International Journal of Information Security and Privacy
Volume 17 • Issue 1

Energy, Reliability, and Trust-Based Security Framework for Clustering-Based Routing Model in WSN

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ABSTRACT

Currently, analysts in a variety of countries have developed various protocols for WSN clustering. Among them, the significant one is LEACH (low-energy adaptive cluster hierarchical) that accomplishes the objective of energy balancing by occasionally varying the CHs in the region. Nevertheless, since it implements a random number method, the appropriateness of the CH is full of suspicions. As a result, this work intends to discover the optimal cluster head selection (CHS) model for maximizing energy aware and secured routing in WSN. Here, optimal CH is chosen based upon constraints such as "trust evaluation (direct and indirect trust), distance, security (risk level evaluation), distance, energy and delay". In addition, the routing model considers the path quality determination of cluster (reliability). For choosing the best CH in WSN, slime wrap food update with cat and mouse optimization (SWFU-CMO) is deployed. Finally, the simulated outcomes verify the efficacy of presented approach related to residual energy, throughput, delay, etc.

KEYWORDS

Cluster Head, Path quality, Security, Trust, WSN clustering

1. INTRODUCTION

A WSN contains varied sensors linked to the wireless medium. In WSN, the sensed data from SNs is typically forwarded to the BS, in which it is composed, evaluated, and specific actions are taken (Alagumuthukrishnan & Geetha, 2016; Yuvaraja & Sabrigiriraj, 2016; Ni et al. 2017). The WSN is used in a wide range of appliances, including meteorological data collection, weather forecasting and field observation, transportation, as well as health-care (Kang & Nguyen, 2012; Leu et al. 2015; Ajay & Verma, 2020). Even so, the SNs in WSN lack a rechargeable storage device as well as the capacity of researchable batteries. As a result, it is difficult to support any system with proficient power consumption (Wang et al. 2017; Kumar et al. 2018; Jia et al. 2016).

Clustering is a popular technique for making data transmission more efficient in terms of energy and power consumption (Mehra et al. 2018). Every cluster in the network has its own CH that is

DOI: 10.4018/IJISP.315817
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responsible for communicating information to the other SN in its cluster. The main task in such scenarios is to determine the optimal CH under a variety of constraints such as less energy utilization, delay, and so on (Al-Sodairi and Ouni, 2018; Nigam and Dabas, 2018; Priyadarshini and Sivakumar, 2018; Bhardwajm and Kumar, 2019). Thus, by forming clusters using data fusion and aggregation systems, there is EE in the network because the amount of data conveyed to BS is significantly reduced (Mahajan et al. 2014; Muthukumaran et al. 2018; Ni et al. 2017).

As a result, cluster-oriented schemes were also involved in extending network lifetime (Darabkh et al. 2019; Kannan & Raja, 2015; Mann & Singh, 2017). Furthermore, "APTEEN, TEEN, LEACH, PEGASIS, and FCM" are the most commonly used schemes (Kaur & Mahajan, 2018; Tianshu et al. 2018; Bhardwajm & Kumar, 2019; Dehghani et al. 2021). So far, a set of centralized cluster-oriented schemes based on meta-heuristic algorithms has been established. PSO, HSA, and other general algorithms are examples. However, the most demanding factors in modeling the routing protocol are EE, QoS, and network lifetime (Li et al. 2020).

Main contribution of the research study;

- Introduces optimal CHS approach via concerning distance, trust, delay, path quality, energy as well as security.
- Establishes SWFU-CMO algorithm for electing the optimal clusters in WSN.

Organization of the study: Section 2 reviews the related studies. Section 3 represents network architecture. Section 4 discusses the varied constraints considered for optimal selection of cluster heads. Section 5 portrays the suggested SWFU-CMO approach. Section 6 presents the outcomes as well as the study is ends in section 7.

2. LITERATURE REVIEW

In Daneshvar et al. (2019) introduced a novel clustering work with finest CHS through taking into account of 4 chief criterions like security, energy, distance, and delay. Furthermore, a novel approach known as FPU-DA is established to choosing the best CH. At last, the efficiency of developed approach was proven in terms of various measures.

In Ajay and Verma, (2020) proposed a DMEERP for balancing the energy utilization as well as path reliability ratio. The path reliability ratio was estimated in order to route the packets rapidly as well as without packet loss. Lastly the improvements in overhead, energy utilization, and so on were demonstrated.

In Bhardwajm and Kumar (2019) modeled a multi objective scheme as well as a developed MOFPL. This scheme selected the best CH from a large number of CH in WSN. Following that, the optimal routing path was established using the utilized multi objective functions. The adopted scheme resulted in best CHS with greater EE.

In Augustine and Ananth (2020) provided a more advantageous plan for CHS employing Taylor KFCM. The "acceptability factor" was determined through energy, distance, and trust, to select the best CH. The effectiveness of this model has been validated in terms of greater energy and trust.

Toenhance EE and lower the cost function, Goswami et al. (2019) developed a cluster formation strategy in the OWSN using the FF as well as the HML technique. The final results have demonstrated that this work was better in terms of EE and cost function.

In Toor and Jain, (2019) deployed MEACBM routing model. The CHs were determined to be the best options based on the updated probability calculation; usually, the SNs were selected as CHs due to their more energy than other SNs. In terms of many measures, the outcomes demonstrated improvements over the existing system.

In Alghamdi, (2020) provided a clustering method that selected CHs using GWO. On the basis of the expected energy utilization as well as the amount of energy left in each node, the solutions were optimized for CH election. The outcomes demonstrated that the concept put into practice guaranteed a lengthy network lifetime.

In Nivedhitha et al. (2020) established BOA to choose a best CH. Consequently, the adopted scheme focused on lessening the energy utilization and increasing the network lifetime. At the end, the superiority of proposed work was proven for dead and alive nodes and energy utilization.

Table 1 shows the reviews on extant routing approaches in WSN. Some drawbacks of the extant works are given as follows**:**

- There was no analysis on computational cost Daneshvar et al. (2019).
- The data availability approaches were not combined Ajay and Verma, (2020).
- No evaluation on resource management Bhardwajm and Kumar, (2019).
- Real-time evaluations were not deliberated Augustine and Ananth, (2020).
- The FF algorithm has local search difficulties Goswami et al. (2019).
- Fault tolerance was not considered in Alghamdi (2020) and Nivedhitha et al. (2020).

To overcome the extant drawbacks, this study introduced a noveloptimal CHS approach.

3. NETWORK MODEL: A SHORT DESCRIPTION

3.1 Network Model

WSN includes diverse SNs denoted as N_S and SN will act as an active sensor during the transmission of data between BS and CH. Generally, the WSN's design is correlated with radio communiqué, data sensing, energy consumption, topology features as well as also sensor allotment. In manual mode, the sensor is manually dispersed among the application areas. The clusters are made up of linked SNs, with the CH selected and its count represented by N_C . The distance between the cluster node and CH should decrease. The full set of SNs from the projected region gathers pertinent information and delivers it to CH. The relevant CH sends the information to BS.

Table 1. Reviews on conventional routing approaches

Author	Techniques	Merits	Demerits
Daneshvar et al.(2019)	FPU-DA	• Reduced delay • Conserves energy in effective manner	• Computational cost should be examined
Ajay and Verma, (2020)	DMEERP	• Better data flow • High PDR	• Data availability schemes should be integrated.
Bhardwajmand Kumar, (2019)	MOFPL	• Reduced time • Good network energy	• Cost efficiency is not computed • Resource management is not computed
Augustine and Ananth, (2020)	Taylor KFCM	• Greatthroughput and energy. • Minimal delay	• Need realistic experiments.
Goswami et al. (2019)	FF	• Minimal cost function. • Improved EE	• Suffers from local searchingproblems.
Toor and Jain, (2019)	MEACBM	• Minimized energy utilization • Increased throughput and life span	• Scalability of SNswas not computed.
Alghamdi, (2020)	GWO	• Low energy utilization	• Fault tolerance was not considered.
(Nivedhitha et al. (2020)	BOA + ACO	• Highalive node count • Negligible energy utilization	• Should consider fault tolerance.

The feasible technique to position the CH is node with least energy utilization as well as accordingly enabling additional data transmission through the exact CH. The distance or energy is found as the major functionalities for determining the CH. Moreover, security is considered as a major factor since it makes secured data transmission. Fig. 1 shows the pictorial depiction of developed model.

4. VARIED CONSTRAINTS CONSIDERED FOR OPTIMAL SELECTION OF CLUSTER HEADS

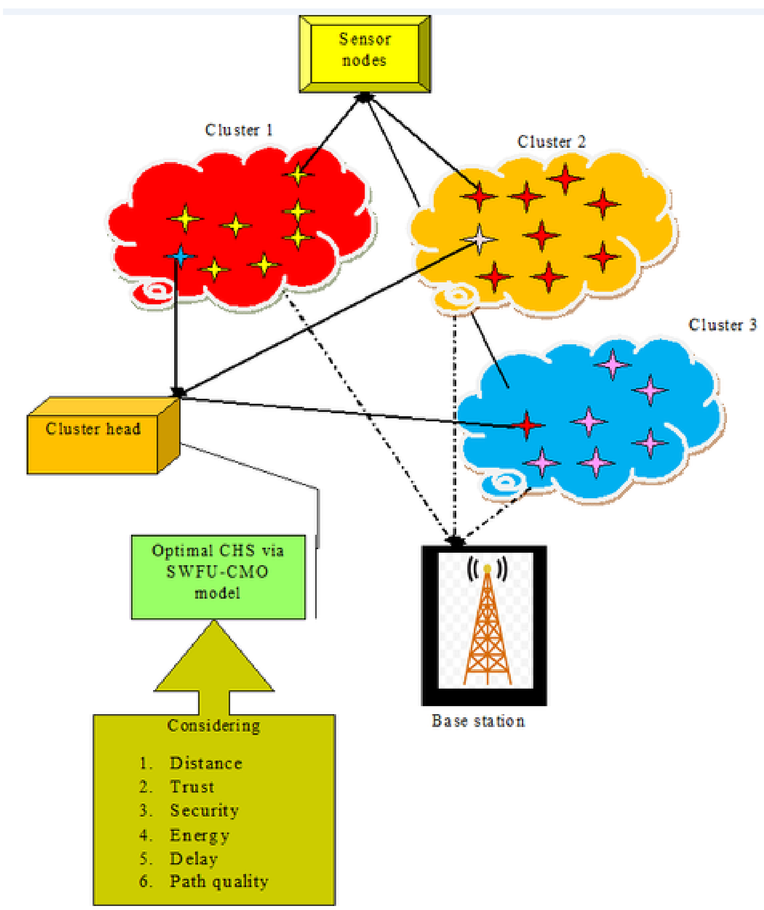
The multi-constraints (Daneshvar et al. 2019) deployed for electing the best CH are as follows; "Energy, security, distance, trust (direct and indirect), path quality (reliability), and delay".

4.1 Objective Function

The objective of the developed approach for electing the optimal CH is specified in Eq. (1).

$$\begin{aligned} Obj &= \left(w_1 * A_{total}\right) + \left(w_2 * G_{risk}\right) + \left(w_3 * D_{dist}\right) \\ &+ \left(w_4 * De_{del}\right) + \left(\left(1-w_5\right) * B_{Tr}\right) + \left(\left(1-w_6\right) * Pa_Q\right) \end{aligned} \tag{1}$$

Figure 1. Pictorialdepiction of developed model



In Eq. (13), w_1 - w_6 are weight factors that ranges from 0 to 1.

4.2 Energy Model

The most important issue linked in WSN is consumption of energy(Khan et al. 2018). Since the WSN battery could not be used for the re-energizing system, it would not be possible to deliver energy if the battery fell. Additionally, the added resources enable efficient data transmission from all SNs to BS. Utilizing energy effectively is crucial for transmitting reasons. The network reportedly needs more energy because it performs a variety of tasks, including as transmission, reception, aggregation, and sensing. The requisite of energy for overall transmission of data is specified in Eq. (2). Depending upon specific modules, the electronic energy is pointed out as A_{el} and it is specified in Eq. (3) and $A_{TX}\left(N : dis\right)$ points out all the energy deployed that is essential to convey N bytes of packets at dis distance. The electronic energy model is portrayed as in Eq. (3), wherein, A_{ea} specify the energy used in aggregation data time.

The received energy A_{RX} is symbolizedas in Eq. (4) and Eq. (5) that is necessary to receive N bytes of packets at a distance dis , which signifies the energy requisite for amplification A_{am} .

$$A_{TX}\left(N : dis\right) = A\begin{cases} A_{el} * N + A_{rs} * N * dis^2, ifdis < dis_0 \\ A_{el} * N + A_{pw} * N * dis^2, ifdis \geq dis_0 \end{cases} \tag{2}$$

$$A_{el} = A_{TX} + A_{ea} \tag{3}$$

$$A_{RX}\left(N : dis\right) = A_{el} N \tag{4}$$

$$A_{am} = A_{fr} dis^2 \tag{5}$$

$$dis_0 = \sqrt{\frac{A_{fr}}{A_{pam}}} \tag{6}$$

In above equations,

dis_0 →Threshold distance based upon Eq. (6)
A_{pam} → Power amplifier Energy
A_{fr} → Requisite energy as employing free space approach
A_1 → Energy necessary for whole idle state
A_E → Energy cost for entire sensing phase

The overall network energy for transmitting data is specified in Eq. (7).

$$A_{total} = A_{TX} + A_{RX} + A_1 + A_E \tag{7}$$

4.3 Security

***Security mode*:** It chooses the CH, which satisfies the security requirements(Khan et al. 2018). In Eq. (8), q_r and q_s points out security requirements connected with CHS and security rank, correspondingly. The nodes are termed as CH, if $q_s \leq q_r$.

Risky mode**:** A prevailing CH is chosen to enable a best CH, to capture every risk. Therefore, it is termed as "insistent mode" at the CHS process.

γ ***-risky mode*****:** The CH, which endures the extreme risk are elected depending upon γ -risky mode. In addition, γ -risk is termed as G_{risk}. Consequently, γ indicate the probability metric with values, $\gamma = 0$ and $\gamma = 1$ similar as security and risky mode.

The probability of security variables is exposed in Eq. (8). Moreover, The risk should be lower than 50% if the selected CH attains the state. The selection procedure would be carried out if the scenario was $0 < q_s - q_r \leq 1$, and it would be delayed if the condition were $1 < q_s - q_r \leq 2$. The CHS procedure would not be finished; hence state $2 < q_s - q_r \leq 5$ should continue performing its related function.

$$G_{risk} = \begin{cases} 0 & if \quad q_s - q_r \leq 0 \\ 1 - e^{\frac{(q_s - q_r)}{2}} & if \quad 0 < q_s - q_r \leq 1 \\ 1 - e^{\frac{3(q_s - q_r)}{2}} & if \quad 1 < q_s - q_r \leq 2 \\ 1 & if \quad 2 < q_s - q_r \leq 5 \end{cases} \tag{8}$$

4.4 Distance

The distance(Khan et al. 2018) of packets conveyed to BS from CH and to CH from normal node is measured as signified in Eq. (9).

$$D_{dist} = \frac{D_{dist}^{(m)}}{D_{dist}^{(n)}} \tag{9}$$

Where,

$$D_{dist}^{(m)} = \left[\sum_{q=1}^{d} \sum_{t=1}^{M_e} d_q^{norm} - M_c^t + M_c^t - I_k\right] \tag{10}$$

$$D_{dist}^{(n)} = \sum_{q=1}^{d} \sum_{t=1}^{d} d_q^{norm} - d_t^{norm} \tag{11}$$

4.5 Delay

The delay is computed as in Eq. (12), wherein, d signify entire cluster count in network and M_c^e signify related CH.

$$De_{del} = \left(\frac{\max_{t=1}^{M_c^e}\left(M_c^t\right)}{d}\right) \tag{12}$$

4.6 Trust

Every hop in WSN offers high trust degree to evaluate the trust level amid hops and adjacent hops (Vinitha and Rukmini 2019). There are 2 constraints for evaluating trust, namely, direct and indirect trust as mentioned in Eq. (13).

$$B_{Tr} = \left\{ B^{d} + B^{id} \right\} \tag{13}$$

Direct trust: It is calculated as revealed in Eq. (14), wherein, $\left(B^{d}\right)_{y}^{z} \rightarrow$ Direct trust for y^{th} transaction at z^{th} time interval fu $\rightarrow$ Satisfaction metric z $\rightarrow$ Time interval y $\rightarrow$ Transaction o $\rightarrow$Evaluation hop $o+1 \rightarrow$ Hop for evaluation.

$$\left[\left(O^{d}\right)_{y}^{z}\left(o,o+1\right)\right] = \left[fu_{y}^{z}\left(o,o+1\right)\right] \tag{14}$$

Here, fu is evaluated as exposed in Eq. (15), in which, $fu_{v} \rightarrow$ satisfaction value of present transmission, as well as $fu_{y-1}^{z}\left(o,o+1\right) \rightarrow y-1$ transmission satisfaction value at z^{th} time interval, η $\rightarrow$ weight.

$$\left[fu_{y}^{z}\left(o,o+1\right)\right] = \left\{\eta \times fu_{v} + \left(1-\eta\right) \times fu_{y-1}^{z}\left(o,o+1\right)\right\} \tag{15}$$

$$fu_{v} = \begin{cases} 0; if \text{transmission } ispurelyunsatisfactory \\ 1;; if \text{transmission } ispurelysatisfactory \\ \in \left(0,1\right); else \end{cases} \tag{16}$$

Indirect trust: Indirect trust (Vinitha et al. 2019)of o^{th} hop concerning $\left(o+1\right)^{th}$ is evaluated as revealed in Eq. (17), in which, V $\rightarrow$ group of agents that interacts with $o+1$, a $\rightarrow$ hop, $K_{y}^{z} \rightarrow$ feedback creditability. K_{y}^{z} is evaluated as in Eq. (18), in which $L_{y}^{z} \rightarrow$ similarity. The similarity between hops is evaluated as in Eq. (19).

$$\left(B^{id}\right)_{y}^{z}\left(o,o+1\right) = \left(\begin{cases} \dfrac{\sum_{a\in U-\left\{o\right\}} K_{y}^{z}\left(o,a\right) \times \left(B^{d}\right)_{y}^{z}\left(a,o+1\right)}{\sum_{a\in U-\left\{o\right\}} K_{y}^{z}\left(o,a\right)}; if \left|V-\left\{o\right\}\right| = 0 \\ 0; if \left|v-\left\{o\right\}\right| > 0 \end{cases}\right) \tag{17}$$

$$K_{y}^{z}\left(o,o+1\right) = \left(\begin{cases} 1 - \dfrac{\ln\left(L_{y}^{z}\left(o,o+1\right)\right)}{\ln\varphi}; if \left(L_{y}^{z}\left(o,o+1\right)\right) > \varphi \\ 0; else \end{cases}\right) \tag{18}$$

$$L_{y}^{z}\left(o,o+1\right) = \left(\begin{cases} L_{y-1}^{z}\left(o,o+1\right) + \dfrac{1 - L_{y-1}^{z}\left(o,o+1\right)}{\varpi}; if \mathfrak{R}_{y}^{z}\left(o,o+1\right) < l \\ L_{y-1}^{z}\left(o,o+1\right) - \dfrac{1 - L_{y-1}^{z}\left(o,o+1\right)}{\delta}; else \end{cases}\right) \tag{19}$$

In Eq. (19), l →similarity deviation constant, δ and ϖ →punishment and reward factor, as well as $\mathfrak{R}_{y}^{z}\left(o,o+1\right)$ →personalized difference.

4.7 Path Quality

The constant clusters prefer consistent paths depending upon their quality*(*Ajay & Verma, 2020*)*. The path quality is portrayed on the basis of packet arrival rates. While carrying accessible packets in its queue, the paths must not drop the packets needlessly. It has to be guaranteed by cluster members closer to sink and source nodes. The PAR is modelled as in Eq. (20).

$$PAR\left(\varphi\right)=\frac{p_{\varepsilon}}{p_{b}}\times 100 \tag{20}$$

The path quality is calculated from PAR as shown in Eq. (21), here PAR_{v} → PAR of path v and PAR_{u} → PAR of entire available paths for transmission of data.

$$Pa_{Q}=\frac{PAR_{v}}{PAR_{u}} \tag{21}$$

5. PROPOSED SWFU-CMO: HYBRID SLIME MOULD AND CAT AND MOUSE ALGORITHMS

5.1 Swfu-Cmo Model

The previous CMBO approach finds the best solutions *(*Dehghani et al. 2021*)*but it affected by poor accuracy. The idea of SMA (Nivedhitha et al. 2020)is linked with CMBO and given the name SWFU-CMO in order to solve the drawbacks of standard CMBO. Specific searching challenges are competent for hybrid optimization models (Beno et al. 2014; Thomas and Rangachar, 2018; Devagnanam and Elango, 2020; Shareef and Rao, 2018). The SWFU-CMO model's steps are provided below.

Step 1: Initialize the population of J search agents.

Step 2: Initialize the parameters of T, T_{c}, T_{m}, J. In which, T is the members number in population matrix H.

Step 3: Eq. (22) shows the initial population.

$$H=\begin{bmatrix} H_{1} \\ H_{2} \\ \vdots \\ H_{T} \end{bmatrix}_{T*m}=\begin{bmatrix} y_{1,1} & \cdots & y_{1,d} & \cdots & y_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ y_{i,1} & \cdots & y_{i,d} & \cdots & y_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ y_{T,1} & \cdots & y_{T,d} & \cdots & y_{T,m} \end{bmatrix}_{T*m} \tag{22}$$

Here, $y_{i,d}$ is the d^{th} problem variable.

Step 4: Based on Eq. (1), search agent's fitness is calculated.

Step 5: Employing Eq. (23) to Eq. (24), update the sorted population matrix H^S. Where, i^{th} population of sorted population matrix is $y^S_{i,d}$ and Obj^S is the sorted objective function based vector.

$$H^S = \begin{bmatrix} H^S_1 \\ H^S_2 \\ \vdots \\ H^S_T \end{bmatrix}_{T*m} = \begin{bmatrix} y^S_{1,1} & \cdots & y^S_{1,d} & \cdots & y^S_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ y^S_{i,1} & \cdots & y^S_{i,d} & \cdots & y^S_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ y^S_{T,1} & \cdots & y^S_{T,d} & \cdots & y^S_{T,m} \end{bmatrix}_{T*m} \tag{23}$$

$$Obj^S = \begin{bmatrix} Obj^S_1 \ \min(Obj) \\ Obj^S_2 \ \min(Obj) \\ \vdots \qquad \vdots \\ Obj^S_T \ \min(Obj) \end{bmatrix}_{T*1} \tag{24}$$

Step 6: Using Eq. (25), the mice population is chosen

$$Z = \begin{bmatrix} Z_1 = X^S_1 \\ \vdots \\ Z_i = X^S_i \\ \vdots \\ Z_{T_m} = X^S_{T_m} \end{bmatrix}_{T_m*m} = \begin{bmatrix} y^S_{1,1} & \cdots & y^S_{1,d} & \cdots & y^S_{1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ y^S_{i,1} & \cdots & y^S_{i,d} & \cdots & y^S_{i,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ y^S_{T_m,1} & \cdots & y^S_{T_m,d} & \cdots & y^S_{T_m,m} \end{bmatrix}_{T_m*m} \tag{25}$$

Step 7: Using Eq. (26), the cat population is selected.

$$C = \begin{bmatrix} C_1 = X^S_{T_m+1} \\ \vdots \\ C_i = X^S_{T_m+j} \\ \vdots \\ C_{T_m} = X^S_{T_m+T_c} \end{bmatrix}_{T_c*m} = \begin{bmatrix} y^S_{T_m+1,1} & \cdots & y^S_{T_m+1,d} & \cdots & y^S_{Y_m+1,m} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ y^S_{T_m+j,1} & \cdots & y^S_{T_m+j,d} & \cdots & y^S_{Y_m+j,m} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ y^S_{T_m+T_c,1} & \cdots & y^S_{T_m+T_c,d} & \cdots & y^S_{Y_m+Y_c,m} \end{bmatrix}_{T_c*m} \tag{26}$$

Step 8: In which, Z, T_m, Z_i, C, T_c, C_j indicate the mice population, mice number, j^{th} mice, cat population, cats number and i^{th} cat.

Step 9: Conventionally, the position update of cats is modelled as in Eq. (27), here, as per SWFU-CMO model, the cat's position are updated based on wrap food update of SMA model as shown in Eq. (28),where, $C_b(t)$ points to individual location with higher concentration of odor, C_A

and C_B symbolize 2 individuals selected arbitrarily from slime mould, W symbolize slime mould weight and t symbolize current iteration. Here, ν symbolize parameter between the range $[-a, a]$ and c symbolize parameter that decreases from 1 to 0. In addition, arithmetic crossover is carried out to ensure better convergence rates.

$$C_j^{new} = \left[C_{j,d} + r * \left(M_{k,d} - I * C_{j,d}\right)\right] \tag{27}$$

$$C_j^{new} = \begin{cases} C_b\left(t\right) + \nu.\left(W.C_A\left(t\right) - C_B\left(t\right)\right) & r < p \\ \rho.C\left(t\right) & r \geq p \end{cases} \tag{28}$$

Step 10: If $j = T_c$

(a)If the above condition is satisfied then Y_i is created using Eq. (29).

$$Y_i = h_{i,d} = y_{l,d} \ \& \ i = 1 : J_m, d = 1 : m, l \in 1 : J \tag{29}$$

Step 11: Then, position update of mice takes place based on Eq. (30) and Eq. (33). Conventionally, I is measured as shown in Eq. (31), however, as per SWFU-CMO model, I is updated based upon random integer $rand$ as in Eq. (32). Here, $rand$ is computed using tent map.

$$Z_i^{new} : m_{i,d}^{new} = m_{i,d} + r * (h_{i,d} - I * m_{i,d}) + Sign(F_i^m - F_i^Y) \ \& \\ i = 1 : T_m, d = 1 : m \tag{30}$$

Here, $I = round\left(1 + rand\right)$ (31)

$$I = round\left(\exp\left(1 + rand\right)\right) \tag{32}$$

$$Z_i = \begin{cases} Z_i^{new} & \mid \ F_i^{m,new} < F_i^m \\ Z_i & \mid \ else \end{cases} \tag{33}$$

Step 12: (b) In case, if the above condition is not satisfied, then increase j by 1, and again update C_j.

(c) Close the if condition

Step 13: If $i = T_m$ then

(a) Check $t = J$,if the aforementioned condition is met.

(b) If the aforementioned criterion is not met, then raise i by 1.

(c) End if

Step 14: If $t = J$, then the best option found thus far is presented.

Step 15: If $t \neq J$, then raise i by 1,then return to step8.

Step 16: End

6. RESULTS AND DISCUSSION

6.1 Expeimentation Procedure

The deployed approach for securedrouting in WSNsvia SWFU-CMO was executed in NS-2 and varied metrics were evaluated. The simulation parameters are shown in Table 2. The examination was done for 3groups of nodes (50, 100, 150). The scrutiny was done for 3variations of nodes regarding throughput, alive nodes, delay and energy. The enhancement of deployed scheme was proven over FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay and Verma, 2020), CMBO (Dehghani et al. 2021*)*, SMA (Li et al. 2020), GOA, ALO, SGO and RHSO correspondingly. Fig. 2 symbolizes the simulated outcomes of deployed scheme for 3node groups.

6.2 Analysis on Delay

The delay analysis using SWFU-CMO scheme over FPU-DA *(*Daneshvar et al. 2019*)*, DMEERP (Ajay & Verma, 2020*)*, CMBO, SMA, GOA, ALO, SGO and RHSOis revealed in Fig. 3. In fact, the delay for transmitting packets should be least for enhanced system performance. In which, delay is represented in seconds. From graphs, as the number of rounds increases, the delay also gets increased. Initially, at round 0, the delay value for 50 nodes using developed method is just 0.14 sec. As the rounds increases, i.e. at 1900th round, the delay value for 50 nodes using developed method is 0.52 sec. Among the evaluated schemes, the extant ALO scheme has revealed worst outcomes over FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay and Verma, 2020), CMBO, SMA, GOA, SGO and RHSO. Therefore, the deployed SWFU-CMOmodel is proven to offerless delay for transmission.

Table 2. Simulation Parameters

“Initial Energy	10
Routing protocol	DSDV
Max packet in IFQ	50
MAC type	Mac/802_11
Idle Power	0.07
Number of nodes	50,100,150
Time gap between two transmissions	0.001
Time of simulation end	150 sec
Link layer type	LL
Antenna model	Antenna/Omni Antenna
X dimension of topography	1501
Tx Power	0.117
Interface queue type	Queue/Drop Tail/Pri Queue
Duration of each transmission	0.015
Radio-propagation model	Propagation/Two Ray Ground
Maximum number of times the transmission simulation repeated	2000
Channel type	Wireless Channel
Sleep Power	0.041
Rx Power	0.09
Network interface type	Phy/Wireless Phy
Y dimension of topography	600”

Figure 2. Simulation outcomes using SWFU-CMO model for node count of (a) 50 (b) 100 and (c) 150

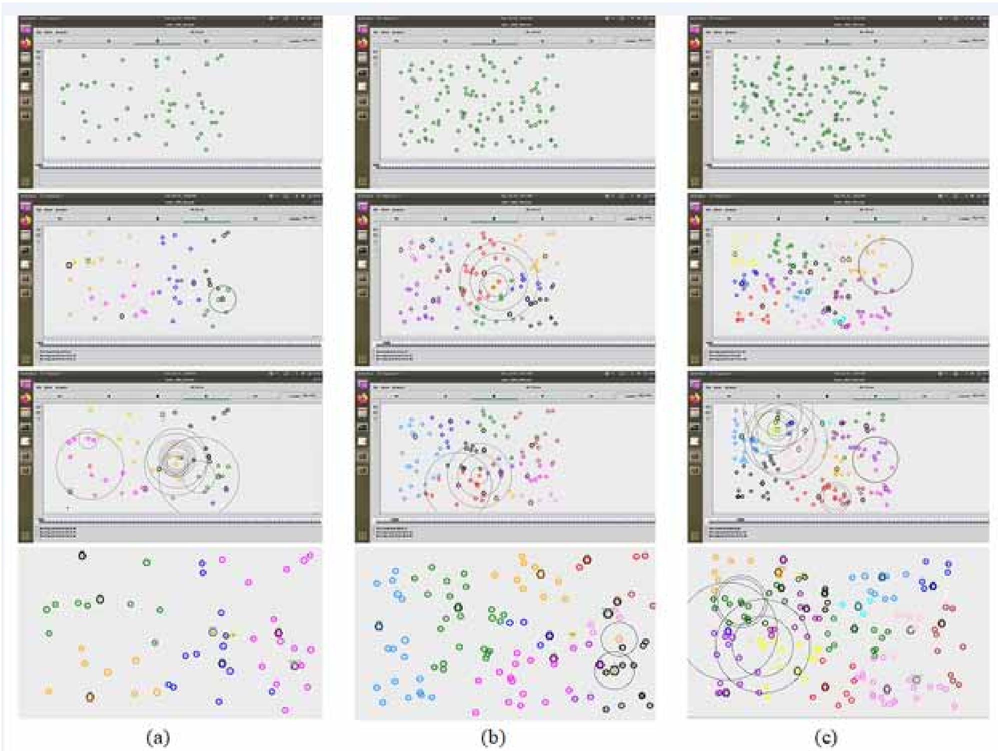
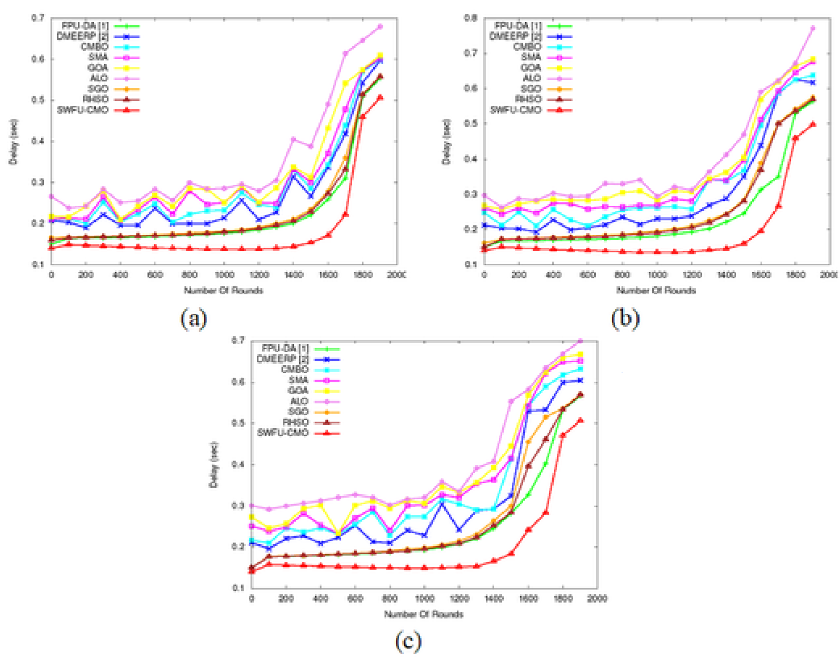


Figure 3. Analysis on delay using SWFU-CMO and extant techniques for node number of (a) 50 (b) 100 and (c) 150



6.3 Overall performance

The overall performance of deployed SWFU-CMO scheme over FPU- FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay & Verma, 2020), CMBO, SMA, GOA, ALO, SGO and RHSO models is summarized in Table 3. From the table, the adopted SWFU-CMO method and extant models are found to offer enhanced outcomes when the node count is 150, when distinguished over100 nodes and 50 nodes. However, when compared over extant model, the deployed SWFU-CMO method provides better resultants for every considered metrics (alive node, delay, residual energy, and throughput).Also, the overall performance reveals a higher residual energy of 3.427744 at 150th node for deployed SWFU-CMO model. In case of throughput, the better values are obtained when the count of nodes is 100.That is, a higher throughput value of 55.85583 is accomplished for deployed scheme at 100th node, which is much better than all other throughput values attained by other models like FPU- FPU-DA *(*Daneshvar et al. 2019*)*, DMEERP *(*Ajay & Verma, 2020), CMBO, SMA, GOA, ALO, SGO and RHSO. As a result, the enhancement of adopted SWFU-CMO model is efficiently confirmed under considered constraints.

6.4 Analysis on Alive nodes

The analysis of SWFU-CMO model regarding alive node is shown in Fig. 3. The enhancement of deployed scheme was proven over FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay & Verma, 2020), CMBO, SMA, GOA, ALO, SGO and RHSO. The count of alive nodes should be high for better system performance. Here, in Fig. 4 (a), the alive nodes for proposed and conventional models are 50 at round 0; however, as the count of rounds increases, the alive node count also starts diminishing. Consequently, at 1900th round, the number of alive nodes has dropped down to 7 for developed model for node 50. However, the count of alive nodes for deployed scheme is higher than conventional models at 1900th round. Among the compared schemes, the extant ALO model has shown worst performance than other models like FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay and Verma, 2020), CMBO, SMA, GOA, SGO and RHSO. From round 0 to round 1600, a constant value of 50 is observed for all schemes (FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay and Verma, 2020), CMBO, SMA, GOA, ALO, SGO and

Table 3. Overall performances of SWFU-CMO model over existing models

No. of Nodes	Number of Rounds	FPU-DA *(Daneshvar* **et al.** *2019)*	DMEERP *(Ajay and Verma, 2020)*	CMBO	SMA	GOA	ALO	SGO	RHSO	SWFU-CMO
Alive nodes										
50	2000	3	1.878889	1.606333	1.400663	1.366715	1.220221	2	3	6
100	2000	19	13.7943	13.37141	13.07409	11.86432	11.76406	15	18	21
150	2000	40	31.70802	31.06334	26.88481	23.41327	22.7955	32	37	42
Delay										
50	2000	0.599408	0.813405	0.835356	0.836718	1.202764	1.70063	0.599604	0.599408	0.549042
100	2000	0.65017	0.958	1.011485	1.12218	1.254163	1.299805	0.843062	0.765757	0.539779
150	2000	0.59989	0.875688	0.940212	1.398581	1.451743	1.674791	0.829867	0.635332	0.539693
Average residual Energy										
50	2000	0.731226	0.920902	0.93509	1.070837	1.327757	1.317748	0.647307	0.648536	1.554434
100	2000	1.250355	1.253387	1.448374	1.537437	1.860894	1.85599	0.366773	1.372325	2.168762
150	2000	2.549694	2.361339	2.573542	2.609209	2.695311	2.691158	1.161463	2.558687	3.427744
Throughput										
50	2000	45.42334	46.15339	43.60336	39.65788	38.90889	26.0363	20.71727	46.02518	54.8693
100	2000	45.21291	45.52586	44.70976	41.6252	39.99956	25.66094	22.15054	46.38168	55.85583
150	2000	42.41338	47.40458	44.69963	42.75249	32.17645	28.19813	21.60977	43.39754	52.33033

RHSO). From 1600th round, a gradual decrease is found in the alive node count. Thus, the development of adopted SWFU-CMO method is established regarding highest alive node count.

6.5 Analysis on Average Residual Energy

The residual energy analysis deploying developed SWFU-CMO and conventional schemes such as FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay and Verma, 2020), CMBO, SMA, GOA, ALO, SGO and RHSO is specified in Fig. 5. The higher the residual energy, higher will be the system performance. Upon seeing the results, the remaining energy continues to decrease as the number of rounds increases. The residual energy for the suggested and traditional models in Fig. 5 (a) is 10 at round 0, but it starts to decrease as the number of rounds rises. Consequently, at 1900th round, the residual energy has dropped down to 1.7 for developed model for node 50. Nevertheless, the residual energy for deployed scheme is higher than conventional models at 1900th round. Amid the evaluated schemes, the extant SGO model has shown worst outcomes than FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay and Verma, 2020), CMBO, SMA, GOA, ALO and RHSO. In this work, higher residual energy is observed for deployed scheme for 150 nodes. Hence, the graphs demonstrate that SWFU-CMO model is better than other models.

6.6 Throughput Analysis

The throughput analysis using SWFU-CMO model over FPU-DA (Daneshvar et al. 2019), DMEERP (Ajay and Verma, 2020), CMBO, SMA, GOA, ALO, SGO and RHSO models is demonstrated in Fig. 6.The amount of information a system can handle in a specific length of time is known as its throughput. Data packets per time slot or data packets per second may also be used to measure throughput in addition to the more common units of bits per second (bit/s or bps). Since throughput is crucial for data transmission, it should be higher. At primary stages, the throughput values are minimal, nevertheless, as the count of round increases, the throughput values also raises. Here, better throughput values are accomplished for deployed scheme at 1900th round. A better throughput value of 55 is observed at 1900th round for developed model when the count of node is 100.This evidently promises in throughput performance of deployed approach.

Figure 4. Alive node analysis using SWFU-CMO and extant techniques for node number of (a) 50 (b) 100 and (c) 150

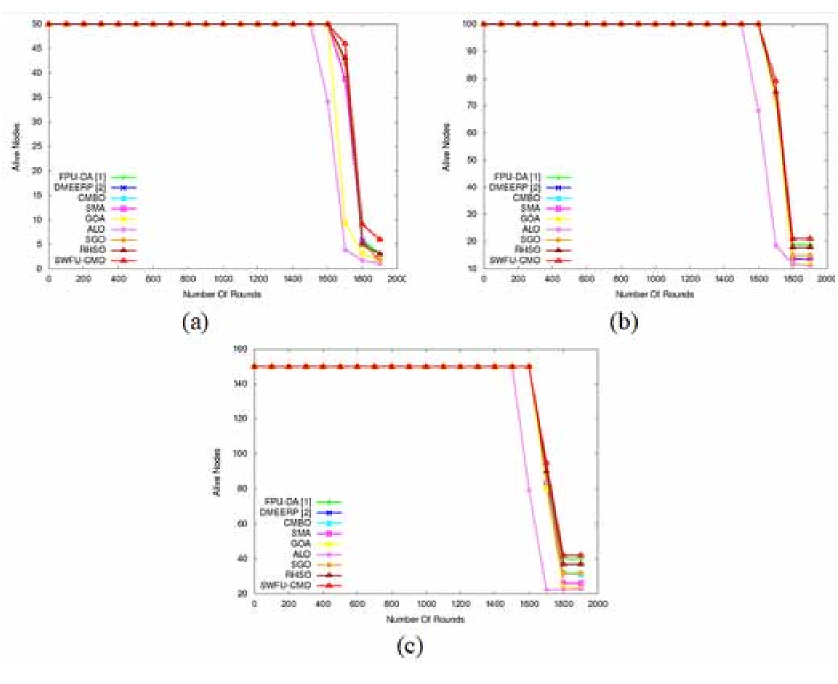


Figure 5. Residual energy analysis using SWFU-CMO andextant techniques for node number of (a) 50 (b) 100 and (c) 150

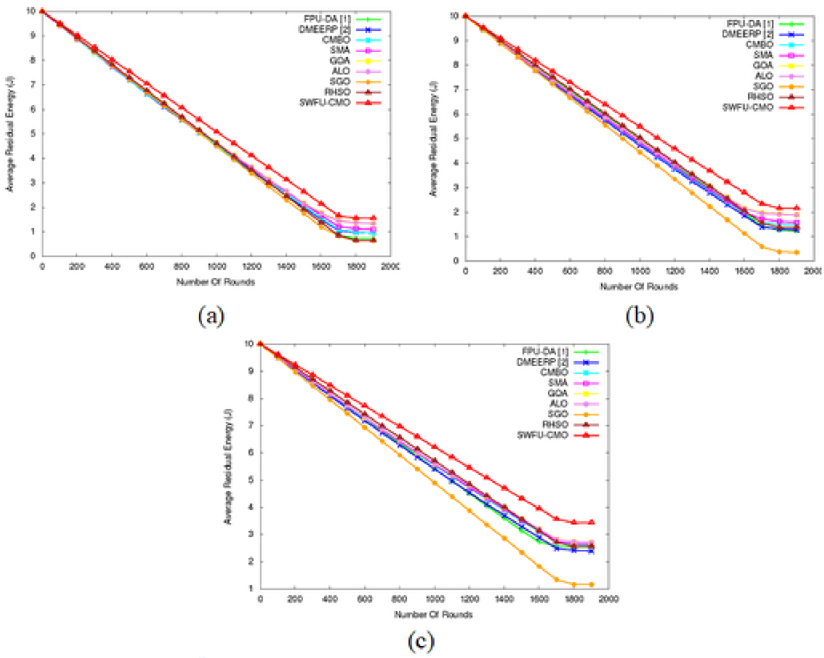
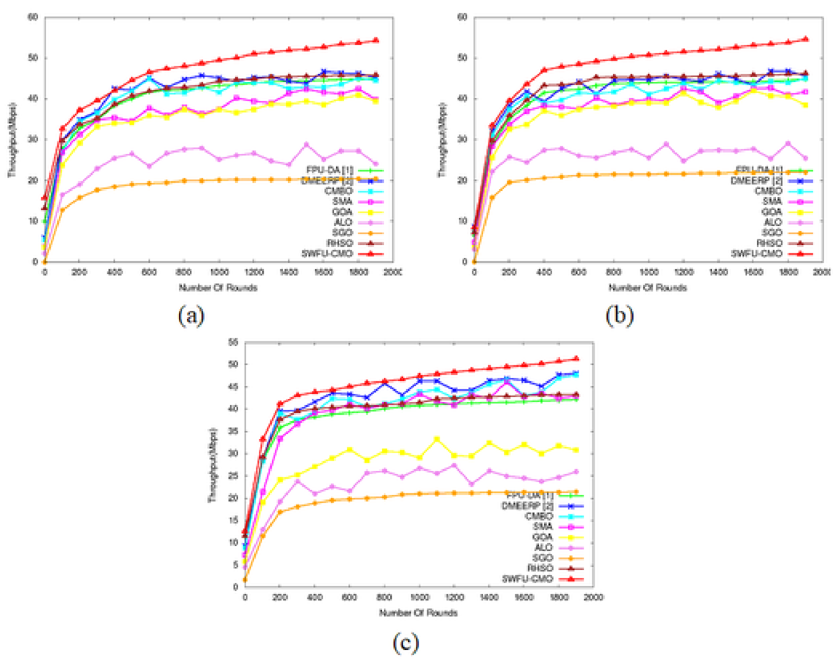


Figure 6. Throughput analysis using SWFU-CMO and extant techniques for node number of (a) 50 (b) 100 and (c) 150



7. CONCLUSION

This study developed an optimal CHS approach for maximizing secured as well as energy aware routing in WSNs. The best CH was chosen on the basis of constraints such as "trust (direct and indirect trust), distance, security (risk level evaluation), distance, energy and delay". Moreover, the routing model considered the path quality determination of cluster (reliability). For selecting the best CH, SWFU-CMO was deployed. At the final stage, analysis was held to validate the efficacy of deployed scheme. Upon seeing the results, the remaining energy continues to decrease as the number of rounds increases. At round 0, the residual energy for both the suggested and the conventional models was 10, but as the number of rounds grew, the residual energy likewise began to decrease. Consequently, at 1900th round, the residual energy has dropped down to 1.7 for developed model for node 50. Nevertheless, the residual energy for deployed scheme washigher than conventional models at 1900th round. Amid the evaluated schemes, the extant SGO model has shown worst outcomes than FPU-DA, DMEERP, CMBO, SMA, GOA, ALO and RHSO.In future, computational cost should be analyzed.

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