Leveraging Deep Learning to Achieve Knowledge-based Autonomous Service Provisioning in Broker-based Multi-Domain SD-EONs with Proactive and Intelligent Predictions of Multi-Domain Traffic

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Abstract *This paper demonstrates a knowledge-based autonomous service provisioning framework for multi-domain SD-EONs supported by a broker plane equipped with a deep-learning based traffic estimator. Simulation results show that the proposed framework achieves $\sim 91\%$ traffic prediction accuracy and $\sim 9\times$ blocking reduction compared to conventional solutions.*

Introduction

Rapid growths of cloud-driven applications and expansion of datacenter networks are driving the demand for advanced networking architectures that support high-capacity and high quality-of-transmission (QoT) guaranteed services across multiple domains end to end. Among the emerging network paradigms, the recently developed multi-domain software-defined elastic optical networking (SD-EON)[1] technologies are known to be able to support flexible and high-capacity inter-domain services with enhanced service reaches. Recent publications reported routing, modulation and spectrum assignment (RMSA) algorithms based on either flat[2] or hierarchical[3] control plane architectures to enable multi-domain SD-EONs with improved network throughput. However, all these existing solutions consider only fixed service provisioning strategies regardless of changing network capacity demands, possibly leading to poor and ineffective utilization of network resources. On the other hand, recent breakthroughs in deep learning offer an opportunity for network operators to intelligently manage their networks using big data analytics[4,5].

In this paper, we propose a deep learning knowledge-based autonomous service provisioning framework for broker-based multi-domain SD-EONs. A deep neural network (DNN) based traffic estimator as well as an inter-domain RMSA approach that can perform autonomous traffic engineering according to the obtained knowledge (*i.e.*, predicted traffic) are developed for the framework. Numerical results indicate that high accuracy in traffic prediction and effective reductions in blocking rates can be achieved.

Autonomous Service Provisioning Framework

Fig. 1 shows the designed block diagram of a broker-based multi-domain SD-EON for enabling knowledge-based autonomous service provisioning. Conceptually, the multi-domain SD-EON employs a hierarchical control and management architecture, where a broker plane lies above the domain manager plane to coordinate cross-domain resource configurations. In addition to performing data monitoring and analytics for the

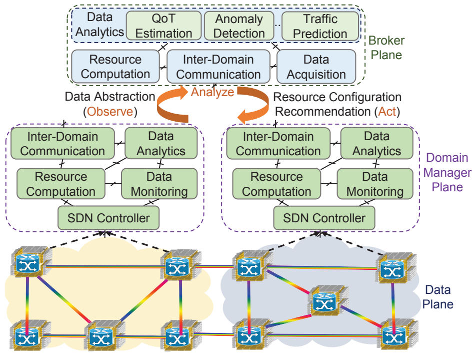

Fig. 1: Broker-based multi-domain SD-EON architecture enabling knowledge-based autonomous service provisioning.

intra-domain management, each domain manager also abstracts the monitored data for the broker to enable a network-wide coordination and service provisioning based on the observe-analyze-act cycle[4]. Specifically, by collecting and archiving the inter-domain lightpath request data over time, the broker can analyze the inherent rules and correlations lying in the multi-domain traffic (*i.e.*, knowledge) and conduct real-time traffic matrix estimations accordingly. Autonomous traffic engineering (*e.g.*, load balancing), thus can be achieved. For instance, in Fig. 3, if the broker perceives the potential burst traffic from D_3 to D_1 and D_3 to D_4 after observing the lightpath request from D_6 to D_3 (*e.g.*, for collaborative computing applications), it may make current requests bypass the links inter-connecting these domains to avoid generating bottlenecks on them. Note that, with proper data modeling and acquisition, the proposed architecture can support variants of other autonomous services, such as QoT-aware path reconfiguration, anomaly detection, failure recoveries.

Deep Learning based Traffic Estimator

We take advantage of deep learning architectures relating to pattern recognition and adopt a DNN-based traffic estimator (as shown in Fig. 2) for the broker. Let $G=\{D_m\}$ denote the multi-domain SD-EON, the input of the DNN can be represented by $\Phi_{t_0} = \left\{\lambda^t_{m,n}, \forall D_m, D_n \in G, t \in [t_0 - T_I, t_0 - 1]\right\}$, where $\lambda^t_{m,n}$ is the traffic demand from domain D_m to domain D_n at time t and T_I is the size of the input time window (*i.e.*, the num-

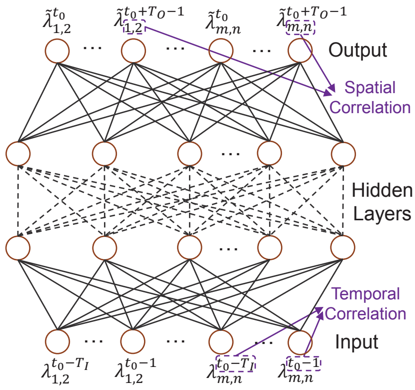

Fig. 2: DNN-based traffic estimator.

ber of nodes in the input layer is $T_I\,|G|\,(|G|-1)$. Each node j in layer $i\,(i>1)$ takes the values from its lower layer (layer $i-1$) as input and calculates its output as,

$$h_{i,j} = f\left(\mathbf{w}^T_{(i-1,j)}\mathbf{h}_{(i-1)} + b\right), \qquad (1)$$

where $f(\cdot)$ is the activation function and $\mathbf{w}_{(i-1,j)}$ is a weight vector for edges from all the nodes in layer $i-1$ to node j. Therefore, each layer is a higher-level representation of the initial input data and by using such multiple hidden-layer representations, the DNN is expected to extract the most useful features, *e.g.*, the spatial and temporal correlations of the inter-domain traffic. Finally, the top layer leverages the learned features and performs a regression task to predict $\Theta_{t_0} = \{\lambda^t_{m,n}, \forall D_m, D_n \in G, t \in [t_0, t_0+T_O-1]\}$. Once the DNN structure is determined, we can train the DNN by iteratively adjusting the values of $\mathbf{w}$ using the back propagation algorithm to minimize the difference between the predicted results and the real labels. Here, we can also include other attributes such as, bandwidth requirements and service durations of the lightpath requests, in order to build a more advanced and complete learning structure.

Inter-Domain RMSA Design

Based on the developed traffic estimator, we design an inter-domain RMSA algorithm (namely, RMSA-DL) that can enable the broker intelligently steering multi-domain traffic to enhance the network throughput. Algorithm 1 shows the principle of RMSA-DL. At each operation time, we first update the input of the traffic estimator to generate new predicted traffic matrixes (*Line* 2). Then, for each pending inter-domain lightpath request, the broker collects virtual links from domain managers to construct a mesh-based topology abstraction[3] for the multi-domain SD-EON in *Line* 4. Physically, virtual links refer to the path segments from the source node to domain border nodes, from domain borders to the destination node and between domain border nodes for source, destination and intermediate domains, respectively. *Line* 5 calculates k shortest paths in the virtual topology for the request, and *Lines* 6-10 count the spectrum utilization and predicted traffic on the inter-domain links traversed by each candidate path. Finally, the broker selects the path by jointly minimizing these two metrics and performs modulation and spectrum allocations accordingly with the first-fit principle (*Lines* 11-12). Here, U_0 and V_0 are for normalization, and we use the exponential operation over $\frac{V_p}{V_0}-\beta$ to nonlinearly scale the weight of predicted traffic, *i.e.*, predicted traffic dominates the path selection when heavy traffic load is anticipated ($\frac{V_p}{V_0} \gg \beta$), and vice-versa.

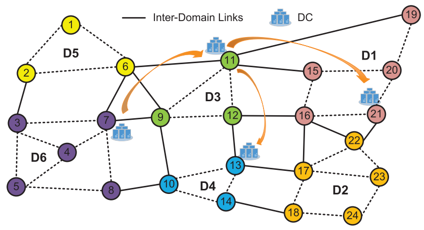

Fig. 3: Six-domain topology used in the simulations.

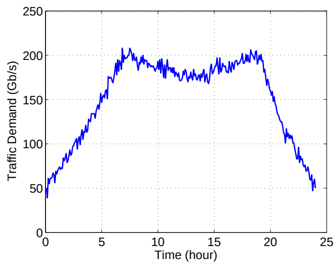

Fig. 4: Basic traffic model for synthetic data generation.

Algorithm 1: Principle of RMSA-DL

1 **for** *each operation time* t_0 **do**
2   predict Θ_{t_0};
3   **for** *each pending inter-domain lightpath request* **do**
4   build a mesh-based virtual topology G';
5   calculate k shortest paths in G';
6   **for** *each candidate path* p **do**
7   store inter-domain links on p in L;
8   calculate U_p as total spectrum usage on L;
9   calculate V_p as total predicted traffic on L;
10   **end**
11   calculate $\omega_p = \frac{U_p}{U_0} + \alpha^{\left(\frac{V_p}{V_0}-\beta\right)}, \forall p$;
12   set up lightpath $p^* = \arg\min_p \{\omega_p\}$ with the first-fit modulation and spectrum allocation scheme;
13   **end**
14 **end**

Simulation Results

We evaluate the performance of the proposed framework with extensive simulations using the six-domain topology in Fig. 3. Synthetic traffic model is measured in the simulations. Specifically, each domain D_m is associated with a basic traffic model $\pi_m(t) = \pi_0(t-\Delta t_m)$, in which $\pi_0(t)$ is depicted by Fig. 4 and $\Delta t_m \in [0,0,4,4,8,8]$ hours is the time offset. Then, given the distance d (number of intermediate domains) among domains, the traffic model for each domain pair (D_m, D_n) is obtained as,

$$\psi_{m,n}(t) = \sum_{D_l} \pi_l(t)\,\eta^l_{m,n}\rho^{-(d_{l,m}+d_{l,n})/2}, \qquad (2)$$

with ρ equal to $11/10$ and $\eta^l_{m,n}$ equal to $1/15$ ($l \neq m,n$) or $3/5$ (otherwise). The idea behind this linear combination is to build a highly correlated and distance dependent multi-domain traffic model in the absence of real traffic traces.

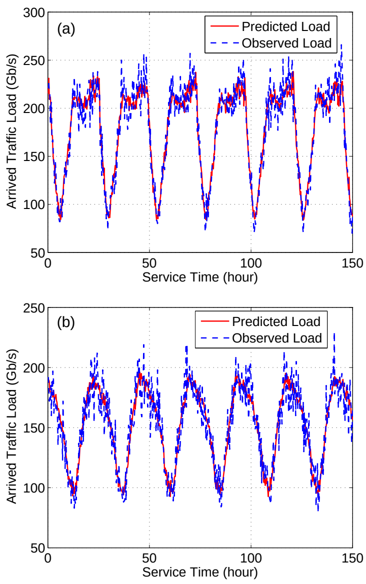

Fig. 5: Comparison between predicted and observed loads ($\gamma = 1$), (a) from D_1 to D_2 and (b) from D_3 to D_6.

Tab. 1: Average prediction accuracy.

Traffic Scenario (γ)	0.4	0.5	0.6	0.7
Prediction Accuracy	88.62%	89.89%	90.73%	91.42%
Traffic Scenario (γ)	0.8	0.9	1.0	
Prediction Accuracy	91.92%	92.49%	92.89%	

We first evaluate the prediction accuracy of the proposed traffic estimator under different traffic scenarios by scaling $\psi_{m,n}(t)$ with a ratio γ ranging from 0.4 to 1. For each scenario, 100000 and 5000 data points together with the corresponding labels are generated for training and testing respectively, where each data point (*i.e.*, Φ_{t_0}) and label (*i.e.*, Θ_{t_0}) follow a Poisson process with the mean values taken from $\psi_{m,n}(t)$. T_I and T_O are set to be 10 and 4, and hence the input and output layers consist of 300 and 120 nodes, respectively. We implement a DNN consisting of 4 hidden layers, which each has a dimension of 100 nodes. Each node in the hidden layers adopts $f_1(x) = \max(x, 0)$ as the activation function while the output layer applies $f_2(x) = x$. Fig. 5 shows two snapshots for the comparison between predicted and observed loads over the testing data when $\gamma = 1$. We observe that the DNN can perfectly predict the trends of the traffic loads between domains. Table 1 summarizes the results on average prediction accuracy for different traffic scenarios, which is defined as $1 - \left(\left|\tilde{\lambda}^t_{m,n} - \lambda^t_{m,n}\right| / \lambda^t_{m,n}\right)$. It can be seen that the prediction accuracy increases with γ and larger than 90% accuracy is achieved for most of the cases. The rationale behind this observation is that the actual traffic at each time point is generated through a Poisson model, and therefore, the produced random deviations are more significant when the mean values are relatively small.

Next, we conduct dynamic multi-domain lightpath provisioning simulations to compare the performance of the designed RMSA-DL algorithm with that of RMSA-KSP-FF, which performs *Lines* 4-5 of Algorithm 1 but provisions the first available path candidate for each request. The modulation and spectrum allocation schemes from the two algorithms are the same. We assume that each fiber link in the multi-domain SD-EON can accommodate 358 frequency slots with a channel bandwidth of 12.5 GHz, and each domain border node is equipped with 50 optical-electrical-optical converters. The dynamic inter-domain lightpath requests are generated according to the aforementioned traffic model, with the demanded transmission rate distributed within $[25, 250]$ Gb/s and the average service duration being 20 time points. For RMSA-DL, α, β, U_0 and V_0 are set as 20, 0.5, 358 and 3500, respectively. Moreover, we generate intra-domain lightpath requests for each domain with a proportion of intra-domain traffic to inter-domain traffic being 0.4. Fig. 6 plots the results on blocking probability for inter-domain traffic from the two algorithms, and we can see that RMSA-DL effectively improves the network throughput. The advantage of RMSA-DL reduces when γ increases, especially when $\gamma \geq 0.8$, due to the fact that the network already gets saturated.

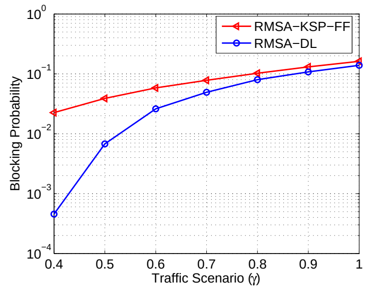

Fig. 6: Blocking Probability.

Conclusions

In this paper, we proposed a knowledge-based autonomous service provisioning framework enabled by a DNN-based traffic estimator for broker-based multi-domain SD-EONs. Simulation results verified the feasibility of the proposed framework for RMSA, demonstrating $\sim 91\%$ traffic prediction accuracy and $\sim 9\times$ blocking reduction for inter-domain traffic compared to RMSA solutions without deep learning (*i.e.*, RMSA-KSP-FF).

Acknowledgments

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