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AI-Enabled Large-Scale Entanglement Distribution Quantum Networks

R. Wang\(^1\), S. K. Joshi\(^2\), G. T. Kanellos\(^1\), D. Aktas\(^2\), J. Rarity\(^2\), R. Nejabati\(^1\), D. Simeonidou\(^1\)

\(^1\) High Performance Networks Group, Department of Electrical and Electronic Engineering, University of Bristol, Bristol, BS8 1UB, UK
\(^2\) Quantum Engineering Technology Labs, H. H. Wills Physics Laboratory, University of Bristol, Bristol, BS8 1FD, UK.

rui.wang@bristol.ac.uk

Abstract: We propose an entanglement distribution switching architecture to support large-scale dynamic quantum networking. Deep neural networks are further developed for predicting the performance of a dynamic entanglement distribution network utilizing the proposed architecture.

1. Introduction

Entanglement-based networks will be the next generation quantum networks since they facilitate distribution of entangled states, a fundamental resource for quantum information processing, among multiple remote nodes [1]. Recently, an 8-user quantum network was demonstrated [2], [3]. Here only passive components are deployed to distribute entangled photons without active switching element, thus prohibiting any dynamic configuration of the quantum networks. Even more recently, active entanglement distribution was demonstrated using WSS [4] or optical switching [5] technology, but for a limited number of nodes and links. However, the increased network reconfiguration flexibility offered by the dynamic characteristics of these works comes at a cost on the performance of the quantum links, since these are significantly affected by the number of quantum channels multiplexed to each user’s detectors and the excessive losses of switching components. Thus, for entanglement distribution networks to scale in size and realistically address the application requirements beyond QKD such as a distributed quantum computing, a new paradigm for dynamic quantum network control is necessary to enable the optimal allocation of the valuable entanglement resources across the network. However, the dynamicity operation offered by quantum networks will lead to various photon noise counts even for the same detector, posing great challenge to enable optimal resources assignment. Similarly, the performance of the entangled quantum links depends on the network topology, a significant step in this direction is the ability to predict the performance of a quantum network under any topology to allow quantum network operators to implement optimization algorithms. Therefore, in this paper, we first present a new quantum reconfigurable add-drop multiplexer (q-ROADM) for entanglement distribution to support large-scale dynamic and flexible quantum networking based on our previous architecture [6]. More importantly, we present for the first time, to best of our knowledge, intelligent deep neural network (DNN) models to capture the impact of dynamic network characteristics and predict the performance of individual entangled quantum communication link under any given network configuration. The results indicate the proposed solution can achieve efficient and accurate evaluation of quantum link performance with agile quantum network configurations.

2. Entanglement distribution-enabled quantum reconfigurable add-drop multiplexer

In bi-particle entanglement-based quantum network, the physical layer consists of several users connected to a single entanglement source in a star topology (Fig. 1a). When two users share different halves of the entangled state, they share entanglement by establishing logical entanglement distribution layer of the network (Fig. 1b). Since a fibre connected to one user can contain halves of many different entangled states (all multiplexed together), it leads to entanglement distribution layer with various shapes. The proposed q-ROADM architecture (in Fig. 1c) based on our previous work [6] allows arbitrary shape or topology of entanglement distribution layer by controlling the entangled states each client receives. It employs an Optical Fibre Switch (OFS) to dynamically distribute C-band polarization-entangled wavelength \((λ_i, λ_{i+1}), \ldots, (λ_{i+15}, λ_{i+15})\) through Fibre Polarisation Controller (FPC), and Mux stages before reaching different clients. Additional 3dB or 6 dB Beam Splitter (BS) stages can be interleaved to allow time sharing of bipartite entangled wavelengths \((λ_i, λ_{i+1})\) by distributing them to multiple clients simultaneously at the cost of extra transmission loss and reduced secure key rate (SKR). For example, by assigning Alice \(λ_1\) without BS (full wavelength, denoted as 1), Bob and Chloe \(λ_{i+1}\) through a 3 dB BS (half photons of \(λ_1\), denoted as 0.5) and two 3 dB BSs (a quarter of photons within \(λ_{i+1}\), denoted as 0.25) as shown in Fig. 1. Alice is able to establish quantum entangled links with Bob and

![Fig.1: Dynamic entanglement distributed quantum network](image-url)
Chloe simultaneously utilizing the same set of entangled wavelength pair \((\lambda_1, \lambda_1)\). The proposed architecture supports a flexible resources assignment allowing suitable hardware integration such as BS, FPC and MUX, and facilitates on-demand control of the quantum links performance requirements. However, different entanglement distribution layer requires a different configuration of the q-ROADM. Even minimum quantum network adaption will lead to different noise counts at clients, thus affecting the quantum link performance. In the next section, we will present the DNN framework to capture the effect of quantum network dynamicity posed by q-ROADM.

3. Deep neural network modeling and training

To reap the advantages offered by the flexible quantum channels allocation of the q-ROADM, we further propose 5-layer DNN framework to abstract the impact of quantum network’s dynamic characteristics, allowing QBER and SKR prediction respectively under any configuration of the quantum network. We apply our study to the 8 clients quantum network similar to [2], employing Alice (A), Bob (B), Chloe (C), Dave (D), Fay (F), Gopi (G), Heidi (H) and Ivan (I). Their fiber distance from q-ROADM is listed as [10.67, 2.18, 16.51, 6.76, 5.87, 14.92, 3.20, 0.97] km for each client respectively. Each client contains 2 single-photon detectors to measure in HV and DA basis for all possible quantum channels, as per in [4]. A coincidence window is set when comparing measured photon basis of two nodes for a quantum link, determining the two photons of the same time (in coincidence). The 1 x 268 input layer of the DNN models contains two main features: 1) resource assignment schemes, and 2) coincidence time window of quantum channels. Resource assignment features is a 1x240 vector, which is the result of flattening 30 (15 pairs of entangled wavelengths) x 8 (8 clients) resource assignment matrix, with an example shown in Table 1. Non-zero elements stand for the wavelength being assigned to the client with corresponding BS (portion of photons within the wavelength), as explained in the previous section. The example illustrates resource assignment schemes for 2 quantum links, A-B and A-C, with different BS settings. The 1x28 coincidence window vector indicates the coincidence time window for all possible 28 quantum links in the network, as shown in Table 2. Element 0 represent the inactive quantum link. Both DNN (for SKR and QBER) consist of 5 hidden layers with 512 neurons and Leaky ReLU served as the activation function with slope = 0.00001. The output layer is of size 1x28 adopting ReLU, presenting the QBER or SKR of all 28 quantum links. In the data collection phase, it is assumed there exists 14 background quantum links. Based on this, around 10.6 million scenarios with different connection requirements, resource (wavelength and BS) allocation schemes and various coincidence time window sizes for each connection according to lookup table are generated. We employ a quantum network simulator (as ground truth in this work) in python to calculate and produce the SKR/QBER results of all the quantum links for each scenario. All the scenarios and their results are shuffled and split to training (80%), validation (10%) and test (10%) data set. Then the training and validation data set are fed into DNN models for SKR/QBER training and validation, while the test data set is used to examine the performance of DNN models.

4. Results Analysis

DNN models proposed in section 3 is able to predict SKR and QBER of quantum links according to assigned wavelength, BS and coincidence window in quantum network. To investigate the dynamicity of the quantum network, we focus on the DNN results analysis of 4 scenarios by demonstrating the SKR variation of individual quantum link when switching to different scenarios, as shown in Fig. 2. The width of the connection flow represents the predicted SKR value. When switching from scenario 1 to scenario 2, the BS settings of connection B-H and B-I changes from using 6 dB BS (0.25) to full wavelength (1), and full wavelength (1) to 6 dB BS (0.25) respectively. Therefore, it leads to significant SKR difference of two links between two scenarios. From scenario 2 to scenario 3, a new quantum link F-H is provisioned, introducing more noise photons to detectors at Heidi. As a result, the QBER of link B-H increases, leading to reduced SKR compared to scenario 2. Scenario 4 is a completely new network setting compared with scenario 1, with improved SKR for link C-I due to increased BS setting (from 0.5 to 1) of wavelength assigned to Ivan, and with reduced SKR for link B-I due to higher noise counts from improved links such C-I at node Ivan.

![Fig. 2: Predicted SKR of individual quantum link for 4 resource assignment scenarios, with width of connection flow indicating the SKR. (a) scenario 1; (b) scenario 2; (c) scenario 3; (d) scenario 4.](image-url)
For the accuracy analysis, Fig. 3 (a) illustrates the normalized mean square error (MSE) and mean absolute error (MAE) of SKR from DNN prediction model, against the increasing number of epoch for 10.6 million scenarios. The figure indicates both types of loss decrease with the increasing number of training iterations. The performance of training data set and validation data set converge after a few epoch, providing the DNN model without obvious overfitting issue. To investigate the impact of number of training data set on the accuracy of DNN model, numbers of scenarios ranging from 1.2E5 to 8.52E6 are used for training DNN model. Fig. 3 (b) depicts relative prediction error of both predicted SKR and QBER drops from > 10% relative error to the region less than 4% error, when increasing training data set number from 1.2E5 to 8.52E6. It shows DNN models can achieve low relative estimation error for both SKR and QBER with 8.52E6 training data set.

Table 3. Execution time for simulator and DNN

<table>
<thead>
<tr>
<th>Number of scenarios</th>
<th>1</th>
<th>10</th>
<th>100</th>
<th>1E3</th>
<th>8.98E3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time for simulator (s)</td>
<td>0.846</td>
<td>8.63</td>
<td>84.5</td>
<td>895.3</td>
<td>8.06E3</td>
</tr>
<tr>
<td>Time for DNN (s)</td>
<td>0.065</td>
<td>0.019</td>
<td>0.023</td>
<td>0.064</td>
<td>0.434</td>
</tr>
</tbody>
</table>

Fig. 4 (a) and (c) show the heatmap of DNN prediction versus original value for SKR and QBER respectively from 1E5 sample scenarios in the test data set. The results reveal that the proposed DNN models can achieve high prediction accuracy for both SKR and QBER. Fig. 4 (b) and (d) depict the probability distribution of absolute error from DNN prediction model for SKR and QBER respectively. 95% of SKR error fall within range of 40 bps and similarly 95% QBER estimation error of DNN model is within 0.0052. The results indicate that the proposed DNN models can accurately capture the dynamicity of quantum network, with execution time listed in Table. 3 compared with time consumption of the simulator. DNN model can offer up-to 18000 times faster than simulator running time, while providing high estimation accuracy.

5. Conclusion

Future quantum networks will be a highly dynamic network that must be able to support entanglement distribution among multiple clients. Control and management of dynamic entanglement networks will be highly complex and often not scalable with classical heuristic and analytical models. To address this problem, in this paper we presented a novel DNN Model for performance prediction to enable efficient control of large scale multi-user dynamic entanglement-based network enabled by q-ROADM. The results reveal DNN models capture the dynamicity of quantum networks posed by q-ROADM, providing accurate and efficient SKR and QBER evaluation with 4% and 2% estimation error.

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7. References