An Energy Aware Clustering Scheme for 5G-enabled Edge Computing based IoMT Framework

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Abstract. 5G networks offer novel communication infrastructure for Internet of Things applications, especially for healthcare applications. There, edge computing enabled Internet of Medical Things provides online patient status monitoring. In this contribution, a Chicken Swarm Optimization algorithm, based on Energy Efficient Multi-objective clustering is applied in an IoMT system. An effective fitness function is designed for cluster head selection. In a simulated environment, performance of proposed scheme is evaluated.

Keywords: energy efficiency, network lifetime, clustering, cluster head selection, delay, chicken swarm optimization, sensor networks, adaptive networks.

1 Introduction

Within Internet of Things (IoT), availability of 5G networks empowers raise of Internet of Everything [1,2]. IoT materializes also in healthcare, and is often referred to as Internet of Medical Things (IoMT) [3,4]. Typically, IoMT systems are linked with wireless body area networks (WBAN) connecting biosensor nodes [5], which act like a personal digital assistant ([6, 7]). However, if the energy in the biosensor is exhausted, the WBAN collapses [8, 9]. Note that biosensor replacement is very difficult, when it is placed inside the patient [10]. Here, energy-efficient clustering protocols are to achieve effective cluster head selection [11, 12]. However, existing energy-aware clustering and routing schemes suffer from network overhead [13, 14]. Separately, fuzzy control based energy efficient clustering protocol [15] still lacks in energy consumption. Moreover, heterogeneity based energy aware clustering protocols have been designed in [16, 17]. The key contribution of this work is to propose a clustering approach, which offers energy-aware communication in 5G enabled, edge-based ecosystems. Here, IoMT deployment consists of resource-limited wearable sensors (SNs), which transmit data through a 5G-enabled base station (BS). Transmission and reception of data takes more power. Hence, to maximize lifespan of system, a multi objective cluster head (CH) selection, based on Chicken Swarm Optimization (CSO), is used for cluster formation.

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2 System model and assumptions

In this work it is assumed that uniform level of energy is allocated to all wearable SNs and energy needed to perform intra-cluster communication is represented by an arbitrary value, within the pre-determined range (including "sleeping mode"). Network lifespan is reduced when SN battery is drained. Hence, energy-efficiency has to be taken into account when electing the CH, amid the accessible SNs. The model of the system illustrating the proposed clustering scheme is depicted in Fig. 1.

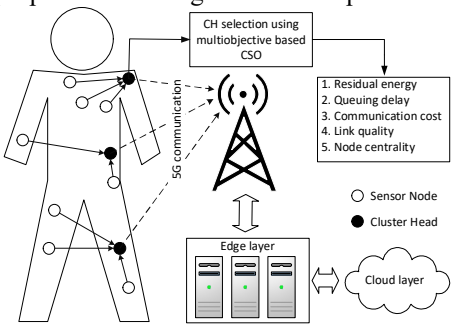

Fig. 1. Proposed Clustering Scheme System Model Framework

In what follows, the energy model, found in [18], has been selected. The equation for calculating energy consumption of data packet of size s bits for distance (d) is $E_{Trans}(d) = (TA_{FS}d^{\alpha} + E_D)s$. E_D denotes energy consumption of a device, TA_{FS} is the free space model amplifier of a transmitter, and α denotes the path loss exponents, with $2 \leq \alpha \leq 4$. Energy use to obtain data packet is represented by $E_{Rec}(d) = s \times E_D$. The cumulative energy use, of each wearable SN (to send or receive data), is based on distance d, and represented as $E_{Cum} = \{(TA)d^{\alpha} + 2(E_D)\}s$. Selection of cluster head relies on the objective function. Here, selection of energy efficient CH depends on residual energy, queuing delay, communication cost, link quality and node centrality.

Residual Energy: Initially, wearable SNs, deployed inside the IoMT, gather sensitive patient data and forward it to the CH. Energy consumption of CHs, during data gathering from SNs, is:

$E_{CH-SN} = D_B \times \left(E_{PB_F} + AE_{PB} \times \left(\sqrt{(a_{CH} - a_{SN})^2 + (b_{CH} - b_{SN})^2}\right)\right)$,

where (a_{CH}, b_{CH}) is the position of CH and (a_{SN}, b_{SN}) is the position of SN; D_B is the number of bits in the data packet, E_{PB_F} is the energy needed, per bit, for data forwarding, and AE_{PB} is the amplification energy. Data forwarding from CH to BS can be computed as follows: $E_{BS-CH} = D_B \times \left(E_{PB_F}\left(\frac{N}{Y} - 1\right) + \left(E_{PB_G} \times \left(\frac{N}{Y}\right)\right) + E_{PB_F} + AE_{PB} \times \left(\sqrt{(a_{BS} - a_{CH})^2 + (b_{BS} - b_{CH})^2}\right)\right)$, where $(a_{BS} - b_{BS})$ is the position of BS, E_{PB_F} is the energy used for data forwarding, N is the total number of *SN*s in the IoMT system,

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Y denotes the number of SNs in the cluster. Finally, the cumulative energy consumption of each cluster is computed as: $E_C = E_{BS-CH} + \left(\left(\frac{N}{Y}\right) - 1\right) \times E_{CH-}$.

Communication Cost: Commination cost is defined as the power needed for data forwarding: $Com_C = \frac{d_{avg}^2}{d_0^2}$, where d_{avg} denotes the average distance between given SN and its neighbor SNs, and d_0 represents the forwarding radius of an SN.

Queuing Delay: D_{Que}, depends on the rate of arrival of packets (to SN), and the outward link forwarding capacity. For A_R, the arrival rate of packets P_i to the SN and F_C the forwarding capacity, the queuing delay D_{Que} becomes: $D_{Que} = (A_R + F_C)/P_i$.

Link Quality: In IoMT, fading of a channel is highly irregular. If the receiver does not receive the complete signal, re-forwarding happens. This requires additional energy from the transmitter. Therefore, the link quality is estimated as: $LQ = \frac{LQ_i - LQ_{min}}{LQ_{max} - LQ_{min}}$, where LQ_{max} and LQ_{min} denote upper and lower range of re-forwarding; and LQ_i represents entire re-transmission cost among neighbors and given (*i-th*) SN.

Node centrality: Node centrality measure i determines number of times a node acts as a link on the shortest paths among two nodes. It is computed as: $N_C = \sum_{m \neq r \neq n \in R} \frac{\lambda_{mn(i)}}{\lambda_{mn}}$, where λ_{mn} is the number of shortest paths between node m and n, and $\lambda_{mn(i)}$ is the number of paths via i. Here, every node follows the fitness function based on calculated objective function values, along with the weighted coefficients, as follows: $Fitness_{final} = w_1 \times E_C + w_2 \times \left(\frac{1}{Com_C}\right) + w_3 \times \left(\frac{1}{D_{Que}}\right) + w_4 \times LQ + w_5 \times N_C$.

Here, $w_1 + w_2 + w_3 + w_4 + w_5 = 1$ and, $0 \leq w_i \leq 1, \forall i, 1 \leq i \leq 5$. The central goal is to: $Maximize \sum_{i=1}^{|CH|} Fitness_{final}$ such that $1 \leq i \leq |CH|$. Node, which fulfills all objectives will be selected as a CH. In every cluster, the selected CH is responsible for data gathering and forwarding to BS. Specifically, after CH selection, for each CH, route will be established for transferring collected data to BS.

The proposed approach is based on the chicken swarm optimization (CSO) introduced in [19] for CH selection. The most important aspects of CSO, in the considered problem, are as follows.

Chicken Movement: "best node" is the rooster, "worst node" is the chick, while the remaining nodes are hens. Let R_n be count of roosters, H_n count of hens, C_n count of chicks, and M_n count of mother hens; while B – be the number of iterations. Chicken positions can be denoted ${c_U}_{i,j}^{t_a}$ where $i \in [1,2,\ldots\ldots N]$ and $j \in [1,2,\ldots\ldots D]$, for time t_a in D dimensional space. In the proposed approach, the rooster is the CH with optimal fitness value.

Rooster Movement: Following [19], movement of roosters is computed as:

$$ {c_U}_{i,j}^{t_a+1} = {c_U}_{i,j}^{t_a} \times [1 + Randn(0, \sigma^2)] \quad (1) $$

$$ \sigma^2 = \begin{cases} 1 if f_i \leq f_k \\ exp\left(\frac{f_k - f_i}{|f_i| + \varepsilon}\right) otherwise \, ; k \in [1, N], k \neq i \end{cases} $$

where ${c_U}_{i,j}^{t_a+1}$ depicts the movement of the rooster, $Randn(0, \sigma^2)$ denotes the Gaussian distribution, with mean value 0 and standard deviation σ^2, ε denotes a constant value

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added to avoid zero-division, k implies the index of the rooster, selected randomly from the group, and f_i denotes the value of fitness of rooster x_i.

Hen Movement: Following [19], hen movement is represented as:

$$c_{U_{i,j}}^{t_a+1} = c_{U_{i,j}}^{t_a} + S1 \times Rand \times \left(c_{U_{r1,j}}^{t_a} - c_{U_{i,j}}^{t_a}\right) + S2 \times Rand \times \left(c_{U_{r2,j}}^{t_a} - c_{U_{i,j}}^{t_a}\right) \quad (2)$$

where $S1 = exp\left(\frac{f_i - f_{r1}}{abs(f_i + \varepsilon)}\right)$, $S2 = exp(f_{r2} - f_i)$, $Rand$ is a random number in [0, 1], $r1 \in [1,2,\ldots..N]$ is the index of the mate of i^{th} hen, $r2 \in [1,2,\ldots..N]$ is the index of randomly chosen rooster (or hen), $S1$ and $S2$ are the influence factors.

Chick Movement: Following [17], chick movement can be formulated as:

$$c_{U_{i,j}}^{t_a+1} = c_{U_{i,j}}^{t_a} + FL \times \left(c_{U_{m,j}}^{t_a} - c_{U_{i,j}}^{t_a}\right) \quad (3)$$

where $c_{U_{m,j}}^{t_a}$ denotes the location of the mother of i^{th} chick, for $m \in [1,2,\ldots.N]$, $FL \in [1,2]$ denotes the randomly selected speed of the chick following the mother.

For selecting the CH among, accessible SNs become chickens; nodes with best fitness values become roosters, with worst fitness are chicks, while the remaining nodes are hens. In each round, location of the rooster is updated using formula (1). Following the rooster, location of every hen is updated using formula (2). The chicks searching for food around their mother explore search spaces, which is captured in formula (3). Ranking of chickens maintains hierarchical order. Based on fitness values, chickens are ranked. After ranking, relationships between mothers and chicks are identified, to find differences between the chicks. ***Algorithm 1*** depicts the proposed algorithm for CH selection. The SN, selected by the CSO algorithm, becomes a CH, while remaining SNs form its cluster. After CH selection, patient data is sent to the CH, and can be removed.

Algorithm 1: Multi objective based CSO Algorithm for CH selection

Input: N number of CHs, CSO parameters; **Output:** Pareto Solution S indicating the nodes that act as CHs.

1.Initialize all the parameters $R_n, H_n, C_n, M_n and\ B$
2.Initialize the chickens in the swarm randomly as $C_{U_i}(i = 1,2,\ldots\ldots y)$
3.Initialize the total count of iterations as Max_{itr}
4.While $T_r < Max_{itr}$ do
5.If $(T_r \% B = 0)$ then
6.Establish the hierarchical order through ranking of chickens
7.Partition the swarm group and identify the mother-child relationship
8.End if
9.For $(i = 1)$do
10.If $(i == rooster)$do
11.Perform local update of the rooster's location using (1)
12.End if
13.If $(i == hen)$do
14.Perform local update of the hen's location using (2)
15.End if
16.If $(i == chick)$do
17.Perform local update of the chick's location using (3)
18.End if
19.Estimate the fitness of the obtained solution using $Fitness_{final}$
20.If the solution outperforms the older one $\rightarrow$update location
21.End for
22.Label the best solution as pareto optimal solution S
23.End while
24.Return S

3 Experimental results and discussion

Performance of the proposed solution was measured using: *cluster formation time; energy consumption:* energy consumed by SNs (in mJ); *network lifetime:* for how many

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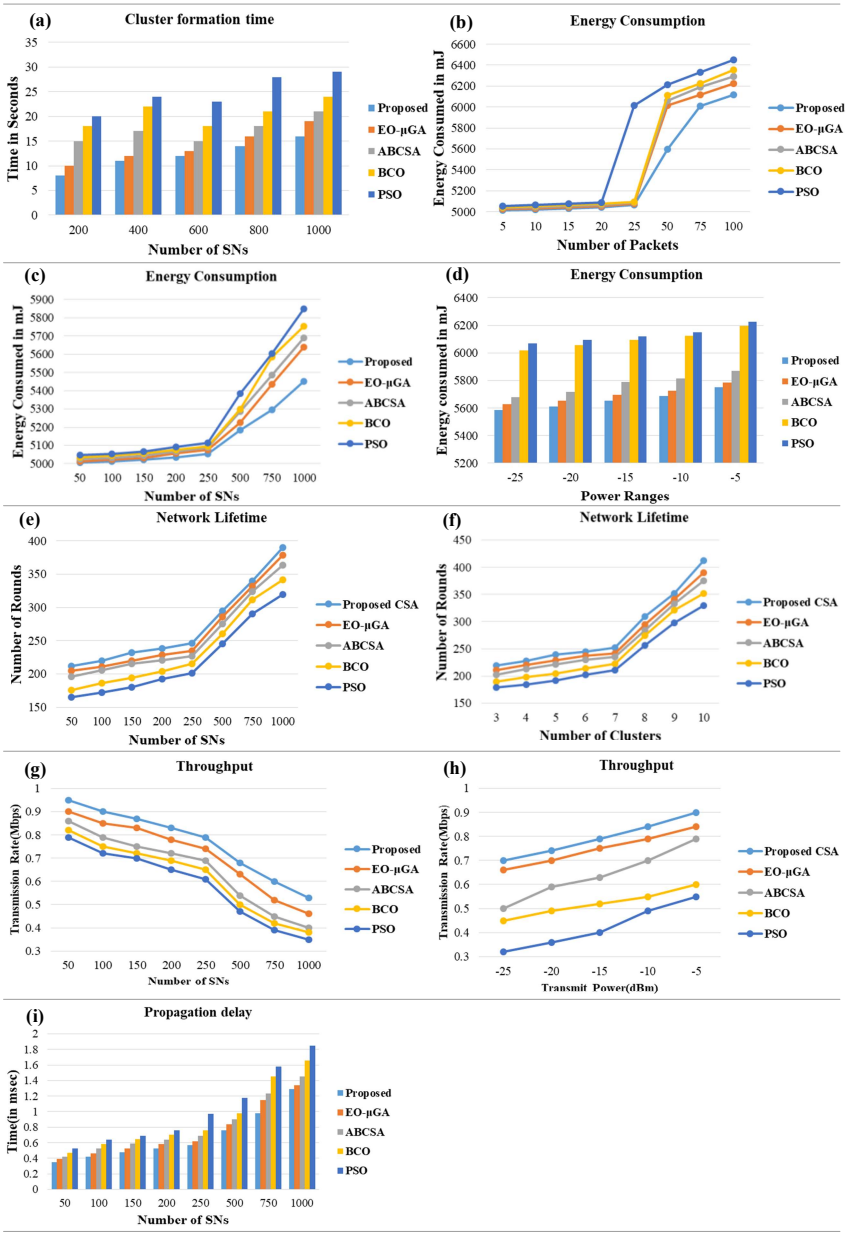

Fig. 2. (a) Cluster formation time; (b) Energy consumption (EC)/number of packets; (c) EC/ number of SNs; (d) EC/transmission power ranges; (e) Network Lifetime (NL)/number of SNs; (f) NL/number of Clusters; (g) Throughput (T)/number of SNs; (h) T/transmission power ranges; (i) Propagation delay/number of SNs.

rounds, network remains operational; *throughput:* CHs-BS (Mb/s); *delay:* transmission time SN-BS via CH (ms). Proposed approach was compared to EO-μGA [20], ABCSA

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[21], BCO [22] and PSO [23]. Simulated network parameters were: Number of SNs: 1000; IoMT sensing area: 500m^2; BS position: (500,500); Packets Size:1500 bits; Max Throughput: 1 Mbps; Initial Node Energy: 2J; Electronics energy: 30 nJ/bit; Data aggregation energy: 3 nJ/bit/signal; Transmitting power: 9 mW; Max number of rounds: 500. The CSO algorithm parameters were: Population Size: 100; Number of rosters: 3; Number of hens: 5; Update time steps: 10; Maximum Iterations: 150.

As shown in Fig. 2a, CSO-based clustering has the lowest cluster formation time. Moreover, the proposed CSO minimizes the cost by 1.9%, 2.7%, 3.8% and 4.9% in comparison to EO-μGA, ABCSA, BCO and PSO, respectively (Fig. 2b). Next, when number of SNs varied from 50 to 1000 (Fig. 2c), the proposed scheme minimized energy consumption by 3.4% to 7.1%. It was also most optimal from the perspective of energy consumption, for transmission power between -25dBm and -5dBm (Fig. 2d). Proposed solution improved network lifetime (for 50 to 1000 SNs; Fig. 2e) by 3.2% to 17%. Network lifetime was also evaluated with respect to the number of clusters (from 3 to 10; Fig. 2f). Here, the gain was between 5.7% and 21.3%. The throughput was simulated for 50 to 1000 SN's (Fig. 2g). The performance gain was 0.1% to 39%. Throughput was also evaluated when varying transmission power (-25dBm to -5dBm; Fig. 2h) and the improvement was 6.8% to 48,2%. Finally, Fig. 2i depicts propagation delay for varying number of SN, from 50 to 1000. Results confirm that proposed SCO scheme reduces propagation delay by 0.05ms to 0.56ms.

4 Concluding remarks

In this work, an energy efficient CSO-based clustering scheme was proposed for IoMT ecosystems. The proposed scheme uses fitness function, based on residual energy, queuing delay, communication cost, link quality and node centrality. Additional details about the approach, including extensive literature review can be found in [24]. The performance of the proposed scheme was compared with EO-μGA, ABCSA, BCO and PSO approaches. CSO-based approach was more efficient in all categories, with reduction of energy consumption by 3-7%. In the future, the proposed scheme will be extended with respect to mobility of nodes, body actions, and cross layer optimization.

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