融合GNN與Tarnsformer技術的智能網路優化

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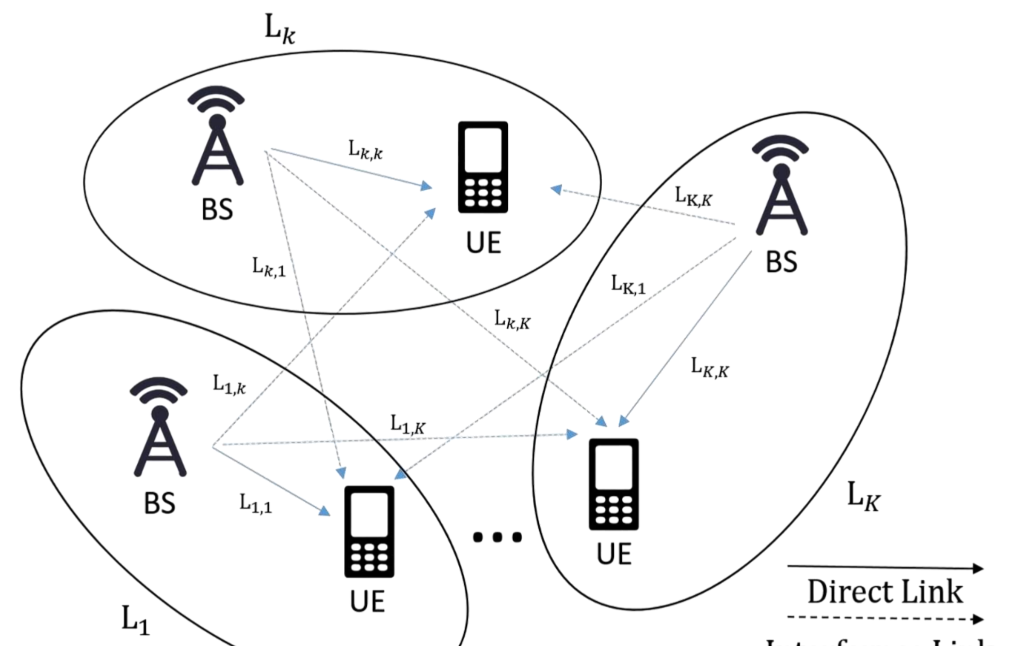
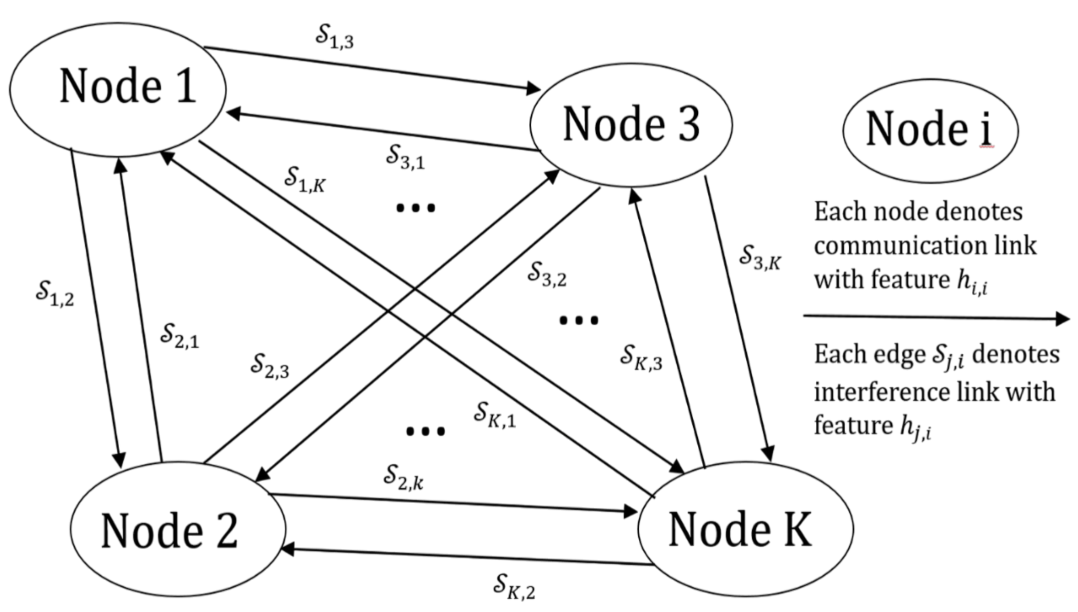
摘要

為滿足大規模超可靠低延遲通訊（mURLLC）對超低延遲、高可靠性與可擴展性的需求，我們提出結合 Transformer 的 G4U 與 PG4U 框架。原有 G4U 透過無線聚合減少訊號與計算開銷，PG4U 則以並行聚合提升穩健性，但兩者皆受限於局部訊息傳遞，難以捕捉長距離依賴關係。為克服此問題，新架構在嵌入更新階段整合 Transformer 編碼器，使模型能全域關注所有節點，實現跨節點依賴建模且無需額外訊號交換。

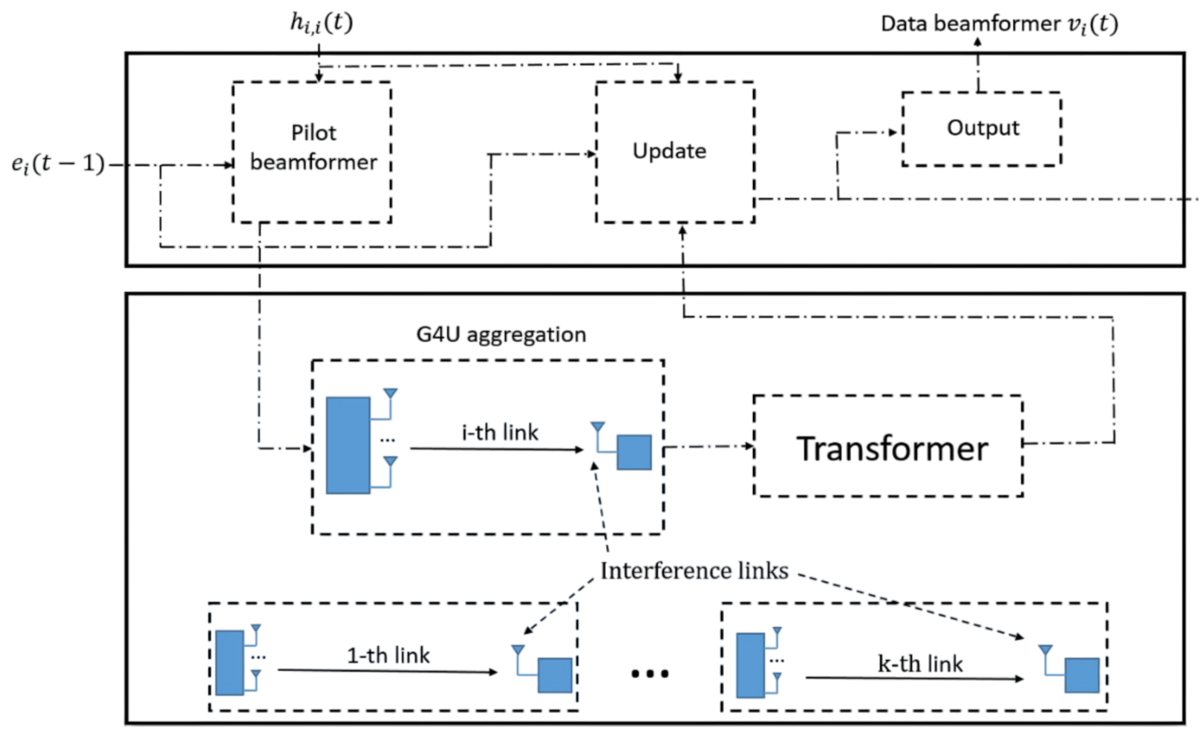
基於 K 連結的所考慮的 mURLLC 網路的系統模型





我們考慮一個由 K 條通訊鏈路 $L_1, L_2, \dots, L_K$ 組成的下行 mURLLC 網路，其中每條鏈路連接一個基地台 (BS) 及其關聯的用戶設備 (UE)，所有鏈路均工作在相同的頻寬上。每個基地台都配備有 N_t 根天線，每個 UE 只有一個天線，所有 BS 同步傳輸。實體網路映射對應圖拓樸結構。

G4U with Transformer 模型圖



訊息的產生、聚合和更新步驟定義如下

$$m_{j\to i}^{(n)}(t) = \Phi\left(h_{j,j}(t), h_{j,i}(t), e_j^{(n)}(t); \theta\right)$$

$$a_i^{(n)}(t) = agg\left(m_{j,i}^{(n)}(t), j \in \mathcal{N}(i)\right)$$

$$e_i^{(n+1)}(t) = U\left(e_i^{(n)}(t), a_i^{(n)}(t), h_{i,i}(t); \omega\right)$$

$$v_i(t) = \Omega\left(e_i^{(N)}(t);\ \varphi\right).$$

連結 L_i 的訊號與干擾加雜訊比 (SINR) 為下

$$\mathrm{SINR}_i(H(t), V(t)) = \frac{\left|h_{i,i}^H(t) v_i(t)\right|^2}{\sum_{j=1, j\neq i}^{K} \left|h_{j,i}^H(t) v_j(t) s_j\right|^2 + \sigma^2}$$

其中 $V(t) = [v_1(t), \dots, v_K(t)]^T \in C^{(K\times N_t)}$ [3]。令 T_o 表示策略推理期間產生的總開銷，包括訊號延遲和計算延遲。

最佳化問題可以表述為:

$$\arg \min_{\mathrm{v_1(t)},\cdots,\mathrm{v_K(t)}} E[U(t)]$$

$$\text{s. t. } \varepsilon_{\max}(t) = \max_{i=1,\cdots,K} \varepsilon_i(V(t), H(t)),$$

$$U(t) \triangleq \log_{10}(\varepsilon_{\max} t + 10^{-\beta}) + \beta,\quad \beta \geq 0,$$

$$0 \leq \|v_i(t)\|^2 \leq P_{\max},\quad \forall i.$$

$$S_q(t) = \sum_{j=1}^{K} \phi(q_j^h(t))\ ;\ S_{kv}(t) = \sum_{j=1}^{K} \phi(k_j^h(t)) \otimes v_j^h(t)$$

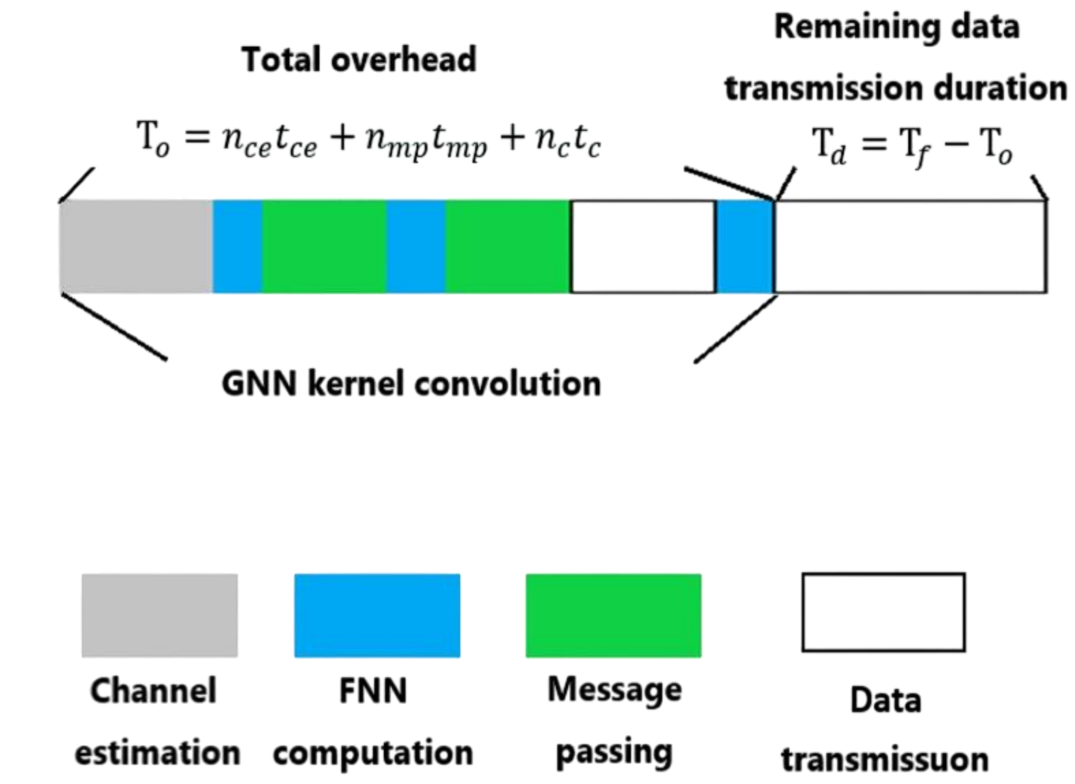
其中 $\phi(\cdot)$ 是 kernel 特徵圖，它將 softmax 注意力線性化，從而允許透過單次 OTA 廣播計算求和。然後每個節點在本地重建其注意力輸出

$$z_i^h(t) = \frac{\phi\left(q_i^h(t)\right)^T S_{kv}(t)}{\phi\left(q_i^h(t)\right)^T S_q(t)}$$

$$\tilde{e_i}(t) = LN\left(x_i(t) + \mathrm{concat}_h\left(z_i^h(t)\right) W_o\right)$$

其中LN(·)表示層歸一化，W_o是輸出投影矩陣，然後應用帶有殘差歸一化的逐位置前饋細化。

在 5G NR 系統中基於 GNN 的策略幀結構設計



$$\varepsilon_i(V(t), H(t)) = Q\left(\frac{-b\ln 2 + B(T_f - T_o)\ln[1 + \mathrm{SINR}_i(t)]}{\sqrt{B(T_f - T_o)V_i(t)}}\right)$$

鏈路 i 的誤塊率(BLER)由 [4]、[5] 給出其中$V_i(t) = 1 - 1/[1 + \xi_i(t)]^{(-2)}$是通道色散[4]，且為高斯 Q 函數。

QoS Outage Probablitiy 計算

在本研究中，實驗評估指標選定為 QoS Outage Probability，其計算方式定義如下

$$\Pr\{\varepsilon_{\max}(t) > 10^{-5}\}$$

參數表

Parameters	Values
Number of antennas N_t	4
Number of frames	10
Number of links	20
Noise power	-174 dBm/Hz
Antenna height	2 m
Maximum transmit power	40 dBm
Bandwidth	5 MHz
Message passing overhead t_{mp}	0.2 µs
Channel correlation coefficient	0.99
Carrier frequency	2.4 GHz
Number of training layouts	2×10^4
Number of testing layouts	5×10^4
Channel estimation overhead t_{ce}	0.2µs
Computation delay t_c	100µs
Number of bits	128
Log-normal shadowing	3 dB

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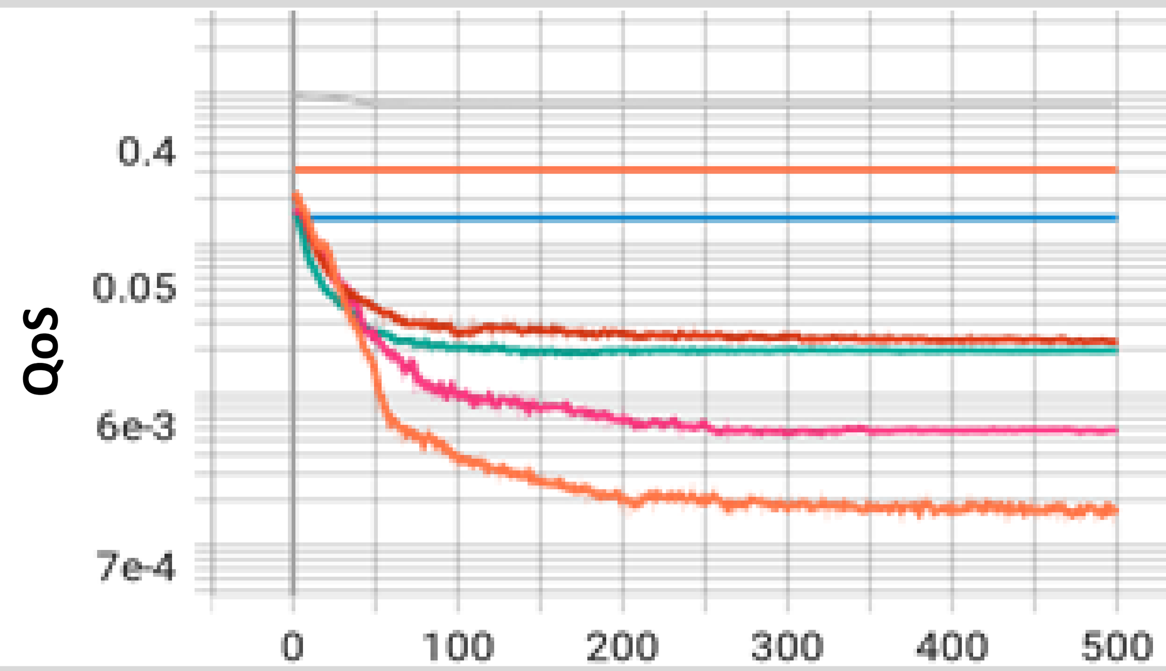
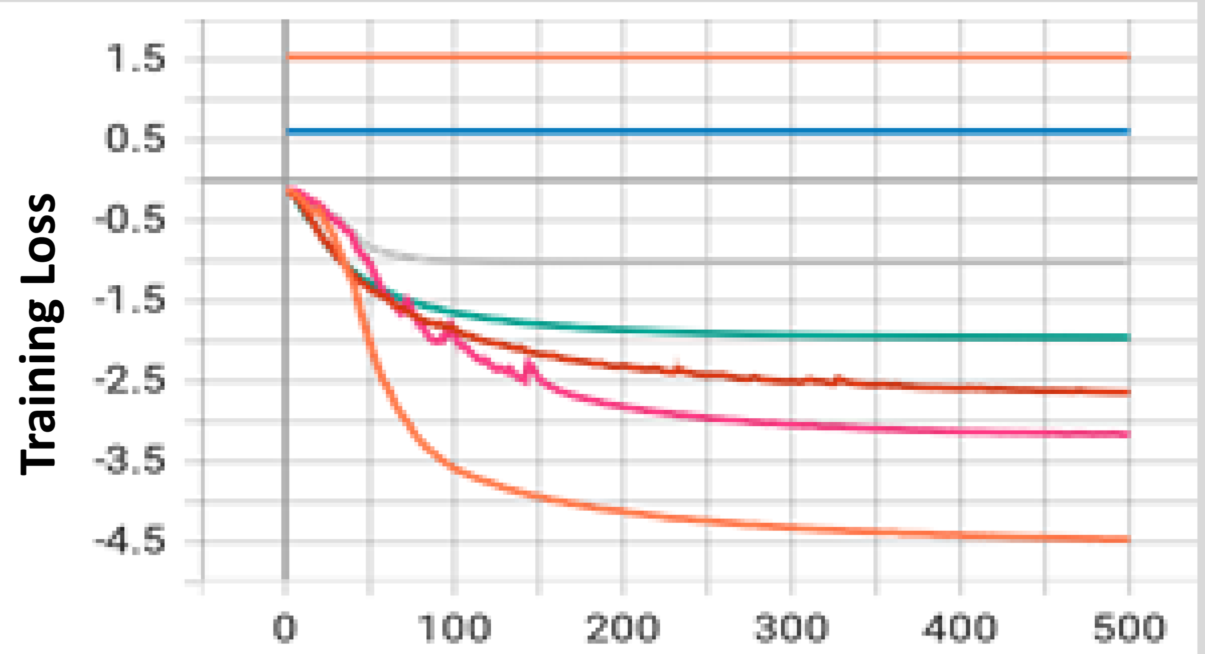
結果

G4U 加 Transformer 能將中斷率降低超過 84%，PG4U 加 Transformer 則降低約 52%。其中，G4U with Transformer 的中斷率最低，甚至優於集中式的 WMMSE，顯示Transformer 的全域注意力能有效提升分散式干擾協調能力。EPA 與 GNN 的中斷率最高，反映其缺乏有效的功率配置機制。



G4U 加入 Transformer 後收斂速度明顯加快，比基線 G4U 快超過 50%，且最終 loss 低約 94%。PG4U 的 Transformer 版本也優於原始 PG4U，但相對改善幅度較小，因其基線本身較低。WMMSE 雖然最終 loss 與 G4U with Transformer 相近，但因為集中式迭代運算，需要更多 epoch 才能收斂；EPA 則維持不變，而分散式 GNN 降幅慢且最終停在較高的 loss。



數線對照表