# Enhanced Chaotic Political Optimizer based Power Management Scheme for Clustered Wireless Sensor Networks

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**Abstract**

The recent advancements in wireless sensor networks (WSN) have enabled the smart environment to offer pervasive real-time applications in a variety of domains, including transportation, healthcare, industry, and the internet of things. Wireless sensor networks (WSN) are becoming increasingly popular in smart environments (IoT). Because the sensor nodes in a WSN are powered by an internal battery unit, effective power management solutions are required to ensure that the network continues to function for an extended period of time. Clustering is a crucial technique for achieving the best possible power management and network longevity in a WSN environment. The selection of appropriate CHs is a critical component of the clustering process, and this can be accomplished through the use of metaheuristics. In this regard, this paper presents an enhanced chaotic political optimizer-based power management (ECPO-PM) strategy for clustered wireless sensor networks (WSNs). The goal of the ECPO-PM technique is to pick the CHs in the most efficient manner while also reducing power consumption through inter-cluster communication. The ECPO algorithm, in addition, is formed from the merging of the classic PO algorithm with the chaotic based initialization notion, which results in the ECPO algorithm. Also included is the development of a fitness function that incorporates three parameters, including residual energy, distance to neighbours, and node degree. In order to investigate the improved performance of the ECPO-PM technique, a wide range of experimental evaluations were carried out in the NS-3 simulator, and the findings obtained revealed that it outperformed previous state-of-the-art approaches in terms of overall performance by a large factor.

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## 1. Introduction

Owing to the latest advancements in the field of wireless telecommunications, Micro-Electro-Mechanical-Systems (MEMS), digital electronics, and smart sensors, inexpensive, low-power, and small sensors could be constructed which have the capacity of wireless transmission. These small sensors are made up of sensors, wireless information transmission, and information processing elements [1-3]. Wireless sensors are driven by battery that is mainly non-rechargeable. The sensor network will fail when the energy of the node is finished. The primary objective of wireless sensor network (WSN) is to gather precise information and increase lifespan of the network by managing the power. In order to attain the secondary objective, viz., to expand lifetime of the network, the energy utilization of the sensor must be as lower as possible. It is well known that sensors do processing, sensing, and transmission. They take maximal energy utilization for transmission, thus, authors concentrate on transmission by launching some new technologies which guarantee effective power consumption [4]. Distinct energy management systems are utilized to expand the network lifetime namely mobile networks, workload management, clustering, intelligent data gathering, energy harvesting from the environment, and optimal deployment of nodes [5, 6]. Some of the selfish sensors exhaust energy by transmission, most of the time keeping off their antennas. Fig. 1 demonstrates the structure of WSN. Hence, we needed some effective tools that could rationally estimate and make the decision. One of the candidate systems to improve power utilization is clustering.

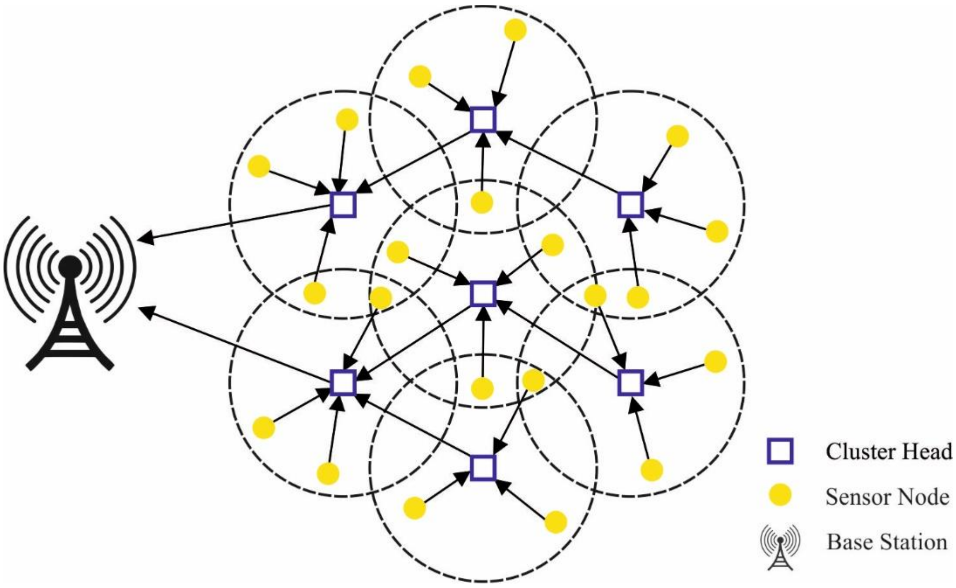


**Fig. 1.** WSN structure

The clustering technique is primarily concerned with the transmission part of the WSN by extending the lifetime. Also, it has been involved in several applications of the WSN [7]. The selection of cluster head (CH) is a major problem in the general procedure. In the CH selection, several parameters are taking into consideration the scenarios and of requirements WSN. In this way, all the nodes could not be applicable for assuming the role of CH because of unimportant location, distance from BS, low energy, and so on. There are two common methodologies where clustering might be eased. The initial one is clustering through selection that is the classical approach cited in existing works on clustering in WSN. The next is to assist clustering is exhibited in naturally clustered WSN, whereas nodes in the highest tiers aren't selected from amongst the nodes. In a naturally clustered system, the highest tier node is a different set of nodes dispersed over the regions with a small intensity of distribution as compared to those standard nodes [8, 9]. Therefore, consider a two-tier hierarchy comprised of two different sets of nodes: processing nodes (N-tier nodes) and sensor nodes (M-tier nodes). The N-tier node is considered to be less power constrained, larger and robust (like localized processing station) which is proficient in intensive computation and processing than that of the M-tier nodes.

Pakdel and Fotohi [10] proposed a technique with the firefly model and four standards of noise rate, residual energy, distance, and number of hops. The presented approach named EM-FIREFLY selects an optimal CH using higher attractiveness and depending on the fitness function and transmits the data packets via this CH to the sink. Ghosh et al. [11] introduced an advanced, smart controller to withstand mobility in WSN. Basically, the focal point is based on the arrangement of fuzzy input parameters (that is., centrality solution, remaining battery power [RBP], and mobility) to critical uses, analogous to security of individuals in an industrialized environment. A mobility controller based on the type-1 fuzzy logic (T1FL) is proposed for supporting sensor mobile nodes (MN). Now, a role model cluster head (RMCH) is chosen between the CHs which might transmit only the messages to the mobile base station (BS) by defining the proper type-1 fuzzy (T1F) descriptors namely mobility of the sink, centrality of the cluster, and RBP.

Goswami et al. [12] presented an advanced technology for effective consumption of energy in WSN, with ANN based self-organizing map (SOM) approach for clustering and distributed artificial intelligence (DAI) to energy supply in the nodes. The hybrid model of SOM and multi-agent-based DAI leads to effective performances than the current methodologies. Kalaimani et al. [13] proposed an energy-effective routing for WSN in AMI network by using density-based Fuzzy C-Means clustering (DFCM) to achieve load balancing. The experimental result shows that DFCM could offer effective performances and is applicable for collecting information in Smart Networks. Osamy et al. [14] proposed a Chicken Swarm Optimization based Clustering Algorithm (CSOCA) to enhance energy efficacy in WSN. The proposed model is discretized by employing a sigmoid function to the individual. Furthermore, presented a CSOCA using Genetic Algorithm (CSOCA-GA) that is an enhancement to CSOCA by applying the Genetic Algorithm process in CSOCA.

This study develops an enhanced chaotic political optimizer based power management (ECPO-PM) scheme for clustered WSN. In addition, the ECPO algorithm is derived by the integration of the traditional PO algorithm with the chaotic based initialization concept. Moreover, a fitness function is derived comprising three parameters such as residual energy, distance to neighbours, and node degree. For investigating the better performance of the ECPO-PM technique, a wide range of experimental analyses were carried out.

## 2. The Proposed Model

In this study, an effective ECPO-PM technique has been designed in order to optimally select the CHs and accomplish reduced power utilization via inter-cluster communication. Primarily, the WSN is deployed in the simulated target region and initiation of nodes is carried out. Then, the nodes begin to exchange information, and afterward, the ECPO-PM technique gets executed. Fig. 2 displays the overall block diagram of ECPO-PM technique.

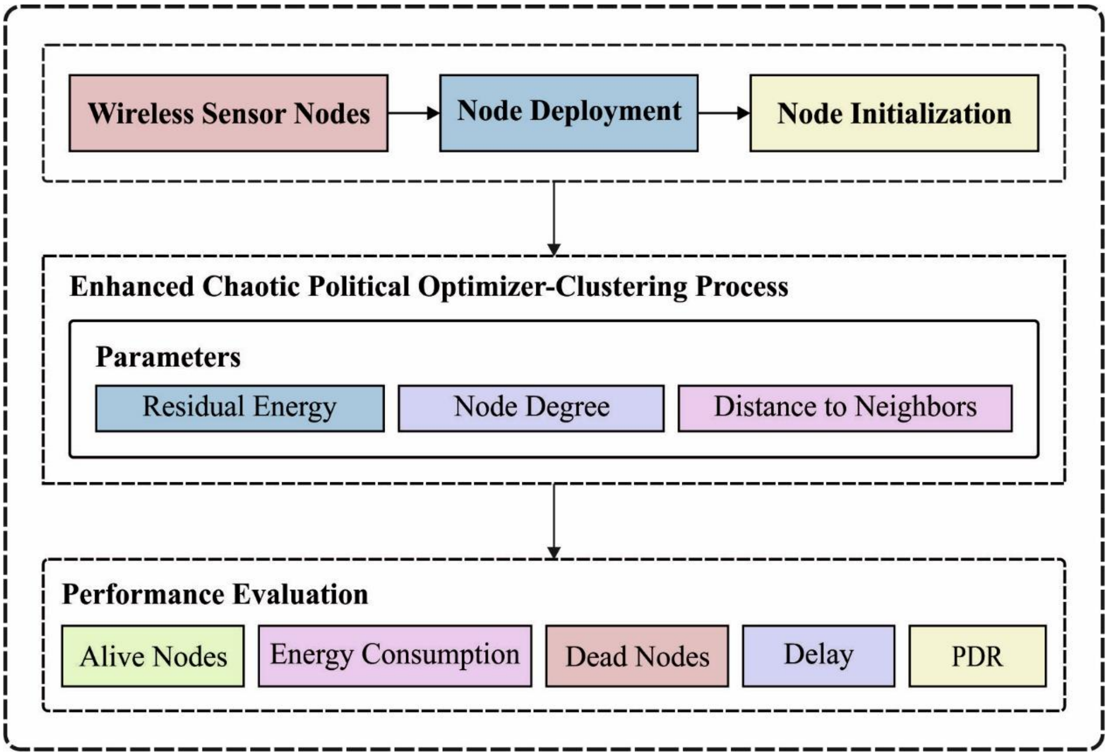


**Fig. 2.** Block diagram of ECPO-PM technique

### 2.1. Design of ECPO Algorithm

A meta-heuristic approach termed as PO approach was developed and the basic model of PO approach was described [15]. The PO approach simulates the distinct stages of politics. The PO method implementation starts with constituency distribution and political party (N) design. This process of model was attained using population (N) i.e., N party in Eq. (1) and the equivalent $N_{p,i}$ party is candidate n as shown below.

$$N_p = N_{p,1} + N_{p,2} + \cdots + N_{p,n} \tag{1}$$

$$N_{p,i} = n_{p,i}^1 + n_{p,i}^2 + \cdots + n_{p,i}^n \tag{2}$$

$$n_{p,i}^j = [n_{p,i1^j} + n_{p,i2}^j + \cdots + n_{p,id}^j]^T \tag{3}$$

In which the dimensionality of the problem was indicated as d and $N_{p,ik}$ denotes the $k^{th}$ dimension of$N_{p,i}^j$. The structure of a set of constituencies is proposed in Eq. (4), whereas each party member has stated in Eq. (4).

$$C_p = C_{p,1} + C_{p,2} +..+ C_{p,n} \tag{4}$$

$$C_{pj} = n_{p,1}^j + n_{p,2}^j +..+ n_{p,n}^j \tag{5}$$

The sum of party candidates, constituencies, and parties is attained as N. An optimal fitness, for instance, the number of $i^{th}$ parties have attained as leader of party and it is carried out afterward selection, as follows:

$$q = \arg \min_{1 \le i \le n} f(n_{p,i}^{j}), \forall i \in \{1,2,\ldots,n\} \quad (6)$$

$$n_{p,i}^{*} = n_{p,i}^{q}$$

The party leader set was indicated as $N_p^* = n_{p,1}^* * + n_{p,2}^* + \cdots + n_{p,n}^*$ and discover the parliamentarian is winner of $j^{th}$ constituency $C_p^* = C_{p,1}^* + C_{p,2}^* + \cdots + C_{p,n}^*$. The elective campaign was exploited to simulate exploitation and exploration capacity. The party-switching obtains the balance between exploitation and exploration capacity. The party switching was attained by electing a party member $n1_{p,i}$ with $\lambda$ switching rate and the member could switch for arbitrarily created party. The subsequent formula computes the least solution.

$$q = \arg \max_{1 \le i \le n} f(n_{p,r}^{j}) \quad (7)$$

The selective was conducted for measuring the fitness to contest from constituency separately and define the optimum solutions as follows.

$$q = \arg \min_{1 \le i \le n} f(n^{j_{p,i}}) \quad (8)$$

$$C_{p,j}^{*} = n_{p,i}^{q}$$

| **Algorithm 1:** Pseudocode of PO algorithm |
|---|
| Input: n (number of party members, constituencies and political parties), $\lambda_{max}$ (upper limits of the party switching rate), $T_{max}$ (overall amount of iterations)<br>Output: final population $P(T_{max})$<br>/* Initialization/*<br>Initialize $(n * n)$ candidate member P<br>calculate the fitness of all the members $p_i^j$<br>calculate the group of the party leaders $P^*$ and the group of the constituency winners $C^*$,<br>$t = 1;$<br>$P(t-1) = P;$<br>$F(P(t-1)) = f(P)$ ;<br>$\lambda = \lambda_{max}$;<br>while $t \le T_{max}$ do<br>    $P_{temp} = P;$<br>    $f(P_{temp}) = f(P)$<br>    for each $P_i \in P$ do |

for each $p_i^j \in P_i$ do

$p_i^j$ =ElectionCampaign ($p_i^j, p_i^j(t-1), p_i^j c_j^*$) ;

end

end

$\mathrm{PartySwitching}\ (P, \lambda)$ ;

/* Election phase */

calculate the fitness of all the members $p_i^j$

calculate the group of the party leaders $P^*$ and the group of the constituency winners $C^*$,

Parliamentary Affairs $(C^*, P)$ ;

$P(t-1) = P_{temp}$;

$F(P(t-1)) = f(P_{temp})$ ;

$\lambda = (\lambda - \lambda_{max} / T_{max})$ ;

$t = t + 1$;

end

While the winner of $j^{th}$ constituency was represented by $c_{pj}^*$. Besides, Eq. (6) upgrades the party leader. The outcome on exploitation is named as parliamentary affair, also it is regarded that final stage of PO as follows.

$$c_{p,new}^* = c_{p,r}^* + (2a-1)\left|\mathcal{C}_{p,r}^* - \mathcal{C}_{p,j}^*\right| \tag{9}$$

Let a be the arbitrary number amongst zero and one, r signifies the arbitrary integer amongst [1-n], and $c_{p,r}^*$ refers the parliamentarians that are arbitrarily chosen.

Initialization of Population is highly significant in intelligent technique since initialization quality has a direct impact on the respective solution quality and global convergence speed. In traditional PO algorithms, due to the absence of a priori information, random initialization is frequently utilized for generating the primary solution of process [16]. However, in ECPO algorithm, a chaotic initialization technique can be presented. For this reason, the presented approach integrates both initialization approaches, and it is utilized for initializing PO algorithm mechanism in the following.

i. Set maximal the population size $2N$ and chaotic iteration step $K \geq 400$. The $N$-$S$ chart of reverse learning and chaotic phases.
ii. choose $2N$ optimal fitness value particle as the primary bee swarm from $\{V(2N) \cup OpLV(2N)\}$.

### 2.2. Application of ECPO-PM Technique for Clustering Process

The presented ECPO-PM technique based clustering focuses on split $n$ sensor nodes as to recent or optimum count of clusters $C_{opt}$. In the clustering, neighboring nodes are chosen to CH with mean of Euclidean distance which creates users that lesser broadcast range outcomes in reduced energy utilization [17]. But, it could be tedious to recognize the distance in highly mobile conditions. For resolving this issue, the distance to neighboring nodes is determined with employment of the ECPO-PM technique. In order to choose CH as well as generating cluster, the ECPO-PM technique treats this problem as maximized problem and developed a fitness function (FF) comprising residual energy (RDE), average distance to neighbors (ADTN), and node degree (DEG). The FF was demonstrated as:

$$F(i) = \alpha \times REL + \beta \times ADTN + \gamma \times DEG, \tag{10}$$

Where $\alpha + \beta + \gamma = 1$. Mostly, the RDE of SN(x) from the transmission of k bit data to take SN(y) which is located at distance $d$, has illustrated in Eq. (11):

$$REL = E - \left(E_T(k,d) + E_{R(k)}\right) \tag{11}$$

where E stands for the present energy level of SN and $E_T$ implies the energy spent on data transmits.

$$E_T(k,d) = kE_e + KE_a d^2 \tag{12}$$

where $E_e$ indicates the energy of electrons and $E_a$ refers the essential amplified energy, $E_{R(k)}$ demonstrates the energy spent on data reception which is written as in Eq. (13):

$$E_{R(k)} = kE_e \tag{13}$$

Besides, the AADTN indicates the average value of distance of the neighboring SN in its 1-hop communication range [20]. It can be defined as in Eq. (14):

$$ADTN = \frac{\sum_{j=1}^{NB_i} dist\left(i, nb_j\right)}{NB_i}, \tag{14}$$

where $dist\left(i, nb_j\right)$ signifies the distance from the SN to nearer $j^{th}$ SN.

At a time t, the DEG means the SN degree signifying the count of neighboring nodes existing to SN which is expressed as:

$$DEG = |N(x)| \tag{15}$$

where $N(x) = \left\{n_y / dist(x,y) < trans_{range}\right\} x \neq y$, and $dist(x,y)$ defines the distance amongst 2 Nodes $n_x$ and $n_y$, $trans_{range}$ denotes the broadcast range of Nodes.

## 3. Results and Discussion

### 3.1 Experimental Setup

The simulation of the projected models is carried out with the help of Network Simulator 3 (NS3).

| Parameter | Values |
|---|---|
| Node count | 50, 100, 200 |
| Target area | 500*500m |
| Simulation prior | 50-200s |
| Pause time | 5-25s |
| Maximum speed rate | 5-25mps |
| Transmission radius | 25-250m |

The experimental result analysis of the ECPO-PM technique with recent methods [18] is discussed in this section. The results are analyzed under dissimilar rounds of execution. A brief Total Energy Consumption (TECN) analysis of the ECPO-PM technique is examined in Table 1 and Fig. 3. The results portrayed that the ECPO-PM technique has resulted in least TECN under each round. For instance, with 200 rounds, the ECPO-PM technique has offered a lower TECN of 20.19J whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM techniques have obtained higher TECN values of 26.53J, 31.43J, 34.02J, and 38.91J respectively. At the same time, with 400 rounds, the ECPO-PM technique has accomplished a reduced TECN of 41.51J whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM techniques have obtained higher TECN values of 54.47J, 64.84J, 74.64J, and 82.99J respectively.

**Table 1** Comparative TECN Analysis of ECPO-PM technique under several rounds

| No. of Rounds | ECPO-PM | VD-PSO | ACO-MSPD | RGBM | PSO-ECSSM |
|---|---|---|---|---|---|
| 200 | 20.19 | 26.53 | 31.43 | 34.02 | 38.91 |
| 400 | 41.51 | 54.47 | 64.84 | 74.64 | 82.99 |
| 600 | 66.57 | 84.72 | 94.8 | 100 | 100 |
| 800 | 92.21 | 100 | 100 | 100 | 100 |
| 1000 | 100 | 100 | 100 | 100 | 100 |

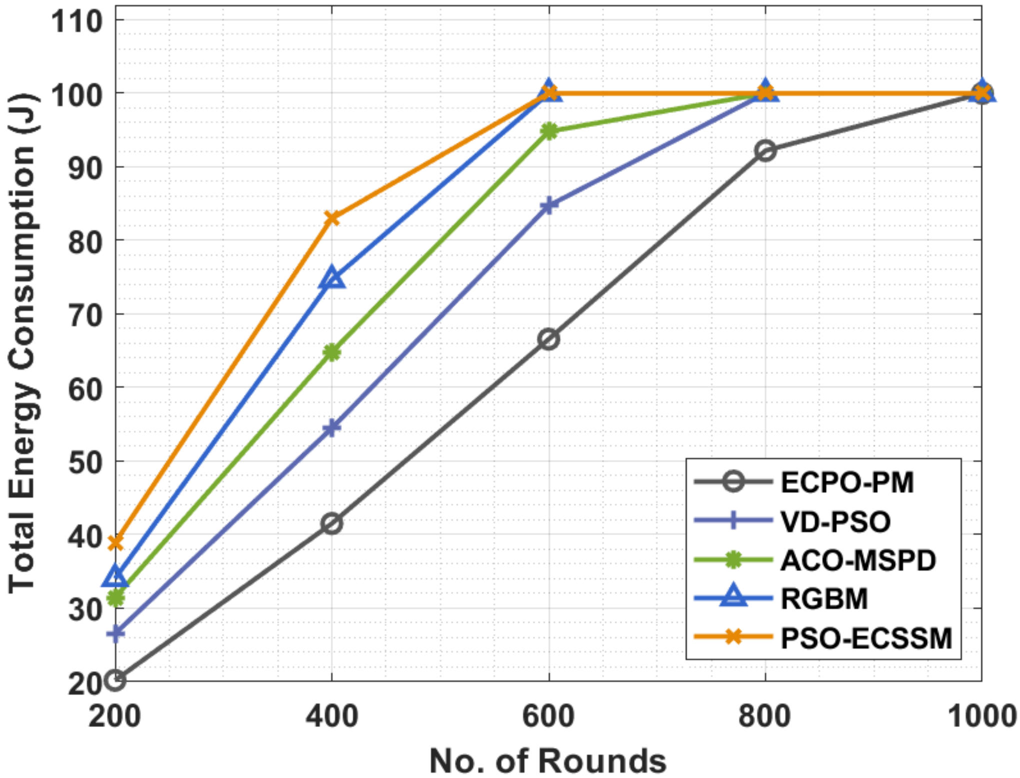


**Fig. 3.** Comparison Study of ECPO-PM technique interms of TECN

Table 2 and Fig. 4 presents the Number of Alive Nodes (NOAN) analysis of the ECPO-PM with recent techniques. The experimental values highlighted that the ECPO-PM technique has shown superior NOAN over the other methods. For instance, with 400 nodes, the ECPO-PM technique has provided a maximum NOAN of 195 nodes whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM techniques have resulted in minimum NOAN of 186, 168, 152, and 147 nodes respectively. Similarly, with 600 nodes, the ECPO-PM technique has reached an increased NOAN of 168 nodes whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM techniques have reached reduced NOAN of 131, 100, 94, and 87 nodes respectively.

**Table 2** Comparative NOAN Analysis of ECPO-PM technique under several rounds

| No. of Rounds | ECPO-PM | VD-PSO | ACO-MSPD | RGBM | PSO-ECSSM |
|---|---|---|---|---|---|
| 200 | 200 | 200 | 200 | 200 | 200 |
| 400 | 195 | 186 | 168 | 152 | 147 |
| 600 | 168 | 131 | 100 | 94 | 87 |
| 800 | 129 | 76 | 47 | 36 | 21 |
| 1000 | 67 | 25 | 0 | 0 | 0 |

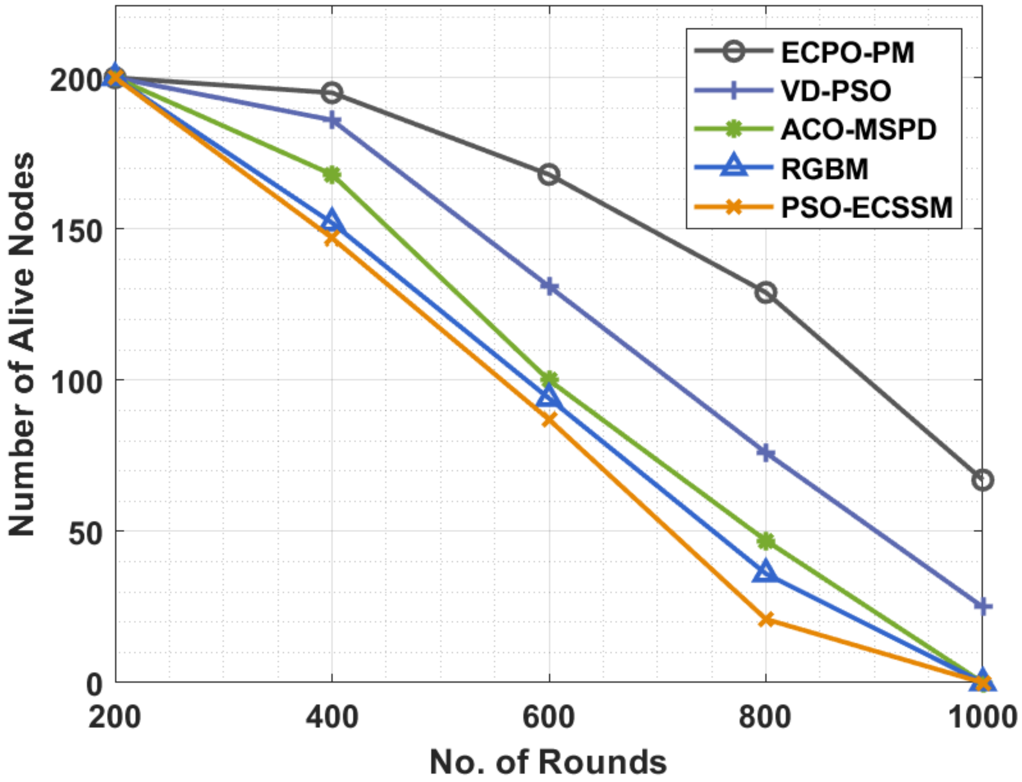


**Fig. 4.** Comparison Study of ECPO-PM technique interms of NOAN

A comparative Number of Dead Nodes (NODN) analysis of the ECPO-PM manner is examined in Table 3 and Fig. 5. The results outperformed that the ECPO-PM system has resulted in worse NODN under each round.

**Table 3** Comparative NODN Analysis of ECPO-PM technique under several rounds

| No. of Rounds | ECPO-PM | VD-PSO | ACO-MSPD | RGBM | PSO-ECSSM |
|---|---|---|---|---|---|
| 200 | 0 | 0 | 0 | 0 | 0 |
| 400 | 5 | 14 | 32 | 48 | 53 |
| 600 | 32 | 69 | 100 | 106 | 113 |
| 800 | 71 | 124 | 153 | 164 | 179 |
| 1000 | 133 | 175 | 200 | 200 | 200 |

For instance, with 400 rounds, the ECPO-PM technique has accessible a lower NODN of 5 whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM algorithms have reached higher NODN values of 14, 32, 48, and 53 correspondingly. Concurrently, with 800 rounds, the ECPO-PM method has accomplished a lower NODN of 71 whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM manners have achieved superior NODN values of 124, 153, 164, and 179 correspondingly.

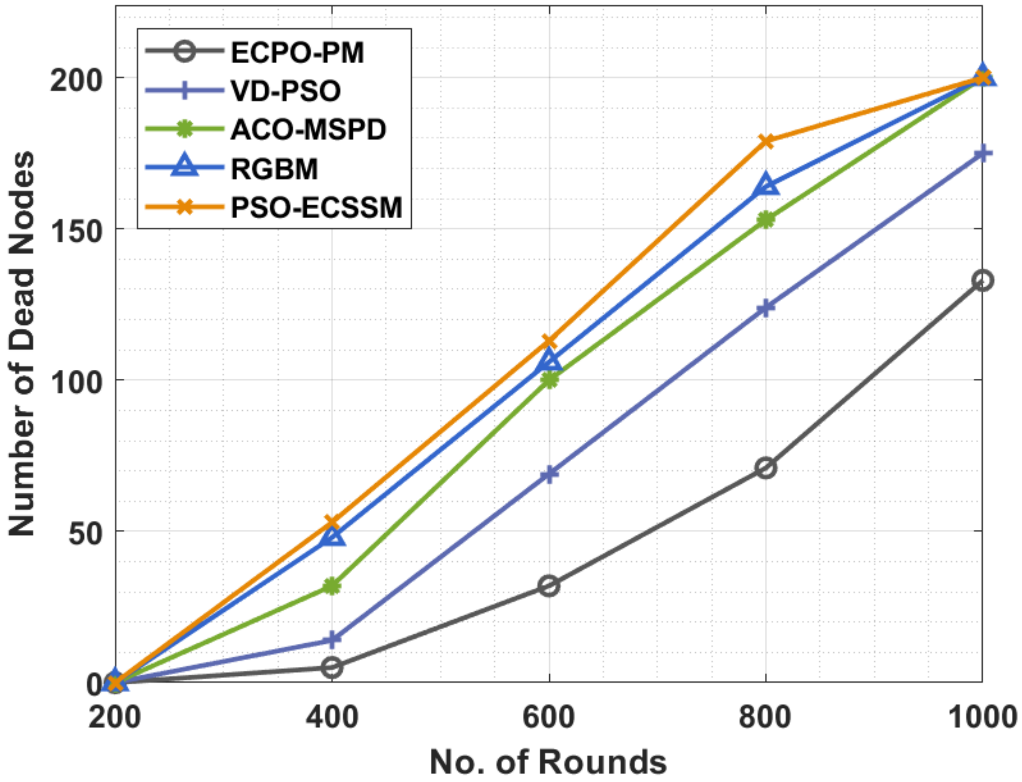


**Fig. 5.** Comparison Study of ECPO-PM technique interms of NODN

**Table 4** Comparative PDR (%) Analysis of ECPO-PM technique under several rounds

| No. of Rounds | ECPO-PM | VD-PSO | ACO-MSPD | RGBM | PSO-ECSSM |
|---|---|---|---|---|---|
| 200 | 89.32 | 85.39 | 75.72 | 74.46 | 69.69 |
| 400 | 85.81 | 81.05 | 70.95 | 69.55 | 65.35 |
| 600 | 81.89 | 78.10 | 68.15 | 67.45 | 63.38 |
| 800 | 79.51 | 75.02 | 67.17 | 63.94 | 59.60 |
| 1000 | 80.49 | 74.18 | 66.47 | 62.82 | 58.20 |

Table 4 and Fig. 6 provide the PDR analysis of the ECPO-PM with recent approaches. The experimental values highlighted that the ECPO-PM technique has shown superior PDR over the other methods. For instance, with 400 nodes, the ECPO-PM technique has provided a maximal PDR of 85.81% whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM methods have resulted in minimal PDR of 81.05%, 70.95%, 69.55%, and 65.35% correspondingly. In addition, with 800 nodes, the ECPO-PM manner has attained to higher PDR of 79.51% whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM methods have gained minimal PDR of 75.02%, 67.17%, 63.94%, and 59.60% nodes correspondingly.

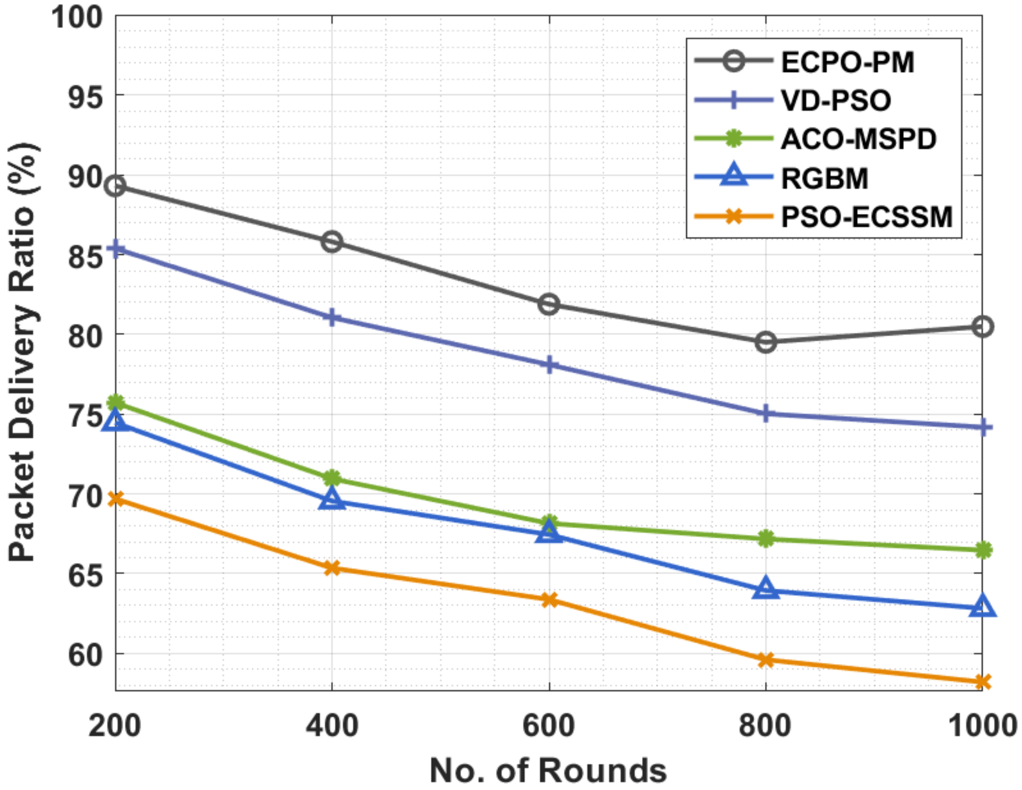


**Fig. 6.** Comparison Study of ECPO-PM technique interms of PDR

**Table 5** Comparative ETED (ms) Analysis of ECPO-PM technique under several rounds

| No. of Rounds | ECPO-PM | VD-PSO | ACO-MSPD | RGBM | PSO-ECSSM |
|---|---|---|---|---|---|
| 200 | 102.12 | 110.37 | 123.13 | 134.57 | 148.13 |
| 400 | 105.05 | 112.76 | 127.12 | 138.55 | 150.79 |
| 600 | 108.77 | 119.14 | 131.11 | 143.34 | 155.31 |
| 800 | 111.70 | 121.27 | 133.50 | 147.60 | 156.37 |
| 1000 | 115.95 | 125.26 | 137.76 | 151.58 | 157.43 |

A detailed ETED analysis of the ECPO-PM manner is examined in Table 5 and Fig. 7. The outcomes outperformed that the ECPO-PM technique has resulted in minimum ETED under each round.

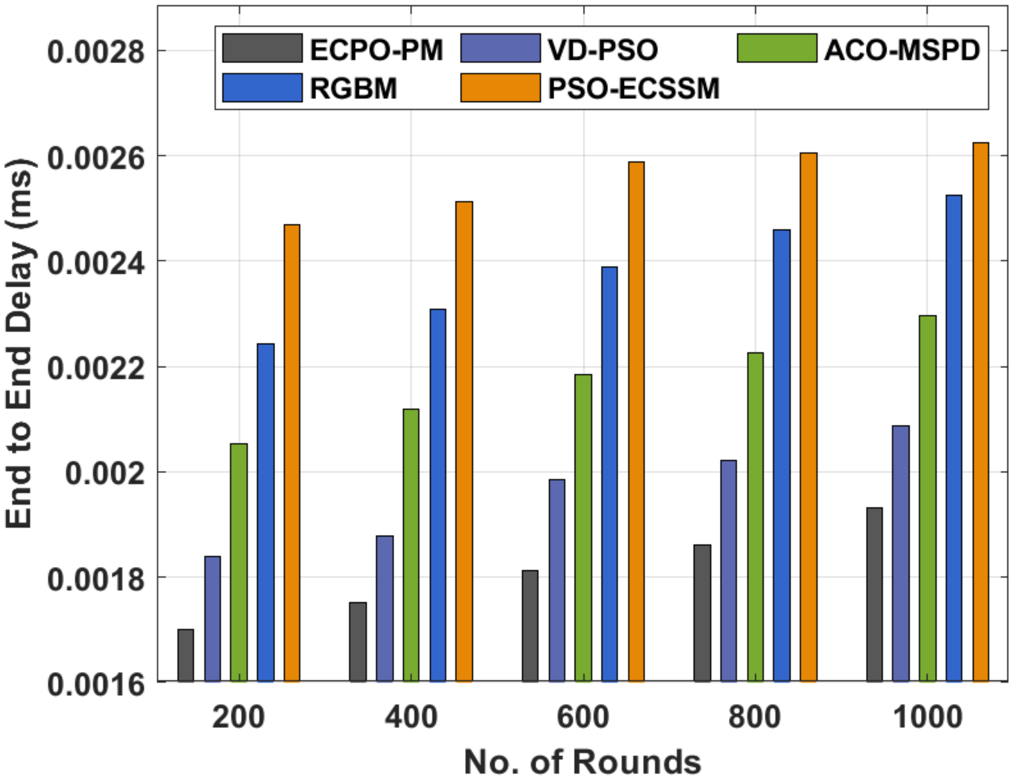


**Fig. 7.** Comparison Study of ECPO-PM technique interms of ETED

For instance, with 200 rounds, the ECPO-PM system has offered a lesser ETED of 102.12ms whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM approaches have obtained superior ETED values of 110.37ms, 123.13ms, 134.57ms, and 148.13ms correspondingly. Simultaneously, with 800 rounds, the ECPO-PM manner has accomplished a decreased ETED of 111.70ms whereas the VD-PSO, ACO-MSPD, RGBM, and PSO-ECSSM methodologies have obtained maximum ETED values of 121.27ms, 133.50ms, 147.60ms, and 156.37ms correspondingly.

## 4. Conclusion

In this study, an effective ECPO-PM technique has been developed in order to optimally choose the CHs and achieve lower power use through inter-cluster communication, both of which are important goals. Furthermore, the ECPO algorithm is generated from the combination of the classic PO algorithm with the chaotic-based initialization approach, which results in the ECPO method being developed. Furthermore, a fitness function is created, which is composed of three components, including residual energy, distance to neighbours, and degree of node connectivity. Experiments were conducted to determine whether the ECPO-PM technique had improved in performance over previous state of the art approaches. The findings of the experiments revealed that it had improved in performance over previous state of the art approaches. When looking at the thorough data analysis, it was clear that the ECPO-PM technique produced better results in terms of many evaluation parameters. In the future, it may be possible to build a multi-hop routing method in order to improve the overall efficiency of power management.

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