ENERGY EFFICIENCY CLUSTERING AND DISTANCE BASED ROUTING (EECD) FOR WIRELESS SENSOR NETWORKS

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Abstract: Wireless Sensor Networks (WSNs) are essential in contemporary observation systems, where maintaining energy efficiency and extending network lifetime are key concerns. This work develops a clustering strategy to conserve energy, employing distance-based cluster membership, adaptive duty cycles, and optimized cluster head (CH) selection. CHs are determined through a composite factor fitness function that accounts for remaining energy, spatial distance to the central node, and connectivity with proximal nodes. A dynamic duty cycle mechanism is added to further cut down on energy usage, enabling CMs to tweak their active schedules in accordance with node status as well as network demands. The introduced EECD (Energy-Efficient Cluster-based Data routing) algorithm allocates duty cycles to subordinate nodes in a distance-dependent manner relative to the CH. Simulation findings show that the suggested approach considerably extends network lifetime, saves energy, and maintains excellent data delivery rates when compared to traditional clustering algorithms.

Key words: wireless sensor networks, energy efficiency, process innovation, duty cycle, optimal cluster head, responsible consumption.

1. INTRODUCTION

WSNs have emerged as an integral technology for modern monitoring systems, supporting applications such as environmental tracking, automated industries, precision farming, healthcare solutions, and smart city initiatives. These networks feature sensor nodes spread across a region, collaboratively sensing environmental or physical conditions and forwarding the data to a central hub. Although highly versatile, WSNs face significant challenges in energy conservation because nodes have limited battery life and transmitting data consumes considerable power. To address these difficulties, experts have presented a number of energy-efficient routing and clustering techniques aimed at improving network lifespan and overall performance. One effective strategy is the deployment of mobile sinks, which help conserve energy by reducing the data transmission distance. For instance, in [1] proposed an intelligent data routing scheme that utilizes a mobile sink to dynamically adapt to network conditions, significantly reducing energy depletion in hotspot nodes.

Cluster-based routing remains a widely adopted technique in WSNs for enhancing scalability and conserving energy. In [2] applied a modified squirrel search algorithm to enhance CH selection, leading to an important rise in network life expectancy. In [9] developed an efficient protocol intended especially for IoT-integrated WSNs, show resilience and efficacy in severe circumstances. In [12] introduced EELCR, a lifetime-aware routing scheme that optimizes clustering and data compression to reduce energy consumption significantly.

Researchers have recently focused on employing artificial intelligence and soft computing techniques to strengthen the efficiency of routing and CH selection in WSNs. In [14], a fuzzy logic-based approach was put forward that utilizes a quantum annealing strategy for accomplishing finest energy savings in CH selection. Even with considerable progress in WSN energy optimization, the diverse and challenging environments encountered in practice demand routing methods capable of adaptability and scalability. This study extends recent developments by presenting a fresh framework designed to strengthen the energy efficiency, stability, and operational lifespan of WSNs through refined clustering and smart routing techniques.

2. RELATED WORK

Over the past decade, significant efforts have been made to establish energy-optimized routing strategies for WSNs, supporting the goals of SDG7. A range of strategies has been explored, including clustering, bio-inspired methods, fuzzy logic, and evolutionary algorithms, to reduce energy expenditure and extend the operational duration.

Clustering- driven routing is a key technique for conserving energy in WSNs. The study in [18] applied a Cuckoo Optimization Algorithm to form energy-efficient clusters, leading to more balanced energy usage among nodes and a longer network lifetime. Building on similar principles, in [19] proposed an improved routing protocol that optimized cluster formation and minimized redundant transmissions, contributing to prolonged network operation.

Fuzzy logic has also been applied in routing decisions to accommodate uncertainties in network parameters. Evolutionary techniques have been effective in enhancing multi-hop routing and cluster head selection. The study in [21] utilized a genetic algorithm to identifying energy-optimized multi-hop routes; leading to a substantial improvement in network longevity. Likewise, in [22] proposed a dynamic CH rotation strategy, which reduces energy depletion of CH nodes through periodic re-election, enhancing the overall network balance and sustainability.

Despite these advancements, there remains a need for more generalized, flexible, and lightweight protocols capable of addressing the diverse and dynamic conditions found in real-world WSN deployments. This paper attempts to resolve unaddressed challenges by introducing an advanced clustering and routing strategy that synergizes heuristic optimization with adaptive learning mechanisms for energy conservation and network performance enhancement.

3. PROPOSED SYSTEM

The proposed framework prioritizes the augmentation of energy efficiency and the extension of the operational lifespan of WSNs through the utilization of dynamic clustering methodologies and adaptive duty cycling strategies. The system workflow comprises six key stages, as illustrated in the Figure.1. The energy expenditure of a sensor node exhibits a direct correlation to the square of the distance that separates them. To optimize energy efficiency, the system allocates lower duty cycles to nodes positioned beyond a defined threshold distance, while nodes situated nearer to the sink are assigned higher duty cycles.

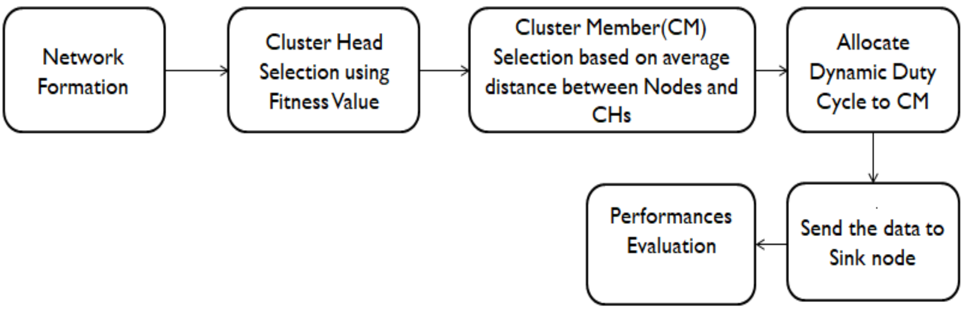

Figure 1. System architecture of proposed method

The duty cycle for any subordinate node n can be estimated employing a new function that is presented below [7]:

$$f(Dist_n) = \frac{1}{a + b \times \tanh\left(\frac{Dist_n}{\tau}\right)} \tag{1}$$

$$\tau = a * (Dist_{mean}) \tag{2}$$

When,

$$\frac{Dist_{nearest\ node}}{Dist_{mean}} \leq a \leq \frac{Dist_{farthest\ node}}{Dist_{mean}} \tag{3}$$

The duty cycle for each subordinate node n of the network can be obtained as below once the function has been computed. [7]:

$$DC_n = \frac{f(Dist_n)}{\sum_{\forall n \in N} f(Dist_n)} \tag{4}$$

Considering the distance to CH, nodes with a distance below τ are considered nearest nodes, while those exceeding this threshold are treated as farthest nodes.

Algorithm for cluster head selection
1. Randomly deploy sensor nodes in the monitoring area.
2. For each node, record residual energy e[i] and compute distances d[i][j] to all other nodes.
3. Randomly select k initial cluster head candidates.
4. Calculate the average inter-node distance $$d_{ave} = \frac{1}{n}\sum_{i=1}^{n}\sum_{k=1\&k\neq i}^{n} d_{ik}$$
5. For each candidate i, evaluate fitness: $$fit_i = \eta e_i + \frac{\lambda}{n-1\sum_{k=1\&k\neq i}^{n} e_k \|d_{ik} - d_{ave}\|}$$
6. Compute total fitness and derive selection probability
7. Find the mean fitness fit_{avg} and define thresholds: $$\text{upper}=\frac{\sum_{i=1}^{n} fit_i}{n}\ ,\ \text{lower}=\sqrt{\frac{\sum_{i=1}^{n} fit_i}{n}}$$
8. Select candidates whose fitness lies within [lower, upper].
9. Mark these nodes as final cluster heads.
10. Return the list of selected cluster heads.

Algorithm for Cluster Formation
1. Initialize cluster_assignment[N] =NULL and CH_members[j] = [] for each CH.
2. Compute distance distance[i][j] between each node i and CH j.
3. Compute average distance avg_distance over all nodes and CHs.
4. For each node i, create eligible_CHs where distance[i][j] < avg_distance.
5. If eligible_CHs is not empty, select CH with maximum residual energy under stable factor limit.
6. Assign node i to best_CH and update CH_members[best_CH].
7. Repeat for all nodes.
8. Return cluster_assignment.

4. PERFORMANCE EVALUATIONS

The developed EECD protocol exhibits substantial performance improvements over existing benchmark protocols, including EELCR (Energy Efficient Lifetime aware Cluster-based Routing), GABR (Genetic Algorithm-Based multi-hop Routing), GWOA (Grey Wolf Optimization Algorithm), and ABCA (Artificial Bee Colony Algorithm). Experimental evaluation demonstrates that EECD achieves enhanced energy efficiency, higher packet delivery ratio, reduced latency, improved throughput, and an extended network lifetime compared to these conventional approaches.

4.1. Simulation environment

The metrics utilized in the simulation are detailed in Table 1. To validate the efficacy of the introduced framework under different network conditions, the model was developed and tested using the NS-2 simulation platform, which enables accurate analysis and evaluation of wireless sensor network behaviours.

Table 1. Simulation Criteria

S.NO.	***Parameter***	***Value***
1	*The total amount of nodes*	*100-500*
2	*The starting energy of every node*	*0.5 joules*
3	*Range of the Transmission*	*150 meters*
4	*Data packet size*	*30 bytes*
5	*The length of the queue*	*10-25 packets*
6	*A type of node queue*	*Priority Queue*
7	*The rate of transmission*	*512 kbps*

4.2. Network Lifespan

The Figure 2 depicts the comparison of network lifespan between the introduced EECD protocol and existing benchmark protocols under varying node densities. The results clearly indicate that the EECD protocol consistently sustains a longer network lifespan across different numbers of sensor nodes, highlighting its efficiency in energy utilization and effective cluster-based communication.

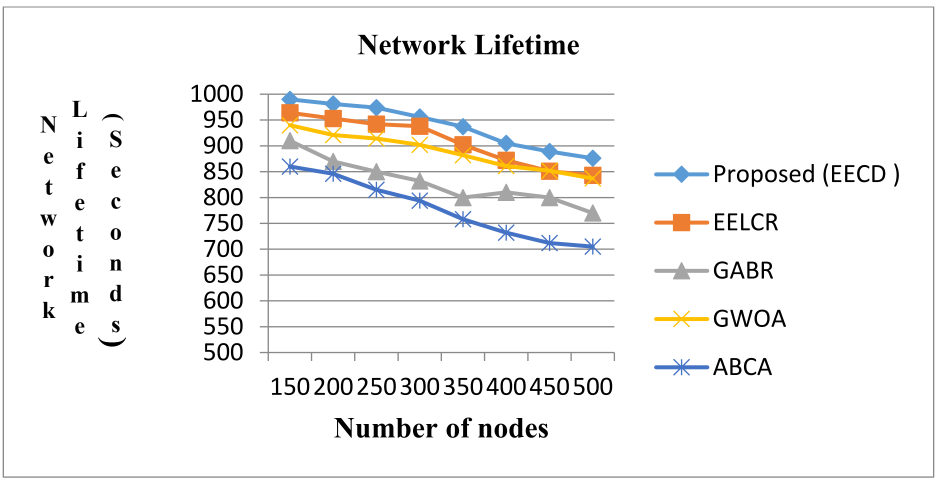

Figure 2. Maximum network life recorded for EECD approach

4.3. Throughput

The throughput performance of the proposed EECD protocol was evaluated under varying network sizes. The Figure 3 indicates that EECD consistently delivers superior throughput when compared to EELCR, GABR, GWOA, and ABCA. These findings indicate that EECD is more capable of handling increased network traffic and maintaining efficient data flow, making it well-suited for high-density WSN deployments.

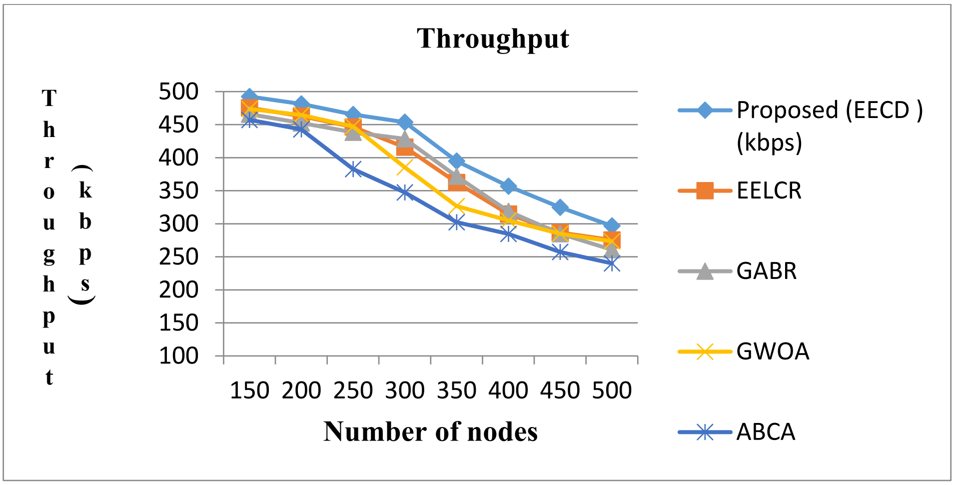

Figure 3. Estimated throughput for EECD in comparison to current models

4.4. End to End Latency

The Figure 4 indicates that EECD achieves the lowest end-to-end latency among all models, ensuring faster data delivery as network size increases. The comparative analysis shows that the EECD protocol achieves lower data transmission delay, highlighting its efficiency in ensuring prompt and stable communication across the network.

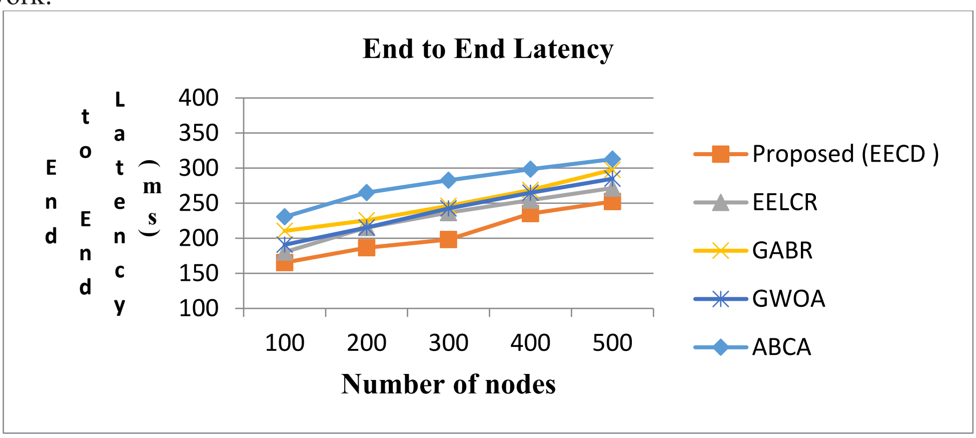

Figure 4. End to End Latency Comparisons of EECD

4.5. Packet Delivery Ratio

The Figure 5 illustrates the results of the experiment, which indicate that the created technology transported packets more efficiently than the conventional way. The EECD protocol demonstrates strong and consistent performance in terms of packet delivery ratio across different node densities. At 100 nodes, EECD achieves a delivery ratio of 99.2%, which is higher than all other compared protocols. As the network becomes more crowded, with nodes increasing up to 500, EECD still maintains a high delivery rate of 95.2%. This trend clearly illustrates that EECD is more effective at ensuring reliable data transmission, making it suitable for both sparse and dense Wireless Sensor Network deployments.

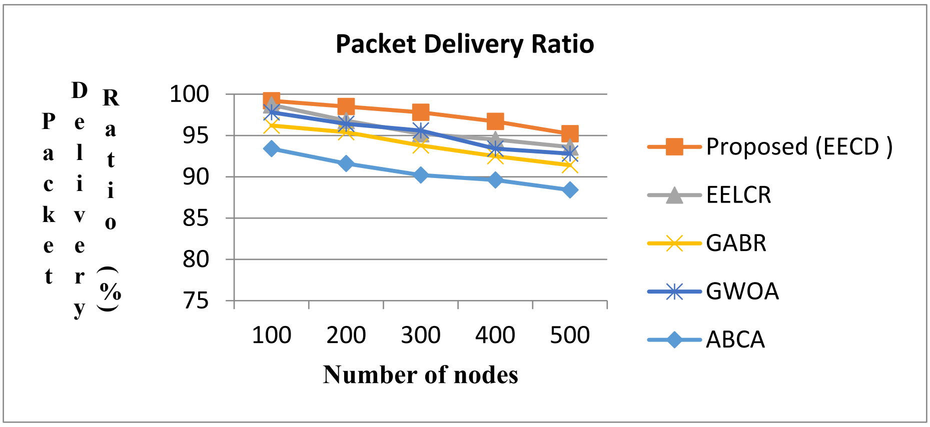

Figure 5. The packet delivery ratios for routes generated through node count are compared

4.6. Efficiency

The figure 6 indicates that EECD protocol delivers the highest level of energy efficiency, reaching 95.1%, which places it ahead of all the compared protocols. EELCR follows with a slightly lower efficiency of 92.5%, while ABCA shows the lowest value at 84.7%. The results confirm that the EECD protocol effectively lowers energy usage through its smart clustering and optimized routing mechanisms.

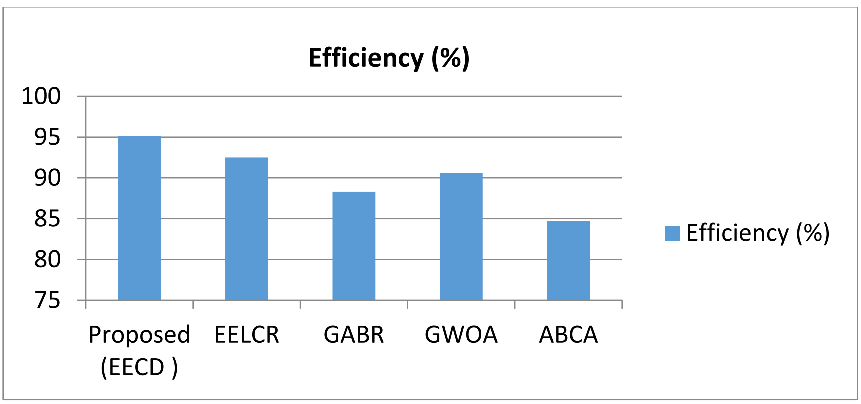

Figure 6. An efficiency comparison graph for the suggested approach

5. CONCLUSION

The proposed EECD protocol shows clear advantages over existing methods like EELCR, GABR, GWOA, and ABCA. It achieves excellent energy efficiency, reaching 95.1%, which is the highest among all compared protocols. EECD maintains a strong packet delivery ratio, starting at 99.2% with 100 nodes and holding 95.2% at 500 nodes. End-to-end latency is kept lower, ranging from 165.4 ms to 252.4 ms as network size increases. Throughput remains consistently high, beginning at 492.5 kbps and sustaining 296.7 kbps in larger networks. Other protocols, such as ABCA, show significantly lower throughput and higher delays. These results confirm that EECD is effective in saving energy, speeding up transmission, and improving reliability. Overall, EECD enables reliable data delivery while maintaining scalability and efficiency in WSNs.

REFERENCES

[1] H. Al-Mahdi, M. Elshrkawey, S. Saad, S. Abdelaziz. An intelligent energy-efficient data routing scheme for wireless sensor networks utilizing mobile sink. *Wireless Communications and Mobile Computing*, 2024, arXiv:pp.1-24.

[2] G. H. Alshammri. Enhancing wireless sensor network lifespan and efficiency through improved cluster head selection using improved squirrel search algorithm. *Artificial Intelligence Review*, vol. 58, 2025, pp. 79.

[3] H. Alsuwat, E. Alsuwat. Energy-aware and efficient cluster head selection and routing in wireless sensor networks using improved artificial bee colony algorithm. *Peer-to-Peer Networking and Applications*, vol. 18, 2025. pp.65.

[4] A. Chaudhari, S. Patel. Energy-efficient Q-learning-based routing in wireless sensor networks. *International Journal on Smart Sensing and Intelligent Systems*, vol. 18, no. 1, 2025, Article ID 0008.

[5] A. Farzaneh, M.-A. Badiu, J. P. Coon. LEAST: A low-energy adaptive scalable tree-based routing protocol for wireless sensor networks. *arXiv preprint,* 2022. arXiv:pp.2211-09443

[6] M Ashok Kumar, K Saravanan. Enhancing energy utilization for high power node multicasting in wireless sensor networks. *Journal of Intelligent & Fuzzy Systems,* vol. 45, no. 3, 2023, pp. 4753-4766.

[7] Indra Kumar Shah,Tanmoy Maity, Yogendra Singh Dohare. Algorithm for energy consumption minimisation in wireless sensor network. *IET Communications*, vol. 14, no. 8, 2020, pp.1301-1310.

[8] M. Kaddi, M. Omari, K. Salameh, A. Alnoman. Energy-efficient clustering in wireless sensor networks using grey wolf optimization and enhanced CSMA/CA. *Sensors*, vol. 24, no. 16, 2024, pp. 5234.

[9] R. B. Pedditi, K. Debasis. Energy efficient routing protocol for an IoT-based WSN system to detect forest fires. *Applied Sciences,* vol. 13, no. 5, 2023, pp.3026.

[10] M. R. Reddy, M. L. R. Chandra, P. Venkatramana, R. Dilli. Energy-efficient cluster head selection in wireless sensor networks using an improved grey wolf optimization algorithm. *Computers*, vol. 12, no. 2, 2023, pp.35.

[11] N. Sikarwar, R. S. Tomar. A new approach for wireless sensor networks based on tree-based routing using hybrid fuzzy C-means with genetic algorithm. *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, 2024, pp. 14141–14147.

[12] N. N. Sulthana, M. Duraipandian. EELCR: Energy efficient lifetime aware cluster based routing technique for wireless sensor networks using optimal clustering and compression. *Telecommunication Systems*, vol. 85, no. 1, 2024, pp. 103–124.

[13] J. Toutouh, S. Nesmachnow, E. Alba. Fast energy-aware OLSR routing in VANETs by means of a parallel evolutionary algorithm. *arXiv preprint*, 2025, arXiv: 2501-09996.

[14] H. Wang, K. Liu, C. Wang, H. Hu. Energy-efficient, cluster-based routing protocol for wireless sensor networks using fuzzy logic and quantum annealing algorithm. *Sensors*, vol. 24, no. 13, 2024, pp. 4105.

[15] Y. Yao, X. Li, Y. Cui, J. Wang, C. Wang. Energy-efficient routing protocol based on multi-threshold segmentation in wireless sensor networks for precision agriculture. *arXiv preprint,* 2023, arXiv:2307.00697.

[16] B. Zhu, E. Bedeer, H. H. Nguyen, R. Barton, J. Henry. Improved soft-k-means clustering algorithm for balancing energy consumption in wireless sensor networks. *arXiv preprint,* 2024, arXiv:2403.15700.

[17] R. Abraham, M. Vadivel. An energy efficient wireless sensor network with flamingo search algorithm-based cluster head selection. *Wireless Personal Communications*, vol. 130, no. 3, 2023, pp. 1503–1525.

[18] M. Khabiri, A. Ghaffari. Energy-aware clustering-based routing in wireless sensor networks using cuckoo optimization algorithm. *Wireless Personal Communications*, vol. 98, no. 3, 2018, pp. 2473–2495.

[19] Y. Liu, Q. Wu, T. Zhao, Y. Tie, F. Bai, M. Jin. An improved energy-efficient routing protocol for wireless sensor networks. *Sensors*, vol. 19, no. 20, 2019, pp. 4579.

[20] S. Nagadivya, R. Manoharan. Energy efficient fuzzy logic prediction-based opportunistic routing protocol (EEFLPOR) for wireless sensor networks. *Peer-to-Peer Networking and Applications*, vol. 16, no. 5, 2023, pp.2089–2102.

[21] A. Rajab. Genetic algorithm-based multi-hop routing to improve the lifetime of wireless sensor networks. *Engineering, Technology & Applied Science Research*, vol. 11, no. 6, 2021, pp. 7770–7775.

[22] S. S. Sushma, A. H. Nalband. Energy efficient cluster head rotation: A strategy for maximizing network lifetime in wireless sensor networks. *Proc. 2nd Int. Conf. Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN)*, 2023, pp. 1–6.

[23] W. Y. Leong. Digital technology for ASEAN energy. *Proc. 2023 Int'l Conference Circuit Power Computing Technology. (ICCPCT)*, August 2023, pp.1480–1486, DOI: 10.1109/ICCPCT58313.2023.1024

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