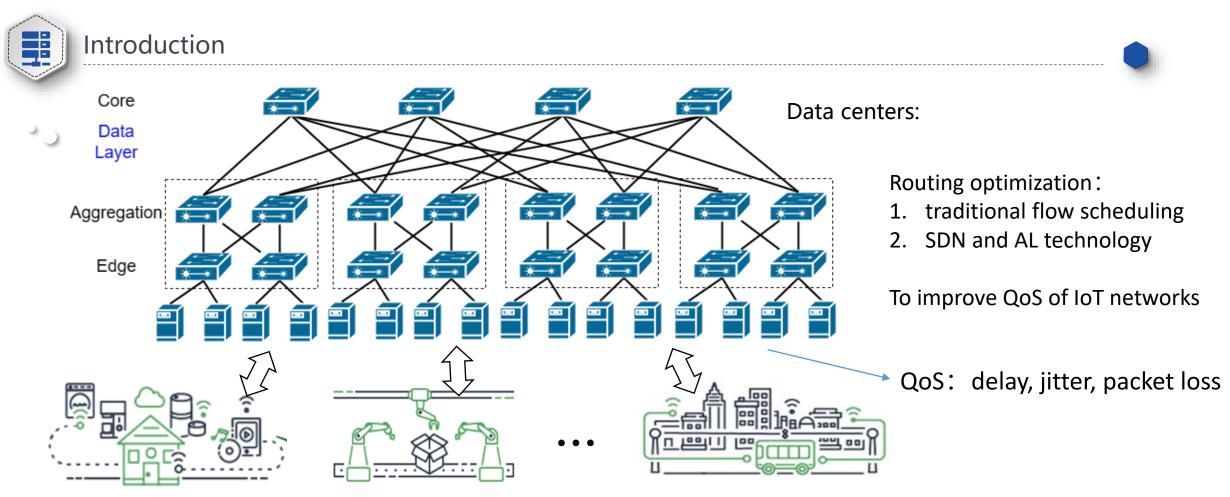


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A CNN-Based Routing Scheme for Minimizing TCP Flow Completion Time in SD-DCNs

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IoT devices at home Smart factory

Smart cities

We use an AI-based routing scheme to reduce the FCT in SD-DCNs. Our contribution is listed :

1) we proposed a flow-based routing algorithm using fixed point iterations;

2) for the first time, we apply the convolutional neural network (CNN) to routing optimization for TCP applications in SD-DCNs.





We consider a basic SD-DCN architecture including three layers: the data layer, the control layer and the application layer.

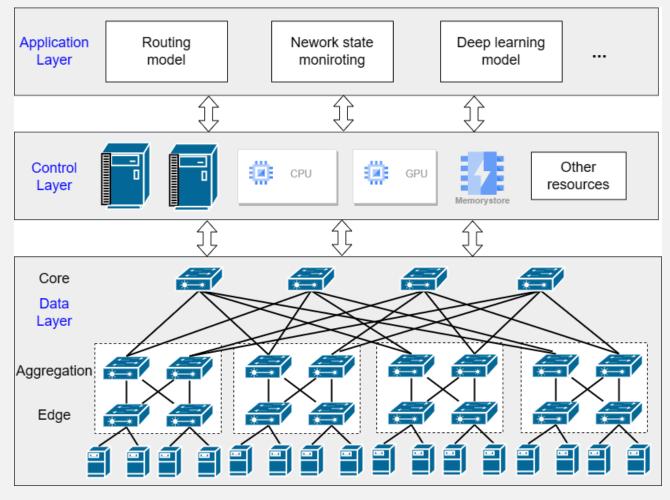
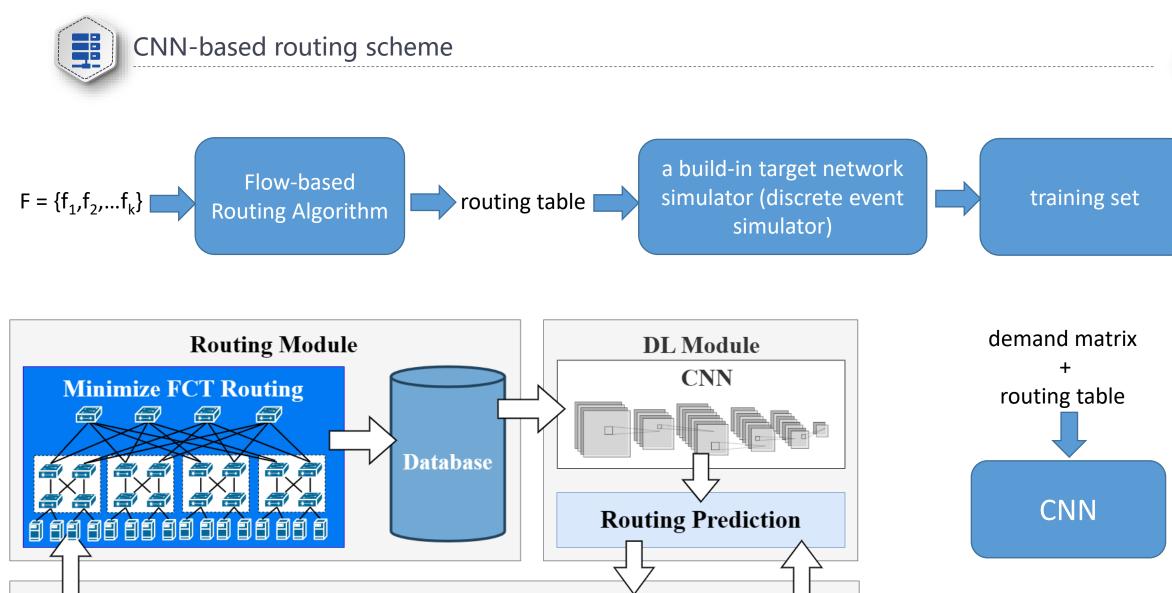


Fig. 1: the architecture of SD-DCN

	Key Information				
V	The set of SDN switches				
E	The set of possible links between switches				
(v _i , v _j)	The link from v_i to v_j				
c _{ij}	The capacity of (v_i, v_j)				
F	The set of flows {f ₁ ,f ₂ ,f _k }				
Р	The set of routes $\{p_{f1}, p_{f2},, p_{fk}\}$				
FCT	Flow completion time				
P ={pf1, pf2,, pfK } \longrightarrow F = {f ₁ , f ₂ ,, f _k }					
Minimize the FCT of all flows					
	np-hard				
The dynamic A CNN-based routing sche					



The resultant model is implemented in the application layer for routing computation.

Traffic

Sampling

Fig. 2: CNN-based routing scheme

The Data Layer

Topology

Monitoring



The flow completion T is :

$$T = \sum_{i=1}^{m} T_i \qquad T_i = \sum_{k \in p} (s_k + q_k)$$

Based on [4], the arrival of packets follows the Poisson distribution, then each queue of the target network can be modeled as an M/D/1/FIFO system.

The average delay of an M/D/1/FIFO system is:

$$D = \frac{1}{\mu} + \frac{\rho}{2\mu(1-\rho)} , SO \qquad T_i = \sum_{k \in p} \left(\frac{1}{\mu_k} + \frac{\rho_k}{2\mu_k(1-\rho_k)} \right)$$

To minimize the FCT, we need to minimize the delay T_i of the flow . Using d_k to represent the delay of packets in the k^{th} flow . Multi-objective(flows) optimization:

$$\min(d_1(A\gamma), d_2(A\gamma), \dots, d_k(A\gamma))$$
 path-edge matrix
s.t. $\lambda = A\gamma$ $A \text{ (aij } \in \{0, 1\})$
 $\sum_{(u,v)\in E} \lambda_{uv} = \sum_{(v,z)\in E} \lambda_{vz}$ $\begin{cases} a_{ij} = 1, \text{flow j chooses li} \\ a_{ij} = 0, \text{otherwise} \end{cases}$
 $\lambda_{uv} L < c_{uv}$ (γ) is the arrival rate of the flow

Algorithm 1 Flow-based Routing Algorithm Using Fixed Point Argument Method

```
Input: network topology G(\mathbb{V}, \mathbb{E}), flow vector \mathbf{f};
      Output: the minimum FCT path vector p;
        1: \mathbf{p}^{(0)} = []
        2: n = 0
        3: for f_i \in \mathbf{f} do
              use the algorithm in [12] to get the initial path p_i for flow f_i
              \mathbf{p}^{(n)}.append(p_i)
        5:
                                                            Initialization
              for each link (u, v) \subset p_i^{(n)} do
        6:
        7:
                 (u, v).pps = (u, v).pps + f_i.pps
                 pps means packets per second
        8:
              end for
        9:
       10: end for
       11: repeat
       12:
              n = n + 1
                                                                Iteration
       13:
              for f_i \in \mathbf{f} do
                 for each link (u, v) \subset p_i^{(n-1)} do
       14:
       15:
                     (u, v).pps = (u, v).pps - f_i.pps
       16:
                 end for
                                                                Update
       N:
                 for each link (u, v) \subset E do
       18:
                     (u, v).pps = (u, v).pps + f_i.pps
                                                                weights
       19:
                 end for
      20:
                  use (6) to calculate the delay as link's weight
      21:
                 use the algorithm in [12] to get the path p_i for flow f_i
                 for each link (u, v) \not\subset p_i do
ink i 23:
                     (u, v).pps = (u, v).pps - f_i.pps
      24:
                  end for
                                                                Termination
                  p_i^{(n)} = p_i
       25:
               end for
                                                                condition
       27: until p^{(n)} == p^{(n-1)}
          \mathbf{p} = \mathbf{p}^{(n)}
```







Fully **Convolution Pooling Convolution Pooling** Output connected Input 60 55 39 58 56 69 Time Intervals Demand Matrix Fig. 3: The structure of CNN model dataset network loads $D = \{(X^k, y^k), k = 1, 2, ..., n\},\$ $X^k \in \mathbb{R}^{n \times n}$, (from $\rho = 0.1$ to $\rho = 0.9$)

 $\mathbf{y}^{k} \in \mathbf{R}^{1 \times 9}$

1) Matrix Input: demand matrix can be obtained in SDN controller, including flows between all hosts.

2) Convolution Layers: extract the distinguished features of the input.

$$x_{i,j}^{l} = (X^{l-1} * W_{l})(i,j) + b^{l}$$
$$= \sum_{m=1}^{M} \sum_{n=1}^{N} W_{m,n} a_{i+m,j+n}^{l-1} + b^{l},$$

$$a_{i,j}^l = f(x_{i,j}^l),$$

3) Softmax Output: adopts Softmax as the classifition function to realize routing selection in DCNs

$$p_i(z) = rac{e^{z_i}}{\sum\limits_{j=1}^m e^{z_j}}, \quad z_i = w_i x + b$$

The resultant CNN will be placed in the application layer. SDN controller will sample the network traffic as the input and utilize the CNN to deliver the flow table for packet forwarding.





TABLE I : The detailed CNN Structure information.

No.	Input Layer	Convolution Layer (Kernel)	Pooling Layer	Convolution Layer	Pooling Layer	Fully Connected Layer	Output Layer
S1	16×16	$3 \times 3 \times 5$	2×2	$3 \times 3 \times 5$	2×2	$16\times 16\times 5\times 9$	1×9
S2	16×16	$3 \times 3 \times 10$	2×2	$3\times 3\times 10$	2×2	$16\times16\times10\times9$	1×9
S3	16×16	$3 \times 3 \times 15$	2×2	$3 \times 3 \times 15$	2×2	$16\times16\times15\times9$	1×9
S4	16×16	$5 \times 5 \times 5$	2×2	$5 \times 5 \times 5$	2×2	$16\times 16\times 5\times 9$	1×9
S5	16×16	$5 \times 5 \times 10$	2×2	$5 \times 5 \times 10$	2×2	$16\times16\times10\times9$	1×9
S6	16×16	$5 \times 5 \times 15$	2×2	$5 \times 5 \times 15$	2×2	$16\times16\times15\times9$	1×9
S7	16×16	$7 \times 7 \times 5$	2×2	$7 \times 7 \times 5$	2×2	$16\times 16\times 5\times 9$	1×9
S 8	16×16	$7\times7\times10$	2×2	$7\times7\times10$	2×2	$16\times16\times10\times9$	1×9
S 9	16×16	$7\times7\times15$	2×2	$7\times7\times15$	2×2	$16\times16\times15\times9$	1×9

TABLE II : The accuracy of different CNN structures.

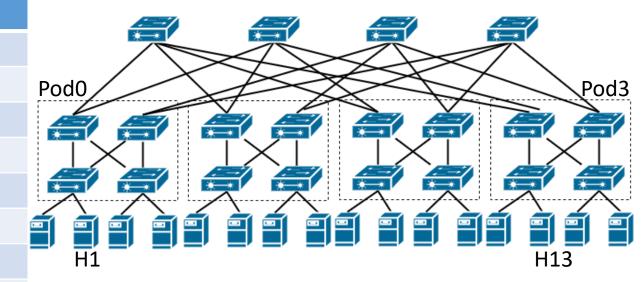
No.	S 1	S 2	S 3	S 4	S 5	S6	S 7	S 8	S 9
The Accuracy	0.9327	0.9956	0.9978	0.9674	1	1	0.9913	1	1
The Convergence Time (s)	8.54	6.93	7.20	6.48	5.12	6.64	7.49	6.21	7.36

S5 √



Simulation parameters

Parameter	Value				
Data Cente	er Networks				
Тороlоду	Fat-tree(k = 4)				
Link bandwidth	1Gbps-10Gbps				
TCP F	Flows				
File size	1 MB				
TCP algorithm	Tahoe				
MSS	1460 bytes				
Sstresh	16 MSS				
Advertised window	65535 bytes				
CN	NN				
Number of layers	10				
Input layer	16 × 16				
Convolution layer	5 × 5				
Max pooling layer	2 × 2				
Activation function	ReLu				
Optimizer	Adam				

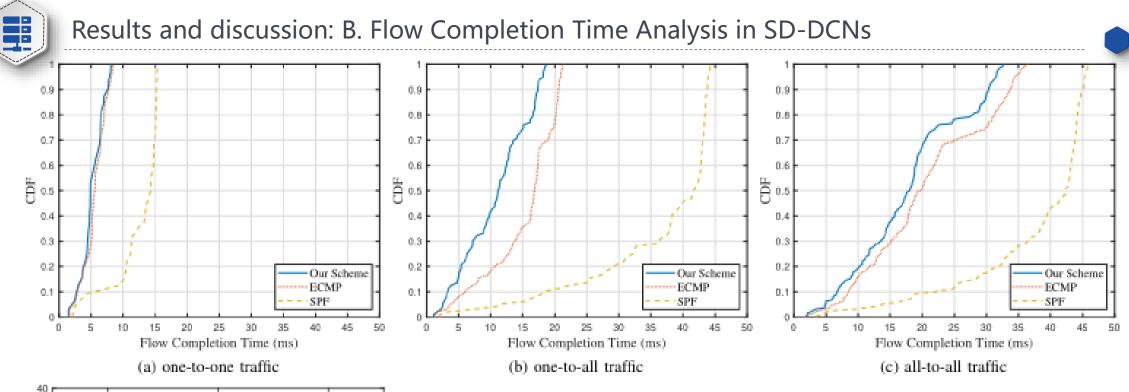


Three traffic patterns:

1) One-to-one traffic: TCP flows between two Pods.

2) One-to-all traffic: TCP flows from one Pod to all other Pods.

3) All-to-all traffic: TCP flows between all Pods.



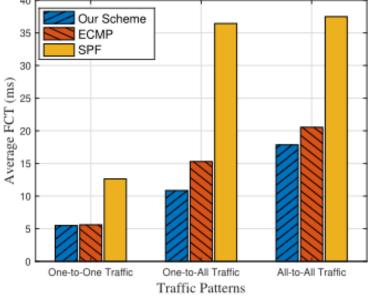


Fig. 4: The CDF of FCT under different traffic patterns.

Conclusions:

- 1. It can be seen that with our scheme, the CDF of FCT is closer to the Y axis than SPF and ECMP. This implies that more TCP flows have shorter flow completion time.
- 2. the performance of our scheme is better than the SPF algorithm and reduces the FCT by up to 50% shorter than the SPF algorithm. For the ECMP, as the load of the network increases, the effect of our scheme is also apparent and reduces FCT by up to 21%. 9



Conclusions

A CNN-based routing scheme for minimizing TCP flow completion time in SD-DCNs is proposed which consists of routing module and CNN model. Our contribution is listed as below:

- we proposed a flow-based routing algorithm using fixed point iterations;.
- we apply the CNN to routing optimization for TCP applications in SD-DCNs.

A simulation platform was implemented based on the three-layer architecture of SD-DCNs with the scheme. The simulation results show that our proposed scheme outperforms the SPF algorithm and ECMP in terms of the flow completion time (FCT).

More importantly, the scheme predicts the path without prior knowledge of traffic input and provides a practical solution to routing problems in real complex SD-DCNs.



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