Energy Efficient Dual Probability-Based Function of Wireless Sensor Network for Internet of Things

Nikhil Ranjan, Parmalik Kumar, and Ashish Pathak

1 Introduction

The growth of the internet is a surprise in every field of communications. The internet of things is a bidirectional communication application in terms of local or device to device communication. In the internet of things, wireless sensors play a vital role in data quality and reliable service. The maximization of the life of the sensor network depends on the utilization of the energy factor [1]. The IoT devices play the role of edge network in the scenario of the wireless sensor network. The integration of sensors network and IoT devices support the property of being dynamic and easy to access [2, 3]. The processing of edge networks provides support of cloud-assisted services through the internet of things in the way of the network's data storage and computational capability. However, with the multiple integrations of the gateway with sensor network and cloud network, the edge network suffers from the problem of bandwidth and energy during the mode of transmission and data receiving [4–6]. The dynamic nature and support system of the sensor network utilized most of the battery-operated energy, the maximum consumption of energy compromised the life of IoT communicating devices. Despite serval energy model and lightweight protocol of energy management in wireless sensor network energy is a significant issue on the internet of things-based communication models—the overall efficiency of IoT based communication based on the life of sensor network [7]. The various research scholar proposed an energy-based model for the proper utilization of energy factors in integrating gateways. The reported survey suggests that the cluster-based

N. Ranjan (✉)
Sarvepalli Radhakrishnan University, Bhopal, M.P., India
e-mail: nikhilranjan101@gmail.com

P. Kumar
Lakshmi Narain College of Technology, Bhopal, M.P., India

A. Pathak
Freemaster Education Centre and Software Development Pvt. Ltd., Bhopal, M.P., India

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routing protocol improves the sensor network's life and enhances the duty cycle of the internet of things. The machine learning-based algorithms apply the case of switching and harvesting the energy factors for the IoT devices [8]. The process of energy harvesting also increases the processing of multiple gateway integration with wireless sensor networks. In current research trends, most authors focus on a lightweight and low-cost routing protocol for the transmission and receiving of data in the scenario of multiple integrations of wireless sensor networks and the internet of things. Furthermore, cost and path optimization using swarm intelligence and heuristic-based function also improves energy efficiency, and the quality of services in IoT enables communication [8, 9]. Other ways to harvest the energy level in the internet of things in the mode of switching are active and passive. The processing of active and passive save the mode of energy reduces the loss of data packet and increases the life of the network and multiple gateways. The probabilistic based function contributes more to the management of energy in a wireless sensor network. The incremental enhancement of probabilistic function derives a dual probability-based function for energy management as an integral function of IoT devices [10]. The concept of dual probability function measures the level of energy in different levels of network and coordinates with sink node for proper communication. The levelling of energy is categorized into three sections: low level, middle level, and high level. The low level of energy processing cannot involve in the process of communication. The middle and high-level energy scheme integrates with gateways of cloud and IoT [11]. The proposed model enhances the service and reliability of IoT enabled communication systems. The methodology of dual probability function cooperates with compressed sensing methods for energy minimization in cloud-assisted IoT networks [12]. The rest of paper organized as in Sect. 2 related work in Sect. 3 proposed model and algorithm in Sect. 4 describe the experimental analysis and finally conclude in Sect. 5.

2 Related Work

The advancement of internet technology derived the concept of the intelligent Internet is called the Internet of things. The Internet of things provides services in all eras of society. The things deal with electronic communication objects connected through the Internet. The acceptability of IoTs is increasing day to day due to easy installation and low-cost maintenance. IoTs change the scenario of remote area data accessing for remote area data such as temperature, pressure, weather and fire event in the forest used sensors networks. The sensors collect the information and transmit it to the base station with IoT devices. Now a day the IoTs application integrates with cloud-based services. Cloud-based services are deployed over intelligent devices [12]. The cloud services support the static infrastructure; IoTs integrates these services with dynamic infrastructure. The dynamicity of the cloud enhances the reachability of IoTs services with the last person in the universe. The IoTs connects real-world objects and embeds the intelligence in the system to smartly process the object specific information and take good autonomous decisions [13]. Thus, IoTs can give birth to enormous valuable applications and services that we never imagined before. With technological advancement, the devices processing power and storage capabilities significantly increased while their sizes reduced. These intelligent devices are usually equipped with different types of sensors and actuators. Also, these devices can connect and communicate over the Internet that can enable a new range of opportunities [14]. Moreover, the physical objects are increasingly equipped with RFID tags or other electronic bar codes that can be scanned by smart devices, e.g., smartphones or small embedded RFID scanners. IoT is the Internet's extending and expanding to the physical world, and its related properties include focus, content, collection, computing, communications and connectivity scenarios. These properties show the seamless connection that between people and objects or between the objects and objects [15, 16]. In [1] authors describe the methods of energy efficiency for wireless sensor networks. The proposed algorithm uses particle swarm optimization to select cluster heads during communication with other cluster heads. The proposed algorithm reduces the utilization of energy and boosts the life of smart things. In [2] authors proposed the methods of energy optimization based on machine learning algorithms. The proposed algorithm enhances the performance of energy in the scenario of the internet of things. The methods applied on the mode of even and odd basis in-network and routing balanced the process of energy optimization. Finally, in [3] authors proposed the methods for energy optimization based on an intelligent fuzzy-based network. The proposed algorithms describe the process of packet-based operation, maintain the switching process, and reduce the impact of energy in IoT communication. [4] authors proposed the method of the dynamic stochastic optimization process for balancing the energy factors in IoTs communication. The design model focusses on the computational efficiency of energy and others parameters for the process of routing. The proposed algorithm is very efficient with certain limitations. The authors [5] proposed a neural network-based optimization model to control data storage and communication traffic, and energy in a wireless sensor network. The applied neural network model selects the optimal sensor node for the communication of the internet of things. The experimental results of the proposed methods suggest that the proposed algorithm is very efficient for wireless sensor networks. In [6] authors proposed the methods based on multi-objective constraints of energy optimization. The process of optimization resolves the issue of optimal node selection in an extensive wireless sensor network. The proposed algorithm uses a memetic algorithm for the sub-group of wireless networks. In [7] authors design the sensor network based on the human body. The human body is a good transmission section of the wireless network. The authors also applied the probability function methods to estimate the energy level of the sensors node. In [8], the authors investigate energy level performance in the internet of things using clustering algorithms and swarm intelligence algorithms such as ant colony optimization. The investigation process suggests that a clustering process is a handy approach for optimising energy in the internet of things. Furthermore, the ant colony optimization algorithm helps to estimate the optimal node selection in a sensor network. In [9] authors proposed the chicken-based optimization algorithm for the clustering of the wireless sensor network. The proposed algorithm is very efficient for the selection of optimal nodes in wireless sensor network environments.

3 Proposed Methodology

The proposed methodology describes in three parts first one dual probability function, second part describe the node distribution in IoT communication and finally in third part describe the integration with cloud network. The dual probability function (DPF) is derived function of probability and its estimate the level of energy in dense network in forward as reverse. The system model describes the approach of integration factor to cloud network. The major contribution of this algorithm is estimation of energy in three levels and reduces the cost function of dense IoT devices.

3.1 Dual Probability Function (DPF)

The derived probabilistic function applies on the source node to measure the level of energy for the categorization of sensors nodes to integrate with gateway. The DP function estimates the level of energy in all condition as directed by communication devices [2, 5].

$P - DP(n)$: Level of energy.

$sink\, probablity(level - Dp(n))$ of a sensor's node n with respect to another sensor's node

$$nlevel - prop_k(p, o) = \max\{n - probablity(o), n(p, o)\} \tag{1}$$

where $n(p, o)$ is the similar probability between p and o.

$sub\, level\, probablity$ (slp) of a sensor's node n

$$slp_k(p) = \left(\frac{1}{k} \sum_{o \in N_{(p,k)}} level - prob_k(p, o)\right)^{-1}, \tag{2}$$

where $N_{(p,k)}$ is the set of n node of similar probability of energy of n.

$sink\, node\, energy$ of a sensor's node n

$$DP\_OT_k(p) = \frac{1}{k} \sum_{0 \in N_{(p,k)}} \frac{slp_k(o)}{slp_k(p)} \tag{3}$$

The value of K is sub group of network and N is total number of nodes.

3.2 System Model

Given $n_t \in \Re^{GP}$ collected at level energy $e \in E$, the goal of DP and DP_E is to assign an DP_OT value to n_t, for the value of energy $E < P$ of the n nodes that have been measured up to level energy E. All n sensor level and their corresponding DP_OT values in sink connection of subgroups. Hence measure the energy value of extended energy DP_OT values of new nodes can be calculated. the goal of DP and DP_E is to detect same level for the whole network's communication and not just for the n last sensor nodes where the available sink connection of subgroups is limited to P. DP_E is an extension to DP.

DP—Dual Probability
DP_OT—Dual Probability Outer Sensor Node
DP_E—Extension to Dual Probability

3.3 Algorithm 1: DP_E Estimation

Input: a sensors node n_t at level energy e
Output: DP_OT value $DP\_OT_{(n_t)}$
Estimate $N_{(n_t,k)}$ and $p-probab(n_t)$
for all $n \in N_{(n_t,k)}$ do
Estimate $level-prob(p_t, o)$ using Equation (1)
end for

$$S_{\text{node}} \leftarrow Pn_{(n_t,k)}\{the\ set\ of\ sink\ node\ n_t\}$$

for all $n \in S_{\text{node}}$ and $q \in P_{(o,k)}$ do
Node $k-prob(o)$ and $level-prob(q, o)$
if $o\ N_{(q,k)}$ then

$$S_{\text{node}} \leftarrow S_{\text{node}} \cup \{q\}$$

end if
end for
for all $o \in S_{\text{node}}$ do
Node $slp(o)$ and $DP\_OT(\{Pn_{o,k}\})$
end for
Estimate $slp_{(n_t)}$ and DP_OTn
return DP_OT

3.4 Algorithm 2: DP (Dual Probability)

Input: set of sensor nodes $N = \{n_1, \ldots \ldots, n_n\}$
sink connection of subgroups size limit of L
Output: set of $DP\_OT = \{DP\_OT(n_1), \ldots \ldots .., DP\_OT(n_n)\}$ nodes
$i \leftarrow 0$; {energy level}
for all $n_t \in n$ do
$DP\_OT(n_t) \leftarrow$ connection (n_t)
if Number of sensor nodes in sink connection of subgroups

$$(sc^i, N^i) \leftarrow GP-Probal\ (n^i)$$

for all $sc_j^i \in n^i$ do
Estimate $k-probab\ (sc_j^i), slp(v_j^i), DP\_OT(v_j^i)$
end for
return DP_OT

The design layout of network models describes in figure q and Fig. 2. The processing of node mention as PD as selection node and BS is base node or sink node.

Integration of IoTs with dual probability-based function with application with internet gateway. The measure probability value DP and DP_OT creates different level of energy group for the integration of application.

If $DP\_OT = 0$), the energy level of all sensor's node is same level and direct connect each node with sink nodes.
If $DP\_OT > 0$) the value of energy level of DP is lower and creates more similar probability-based node connection.
If $DP\_OT < 0$), the value of energy level is average and some node are not alive so gateway only maintain a connection.

3.5 Algorithm 3: Integration of Sink Nodes

Input: Sensor nodes set $s = \{n_i, i = 1, \ldots \ldots .., n\}$
Output:S - the selected sensor nodes subset
Begin
Define the initial value of request $R = \emptyset$
Calculate $GP(DP_OT;\ ni)$for each sensor nodes, $i = 1, \ldots \ldots \ldots .., n$
$n_f = n$; Select the sensor nodes ni
Then, set $S \leftarrow S\{ni\}; S \leftarrow S \cup \{ni\};\ n_s = n_s - 1$
while$s \neq \emptyset$ do
Measure DP_OT in (2) to find $n_i$where $i \in \{1,2, \ldots .., ns\}$;
$n_s = n_s - 1$;
if $(DP_OT > 0)$then
$S \leftarrow S \cup \{n_i\}$
end
end
Set level of energy of each group selected sensor nodes.
return S

Figure 3 represents the real scenario of the communication of wireless sensors network with IoTs and cloud-based services. I have deployed network send the information to sink node (Base station) and base station integrate with the waterway through IoTs elements. The mention DPF represents the value of energy level for the selection of sink node to communicate to things.

Integration of IoTs with dual probability-based function with application with internet gateway. The measure probability value DP and DP_OT creates different level of energy group for the integration of application.

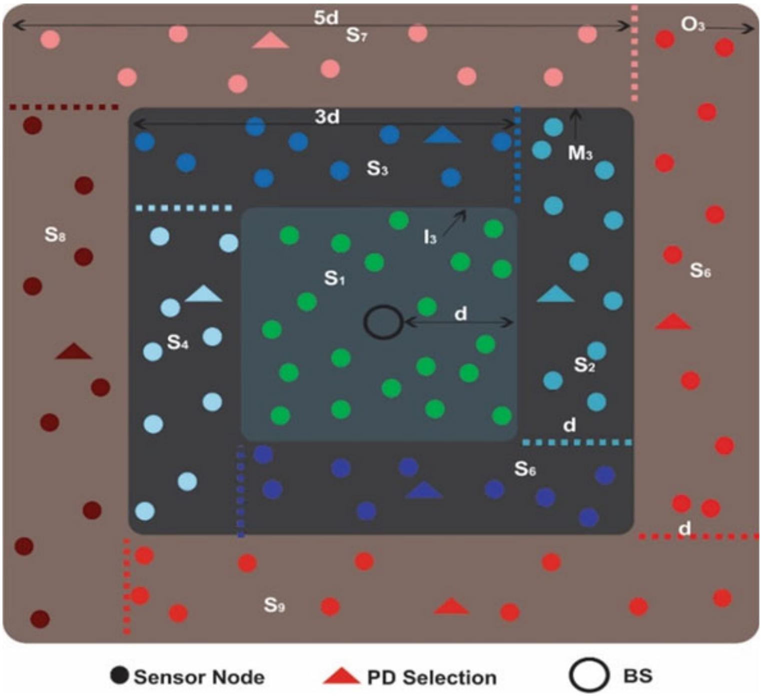

Fig. 1 Scenario of dense sensor network for the selection of PD node and process of BS (base station)

1. If $DP\_OT = 0$), the energy level of all sensor's node is same level and direct connect each node with sink nodes
2. If $DP\_OT > 0$) the value of energy level of DP is lower and creates more similar probability-based node connection.
3. If $DP\_OT < 0$), the value of energy level is average and some nodes are not alive so gateway only maintain a connection.

4 Experimental Results

To evaluate the performance of the proposed model for cloud integration with IoT simulated in MATLAB environments. The distribution of nodes mentioned in Fig. 1 and Fig. 2—the number of sensor node selections in a random fashion and fixed patterns. The selection of nodes cannot impact on design model—the process of simulation conducted on the scenario of 50,75,100 and 5000 nodes. The traffic of data is CBR 512. The dual probability function (PDF) controls and manage the level of energy value. Initially, all sensors node assigns the range value of energy is 12–14 J. The data are collected from the sink node is every 120 s. The transmission interval of data is 10 s. The total simulation time is 600 s. The process includes aggregated connectivity data, representing the link quality between any two sensor nodes and between sensor nodes and the base station. In our simulations of the DPF protocol, we selected a time interval of 120, such that at least 60% of data are transmitted successfully to the base station. In our simulations, the integration factor deals with algorithm three and sets the condition value DP_OT = 0, DP_OT > 0 and DP_OT < 0. in the case of DP_OT < 0, the data transmission process is terminated. Analyzed the performance of the proposed model and existing model estimates these parameters, energy utilization parameter, data utility and data error correction during the transmission [2, 7].

RESULT ANALYSIS

See Tables 1, 2 and 3.

The Fig. 4 describes the analysis of results in terms of proposed algorithm as well as existing algorithm in variation of sensor node as 5, 10, 15, 20, 25, 30, 35, 40, 45. In the case of node variation the results of proposed algorithm is increases instead of existing algorithms.

Figure 5 describe the process of energy utilization in mode of variable nodes such as 5, 10, 15, 20, 25, 30, 35, 40, 45 sequentially decreased percentage 2, 7, 15, 25 and 33%. The proposed algorithm gains maximum utilization of energy factor instead of existing algorithm.

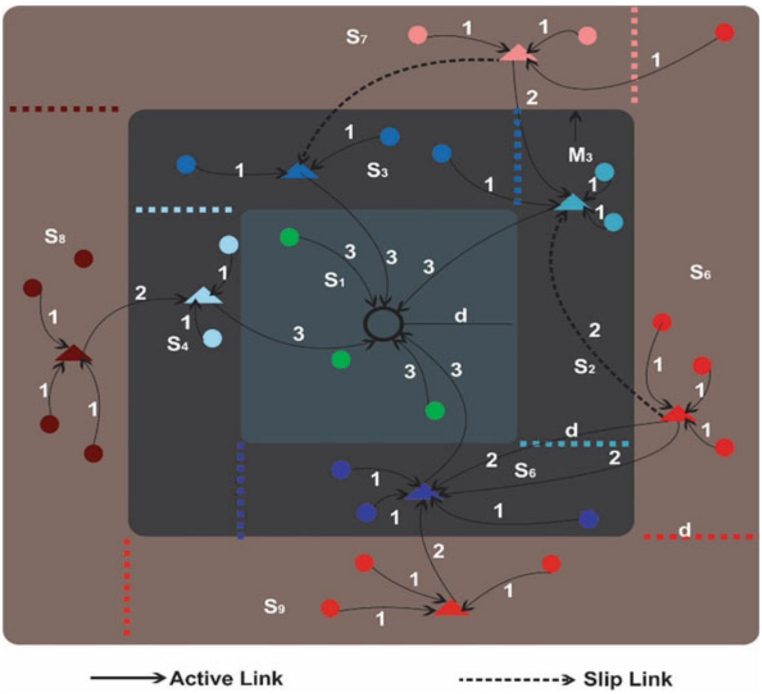

Fig. 2 Scenario of active link and slip link of inner node and outer node for the base station

Fig. 3 Proposed system model of IoT enable cloud data storage

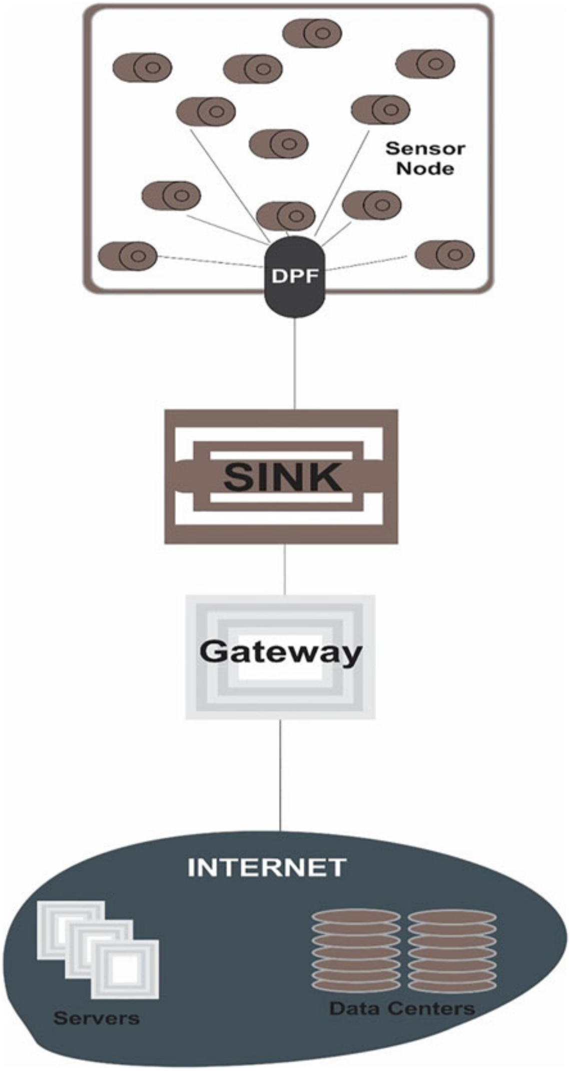

Table 1 Comparative result of data utility using reference [1], reference [5] and proposed techniques

Number of nodes	5	10	15	20	25	30	35	40	45
Reference [1]	−110	−50	0	−50	−150	−200	−250	−275	−280
Reference [5]	−20	25	35	30	−10	−50	−100	−200	−270
Proposed	25	60	60	80	70	40	10	−100	−250

Table 2 Comparative result of energy consumed in transmission using reference [1], reference [5] and proposed techniques

Number of nodes	5	10	15	20	25	30	35	40	45
Reference [1]	300	500	800	1200	1500	1900	2800	3200	3500
Reference [5]	400	600	1000	1500	2000	2400	3200	3500	3800
Proposed	200	400	600	1000	1200	1600	2500	2800	3000

Table 3 Comparative result of data reconstruction error using reference [1], reference [5] and proposed techniques

Number of nodes	5	10	15	20	25	30	35	40	45
Reference [1]	12	11	10	9	8	8	7	5	4
Reference [5]	15	14	13	12	10	9	8	7	5
Proposed	11	10	9	8	7	6	6	4	2

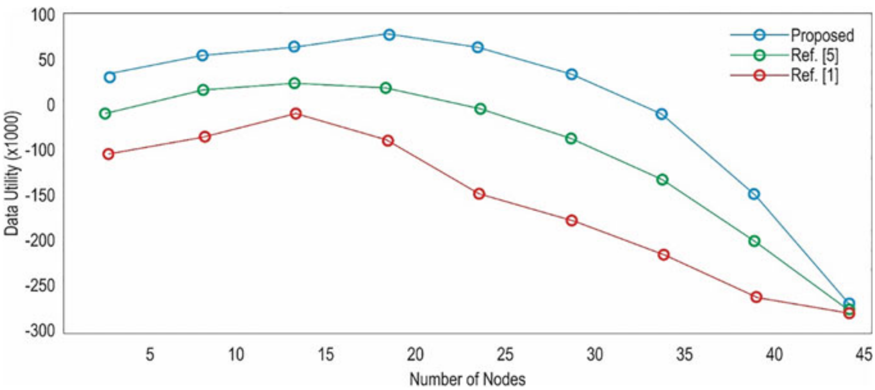

Fig. 4 Comparative result analysis between data utility with number of nodes (0–45)

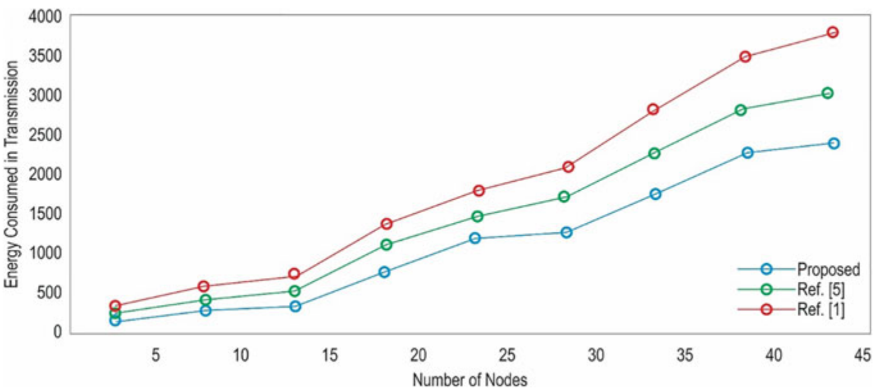

Fig. 5 Comparative analysis between energy consumed and number of nodes (0–45)

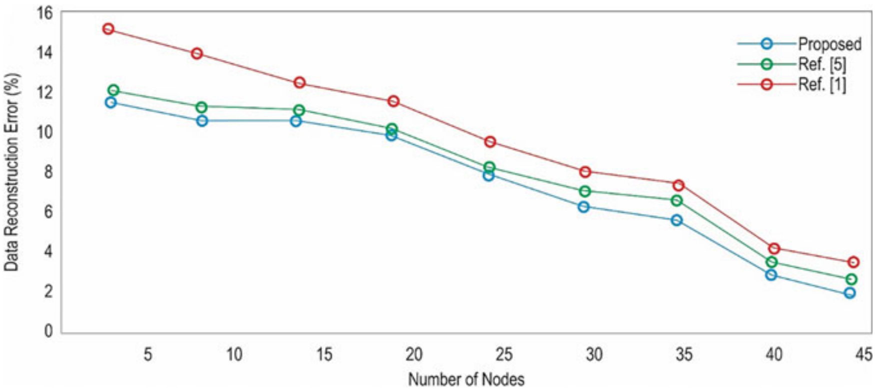

Fig. 6 Comparative result analysis of data reconstruction and number of nodes (0–45)

Figure 6 describe the analysis of error reconstruction parameter with variation of sensors node in simulation environments such as 5, 10, 15, 20, 25, 30, 35, 40, 45 sequentially decreased percentage 0.2, 0, 0.5, 0.8 and 1%. The rate of deceasing error indicates that proposed algorithm is better than existing algorithm.

5 Conclusion and Future Scope

The sensor node and networks are the backbones of the internet of things (IoT). Integrating multiple devices and communication models consumes a high energy rate and expires the life of sensor nodes and networks. We have proposed an energy-efficient integration model for the internet of things. The proposed algorithm reduces the energy level during the transmission and receiving of data. The proposed algorithm designs a probability-based function to estimate the energy level of sensor nodes for the integration of devices. The estimated energy factors decide the inner and outer function for connecting the gateway of intelligent devices. The design function of probability measures the utilization of data quality of IoTs device. To evaluate the performance of the proposed algorithm, use MATLAB software and design different network scenarios in terms of small, medium and large scale, such as 50, 75, 100 and 500. The UDP data traffic is used to estimate a delivery function of the IoTs communication model. The proposed model increases the efficiency of energy utilization during the integration of IoT devices. The proposed algorithm compares with the existing compressive sensing (CP) algorithm. The proposed algorithm performs only single source node. If the node of the source increases, the performance of networks decreases. In future, the single node will proceed in a group of sensor nodes and enhance the possibility of energy factors in IoT devices.

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