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A POWER AWARE PROBABILISTIC CLUSTER HEAD SELECTION STRATEGY FOR IOT ENABLED DEVICES ON AGICUTURAL APPLICATIONS FOR TYPESETTING

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ABSTRACT

IoT enabled devices are becoming highly popular in various domains of industrial and domestic usages. The gain in the popularity is primarily due to the higher adoptability to the situations, effective mobility, availability of the applications for managing data collected from the IoT devices. Also, few of the IoT implementations have demonstrated significant improvements for open IoT stack deployment using Wireless Sensor Networks, which is again accelerated the growth of adaptations. Nonetheless, the IoT enabled device implementations comes with fundamental challenges due to group or cluster-based aggregations. The primary challenge is low battery life due to the higher computational loads and due to the proximity-based load distribution during cluster head-oriented computations. This issue is more prominent for the IoT enabled device deployments for agricultural purposes due to the huge size of the deployment site. Number of research attempts aimed to solve this problem in the recent times. Nevertheless, the existing solutions are highly criticized for higher complexity for deployment and adaptations. Hence, this work proposes a novel solution to balanced workload distribution using probabilistic and regression-based analysis, which results into a highly energy efficient and time efficient cluster head node selection strategy. The probabilistic selection strategy is integrated and optimized with the regression driven analysis to ensure highly random selection and at the same time highly effective selection based on various parameters such as mobility, computational capacity, proximity, and memory consistency. As a result, this strategy demonstrates nearly 92% improvements for time efficiency and nearly 94% improvements for energy efficiency compared with the parallel research outcomes.

Keywords: *Agro-IoT; Probability Distribution; Probabilistic Selection; Equivalency Coefficient; Energy Efficient*

1. INTRODUCTION

In the recent times, the applications of IoT devices have increased to a very great extend. This exponential growth is solely since the mobility of the wireless devices and internet-based activities can be incorporated in IoT infrastructures. Nevertheless, the complete focus of the industry, who are building IoT devices with solutions and the researchers, who are designing various architecture for IoT systems, is primarily on the solving the power awareness problem of the IoT devices. The power awareness has multiple implications as the routing or the data transmission or the computation operations reduces the battery levels and with the reduces batter levels the IoT devices turn into a dead network, which is completely unusable.

The work by J. Shen et al. [1] have clearly listed the possibilities and outcomes of the power awareness of IoT networks and the possible solutions to the problem. This work can be considered as the bench marking of the problem domain identification case studies. Also, the work by V. Reddy et al. [2] have clearly suggested the benefits of inclusion of WSN functionalities into IoT enabled and the vice versa for gaining better productivity over the network capabilities, which confirms the claims made in this literature.

Also, the data requirements from the sensor nodes are increasing. This increment is directly influencing the computational and memory requirements of the deployed network. The work by Q. Wang et al. [3] have submitted sufficient proofs in this direction of the comment. Regardless to mention that the increase in the data collection is directly proportional to the demand of the computing capacity, which is again directly proportional to the power requirements from the network. Thus, all the challenges direct towards a single solution that is power aware management methods for the IoT networks, which enables the WSN devices. Henceforth, it is evident to confirm that the probabilistic selection of the node management or the cluster head can contribute towards the power improvement or the improvement of the total network life span.

The rest of the literature is furnished such that, understanding of the cluster head selection is discussed in the Section – 2, which enables this work to understand the improvements made in the recent parallel research outcomes. Hence, the next section, Section –3 critically discusses the parallel research outcomes. The parallel research outcomes have enabled this work to correctly formulate the problems, which are listed and elaborated mathematically in the Section 4 and the proposed solutions by this research are furnished in the next section, that is Section 5 in this work. Based on the mathematical models proposed, in the Section 6, the algorithms are elaborated and subsequently the obtained results are discussed in Section 7, which are again compared with parallel research outcomes quantifiably in the Section 8. Finally, the conclusion of this research is furnished in the Section 9.

2. FUNDAMENTAL OF CLUSTER HEAD SELECTION

The cluster head selection for the IoT enabled networks are important for various reasons. Firstly, the communication over the other clusters in the same network, or the communication with the external node are done through the cluster head nodes. Secondly, for the IoT device data managements is primarily relies on the cluster heads and finally, the device registration policies are solely maintained from the cluster node in any network, which are WSN and IoT enabled. Hence, the fundamental criterion for cluster head selection must be understood. Thus, this section elaborates the fundamental cluster head selection process.

If the total IoT network, I[], and each IoT node is denoted as I_X. Thus, for n number of nodes in the network, thus the relation can be formulated as,

$$I[] = < I_1, I_2, \ldots . I_n > \quad (1)$$

Again, each node is having the characteristics as BT as battery level, M as mobility factor, C(X, Y) as the present coordinate, CP as the computing capacity and MC as the memory capacity. Thus, this can be presented as,

$$I_X = < BT, M, C(X,Y), CP, MC > \quad (2) \quad (2)$$

The cluster head selection process outcome is a time dependent factor as the selection of the cluster head completely depends on the associated factors at that time instance. Assuming that, the selected cluster head at the time instance t, can be represented as CH(t). Further the selection of cluster head follows few essential steps as the available battery level must be high among the available nodes and this can be formulated as,

$$CH(t) = \prod_{MAX(BT)} I[] \quad (3)$$

Also, assuming that the present coordinate of the IoT node is $C(X_1,Y_1)$ and the communicating coordinate $C(X_2,Y_2)$, thus the IoT cluster head selection process shall be intended to find the nearest location as,

$$CH(t) = \prod_{Near\{C(X_1,Y_1) \to C(X_2,Y_2)\}} I[] \quad (4)$$

Thus, considering the Eq. 3 and Eq. 4 together for final selection criterion,

$$CH(t) = \prod_{MAX(BT)} I[] \bigcap \prod_{Near\{C(X_1,Y_1) \to C(X_2,Y_2)\}} I[] \quad (5)$$

Hence, $CH(t)$ can be considered as selected cluster head at the time "t".

In the recent time, a good number of improvements are made to the fundamental strategy for cluster head selection and these improvements are critically analysed in the next section of this literature

3. PARALLEL RESEARCH OUTCOMES

The recent improvements over the fundamental strategies of cluster head selection have seen multiple milestones. The initial research strategies have focused on the WS networks without the enablement of the IoT devices. However, the fundamental challenges addressed in these parallel research outcomes are same that is the power or energy awareness. The initial work by S. Dehghani et al. [4] have demonstrated the possible reduction in the energy consumption during the routing. The work showcases the effectiveness of the routing strategies in increasing the power awareness. Nonetheless, this work generates more questions in the research community as this work produces a generic solution to the existing networks. In one hand, this is expected by most of the researchers and in other hand, this cannot confirm the adaptability of the same solution to various customizable network architectures.

The use of primitive machine learning algorithms has always been the supporting strategies for selecting cluster head by generic clustering methods. The work by S. Su et al. [5] is one of the most evident proof of such applications. Nonetheless, these generic machine learning methods from clustering have multiple challenges and these challenges have demoted the other researchers for limiting the use of such methods. Moreover, the fundamental problem of routing and cluster head selection can barely be addressed using these methods as clarified in the work by S. B. Shah et al. [6]. Hence, yet another set of activities such as generic optimizations have to come for rescue. The work by Q. Ni et al. [7] have showcased the effective use of the generic optimization methods. The genetic optimization methods such as particle swarm optimization or ant colony optimization are such methods, which can reduce the time complexity of the solution search operations to a great extends, by exploiting the concept of feasible solutions over optimal or best solutions.

The parameters discussed in the previous section of this work have showcased the use of primitive parameters such as mobility or location or energy efficiency or capacity of the nodes, which are internal parameters. Also, there are parameters which are external to the devices such as traffic demand or the data demand, which can also help in designing effective routing or at the least cluster head selection. The work by A. Jain et al. [8] have elaborated on such possibilities and demonstrated significant outcomes. The immediate solution to such problems can be utilization of the machine learning driven methods, which has predictive capacities or sometimes aggregating capacities. The work by S. A. Sert et al. [9] have emphasised on these possibilities. Nonetheless, all these parallel research outcomes driven by external factors must also demonstrate significant optimization as naturally increase in the number of parameters for identification of the most suitable or the best solution increases the time complexity. The work by M. Shokouhifar et al. [10] is one of evidence towards this argument, which is further extended more prominently in the work by H. Mostafaei et al. [11].

In general, the selection of the cluster head always focuses on the selection or forming the clusters as the first step. Thus, a significant number of researchers have aimed to solve both the challenges, clustering and cluster head selection, under one single framework as can be seen in the work produced by H. El Alami et al. [12]. Further, these research outcomes similar to the previous are motivated by the generic guidelines formed and produced in the work by M. Elshrkawey et al. [13]. Here the challenge is to adapt to the most volatile nature of the network. Thus, most of the parallel research outcomes have concentrated in building fuzzy solutions as showcased in the work by N. Shivappa et al. [14].

As already stated by multiple authors in various literatures such as the work by M. Baniata et al. [15], the applications of the IoT enabled wireless devices are huge and challenging as well. In this section few of the existing challenges are discussed, which is again comprehended in the work by A. A. Hassan et al. [16]. Further, in the next section of this literature, the existing problems in the parallel research outcomes are discussed.

After realizing the proposals from the parallel research outcomes, it is evident to identify that the existing methods suffers from the following shortcomings:

- The selection process for the cluster head is highly dependent on the location and further cannot be improved based on any other given parameters.
- Also, the repetitive selection of the cluster heads can lead to a complete draining of power and further lead to a non-sustainable network.
- Further, the selection of the cluster heads cannot be improved using any cost optimization functions such as combination of the parameters such as power consumption, network bandwidth or network congestion.

Hence, a clear research bottleneck is identified

4. PROBLEM FORMULATION

The existing proposals from various research attempts are analysed in the previous section of this work and the problems in the available proposals are also realized. This section is dedicated to the formulation of the problems using the mathematical models. Assuming that, the cluster head must be selected close to the location $C(X_X,Y_Y)$. Continuing from the Eq. 5, assuming that at time instances t1 and t2, two cluster heads are selected as CH1(t1) and CH2(t2). Here the cluster heads are selected, which are closure to the coordinate $C(X_X,Y_Y)$ and also assuming that the node I_X is associated with coordinate $C(X_X,Y_Y)$.

Here the mobility factor of I_X, CH1(t1) and CH2(t2) are respectively M1, M2, and M3 and these mobility factors are low and close to zero. This can be formulated as,

$$M1 \rightarrow 0 \tag{6}$$

$$M2 \rightarrow 0 \tag{7}$$

And, $$M3 \rightarrow 0 \tag{8}$$

Assumed that, the time instances are different, as,

$$t1 \neq t2 \tag{9}$$

But, due to Eq. 6 to Eq. 8, that is due to the lesser mobility of the network and peer nodes, it is possible that the selected cluster heads are same. As,

$$CH1(t1) = CH2(t2) \tag{10}$$

The implementation of this redundant selection of the cluster heads over multiple times will impact the battery level. Assuming that the battery level for the node CH1 is BT1, thus the energy level reduction can be formulated as,

$$BT1(t1) = BT1(t0) - \frac{BT1(t0)}{(CP + MC).(t0 - t1)} \tag{11}$$

After the first selection and after the second selection,

$$BT1(t2) = BT1(t1) - \frac{BT1(t1)}{(CP + MC).(t1 - t2)} \tag{12}$$

Hence, it is natural to realize that the same cluster head is selected multiple times under the consideration of Eq. 6 to Eq. 8, the battery level reduction will be much higher and thus,

$$BT1 \rightarrow 0 \tag{13}$$

This will make the complete network non sustainable as the dead nodes will make the complete network disconnected and unreachable.

The location plays a crucial role in the cluster head selection process, which cannot be optimised using any other parameters. Furthermore, no cost optimization functions, such as the combination of parameters like power consumption, network bandwidth, or network congestion, can improve the selection of the cluster heads. It is possible to completely drain the network's resources by repeatedly selecting the cluster heads, which is not a sustainable configuration. Consequently, there is a need to find a way to overcome this research impasse.

Thus, after realizing the problem in the existing available solutions, in the next section of this literature the proposed solution is furnished using mathematical models.

5.PROPOSED SOLUTIONS

After realizing the fundamental challenge of the network sustainability due to lesser mobility of the network nodes, implying the repetitive node selections for cluster heads, this section of the work is dedicated to formulating the proposed solution. The proposed solution is intended to consider multiple parameters for the cluster head selection. Nonetheless, each parameter in the characteristics, internal and external, of the IoT devices have specific units of measures. Thus, considering all the parameters in single arithmetic equation cannot be made possible.

Thus, this work considers equivalency coefficients for each parameter to be consider. As β_1, β_2, and β_3 for battery level, mobility and computational – memory capacity respectively.

These coefficients can be formulated as,

$$\beta_1 = \frac{mean[C(X,Y)] + mean[M] + mean[CP,MC]}{StdDev[BT]} \tag{14}$$

$$\beta_2 = \frac{mean[C(X,Y)] + mean[BT] + mean[CP,MC]}{StdDev[M]} \tag{15}$$

And, finally,

$$\beta_3 = \frac{mean[C(X,Y)] + mean[BT] + mean[M]}{StdDev[CP,MC]} \tag{16}$$

Here mean[] and the StdDev[] denotes mean and standard deviations, which are again calculated as per the standard formulations.

Again, the parameter used in this consideration must be optimized as for mobility the optimization must be lowest, for computation and memory capacity must be maximum and finally the coordinate must be optimized to be nearest. These can be formulated as,

$$f1(M) \rightarrow Lowest \tag{17}$$

$$f2(CP,MC) \rightarrow Maximize \tag{18}$$

And, $$f3(C(X,Y)) \rightarrow Nearest \tag{19}$$

Where f1, f2 and f3 are the functions for optimizations.

Further, with the help of these equivalency coefficients, the final selection coefficient, $\Re$, formulation is furnished.

$$\Re = \beta_1.BT + \beta_2.f1(M) + \beta_3.f2(CP,MC) + f3(C(X,Y)) \tag{20}$$

Assuming that, using Eq. 20, a set of clusters heads are identified as CH [], which can be formulated as,

$$CH[] = \prod_{\Re} I[] \tag{21}$$

Further, from the set of available cluster heads, CH[], one cluster can be selected using the probability distribution coefficient as PD. PD can be formulated as,

$$PD = \frac{P\{CH[x] \cap CH[]\}}{P\{CH[x]\}} \tag{22}$$

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Where CH[x] is the selected node as cluster head. Further, Eq. 21 can be re-written as,

$$CH[x] = \Big|_{PD} CH[] = \prod_{\Re} I[] \qquad (23)$$

The benefit of this method can be directly observed in case of the battery level or energy efficiency. Continuing from Eq. 9, assuming that at time t1 and time t2, two cluster heads are selected as CH[x1] and CH[x2]. Then,

$$CH[x1] \neq CH[x2] \qquad (24)$$

Also, assuming that the battery level of these two nodes is BT1 and BT2 respectively, then BT1 and BT2 can be formulated as,

$$BT1(t1) = BT1(t0) - \frac{BT1}{(CP + MC).(t1 - t0)} \qquad (25)$$

And,

$$BT2(t2) = BT2(t0) - \frac{BT2}{(CP + MC).(t2 - t0)} \qquad (26)$$

As, $CH[x1] \neq CH[x2]$, thus $BT1 \neq BT2$.
Hence, the collective lifetime of the network will be significantly higher compared with the parallel research outcomes. Further, based on the mathematical model proposed in this section of the work, in next section, the proposed algorithm is furnished.

6.PROPOSED ALGORITHMS

After the qualitative proof in the previous section of this work, in this section the proposed algorithm is furnished.

Algorithm: Probabilistic Cluster Head Selection using Equivalency Coefficients (**PCHS-EC**)

Input:
I[] as IoT enabled network
BT as Battery Level
M as Mobility factor
C(X,Y) as coordinates
CP as computing capacity
MC as memory capacity

Output:
CH(t) as selected cluster head at t time instance

Process:
Step - 1. Load the network information as I[]
Step - 2. For each element in the network information as I[i]
a. Build the equivalency coefficient as B1.I[i] using Eq. 14
b. Build the equivalency coefficient as B2.I[i] using Eq. 15
c. Build the equivalency coefficient as B3.I[i] using Eq. 16
d. Apply the optimization function f1(M).I[i] using Eq. 17
e. Apply the optimization function f2(CP,MC).I[i] using Eq. 18
f. Apply the optimization function f1(C(X,Y)).I[i] using Eq. 19
g. Calculate the final selection coefficient, R as Eq. 20
h. Build the possible cluster head set, CH[] using Eq. 21
Step - 3. For each element in the set CH[] as CH[j]
a. Calculate the probability distribution factor using Eq. 22
Step - 4. Return the selected cluster head, CH[x] using Eq. 25 for time instance t
Step - 5. Repeat from Step - 3 for time instance t+1

In likelihood hypothesis and insights, circulation of an amount of the squares of k autonomous standard typical arbitrary factors. The dispersion is an exceptional instance of the gamma circulation and is perhaps the most broadly utilized likelihood distribution in inferential measurements, prominently in theory testing and in development of certainty spans. This dispersion is now and again called the focal circulation, an uncommon instance of the broader noncentral dissemination.
The dispersion is utilized in the normal tests for decency of attack of a noticed circulation to a hypothetical one, the autonomy of two rules of order of subjective information, and in certainty span assessment for a populace standard deviation of an ordinary conveyance from an example standard deviation. Numerous other factual tests additionally utilize this dispersion, for example, Friedman's investigation of change by positions.
In the next section of this work, the obtained results are analysed and discussed.

7.RESULTS AND DISCUSSIONS

The obtained results are highly satisfactory and are furnished in this section. The proposed algorithms are tested on three different agricultural fields with different dimensions and sensor placements. These three sample fields are selected randomly from an available 20 field datasets.
The initial setup is formulated here in Table.1

Table 1. Initial Test Setup

Parameter Name	Number
Initial Agro – Field Data	10
Randomly Selected Agro – Field Data	3
Number of Test Run without Probability Distribution	1
Number of Test Runs with Probability Distribution	3
Number of Time Instances	100

The initial setup is also visualized graphically here in Figure 1.

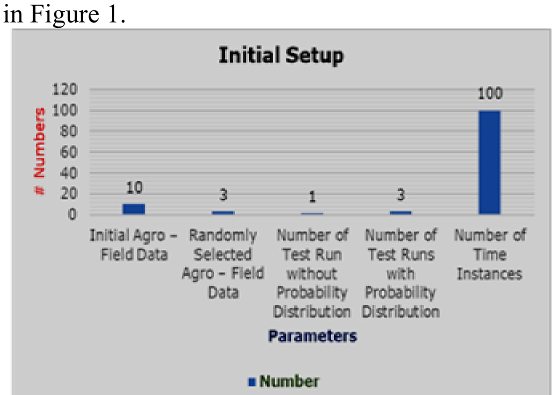

Figure 1.Initial Test Setup

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Nonetheless, for this literature results for only 20-time instances are presented. Further, the time analysis results for cluster head selection are furnished here in table.2. As explain in the initial setup, a total of 4 trials are conducted for 100-time instances. One trial is without the probability distribution and three with the probability distribution. Also, only 20-time instances are furnished in this literature.

Table 2. Cluster Head Selection Time Analysis

CH Selection without Probability Distribution Time (ms)	CH Selection with Probability Distribution Time (ms) – Trial - 1	CH Selection with Probability Distribution Time (ms) – Trial – 2	CH Selection with Probability Distribution Time (ms) – Trial - 3
0.056	0.018	0.013	0.015
0.046	0.01	0.008	0.008
0.051	0.005	0.005	0.005
0.039	0.006	0.005	0.006
0.044	0.009	0.006	0.007
0.046	0.006	0.005	0.004
0.037	0.007	0.005	0.006
0.043	0.007	0.005	0.005
0.051	0.005	0.005	0.003
0.04	0.006	0.005	0.006
0.04	0.007	0.006	0.005
0.053	0.005	0.004	0.004
0.036	0.006	0.004	0.005
0.041	0.007	0.005	0.005
0.053	0.005	0.005	0.002
0.043	0.007	0.004	0.004
0.04	0.007	0.005	0.005
0.049	0.005	0.005	0.004
0.037	0.007	0.004	0.004
0.039	0.007	0.005	0.004

The graphical visualization for the obtained results is presented for all 100-time instances figure.2.

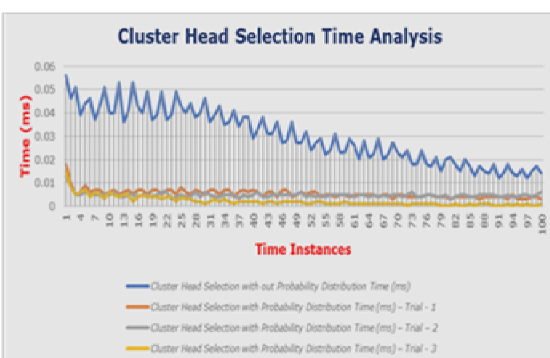

Figure 2. Cluster Head Selection Time Analysis

Regardless to mention that the time required to select the cluster heads are significantly lower compared with the non-probabilistic distribution algorithms. Also, it is to be noted that, due to the adaptation of time reduction at Step – 3 to Step – 5 in the proposed algorithm, the iteration time is also reducing, which can be observed between trial 1 to trial 3. The data presented in the table – 2 is highly confirmatory. Nonetheless, the mean time analysis is furnished again to confirm the claim with noted improvements in table 3.

Table .3. Mean Time Analysis

Trial Runs	Mean Time (ms)	Improvement (%) Compared with the final trial
Cluster Head Selection with out Probability Distribution	0.030	92.93
Cluster Head Selection with Probability Distribution – Trial - 1	0.005	60.40
Cluster Head Selection with Probability Distribution – Trial – 2	0.005	56.17
Cluster Head Selection with Probability Distribution – Trial - 3	0.002	46.2

The results are visualized graphically here in Figure.3.

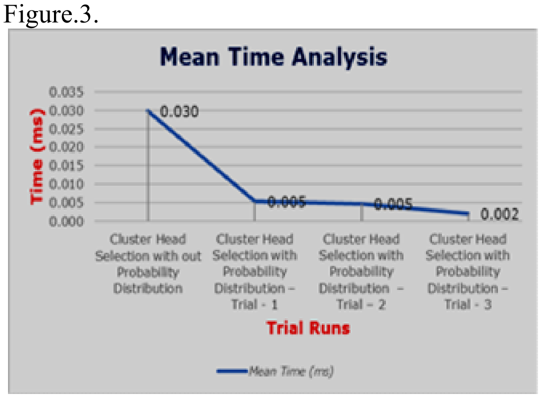

Figure 3. Cluster Head Selection Mean Time Analysis

Nonetheless, the primary objective of this proposed work is to improve the sustainability of the network by reducing the power consumption and increase the overall lifetime of the IoT enabled network. Thus, the network power decay analysis is furnished here in table 4.

Table 4. Power Decay Analysis

Rate of Power Decay - without Probability Distribution (eV)	Rate of Power Decay - with Probability Distribution Trail 1 (eV)	Rate of Power Decay - with Probability Distribution Trail 2 (eV)	Rate of Power Decay - with Probability Distribution Trail 3 (eV)
0.98892	1.4891	1.1977	0.095022
0.97745	1.4782	1.1945	0.089575
0.96572	1.4684	1.1921	0.087139
0.95418	1.4578	1.1902	0.081971
0.94304	1.4471	1.1871	0.081971
0.93161	1.4365	1.1843	0.079071
0.92024	1.4256	1.1811	0.079071
0.90869	1.4154	1.179	0.07346
0.89702	1.405	1.1766	0.071161
0.88619	1.395	1.1745	0.065757
0.87486	1.3843	1.1708	0.061902
0.86398	1.3732	1.1686	0.061902
0.85256	1.3627	1.1661	0.061902
0.84086	1.3518	1.1637	0.05755
0.83041	1.3412	1.1612	0.05755
0.81853	1.3305	1.159	0.054381
0.80753	1.32	1.1563	0.054381

Rate of Power Decay - without Probability Distribution (eV)	Rate of Power Decay - with Probability Distribution Trail 1 (eV)	Rate of Power Decay - with Probability Distribution Trail 2 (eV)	Rate of Power Decay - with Probability Distribution Trail 3 (eV)
0.79682	1.3095	1.1529	0.051627
0.78532	1.2987	1.151	0.051627
0.77401	1.288	1.148	0.048762

The graphical visualization for the obtained results is presented for all 100-time instances in Figure 4.

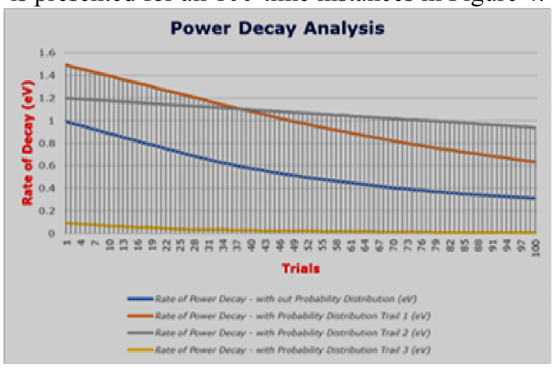

Figure 4.Power Decay Rate Analysis

It is highly evident that, the probability distribution factor along with the selection coefficient enabled algorithm, proposed in this work, have significantly improved the decay rate of total network power or battery levels. From the results it is also evident that the final trial has shown steady decay, which is also helpful for predicting the network lifetime. The data presented in the table – 4 is highly confirmatory. Nonetheless, the mean decay analysis is furnished again to confirm the claim with noted improvements in table 5.

Table 5. Mean Power Decay Analysis

Trial Runs	Mean Decay (eV)	Improvement (%) Compared with the final trial
Cluster Head Selection with out Probability Distribution	0.558	94.69
Cluster Head Selection with Probability Distribution – Trial - 1	1.010	97.06
Cluster Head Selection with Probability Distribution – Trial – 2	1.067	97.22
Cluster Head Selection with Probability Distribution – Trial - 3	0.029	94.69

The results are visualized graphically here in figure 5.

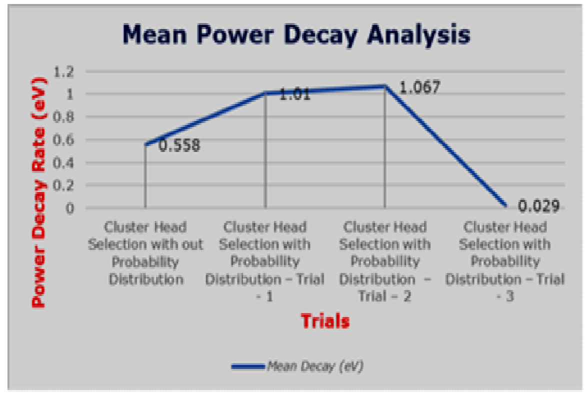

Fig.5.Final results

Henceforth, it is evident to mention that the proposed algorithm has improved the time for cluster head selection and as well as the network lifetime to greater extend. Further, in the next section of this literature, the conclusion is furnished.

The improvement of this proposed framework is clearly observable and in this section of the work, the quantitative values are presented in the table – 6.

Table 6. Comparative analysis

Author, Year	***Model Complexity***	***Mean - Cluster Head Selection Time (ns)***	***Mean – Power Decay (Over 20 iterations) (eV)***
A. A. Hassan et al. [16], 2020	$O(n^2)$	0.101	0.852
H. Mostafaei et al. [11], 2019	$O(n^2)$	0.185	0.749
H. El Alami et al. [12], 2019	$O(n^2)$	0.133	0.745
Proposed Method	$O(n)$	0.005	0.029

In the final section of this work, we discussed the use of primitive parameters, also known as internal parameters. These include the nodes' mobility, location, energy efficiency, and capacity. In addition, factors external to the devices, such as the volume of traffic or the amount of data to be transmitted, can help design effective routing or at least select the cluster head. However, because this work provides a general solution to the problem of existing networks, it prompts the research community to pose additional inquiries. This is consistent with what the majority of researchers have discovered, but it does not prove that the same solution can be applied to a wide variety of networks with variable topologies.

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8.CONCLUSION

Driven by the growth in the IoT enabled services and specifically adaptation into agriculture, this work proposed an algorithm to improve the network lifespan by selecting the cluster heads for building a better communicating network, which are designed for large area deployment. The proposed algorithm has considered various parameters to build the most suitable selection criterion to select the possible cluster heads in the network and further to increase the life span of the network, used a probability distribution function with significant optimizations. The results demonstrated higher improvements over the standard benchmarks. Also, this work raises few further questions as the analysis of the implications of memory or data distribution over the network for further optimization for the cluster formations. IoT nodes' data and the applications that process it will eventually be moved to the cloud, but this process will be time-consuming. The challenge here is finding a cloud-based load balancer that can accommodate the protocols used in IoT networks. In this research, we propose a novel method for managing the load in IoT network architectures.

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