DATA FUSION BASED SCHEME FOR CLUSTER BASED WIRELESS SENSOR NETWORKS

Abhilasha Sharma
M. Tech. Scholar
Digital Communication
PCST, Bhopal (M.P.)

Mr. Jitendra Mishra
Associate Professor & HOD
Department of Electronics & Communication
PCST, Bhopal (M.P.)

ABSTRACT
Practical aspect in the operation of the WSNs is the sensitivity of the statistical inference procedures to uncertainties in modeling the environment in which the WSN operates. The inference schemes and their performances are characterized by many parameters, some of which are obtained via experimentation, while a few are obtained during the deployment stage of the WSN.
An improved approach used hypothesis-based probability which aims to enhance the network lifetime by determining the optimal trajectory and cluster head for the base stations. Unlike the scheme carried out, this approach works for large-scale sensor networks with irregular node distribution. The process of hypothesis measures the normal condition of energy utilization and packet transmission. It cannot consider the process of interference and lower probability value.
Keywords: WSN, Cluster, Cluster Head, Multi-Hope, MS, Time Optimization, Hypothesis, Probability.

I. INTRODUCTION

Wireless sensor networks (WSNs) consist a large number of small and tiny nodes which are scattered over the physical environment to monitor humidity, temperature, pressure, vibration, etc. These devices are highly resource constrained, equipped with small processors and wireless communication antennas, and battery powered. A sensor network is typically expected to perform multiple tasks. Tasks can be categorized into multiple sub-tasks[1-3]. As an example, monitoring a large area can be categorized into monitoring multiple smaller areas[4]. In heterogeneous networks, the requirement of a task is specified by its needs for different types of sensors. In such cases, sensors must be bundled together before performing task assignments. Due to the limited number of sensors and potentially large number of tasks, competition will arise[6]. Given all currently available information, the goal is to perform the best assignment of available sensors to tasks, to maximize the utility of the network[8-9]. A large mass of sensor nodes is supposed to scatter in a geometric region, with nearby nodes communicating with each other directly. Without the help of a large amount of uniformly deployed seed nodes, this scheme fails in WSNs with possible holes. The global geometry and topology of a WSN has a great influence on the design of basic networking functionalities, for example, point-to-point routing and data collecting mechanisms, or if they are desirous to spread some mobile sensors in an unknown region formed by static sensor nodes, knowing the border of the region permits us to guarantee that newly added sensors are deployed only in the expected region[5, 7].

In the rest part of our research work described the sojourn times calculation and optimization, proposed algorithm and model, experimental work and result analysis, performance improvement and finally conclusion and future scope sequences manner in section II, III, IV, V, VI.

II. SOJOURN TIMES CALCULATION AND OPTIMIZATION

Calculation: CMS2TO aims to equalize the lifetime of the CH located at the residence cluster with the other CHs located at the same sector and different coronas. To achieve this goal, in this phase, for each CH located at other coronas (CHj), a time is suggested for sojourning of MS at residence cluster (CHi) in order to achieve balanced lifetime between residence CH and CHj[10].

The Suggested Sojourn Times Calculation phase is started when MS identifies the residence CH. Afterwards, MS requests the residual energy of the CHs belonging to the other coronas (CHj). Upon receiving the residual energy information, the lifetime of the CH located at the residence cluster (CHi) is separately equalized with the CHs located at the j^{th} corona as relation 6[11-14].

$$l_i = l_j \;\; 1 \le j \le k, \qquad j \ne i \qquad (1)$$

Where K is the total number of coronas. Then by substituting the Equation 4 in the Equation 6, Equation 7 can be concluded.

$$\frac{\varepsilon 0.NCH_i}{ECH_i} = \frac{\varepsilon 0.NCH_j}{ECH_j} \qquad (2)$$

In addition, since, computing the sojourn time is performed according to the current remaining energy of the CHs, Equation 7 can be rewritten as Equation 8.

$$\frac{Eres_i}{ECH_i} = \frac{Eres_j}{ECH_j} \qquad (3)$$

Where Eres denotes the summation of residual energy of CH candidate nodes, which are located at the control region of the clusters.

Based on the previous discussion, the lifetime of CHs located at i[th] (residence CH) and j[th] coronas can be balanced, if MS serves the i[th] CH sufficiently to compensate its extra energy consumption in comparison with j[th] CH. In other words, MS should stay at the ith cluster as long as the excess residual energy of j[th] CH in comparison with i[th] CH is consumed. Then, Equation 8 can be rewritten as Equation 4[15].

$$\frac{Eres_i}{ECH_i} = \frac{Eres_j - (ST_j * ECH_j)}{ECH_j} \;\; 1 \le j \le k, j \ne i \qquad (4)$$

Where ST_j denotes the suggested time for staying MS at residence cluster to balance the lifetime of residence CH with CH_j, which can be calculated using Equation 5.

$$ST_j = \frac{Eres_i.Eres_j - ECH_j.Eres_i}{ECH_i.ECH_j} \;\; 1 \le j \le k, j \ne i \qquad (5)$$

Based on Equation 10, MS should stay in i[th] cluster for ST_j time to balance the energy depletion of the CHs located at the clusters belonging to the i[th] and j[th] coronas. In addition, since, outer CHs consume less energy, their residual energy is more than inner CHs. Consequently, the relation 6 can be concluded.

$$ST_1 \, < \, ST_1 \, <, \ldots \ldots ST_k \qquad (6)$$

Optimization: In order to achieve balanced energy depletion of CHs located in a sector, the sojourn time of MS in residence clusters should be chosen in such a way that there is the minimal difference between the sojourn times suggested at the first phase. This problem is modelled as an Integer Linear Programming (ILP) and the cost function is formulated using relation 11.

$$minimize \sum_{i=1}^{K} (OST - ST_i)^2 \qquad 0 \le OST \le threshold \qquad (7)$$

Where OST is the optimal sojourn time of MS in the residence cluster. In addition, the constraint denotes that the OST cannot exceed the threshold determined in the second phase of CMS2TO.

III. PROPOSED ALGORITHM AND MODEL

In this section, the distributed detection model is presented in order to fuse the decisions made by the low-quality sensor nodes during the observation phase. Suppose that N sensors are displaced in the observation area. Each sensor node processes its observation and makes the decision based on its observation. Then each sensor node sends its decision to the fusion center through the wireless channel. The fusion center makes the final decision based on some rules.

Here suppose that the a priori probabilities of the two hypotheses are denoted by $P(H_0)=P_0$ and $P(H_1)=P_1$. Each sensor node uses a decision rule such as the Bayesian decision rule to make its decision u_i, i = 1, ...,n:

$$u_i = \begin{cases} 0 & if\ local\ decision\ is\ H_0 \\ 1 & if\ local\ decision\ is\ H_1 \end{cases} \qquad (8)$$

After making its decision, the sensor node sends its decision to the fusion center in order to make the final decision. The fusion center determines the final decision u based on these individual decisions:

$$\bar{u} = f(u_1, u_2, \ldots \ldots \ldots \ldots \ldots \ldots u_n) \qquad (9)$$

The likelihood ratio test can be written as follows [14]:

$$\frac{P(u_1, u_2, \ldots u_n \text{ I } H_1)}{P(u_1, u_2, \ldots u_n \text{ I } H_0)} >< \frac{P_0}{P_1} \qquad (10)$$

The quantity on the left-hand side is the likelihood ratio and the Bayes optimum threshold is on the right-hand side. The optimum decision fusion rule is the

Chair-Varshney fusion rule which can be written as follows:

$$\bar{u} = f(u_1, u_2, \dots \dots \dots \dots \dots \dots u_n) = \begin{cases} 0 & if\ \Lambda > 0 \\ 1 & otherwise, \end{cases} \quad (11)$$

Where,

$$\Lambda = \sum_{i=1}^{N} \left[u_1 \ln \frac{P_{d_i}}{P_{fa_i}} + (1 - u_i) \ln \frac{1 - P_{d_i}}{1 - P_{fa_i}} \right] + \ln \frac{P(H_1)}{P(H_0)} \quad (12)$$

From the equation, the optimal decision fusion rule needs the performance parameters of each sensor node like the detection probability and the false alarm probability. But in practice, the performance parameters of the low-end sensor can hardly be known due to its limited performance. The low-quality sensors are also easily affected by the environment. In order to use the optimal decision fusion rules, we need to know the performance parameters of these low-quality sensors in order to reach the optimal result.

SYSTEM MODEL

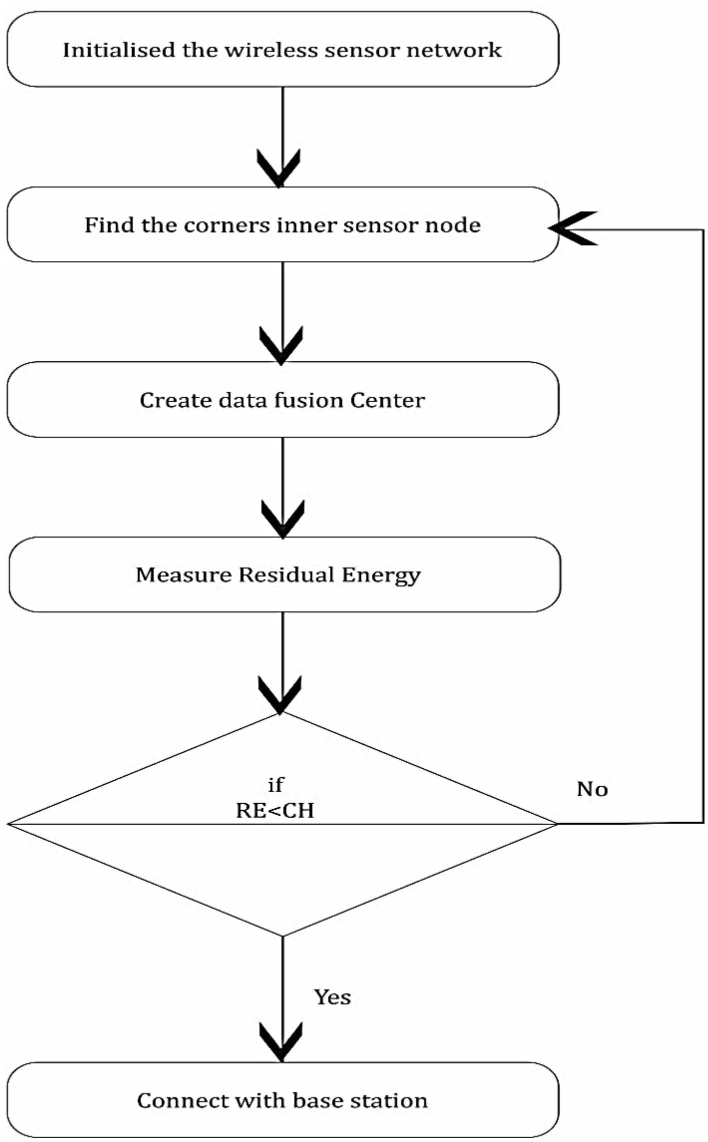

Figure 1: process block diagram of data fusion in cluster based wireless sensor network.

IV. EXPERIMENTAL WORK AND RESULT ANALYSIS

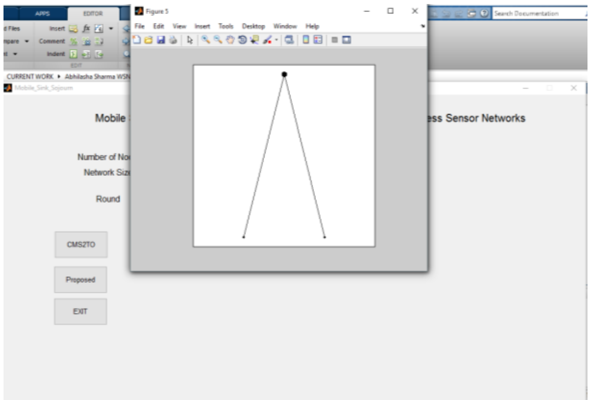

Figure 2: show that the output window of our mobile sink sojourn time optimization scheme for cluster based WSNs simulation with three input fields number of nodes is 50, network size is 20 and round is 30. Here click on CMS2TO methods button.

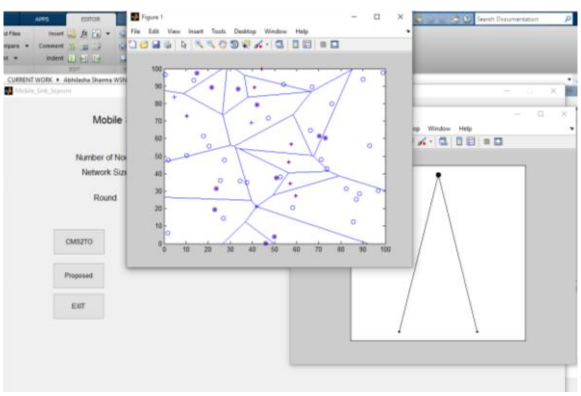

Figure 3: show that the output window of our mobile sink sojourn time optimization scheme for cluster based WSNs simulation with three input fields number of nodes is 50, network size is 20 and round is 30. Here click on Proposed methods button.

PARAMETERS	CMS2TO Method	PROPOSED Method
Total Energy Consumption	0.0100	0.0020
Network Life Time	200	202
Residual Energy	2	1.5000
Number of Alive Node	17	18
Elapsed Time	4.461384	0.344684

Table 1: show that the comparative analysis between CMS2TO and proposed method for Total Energy Consumption, Network Life Time, Residual Energy, Number of Alive Node and Elapsed Time using number of nodes is 50, network size is 20 and round is 30.

PARAMETERS	CMS2TO Method	PROPOSED Method
Total Energy Consumption	0.0750	0.03700
Network Life Time	200	205
Residual Energy	2.1000	1.6000
Number of Alive Node	14	15
Elapsed Time	4.491598	0.394989

Table 2: show that the comparative analysis between CMS2TO and proposed method for Total Energy Consumption, Network Life Time, Residual Energy, Number of Alive Node and Elapsed Time using number of nodes is 70, network size is 30 and round is 35.

PARAMETERS	CMS2TO Method	PROPOSED Method
Total Energy Consumption	0.0274	0.0125
Network Life Time	210	202
Residual Energy	2.2	1.4
Number of Alive Node	19	20
Elapsed Time	8.512520	0.345468

Table 3: show that the comparative analysis between CMS2TO and proposed method for Total Energy Consumption, Network Life Time, Residual Energy, Number of Alive Node and Elapsed Time using number of nodes is 100, network size is 45 and round is 40.

V. PERFORMANCE IMPROVEMENT

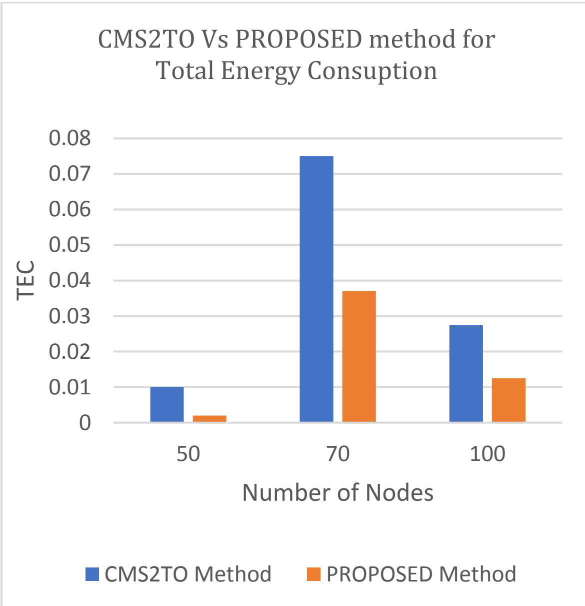

Figure 4: show that the comparative analysis between CMS2TO and proposed method for Total Energy Consumption using number of nodes are 50, 70 and 100.

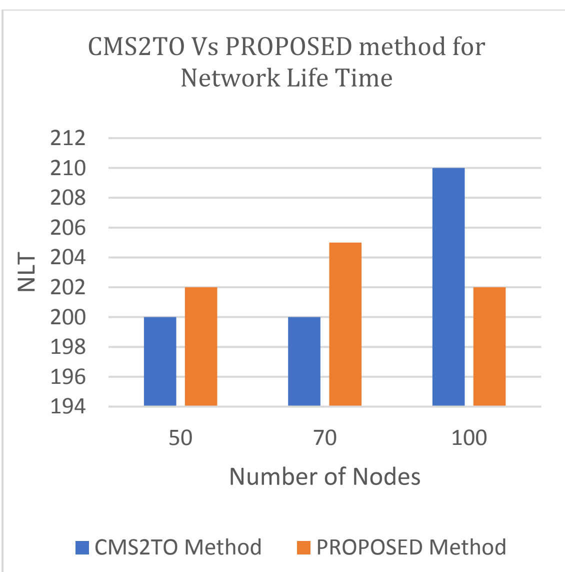

Figure 5: show that the comparative analysis between CMS2TO and proposed method for Network Life Time using number of nodes are 50, 70 and 100.

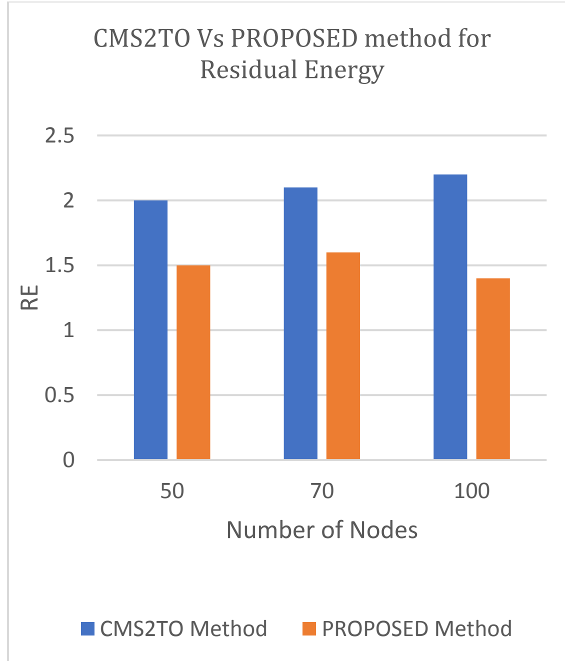

Figure 6: show that the comparative analysis between CMS2TO and proposed method for Residual Energy using number of nodes are 50, 70 and 100.

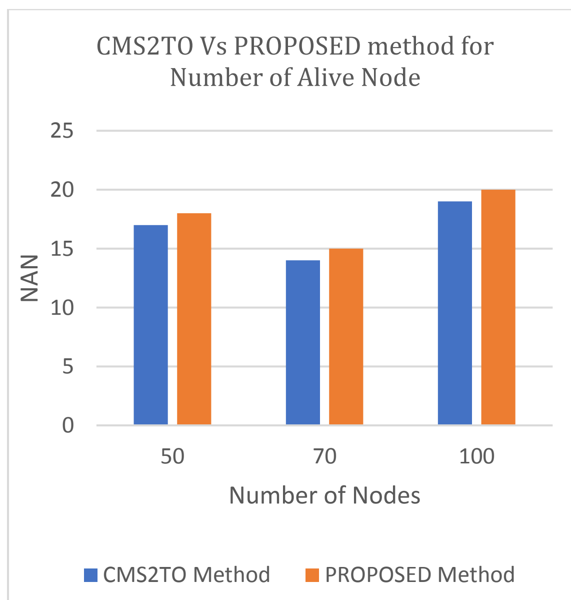

Figure 7: show that the comparative analysis between CMS2TO and proposed method for Number of Alive Node using number of nodes are 50, 70 and 100.

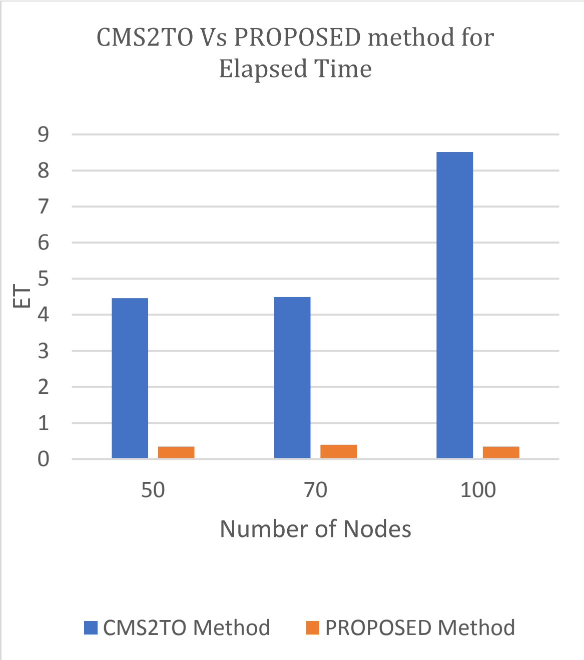

Figure 8: show that the comparative analysis between CMS2TO and proposed method for Elapsed Time using number of nodes are 50, 70 and 100.

VI. CONCLUSION AND FUTURE SCOPE

Through the simulations and the analyses, we can see that the estimated values can converge to the true values without biases. This method is valuable as this system can achieve high precision and consume low energy in practice. decrease of the threshold, the system still costs less energy than only one high-quality sensor due to the relative low energy consumption of the low-quality sensor nodes. The cluster node or the base station can be considered as the fusion center which is used to fuse the decisions of the method which is used to estimate the performance parameters of the low-quality sensors during the estimation phase is given in this section. The data fusion-based cluster head selection methods are better than time optimization algorithms. The fusion based clustering techniques based on the process of hypothesis. The process of hypothesis measures the normal condition of energy utilization and packet transmission. It cannot consider the process of interference and lower probability value. In future design the optimal threshold function for the process of lower value of energy.

REFERENCES

[1] Niayesh Gharaei, Kamalrulnizam Abu Bakar, Siti Zaiton Mohd Hashim, Ali Hosseingholi Pourasl and Suhail Ashfaq Butt “Collaborative Mobile Sink Sojourn Time Optimization Scheme for Cluster-Based Wireless Sensor Networks”, IEEE, 2018, Pp 6669-6676.

[2] Abhinav Goel, Adarsh Patel, Kyatsandra G. Nagananda and Pramod K. Varshney “Robustness of the Counting Rule for Distributed Detection in Wireless Sensor Networks”, IEEE, 2018, Pp 1191-1195.

[3] M. Zeeshan, Huma Javed and Sifat Ullah “Discrete R-Contiguous Bit Matching Mechanism Appropriateness for Anomaly Detection in Wireless Sensor Networks”, IJCNIS, 2017, Pp 157163.

[4] Mohammad Hammoudeh and Robert Newman “Adaptive routing in wireless sensor networks: QoS optimisation for enhanced application performance”, Information Fusion, 2013, Pp 1-13.

[5] Amitav Mukherjee “Physical-Layer Security in the Internet of Things: Sensing and Communication Confidentiality Under Resource Constraints”, IEEE, 2015, Pp 1747-1761.

[6] Shiyu Ji, Tingting Chen and Sheng Zhong “Wormhole Attack Detection Algorithms in Wireless Network Coding Systems”, IEEE, 2015, Pp 660-674.

[7] Chirihane Gherbi, Zibouda Aliouat and Mohamed Benmohammed “An adaptive clustering approach to dynamic load balancing and energy efficiency in wireless sensor networks”, Elisevier, 2016, Pp 647-662.

[8] Xuelian Cai, Yulong Duan, Ying He, Jin Yang and Changle Li “Bee-Sensor-C: An Energy-Efficient and Scalable Multipath Routing Protocol for Wireless Sensor Networks”, Hindawi Publishing Corporation, 2015, Pp 1-15.

[9] Irfan Mehmood, Muhammad Sajjad, Waleed Ejaz and Sung Wook Baik “Saliency-directed prioritization of visual data in wireless surveillance networks”, Information Fusion, 2014, Pp 1-16.

[10] Muhammad Akram and Tae Ho Cho “Energy efficient fuzzy adaptive selection of verification nodes in wireless sensor networks”, Ad Hoc Networks, 2016, Pp 16–25.

[11] Weiwei Wang, Behzad Kasiri, Jun Cai and Attahiru S. Alfa "Channel assignment schemes for cooperative spectrum sensing in multi-channel cognitive radio networks" Wireless Communications and Mobile Computing, 2015, Pp 1471-1844.

[12] Georgios B. Giannakis, Qing Ling, Gonzalo Mateos, Ioannis D. Schizas and Hao Zhu "Decentralized Learning for Wireless Communications and Networking", arXiv, 20155, Pp 1-37.

[13] Guangjie Han, Yuhui Dong, HuiGuo, Lei Shu and Dapeng Wu "Cross-layer optimized routing in wireless sensor networks with duty cycle and energy harvesting", Wireless Communications and Mobile Computing, 2015, Pp 1957-1981.

[14] Nilanjan Biswas, Priyadip Ray and Pramod K. Varshney "Distributed Detection over Channels with Memory", IEEE, 2015, Pp 1-10.

[15] Dongjin Park and Taeho Cho "A Fuzzy Rule-based Key Re-Distribution Decision Scheme of Dynamic Filtering for Energy Saving in Wireless Sensor Networks", I.J. Information Technology and Computer Science, 2017, Pp 1-8.

Jitendra Mishra received the BE degree in Electronics and Communication and Master of Technology degree in Digital Communication. Currently he is an associate professor with head of department electronics and communication engineering from PCST, Bhopal India. His research interests are Digital Signal Processing, Antenna Designing, Wireless Communication and Digital Image Processing.