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QoS based Optimal Path Selection Using Adaptive Sparse Bayesian Find-Fix-Finish-Exploit-Analyze Based Extreme Learning Machine for SDN based IoT Networks

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Abstract: SDN (software defined network) is a networking approach which enables the IoT (internet of things) to be maintained through programming. The assessment of best routing path satisfying the requirements of QoS (quality of service) possess a significant role in networking. Several methods have been employed by the researchers for maintaining the necessities of QoS. But due to certain limitations like data latency, protocol complexity and bursty traffic which affects the network performance. In the proposed work, adaptive sparse bayesian-find fix finish exploit analyze- extreme learning machine (ASB-F3EA-ELM) is employed with four steps such as cluster formation, cluster head selection, rule caching policy and optimal path selection. The cluster formation is performed by using grid structures for forwarding the data packets. To avoid data transfer from all the IoT nodes, process of cluster head selection for each cluster is performed by modified aquila optimizer (MAO). A prominent rule caching policy is implemented for reducing rule caching cost in SDN based IoT architecture. The best routing path for effective data transfer is performed by the approach of ASB-F3EA-ELM. The performances of proposed approach are analyzed in the NS2 platform. The outcomes are estimated in terms of bandwidth, rule caching cost, delay, throughput, network lifetime and packet loss rate. When comparing to the existing methods, the proposed work shows better output in satisfying the requirements of QoS as it achieved improvement in throughput of 3.89% to 7.97%, packet loss rate reduced from 0.11% to 0.07%, network lifetime increased by 13.75% to 27.5% as compared to PSO, GA, ACO and GWO methods.

Keywords: SDN, IoT, Data transfer, Cluster head, Rule caching policy, Optimization, Routing, QoS.

1. Introduction

The generation of enormous physical devices day by day holds the tendency to link with worldwide IoT (internet of things). Efficient transmission of data between IoT devices is the major requirement of a network [1]. Various applications indulged in the IoT field are transportation, banking services, healthcare department and smart agriculture [2]. There are so many challenges existing in the adoption of IoT devices like guarantee providence of safety, large connection of devices, unregulated levels of QoS (quality of service), storage and handling capacity of data [3]. In order to overcome these challenges, it is highly necessary to generate the upgraded protocols of networking [4-5]. The significant network called SDN (software defined network) which divides the function of control, transmission in to data and control plane [6]. The controllers are established in the control plane to limit the bursty traffic over the network communication.

The traffic condition of the communication network is managed by the controller which is programmable [7-8]. The transaction of data flows between the devices and controller are performed in the data plane. The structure of SDN indulges three layers called application layer, control layer and infrastructure layer [9]. Different application which relays the network details or requests for the presence of valuable resources. The controllers of SDN contact with the applications to acquire the destination details about the information packets [10-11]. The controllers are programmed to efficiently use the cache and indulge load balancing inside the SDN architecture. The IoT devices gathers guidance from the controller for providing the packet routes [12]. A programmable protocol of network communication is established in the SDN for directing traffic among the IoT devices [13]. The main components involved in SDN process are control plane, data plane, communication protocol, network switch, centralized computing and programming paradigm.

Different approaches are generated for improving QoS and the problem of dissimilar data flow created due to the distribution of irrational resources should be solved in the network [14]. Certain traditional models like best effort, diffserv and int-serv have some drawbacks to achieve efficient traffic control and provides negligible service quality [15-16]. The QoS can be improved by dispersing the traditional systems for the effective transfer of data in every router [17]. Normally, SDN requests to the controller for attaining the linked rules in packet forwarding but, there occurs a drawback of transmission delay to the controller [18]. To solve the issue of delay, flow tables are assigned in a temporary manner to cache certain rules for the respective amount of time [19]. The generation of temporary cache avoids frequent contact to the controller and the delay is reduced. The IoT devices generate a temporary cache called TCAM (ternary content addressable memories) for the quick process of entry packets.

The entire memory of TCAM is analyzed with a clock cycle where high speed is generated in the flow table [20]. The TCAMs are considered to be more powerful in power consumption and more valuable when compared to RAM storages [21]. But still the issue tends to complex when the IoT devices are huge in network. Even though, the resources of TCAM plays a major role over the network performance, satisfaction of QoS among data flows is a challenging one [22]. The necessity of QoS is very high in the form of differentiable data flows and so, the procedure of efficient classification is performed in SDN [23]. The differentiable data flows in SDN network are not efficient to choose an optimal path to acquire QoS [24]. When the network link is in heavy traffic, the IoT services are influenced. For satisfying the requirements of QoS, hybrid novel methods are possessed to determine the best routing path in SDN based IoT networks.

Motivation

An effective network should satisfy several parameters of QoS based on the dissimilar data flows in enormous services of IoT. An approach of best routing optimization is highly required for the network operator to promote the system performance. While considering SDN, it acts as a significant model of networking and offers flexible programmable control for the fine transfer of data. The strategies of routing are analyzed in SDN through the utilization of flow rules. These rules are stored in TCAM with limited capacity and cannot be accessed rapidly when the users are huge. In SDN, the routing process selects the appropriate path based on the necessities of QoS dataflow. In case of dissimilar data flows, the attainment of QoS becomes the major issue which degrades the network performance. Another issue is to find the best route for data flows with dissimilar requirements of QoS. These QoS issues motivated many of the researchers to overcome. Hence to promote better QoS in SDN based IoT, an efficient technique called rule caching policy is implemented for the selection of best routing path which assures the requirements of QoS.

The major contributions of the proposed work are represented below;

- To undergo a process of cluster selection by adopting modified aquila optimizer (MAO) on the basis of residual energy, intra-cluster distance and sink station distance for improving the network lifetime.
- To design RCP (rule caching policy) to meet the requirements of SDN based IoT network which reduces the rule caching cost and packet loss rate (PLR).
- To determine an efficient routing path using adaptive sparse Bayesian find-fix-finish-exploit-analyze based extreme learning machine (ASB-F3EA-ELM)for assuring QoS constraints.

The proposed work is comprised of various categories which are described as follows. The recent related works for selecting the optimal path based on QoS are mentioned in section 2. The proposed methodology is described in section 3 which presents selection of cluster head and optimal routing path. The performance results and discussion are provided under section 4. Finally section 5 includes the conclusion of proposed work and future scope with references.

2. Related works

Based on the analysis of various research papers, the related works are summarized below.

Mahantesh et al. [25] established a SDN architecture based on IoT devices for the efficient selection of optimal path for data forwarding. In order to attain effective heterogeneous flows, maintenance of cache, method of QOPS-RCP (QoS aware optimum path selection and rule caching policy) were implemented. The best routing path was chosen through this research and satisfied several constraints of QoS such as cost of RC (rule caching), delay and PLP (packet loss probability). Rule caching policy was contributed for satisfying the necessities of SDN based IoT devices where the RC cost was reduces. This research was implemented in the open flow module and the performances were calculated with respect to E2E (End to end) delay and throughput. The advantage of this research was, high performance was attained and the drawback was, increased access latency.

QoS based routing in SDN architecture was investigated by Jalil et al. [26] and the parameters of QoS examined were loss, delay, bandwidth and cost. A fresh learning result of deep reinforcement in online QoS routing called DQR (deep Q routing) was implemented in this research. DQR adopted a DDQR (dueling deep Q routing) with respective experience for the computation of routing path regarding any S-D (source to destination) request in the presence of various QoS metrics. When compared to the existing deep reinforcement learning (DRL) based routing, DQR overcome the discrete control problem and a reward function was used for satisfying the parameters of QoS. The E2E throughput was highly improved in the simulation results. The limitation faced here was, maximization of bandwidth is not sufficient.

A routing protocol based on ACO (ant colony optimization) was proposed by Kulkarni et al. [27] to attain important values of QoS parameters. To achieve better performance and higher flexibility, QoS based routing algorithm was implemented in SDN. This research was related to classification of different types of network traffic. For performing classification process, Bandwidth necessity was introduced for differentiating multi-media traffic including audio, text and video. ACO is compared with PSO-SDN (Particle swarm optimization-SDN) and the performance analysis of this research showed better capability over the parameters of QoS. High performance was achieved and the major drawback was, the routing protocol can be more effective which can be implemented with other optimization algorithm for optimal results.

An approach of EFQM (enhanced flow based QoS management) was implemented by Bassene et al. [28]. A mechanism of QoS management in SDN based IoT network was illustrated in this research. The utilized time was lowered within the control plane and SDN controller was adopted to decrease loss. The bandwidth was optimized based on the latency flow and bandwidth necessities. By the consideration of default routing and delay as performance metrics, the average E2E flow was improved, delay and PLR (packet loss rate) was reduced. The runtime required in EFQM was minimized and the issues of SDN technology was lowered. When EFQM is compared with the performance of AQRA (application aware QoS routing algorithm), EFQM promoted better output. The drawback faced here was, traffic programmability was not efficient.

Liu et al. [29] implemented an approach of SDN based active measurement to calculate the evaluation parameters for accessing the smart network over power communication. The QoS was increased for the users by assembling the key of traffic QoS sensing. The statistical data were collected from open flow switches by possessing the instructions of OFP (open flow protocol). The network performance was estimated through the measurement of network parameters in power communication. An algorithm of SDN based active measurement updated the measurement interval by utilizing the throughput variations. This research was verified through the adoption of POX controller and Mininet simulator. The performance results of this research showed better accuracy results and the drawback faced here was, throughput efficiency did not meet the requirements.

A SDN based routing algorithm known as QoS guaranteed and congestion limited open flow routing strategy (QCORS) was proposed by Su et al. [30]. Through this model, numerous communication demands can be fulfilled through the utilization of SDN with high flexibility. The proposed policy in this research was expected to separate the link into diverse traffic levels on the basis of predicted congestion status for future from transmission connections. The corresponding packets are expected over router transmission through the connections under less load conditions. The network reliability can be guaranteed and the average peer to peer delay can be minimized. The performances were analyzed by considering the metrics including delay, jitter and packet loss. The major drawbacks were, huge assumption of artificial parameters and subjects over security threats.

Alidadi et al. [31] introduced a low complexity algorithm called SDN-MPLS (multi-protocol label switching) in this research work. The major

Table 1. Review of various approaches in SDN based IoT network

Author name	Approaches used	Objective	Advantages	Limitations
Mahantesh *et al.* [25]	QOPS-RCP (QoS aware Optimum Path Selection and Rule Caching Policy)	To select the best routing path and satisfy various parameters of QoS.	High performance is attained.	Access latency is increased.
Jalil*etal.* [26]	DQR (Deep Q routing)	To compute the best routing path and examine QoS parameters like delay, loss and bandwidth.	E2E throughput is highly improved.	Bandwidth maximization is not sufficient.
Kulkarni *et al.* [27]	QoS based routing algorithm with Ant Colony Optimization	To acquire better performance and higher flexibility.	QoS parameter shows better capability.	Routing protocol is not effective enough.
Bassene *et al.* [28]	SDN based QoS management using EFQM (Enhanced Flow based QoS management)	To optimize the bandwidth on the basis of latency flow and bandwidth requirements.	Delay, PLR and runtime are reduced.	Inefficient traffic programmability.
Liu *et al.* [29]	SDN based active measurement for estimating the QoS parameters.	To gather the statistical data from open flow switches and to evaluate the network performance.	Performance shows accurate results.	Efficiency of throughput does not meet the requirements.
Su *et al.* [30]	QCORS (QoS guaranteed and congestion limited open flow routing strategy)	To present a routing algorithm with guaranteed QoS and limited congestion.	Better network reliability and less delay can be obtained	Huge assumption of artificial parameters and prior to security threats.
Alidadi *et al.* [31]	SDN-MPLS(Multi-Protocol Label Switching)	To manage the resources effectively and to satisfy the QoS metrics.	Effective examination of critical path connections.	Higher consumption of CPU time.

objective of SDN-MPLS model is to manage the resources effectively and to satisfy the QoS metrics. The model improves bandwidth restricted routing whereas a trade off can be attained between route length, load balancing of network and energy storage with less complexity. The performances including average path length, maximum available flow, call blocking ratio and CPU time were analyzed. In accordance to the link weights, the links were chosen to satisfy the maximum amount of future demands. The critical connections can be effectively examined whereas the CPU time taken in finding the paths were found to be very high. Table 1 represents the review of related works including SDN based IoT network.

Due to certain drawbacks like increased latency during data accessing, unavailability of required bandwidth, complexity issues, throughput scarcity, ineffective routing protocol and traffic programmability in the existing approaches, the efficiency of network communication is degraded. To overcome these issues, a new model is proposed in this research for effective data transfer with minimized traffic flow.

3. System model of SDN based IoT network

In the system model of SDN based IoT architecture, a set of IoT nodes are assembled in the network region. The different clusters are formed on the basis of grid. For each cluster a cluster head is selected and the data are transmitted to the SDN controller from cluster head. The SDN network comprises of data plane and control plane for data communication. When the cluster head requests for

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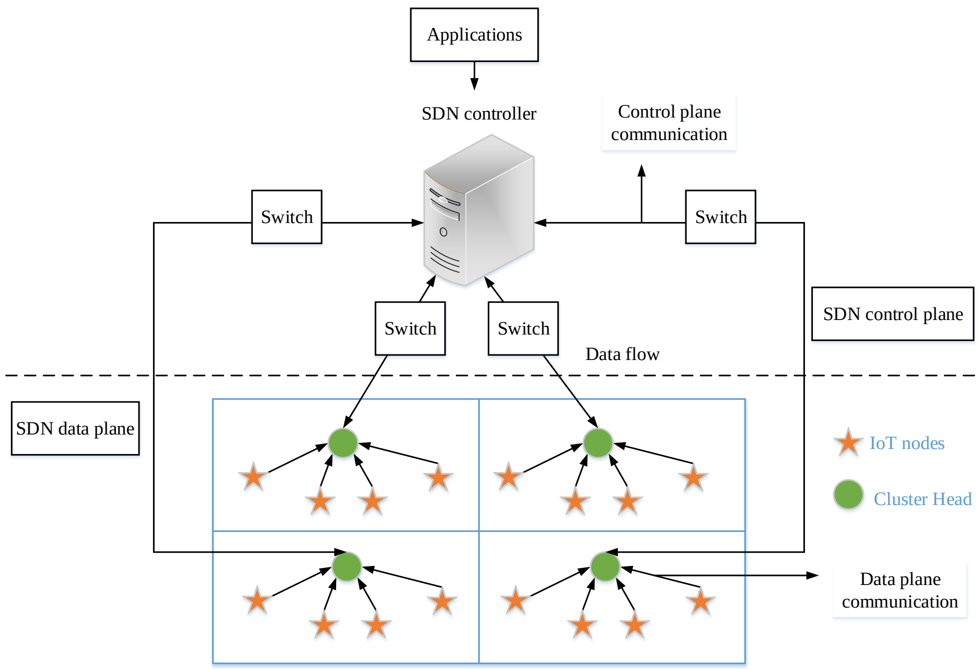

Figure. 1 System model of SDN with IoT

data to the SDN controller, it offers a program to the cluster head. To avoid delay in the data packets, the rule caching policy is used for transmitting the data packets. The network performance and reliability of SDN based IoT network can be enhanced. Fig. 1 describes the system model of SDN based IoT network for satisfying the QoS requirements.

4. Optimized routing protocol model

The selection of optimal routing path is discovered by undertaking the process of cluster formation, cluster head selection and implementation of rule cache policy. The steps involved in cluster formation by using grid, selection of cluster head by adopting MAO technique, rule cache policy, constraints of QoS and ASB-F3EA-ELM technique for choosing the best routing path are explained as follows.

4.1 Cluster formation

The process of clustering is one of the efficient techniques in SDN based IoT network which provides significant network performance. The SDN network is assembled in to several groups by considering the requirements of applications and network characteristics [32]. Several IoT nodes are deployed in the region and the formation of different clusters are performed on the basis of grid. For that, the entire region is separated in to different grids possessing same size. The division of clusters should be done on the basis of transmission range of IoT node. Every grid promotes a cluster and the size

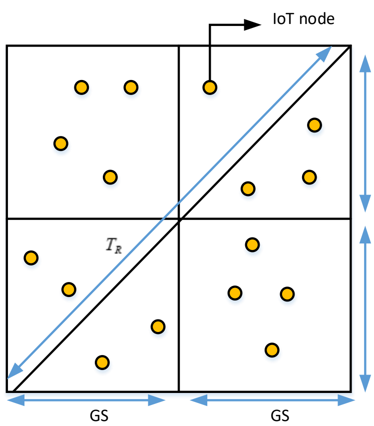

Figure. 2 Cluster grid

of grid can be calculated as follows.

$$T_R^2 = (2GS)^2 + (2GS)^2 \quad (1)$$

$$T_R^2 = 8(GS)^2 \quad (2)$$

$$GS = \frac{T_R}{2.83} \quad (3)$$

where $GS \times GS$ represents the grid size and T_R denotes the transmission range of IoT node. Fig. 2 represents the grid construction for the formation of clusters.

The category of SDN network model comprises of node type and network type. An IoT node can be described either as mobile or stationary. Mobile IoT nodes are the movable one which varies its position dynamically with respect to other nodes. Deployment of mobile IoT nodes retains the lifetime of cluster for a long time and overcomes the issue of packet loss. The stationary IoT node remains stable which do not vary its position. The SDN network type can either be centralized or distributed. In centralized network type, the base station requires details regarding SDN network. While in the distributed type, a node becomes the member node with gathering the network information.

In the phase of cluster formation, the active IoT nodes transmits the data packet to the base station (BS) and becomes the part of cluster. In case of single transmission, only one IoT node transfers the data and that will be successfully captured by the BS. In case of multi-transmission, the data packets lead to congestion and needs retransmission. To avoid the issue of bursty traffic, proper selection of cluster head should be established.

4.2 Cluster head selection

In order to minimize the congestion issues during the data transfer from all the clusters simultaneously, proper selection of cluster head (CH) is adopted. In each group of clusters, an optimal CH is chosen among the IoT nodes. In aquila optimizer (AO), the optimal cluster head is not selected and more energy is consumed during data transfer [33]. Hence, the process of CH selection is implemented by using modified aquila optimizer (MAO). The total number of nodes configured in SDN based IoT network is 100. The parameters considered in MAO are residual energy, intra-cluster distance and sink station distance. Through the utilization of these three parameters, fitness function is generated for the selection of CH.

Evaluation of fitness function

The fitness functions are derived by using the considered parameters as discussed above.

Residual energy

The first parameter considered for deriving the fitness function of IoT node is residual energy. The main objective of this function is to increase the overall residual energy in every cluster head of SDN based IoT network. The following fitness function should be increased in the process of CH selection.

$$\text{Fitness}\ _1 = \sum_{G=1}^{g} REN_{CH_G} \tag{4}$$

here REN_{CH_G} is described as the residual energy of CH_G and the distance of IoT nodes ranges from$1 \leq G \leq g$.

Intra-cluster distance

Intra-cluster distance is contemplated as the second parameter for the objective function which provides the distance between IoT nodes and CH in each cluster. When communication is enabled between several nodes, energy is consumed more. Hence, the distance of intra-cluster should be reduced to minimize consumption of energy. The CH is selected based on the least distance between all the IoT nodes in a cluster. The following fitness function should be decreased in the process of CH selection.

$$\text{Fitness } s_2 = \frac{1}{g}\sum_{G=1}^{g}\left(\frac{1}{N_s}\sum_{i=1}^{N_s} g(I_N, CH_G)\right) \tag{5}$$

From Eq. (5), $N_s$denotes the total number of Iot nodes and $g(I_N, CH_G)$ represents the distance between IoT nodes and CH.

Sink station distance

Sink station distance offers the distance between CH_G and the sink station or base station. For effective processing of data, the relevant information from the IoT node needs to be transferred to the sink station. Hence, the distance between CH and sink station should be reduced and so the following fitness function needs to be minimized.

$$\text{Fitness}\ _3 = \frac{1}{g}\sum_{G=1}^{g}\left(g(\mathrm{CH}_G, \mathrm{SS})\right) \tag{6}$$

The fitness function for MAO should possess increased Fitness $_1$ and decreased Fitness $_2$,Fitness $_3$. Hence the fitness function for MAO is described in Eq. (7).

$$\text{Fitness}\ _k = \mu_1 * \frac{1}{\text{Fitness}\ _1} + \mu_2 * \text{Fitness}\ _2 + \mu_3 * \text{Fitness}\ _3 \tag{7}$$

here, μ_1, $\mu_2$and $\mu_3$are the constant values which offers weight to the objective functions. The addition of these constant values should be equal to 1. Each IoT node in a cluster is checked with the fitness function and cluster head is selected based on the criteria of increased residual energy, decreased intra-cluster distance and sink station distance. Using the method of MAO, cluster head is selected for effective data forwarding to the SDN controller. The random initialization of IoT nodes is represented in Eq. (8)

IoT nodes =

$$\begin{bmatrix} u_{1,1} & \cdots & u_{1x} & u_{1,NS-1} & u_{1,NS} \\ u_{2,1} & \cdots & .u_{2x} & \cdots & u_{2,NS} \\ \cdots & \cdots & u_{wx} & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ u_{M-1,1} & \cdots & .u_{M-1x} & \cdots & u_{M-1,NS} \\ u_{M,1} & \cdots & u_{Mx} & u_{M,NS-1} & u_{M,NS} \end{bmatrix} \quad (8)$$

where, u_w denotes the node position, M represents the total number of nodes and NS denotes the node size.

$$I_{wx} = \text{randomx}(UB_x - LB_x) + LB_x, w = 1,2, \dots M, x = 1,2, \dots . NS \quad (9)$$

From Eq. (9) *random* denotes the random number, UB_x representsx^{th} upper bound and LB_xdenotes x^{th} lower bound. Several IoT nodes are deployed in the region and fitness of each node is analyzed for performing the selection of cluster head. Consider the IoT node of SDN network and the fitness is calculated on the basis of three parameters which is described below.

$$I_1(t+1) = I_{\text{best}}(t) \times \left(1 - \frac{t}{T}\right) + (I_N(t) - X_{\text{best}}(t) * \text{random}) \quad (10)$$

$I_1(t+1)$denotes the solution of next iteration t, $I_{\text{best}}(t)$represents the optimal node solution for data forwarding from IoT node and $\left(1 - \frac{t}{T}\right)$ adopts number of iterations. t Represents the present iteration, highest count of iteration is denoted as T , the population size of IoT nodes is described as M and the random number ranges from 0 to 1. The mean value is estimated using Eq. (11).

$$I_N(t) = \frac{1}{M} \sum_{w=1}^{M} I_w(t), \forall_x = 1,2, \dots, NS \quad (11)$$

Where M is the total number of population, $t$and T denotes the current iteration. The computation of second iteration is given as,

$$I_2(t+1) = I_{bst}(t) \times \text{Mod Levy}(G) + I_R(t) + (a - u) * \text{random} \quad (12)$$

From Eq. (12), I_R denotes a random node and $\text{Mod Levy}(G)$ represents the modified levy flight distribution. In levy flight distribution, certain drawbacks arise like complex power conditions and optimal routing cannot be attained. Hence in MAO, modified levy flight distribution is implemented for providing better outcome. The iteration size $(\tau(q))$ for a certain generation q is modified and it is represented in Eq. (13).

$$\tau(q) = Z \times \delta(q) \times C_{LC} \quad (13)$$

where $\delta(q)$ is calculated from $\delta = \frac{v}{|u|^{1/\alpha}}$, the value of $Z$is set to be 0.0018 and $C_{LC}$is the cultural learning component, which provides the valuable output of levy function. The updated value of modified levy distribution is denoted as,

$$u_{w,x}^{q+1} = u_{w,x}^{q} + \delta(q) \cdot \text{random}\ (0,1) \quad (14)$$

From Eq. (14) $\delta(q) \cdot \text{random}\ (0,1)$denotes the equation of actual levy flights in the MAO. The average of individual node is denoted as,

$$I_3(t+1) = (I_{\text{best}}(t) - I_N(t)) \times \beta\text{-random} + ((UB - LB) \times \text{random} + LB) \times \delta \quad (15)$$

From Eq. (15), $random \in [0,1]$ represents random number, β and δ denotes the adjustment parameters. Eq. (16) depends on I_{best} , $ModLevy$ and quality function $QFun$.

$$I_4(t+1) = \text{QFun} \times I_{\text{best}}(t) - (P_1 \times I(t) \times \text{random}) - P_2 \times \text{Mod Levy}(G) + \text{random} \times P_1 \quad (16)$$

The main focus of using quality function is to manage the search strategy which is defined as,

$$\text{QFun} = t^{\frac{2 \times \text{randon}() - 1}{(1-T)^2}} \quad (17)$$

The value of P_1 is applied to find the best solution and it is described as,

$$P_1 = 2 \times \text{random}() - 1 \quad (18)$$

The value of P_2 is reduced from 2 to 0 and it is described as,

$$P_2 = 2 \times \left(1 - \frac{t}{T}\right) \quad (19)$$

Based on the fitness values of IoT nodes, optimal CH is selected for every cluster. Reliable data forwarding can be performed in the communication between CH among IoT nodes and SDN controller. Table 2 describes the pseudo code for different cluster head selection steps involved in

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Table 2. Pseudo codefor CH selection

```
Initialize the population of IoT nodes
Represent the number of parameters, iterations, number of nodes.
  while (condition is not satisfied) do
    Specify the fitness values of three parameters
      Calculate the fitness function using equation (7)
        Perform iteration functions
          If random number ranges between 0 to 1 then
            Calculate I_1(t+1) using equation (10)
            Upgrade the mean value using equation(11)
  Perform the second iteration I_2(t+1)
            Implement modified levy distribution function
            Modify the iteration size using equation(13)
    Update the value of modified levy using equation (14)
              Calculate the average of random node
Update the quality function using equation (17)
      Initialize the values of P_1 and P_2 for best solution
              Compare the solutions with fitness function
                consider the best fitness value
                  Select the optimal cluster head
           return CH for each cluster
          end if
  end while
```

MAO.

4.3 Rule caching policy

Basically, a significant memory source called TCAM holds data in SDN switches [34]. TCAM compares the entry packet to the patterns and in this proposed work, RCP is implemented to conquer the drawbacks of normal TCAM by contemplating the parameters of Rule caching cost, bandwidth, delay and packet loss rate. Assume the set of switchesas$P = \{p_1, p_2, \dots, p_s\}$, set of network flows as $N = \{n_1, n_2, \dots, n_s\}$ associated with the set of forwarding rules as $D = \{d_1, d_2, \dots, d_s\}$ among SDN switches. The rule caching is denoted by the variableW_{uv} which is mentioned as follows.

$$W_{uv} = \begin{cases} 1 & d_u \quad \text{is cached in } p_v \\ 0 & d_u \quad \text{is notcached in } p_v \end{cases} \quad (20)$$

The cache capacity with respect to each switch is denoted by,

$$\sum_{u=1}^{m} W_{uv} \leq S_v \quad (21)$$

The cache hits related to time instance are described as follows.

$$b_u(t) = n_u(t) \sum_{p_v \in P_u} W_{uv} \quad (22)$$

where$n_u(t)$ denotes the traffic density of flow n_u

Hence the cache hits $B_u(t)$ ranging from time 0 to t can be derived as

$$B_u(t) = \int_0^t b_u(t)dt = \int_0^t n_u(t) \sum_{p_v \in P_u} W_{uv} dt \quad (23)$$

At last, the entire traffic ranging from time 0 to t can be expressed using $N_u(t)$ as

$$N_u(t) = \int_0^t n_u(t)dt \quad (24)$$

The attained hit ratio $C_u(t)$ ranging from 0 to $t$is represented as follows.

$$C_u(t) = \frac{B_u(t)}{N_u(t)} = \frac{\int_0^t n_u(t) \sum_{p_v \in P_u} W_{uv} dt}{\int_0^t n_u(t)dt} \quad (25)$$

In the same way, the total hit ratio $C(t)$ is expressed using EQ. (26)

$$C(t) = \frac{\sum_{u=1}^{m} B_u(t)}{\sum_{u=1}^{m} N_u(t)} = \frac{\sum_{u=1}^{m} \int_0^t n_u(t) \sum_{p_v \in P_u} W_{uv} dt}{\sum_{u=1}^{m} \int_0^t n_u(t)dt} \quad (26)$$

The cache hit ratio is defined as the ratio of total count of requests which matches the cached rule over total count of received requests.

4.4 QoS constraints

Certain constraints of QoS which affects the routing performance with respect to complex applications holding limited capacity, increases the network traffic are discussed below.

4.4.1. Rule caching cost

The rule caching cost needed for the flow N_v is evaluated as the addition of total hit ratio of all the rules gets multiplied with the size of data flow.

$$RCC = \mu * \text{size } (N_v) * \text{Sum } (C(t)\text{rules }) \quad (27)$$

The necessary rule caching cost for a flow N_v denotes RCC , μ represents the weighted constant adopted to normalize the flow size values and sum of hit ratio. The weighted value is assembled in a well adaptive manner in the middle of simulation experiments. The evaluation of flow size is done well with the data rate and flow duration. The constraint of rule caching cost for flowN_v is represented as,

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$$RCC(N_v) < C_v \quad (28)$$

Where C_v denotes the switch capacity.

4.4.2. Packet loss rate

During the accessing of SDN network, accumulation of small data called packets which are sent from the source and received by the destination. When more than one data packet fails to attain its destination, packet loss occurs. The probability of packet loss rate is denoted as,

$$PL_p = PL_p(u,v) + PL_p(v,r) + \cdots .. + PL_p(a,b) \quad (29)$$

The PL_p at each node along the path P at intermission t can be represented as,

$$PL_{p_u} = PL/FR \quad (30)$$

here PL represents the lost amount of packets and FR denotes the flow onset rate.

The total probability of packet loss rate at receiver can be expressed as,

$$PLP^t = \sum PL_{p_u}^t \quad (31)$$

The flow requirement corresponding to the probability of packet loss rate for any path P_k can be expressed as

$$PLP_k(N_v) < L_{th} \quad (32)$$

where L_{th} is the minimum value of threshold.

4.4.3. Delay

When the total amount of time decreases while transmitting the data packets from source to destination in SDN network, there occurs a delay. The packet delay for any path P can be expressed as,

$$DEL_p = d(u,v) + d(v,r) + \cdots . + d(a,b) \quad (33)$$

The flow requirement with respect to network delay for any path can be denoted as

$$DEL_k(N_v) < DEL_{th} \quad (34)$$

From Eq. (34) $DEL_k = \sum_{u,v \in p1} d(u,v)$ and $d(u,v)$ represents the link from u to v. The L_{th} and DEL_{th} values depend upon the flow of IoT traffic.

4.4.4. Bandwidth

The bandwidth of a network is measured by the increased capacity of communication link during data transmission at specified amount of time. The bandwidth can be estimated by the below mentioned expression.

$$BW = (T_D * (100/DD_R) * 8192)/(RWT * 3600) \quad (35)$$

where Tot_D denotes the total data, DD_R denotes the ratio of data duplication and RWT describes the replication window time.

4.5 Best routing path selection using ASB-F3EA-ELM

Extreme learning machine (ELM) is an advanced version of single layer feed forward network. Through the adoption of random hidden node parameters, ELM estimates the output by performing the inverse of hidden matrix without iterative optimization. ELM possess certain drawbacks like high computational complexity, large memory requirement and degraded generalization performance. To meet the requirements of Qos in SDN network, a novel method called adaptive sparse Bayesian find-fix-finish-exploit-analyze based extreme learning machine (ASB-F3EA-ELM) is implemented. The different routing paths between IoT nodes and SDN controller are checked and optimal path is determined by ASB-F3EA-ELM. The different paths in SDN network are initialized at first. By excluding the excess hidden neurons in a neural network, a regression model is contemplated as,

$$o = \tilde{R}\tilde{\alpha} + \delta \quad (36)$$

From Eq. (36) $\tilde{R} = [R, \text{ones } (N,1)] \in \lambda^{N\times(M+1)}$, $\tilde{\alpha} = [\alpha; \alpha_0]$ and δ represents the Gaussian noise with zero mean and variance σ^2. The likelihood function of regression vector can be expressed as,

$$p(o \mid \tilde{\alpha}, \sigma^2) = \left(\frac{1}{2\pi\sigma^2}\right)^{\frac{N}{2}} \exp\left(-\frac{1}{2} \parallel 0 - \tilde{R}\tilde{\alpha} \parallel_2^2\right) \quad (37)$$

where N denotes the total number of IoT nodes. To control the routing complexity using Bayesian rule, the zero mean Gaussian prior is formulated as,

$$p(\tilde{\alpha} \mid \theta) = \left(\frac{\theta}{2\pi}\right)^{\frac{D}{2}} \exp\left(-\frac{\theta}{2} \parallel \tilde{\alpha} \parallel_2^2\right) \quad (38)$$

here θ denotes the hyper parameter representing inverse variance. Using Eqs. (37) and (38), the posterior can be calculated as

$$p(\tilde{\alpha} \mid \theta, \sigma^2, o) = \frac{p(o|\tilde{\alpha},\sigma^2)p(\tilde{\alpha}|\theta)}{p(o|\theta,\sigma^2)} \quad (39)$$

Here o represents the output weight, The Gaussian posterior with mean and covariance can be estimated by

$$\hat{\mu} = \sigma^{-2}\sum \tilde{R}^T o \quad (40)$$

$$\sum = \left(\sigma^{-2}\tilde{R}^T R + \theta I\right)^{-1} \quad (41)$$

where $\hat{\mu} = [\mu; \mu_0]$, $\sum$ represents the covariance and I denotes the inverse function. The two hyper parameters can be expressed as,

$$\theta \leftarrow \frac{\eta}{\tilde{R}^T\tilde{R}} \quad (42)$$

$$\sigma^2 \leftarrow \frac{\|-\tilde{R}\hat{\mu}\|_2^2}{N-\eta} \quad (43)$$

In order to optimize the hyper parameter of routing path, weights are initialized using the optimization method called F3EA (find-fix-finish-exploit-analyze). The weight optimization in the routing path can be expressed by the following equation.

$$\vec{C}_u^t = \vec{D}_u^t + x\left(T_{uk}^t \frac{(\vec{D}_k^t - \vec{D}_u^t)}{\|\vec{D}_k^t - \vec{D}_u^t\|} + z(T_{uk}^t)\frac{(\vec{Q}_{uk\perp})}{\|\vec{Q}_{uk\perp}\|}\right. \quad (44)$$

Where xT_{uk}^t and $z(T_{uk}^t)$ are the position of IoT node, $\vec{D}_k^t$ and $\vec{D}_u^t$ are the imaginary axis perpendicular to x-axis, $\vec{Q}_{uk\perp}$ is perpendicular to the hyper line $\vec{D}_k^t, \vec{D}_u^t$ in the z axis.

For the detection of effective routing path, a probabilistic mode is expressed in the proposed ASB-F3EA-ELM.

$$p(t \mid w, r) = \prod_{u=1}^{N} \sigma\{\varphi(r_u; w)\}^{t_u}[1 - \sigma\{\varphi(r_u; w)\}]^{1-t_u} \quad (45)$$

From Eq. (45), $p(t \mid w, r)$ denotes the bernouli probabilistic distribution, $t = (t_1 \ldots t_N)^T t_u \in \{0,1\}$, $w = (w_1 \ldots w_M)^T$ and the sigmoid function $\sigma(.)$ is represented as,

$$\sigma[\varphi(r; w)] = \frac{1}{1+e^{-\phi(r;w)}} \quad (46)$$

From Eq. (46) $\varphi(r; w) = rw$

The best routing path is determined by the following criteria

$$\hat{o} = \begin{cases} \text{Optimal paths} & \text{if } \hat{\mu} > 0 \\ \text{Paths} & \text{if } \hat{\mu} < 0 \end{cases} \quad (47)$$

The proposed ASB-F3EA-ELM provides better QoS in SDN based IoT network by selecting the optimal routing path and increases the performance of data transfer. The issues of network traffic and complexity issues can be overcome. Table 3 describes the pseudo code for optimal path selection.

Table 3. Pseudo code for optimal path selection

```
Initialize the population of IoT nodes
Represent the number of parameters, iterations, number of nodes.
while (condition is not satisfied) do
Specify the regression model of hidden neurons using equation (36)
Compute the output using
R̃ = [R, ones (N,1)] ∈ λ^{N×(M+1)}, α̃ = [α; α_0]
Denote the noise δ // Gaussian noise
If condition satisfied then
initialize the values of mean and variance
    Represent the likelihood function of regression vector
Perform Bayesian rule
If rule satisfies then
 Formulate the zero mean Gaussian prior p(α̃ | θ)
Calculate the posterior using equation (39)
Estimate the Gaussian posterior
Assume mean μ̂ = σ^{-2} ∑ R̃^T O and
covariance ∑ = (σ^{-2} R̃^T R + θI)^{-1}
Represent θ and σ^2 using equation (42) and (43)
// hyper parameters
Optimize the weights of hyper parameters using equation (44)
Calculate p(t | w, r) using equation (45)
// probabilistic mode
Represent the sigmoid function using equation (46)
if μ̂ > 0 satisfied then
Select the optimal routing path
else
Repeat the process
end if
end if
end if
end while
```

5. Results and discussion

The proposed ASB-F3EA-ELM method is implemented by utilizing NS2 platform to evaluate the performance of the optimized routing protocol. The developed process is compared with certain approaches including PSO (particle swarm

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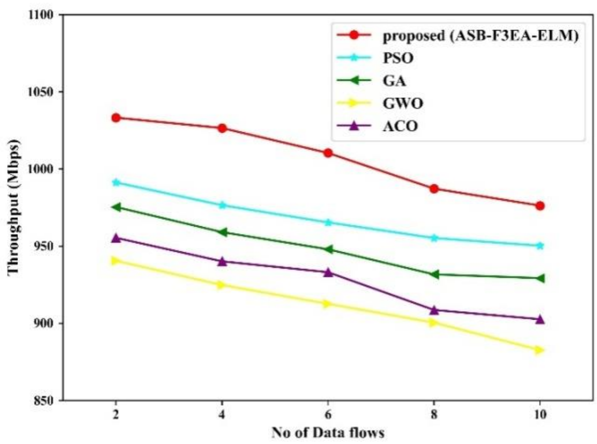

Figure. 3 Throughput for varied data flows

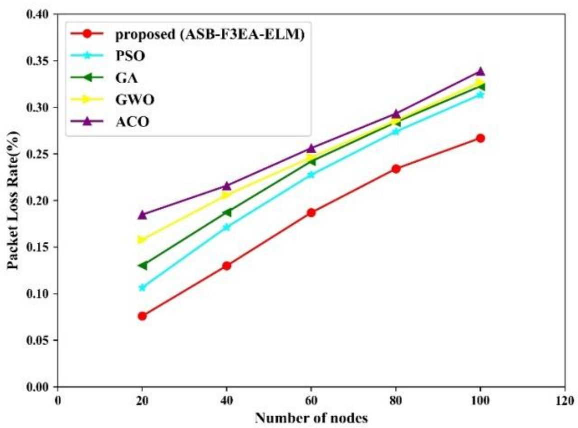

Figure. 4 Packet loss rate vs nodes

optimization), GA (genetic algorithm), GWO (gray wolf optimizer) and ACO (ant colony optimization) to bring out the efficient performance of the proposed approach. Normally, the IoT devices in the SDN network are constrained with respect to delay, bandwidth, rule caching cost, packet loss ratio, network lifetime and throughput. In the proposed method, the IoT nodes are deployed randomly in the region of SDN network. The simulation parameters of the proposed method are network size as 600x600m, initial energy is set as 0.5J, packet size as 4000 bits.

5.1 Performance analysis

The performance of optimal routing path which satisfy the QoS requirements are measured in terms of throughput, packet loss rate, delay, network lifetime, rule caching cost and bandwidth. The output of performance metrics is described in a graphical representation.

Fig. 3 describes the throughput in terms of megabits per second (mbps) with respect to the number of data flows. The network throughput can be calculated by the total number of data transmitted from source to destination and vice versa with respect to time. When the range of data flow is 2, the existing method of PSO attains 990 mbps, GA attains 970 mbps, GWO achieves 948 mbps and ACO achieves 952 mbps. The proposed method attains higher throughput value 1030 kbps. When the range increases to 10 the proposed ASB-F3EA-ELM achieves increase in throughput outcomes as 3.89%, 5.83%, 7.58% and 7.97% as compared to PSO, GA, ACO and GWOmethods. The attained throughput is highly efficient to perform best path selection for data transfer.

Fig. 4 represents the packet loss rate with respect to the total number of nodes. The packet loss rate is equal to the number of lost data packets to the total number of sent packets. For an effective network communication, the packet loss rate should be minimized for better performance. When the total number of nodes deployed is 20, the existing method of PSO attains (0.11%), GA attains (0.13%), GWO achieves (0.15%) and ACO achieves (0.18%). The packet loss rate of the proposed method is (0.07%). When the number of nodes increases to 100,the packet loss rate of the proposed ASB-F3EA-ELM is (0.25%) which provides better data flow efficiency when compared to the existing methods. The minimized packet loss rate improves the network performance.

Fig. 5 represents the attained delay regarding total number of nodes. When the total number of nodes are set to be 100, the delay occurred in the proposed method is reduced which paves for effective routing path. During the data transmission of the existing methods the delay is augmented which leads to degraded performance. When compared to the existing approaches, the delay is lessened and high amount of data delivery is promoted in the proposed approach.

Fig. 6 describes the network lifetime regarding total number of IoT nodes. The network lifetime is represented on the basis of failure time of the first IoT node and it is measured by the number of successful packets received by the SDN controller. When the total number of nodes deployed is 20, the existing method of PSO attains 6.9mbps, GA attains 6.5mbps, GWO achieves 5.8mbps and ACO achieves 6mbps. The network lifetime for the proposed method is 8mbps. When the number of nodes increases to 100, the network lifetime of the proposed ASB-F3EA-ELM is 6mbps which provides efficient data flow when compared to the existing methods. The network lifetime is increased by 13.75%, 18.75%, 25% and 27.5% compared to PSO, GA, ACO and GWO methods.

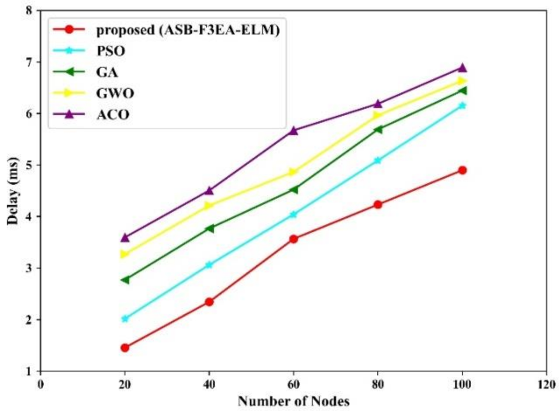

Figure. 5 Delay with respect to nodes

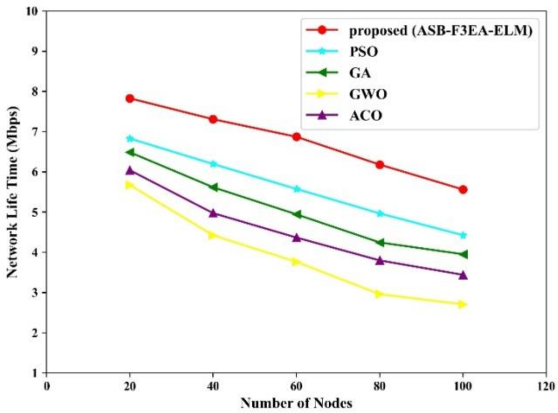

Figure. 6 Network lifetime vs nodes

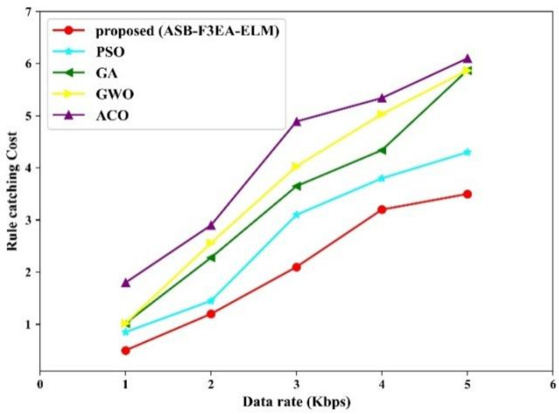

Figure. 7 Rule caching cost for data rate

The rule caching cost regarding data rate in kbps (kilobits per second) is described in Fig. 7. For the selection of effective routing path, the rule caching cost should be minimized. The proposed ASB-F3EA-ELM outperforms the best output by lowering the rule caching cost. Through the analysis of existing approaches, the rule caching cost is increased which maximizes the complexity issues. When the data rate varies, the rule caching cost of proposed approach outperforms the better result with 5kbps.

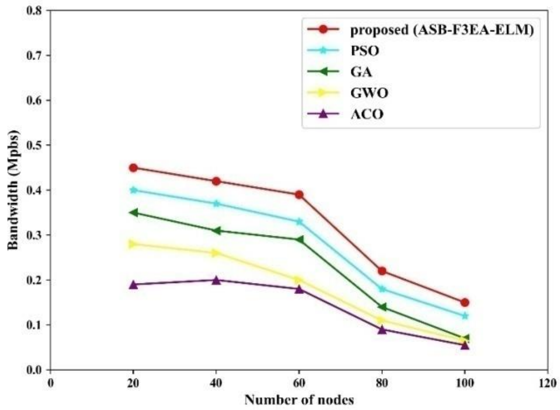

Figure. 8 Bandwidth with respect to nodes

The bandwidth with respect to number of nodes is described in Fig 8. For the selection of optimal routing path for data transfer, increased bandwidth is required. Bandwidth represents the entire data transferred over the internet with respective time. When the number of nodes increases, the bandwidth is also raised in the proposed ASB-F3EA-ELM which offers best results when compared to the existing methodologies.

6. Conclusion

An efficient approach for satisfying the requirements QoS in SDN based IoT network through the selection of optimal routing path is implemented in the proposed ASB-F3EA-ELM method. The major objective of the proposed approach is to overcome the problems of QoS constraints in the network. Hence a grid based cluster formation is performed and followed by this, selection of cluster head is adopted through MAO method for minimizing the network traffic during data transfer. Rule caching policy is established for efficient data forwarding and reducing the rule caching cost. For the optimal selection of routing path, ASB-F3EA-ELM is implemented for satisfying the QoS requirements. The results of proposed approach show high throughput, increased network lifetime, maximum bandwidth, decreased rate of packet loss, lowered delay and rule caching cost. When compared with the existing approaches, better performance is achieved in the proposed method. In future, the proposed work can be extended with better optimization and path selection method for improving the network reliability.

Conflicts of interest

All the authors declare no conflict of interest.

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Author contributions

Conceptualization, Mahantesh H M, Nageswara Guptha M, Hema M S; methodology, Mahantesh H M, Nageswara Guptha M, Hema M S; software, Mahantesh H M; validation, Nageswara Guptha M, Hema M S; formal analysis, Mahantesh H M, Nageswara Guptha M; investigation, Mahantesh H M, Hema M S; resources, Mahantesh H M, Nageswara Guptha M, Hema M S; data curation, Mahantesh H M, Nageswara Guptha M, Hema M S; writing—original draft preparation, Mahantesh H M, Nageswara Guptha M, Hema M S; writing—review and editing, Mahantesh H M, Nageswara Guptha M, Hema M S; visualization, Mahantesh H M, Nageswara Guptha M, Hema M S; supervision, Nageswara Guptha M, Hema M S.

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