Demonstration of AI-Assisted Energy-Efficient Traffic Aggregation in 5G Optical Access Network

Luyao Guan, Min Zhang*, Danshi Wang
State Key Laboratory of Information Photonics and Optical Communications, Beijing University of Posts and Telecommunications (BUPT), Beijing, 100876, China
**email address of corresponding author: mzhang@bupt.edu.cn.*

Abstract: We propose an AI-assisted energy-efficient traffic aggregation scheme, which is demonstrated in software-defined optical network testbed. The experimental results show proposed scheme can efficiently reduce energy consumption by traffic aggregation according to traffic prediction.

1. Introduction

With the exponential growth of power consumption in telecommunication industry, the topic of energy efficiency has attracted extensive interest in the related fields in recent years[1,2]. Nowadays, most of researches achieve energy saving by configuring resource according to real-time services resource requests[2]. However, as increasing dynamic and burst traffic being generated in optical access network, above methods are no longer able to efficiently configure resource to reduce energy consumption and satisfy low latency requirement due to their frequent policy response and inevitable reconfiguration process[3]. Motivated by this challenge, proactive traffic prediction approach is one of the most effective solutions, which can track on and predict traffic value of base station in the future, avoiding executing policy and configuration frequently according to real-time services resource requests. But in existing studies, little researchers consider the integrated research of traffic prediction and resource scheduling schemes to achieve traffic aggregation and reduce energy consumption.

Thereby, our work focuses on achieving AI-assisted energy-efficient traffic aggregation scheme. According to the results of traffic prediction, we can execute energy-efficient traffic aggregation (ETA) scheme and timely reconfigure resources in advance. What's more, the proposed scheme is experimentally demonstrated in our software-defined optical access network testbed (SD-OANet). The experimental results show that the proposed scheme decreases average delay and reduces the energy consumption by 29.17% via decreasing the number of active vBBU.

2. SD-OANet Architecture And AI-Assisted Energy-Efficient Traffic Aggregation Signalling Procedure

2.1. SD-OANet Architecture

In order to achieve energy-efficient traffic aggregation according to the traffic prediction, we design a more flexible and programmable SDN-based optical access network architecture, namely SD-OANet.

For data plane, as shown in Fig. 1, BBUs are separates from cell sites and centralized into central offices, meanwhile leaving RRHs in cell sites. Time Wavelength Division Multiplexing-based optical links are used to connect the BBUs pool (colocated with OLTs)and the separated RRUs (integrated with ONUs). And each physical nodes (i.e., BBU, RRH, and remote nodes) are attached with an OpenFlow agent that communicates with RYU controller through extended OpenFlow protocols. At first, assumed without AI-ETA scheme, resource utilization of vBBUs are 50%, 50% and 80% respectively. After implementing AI-ETA scheme, the resource utilization of vBBUs are 90%, 0% and 90%. The scheme achieves saving energy by traffic aggregation to reduce the number of activated vBBU.

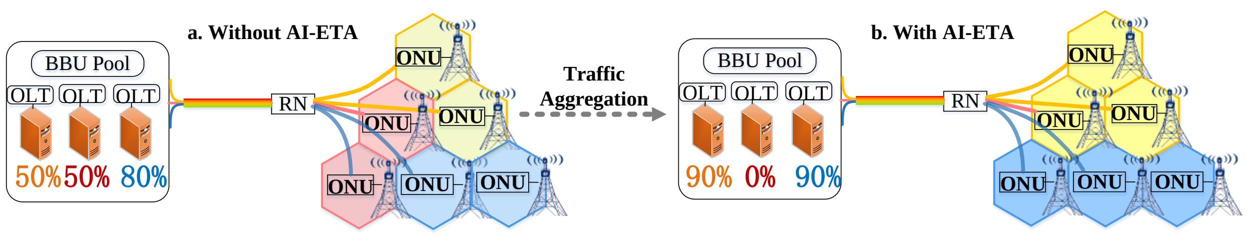

Fig. 1 Data plane architecture and illustration of energy-efficient traffic aggregation scheme: (a) Without AI-ETA; (b) With AI-ETA.

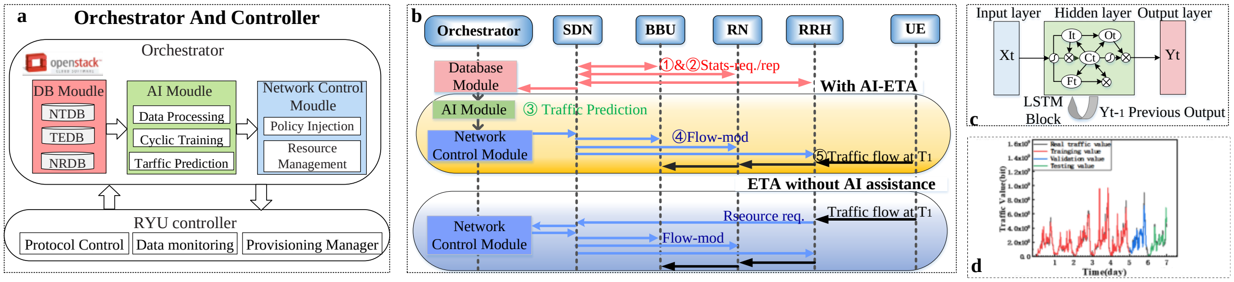

Fig .2 (a) Network orchestrator and controller; (b) Signalling procedure of AI-assisted ETA and ETA without AI assistance; (c) LSTM model; (d) Prediction results.

The network orchestrator and controller is shown in Fig. 2(a). The orchestrator consists of database module (DB module), AI module and network control module. The DB module includes network topology database, network resource database and traffic engineering. In AI module, the data processing applies data stream mining techniques on the received data and periodically transforms monitored data into cyclic training. Modelled data is used to train traffic prediction model based LSTM. In the network control module, policy injection module injects and executes AI-ETA scheme, and network resource management module achieves resource allocation according to the scheme by notifying the controller pushing corresponding flows.

2.2. AI-Assisted Energy-Efficient Traffic Aggregation Signalling Procedure

With AI-ETA, the workflow of interaction in SD-OANet is shown as Fig. 2(b). Step 1&2: the controller requests state information by sending state-request message to vBBUs, RN and RRHs in real time. The agents respond with feature report messages carrying physical properties of devices. When controller receives state reply message from each of them timely, all of the information are stored and updated in the corresponding database. Step 3: the collected traffic statistics are forwarded to AI module consistently. When the next period traffic conditions has been predicted, it will be transmitted to network control module. Step 4: according to the prediction traffic value, the policy injection module executes our injected ETA scheme. Then, controller will send flow-mod message to inform corresponding RRHs, RN and vBBUs to switch path in advance. Step 5: transmit the traffic flows to corresponding vBBU servers. Compared with AI-ETA scheme, signalling procedure of energy-efficient traffic aggregation according to real-time services resource requests (ETA without AI assistance) is also shown in Fig. 2(b). It is obviously that the scheme without AI-assisted ETA increases average delay due to the process of resource request, policy response and configuration, degrading the user experience.

3. AI-Assisted Energy-Efficient Traffic Aggregation Scheme

As prediction model, LSTM algorithm can learn long-term dependency information which has good performance in predicting time series problems, as shown in Fig. 2(c). It is trained and evaluated by the traffic recording dataset of existing optical networks from China Telecom, from 12 base stations in 9 km2 area. The dataset was divided into 3 sets that are training set, verification set and test set and the ratio of them is 6:2:2. We trained the prediction model to obtain the set of weights of the LSTM that minimizes the error between the predicted value and the true value of the traffic. By training prediction model, we perform a 30-minutes prediction given the previous six-hours historical data and average percentage accuracy is up to 90.2%. The predicted traffic value and the true traffic value of one of these base stations is given in Fig. 2(d).

According to the predicted traffic, network operators can execute AI-ETA algorithm in advance and timely reconfigure resources, decreasing the number of active vBBU and the energy consumption. In the algorithm, as shown in Fig. 3, first, we standardize the predicted traffic of RRHs according to the vBBU capacity and put them in list L in decreasing order. Then determine the number of active vBBU and their threshold as B_{th}. Each packing tests all possible subsets of predicted traffic to find one that fits the vBBU capacity. When a subset is determined, these traffic will be removed from L and aggregated to a same vBBU. The procedure will end when all the RHHs are assigned. $G = G* = \emptyset$ and $r = 1$, where r is the index of the traffic in list L, G is the subsets of tasks currently assigned for the vBBU and $G*$ is the subsets of tasks in the best packing, which will be equal to the new

Algorithm 1 :Energy - Efficient Traffic Aggregation
Input: L, N
Output: traffic aggregation solution
Sort L in decreasing order
find the N_B and $B_{th} = A*$
switch off the leaving $vBBU$
for $i = 1$ to N **do**
  if $0 < Z_i \leq S(G)$ **then**
    $G = G \cup \{Z_i\}$;
    Based minimum bin slack one packing search $(i+1)$;
    $G = G \setminus \{Z_i\}$;
    if $S(G*) = 0$ **then**
      Exit ;
    end if
  end if
  if $S(G) < S(G*)$ **then**
    $G = G*$;
  end if
end for

Fig. 3 Energy-efficient traffic aggregation algorithm

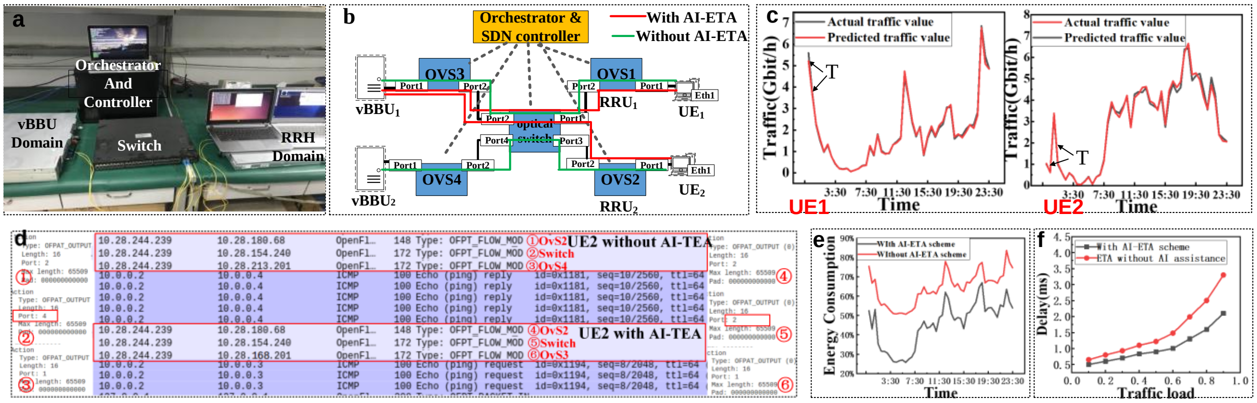

Fig. 4 (a) SD-OANet testbed; (b) Network topology; (c) Traffic prediction results of two users; (d) Capture of OpenFlow messages; (e) Energy consumption with AI-ETA and without AI-ETA; (f) Average delay with AI-assisted energy-efficient traffic aggregation scheme and average delay of energy-efficient traffic aggregation scheme without AI assistance.

B_{th}. The slack in packing G is represented by $S(G)$, and $S(G)$ can be basically computed by starting from $S(G) = v_{th}$ and updating every time a task is added to or removed from G.

4. Experimental Setup and Results

The SD-OANet testbed includes three Linux servers equipped with Gigabit Fiber interfaces and one optical switch, as depicted in Fig. 4(a). The orchestrator and controller are implemented on a separate Linux server using Ryu version 3.20.29. The interfaces are connected with a virtual switch supporting OpenFlow 1.3, that is implemented by using OpenvSwitch (OvS) 2.48. The specific network connection topology as shown in Fig. 4(b), OvS1 and OvS2 are the switches to which two RRUs (i.e., RRU1 and RRU2) are connected respectively. Optical switch connects the RRUs and the vBBUs. OvS3 and OvS4 are the switches to which two BBUs (i.e., BBU1 and BBU2) are connected respectively. We generated two data flows according to existing optical networks from China Telecom as inputs of UE1 and UE2 by OP WILL OTP-6200 traffic analyser. And in our testbed, we achieve traffic prediction according to the traffic inputs of UE1 and UE2, as shown in Fig. 4(c).

To verify the performances of the proposed scheme in terms of average delay and energy consumption, we perform the experiment on the testbed. The traffic inputs of UE1 and UE2 is shown in Fig. 4(c), generated by OP WILL OTP-6200 traffic analyser. During time T in Fig. 4(c), the corresponding OpenFlow protocol messages have been captured. The SDN controller inform the switch to modify flow entries by using an OFPT FLOW MOD message, which shows the successful configuration of the flow entry as shown in Fig. 4(d). As shown in Fig. 4(e), compared with the scheme without AI-ETA, the proposed AI-ETA scheme reduces the energy consumption by 29.17% via traffic aggregation to decrease the number of active vBBU. What's more, AI-ETA can preferably satisfy low latency requirements of subscribers. Because policy response and resource configuration can be executed in advance according traffic prediction, which can avoid the process of services resource request, policy response and configuration and improve user experience. As shown in Fig. 4(f), it is clearly that the experimental results show the average delay of the scheme with AI-assisted energy-efficient traffic aggregation scheme is much better than the energy-efficient traffic aggregation scheme without AI assistance, especially in heavy load.

5. Conclusion

This paper presented an AI-assisted energy-efficient traffic aggregation scheme to efficiently configure resource, reduce energy consumption and satisfy latency requirements according to the traffic prediction. The scheme is demonstrated in our software-defined optical access network testbed and the experimental results demonstrate the feasibility.

6. References

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