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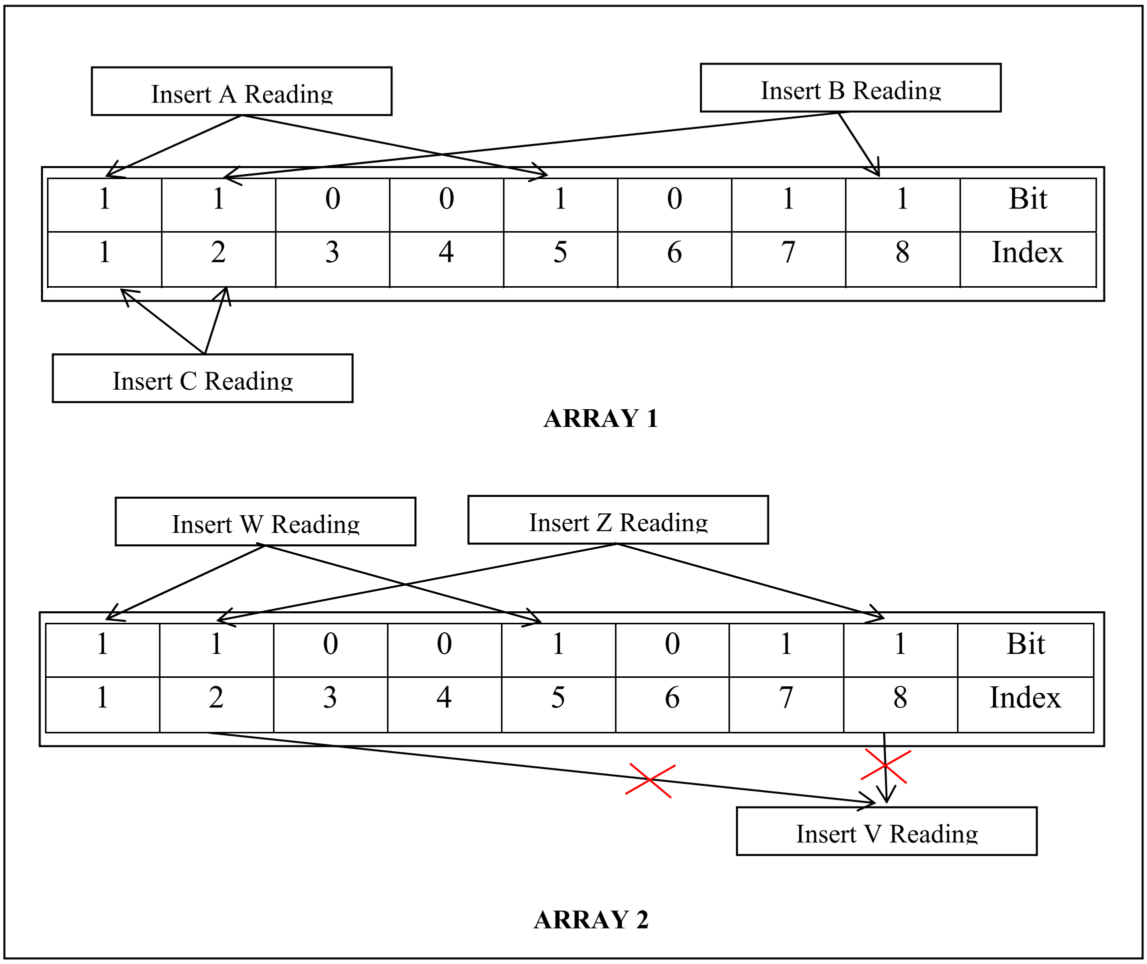

Fig 2: DHBF Process

INPUT: RID
BEGIN
  IF (Time == True) **then**
    array1 = array2 = {0}
  ENDIF
FOReach RID **do**
Pos 1 ← Hash1(RID)
Pos 2 ← Hash2(RID) //get two hash values for RID
  IF ((array1[pos1 & pos 2] == 1) && (array2[pos1& pos 2] == 1)) **then**
    Remove Duplicate reading
    ELSEIF ((array1[pos1 & pos 2] == 0) || (array2[pos1& pos 2] == 0)) **then**
    Array1[Pos1 & Pos2] ← 1 //store in array1
    ELSEIF ((array1[pos1 & pos 2] == 0) || (array2[pos1& pos 2] == 1)) **then**
    Array1[Pos1 & Pos2] ← 1 //store in array1
    ELSE ((array1[pos1 & pos 2] == 1) && (array2[pos1& pos 2] == 0)) **then**
    Array2[Pos1 & Pos2] ← 1 //store in array2
ENDIF
ENDFOR

Algorithm 1: Algorithm for Double Hash Bloom Filter

Instead of using a single array, the proposed MLDA exploits two arrays and minimizes the false positive, but it is not eliminated. There is less possibility for the corresponding bits of one reading to set as 1 when inserting other readings, resulting in a false positive. It is demonstrated in figure 2, and it explains two different cases in the DHBF algorithm.

Case 1: In figure 2, a sensor reading W returns the same positions (1 and 5) of reading B in array 1, and so it is stored in array 2.

Case 2: A sensor reading V also returns the same positions (2 and 8) of reading B in array 1 and reading Z in array 2 using the same set of k hash functions. Thus, the DHBF returns that it is a duplicate reading, but it is a false positive since the reading V is not stored in the parent node already.

If a sensor reading returns the new positions, not stored in both the arrays, it means that the reading is not defined in the array. After that, it is appended in the array. The readings in the arrays are cleared after performing the data aggregation. Using a Bloom filter, there is no way to eliminate the false positive completely, and thus a special technique, such as the Observe scheme assists in addressing and solving this problem effectively.

3.5 *MAX-MIN functions using Merge Sort*

Like the AVG and SUM aggregation measures, the MAX and MIN are also the basic measures for the observed temperature in an IoT environment. Sorting temperature readings in an area at the parent node during MAX and MIN aggregation measures in an energy-efficient way is a challenging task to perform. There are several sorting algorithms developed, but their execution time is still to be optimized. The merge sorting is an efficient technique since it exploits a comparison-based sorting algorithm [Auger, *et al*.(2015)].

For instance, to sort n temperature readings in the array, A[1,....n], the following steps are executed.

Divide: It divides the temperature readings into two lists of n/2 readings. It continues the process until reaching the smallest unit, one reading.

Conquer: It sorts the readings using merge sorting compares each reading with the adjacent list to sort.

Merge: It merges those sublists to generate a sorted list.

Thus, the proposed scheme efficiently supports SUM, AVG, MAX, and MIN aggregation functions in an aggregation layer by reducing the amount of redundant temperature readings transmission and energy consumption of sensor devices. The final readings are accessed in the application layer via the transport layer from the aggregation layer.

4. Performance Evaluation

The proposed protocol is assessed using the Cooja simulator. The simulation settings are utilized to complete an execution investigation of the proposed MLDA to contrast with CLCP [Alkhamisi, *et al*(2016)]. In these simulations, 15, 30, 45, and 60 homogeneous sensor nodes are deployed with equal battery energy, and they are placed in an area of 500 × 500 m^2. Based on the proposed data aggregation approach, the network performance is simulated in terms of the Aggregation Ratio, Transmission count coefficient, and Energy cost by varying the number of sensors.

1. **Aggregation Ratio:** The ratio of the number of aggregated packets to the number of generated packets.

2. **Transmission Count:** The ratio of the number of aggregated packets compared to the total packets that have been aggregated.

3. **Energy Cost:** The ratio of consumed energy per parent node during data aggregation to the energy of a parent node.

4.1 *Simulation Results*

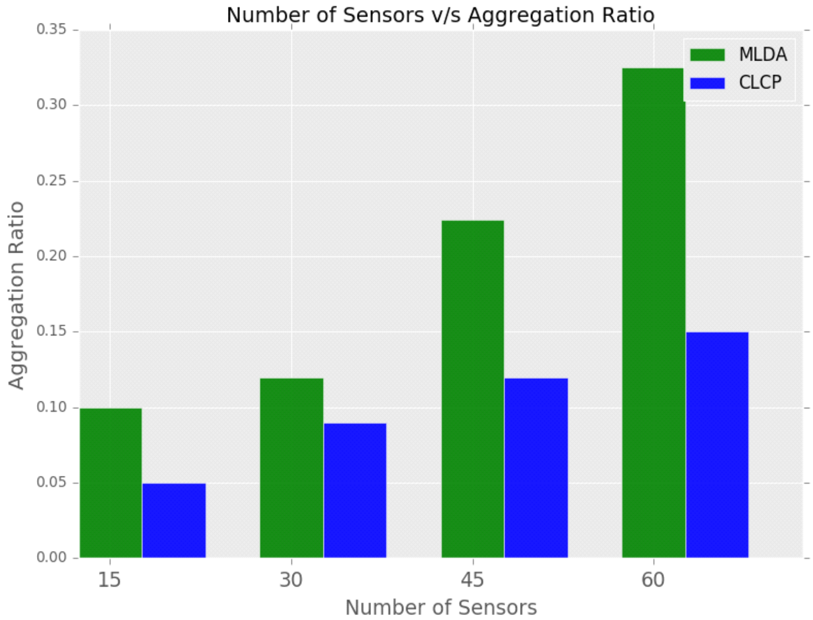

Fig 3: Number of Sensors vs. Aggregation Ratio

From figure 3, it is observed that the aggregation ratio of MLDA gets incremented when the number of sensors or the node density per particular area increases. Compared to MLDA, the CLCP also increases the aggregation ratio with the number of sensors, but it achieves a poor aggregation ratio than MLDA. In the case of high node density, the CLCP experiences a sudden decrease in aggregation ratio. High network traffic incurs packet loss in CLCP since it builds cluster structure using energy and distance factor only. The MLDA experiences up to 0.325 of aggregation ratio, while that of CLCP is above 0.15. In Figure. 3, the aggregation ratio in the proposed work is higher than 0.1 in all four network traffic scenarios. Because the redundant transmission removal using DHBF and observation scheme in the proposed work avoids unnecessary packet loss and ensures a better aggregation ratio.

Figure 4 demonstrates the result of transmission count for both the proposed MLDA and CLCP. When the network has high traffic, the MLDA attains less transmission count than other scenarios. As the spatially related sensors generate similar temperature readings, MLDA can find redundant readings and remove them during data aggregation.

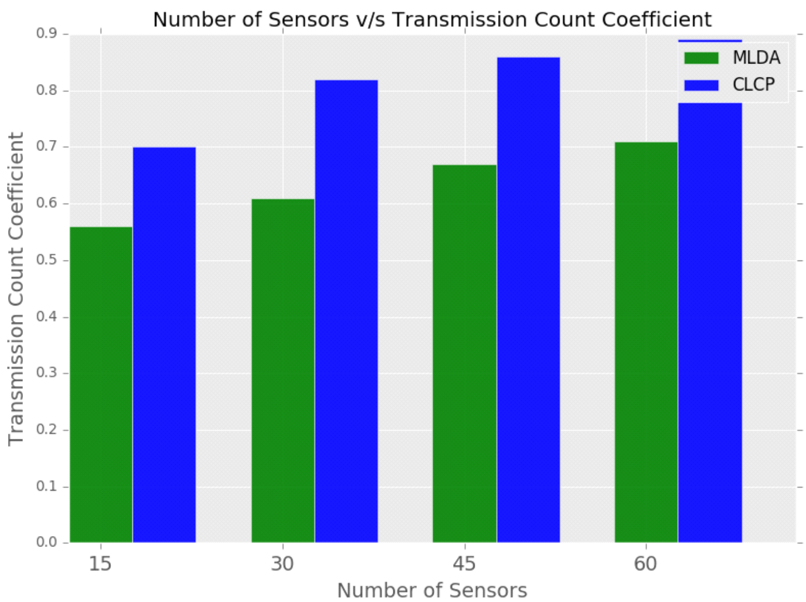

Fig 4: Number of Sensors vs. Transmission Count

However, CLCP work does not handle the data redundancy problem. The CLCP attains poor transmission count since it experiences more packet loss due to the lack of considering expected transmission count and traffic impact on communication. When the network traffic increased, the transmission count of CLCP is increased. Because the CLCP builds a separate cluster structure and simply applies aggregation function on all the received temperature readings. It increases the transmission count as well as the delay of packets. It results in poor communication performance in CLCP than MLDA. For instance, the MLDA attains 0.891 transmission count when the number of sensors is 60, whereas the CLPC attains 0.71 in the same scenario.

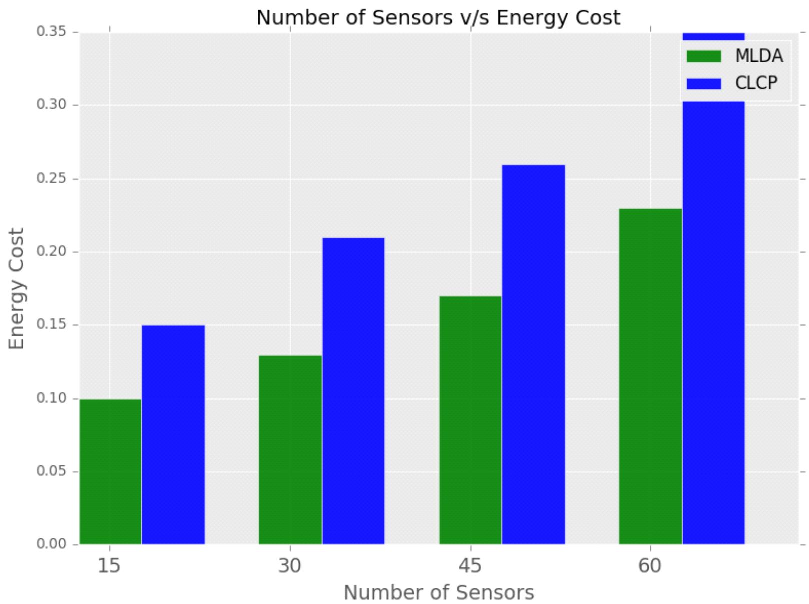

Fig 5: Number of Sensors vs. Energy Cost

Figure 5 shows that the proposed MLDA provides less energy cost due to network topology reuse from the network layer and redundant transmission removal. The MLDA based observation scheme enables the nodes to mostly avoid the transmission of redundant readings more than two times and to execute the aggregation function successfully at parent nodes. Another reason behind that the MLDA provides energy-efficient data aggregation is removing separate topology creation in the application layer. Moreover, with the number of sensors, the energy cost increases in both works. When the number of sensors is 60, the energy cost of MLDA is 0.23, whereas CLCP attains 0.35 energy cost in the same scenario. Moreover, the difference in energy cost between the proposed and existing works is approximately more than 5% in all scenarios.

5. Conclusion

This paper presented an energy-efficient aggregation scheme for IoT with the support of multiple layers, such as network and aggregation layer. To attain energy-efficient IoT communication, the proposed MLDA has incorporated the composite metric based network structure creation and such network structure based data aggregation in the aggregation layer. By applying the double hash filter model and observation field, the impact of redundant data transmissions on network resources and data aggregation efficiency are eliminated. Finally, the proposed scheme performs SUM, AVG, MAX, and MIN aggregation functions without redundant data transmissions, and merge sort is useful in executing the MAX and MIN aggregation functions. From the simulation results, it is concluded that the performance of MLDA is better than the CLCP in all the metrics. The proposed MLDA increases the aggregation ratio from 0.10 to 0.35 when the number of sensors has increased from 15 to 60. However, the existing work varies the aggregation ratio from 0.04 to 0.14.

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Authors Profile

Vanathi Arunachalam, Received her B.E in CSE from Bharadhidasan University, Trichy,T.N, India and M.E., in CSE from Anna University Chennai, TN , India. She is currently pursuing Ph.D in Acharya Nagarjuna University, Guntur. She was a lecturer,Assistant Professor and currently working as an Associate professor and Head Of the Department CSE ,Aditya Engineering College, Surampalem,AP, India.She is qualified in APSET and TNSET. She published papers in international journals and conferences. She guided a Project " Automated Plant Watering" ,which is selected for the First Prize with Cash award of Rs 50,000/- in CSI InApp , a National Level Project Competetition conducted by CSI Trivandrum Chapter. Her research interests include Information Security, Mobile Computing, WSN and IoT. She is a Lifetime Member of CSI and ISTE..

Dr. N. Nagamalleswara Rao, working as Professor, Department of IT, RVR& JC College of Engineering, Guntur (Dt). He Completed his B.Tech(1988) in Bapatla Engineering College, M.Tech (1991) in Motilal Nehru National Institute of Technology, Allahabad and Ph.D (2013) in Acharya Nagarjuna University. He has 30 years teaching experience. His research interests are Computer Algorithms, Compilers, Image Processing. He has published papers in many International conferences, National Conferences and International Journals. He has published many patents. Three Scholars completed their PhD under his guidance. He is a Life member of CSI, ISTE, IEEE.