize the communication distance and

Table 4. Wireless Sensor Network Clustering Survey

Technique	Optimization Criteria	Reference
GA	communication distance; number of cluster heads	[42]
GA	energy consumption	[45]
GA	communication distance; number of cluster heads	[43]
GA	communication distance	[46]
GA	communication distance; number of cluster heads; energy consumption	[44]
GA	communication cost	[47]
NN	life time	[20]
PSO	communication distance	[48]
PSO	inter cluster distance; average energy level	[26]
PSO	communication distance	[29]
CS-PSO	communication distance	[50]

energy consumption. The fitness was selected to minimizing both the communication distance and the energy consumption. The model used for the energy calculation is the radio model. Authors assumed uniformly distributed nodes, a predefined number of clusters and predefined nodes that have more energy than others. The fitness function adopted is presented in Equation 9:

$$F = c * f_1 + (1 - c) * f_2 \tag{9}$$

where:

$$f_1 = \frac{\sum E(n)}{\sum E(CH)}$$
$$f_2 = \sum d(n, CH)$$

f_1 is the ratio between the total nodes' energies to the total CHs energies. f_2 is the total distances from each node to its CH. c is the energy consciousness weight. The proposed algorithm aimed to speedup convergence. Instead of abandoning discovered nests, the proposed algorithm used PSO on those nests to move them to an acceptable solution. These new solutions replaced the abandoned ones in the cuckoo search individually. The results showed faster convergence when compared with GA, PSO, and CS seldom. The lifetime considerably increased compared to LEACH. This model considered only the global distance between the nodes and its cluster head. Table 4, shows a survey on WSN clustering problems.

8. CONCLUSION

In this paper, an overview of WSN applications and technology was give. Energy consumption problem was outlined. Various clustering technique were emphasized and the problems associated with traditional clustering methods were listed. CI paradigms used in clustering were briefly described and CI-clustering works were analyzed. CI paradigms showed promising results in solving energy consumption problem in WSN. It was found that there is still no clear decision about what the optimal number of clusters should be, or an approved mathematical model for optimization. Hybrid CI such as PSO and CS showed more adaptability to the dynamic nature on WSN. We believe that the contribution of other CI techniques, seldom or hybridized, will be fruitful.

9. REFERENCES

[1] Z. Rezaei and S. Mobininejad. Energy saving in wireless sensor networks. *”International Journal of Computer Science and Engineering Survey (IJCSES)”*, 3(1):23–37, 2012.

[2] Neelam Srivastava. Challenges of next-generation wireless sensor networks and its impact on society. *Journal of Telecommunications*, 1(1):128–133, 2010.

[3] I. Khemapech, I. Duncan, and A. Miller. A survey of wireless sensor networks technology. In *PGNET, Proceedings of the 6th Annual PostGraduate Symposium on the Convergence of Telecommunications*. 2005.

[4] Chiara Buratti, Andrea Conti, Davide Dardari, and Roberto Verdone. An overview on wireless sensor networks technology and evolution. *Sensors*, 9:68696896, 2009.

[5] Fernando Martincic and Loren Schwiebert. *Introduction to Wireless Sensor Networking*, chapter 1, pages 1–40. John Wiley and Sons Inc., 2005.

[6] Chee-Yee Chong and S.P. Kumar. Sensor networks: evolution, opportunities, and challenges. *Proceedings of the IEEE*, 91(8), 2003.

[7] David C. Steere, Antonio Baptista, Dylan McNamee, Calton Pu, and Jonathan Walpole. Research challenges in environmental observation and forecasting systems. In *Proceedings of the 6th annual international conference on Mobile computing and networking*, MobiCom ’00, pages 292–299, New York, NY, USA, 2000. ACM.

[8] Mani Srivastava, Richard Muntz, and Miodrag Potkonjak. Smart kindergarten: sensor-based wireless networks for smart developmental problem-solving environments. In *Proceedings of the 7th annual international conference on Mobile computing and networking*, MobiCom ’01, pages 132–138. ACM, 2001.

[9] Kshitij Shingha, Arti Noor, Neelam Srivastava, and Raghuvir Singh. Wireless sensor networks in agriculture for potato farming. *International Journal of Engineering Science and Technology*, 2(8):3955–3963, 2010.

[10] Dae-Heon Park, Beom-Jin Kang, Kyung-Ryong Cho, Chang-Sun Shin, Sung-Eon Cho, Jang-Woo Park, and Won-Mo Yang. A study on greenhouse automatic control system based on wireless sensor network. *Wirel. Pers. Commun.*, 56(1):117–130, January 2011.

[11] Jennifer Yick, Biswanath Mukherjee, and Dipak Ghosal. Wireless sensor network survey. *Computer Networks*, 52(12):2292–2330, 2008.

[12] Kiran Maraiya, Kamal Kant, and Nitin Gupta. Application based study on wireless sensor network. *International Journal of Computer Applications*, 21(8):915, 2011.

[13] Loren Schwiebert, Sandeep K.S. Gupta, and Jennifer Weinmann. Research challenges in wireless networks of biomedical sensors. In *Proceedings of the 7th annual international conference on Mobile computing and networking*, MobiCom ’01, pages 151–165. ACM, 2001.

[14] A. Fernandez-Montes, L. Gonzalez-Abril, J.A. Ortega, and F.V. Morente. A study on saving energy in artificial lighting by making smart use of wireless sensor networks and actuators. *IEEE Network*, 23(6):16–20, 2009.

[15] T. P. Huynh, Y.K. Tan, and K. J. Tseng. Energy-aware wireless sensor network with ambient intelligence for smart led lighting system control. In *IECON 2011 - 37th Annual Conference on IEEE Industrial Electronics Society*, pages 2923–2928, 2011.

[16] I.F. Akyildiz, Weilian Su, Y. Sankarasubramaniam, and E. Cayirci. A survey on sensor networks. *IEEE Communications Magazine*, 40(8):102–114, 2002.

[17] R.V. Kulkarni, A. Forster, and G.K. Venayagamoorthy. Computational intelligence in wireless sensor networks: A survey. *IEEE Communications Surveys Tutorials*, 13(1):68 – 96, 2011.

[18] J.P.M. Torregoza, In-Yeup Kong, and Won-Joo Hwang. Wireless sensor network renewable energy source life estimation. In *8th International Conference on e-Health Networking, Applications and Services*, pages 13–18, 2006.

[19] W.K.-G. Seah, Zhi Ang Eu, and H. Tan. Wireless sensor networks powered by ambient energy harvesting (wsn-heap) - survey and challenges. In *1st International Conference on Wireless Communication, Vehicular Technology, Information Theory and Aerospace Electronic Systems Technology*, pages 1–5, 2009.

[20] A. Hosseingholizadeh and A. Abhari. A neural network approach for wireless sensor network power management. In *Proceedings of 2nd International Workshop on Dependable Network Computing and Mobile Systems*. 2009.

[21] Giuseppe Anastasi, Marco Conti, Mario Di Francesco, and Andrea Passarella. Energy conservation in wireless sensor networks: A survey. *Ad Hoc Networks*, 7(3):537–568, 2009.

[22] O. Younis, M. Krunz, and S. Ramasubramanian. Node clustering in wireless sensor networks: recent developments and deployment challenges. *IEEE Network*, 20(3):20–25, 2006.

[23] R. Khanna, Huaping Liu, and Hsiao-Hwa Chen. Self-organization of sensor networks using genetic algorithms. In *IEEE International Conference on Communications*, volume 8, pages 3377 – 3382, 2006.

[24] Ameer Ahmed Abbasi and Mohamed Younis. A survey on clustering algorithms for wireless sensor networks. *Computer Communications*, 30(1415):2826 – 2841, 2007.

[25] Vinay Kumar, Sanjeev Jain, and Sudarshan Tiwari. Energy efficient clustering algorithms in wireless sensor networks: A survey. *International Journal of Computer Science Issues*, 8(5):259–268, 2011.

[26] N. Latiff, C. Tsimenidis, and B. Sharif. Energy-aware clustering for wireless sensor networks using particle swarm optimization. In *Personal, Indoor and Mobile Radio Communications, 2007. PIMRC 2007. IEEE 18th International Symposium on*, pages 1–5, 2007.

[27] Prakashgoud Patil, Umakant Kulkarni, and N. H. Ayachit. Some issues in clustering algorithms for wireless sensor networks. *IJCA Special Issue on 2nd National Conference-Computing, Communication and Sensor Network (CCSN)*, (4):18–23, 2011.

[28] Chengfa Li, Mao Ye, Guihai Chen, and Jie Wu. An energy-efficient unequal clustering mechanism for wireless sensor networks. In *IEEE International Conference on Mobile Adhoc and Sensor Systems Conference*, pages 8 pp.–604, 2005.

[29] Jiabin Hou, Xinggang Fan, Wanliang Wang, Jing Jie, and Yi Wang. Clustering strategy of wireless sensor networks based on improved discrete particle swarm optimization. In *The 2010 Sixth International Conference on Natural Computation (ICNC)*, volume 7, pages 3866–3870, 2010.

[30] Malik Braik, Alaa Sheta, and Amani Arieqat. A comparison between ga and pso in training ann to model the te chemical process reactor. *Proceedings of the AISB symposium on swarm intelligence algorithms and applications*, 11:24–30, 2008.

[31] Malik Braik and Alaa Sheta. *Exploration of Genetic Algorithms and Particle Swarm Optimization in Improving the Quality of Medical Images*, pages 329–360. Lambert Academic Publishing (LAP), Germany, 2011.

[32] Andries P. Engelbrecht. *Computational Intelligence: An Introduction*. Wiley Publishing, 2nd edition, 2007.

[33] D. Bratton and J. Kennedy. Defining a standard for particle swarm optimization. In *IEEE Swarm Intelligence Symposium*, pages 120 – 127, 2007.

[34] Ioan Cristian Trelea. The particle swarm optimization algorithm: convergence analysis and parameter selection. *Information Processing Letters*, 85(6):317–325, 2003.

[35] J. Kennedy. Small worlds and mega-minds: effects of neighborhood topology on particle swarm performance. In *Proceedings of the 1999 Congress on Evolutionary Computation*, volume 3, pages –1938 Vol. 3, 1999.

[36] J. Kennedy and R. Mendes. Population structure and particle swarm performance. In *Proceedings of the 2002 Congress on Evolutionary Computation*, volume 2, pages 1671 – 1676, 2002.

[37] Xin-She Yang and Si Deb. Engineering optimisation by cuckoo search. *International Journal of Mathematical Modelling and Numerical Optimisation*, 1(4):330–343, 2010.

[38] Xin-She Yang and S. Deb. Cuckoo search via levy flights. In *World Congress on Nature Biologically Inspired Computing*, pages 210 – 215, 2009.

[39] Ehsan Valian, Shahram Mohanna, and Saeed Tavakoli. Improved cuckoo search algorithm for feedforward neural network training. *International Journal of Artificial Intelligence and Applications (IJAIA)*, 2(3):36–43, 2011.

[40] Hongqing Zheng and Yongquan Zhou. A novel cuckoo search optimization algorithm base on gauss distribution. *International Journal of Computational Information Systems*, 8:4193–4200, 2012.

[41] Ahmed S. Tawfik, Amr A. Badr, and Ibrahim F. Abdel-Rahman. One rank cuckoo search algorithm with application to algorithmic trading systems optimization. *International Journal of Computer Applications*, 64(6):30–37, 2013.

[42] Shiyuan Jin, Ming Zhou, and Annie S. Wu. Sensor network optimization using a genetic algorithm. In *the Proceedings of the 7th World Multiconference on Systemics,Cybernetics, and Informatics*. 2003.

[43] Mohaned Al-Obaidy, Aladdin Ayesh, and Alaa F. Sheta. Optimizing the communication distance of an ad hoc wireless sensor networks by genetic algorithms. *Artificial Intelligence Review*, 29(3):183–194, 2008.

[44] Moslem Afrashteh Mehr. Design and implementation a new energy efficient clustering algorithm using genetic algorithm for wireless sensor networks. *World Academy of Science, Engineering and Technology*, 52:430–433, 2011.

[45] S. Hussain, A.W. Matin, and O. Islam. Genetic algorithm for energy efficient clusters in wireless sensor networks. In *Fourth International Conference on Information Technology*, pages 147–154, 2007.

[46] Hyun-Sik Seo, Se-Jin Oh, and Chae-Woo Lee. Evolutionary genetic algorithm for efficient clustering of wireless sensor networks. In *6th IEEE Consumer Communications and Networking Conference*, pages 1–5, 2009.

[47] K. LingaRaj, D. Aradhana, and Nagaveni B.Biradar. Multiple mobile agents in wireless sensor networks using genetic algorithms. *International Journal of Scientific and Engineering Research*, 3(8):1–5, 2012.

[48] S.M. Guru, S.K. Halgamuge, and S. Fernando. Particle swarm optimisers for cluster formation in wireless sensor

networks. In *Proceedings of the International Conference on Intelligent Sensors, Sensor Networks and Information Processing*, pages 319–324, 2005.

[49] R.V. Kulkarni and G.K. Venayagamoorthy. Particle swarm optimization in wireless-sensor networks: A brief survey. *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, 41(2):262 – 267, 2011.

[50] M. Karthikeyan and K. Venkatalakshmi. Energy conscious clustering of wireless sensor network using PSO incorporated cuckoo search. In *Third International Conference on Computing Communication Networking Technologies (ICCCNT)*, pages 1–7, 2012.