Energy-Efficient Hybrid Routing Protocol to Extend the Network Lifetime in IoT Applications

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Abstract - A Wireless Sensor Network (WSN) is made up of several inexpensive, low-power, compact sensor nodes that are densely placed across the monitoring area. Wireless connection creates a multi-hop wireless network system. WSN is particularly well suited for deployment in harsh environments and remote monitoring locations that are not suitable for personnel. It has significant advantages like a large coverage area and broad application prospects in the fields of military, environmental monitoring, industrial control, and urban transportation. IoT-enabled networks, however, suffer a variety of difficulties because of the enormous heterogeneous data generated by many sensing devices, including long communication delays, limited throughput, and short network lifetimes. In this study, a hybrid cluster-based routing protocol model is suggested that makes use of the advantages of both butterfly and particle swarm optimization methods. The suggested approach splits the network into many clusters and chooses the best node as the cluster leader to exacerbate the network's premature demise. The typical cluster-based routing protocols PSO and BOA are assessed using simulation results in terms of the quantity of alive nodes, throughput, and remaining energy of the nodes.

Keywords-Butterfly Optimization, Particle Swarm Optimization, Energy optimization, Cluster based IoT Routing, Hybrid Routing Protocols.

1. INTRODUCTION

In wireless sensor networks, the energy is consumed when the communication is between nodes to nodes and between nodes and base stations, so efficient routing protocols have a crucial impact on the performance of the entire network. Clustering routing protocols, a class of efficient wireless Compared with the plane routing protocol, the sensor network routing protocol can better balance the energy consumption of the network, improve the efficiency of energy utilization, and prolong the life cycle of the network. Because the Internet of Things (IoT) demands a lot of power to sense, process, and send data, the application of IoT to Wireless Sensor Networks (WSNs) presents a big barrier for network durability. As a result, there are multiple known algorithms that combine diverse optimization methodologies to increase the performance of WSN networks. Many energy-efficient clustering routing protocols have been suggested in recent years as more and more academics have concentrated on the study of wireless sensor network clustering routing protocols: Through the cluster head node's rotational mechanism, Leach [1], a common low-power clustering routing protocol, assures the nodes' energy efficiency. PEGASIS [2] is an energy-efficient protocol. The Leach protocol's frequent cluster head replacements consume a lot of communication energy; Leach-C [3] is an enhancement to the Leach protocol. The life cycle of the network is prolonged by reducing the energy of the candidate cluster heads during the cluster head selection process. protocol balances the network's energy usage by introducing sophisticated nodes, making full advantage of the nodes' heterogeneity; PSO-C [4] To enhance the performance of the network, the Leach protocol's cluster head selection procedure is optimised using the Particle Swarm Optimization method (PSO) [5].

A routing protocol based on Particle Swarm Optimization (PSO) and the Butterfly Optimization Algorithm is proposed in this study (BOA). The method for hybrid meta-heuristic algorithms, which integrates chaos theory with the fundamental PSO and BOA, is also used to improve the algorithm's capacity for the optimization problems we specified. Additionally, a nonlinear control method is presented for adjusting the global and local search capabilities of the improved algorithm.

The remainder of the paper is organised as follows. The earlier study on energy conservation in IoT networks is described in Section 2. The suggested model is described in Section 3. The suggested method's simulation results are discussed in Section 4, and the paper's mentioned sources are listed in Section 5.

2. Literature Survey

Wireless sensor networks are gradually becoming a new attractive communication mode due to their low cost and rapid deployment [6]. In most sensor networks, reducing energy consumption is the main challenge [7]. Battery charge must be minimized because sensor networks are typically made to operate unattended for extended periods of time [8]. This will increase the lifespan of each sensor and the network as a whole. Energy efficiency is one of the primary factors in the design of routing protocols for wireless sensor networks, and it should always be taken into account when a routing protocol is applied to a sensor network [9–10]. At the moment, a growing number of WNS protocols are created with consideration for energy efficiency, including scale-free topology models for energy-efficient wireless sensor networks [12] and energy-efficient data collecting protocols for heterogeneous wireless sensor networks [11].

Energy-efficient routing methods for wireless sensor networks have been the subject of extensive research. For wireless sensor networks with mobile sinks, Tunca et al. (2015) [13] offer an energy-saving ring routing system that minimises the energy consumption and packet delay caused by the position broadcast of mobile sinks to the network. For wireless sensor networks, Kuila and Janap (2014) [14] suggest PSO-based routing and clustering. The clustering algorithm balances the energy consumption of CH, while PSO routing provides a trade-off between transmission distance and hop count. Su and Zhang (2016) [15] provide a non-uniform clustering-based wireless sensor network routing algorithm that chooses cluster heads based on many factors (such as amount of energy left, distance from nodes, etc.) and delivers data using a combination of single-hop and multi-hop techniques. This approach can lessen the issue of energy holes and increase network longevity.

In opportunistic routing, the distribution of nodes is sparse, and the network topology is constantly changing. The data method is multi-hop, and its forwarding node selects the final forwarding node from multiple candidate nodes. Higher transmission reliability and end-to-end throughput are two of its benefits. quantity. Opportunistic routing enables forwarder list nodes to take part in packet protection and make opportunistic selections depending on the link quality circumstances to get routing pathways [16]. These nodes may listen in on transmissions and are closer to the destination. Shi et al., (2017) [17] proposes an opportunistic routing protocol with optimal cooperative delay between candidate nodes, realizes the mechanism modeling of the cooperative forwarding process of candidate nodes, and obtains the expected end-to-end cooperative delay, which is used as a routing measure to increase the network throughput, reduces the average end-to-end delay. So an Byun (2014) [18] proposes opportunistic routing for intra-network aggregation of asynchronous duty cycle wireless sensor networks, which can increase the duty cycle of nodes that keep data packets and increase the chance of intra-network aggregation, thereby reducing energy consumption and prolonging the network life cycle.

In multi-hop sensor networks, Zhao (2015) [19] introduced an energy-aware opportunistic routing protocol and a novel routing measure based on the idea of balancing link quality and energy. Based on this criterion, a candidate set selection was created. Mechanisms for node coordination and algorithms. Yao (2018) [20] proposes an opportunistic routing optimization algorithm for WSN based on network coding, which reduces the number of retransmissions of coded packets by calculating the failure probability of receiving coded packets, so as to prolong the network lifetime and reduce the average energy consumption. A queue-based swarm optimization approach was presented by Praveen and Joe (2021) [21] to choose a better route for a future route based on numerous restrictions, which enhances the route-discovering process. In terms of energy consumption, node lifespan, throughput, end-to-end latency, packet delivery ratio, and packet overheads, the proposed ECRR approach is implemented in the Network Simulator (NS-2) tool. The simulation results are then compared with the current state-of-the-art techniques. In energy-efficient green-IoT networks with a mobile sink, Yarinezhad & Azizi (2021) [22] presented a tree-based routing protocol that is efficient in power consumption and decreases end-to-end latency. The suggested protocol adds two new, distinct ways for controlling network routing. For IoT-enabled WSNs, Kaur et al.

(2021) suggested an intelligent routing system based on Deep Reinforcement-Learning (DRL) that greatly reduces latency and extends network lifetime. The suggested approach separates the whole network into many uneven groups based on the data load that is now present in the sensor node, considerably preventing the network from dying prematurely.

It is evident from the aforementioned studies conducted by various academics that much work is being done on energy-efficient routing in various IoT network topologies. The capacity of clustering to achieve energy efficiency has been demonstrated in a variety of methods, which inspired the authors to conduct this research.

3. Network Model

The network models utilised in this study are discussed in this section. The used system model, together with its setup settings and presumptions, are briefly presented. This study takes into account a two-dimensional network model with sensor nodes arranged in a clustered topology. There was a single base station that gathered all of the IoT nodes coming from the source. The energy consumption model for the transmission and reception of messages with the same length, n bits, was a first order radio model.

3.1 General Particle Swarm Optimization For Optimized Cluster Head Selection

The clustering routing algorithm based on PSO optimization needs to firstly divide the network into clusters, then use the PSO algorithm to synthesize the state information of neighbor nodes to optimize the selection of cluster heads, and finally publish the determined cluster head information to the entire cluster.

(1) The initial stage of cluster formation.

Several clustering techniques, like the LEACH algorithm, can be utilised at this point to cluster the wireless sensor network in an initial manner. The cluster heads and clusters are essentially established after this stage, although the generated clusters are vulnerable to the blind nodes issue. At this point, each cluster's constructed cluster head is referred to as the auxiliary cluster head.

(2) The auxiliary cluster head gathers data about the cluster nodes' states. The position and energy status data of each neighbour node in the cluster is sent to the auxiliary cluster head. The auxiliary cluster head now stores the location information P (p1, p2,..., pn) and energy information E of the neighbouring nodes. where n is the number of nodes in the cluster, pi is the ith node's position value, and ei is the ith node's energy value

(3) Use the PSO technique to find the cluster head stage and to optimise.

The position updation formulas in the normal PSO method must be updated in order to make the algorithm acceptable for this problem domain, and the corresponding fitness function f(x) is provided at the same time. This step is the heart of the optimization algorithm. The search is carried out on the network plane, and as a result, the velocity is a vector with components in the x and y directions as well as a magnitude. so there are,

$V_{xid}=WV_{xid} + c_1rand() . (P_{id}-X_{xid}) + c_2 rand() . (P_{gd} -X_{xid})$ --- (1)

$V_{yid}=WV_{yid} + c_1rand() . (P_{id}-X_{yid}) + c_2 rand() . (P_{gd} -X_{yid})$ --- (2)

Similarly, there are position components in the x and y directions, we have,

$X_{xid} = X_{xid} + V_{xid}$ --- (3)

$X_{yid} = X_{yid} + V_{yid}$ --- (4)

Since the distribution of nodes in the wireless sensor network is discrete, the values calculated by the nodes according to equations (3) and (4) cannot be mapped to the corresponding network nodes one by one. $X_{xid} \in \{p_{x1}, p_{x2}, \ldots, p_{xn}\}$, $X_{yid} \in \{p_{y1}, p_{y2}, \ldots, p_{yn}\}$, where p_{xi} is the x component of the i^{th} node in the cluster, and p_{yi} is the i^{th} node in the cluster y component of i nodes.

Let $\Delta p_{xj} = ûX_{xid} - p_{xj}û$, $\Delta p_{yj} = ûX_{yid} - p_{yj}û$, $\Delta p_j = (\Delta p_{xj})^2 + (\Delta p_{yj})^2$. where Δp_{xj} represents the relationship between X_{xid} and network node j in the cluster. The absolute value of the x-component difference, Δp_{yj} represents the absolute value of the y-component difference between X_{yid} and the network node j in the cluster, and $\Delta p_k = \min\{\Delta p_1, \Delta p_2, \ldots, \Delta p_n\}$, it means that the position of the k^{th} node in the network is the closest to X_{id}, so the adjusted value is $X_{xid} \approx p_{xk}$, $X_{yid} \approx p_{yk}$, that is, the search point is now located at the position of node k.

The properties of the issue domain are directly tied to how the fitness function is determined. A node's fitness should take into account both the magnitude of its own energy as well as the energy distribution of the nodes around it. The neighbouring node's energy should increase with distance from the node. The distance from the node should instead be greater. The fitness function is built using this feature, and the closer neighbour nodes should have less energy.

$f(k) = \eta_{ek}+ \lambda_{\hat{e}}$ ---(5)

where: $\eta+ \lambda= 1$ and η and $\lambda \in [0, 1]$; e is the equivalent average energy of other nodes; k is the current network node number; η is the current node energy influence factor, λ is the neighbor node energy influence By adjusting the factor, the contribution ratio of neighbor nodes to the fitness value can be determined.

At this point, the auxiliary cluster head node broadcasts the optimised cluster head information to the cluster nodes and enables the optimised cluster head to acquire the information of the cluster nodes. The energy loss of the nodes in the cluster is balanced because the building of the optimised cluster carefully takes into account the state information of the neighbouring nodes, thereby preventing the frequent occurrence of blind nodes.

3.2 General Butterfly Optimization Algorithm

In the standard BOA algorithm, the butterfly population uses random initialization of the butterfly population:

$X_{Nxd} = lb + rand (N,d) x (ub – lb)$ ---(6)

In the equation (6), N represents the butterfly population size, and d represents the search space dimension.

The butterfly algorithm assumes that each individual in the search space can perceive each other's fragrance; the butterfly can move randomly or move towards the best butterfly according to the intensity of the fragrance concentration; the sensory mode of the butterfly is affected or determined by the range of the objective function. The transition probability P is utilised to govern the butterfly's search mode, which may be either local or global, while it is looking for food sources because the magnitude of the fragrance is impacted and constrained by elements like wind, rain, temperature, etc.

Butterfly fragrance calculation as in the equation (7):

$f=cI^a$ ---(7)

$c=0.01 + (0.025/0.1T_{max})$ ---(8)

where f is the size of the scent, c is the intensity of the sensory modality, I is the intensity of the stimulus, an is the power exponent that depends on the sensory modality, and Tmax is the maximum number of repetitions. The butterfly uses both local and global search to update its position. If a butterfly can smell other butterflies but can't because of distance or other natural causes, it will randomly scan its immediate area; if it can smell other butterflies, it will fly to the best butterfly based on the strength of the scent. The populace hunts for nearby food sources as a result of location updates.

When r1≥p, perform a local search:

$$\mathrm{dis}_1 = r_1^2 x_j^t - x_i^t \qquad ---(9)$$

$$x_i^{t+1} = x_i^t + \mathrm{dis}_1 f_i \qquad ---(10)$$

Among them, dis_1 is the distance formula between two butterflies in the local search, x_i^t x_i^t represents the position of the j^{th} and i^{th} butterflies in the t^{th} iteration, and if represents the fragrance size of the i^{th} butterfly.

When r1<p, perform a global search:

$$\mathrm{dis}_2 = r_2^2 g^* - x_i^t \qquad ---(11)$$

$$x_i^{t+1} = x_i^t + \mathrm{dis}_2 f_i \qquad ---(12)$$

Among them, dis_2 is the distance between the current butterfly and the best butterfly in the global search, *g is the position of the best butterfly, and x_i^t is the position of the i^{th} butterfly in the t^{th} iteration. Equations (10) and (12) can simulate the feeding behavior of butterfly populations.

3.3 Proposed Hybrid Chaotic Particle Swarm Optimization And Butterfly Optimization Algorithm

In this part, a novel hybrid chaotic HCPSOBOA that combines different PSO and BOAs is suggested. The primary distinction between PSO and BOA is how new members are produced. The PSO approach has the drawback of being able to tackle high-dimensional optimization problems only in a small area. To optimise the advantages of both methods, we combine their capabilities rather than applying them sequentially. In other words, the two algorithms' end results are heterogeneous because of the method employed to get them. Here, a brand-new hybrid method is put forward, along with the initialization of BOA using a cubic one-dimensional map and a nonlinear parameter management technique. Additionally, BOA and PSO are combined to enhance the fundamental BOA for global optimization. The cubic map for the initial population, the nonlinear parameter management technique of power exponent a, the PSO algorithm, and BOA are then combined to form the unique Hybrid Chaotic HCPSOBOA.

Algorithm 2. Proposed Algorithm (HCPSOBOA)

Step 1: Generate the initial population of butterflies using cubic map and initialize the parameter r1, r2, c1, c2, switch probability, senser modality c and power exponent a.

Step 2: Evaluate the fitness of each butterflies.

Step 3: Update the fragrance of each search agent in a population by Equation $fi=cI^a$

Step 4: Find the best fitness f.

Step 5: Based on the search criteria either move towards best position($r<p$) by equation (12) or random ($r>=p$) by equation (10).

Step 6: Update velocity using equation 11and calculate the new butterflies' fitness and update the best fitness f.

Step 7: If newf < best f then updates the best f using equation $X_i^{t+1} = X_i^t + V^{t+1}$.

Step 8: Evaluate the power exponent using equation

$$a(t) = a_{first} - (a_{first} - a_{final}).\sin(\frac{\pi}{\mu})\left(\frac{t}{T_{max}}\right)^2)$$

Step 9: Repeat the steps 3 to step 8 until termination criteria reached.

In the field, butterflies can search both locally and globally for food and a mate. A switch probability p is given to transform the regular global search and the intense local search. In order to decide whether to do a local or global search, the BOA generates a number at random in the range [0,1] for each iteration. This number is then compared to the switch probability p. It is clear from the suggested model that during the search phase, the chaotic map can disperse the butterfly population to a random value in the range (0, 1). The cubic map was recommended to initialise the location of the algorithm, and the proposed approach sets the cubic map's z(0) value to 0.315 to guarantee that the initialised interval is in the range (0, 1).

4. RESULT OF SIMULATION

Network Simulator 3 software is used to run the simulation. The proposed routing architecture is first subjected to three types of jamming assaults, with activity limitations set between (0.1 to 0.9). It has been noted that the proposed strategy gradually increases the packet delivery ratio. Standard cluster-based protocols BOA and PSO are compared in order to assess the performance of the proposed model. In Table 1, simulation setups are displayed.

Table 1. Simulation Parameters

Parameter	**Value**
Area for simulation	1000*1000 meter
Probability	0.3
Receiver energy	$20*10^{-8}$
Nodes	100
Bandwidth of the channel	2mhz
IoT threshold	3db
Transmission Energy	0.1
Transmitter Energy	$20*10^{-8}$
Maximum lifetime	$3*10^{-8}$
Jamming Duration	3, 0.2, 3, 1.1, 4, 2.5, 1, 1.4 ,7, 0.1ms

The parameters such as network lifetime, average energy, harvested energy are used to evaluate the performance. The network parameters are set up with different nodes between 50 to 200 nodes. The number of packets transmitted successfully gives the network throughput. The stability period is chosen for estimating the average energy with the throughput of the receiver nodes.

Table 2. Energy Comparison with Proposed HCPSOBOA

Nodes	**Proposed HCPSOBOA**	**BOA**	**PSO**
50	80.7	77.2	76.8

100	78.2	75.7	74.3
150	75.8	73.1	72.6
200	72.9	71.5	70.7

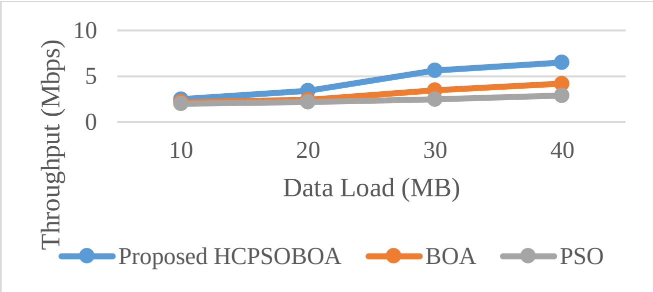

Figure 1. Throughput Analysis

The throughput performance is shown in Figure 1, and it is evident that the suggested HCPSOBOA has greatly outperformed both the BOA and PSO.

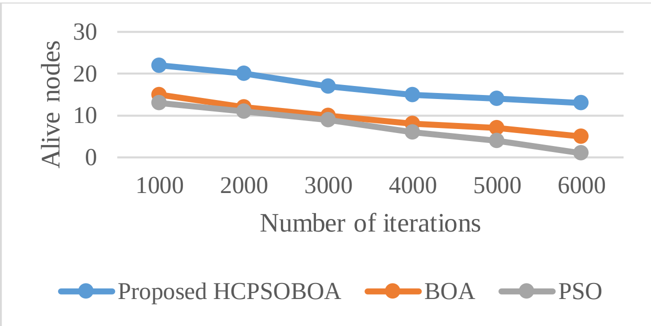

Figure 2. Network Lifetime Estimation

Figure 2 shows the Network life time performance when it is compared to the node that is still operational even after an assault, and it is evident that the suggested approach has been greatly enhanced. The time it takes for each node in the network to reach the maximum amount of time a node may stay alive in the network is used to calculate the average energy.

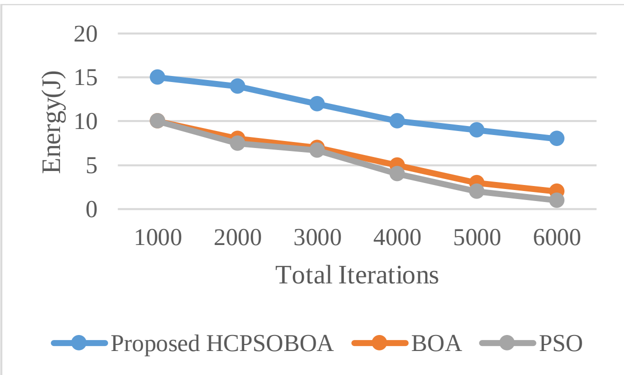

Figure 3. Comparison of Residual Energy of Proposed Model with BOA and PSO

Figure 3 shows the energy performance, and it is evident from the graph that the proposed approach has significantly increased energy savings. When compared to BOA and PSO based approaches, the suggested HCPSOBOA method retains the greatest amount of residual energy during the simulation.

5. Conclusion

This paper proposes a unique hybrid chaotic particle swarm optimization technique with butterfly optimization. In order to address the energy issues in cluster-based routing in IoT-enabled wireless sensor networks, the suggested model makes use of the advantages both optimization methods. When the IoT uses this hybrid approach, data is gathered through clustering, and energy-conscious devices are used. It is adequately proved via the simulation results and data analysis that the proposed routing protocol improves the balance of energy consumption throughout the whole network and accomplishes the goal of prolonging the network life cycle.

References

1. Heinzelman WR, Chandrakasan A, Balakrishnan H. Energy-efficient communication protocol for wireless microsensor networks. Annual Hawaii International Conference on System Sciences. 2000.
2. Lindsey S, Raghavendra C, Sivalingam KM. Data gathering algorithms in sensor networks using energy metrics. IEEE Trans. on Parallel and Distributed Systems, 2002, 13(9): 924-935.
3. Heinzelman WR, Chandrakasan AP, Balakrishnan H. An application-specific protocol architecture for wireless microsensor networks. IEEE Trans. on Wireless communications, 2002, 1(4): 660-670.
4. Latiff NA, Tsimenidis C, Sharif B. Energy-aware clustering for wireless sensor networks using particle swarm optimization. Personal, Indoor and Mobile Radio Communications, 2007: 1-5.
5. Kennedy J. Particle swarm optimization. Encyclopedia of Machine Learning, 2010. 760-766.
6. Li Wenfeng, Fu Xiuwen. Invulnerability of wireless sensor network [J]. Chinese Journal of Computer, 2015, 38(3): 625-647.
7. Brar, G.S., Rani, S., Chopra, V., Malhotra, R., Song, H., & Ahmed, S.H. (2016). Energy Efficient Direction-Based PDORP Routing Protocol for WSN. IEEE Access, 4, 3182-3194.
8. P. Nayak and A. Devulapalli, "A Fuzzy Logic-Based Clustering Algorithm for WSN to Extend the Network Lifetime," in IEEE Sensors Journal, vol. 16, no. 1, pp. 137-144, Jan.1, 2016, doi: 10.1109/JSEN.2015.2472970.
9. Ang, Liul, Jiangj, Analysis software-efficiency city connected targeted coverage algorithms for industrial Wireless sensor networks[J]. IEEE Transaction Industrial Information, 2017, 13(1): 135-143.
10. Cheng Guoying, Wang Yan. Multi-mobile agent cooperative control data offloading method in wireless sensor network [J]. Computer Applications, 2015, 35(4): 910-915.

11. Yaoy, Caoq, Vasilakosav. Edal: An energy-efficient, delay-aware, and lifetime-balancing data collection Protocol for heterogeneous wireless sensor networks[J]. IEEE/ACM Transaction on Networking, 2015, 23(3):810-823.
12. Liu Zhouzhou, Wang Fubao. Energy Efficient Wireless Sensor Networks Scale-Free Topological model [J]. Journal of Beijing University of Posts and Telecommunications, 2015, 38(1): 87-91.
13. Deepak Mathur, N. K. V. . (2022). Analysis & Prediction of Road Accident Data for NH-19/44. International Journal on Recent Technologies in Mechanical and Electrical Engineering, 9(2), 13–33. https://doi.org/10.17762/ijrmee.v9i2.366
14. Tunca C, Isik S, Donmezm Y, Ring routing: An energy-efficient routing protocol for wireless sensor networks with a mobile sink[J]. IEEE Transactions on Mobile Computing, 2015, 14(9): 1947-1960.
15. Kuila P, Janap K. Energy efficient clustering and routing algorithms for wireless sensor networks: Section Swarm optimization approach [J]. Engineering Application of Artificial Intelligence, 2014, 33:127-140.
16. Su Bing, Zhang Yujing. Wireless sensor network based on non-uniform clustering by the agreement [J]. Computer Measurement and Control, 2016, 24(2): 325-327.
17. Jadhavp, Sataor. A survey on opportunistic routing Protocols for wireless sensor networks [J]. Procedure Computer Science, 2016, 79: 603-609.
18. Shi Xiaodong, Yang Bo, Hao Jun, The optimal coordination delay between candidate nodes Opportunistic routing [J]. Computer Engineering and Design, 2017, 38(3): 576-580.
19. So J, Byun H. Opportunistic routing within-network aggregation for asynchronous duty cycled wireless sensor networks[J]. Wireless networks, 2014, 20(5): 833-846.
20. Zhao Jie. Opportunistic Routing Algorithm Based on Energy Awareness in Multi-hop Sensor Networks Law [J]. Journal of Jilin University (Science Edition), 2015, 53(6): 1241-1245.
21. Yao Yukun, Zhang Yi, Li Juan. Opportunistic Routing of WSN Based on Network Coding Optimization algorithm [J]. Computer Engineering, 2018, 44(6): 68-73.
22. Praveen, K.V., Prathap, P.M.J. Energy Efficient Congestion Aware Resource Allocation and Routing Protocol for IoT Network using Hybrid Optimization Techniques. Wireless Pers Commun 117, 1187–1207 (2021). https://doi.org/10.1007/s11277-020-07917-8.
23. Yarinezhad, R., & Azizi, S. (2021). An energy-efficient routing protocol for the Internet of Things networks based on geographical location and link quality. Computer Networks, 193, 108116.
24. Kaur, G., Chanak, P., & Bhattacharya, M. (2021). Energy efficient intelligent routing scheme for IoT-enabled WSNs. IEEE Internet of Things Journal.
25. Nouby M. Ghazaly, A. H. H. . (2022). A Review of Using Natural Gas in Internal Combustion Engines. International Journal on Recent Technologies in Mechanical and Electrical Engineering, 9(2), 07–12. https://doi.org/10.17762/ijrmee.v9i2.365