Optimal Node Selection in Mobile Cloud Offloading Using Hybrid Swarm Intelligence

S.K. Piramu Preethika, R. Gobinath

Abstract--- ***Smart Mobile Devices engage and entertain all age group of the world all time all day long which leads to battery down problem. In order to avoid this issue mobile handshaking with powerful cloud is called as mobile cloud offloading. Earlier our work gave focus to send extracted electrocardiogram data packets from mobile to cloud in which void and energy holes were alleviated by partitioning into concentric circles and sensor node distribution using enhanced behavioural pattern. The research work carried out in this paper broadens its novelty by applying fitness value and selecting the best forwarding nodes using hybrid swarm intelligence. After the selection of strong forwarding nodes, the optimal path is discovered using fuzzy inference system, the energy is efficiently consumed and hence it avoids early energy depletion of sensor nodes closer to base station. Furthermore the optimal node transmitted the extracted Electrocardiogram data packets to healthcare centres.***

Keywords--- ***Mobile Cloud Offloading, Fuzzy Inference System, Sensor Nodes, Particle Swarm Optimization.***

1. INTRODUCTION

In recent internet era smart phones, laptops, tablets are being utilized for communications and many entertainments because it provides flexibility of anytime and anywhere accessing facility [1]. Due to the exponential growth of data, handling such big data becomes an important issue in the field of smart mobile devices. Mobile devices are restricted to the resources and they are not feasible to handle the complicated computation data. To overcome this issue by integrating cloud computing with portable devices devised an innovative domain termed as mobile cloud computing (MCC). In this MCC environment the mobile devices can execute on the front end of the application while the complex computation part which needs heavy resources is offloaded to the cloud server [2]. The entire mobile applications may be offloaded, or some part of the application can be offloaded it depends on the resource availability of the mobile devices.

Modern life style habits of human leads to heart related sickness which can be diagnosed using electrocardiogram (ECG) that predicts hearts sensitivity, pattern and cardiac abnormalities [3]. In a crisis situation ECG captures waveform signals can be separated into data packets and transmitted to network, while dispatching it faces disturbances like node failure, load imbalance , in order to overcome this issue network divided into concentric circles and sensor nodes deployed uniformly which alleviates energy and void hole using hybrid swarm intelligence. This research proceeds further to find out the best forwarding node using intelligence pattern.

2. RELATED WORK

R. Kaewpuang, D. Niyato, P. Wang, et al. shared their knowledge of sharing resources in mobile cloud computing paradigm [4]. Kaiyang Liu, Jun Peng et al [5] presented a large scale parallel workload and cost reduction tactic in cloud environment.

Aftab Ali ,Aslam Khan et al. predicted energy management key using cluster based health care framework in wireless body area network [6].

A.I Awad, El-Hefnawy NA, Abdel_kader HM et al projected a mathematical model using balancing concepts and scheduling algorithm steps from LBMPSO to reduce the cost, broadcast time through that it gains reliability[7].

Suraj Pandey, Linlin Wu1, Rajkumar Buyya et al presented PSO based algorithms to have lowest cost and workload allotment [8].Lin, Yong. Focussed on two constraints called energy saving and delay time using improved swarm based algorithm [9].

S. Chaisiri, B. Lee, D. Niyato, [10] discussed a principle of continuous time Lagrange dual to program data assets, the intention of optimization is to make light of communication power consumption. F. Tian, K. Chen [11] deliberated online professed competence and show delay formation.

3. PROPOSED METHODOLOGY

Selection of Optimal Forwarding nodes using Swarm Intelligence

An exclusive field which study about the groups of simple representatives is known as Swarm Intelligence that enable intelligent behavior in complex environments in this work it is used in forwarding nodes selections for optimal energy consumption in mobile-cloud paradigm. These agents are natural systems like group intelligence of fish, bees, termites and birds which are generally used for solving the issues in distributed systems.

Significantly, Swarm Intelligence comprises models that have the ability to obtain information and acclimatize to various conditions.

This paper adapts the behavior of swarm of birds which moves to achieve best solution in selection of forwarded nodes, for optimized energy consumption to overwhelm energy hole by evenly balancing distribution of load.

Each entity in flock consists of velocity and position vector to signify the candidate solution [12].

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S.K. Piramu Preethika, Research Scholar & Department of Computer Science, VISTAS. (e-mail: preethikamanikandan@gmail.com)

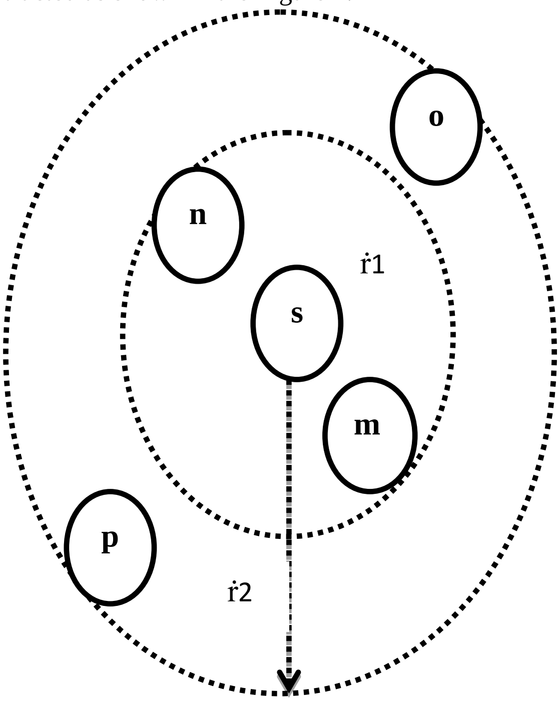
R. Gobinath, Assistant Professor & Department of Computer Science, VISTAS. (e-mail: iamgobinathmca@gmail.com)

Further, each bird has minute storage space unit to learn its global finest position and local best position assignment through its neighbour birds. The critical part of swarm intelligence is to establish the best arrangement of specific bird.

In behaviour of swarm of birds-based approach, the mutual exchanges of information among their neighbours are achieved through successful experience between birds in the same neighbourhood.

In mobile-cloud network model, it is not well-suited for global optimization by entire network communication in the constraint of sensor nodes with restricted ability of communication range and energy. To get rid-off convergence speed and optimal solution, the nodes organize a specific number of neighbours to create a spatial neighbourhood; in other means they frame multiple local optimal solution of spatial neighbourhood by decomposing the global optimal solution [13].

The neighbourhood with fixed radius, in which the number of nodes in each neighbourhood may be different, is constructed as shown in the Figure 1.



a) Neighbours deployment of s

$\dot{R}_c$	$\hat{U}_i$
ṙ1	{s,m,n}
ṙ2	(s,m,n,o,p}

b) $\hat{U}_i$ with fixed radius

Figure 1: Representation of Sensor Node's spatial neigborhood

From the source node to the bastion the optimal forwarding nodes are selected by applying swarm of bird's intelligence. In this proposed methodology, the Swarm intelligence is adopted into the energy model by updating its fitness criteria. The fitness function falls under three criteria.

1. Residual energy between sensor nodes
2. Distance between nodes to base station
3. Bandwidth Available

The fitness function of each bird is computed as follows

$$\text{Fit\_fun fit(x)} = h * \frac{1}{q} + l * \frac{1}{Enc} + NI_j * En_{\dot{r}}$$

Where, h denotes weighted factor which is based on distance, q is distance from source to base station,l refers to weighted factor which is based on energy, Nj is information about node and Enc, $En_{\dot{r}}$ are energy consumed and residual energy respectively.

The range of coverage of sensor node sni is the circular area of its own co-ordinates (xi,yi) as the center and the observing distance ṙ as the radius. The Euclidean distance among sensor node and the observing target k with coordinates (x, y) is $dist_{ik}$ and it is calculated as follows

$$dist_{ik} = \sqrt{(x_i - x)^2 + (y_i - y)^2}$$

Because of the signal strength reduction and environmental noise with large transmission of distance, the sensing or monitoring ability of the sensor nodes shows some uncertainty, $prob_{ik}$ is used to specify the probability of observing target k covered by sensor node sni and it is calculated using the formula as follows

$$prob_{ik} = \begin{cases} 1 & if\ dist_{ik} \le \dot{r} - \dot{r}_e \\ e^{-\beta(dist_{ik} - (\dot{r} - \dot{r}_e))} & else\ if\ \dot{r} - \dot{r}_e < dist_{ik} < \dot{r} + \dot{r}_e \\ 0 & otherwise \end{cases}$$

Where, ṙ is the observing radius, $\dot{r}_e$ ($0<\dot{r}_e< \dot{r}$) is the uncertain observing radius error of the sensor node. β is the coefficient of uncertain observing which reflects the fitness atmosphere for monitoring.

So, the β value is assigned depending on uncertain environmental noise.

It is advisable to choose a bigger coefficient to reduce the coverage probability rapidly in a mobile cloud paradigm. The neighborhood of node is altered constantly, so the neighborhood should be updated in each round of coverage optimization.

During the initialize phase of swarms, each bird is allocated with arbitrary values for position and velocity that travel in an n-dimensional space to search best solution. An individual bird i occupies the position Pos_{ik} and velocity Vel_{ik} in the kth dimension.

In each phase of generation, the birds best position p-$best_{ik,}$ and universal best position g_$best_{ik}$, is memorized. During each iteration, the personal best and global best position [14] will be updated as shown in the formula

Velik(m + 1) = wt.Velik(m) + cons1.rand1.(p_$best_{ik}$– Pos_{ik}) + cons2.rand2.(g_$best_k$– Pos_{ik}),Posik(m + 1) = Posik(m) + Velik(m + 1).

This process is sustained until whichever a suitable *gbest*is arrive at or a preset number of iterations *m*max , is met.

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Algorithm: Forward node selection using behavior of Swarm of birds

Input: The coordinates (x_i, y_i) of sensor node s_i and the fixed radius Ṙc

Output: Set of spatial neighborhoods Û and the number of optimal forwarded Nodes FN_u

Step 1: Count Cnt = 0

Step 2: For each node k=1,2,..n do

Step 3: The position of the node and its mobility are calculated as each bird is assigned to these nodes

Step 4: Fitness function is calculated

$$\text{fit}(x) = h * \frac{1}{q} + l * \frac{1}{Enc} + NI_j * En_{\dot{r}}$$

Step 5: Map the nodes position with nearest (x, y) coordinates

$$dist_{ik} = \sqrt{(x_i - x)^2 + (y_i - y)^2}$$

Step 6: Update nodes position and mobility

$$Vel_{ik}(m+1) = wt.Vel_{ik}(m) + cons1.rand1.(p\_best_{ik} - Pos_{ik}) + cons2.rand2.(g\_best_k - Pos_{ik}),$$

$$Pos_{ik}(m+1) = Pos_{ik}(m) + Vel_{ik}(m+1)$$

Step 7: Validate fitness function

Step 8: If node_ fitness <Crfit

Step 9: Update Crfit

Step10: Repeat until the optimal forwarding nodes has been identified from source to BS.

Fuzzy inference based optimal route discovery

The optimal forward nodes are discovered by swarm intelligence is inferred using fuzzy logic [15]. The steps involved in fuzzy rule implication system are as follows:

- *Fuzzification:* In this step from the selected input variables of nodes which are generally in crisp form is converted to linguistic values. It is done by determining degree to which the input fit in to every appropriate fuzzy set is assessed.
- *Evaluation of rule:* The inputs which are fuzzified are functional to the antecedents of the fuzzy rules. After that it is applied to its resultant membership function.
- *Rule outputs are Aggregated*: In this step all output rules are merged together
- *Defuzzification*: The merged output rules are given as input to the defuzzification process and finally it produces a solitary crisp number as output.

After selection of optimal forwarding nodes by behavior of swarm intelligence the nodes are marked with status strong, normal and weak depending on its fitness capability. The fuzzy inference system chooses best shortest path based on the Residual Energy (RE), Distance (DT) and Bandwidth Available (BA).

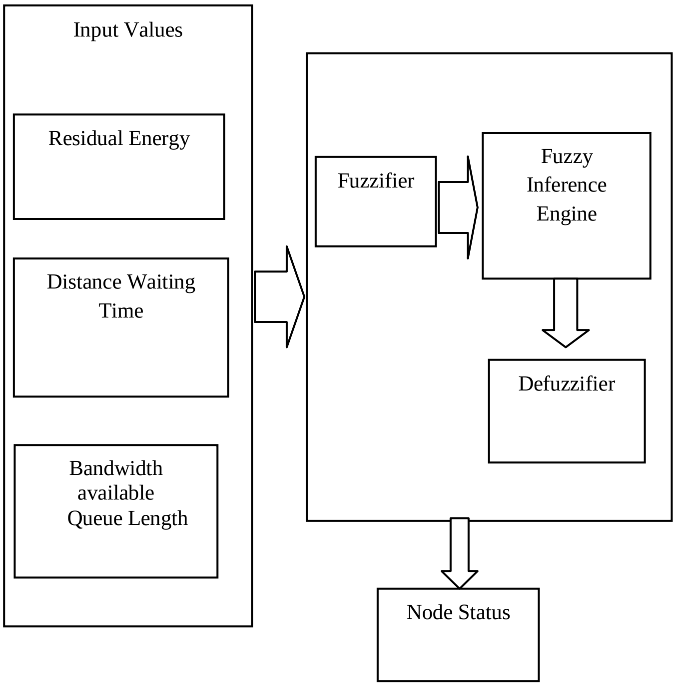

Figure 2: Fuzzy based Optimal Shortest path selection

Fuzzification

The input variables link Residual Energy (RE), Distance (DT) and Bandwidth Available (BA) are fuzzified and they are given a suitable degree of attachment in terms of fuzzy sets which they belong. The output crisp inputs are the permutation of RE, DT, and BA. This paper takes three possibilities, high, medium and low, for representing the input values RE, DT, and BA and Output variable NS.

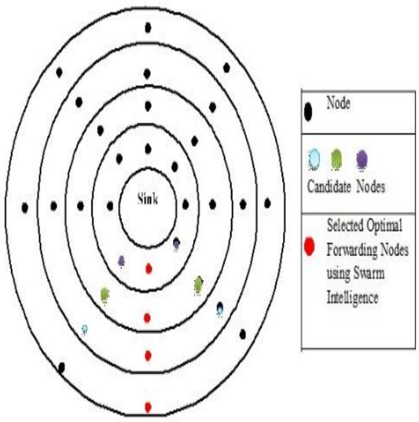

Figure 3: Membership function of Residual Energy

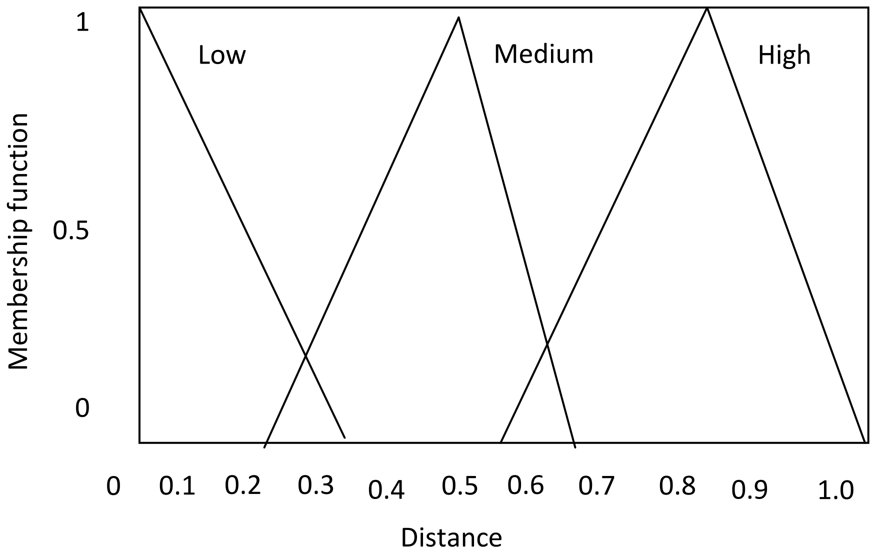

Figure 4: Membership function of Distance

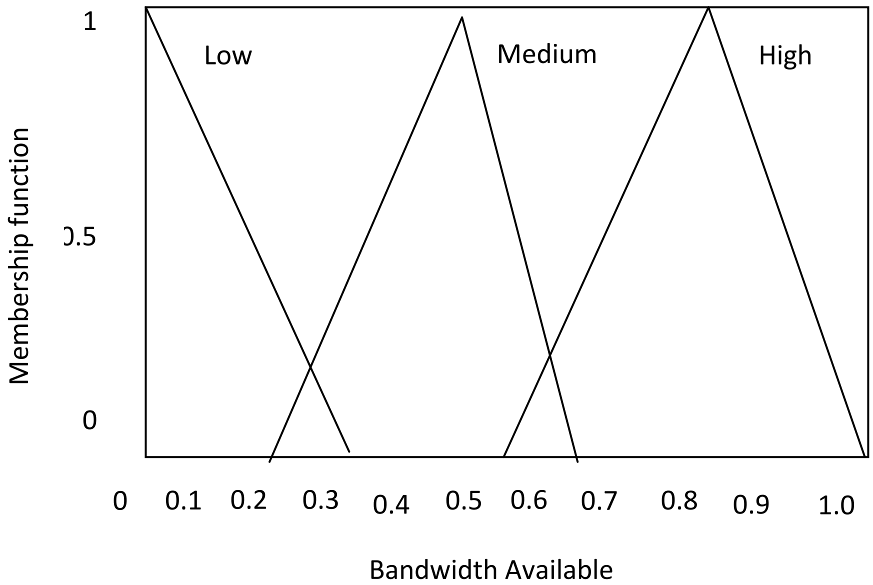

Figure 5: Membership function of Bandwidth

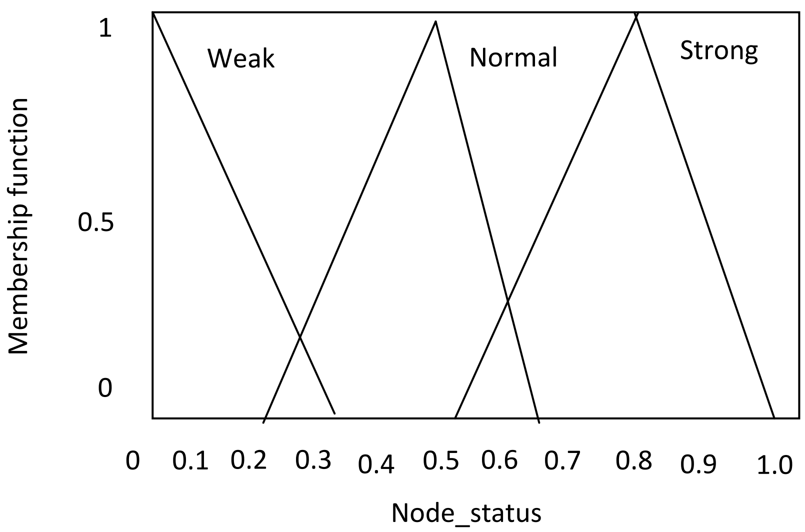

Figure 6: Membership function of Node Status

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Triangulation membership function is used in to represent input and output variables this work to reduce computational complexity which is depicted in the figures. The real brain of the fuzzy inference system is using IF-then type fuzzy rules. The fuzzy inference engine uses these rule-based interpretations and fires the appropriate if then rules in the knowledge base [16].
Fuzzy rule has the form:

Rule: IF condition THEN consequent

Where,

- *Condition is a representation of fuzzy expression, which comprises fuzzy expressions which are atomic and fuzzy logic operators*
- *Consequent denotes atomic expression*

Sample Fuzzy Rules generated for shortest path selection is as follows.

- ➢ If (RE is HIGH) and (DT is HIGH) and (BA is HIGH) then (NS is STRONG)
- ➢ If (RE is LOW) and (DT is LOW) and (BA is LOW) then (NS is WEAK)
- ➢ If (RE is MEDIUM) and (DT is LOW) and (BA is MEDIUM) then (NS is NORMAL)

Defuzzification

In this process fuzzy sets are converted to crisp value by taking centroid area into consideration and the formula is applied

$$\text{Fzy\_cost}=\frac{[\sum_{allrules} V_i * \vartheta(V_i)]}{[\sum_{allrules} \vartheta(V_i)]}$$

Fzy_cost is used to represent degree of decision making, V_i is the fuzzy all rules and variable and $\vartheta(V_i)$ is its membership function [15].The output of the fuzzy cost function is modified to crisp value as per this defuzzification method.

In this way, the model selects the optimal shortest path by fuzzy inference system and based on the status of the forwarding nodes, the decision is swapped between all neighbor nodes via Hello message. When the sender node transfers data to the base station, the ECG data packets are transferred through these optimal selected forwarded nodes which are strong in their status. During the initial phase all the nodes status are assumed to be normal. Afore a node transfers the records to the next node, it verifies the status of that node.

If the status of successor node is either normal or strong the data packets will be transmitted to the next neighbor node. Else if its status is weak then it will send a route recovery word of warning message to every adjacent node.

Once they receive route recovery warning the neighbor nodes start search to discover strong nodes nearby. After discovering strong nodes, they start local route recovery practice by altering the traversal path to tough nodes. If there are no strong nodes then they will search for normal and continue its route recovery process.

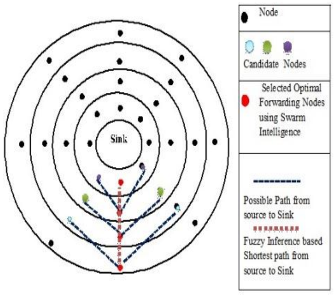

Figure 7: Possible paths from source to sink and fuzzy inference based shorted path

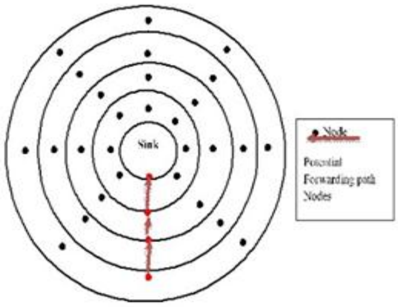

Figure 8: After applying fuzzy inference system the optimal forwarding path and its nodes are shown

4. RESULTS & DISCUSSION

Performance Metrics

The performance of this work is evaluated with existing methods like Lagrange Relaxation based Aggregated Cost (LRAC) [18] [19] and WSNEHA [17] and graphs drawn to show their efficiency. The performance is evaluated using different metrics as follows:

Packet Dropped

It is a measure taken while transmission of ECG data packets over the network the number of packets Dropped is considered

Pkt - Dropped = Number of packets send – Number of packets received

Results based on packets drop

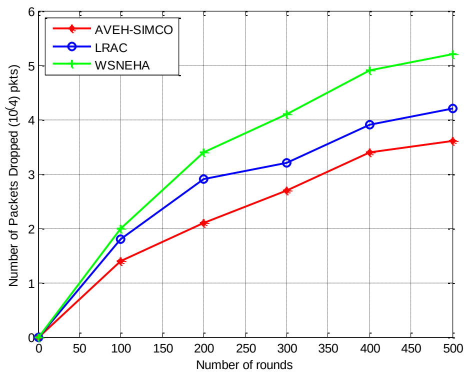

Figure 9: Dropped packets count

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From the figure it is observed that the packet drop of AVEH-SIMCO is less compared to LRAC and WSNEHA approaches. It is due to the fact status of each node is determined from during initial stage of data transfer in AVEH-SIMCO and thus the mortality rate of sensor nodes are reduced thus it alleviates the energy hole. Furthermore, the optimal selection of shortest path based on the dynamic node_status inferred by the fuzzy knowledge base greatly resists the packets drop ratio.

Load Distribution

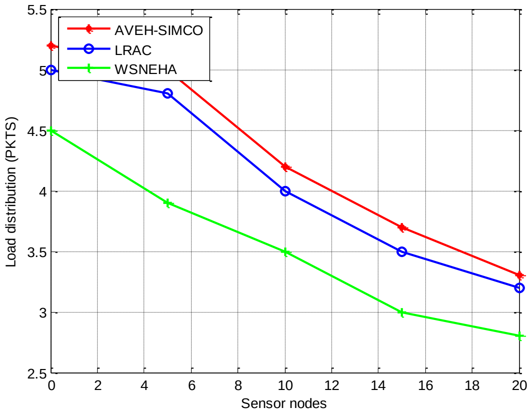

Figure 10: Load Distribution

The figure depicts the distribution of data packets on each of the forwarding nodes. As shown in the figure in AVEH-SIMCO data load is distributed uniform randomly among base station proximal neighbor nodes. This is due to the reality that every time the node with elevated residual energy is chosen by swarm intelligence by computing the fitness value and considering the nodes with highest fitness values as strong nodes and the fuzzy logic selects such forwarder node for data transfer. Additionally, when there are no strong neighbors then they discover the nodes with normal status and start the data transmission process. This strategy greatly avoids the selection of weak nodes which leads to energy hole. The WSNEHA distributed load among senor nodes in an unbalanced manner so that it results in immense data load. LRAC fails to partition the network area so that the sensor nodes are not deployed equally.

5. CONCLUSION

This work contributes to discovering enhanced route discovery using fuzzy inference engine and its rule system for choosing finest shortest path. Using Swarm intelligence, the energy depletion is highly controlled not only to the sensor nodes closer to base station but to the entire network by its parallel processing capability. The behavior of swarm of birds is adapted to choose the optimal forwarding nodes and based on its status the fuzzy intelligent system selects the best shortest path. With suitable simulation result the optimized usage of mobile cloud offloading is achieved in the field of health supervising system more competently while comparing other state of art.

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