

# Lucid Firefly Based Routing Protocol (LFRP) for Accessing Big Data in Cloud

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Abstract – Minimizing energy consumption is a significant issue in cloud computing. Nodes present in cloud computing are heterogeneous in nature. Traditional routing protocols fit best for homogenous networks and while using in heterogeneous network it will never give its better performance. Accessing big data in cloud is a challenging task because more stable route is necessary for the access of big data. Routes failures are unexpected and if a route gets failed in cloud computing while accessing big data, then it will affect the network performance drastically. In this paper, Lucid Firefly based Routing Protocol (LFRP) is proposed to identify the optimized route to access the big data and to minimize the energy consumption. LFRP utilizes the natural characteristics of firefly to identify the best route and to share the identified best route with others. LFRP finds the route based on the size of data where the fitness function plays a major role in identifying the best route. The simulation results make an indication that the proposed routing protocol LFRP has consumed less amount of energy i.e., 3.95J in accessing the big data than other routing protocols which makes an indication that the routing protocol has found the better route to destination which faces low delay (65ms) and packet delivery ratio as 94.20%.

Index Terms – Big Data, Cloud Computing, Energy, Firefly, Lifetime, Network, Routing.

#### 1. INTRODUCTION

On-demand accessing of data has arisen as the tipping point for information technology where cloud computing (CC) plays a major role [1]. CC has the potentiality to connect to multiple networks and devices at any time anywhere. Cloud data centers are dependent on different significant technologies, but the virtual machine is the essential foundation. CC denotes the storing and accessing of data via inter-network instead of accessing in local drive or network [2], [3]. CC provides the advantage of storing and retrieving a huge amount of data and also it supports better [4], [5]: (i) availability (ii) fault tolerance (iii) scalability and (iv) reduced complexity. Big Data (BD) indicates the huge volume of data which can be either structured or unstructured or semistructured. Sources of BD generation are heterogeneous and generated at a rapid rate. By nature, BD is complex and it requires potential methodologies to handle where traditional methodologies won't give their best performance while handling BD [6]. The CC and BD are bundled together by default. The extensive size of BD makes traditional techniques of accessing to get lack. Anytime anywhere computing is the biggest advantage of CC and which is most needed for BD.

The processing of BD involves different radio connectivity nodes for different parts of the network [7]. Based on the requirement of radio accessing, the nodes are placed in an adhoc manner in the network. It provides progress in a better manner for managing the data that flow across the disasteraffected areas [8]. The radio coverage area of ad-hoc nodes acts as merit to increase the throughput and packet delivery ratio. This method involves two key components [9], [10]: (i) gathering knowledge about the places that have experienced environmental devastation and (ii) relaying the information about those locations to where it is needed.

#### 1.1. Problem Statement

Routing indicates the process of finding an exact path to send the data to the destination. Finding a path to send BD is entirely different from sending data in general computer networks or ad-hoc networks [11], [12]. BD is handled in CC where the network is geographic, heterogeneous and most nodes are ad-hoc. Commonly used routing protocols will never suit CC-based networks, especially while handling BD [13], [14]. To access BD, the route must be more stable because the count of data packets will be more and it flows like a stream and if any route failure occurs means it will tremendously affect the network performance which results in network congestion [15], [16].



#### 1.2. Motivation

Currently, the access to big data is increased. Quantity of big data is drastically increasing day by day. The important source of big data is sensor network which is used in hospital and in multiple environments. In order to access the big data and to meet cloud computing needs, traditional routing protocols is never suited. Also, to effectively utilize the available limited bandwidth, an optimization based routing protocol is needed.

#### 1.3. Objective

This paper aims to propose an optimization-based reactive multicast routing protocol to access BD in CC, namely Lucid Firefly Based Routing Protocol (LFRP). It applies the natural characteristics of firefly to find the best and stable route in CC to access BD where the main features include: (i) avoidance of network congestion (ii) reduced energy consumption (iii) increased network lifetime.

#### 1.4. Organization of the Paper

Current section of the paper has discussed about the introduction to cloud computing, big data, problem statement, motivation and objective of the paper. Section 2 of the paper discusses the literature review with its merits and demerits. Section 3 discusses about the Firefly Algorithm. Section 4 Proposes the routing protocol based on firefly algorithm. Section 5 discusses the results and discussion. Section 6 concludes the paper with future enhancement.

#### 2. LITERATURE REVIEW

"Fuzzy-based Routing Scheme (FRS)" [17] is proposed to find a route in urban SDN. Initially, the network is divided into sub-areas (i.e., clusters). The routing table is used to maintain the priorities of the packet. Using a fuzzy logic system, values in routing tables are initialized. Greedy approach is applied to calculate the distance in different routes to the destination. Reinforcement Learning is used for updating the routing table. "Deep Reinforcement Learningbased Routing (DRLR)" [18] is proposed to recombine the different network resources i.e., recombining bandwidth and cache memory. It quantifies the score of contribution towards minimizing the delay. Resource recombined state is used to find the route to a destination where it effectively allocates network resources for the nodes. "Dynamic Multi-Sink Routing Protocol" [19] is proposed to organize the nodes in a wireless sensor network in self and find the best route to the destination. Basically, it forms different clusters and performs multipoint communication between separated areas. The methodology of multi-hop forwarding is used to send and receive data. "Security Disjoint Routing" [20] is proposed to increase the ratio of data arriving and decrease the delay that arises in transmission. It aims to estimate the presence of malicious nodes and residual energy. Routes are established by considering the threshold level of energy in nodes. The energy present in the nodes are divided into three different levels.

"Personalized Route Prediction" [21] is proposed to utilize machine learning-based algorithms for predicting the routes to destination using probability transition matrix. It is aimed to be utilized in transport systems and intelligent vehicles (i.e., real-world driving). Data reduction algorithms are used to minimize probability transition matrix size. "GreeDi" [22] is proposed to identify the minimum energy consumption route to the cloud data centre for storing and retrieving big data. Approaches related to dynamic and linear programming are used to develop the routing protocol. Bandwidths are adjusted for different routes for delivering the big data to and from the data centre. "Joint Coflow Routing (JCR)" [23] is proposed to address the issues present in routing map reducing in data center. It aims to address the minimum bandwidth issues when the leaf-spine topology is used. While selecting a route, more preference is given to bandwidths. "Cloud-Assisted Routing (CAR)" [24] is proposed to find the better route in wide-area SDN. New features are developed to handle network traffic that reduces delay and attempts to provide better service at minimum cost. Memory complexities that arise in routing are focused to minimize. Existing features are ensemble with new features for minimizing the cost.

"Distributed Online Approach" [25] is proposed to schedule and perform routing in inter datacenter network with random topologies. It influences Lyapunov optimization strategy to increase the accessing of local information. The destination grouping method is utilized to face network performance degradation issues. "Approximate Algorithms" [26] are proposed to solve the optimization issues that arise in software-defined networking. It calculates the routing distance by not considering the link capacity where it analyzes different methodologies to adjust the route in specific flows and focuses on balancing the load that results in congestion avoidance. Multi Adaptive Routing Protocol [27] is proposed to access the big data using IoT where it is inspired from natural characteristics of fishes. Using swarming behaviour it shared the identified route with neighbor nodes for better results. Wolf Prey Inspired Protocol [28] is a bio-inspired routing protocol inspired from wolves hunting characteristics developed for cognitive radio based ad hoc networks. It is applied to access big data where it makes use of spectrum wireless medium. In this protocol, all nodes together find the best route and share the same with its member in the cluster. Different Optimization based Routing Protocols [15], [29], are proposed for different networks but the major of all protocols is to minimize the delay and energy consumption.

#### 2.1. Limitations of Existing Methodologies

This paper focused on developing the better routing protocol for cloud computing environment specifically to access big



data. Merits and Demerits of the previous approaches are provided in Table 1. Overall limitations identified in the existing methodologies (i.e., protocols) are:

- Focusing only on finding the routes and not on its quality.
- Consumption more energy on finding the route.
- Protocol suitable for general networking will not suit for cloud computing especially to access big data.
- Consumption of more time in finding the alternate routes.
- Consumption of more bandwidth.
- Increased length of queues to send and receive data.

Previous Approaches	Merits	Demerits		
Fuzzy-based Routing Scheme (FRS) [17]	Efficient forwarding of the packet	Increased bandwidth utilization		
Deep Reinforcement Learning-based Routing (DRLR) [18]	Improved throughput	Unbalanced load across the network		
Dynamic Multi-Sink Routing Protocol [19]	Increased network lifetime	Reduced delivery of packets		
Security Disjoint Routing [20]	Network traffic when transmitting the data	Unexpected failures of nodes		
Personalized Route Prediction [21]	Minimum delay in delivering the data	Utilization of more bandwidth		
GreeDi [22]	Finding of minimum energy consumption route	Unexpected link failures between nodes		
Joint Coflow Routing (JCR) [23]	Better utilization of network resources.	More time consumption for selecting the best route		
Cloud-Assisted Routing (CAR) [24]	Low utilization of memory	Increased latency in tackling the routing issues.		
Distributed Online Approach [25]	Increase of accessing local information	Significant increase in queue length to access the datacenter		
Approximate Algorithms [26]	Increased performance in load balancing	Limited to a specific topology		
Multi Adaptive Routing Protocol [27]	Sharing of identified routes with neighbor nodes	Consumption of more time to identify the route.		
Wolf Prey Inspired Protocol [28]	Minimized end to end delay to deliver the packets	Finding more number of alternate routes.		

Table 1 Merits and Demerits of Previous Approaches

## 3. FIREFLY ALGORITHM

$$LA(df) = LA_0 \times e^{-(LAC \times df^2)}$$
(1)

Firefly Algorithm (FA) is one of the benchmark swarm intelligence-based optimization algorithms which intends to resolve the issues that are highly complex. Artificially, fireflies are deployed in a random manner where they are created artificially in FA. Each firefly then sends out light as a signal to make communication with other fireflies. The intensity of the light signal from fireflies are contrasted with others fireflies in the swarm. Fireflies move closer to the other firefly in the swarm that has a higher intensity of light. In FA, absorption of light by firefly is calculated using Equation.(1).

Where *LA* represents light absorption,  $LA_0$  indicates the light absorption at the initial stage, df represents the distance between fireflies, and *LAC* denotes the coefficient of light absorption. Distance present between fireflies are calculated by using Equation (2).

$$df = \left(\sum_{x=1}^{d} (ff_{ix} - ff_{jx})\right)^{0.5}$$
(2)

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Where ff indicates firefly, df indicates the distance present between the fireflies  $ff_i$  and  $ff_j$ . The fireflies "*i*" movements are entirely dependent on the attraction of light emitted by "*j*" and it is mathematically expressed as Equation (3).

$$ff_i = ff_i + LA_0 \times e^{-(LAC \times df)^2} (ff_{ix} - ff_{jx})$$
  
+ a(rand - 0.5) (3)

Where *a* indicates random parameter,  $LA_0$  indicates the light absorption at initial stage and *LAC* indicates the coefficient of light absorption. Fireflies make communication via the light that they emit. The firefly that emits the brightest light act as an optimum solution for the problem domain. The main goal of an individual firefly in the swarm is to attain the brightest firefly in the problem domain. The pseudocode of *FA* is provided in Algorithm 1.

Input: *c*-fireflies count,  $LI_i$ - light intensity, LAC- coefficient of light coefficient

Output: Preeminent firefly in the *p*th iteration

Initialization of firefly optimization

Fix vector values for individual firefly

Calculate light intensities for individual firefly

 $iteration\_count = 0;$ 

While (*iteration\_count < highest iteration\_count*) do

for each p=1 to m do

for each q=1 to m do

if 
$$(LI_n < LI_a)$$
 then

firefly  $LI_p$  progress its movement towards  $LI_q$ 

end if

end for each

end for each

 $iteration_{count} = iteration_{count} + 1$ 

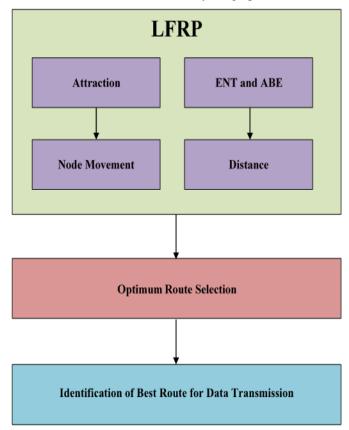
end while

Achieve the brightest firefly in problem domain

Algorithm 1 Firefly Algorithm

## 4. LUCID FIREFLY BASED ROUTING PROTOCOL (LFRP)

This section presents the proposed routing protocol *LFRP* to enhance the lifetime of the cloud network by minimizing energy consumption while accessing big data. The term "accessing" denotes the sending and receiving data between mobile nodes or from the cloud server. In a cloud network, energy is treated as a scarce (i.e., limited) resource. Hence, enhancing the lifetime of cloud networks is a significant task. *LFRP* utilizes a modified version of *FA* to find the optimum route for transmitting the data. Additionally, in solution space, *FA* makes use of (i) the most recent position of firefly (ii) random function, and (iii) attraction of light. The position of the firefly is indicated as vector value y(p). Firefly attraction rate is calculated using two different routing parameters namely: (i) expected number of transmission (*ENT*) and (ii) available balance energy (ABE). Movements of the firefly in the swarm are calculated with the utilization of metric "distance". Finally, participating nodes prefer the best node in a destination-oriented directed acyclic graph.



#### Figure 1 Route Identification

#### 4.1. Optimum Route Selection

Selection of optimum route is one among important issues present in cloud networks where most devices are limited to the resource. *LFRP* utilizes *FA* to select the optimum route to transfer the data. In *LFRP*, every firefly present in the swarm is treated as vectors y(p) and it holds information related to firefly movement, attraction level between fireflies, and light absorption. Equation.(1) is used to calculate the firefly's light absorption. The light attraction ratio is calculated by depending on two metrics namely *ENT* and *ABE*.



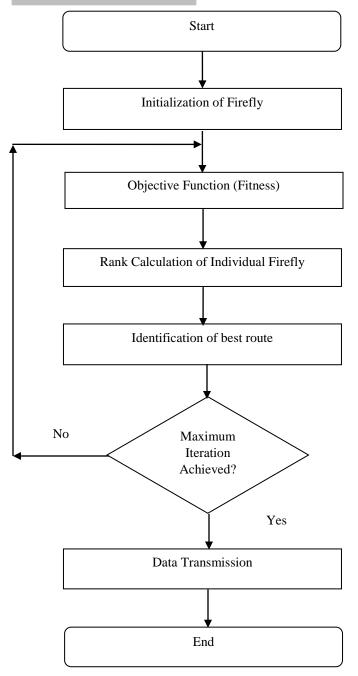


Figure 2 Flowchart of LFRP

## 4.2. Available Balance Energy

ABE represents the amount of energy available in the intermediate node x in the cloud computing-based network. The calculation of ABE is mathematically expressed as Equation (4).

$$ABE(s) = \frac{Energy_{present}}{Energy_{initial}}$$
(4)

Where  $Energy_{present}$  indicates available energy in the network currently and  $Energy_{initial}$  indicates the overall energy at the initial stage.

#### 4.3. Expected Number of Transmission

ENT is a network metric and it is used in the prediction of the quality of the link between 2 nodes. ENT is calculated between x and y nodes, and it is mathematically expressed as Equation (5).

$$ENT = \frac{1}{DDFD \times DDRD} \tag{5}$$

Where *DDFD* and *DDRD* represent the data delivery in the forward direction and reverse direction.

#### 4.4. Distance

For every firefly, vector value initialization is done as an initial value. The vector having the highest *ABE* value and better link quality act as the optimum route and it is calculated using a fitness function. By default, vector value will be more or less (i.e., approximately) equivalent to the value of fitness function in all iteration and the route satisfying this constraint will act as an optimum route. Else, iteration gets continued for finding a different route to act as an optimum route. The movement of the firefly is calculated based on the distance and it is expressed as Equation (6).

$$df(ff_{ix}, ff_{jx}) = LA + \left(\sum_{x=1}^{m} (ff_{jx} - ff_{ix})^2\right)^{0.5} + a(rand - 0.5)$$
(6)

Individual firefly's vector representation is mathematically expressed as Equation (7).

$$ff_{(p)} = \sum_{p=1}^{m} ABE(ff_i) + \sum_{p=1}^{m} ENT(ff_p, ff_q) + \sum_{p=1}^{m} df(ff_p, ff_q)$$
(7)

Where  $ff_{(p)}$  represents *ABE* of node in vector space and  $df(ff_p, ff_q)$  indicates the distance present between *p*th node and its neighbor *q*th node.

### 4.5. Fitness Function

Fitness function  $(fit_fun)$  act as sub secondary objective in choosing the optimum route for transferring the data.  $fit_fun$  is calculated using ENT and ABE. The average values of weight are represented as  $wt_1$  and  $wt_2$ . The average values of weight are made to adjust from 0 to 1. Lastly, while attaining the optimum solution (i.e., best route), the values of weight  $wt_1$  and  $wt_2$  are 0.5.  $fit_fun$  is mathematically expressed as Equation (8).

$$fit_fun = (wt_1 \times ABE(ff_i)) + (wt_2 \times ENT(ff_i))$$
(8)

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Optimum route selection based on LFRP consumes minimum time and high efficiency.

4.6. Rank Calculation of Route

Rank provides the information about distance present between participating node and root of Destination Oriented Directed Acyclic Graph (DODAG). Rank is calculated by finding the difference between rank-increased  $Rank_p$  and route-rank p. The value of  $Rank_p$  is estimated using node movement and Min-Hop-Rank-Increase (*MHRI*) strategy.

The value of node movement is calculated using the preeminent fitness value where the default value for MHRI is 256. Equation (9) and Equation (10) mathematically express the rank calculation.

 $Rank(p) = Rank(parent_node(p)) + Rank_p$  (9)

 $Rank_{p} = node_movement + MHRI$  (10)

Algorithm 2 shows algorithm of LFRP.

Input: ENT, DF, ABE, Attraction, Movement

Output: Best Route

While *iteration\_count*  $\leq$  *highest iteration\_count* do

Initialize firefly population using Equation.(7)

Update movement of node using Equation.(6)

Check fitness function value at each iteration using Equation.(8)

if  $ff_i \ge fit_fun$  then

Calculate rank for every route using Equation.(9) and Equation.(10)

else

Update movement of node

end if

end while

Choose optimum route to transfer data

Return preeminent node in DODAG

Algorithm 2 Algorithm of LFRP

## 5. RESULTS AND DISCUSSION

## 5.1. Performance Metrics

Metrics used to evaluate the performance of LFRP against FRS, DRLR, JCR and CAR are:

✓ End-to-End Delay: It indicates the time consumed to transmit the data packet across networks from source to destination.

- ✓ Packet Delivery Ratio: It indicates the successful delivery of packets sent from the source node and delivered to the destination node.
- ✓ Energy Consumption: It indicates the consumption of energy to deliver a packet from the source node to the destination node.
- ✓ Throughput: It indicates the quantity of data transmitted in a given amount of time.
- 5.2. Simulator and Simulation Setting

This research work has used Greencloud to simulate the proposed routing protocol against the existing routing protocols. Greencloud is the extension of network simulator version 2 (i.e., NS2). Greencloud is used to focus cloud network, its energy resources, memory utilization, routing, resource allocation and virtualization. Simulation settings used for the evolution are provided in Table 2.

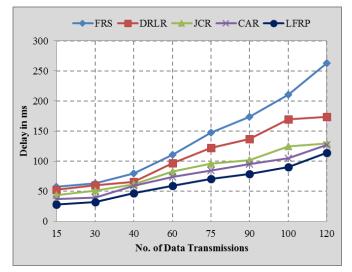
ENTITIES	PARAMETERS	VALUES
Cloudlet	Count of Cloudlets	100
Cioudici	Count of Data Center	3
Data Center	Cloudlet length	80
	Host Count	2
Host	Bandwidth	8 GB
11031	RAM	20 GB
	Storage	1 TB
Node	Count of Nodes	250
	Count of Virtual Machines	30
Virtual Machine	Bandwidth	8 GB
	Count of CPU	3
	MIPS	2048

Operating System	Ubuntu 19.10
Policy Type	Time-Sharing
RAM	8 GB

Table 2 Simulation Setting

5.3. Experimental Results

## 5.3.1. End-to-End Delay Analysis



## Figure 3 End-to-End Delay Analysis

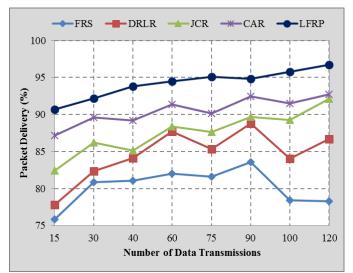
Number of Data Transmission	FRS	DRLR	JCR	CAR	LFRP
15	58	53	44	37	28
30	63	60	51	40	32
40	80	66	62	59	47
60	111	97	83	74	59
75	148	122	96	85	71
90	174	137	102	95	79
100	211	170	125	105	90
120	263	174	130	127	114

Table 3 LFRP vs End-to-End Delay

In Figure 3, the x-axis is marked with number of data transmissions and the y-axis is marked with delay (in

milliseconds (ms). From Figure 3, it is evident that the proposed protocol LFRP has very low when comparing with the existing protocols namely CAR, JCR, DRLR and FRS. The average delay faced by LFRP is 65 ms, where FRS, DRLR, JCR and CAR have faced average delay as 138.5 ms, 109.875 ms, 86.625 ms and 77.75 ms respectively. The role of optimization present in LFRP assists in achieving low end-to-end delay than other considered existing protocols. Figure 3 corresponding values are provided in Table 3.

5.3.2. Packet Delivery Ratio



Number of Data Transmission	FRS	DRLR	JCR	CAR	LFRP	
15	75.84	77.84	82.44	87.16	90.70	
30	80.88	82.38	86.18	89.58	92.20	
40	81.04	84.14	85.14	89.22	93.80	
60	81.98	87.68	88.38	91.38	94.50	
75	81.64	85.34	87.64	90.16	95.10	
90	83.58	88.78	89.68	92.45	94.80	
100	78.44	84.04	89.24	91.51	95.80	
120	78.28	86.68	92.08	92.69	96.70	
Table 4 I FRP vs Packet Delivery Ratio						

Table 4 LFRP vs Packet Delivery Ratio

In Figure 4, the x-axis is marked with number of data transmissions and the y-axis is marked with packet delivery (in %). From Figure 4, it is evident that the proposed protocol



LFRP has delivered more number of packets to destination than the existing protocols namely CAR, JCR, DRLR and FRS. The average packet delivery ratio of LFRP is 94.20% where CAR, JCR, DRLR and FRS has average packet delivery ratio as 80.21%, 84.61%, 87.59% and 90.52% respectively. Fitness function-based route selection makes LFRP attain better packet delivery ratio than other considered existing protocols. Figure 4 corresponding values are provided in Table 4.

#### 5.3.3. Energy Consumption

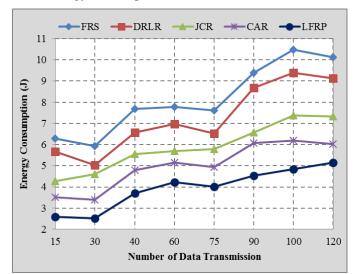


Figure 5 Energy Consumption Analysis

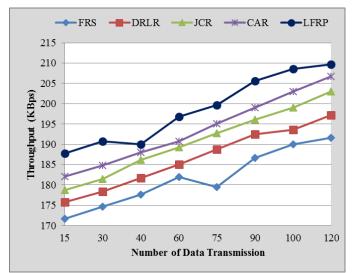
Number of Data Transmission	FRS	DRLR	JCR	CAR	LFRP
15	6.28	5.68	4.28	3.52	2.59
30	5.92	5.02	4.60	3.39	2.51
40	7.68	6.58	5.56	4.80	3.70
60	7.78	6.98	5.70	5.16	4.22
75	7.62	6.52	5.80	4.93	4.02
90	9.38	8.68	6.58	6.08	4.53
100	10.48	9.38	7.38	6.18	4.84
120	10.12	9.12	7.32	6.02	5.15

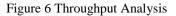
Table 5 LFRP vs Energy Consumption

In Figure 5, the x-axis is marked with number of data transmissions and the y-axis is marked with energy consumption (in Joules (J). From Figure 5, it is evident that

the proposed protocol LFRP has consumed minimum energy than the existing protocols namely CAR, JCR, DRLR and FRS. The average energy consumed by LFRP is 3.95J where CAR, JCR, DRLR and FRS have consumed average energy as 8.16J, 7.25J, 5.90J and 5.01J respectively. The selection of optimized route makes LFRP to spend minimum energy to deliver the packets than other considered existing protocols. Figure 5 corresponding values are provided in Table 5.

5.3.4. Throughput





Number of Data Transmission	FRS	DRLR	JCR	CAR	LFRP
15	171.74	175.73	178.74	182.06	187.73
30	174.71	178.36	181.43	184.82	190.80
40	177.60	181.73	186.14	188.01	189.99
60	181.98	185.03	189.24	190.73	196.80
75	179.48	188.73	192.69	195.06	199.72
90	186.69	192.48	196.07	199.02	205.58
100	190.06	193.60	199.06	203.05	208.60
120	191.58	197.25	203.03	206.71	209.70

Table 6 LFRP vs Throughput

In Figure 6, the x-axis is marked with number of data transmissions and the y-axis is marked with throughput (in Kilobytes per second (KBps). From Figure 6, it is evident that



the proposed protocol LFRP has attained maximum throughput than the existing protocols namely CAR, JCR, DRLR and FRS. The average throughput attained by LFRP is 198.62 KBps, where CAR, JCR, DRLR and FRS has attained average throughput as 181.73 KBps, 186.61 KBps, 190.80 KBps and 193.68 KBps respectively. The attraction ratio strategy of LFRP leads to achieve maximum throughput than other considered existing protocols. Figure 6 corresponding values are provided in Table 6.

#### 6. CONCLUSION

Routing algorithm plays a major role in all type networks including cloud computing. Cloud networks perform its operation only by depending on inter-network (i.e., internet) where the nodes are heterogeneous in nature. Traditional multicasting routing protocols will not give better performance in delivering the packets because nodes present in cloud networks are geographic; also it will not support delivering big data. To deliver the big data, it's necessary to maintain the route for a threshold amount of time or more than that. This paper has proposed a novel optimization-based routing protocol namely Lucid Firefly Based Routing Protocol (LFRP) which adopts the natural characteristics of firefly to find the best route in the cloud to deliver the big data to the destination. Fitness function in LFRP evaluates the size of big data, time and bandwidth required for data transmission. LFRP finds the optimized route to a destination by utilizing the fitness function. Selection of better optimized route with fitness function helps LFRP achieving better results. Greencloud simulator has been used to evaluate the performance of LFRP against existing protocols where it uses end-to-end delay, packet delivery ratio, energy consumption and throughput to measure the performance. Results make a clear indication that LFRP outperforms the existing protocols in terms of all considered performance metrics. The future direction of this work can be focused to balance the load in cloud networks while accessing big data.

#### REFERENCES

- X. Ma, Y. Wang, and X. Pei, "A Scalable and Reliable Matching Service for Content-Based Publish/Subscribe Systems," IEEE Trans. Cloud Comput., vol. 3, no. 1, pp. 1–13, 2015, DOI: 10.1109/TCC.2014.2338327.
- [2] A. M. Manasrah, T. Smadi, and A. ALmomani, "A Variable Service Broker Routing Policy for data center selection in cloud analyst," J. King Saud Univ. - Comput. Inf. Sci., vol. 29, no. 3, pp. 365–377, 2017, DOI: 10.1016/j.jksuci.2015.12.006.
- [3] Y. Wang, A. Zhang, P. Zhang, and H. Wang, "Cloud-Assisted EHR Sharing With Security and Privacy Preservation via Consortium Blockchain," IEEE Access, vol. 7, pp. 136704–136719, 2019, DOI: 10.1109/ACCESS.2019.2943153.
- [4] K. Saleem, A. Derhab, J. Al-Muhtadi, and M. A. Orgun, "Analyzing ant colony optimization based routing protocol against the hole problem for enhancing user's connectivity experience," Comput. Human Behav., vol. 51, pp. 1340–1350, Oct. 2015, DOI:10.1016/j.chb.2014.11.030.
- [5] A. S. Albahri et al., "IoT-based telemedicine for disease prevention and health promotion: State-of-the-Art," J. Netw. Comput. Appl., vol. 173,

p. 102873, 2021, DOI: 10.1016/j.jnca.2020.102873.

- [6] S. A. Bello et al., "Cloud computing in construction industry: Use cases, benefits and challenges," Autom. Constr., vol. 122, p. 103441, 2021, DOI: 10.1016/j.autcon.2020.103441.
- [7] S. Meng, X. He, and X. Tian, "Research on Fintech development issues based on embedded cloud computing and big data analysis," Microprocess. Microsyst., vol. 83, p. 103977, 2021, DOI: 10.1016/j.micpro.2021.103977.
- [8] X. Li et al., "Curriculum Reform in Big Data Education at Applied Technical Colleges and Universities in China," IEEE Access, vol. 7, pp. 125511–125521, 2019, DOI: 10.1109/ACCESS.2019.2939196.
- [9] P. Li, S. Guo, S. Yu, and W. Zhuang, "Cross-Cloud MapReduce for Big Data," IEEE Trans. Cloud Comput., vol. 8, no. 2, pp. 375–386, 2020, DOI: 10.1109/TCC.2015.2474385.
- [10] L. Hu, Q. Ni, and F. Yuan, "Big data oriented novel background subtraction algorithm for urban surveillance systems," Big Data Min. Anal., vol. 1, no. 2, pp. 137–145, 2018, DOI: 10.26599/BDMA.2018.9020013.
- [11] C. Li and H. Dai, "Throughput Scaling of Primary and Secondary Ad Hoc Networks With Same-Order Dimensions," IEEE Trans. Veh. Technol., vol. 63, no. 8, pp. 3957–3966, 2014, DOI: 10.1109/TVT.2014.2310424.
- [12] C. Cramer, O. Stanze, K. Weniger, and M. Zitterbart, "Reactive clustering in MANETs," Int. J. Pervasive Comput. Commun., vol. 2, no. 2, pp. 81–90, May 2007, DOI:10.1108/17427370780000143.
- [13] A. Yassine, A. A. N. Shirehjini, and S. Shirmohammadi, "Bandwidth On-Demand for Multimedia Big Data Transfer Across Geo-Distributed Cloud Data Centers," IEEE Trans. Cloud Comput., vol. 8, no. 4, pp. 1189–1198, 2020, DOI: 10.1109/TCC.2016.2617369.
- [14] P. Sen, R. Prasad, and P. Saurabh, "A New Approach for Cloud Security Using Hybrid Querying System Over Cloud Scenario," in Advances in Intelligent Systems and Computing, 2019, vol. 904, pp. 367–376, DOI: 10.1007/978-981-13-5934-7\_33.
- [15] J. Ramkumar and R. Vadivel, "Improved frog leap inspired protocol (IFLIP) – for routing in cognitive radio ad hoc networks (CRAHN)," World J. Eng., vol. 15, no. 2, pp. 306–311, 2018, DOI:10.1108/WJE-08-2017-0260.
- [16] J. Ramkumar and R. Vadivel, "Meticulous elephant herding optimization based protocol for detecting intrusions in cognitive radio ad hoc networks," Int. J. Emerg. Trends Eng. Res., vol. 8, no. 8, pp. 4549–4554, 2020, DOI: 10.30534/ijeter/2020/82882020.
- [17] L. Zhao, Z. Bi, M. Lin, A. Hawbani, J. Shi, and Y. Guan, "An intelligent fuzzy-based routing scheme for software-defined vehicular networks," Comput. Networks, vol. 187, p. 107837, Mar. 2021, DOI: 10.1016/j.comnet.2021.107837.
- [18] W. xi Liu, J. Cai, Q. C. Chen, and Y. Wang, "DRL-R: Deep reinforcement learning approach for intelligent routing in softwaredefined data-center networks," J. Netw. Comput. Appl., vol. 177, p. 102865, Mar. 2021, DOI: 10.1016/j.jnca.2020.102865.
- [19] M. S. Daas, S. Chikhi, and E.-B. Bourennane, "A dynamic multi-sink routing protocol for static and mobile self-organizing wireless networks: A routing protocol for Internet of Things," Ad Hoc Networks, vol. 117, p. 102495, Jun. 2021, DOI: 10.1016/j.adhoc.2021.102495.
- [20] X. Liu et al., "Adaptive data and verified message disjoint security routing for gathering big data in energy harvesting networks," J. Parallel Distrib. Comput., vol. 135, pp. 140–155, Jan. 2020, DOI: 10.1016/j.jpdc.2019.08.012.
- [21] X. Wang et al., "Building efficient probability transition matrix using machine learning from big data for personalized route prediction," in Procedia Computer Science, Jan. 2015, vol. 53, no. 1, pp. 284–291, DOI: 10.1016/j.procs.2015.07.305.
- [22] T. Baker, B. Al-Dawsari, H. Tawfik, D. Reid, and Y. Ngoko, "GreeDi: An energy efficient routing algorithm for big data on cloud," Ad Hoc Networks, vol. 35, pp. 83–96, Dec. 2015, DOI: 10.1016/j.adhoc.2015.06.008.
- [23] Y. Chen and J. Wu, "Joint coflow routing and scheduling in leaf-spine data centers," J. Parallel Distrib. Comput., vol. 148, pp. 83–95, 2021,



DOI: 10.1016/j.jpdc.2020.09.007.

- [24] P. K. Dey and M. Yuksel, "An Economic Analysis of Cloud-Assisted Routing for Wider Area SDN," IEEE Trans. Netw. Serv. Manag., vol. 17, no. 1, pp. 445–458, 2020, DOI: 10.1109/TNSM.2019.2947030.
- [25] K. Wu, P. Lu, and Z. Zhu, "Distributed Online Scheduling and Routing of Multicast-Oriented Tasks for Profit-Driven Cloud Computing," IEEE Commun. Lett., vol. 20, no. 4, pp. 684–687, 2016, DOI: 10.1109/LCOMM.2016.2526001.
- [26] S. Xu, X. Wang, G. Yang, J. Ren, and S. Wang, "Routing optimization for cloud services in SDN-based Internet of Things with TCAM capacity constraint," J. Commun. Networks, vol. 22, no. 2, pp. 145–158, 2020, DOI: 10.1109/JCN.2020.000006.
- [27] J. Ramkumar and R. Vadivel, "Multi-Adaptive Routing Protocol for Internet of Things based Ad-hoc Networks," Wirel. Pers. Commun., pp. 1–23, Apr. 2021, DOI: 10.1007/s11277-021-08495-z.
- [28] J. Ramkumar and R. Vadivel, "Performance Modeling of Bio-Inspired Routing Protocols in Cognitive Radio Ad Hoc Network to Reduce Endto-End Delay," Int. J. Intell. Eng. Syst., vol. 12, no. 1, pp. 221–231, 2019, DOI: 10.22266/ijies2019.0228.22.
- [29] J. Ramkumar and R. Vadivel, "CSIP—Cuckoo Search Inspired Protocol for routing in Cognitive Radio Ad Hoc Networks," in Advances in Intelligent Systems and Computing, 2017, vol. 556, pp. 145–153, DOI: 10.1007/978-981-10-3874-7\_14.
- [30] J. Ramkumar and R. Vadivel, "Bee inspired secured protocol for routing in cognitive radio ad hoc networks," Indian Journal of Science and Technology., vol. 13, no. 30, pp. 3059–3069, 2020, DOI: 10.17485/JJST/v13i30.1152.

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