Social Impact Theory-Based Node Placement Strategy for Wireless Sensor Networks

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Abstract The network density, energy consumption, and connectivity are the most important design parameters for a self-organizing wireless sensor network. This paper presents a social impact theory-based multi-objective strategy for optimizing these parameters. The proposed strategy optimizes the clustering schemes and signal strengths along with the operational modes of the sensor nodes. The algorithm has been implemented in MATLAB using an open source social impact theory Optimization toolbox (http://mloss.org/software/view/457/). The suggested algorithm offers the achievement of optimal designs and satisfies the different design parameters.

Keywords Component social impact theory · Network configuration · Sensor placement · Wireless sensor networks

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1 Introduction

Wireless sensor networks (WSNs) have incited remarkable research interests due to their vast potential in sensors, electronics, and computational fields. They have been exploited for civil as well as defense-related purposes. A WSN typically comprises large numbers of sensor nodes, which are energy constrained with limited computational and communication capabilities [1, 2]. The deployment of WSN nodes is usually based upon its application and could be random or deterministic [3–5]. Random deployment is usually done in hostile scenarios such as battlefield or hazardous environments, whereas amiable scenarios call for the deterministic deployment. In general, WSNs are expected to provide access to information about the physical world, regardless of time and space, this vision poses significant challenges for WSNs. The pervasiveness of WSN's limits its centralized control and is not practical and calls for capabilities of scalability, self-organization, self-adaptation, and survivability [6].

Energy utilization is a major issue for a WSN as the energy resources are consumed during the operation of nodes. The replacement of batteries or their recharge may sometimes be infeasible. Energy efficiency and utilization of a WSN depends upon the temporal resolution of information being collected, routing strategies, node placements, etc. [7–9]. Another important issues to be taken care of in a WSN are the network lifetime and connectivity. Cluster-based architectures are generally employed, in which the nodes are arranged in their network. These networks communicate with their respective cluster head node. Thus, collected information from the nodes is transmitted to the base station. The network connectivity problems include not only the load handling capability of the sink nodes, but also the ability of the sensor nodes to communicate with the cluster heads. Apart from the above issues, the application-specific design parameters also pose some issues. Several algorithms [3, 10–21] have been reported for the WSN design optimization in terms of scalability, self-organization, self-adaptation, and survivability. However, most of those suggested algorithms do not necessarily address the application-specific issues and make design parameterization and optimization a challenging task.

The design of a WSN system hence calls for simultaneous optimization of multiple nonlinear design parameters. This is a challenging task, as it requires finding pareto-optimal solutions under severe computational limitations. Such problems have been reported to be tackled with the application of computational approaches, such as neural networks, swarm optimization, genetic algorithm (GA), and ant colony optimization [22–28]. Social impact theory (SITO) is a recently introduced approach based on the application of a novel [29]. In this approach, a spatially distributed population of individuals in a two-dimensional lattice networks with each other to generate an optimal solution. In the process, the individuals change their attitude for a particular feature under influence of their neighbors' number, attitude, strength, and immediacy. The optimizer has been tested on benchmark problems for feature subset selection [29–33]. However, this optimizer has not been attempted for WSN optimization as yet.

In the present work, we have tried to analyze the application of SITO in WSN by integrating the network characteristics according to the application-specific requirements. In general, the algorithm under the constraints of application-specific requirements and energy consumption determines operational modes of the nodes. In particular, the network design has been investigated with respect to the sensor placements, communication range, and clustering. The performance of the proposed approach has been investigated by the study of connectivity and related energy characteristics and application-oriented properties (e.g., uniformity/spatial density of the sensing nodes). The work finally proposes an optimal design in which the mode of operation has been specified for each sensor node.

2 Methodology

2.1 Social Impact Theory-Based Optimization (SITO)

The social impact theory was proposed by Latané [34] wherein the author defined the social impact as any influence on an individual's feelings, thoughts, or behavior that is exerted by the real, implied, or imagined presence or actions of others. This meta-theory characterized the spatiotemporal variabilities of human opinion formation. This theory was modified by Nowak et al. [35] by taking into consideration the reciprocal influence of the individuals on their environment. Further, Macaš et al. [29] and Bhondekar et al. [30] implemented the above theory for optimal feature extraction and classification. The SITO algorithm is advantageous because of the requirement of few control parameters and capability of analyzing spatially distributed population.

In the SITO algorithm, an individual represents a probable solution for the problem at hand by maintaining a set of spatially distributed population in a two-dimensional lattice. The strength of the individual is estimated by taking in account the fitness value of its opinion. This opinion is subsequently modified at every iteration with respect to number of neighbors, strength, and immediacy. Total societal impact (I) is calculated by difference between the persuasive impact (I_{p}) of individuals holding the opposite opinions and the supportive impact (I_{s}) of individuals with the same opinion. I_{p} and I_{s} are defined as expressed by the following equations.

$$I_{\mathrm{p}} = N_{\mathrm{o}}^{1/2}\left[\sum \left(p_i/d_i^2\right) \Big/ N_{\mathrm{o}}\right] \tag{1}$$

$$I_{\mathrm{s}} = N_{\mathrm{s}}^{1/2}\left[\sum \left(s_i/d_i^2\right) \Big/ N_{\mathrm{s}}\right] \tag{2}$$

where, p_i is the persuasiveness of source i

s_i denotes the supportiveness of source i

N_o represents number of sources (individuals with opposing opinion)

N_s represents the number of individuals with individual opinions and d_i refers to the distance between the source i and the recipient

Generally, the individuals' opinions are modulated by comparing I_p and I_s, if I_p is greater than I_s, the of the individual changes with a probability $1 - K$. Similarly, the attitude may change with a probability K if I_p is lesser than I_s. The probability K improves the explorative capability by preventing loss of diversity.

The pseudocode as proposed by Macaš [29] is expressed as under:

```
Initialize attitudes by random assignment of binary values from
(0,1) to   society.attitudes;
iter = 0;
WHILE (iter < max_iter) DO
      Compute society.fitness using Eq. 3 for corresponding
society.attitudes;
      Find maximum fitness value, fmax, from society.fitness;
      Find minimum fitness value, fmin, from society.fitness
      Calculate society.strength = ( fmax  - society.fitness ) / (
fmax - fmin );
      iter = iter+1;
      FOR each individual i and each dimension z DO
            Find sources and supporters in neighbourhood of i;
            Compute number of sources and supporters (No, Ns) in
            neighbourhood of individual i with respect to
            dimension z.
            Compute total persuasive impact Ip using Eq.1
            Compute total supportive impact Is using Eq. 2
             IF (Ip>Is) and (i is not the best of all),
                   Invert the attitude of individual i in
                  dimension z with probability 1-K
            ELSE,
                  Invert the attitude of individual i in dimension
                  z with probability K;
            END (IF)
      END (FOR)
END (WHILE)
```

2.1.1 Problem Outline

In this work we have assumed a two-dimensional field employing three types of sensors, which monitor parameters related to X, Y, Z. The spatial variability is such that sensor nodes' density in Z is greater than Y and X and for Y it is greater than X [36].

2.1.2 Network Model

A grid-based Euclidian model has been considered here, wherein the nodes have been placed at the intersections (see Fig. 1).

The active sensing nodes considered for this simulation are identical and have the usual features like power control and selection parameter for different sensing modes in X, Y, Z along with power control in transmission. We have assumed a cluster architecture where, the cluster-in-charge are the nodes operating in X-sense, along with Y and Z sensing modes with middle and small transmission ranges, respectively. It should be noted that the nodes present in the X mode can communicate with the base station using a multi-hop protocol and this leads to clustering of nodes in their vicinity [30].

Apart from sensing the X parameter the node in X-sense mode also performs tasks of data collection and its accumulation along with complex computations.

2.1.3 Problem Statement

The design parameters of WSN can be categorized into 3 classes [37]. First category incorporates the parameters of sensor deployment, e.g., uniformity and coverage. The second category deals with the connectivity parameters in a manner that no node remains unconnected. The last category involves the variables or parameters responsible for the survivability of the network, such as operational energy. In the proposed work, we have explored a multi-objective algorithm to optimally select these design parameters by scalarizing them into a single fitness function as

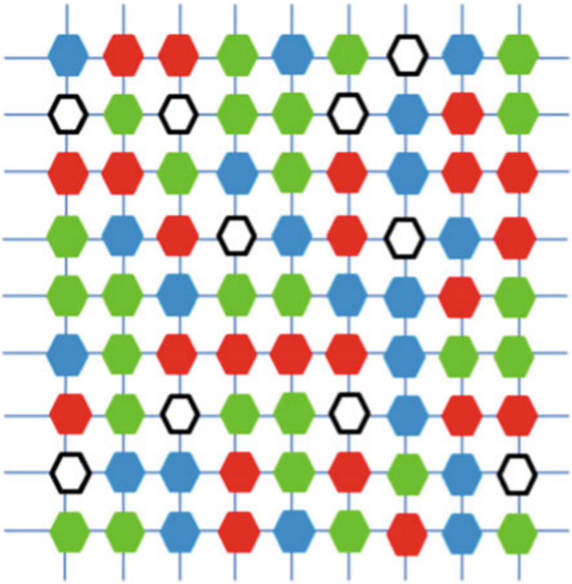


Fig. 1 The layout of a wireless sensor network

given by Eq. 3. The design optimization has been achieved by minimizing constraints such as number of unconnected sensors, operational energy and number of overlapping cluster-in-charge. The parameters namely number of sensors for each cluster-in-charge and field coverage are maximized. The measurement of quality of each probable solution of the optimization problem is given by the objective function in form of a numerical figure [36].

$$f = \min\left\{\sum_{i=1}^{5} k_i P_i\right\} \tag{3}$$

where, k and P_i are the corresponding weight and optimization parameter, respectively [36].

2.2 WSN Representation, Optimization Parameters, and Fitness Function

A square field ($L \times L$ length units) has been subdivided into several grids of unit lengths. The nodes are arranged on the grids. A bit-string represents an individual attitude in the society, which is employed for the encoding of the sensor nodes in a row-wise pattern as depicted in Fig. 2. Two bits are needed for the encoding of four states of the sensing nodes, viz. X, Y, Z, and inactive. Thus, the total length of the bit-string is set to be $2 \cdot L2$.

The optimization parameters listed in Table 1 are derived from following network attributes

n_x is the X Sensors (cluster-in-charge) in terms of numbers. Similarly,
n_y Y Sensors
n_z Z Sensors
n_{OR} Out-of-Range Sensors

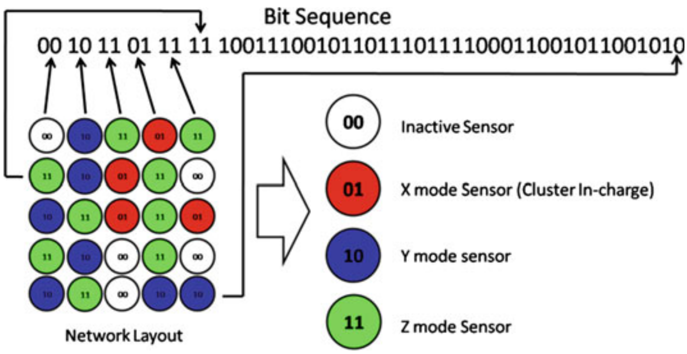


Fig. 2 Representation of Bit-string network layout [30]

Table 1 Correspondences between objectives and optimization parameters [36]

Objective	Parameters for optimization	Symbols
P1	Field coverage	FC
P2	Overlaps in unit cluster-in-charge error	OpCiE
P3	Out-of-range sensor error	SORE
P4	Sensors in unit cluster-in-charge	SpCi
P5	Network energy	NE

n_{inactive} Inactive Sensors
n_{total} total sensing points
n_{o} overlaps of cluster heads

The parameters to be optimized are derived as follows and are defined in [36]:

$$\mathrm{FC} = \frac{(n_x + n_y + n_z) - (n_{\mathrm{OR}} + n_{\text{inactive}})}{n_{\text{total}}} \tag{4}$$

$$\mathrm{SpCi} = \frac{n_{\mathrm{y}} + n_{\mathrm{z}} - n_{\mathrm{OR}}}{n_x} \tag{5}$$

$$\mathrm{SORE} = \frac{n_{\mathrm{OR}}}{n_{\text{total}} - n_{\text{inactive}}} \tag{6}$$

$$\mathrm{OpCiE} = \frac{n_{\mathrm{o}}}{n_x} \tag{7}$$

$$\mathrm{NE}\frac{4 \cdot n_x + 2 \cdot n_y + n_z}{n_{\text{total}}} \tag{8}$$

Therefore, there is a unique bit-string sequence for every unique WSN Design whose feature and performance can be estimated using fitness or weighting function. The fitness or weighting function needs to properly signify all the significant design parameters to influence the desired quality/performance of the WSN design. Each of the design parameter is equally important. Therefore for the present problem, the fitness function may be formulated as

$$f = -\alpha_1 \mathrm{FC} + \alpha_2 \mathrm{OpCiE} + \alpha_3 \mathrm{SORE} - \alpha_4 \mathrm{SpCi} + \alpha_5 \mathrm{NE} \tag{9}$$

In the above fitness function, the appropriate weighting coefficients α_i: $i = 1, 2\ldots 5$ define the significance of each design parameter. Therefore, the SITOs objective is to minimize the value of fitness function, to maximize some parameters their coefficients must be negative. The coefficient values are determined on the basis of design requirements and related experimentation. The desired values of the individual parameter coefficient were manually computed. The well-performing weight are listed in Table 2.

Table 2 Optimized values of the weighing coefficients

Parameters	Coefficient	Optimized value
Field coverage	α_1	6
Overlaps-per-cluster-in-charge error	α_2	0.65
Out-of-range sensors-error	α_3	9
Sensors-per-cluster-in-charge	α_4	1
Network energy	α_5	1.2

During the analysis (Table 2), the network connectivity variables (weights α_1, α_4) were considered as constraints such that all the sensor nodes are in the limit of a cluster-in-charge, and no cluster-in-charge connects to higher than a predefined number of the sensors nodes.

3 Experimental Results

A network size of 10 × 10 was considered for experimentation. A total of 100 runs were carried out wherein four different machines performed 1000 iterations on four separate segments of 25 samples. Various combinations of society size and neighborhood were experimented and the best results in terms of convergence rate were obtained for society size of 225, and neighborhood size of 2. The convergence results obtained for neighborhood size 2 at different society sizes are shown in Fig. 3. It may be observed that increasing the society size beyond 225 does not

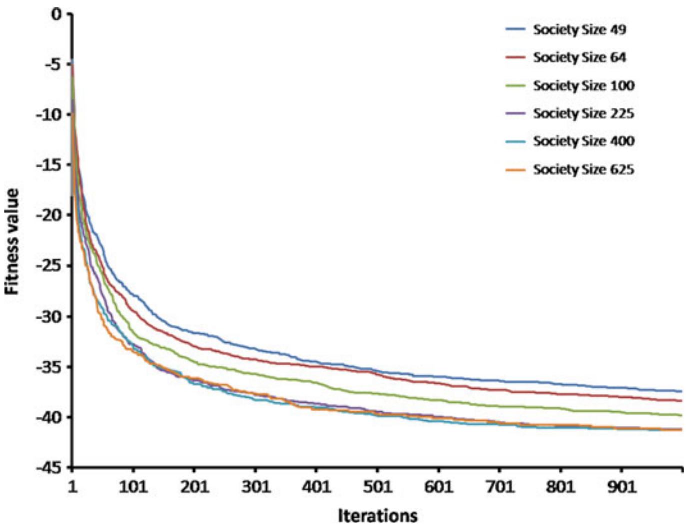


Fig. 3 A comparison between the convergence rates obtained at different society sizes with constant neighborhood size of 2

improve the performance of the algorithm. Moreover, by further increasing the society size, the convergence time increases exponentially. Similarly, Fig. 4 shows the convergence rate of the fitness value for a society size of 225 with varying neighborhood sizes. It may be observed that the neighborhood size of 2 gives the best convergence rate.

The optimized network by the algorithm is graphically represented employing a customized MATLAB script. One of the observed designs is shown in Fig. 5 in which the red, blue, and green circle, respectively, denote the X (cluster-in-charge),

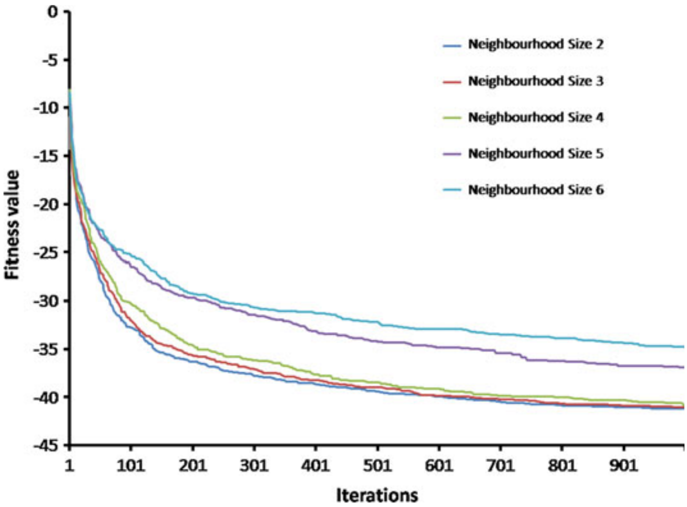
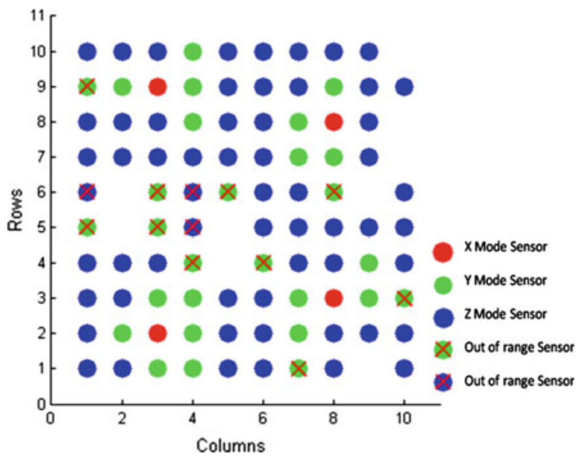


Fig. 4 Comparison of convergence rates obtained at different neighborhood sizes with constant society size of 225

Fig. 5 A graphically represented network as optimized by the algorithm



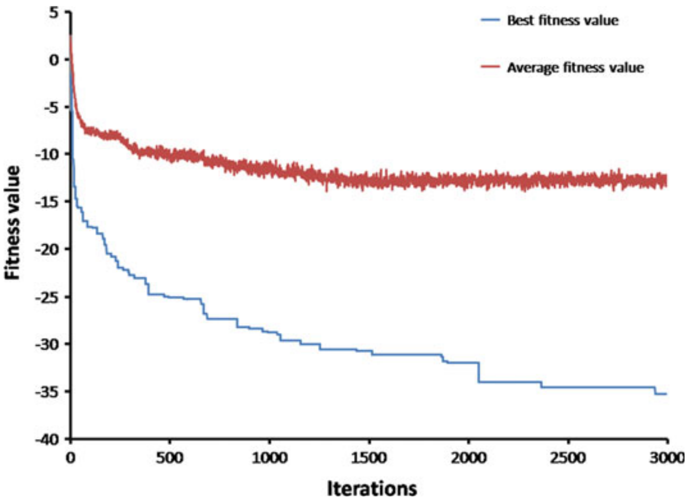


Fig. 6 Evolution progress for the identification of best individual (highest fitness value) and the entire society (average fitness value) using SITO approach

Y, and Z sensor positions. A cross-mark circle represents the out-of-range sensor node, whereas an inactive sensor node is represented by the empty space.

Figure 6 shows the progress of average value and minimum value of society fitness of one of the best runs. The three best SITO runs (abbreviated as S1, S2, and S3) that yielded the best results after 3000 iterations were observed and their results are in Table 3.

Table 3 Values of optimized parameters for 3 SITO-generated layouts of the network

Design parameter	S1	S2	S3
FC	0.85	0.9	0.75
OpCiE	2	1	0
SORE	0.2	0	0.01
SpCi	21.5	20.25	22.75
NE	1.6	1.5	1.41
Active sensors	91	87	93
X mode sensors	4	4	4
Y mode sensors	18	58	74
Z mode sensors	56	21	10
Inactive sensors	9	10	7
Out-of-range sensors	13	7	5
X mode or active sensors	0.043	0.044	0.043
Y mode or active sensors	0.197	0.644	0.795
Z mode or active sensors	0.615	0.233	0.107

4 Conclusions

A human opinion formation-based strategy (SITO) was used to optimize the nodes deployment of a fixed WSN. A grid-based fixed WSN having nodes of different operating modes was considered. The optimization was based upon various network parameters viz. field coverage, cluster overlapping, out-of-range errors, and network energy. The results showed that human opinion formation-based algorithm such as SITO can be used in WSN applications.

References

1. Yick, J., B. Mukherjee, and D. Ghosal, *Wireless sensor network survey.* Computer Networks, 2008. **52**(12): p. 2292–2330.
2. Rawat, P., et al., *Wireless sensor networks: a survey on recent developments and potential synergies.* The Journal of Supercomputing, 2014. **68**(1): p. 1–48.
3. Ishizuka, M. and M. Aida. *Performance study of node placement in sensor networks*. in *Distributed Computing Systems Workshops, 2004. Proceedings. 24th International Conference on*. 2004.
4. Izadi, D., J. Abawajy, and S. Ghanavati, *An Alternative Node Deployment Scheme for WSNs.* Sensors Journal, IEEE, 2015. **15**(2): p. 667–675.
5. Bhondekar, A.P., et al., *A multiobjective Fuzzy Inference System based deployment strategy for a distributed mobile sensor network.* Sensors & Transducers, 2010. **114**(3): p. 66.
6. Viani, F., et al. *Pervasive remote sensing through WSNs*. in *Antennas and Propagation (EUCAP), 2012 6th European Conference on*. 2012.
7. Kim, K.T., et al. *An energy efficient and optimal randomized clustering for wireless sensor networks*. in *Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD), 2015 16th IEEE/ACIS International Conference on*. 2015.
8. Shafali, et al. *An algorithm to minimize energy consumption using nature-inspired technique in wireless sensor network*. in *Circuit, Power and Computing Technologies (ICCPCT), 2015 International Conference on*. 2015.
9. Srbinovski, B., et al. *Energy aware adaptive sampling algorithm for energy harvesting wireless sensor networks*. in *Sensors Applications Symposium (SAS), 2015 IEEE*. 2015.
10. Slijepcevic, S. and M. Potkonjak. *Power efficient organization of wireless sensor networks*. in *Communications, 2001. ICC 2001. IEEE International Conference on*. 2001.
11. Krishnamachari, B. and F. Ordonez. *Analysis of energy-efficient, fair routing in wireless sensor networks through non-linear optimization*. in *Vehicular Technology Conference, 2003. VTC 2003-Fall. 2003 IEEE 58th*. 2003.
12. Zhou, C. and B. Krishnamachari. *Localized topology generation mechanisms for wireless sensor networks*. in *Global Telecommunications Conference, 2003. GLOBECOM '03. IEEE*. 2003.
13. Chen, S.Y. and Y.F. Li, *Automatic sensor placement for model-based robot vision.* Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 2004. **34**(1): p. 393–408.
14. Alageswaran, R., et al. *Design and implementation of dynamic sink node placement using Particle Swarm Optimization for life time maximization of WSN applications*. in *Advances in Engineering, Science and Management (ICAESM), 2012 International Conference on*. 2012.
15. Deif, D.S. and Y. Gadallah, *Classification of Wireless Sensor Networks Deployment Techniques.* Communications Surveys & Tutorials, IEEE, 2014. **16**(2): p. 834–855.

16. Dondi, D., et al., *Modeling and Optimization of a Solar Energy Harvester System for Self-Powered Wireless Sensor Networks.* Industrial Electronics, IEEE Transactions on, 2008. **55**(7): p. 2759–2766.
17. Elshaikh, M., et al. *Energy consumption optimization with Ichi Taguchi method for Wireless Sensor Networks*. in *Electronic Design (ICED), 2014 2nd International Conference on*. 2014.
18. Hortos, W.S. *Bio-inspired, cross-layer protocol design for intrusion detection and identification in wireless sensor networks*. in *Local Computer Networks Workshops (LCN Workshops), 2012 IEEE 37th Conference on*. 2012.
19. Kolega, E., V. Vescoukis, and D. Voutos. *Assessment of network simulators for real world WSNs in forest environments*. in *Networking, Sensing and Control (ICNSC), 2011 IEEE International Conference on*. 2011.
20. Menon, K.A.U., D. Maria, and H. Thirugnanam. *Power optimization strategies for wireless sensor networks in coal mines*. in *Wireless and Optical Communications Networks (WOCN), 2012 Ninth International Conference on*. 2012.
21. Mohamaddoust, R., et al. *Designing the Lighting Control System Based on WSN with Optimization of Decision Making Algorithm*. in *Computational Intelligence and Communication Networks (CICN), 2010 International Conference on*. 2010.
22. Iram, R., et al. *Computational intelligence based optimization in wireless sensor network*. in *Information and Communication Technologies (ICICT), 2011 International Conference on*. 2011.
23. Lejiang, G., et al. *WSN Cluster Head Selection Algorithm Based on Neural Network*. in *Machine Vision and Human-Machine Interface (MVHI), 2010 International Conference on*. 2010.
24. Payal, A., C.S. Rai, and B.V.R. Reddy. *Artificial Neural Networks for developing localization framework in Wireless Sensor Networks*. in *Data Mining and Intelligent Computing (ICDMIC), 2014 International Conference on*. 2014.
25. Serpen, G., et al. *WSN-ANN: Parallel and distributed neurocomputing with wireless sensor networks*. in *Neural Networks (IJCNN), The 2013 International Joint Conference on*. 2013.
26. Singh, P. and S. Agrawal. *TDOA Based Node Localization in WSN Using Neural Networks*. in *Communication Systems and Network Technologies (CSNT), 2013 International Conference on*. 2013.
27. Subha, C.P., S. Malarkan, and K. Vaithinathan. *A survey on energy efficient neural network based clustering models in wireless sensor networks*. in *Emerging Trends in VLSI, Embedded System, Nano Electronics and Telecommunication System (ICEVENT), 2013 International Conference on*. 2013.
28. Wen-Tsai, S., et al. *Enhance the efficient of WSN data fusion by neural networks training process*. in *Computer Communication Control and Automation (3CA), 2010 International Symposium on*. 2010.
29. Macaš, M., L. Lhotská, and V. Křemen, *Social Impact based Approach to Feature Subset Selection*, in *Nature Inspired Cooperative Strategies for Optimization (NICSO 2007)*, N. Krasnogor, et al., Editors. 2008, Springer Berlin Heidelberg. p. 239–248.
30. Bhondekar, A.P., et al., *A novel approach using Dynamic Social Impact Theory for optimization of impedance-Tongue (iTongue).* Chemometrics and Intelligent Laboratory Systems, 2011. **109**(1): p. 65–76.
31. Kaur, R., et al., *Enhancing electronic nose performance: A novel feature selection approach using dynamic social impact theory and moving window time slicing for classification of Kangra orthodox black tea (Camellia sinensis (L.) O. Kuntze).* Sensors and Actuators B: Chemical, 2012. **166–167**: p. 309–319.
32. Macaš, M., et al., *Binary social impact theory based optimization and its applications in pattern recognition.* Neurocomputing, 2014. **132**: p. 85–96.
33. Kaur, R., et al., *Human opinion dynamics: An inspiration to solve complex optimization problems.* Sci. Rep., 2013. **3**.
34. Latané, B., *The Psychology of Social Impact.* American Psychologist, 1981. **XXXVI** (4): p. 343–356.

35. Nowak, A., J. Szamrej, and B. Latané, *From private attitude to public opinion: a dynamic theory of social impact.* Psychological Review, 1990. **97**(3): p. 362–376.
36. Bhondekar, A.P., et al. *Genetic Algorithm Based Node Placement Methodology For Wireless Sensor Networks*. in *International MultiConference of Engineers and Computer Scientists*. 2009. Hong Kong: IAENG.
37. Ferentinos, K.P. and T.A. Tsiligiridis, *Adaptive design optimization of wireless sensor networks using genetic algorithms.* Computer Networks, 2007. **51**(4): p. 1031–1051.