Abstract — Accurate routing network status estimation is a key component in Software Defined Networking. However, existing deep-learning-based methods for modeling network routing are not able to extrapolate towards unseen feature distributions. Nor are they able to handle scaled and drifted network attributes in test sets that include open-world inputs. To deal with these challenges, we propose a novel approach for modeling network routing, using Graph Neural Networks. Our method can also be used for network-latency estimation. Supported by a domain-knowledge-assisted graph formulation, our model shares a stable performance across different network sizes and configurations of routing networks, while at the same time being able to extrapolate towards unseen sizes, configurations, and user behavior. We show that our model outperforms most conventional deep-learning-based models, in terms of prediction accuracy, computational resources, inference speed, as well as ability to generalize towards open-world input.

Index Terms— Graph Convolution, Software Define Networks, Open World Learning

I. INTRODUCTION

Software-defined networking (SDN) is a state-of-the-art approach to network management, which permits dynamic and programmatic network configurations (e.g., routing), aimed at improved network performance and monitoring, abstracted away from individual network elements into a centralized network control layer. Consequently, the orchestration and SDN control software is expected to operate on and adapt to unseen network deployments and topologies. Precise routing-network modeling is a prerequisite for SDN to efficiently estimate and forecast network state. As a result, in certain scenarios, such as during network expansion, it is expected that: (i) several network features (possibly used in model training) become greatly imbalanced; (ii) unseen attribute values are expected to be out-of-distribution; (iii) varying, often larger, network sizes are encountered; and (iv) relational dependencies expand among longer node chains. An illustrative example of above is shown in Fig. 1. A successful approach to deal with the above-mentioned challenges, is to employ ideas from the domain of open-world machine learning (OWL) [1]. Compared with traditional machine learning, OWL is expected to extrapolate towards unseen input distribution, classes, and scaling in the training set. Note, that the problem of estimating the network state is EXPTIME-complete, as shown by [2], and has been extensively studied in the literature [3], where most commonly conventional deep-learning methods are employed in the context of reinforcement learning (RL) based network orchestration as well as deep-learning-based service optimization.
In this paper we consider the problem of estimating the latency between a source and a destination network node (denoted as OD pair) in a routing network. The problem setting is to learn a model on smaller networks and extrapolate the predictions on larger networks assuming open-world input, as illustrated in Fig. [1].

Conventional deep learning (DL) methods have focused in predictive user behavior modeling on service demand and data usage. In this setting, a line of work focuses on leveraging deep neural networks for adaptive optimisation of routing schemes, as by [4], which typically require similar data distribution in the test environment. Only few papers have considered to extrapolate their proposed model on a larger network [5], something which, this far, has been considered infeasible in real-world scenarios. Moreover, successful extrapolation would require introducing task-specific non-linearity (i.e., queuing theory and network calculus in the routing network [6]) in the model [7], something which, this far, has not been considered in state-of-the-art DL solutions.

Graph Neural Networks (GNNs) have been used successfully for incorporating domain knowledge into different problem settings, which in turn, help to devise robust models better suited for OWL in learning complex-system representations. Moreover, our work is primarily inspired by [8] who reveal that by solely observing key nodes in the SDN topology, the deep network can produce effective embeddings capable of predicting network performance.

Our study is among the first approaches that attempt to model the routing network state snapshot by learning the given topology structure for the task of estimating the network latency using open-world input. Our proposed solution transforms the task of estimating the latency between source and destination nodes, to a link-attribute prediction task, i.e., predicting each link that can potentially contribute to traffic delays occurring in the routing trajectory. Estimating every link’s latency contribution requires three aspects: (i) the traffic amount passing through the link; (ii) the capacity of the link; and (iii) link’s structural features. The link traffic and capacity jointly denote the data throughput, and the congestion state of the given link. The link’s structural features can be learned from the network topology and they serve two purposes: (i) to identify key links that can become bottleneck of the network performance; and (ii) to compute pair-wise similarities, which are used to discover similar links. We train our model on distributions of a particular network size, yet, the model achieves at least 75% reduction in mean absolute percentage error (MAPE) measured in different sized networks during inference, i.e., without explicit training using the larger (up to $6\times$) network topologies. Last but not least, our solution requires no GPU resource while still ensures a faster training as well as 3–7 times faster inference speeds, with only 6–25% embedding size required, when compared, for example, with the best-performing benchmark models. The remaining sections are organised as follows: In Sec. [II] we discuss the related approaches in the domain of size generalisation of GNNs and graph-based ML in SDN routing, while in Sec. [III] we present our problem formulation in more detail. In Sec. [IV] we present our methodology followed by Sec. [V] which contains the experimental evaluation of our algorithm. Finally Sec. [VI] concludes with a discussion of our main contributions and considerations for future work.

II. RELATED WORK

Graph Convolutional Networks (GCN) is a known feature-extraction technique for non-Euclidean spaces [9]. GCNs are capable of learning the graph structure by aggregating each node’s embedding with its neighbors. In the conventional architecture, GCN is proven to be capable of incorporating node and edge information in a undirected graph scope. We are currently witnessing an increasing number of publications on GCN models, which, on the one hand reveal the success of this model, and on the other hand expose its limitations.

GCN models are constrained due to aggregating only local neighbors. For large enough graphs, GCN may fail to capture distant (long-range) dependencies entirely. Efforts have been made towards both building deeper GNN models [10] and building expressive GNN layers on long-range dependencies. For example, [11] proposed the first effective method to encode long-range dependencies, between any two nodes, of the graph in the node embedding. Furthermore, [12] propose to apply graph attention network (GAT), to compute shortest-path-to-node attention, based on a transformer [13] architecture. This work is one of the most related approaches to the one presented here. Contrary to the aforementioned contributions, which are based on transductive settings, our work focuses instead on an inductive setting. In our model, we are incorporating path-to-node attention, but passively between the path’s structurally similar node and the targeting node, to tackle longer chains of dependencies in the test data. In addition, we do not build very deep GNN solutions to enlarge the receptive field up to the length of dependency, for balancing between model accuracy, resource usage and inference speed trade-off.

In a survey by [7], the extrapolation ability of GNNs regards mainly two aspects: the ability to extrapolate towards unseen structural features as well as to extrapolate towards out-of-distribution attributes. [14] conclude that the size generalization can only be applied on graphs with certain structural features. Moreover, they suggest that the expressiveness of the GNN model must be still sufficient for applying it to larger graphs. [15] further elaborate from the perspective frequency response, pointing out that spectral graph convolution is inherently transferable for graphs with similar degree distribution.

In our model, we leverage the conclusions from the aforementioned works and cast the graph-size-generalization problem to a transferred formulation of graph, which is considered to be learnable by spectral graph-convolution methods. On the other hand, extrapolation towards out-of-distribution data is a fundamental challenge for most neural networks. For out-of-distribution attributes, the extrapolation ability relies more on the embedding and readout function of the GNN architecture. [7] have shown the multi-layered perception models (MLP)
can only extrapolate if the test set is expanded from the training set in all geometrical directions in the latent space. Both [16] and [17] have studied on approximating simple arithmetic computation (+, −, ×, and ÷) when extrapolate towards drifted numerical values. In our proposed model, we utilize building blocks from [16] to encourage the model to learn the arithmetic impact, when tackling drifted numerical input features.

More recent related works focus on learning the tuned graph representation of routing networks. [18] propose RouteNet, which is regarded as a first work that introduces message passing in deep-learning-based network modeling, in a bipartite graph formulation. [19] and [20] extend RouteNet to be adaptive to heterogeneous scheduling policies and routing scheme, while improving its accuracy and inference speed on similar topology structures. Finally, [5] present their work on be adaptive to heterogeneous scheduling policies and routing which is regarded as a first work that introduces message learning the arithmetic impact, when tackling drifted numerical values. In our proposed model, we utilize building blocks from [16] to encourage the model to learn the arithmetic impact, when tackling drifted numerical input features.

III. PROBLEM FORMULATION

The task we consider in this paper is to perform mean latency estimation on every OD pair \( p \) in the network. We summarize the defined notation in Table. I. The input to our problem is the following:

1) A sequence of attributed size-varying networks \( G = \{G_i(V_i, E_i; X_i, Y_i)\} \), where \( V_i \) denotes the \( |V_i| = n_i \) network nodes and \( E_i \) denotes the \( |E_i| = m_i \) links between pairs of nodes in \( V_i \). For each node \( v \in V_i \), a set of node attributes \( x(v) \) are provided to describe the heterogeneous routing configuration on the network node level. Similarly, a set of link attributes \( y(e) \) is introduced for each link \( e \in E_i \) to denote link configuration attributes with respect to routing. The set of all node attributes in \( G_i \) is denoted by \( X_i \), and the set of all link attributes is denoted by \( Y_i \). Each network \( G_i \) includes \( k_i \) OD pairs \( P_i = \{p_{i,j}\} \), with \( j = 1, \ldots, k_i \).

2) A sequence of traffic matrices \( T = \{T_i\} \), where each \( T_i \) corresponds to a network \( G_i \). Each traffic matrix \( T_i \) consists by \( k_i \) vectors \( \{t_{i,j}\} \), with \( j = 1, \ldots, k_i \), where each \( t_{i,j} \in \mathbb{R}^2 \) denotes the mean throughput and peak throughput features for the OD pair \( p_{i,j} \). Note that there exist OD pairs with same source and destination nodes but different throughput features.

3) A sequence of routing matrices \( R = \{R_i\} \), where each \( R_i \) with dimension \( \mathbb{R}^{n_i \times k_i} \), with 0’s on the diagonal elements, corresponds to network \( G_i \). Each element in \( R_i \), denoted by \( R_{i}(c,d) = r_{i}(v_c, v_d) \), with \( v_c, v_d \in V_i \), represents the next-hop per OD pair, given the current node \( v_c \) and the destination node \( v_d \). Note that \( R_i \) contains information for all possible routing pairs, regardless of the given OD pair elements in \( T_i \).

4) The ground truth: A sequence of performance matrices \( Q = \{Q_i\} \), where each \( Q_i \) corresponds to network \( G_i \). Each performance matrix \( Q_i \) consists of \( k_i \) vectors \( \{q_{i,j}\} \), with \( j = 1, \ldots, k_i \), denoting the performance of each OD pair \( p_{i,j} \) in global (mean latency) and local (per-link occupancy) metrics. The task is to estimate the mean latency value of each OD pair, denote as an element in \( q_{i,j} = Q_i(p_{i,j}) \), with \( j = 1, \ldots, k_i \). Previous works [5], [18]–[20] formulate the problem defined above as a multi-step prediction problem. More specifically, given network snapshots \((G_i, T_i, R_i)\), the goal is to predict the future \( \Delta \) steps of the network state \([Q_i^{1}, \ldots, Q_i^{\Delta}]\) and pool the result of each step for a prediction \( Q_i' \). In contrast, in our model, we consider this problem as a node attribute prediction problem. We introduce a modified problem formulation:

1) Given the input to our problem specified by a sequence of tuples \((G_i(V_i, E_i; X_i, Y_i), T_i, R_i)\), we first transform \( G_i(V_i, E_i; X_i, Y_i) \) to a directed graph, where each undirected edge \((u, v) \in E_i \) is replaced by two directed edges \((u, v) \) and \((v, u) \), and then transform it to a line graph \( G_i^L(V_i^L, E_i^L) \). We define a projection \( L^{-1} \), to project the representation (i.e. \( v_i \in V_i^L, e_i^L \in E_i^L \)) in line graph \( G_i^L \), back to its representation in \( G_i \).

2) The edge set \( E_i^L \) of the line graph \( G_i^L \) is directed. The node set \( V_i^L \) includes only valid routings in \( R_i \), i.e., for all \( v \in V_i^L \) its respective edge representation \( L^{-1}(v) = e(v_x, v_y) \) is in \( E_i \). Thus, there exists \( v_d \in V_i \) such that \( r_i(v_x, v_d) = v_y \) holds.

3) We can compute the summed traffic \( T_i^s \) per-link over all OD trajectory pairs passing through, for each \( n_i \) nodes. Each element is denoted by \( t^s(i, v) = T_i^s(v) \), for all \( v \in V_i^L \). Given node \( v \)'s edge representation \( L^{-1}(v) = e(v_x, v_y) \in E_i \), we define the node attributes \( X_i^L(v) \) in \( G_i^L \) as follows:

\[
X_i^L(v) = \sum_{p_{i,j} \in p_{i,j}} \frac{T_i(p_{i,j})}{c(Y_i(e_{v}))}
\]

(1)

4) For each edge \( e \in E_i^L \) connecting node \( v_e \) to node \( v_d \) in \( G_i^L \). We introduce corresponding edge weight \( w_i(v_e, v_d) \) as follows:

\[
w_i(v_e, v_d) = \sum_{p_{i,j} \in p_{i,j}} \frac{T_i(p_{i,j})}{c(Y_i(e_{v}))}
\]

\[
\frac{Y_i(e_{v_d})}{Y_i(e_{v_e})},
\]

(2)

The motivation behind this re-formulation is multi-faceted: (i) Using directed links in \( G_i^L \) introduces OD trajectory pairs information into the graph structure. The new formulation separates the link’s adjacency into in-degree and out-degree, which will be used to represent the link’s in-coming traffic
Appendix/blob/

(ii) For the task of estimating path latency \( Q_i(p_{i,j}) \), the problem can be decomposed into estimating the latency contribution of each hop \( v \in V^L_i \) into \( \sum_{v \in p_{i,j}} Q_i(v) \). According to queuing theory, such latency contribution further reduces to estimating \( v \)'s queue occupancy state \( O(i,v) \). Thus, in the graph \( G_c^L \), the problem is reduced to a node attribute prediction task \( ^1 \).

(iii) Inspired by previous work, identifying key link that is shared by many OD pairs could have a dominating impact on the whole network performance. In the graph \( G_c^L \), such feature is disclosed within the ego-networks of nodes \( v \in V^L_i \), which can be jointly formed by the trajectories of all paths passing through \( v \). Thus, one can discover the importance of node \( v \) in network topology by its role in \( G_c^L \). (iv) The features computed in Eq. 1 and Eq. 2 are supported by queuing theory\(^2\). Here we consider domain knowledge to be the key in producing a size-invariant graph signal on \( G_c^L \). An illustrative example of re-formulation, comparing with the previous work's is given in Fig. 2.

IV. METHODOLOGY

Fig. 3 provides an overview of our proposed model for the prediction task. In the first phase (Fig. 3a), we transform the input graph \( G_i \) (Fig 3a (i), (ii)) into the line graph \( G^L_c \) (Fig 3a (iii), (iv)) for the model to learn in a latent space that generalizes well on different input graph sizes. Next (Fig. 3b), we separate the graph into a directed sub-graph and a undirected sub-graph that capture the neighboring sequential relation as well as the impact of key nodes. We design the corresponding components that capture each impact and handle out-of-distribution features, so as to get consistent results across different graph sizes. Below, we discuss each component separately.

A. Directed Spectral Graph Convolution

To capture the sequential relation between nodes consisting of the OD pair’s trajectory, as well as the OD pair’s direction, we use the architecture designed by [21]. It is a spectral convolution block with its reception field encoded with direction information, named Directed Graph Convolution Network (DGCN). Given the processed directed \( G^L_c \), we separate the adjacency matrix into three different formations: \( A^F, A^S_{in}, \) and \( A^S_{out} \), which denote first-order proximity, second-order in-proximity and second-order out-proximity, as shown in Fig. 3b. Given the weighted adjacency matrix \( A_F \) of the line graph \( G^L_c \), one can compute the aforementioned quantities:

\[
A^F = \left( A_F + A_T^F \right) / 2, \quad (3)
\]

\[
A^S_{in}(i,j) = \sum_k \frac{A^L_{F}(k,i)A^L_{T}(k,j)}{\sum_v A^L_{T}(k,v)} \quad \text{and} \quad A^S_{out}(i,j) = \sum_k \frac{A^L_{F}(k,i)A^L_{T}(k,j)}{\sum_v A^L_{T}(k,v)},
\]

\[
\text{for} \ (i,j) \in V^L_c.\quad (4)
\]

We apply graph convolution to the aforementioned adjacency matrix, with adding self-loops, denoted by \( A^F = A^F + I, A^S_{in} = A^S_{in} + I, A^S_{out} = A^S_{out} + I \). We concatenate (denote

| Table I: Notation Table |
|-------------------------|
| **Network Topology Feature Notation:** |
| \( G = \{G_i\} \) | Training/testing set of Topology |
| \( G_i(V_i,E_i;X_i,Y_i) \) | Topology snapshot graph |
| \( V_i \) | Network nodes in \( G_i \) |
| \( n_i \) | Size of \( G_i \) |
| \( E_i \) | Communication links between network nodes |
| \( X_i = \{x(v_i)\} \) | Network node configuration of \( G_i \) |
| \( Y_i \) | Communication link configuration of \( G_i \) |
| \( c(Y(e)) \) | Configured link capacity of \( e \in E_i \) |

| **Network Service Feature Notation:** |
| \( P_i = \{p_{i,j}\} \) | OD pairs in \( G_i \) |
| \( p_{i,j} \) | \( j \)-th OD-pair in \( G_i \) |
| \( k_{i,l} \) | Number of OD pairs in \( G_i \) |
| \( T = \{T_i\} \) | Training/testing set of user traffic |
| \( T_i = \{t_{i,j}\} \) | User traffic matrix for all \( P_i \) |
| \( t_{i,j} \) | User traffic features for \( p_{i,j} \in P_i \) |

| **Ground Truth Notation:** |
| \( Q = \{q_i\} \) | Training/testing set of performance matrix |
| \( q_{i,j} \) | Performance measurement (i.e: latency) of \( p_{i,j} \) |

**Novel Feature Notation in reformulating the problem:**

- \( G^L_c(V^L_i,E^L_c) \): Line graph transformation of \( G_i(V_i,E_i) \) to its corresponding representation in \( G^L_c \).
- \( T^L_c \): Matrix of summed traffic of \( p_{i,j} \), who share the same node \( v \in V^L_i \) in \( G^L_c \).
- \( t^L(i,v) \): Summed traffic for all \( p_{i,j} \) passing through node \( v \in V^L_i \).
- \( X^L_c(v) \): Line graph node feature, introduced in Eq. 1.
- \( u_{i,j} \): Line graph edge weight, introduced in Eq. 2 for node \( v \)'s queue occupancy state (ground truth), for \( v \in V^L_i \) in Fig. 2.
each DGCN block can be formulated as:

\[ \hat{D}_x A_x \hat{D}_x X \Theta, \]

where \( \hat{D}_x = \sum_j (A_x)_{ij} \) is a diagonal matrix. The result of each DGCN block can be formulated as:

\[ H^{(l+1)} = \|(f_F(H^{(l)}), A_x f_x(H^{(l)}, \hat{A} S_{in})), \alpha f_{S_{in}}(H^{(l)}, \hat{A} S_{in}), \beta f_{S_{out}}(H^{(l)}, \hat{A} S_{out}) \|, \] (6)

\[ \beta f_{S_{out}}(H^{(l)}, \hat{A} S_{out}) \] (7)

We expect \( f_F, f_{S_{in}} \) and \( f_{S_{out}} \) to capture the global traffic dependency, in-traffic dependency and out-traffic dependency respectively. One could foresee that the deeper the model is build, such dependency can be more precisely captured. We used EdgeDrop \[22] as well as skip-connection to avoid over-smoothing, both of which have been found to help building deeper networks during the experimentation.

**B. Embedding and Readout Function with Extrapolation Ability**

For handling the out of distribution attribute value per-node in larger graph, we have used NALU \[16\] to replace MLP in common GNN setup. Another motivation is to build equivalence in the embedding space between a node’s out-traffic attribute and its in-traffic attributes’ from its neighbors. This is because the in-traffic and out-traffic of a node should remain equal, unless packet drop happens. \[16\] have verified its superiority in numerical extrapolation in neural network readout.

**C. Routing Role Recognition based Attention**

Inspired by the work of \[8\], identification of key nodes in the SDN is essential to estimate the whole networks performance. For this purpose, we involve role recognition \[23\] during the pre-processing phase (denote as different colors in Fig. 3a (iv)). By defining \( v_s, v_d \in V^G \) as nodes in \( G^C \), we consider their role to be \( R(v_s), R(v_d) \). We define the role adjacency matrix \( A_R \) of \( G^C \):

\[ A_{R_{(x, d)}} = \begin{cases} 1, & \text{if } R(v_s) = R(v_d), \text{ and exists } p \in P_t, \\ 0, & \text{otherwise} \end{cases} \]

We consider the pair-wise similarity between the role of a node and its neighbors to be crucial, since an OD pair’s source or destination can bring its impact towards close neighbours of nodes of interest and formulate their embedding as an “augmented source.” GAT is reported to be a well-suited solution to capture such pair-wise similarity impact. Thus, we apply GAT layers on node embedding between each role adjacency pair. The motivation is to capture the long-range dependency of in-trajectory of OD pair, without collecting all hops’ feature in the trajectory. For the aforementioned \( A_{i} \), one can consider that denser connected nodes in \( G^C \) are usually congested. Thus, its state (e.g., occupancy) is dependant on its neighbors’ states. For less connected nodes, one can infer that they have few OD’s pairs passing through. Thus, their states are more dependent on the few passing through OD pair’s demanding traffic. This information might be submerged for those well-connected nodes in the OD pair trajectory, but more obvious on the weakly-connected nodes sharing the same trajectory. Such pair-wise state similarity forms \( A_{R} \), which enlarges the receptive field of the model beyond topological neighbors. Our results show that this approach improves the model performance as well as it introduces generalization ability when training and inference takes place using samples with longer chains of trajectories.

**V. EXPERIMENTS**

**A. Dataset and Baselines**

**Dataset.** We verify the performance of the model on a simulated dataset provided by \[24\]. The training, validation and test sets are produced by a packet level simulator (OMNeT++ v5.5.1 \[25\]). Though lacking of other benchmark dataset, this dataset includes a summary of patterns of real-world network topologies from The Internet Topology Zoo \[26\]. The training set includes a variety of networks sized from 25 to 50 network nodes, while the test and validation set are sized from 50 to
300 network nodes. The larger network brings the following attribute changes: (1) Network topology samples introducing a few longer OD pair’s trajectories; (2) Network topology samples introducing larger capacity attribute per link, as well as different “next-hop” choice encoded in $R_i$, for OD pairs to generate their trajectory in a different routing preference; (3) Network topology samples introducing both sampling methods (1) and (2), as described above. A description of the used dataset is shown in Table II.

**Baselines.** We have considered several state-of-the-art models to compare our proposed model.

1) **RouteNet** [18] is a message-passing-based GNN solution to estimate per OD pair’s latency in SDN on bipartite graph problem formulation.  
2) **RouteNet-Salzburg** [19] is an optimization model based on RouteNet that scales to different routing policies on same sized network topologies on estimating per OD pair’s latency. This is a winning solution of [24].  
3) **RouteNet-GA** [4] is a fine-tuned solution based on RouteNet with better generalised performance on various OD pair trajectory length, this is a winning solution of [24].  
4) **DGCN** [21] is a graph spectral convolution solution generalized for directed graph scenario. In our experiment, we apply NALU as its embedding and readout function, as well as same hyper-parameters and pre-processing scheme as the proposed model for a fair comparison.  
5) **Scalable-RouteNet** [5], [27] is a RouteNet based improved solution to estimate per OD pair’s latency in size-variant SDN on tripartite graph problem formulation.

**B. Experiment Settings**

We have implemented our proposing solution with Keras as well as tf-geometric [28]. Furthermore, our solution requires no-GPU, whereas for the other benchmark solutions that do require GPU, we have been training using one Nvidia GeForce 1080 Ti and GNU-Parallel for resource management. For training the comparative benchmark models, we used the recommended parameter sets reported by the authors, but with the unified learning rate $r = 10^{-3}$, epoch number $= 250$, epoch size $= 4000$, loss function as MAPE as well as input feature space for a fair comparison. We train five independent random seeds for each model and report the averaged solution. The proposed method, based on aforementioned preprocessing and formulation, are taking the $G_i^L (V_i^L, E_i^L)$ as well as node feature $X_i^L (v)$ and edge weight $w_i$ in its input layer, with a 32-dim output layer for each node embedding in $V_i^L$. A detailed list of training parameters is published on [https://github.com/bluelancer/GNNET.git](https://github.com/bluelancer/GNNET.git).

**C. Experiment Result**

We evaluate the performance of our model in the following experiments: (1) Table III reports the overall performance of all the test set and we note their difference in MAPE through Delta: (2) Fig. 4 reports model performance on each interval of size samples from the test set; (3) Table IV reports mean inference speed on a selection of certain sized samples from test set. Here we are only concerned with the time interval of inference, without any pre/post-processing time, as they can be parallelized in an actual application. We do not include results from Scalable-RouteNet due to the use of different hardware. (4) Fig. 5 reports an ablation study towards the decision of adopting NALU instead of MLP in proposed model when extrapolating towards different size of graph. Fig. 6 reports a sensitivity study result on most affecting parameter and configuration in training the proposed model.

**Table III: Average Performance (%)**

| Model                  | MAPE  | Delta |
|------------------------|-------|-------|
| Our model              | 2.317 | –     |
| RouteNet               | 274.5 | 272.2 |
| RouteNet-Salzburg      | 596.8 | 594.5 |
| RouteNet-GA            | 557.8 | 555.5 |
| DGCN                   | 2.935 | 0.618 |
| Scalable-RouteNet-F    | 10    | 7.683 |

**Table IV: Inference Speed (ms) per Topology vs. Topology Size**

| Topology Size | 50  | 100 | 200 | 300 |
|---------------|-----|-----|-----|-----|
| Our model     | 161.5 | 373.3 | 1115 | 2718 |
| RouteNet      | 485.3 | 1972 | 6084 | 21264 |
| RouteNet-Salzburg | 0.41 hr | 0.4 hr | 0.39 hr | 0.44 hr |
| RouteNet-GA   | 1363 | 4786 | 19913 | 71767 |
| DGCN          | 105.5 | 220.3 | 861.9 | 1770 |

Based on the above results, one can see that our model outperforms all baselines in terms of accuracy, inference speed and generalization ability to open-world input. For Table III we observed that our model outperforms in terms of accuracy. We consider this verifies the validity of both our modified problem formulation, and the superiority of the proposed model. One can observe that other well-studied GNN benchmark (i.e:DGCN) can also outperform greatly against the carefully designed task-specific model, which can be concluded into the effect of problem formulation. For Table IV one can conclude that our model is faster.

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3Detailed information on feature distribution as well as comparison of the training and testing dataset is given in Appendix.D. Link to the appendix same as above.

4Code available at [https://github.com/ITU-AI-ML-in-5G-Challenge/PS-014.2-GNN-Challenge-Gradient-Ascent](https://github.com/ITU-AI-ML-in-5G-Challenge/PS-014.2-GNN-Challenge-Gradient-Ascent)

5We report their published results, however, we have not been given access to their implementation to reproduce their results.

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| Dataset       | Training Set | Validation & Test set |
|---------------|--------------|-----------------------|
| Number of Samples | 120000       | 3120                  |
| Graph size    | [25, 50]     | [50, 300]             |
| Average Degree (mean, std) | (9.778, 0.9401) | (9.523, 1.268)         |
| Average Shortest Path (mean, std) | (2.379, 0.1372) | (3.384, 0.456) |
| Diameter (mean, std) | (4.458, 0.6441) | (6.667, 1.280)         |
| Cluster Coefficient (mean, std) | (0.131, 0.0243) | (0.0427, 0.0342) |

6The reported result is referenced from [5].
than most task-specific benchmark models (i.e: Routenet, RouteNet-Salzburg, and RouteNet-GA). The proposed model's inference time remains tolerable for SDN routing estimation component, even for the largest network we have (300 nodes). DGCN performs marginally faster as it is one of the building blocks of the proposed model, while the proposed model is more accurate and has a more stable generalization performance against open-world input.

For Figure 4, we conclude our proposed solution performs best in generalization ability to open-world input. Note that comparing solely DGCN and our model, we could see $A_R$ not only introduces more accurate estimation, but also increases the performance stability. We believe that this improvement is due to introducing role inference in our model, which provides an easy way to diffuse long-range dependencies.

For Figure 5, we verified the benefit that we bringing in NALU instead of MLP in common GNN architecture, we observed using NALU obtains marginal gain on median accuracy but more on variance of the accuracy. This verified the conclusion from [16] that NALU assists in modeling numerical extrapolation in larger routing network samples.

**VI. CONCLUSION**

The paper offers the following contributions from the state of art: (i) We proposed a novel formulation of the latency prediction task in SDN. (ii) We proposed a solution that incorporates domain knowledge in SDN optimization aimed at an open-world learning setup. (iii) Our proposed model achieves better accuracy, inference speed and generalization ability beyond state of the art, all while using less computational resources. A limitation in our approach is that we do not incorporate the scenarios of peak hours, where unseen amount and duration of burst traffic triggers the network orchestration scheme, which eventually results in a dynamic-routing topology. Generalization to dynamic and size-variant graphs with GNN models remain to be studied in future work.

**ACKNOWLEDGEMENT**

This work was partially supported by the Wallenberg AI, Autonomous Systems and Software Program (WASP) funded by the Knut and Alice Wallenberg Foundation. We thank...
Figure 6: Sensitivity Study on the criteria of Mean Absolute Relative Error (MAE) w.r.t a Selection of Most Performance-affecting Hyper-parameter

Dr. Pedro Batista and Dr. Alessandro Previti from Ericsson Research for the insightful discussions.

REFERENCES

[1] J. Parmar, S. S. Chouhan, and S. S. Rathore, “Open-world machine learning: Applications, challenges, and opportunities,” arXiv preprint arXiv:2105.13448, 2021.

[2] D. Gamarnik and S. K. Gupta, “Algorithmic challenges in the theory of queueing networks,” 2011.

[3] R. Amin, E. Rojas, A. Aqdus, S. Ramzan, D. Casillas-Perez, and J. M. Arco, “A survey on machine learning techniques for routing optimization in sdn,” IEEE Access, 2021.

[4] V. Srivastava and R. S. Pandey, “Machine intelligence approach: To solve load balancing problem with high quality of service performance for multi-controller based software defined network.” Sustainable Computing: Informatics and Systems, vol. 30, p. 100511, 2021.

[5] M. Ferriol-Galmés, J. Suárez-Varela, K. Rusek, P. Barlet-Ros, and A. Cabellos-Aparicio, “Scaling graph-based deep learning models to larger networks,” arXiv preprint arXiv:2110.04261, 2021.

[6] F. Ciucu and J. Schmitt, “Perspectives on network calculus: no free lunch, but still good value,” in Proceedings of the ACM SIGCOMM 2012 conference on Applications, technologies, architectures, and protocols for computer communication, 2012, pp. 311–322.

[7] K. Xu, M. Zhang, J. Li, S. S. Du, K.-i. Kawarabayashi, and S. Jegelka, “How neural networks extrapolate: From feedforward to graph neural networks,” arXiv preprint arXiv:2009.11848, 2020.

[8] P. Sun, J. Li, Z. Guo, Y. Xu, J. Lan, and Y. Hu, “Sinet: Enabling scalable network routing with deep reinforcement learning on partial nodes,” in Proceedings of the ACM SIGCOMM 2019 Conference Posters and Demos, 2019, pp. 88–89.

[9] T. N. Kipf and M. Welling, “Semi-supervised classification with graph convolutional networks,” arXiv preprint arXiv:1609.02907, 2016.

[10] G. Li, M. Müller, B. Ghanem, and V. Koltn, “Training graph neural networks with 1000 layers,” arXiv preprint arXiv:2106.07476, 2021.

[11] B. Chen, R. Barzilay, and T. Jaakkola, “Path-augmented graph transformer network,” arXiv preprint arXiv:1905.12712, 2019.

[12] Y. Yang, X. Wang, M. Song, J. Yuan, and D. Tao, “Spanag: Shortest path graph attention network,” arXiv preprint arXiv:2101.03464, 2021.

[13] P. Veličković, G. Cucurull, A. Casanova, A. Romero, P. Lio, and Y. Bengio, “Graph attention networks,” arXiv preprint arXiv:1710.10903, 2017.

[14] G. Yehudai, E. Fetaya, E. Meirion, G. Chechik, and H. Maron, “From local structures to size generalization in graph neural networks,” in ICML. PMLR, 2021, pp. 11975–11986.

[15] M. Balciar, G. Ronton, P. Héroux, B. Gaižiūre, S. Adam, and P. Honeine, “Analyzing the expressive power of graph neural networks in a spectral perspective,” in ICLR, 2020.

[16] A. Trask, F. Hill, S. E. Reed, J. W. Rae, C. Dyer, and P. Blunsom, “Neural arithmetic logic units,” in NeurIPS, 2018.

[17] A. Madsen and A. R. Johansen, “Neural arithmetic units,” in ICLR, 2019.