1. Interference Graph Prediction with Edge-Aware GNNs

1.1 Introduction

Constructing an accurate interference graph is fundamental for optimizing wireless networks. Traditional approaches often rely on precise physical location data and complex electromagnetic propagation models, which are often unavailable or impractical to maintain in dynamic environments. We propose an **Edge-Aware Graph Neural Network (GNN)** that infers the true interference graph solely from available AP telemetry and statistics, without requiring any knowledge of the physical AP locations. This approach enables robust interference estimation even in scenarios where physical topology is unknown or changing.

1.2 System Model & Inputs

We model the wireless network as a graph $G = (V, E)$, where nodes V represent APs and edges E represent potential interference.

1.2.1 Input Features

Each AP is characterized by a feature vector $\mathbf{x}_i \in \mathbb{R}^{11}$. Recent updates have refined the energy features to be channel-specific. The features are:

- **RF Environment (3)**: Incident Energy on Channel 1, 6, and 11 ($E_{ch1}, E_{ch6}, E_{ch11}$).
- **Traffic Load (2)**: Total Allocated Throughput (T_i), Number of Connected Clients (C_i).
- **Operational State (2)**: Duty Cycle (D_i), Transmit Power (P_i).
- **Mobility Dynamics (2)**: Roaming In Events (R_i^{in}), Roaming Out Events (R_i^{out}).
- **Configuration (2)**: Operating Channel (Ch_i), Bandwidth (BW_i).

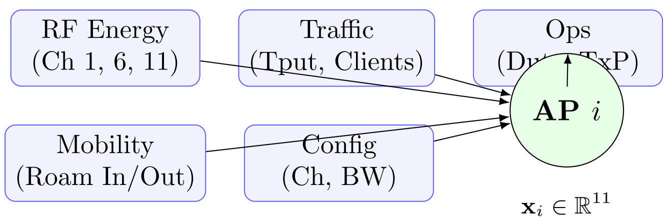

Figure 1.1: Input Feature Composition for each Access Point.

1.3 Architecture

The core of our approach is the **EdgeConv** operator, which dynamically learns edge features by aggregating local neighborhood information.

1.3.1 EdgeConv Layer

For each edge (i, j), the layer computes:

$$\mathbf{e}_{ij} = \mathrm{MLP}(\mathbf{x}_i \,\|\, \mathbf{x}_j - \mathbf{x}_i)$$

This formulation captures both the global properties of node i and the local difference relative to neighbor j, essential for determining directional interference.

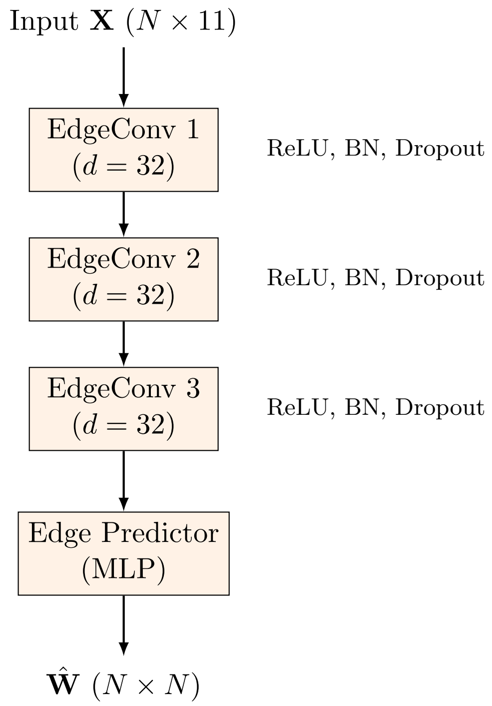

Figure 1.2: GNN Architecture: Stacked EdgeConv layers extract spatial dependencies to predict the interference matrix.

1.4 Experimental Results

The model was trained on 1001 network snapshots (Train: 700, Val: 150, Test: 151) and evaluated on the held-out test set of 151 graphs.

1.4.1 Performance Metrics

Metric	**Value**	**Baseline (Mean)**	**Improvement**
MAE	**0.0155**	0.104	85.1%
RMSE	**0.0246**	0.127	80.6%
R^2	**0.986**	0.000	–
Pearson r	**0.993**	–	–

Table 1.1: Test set performance on diverse dataset (weights 0.0-0.7).

1.4.2 Visual Analysis

The training curves (Fig. **??**) demonstrate rapid convergence. The prediction scatter plot (Fig. **??**) confirms the strong linear correlation between ground truth and predicted interference weights across the full range of interference conditions.

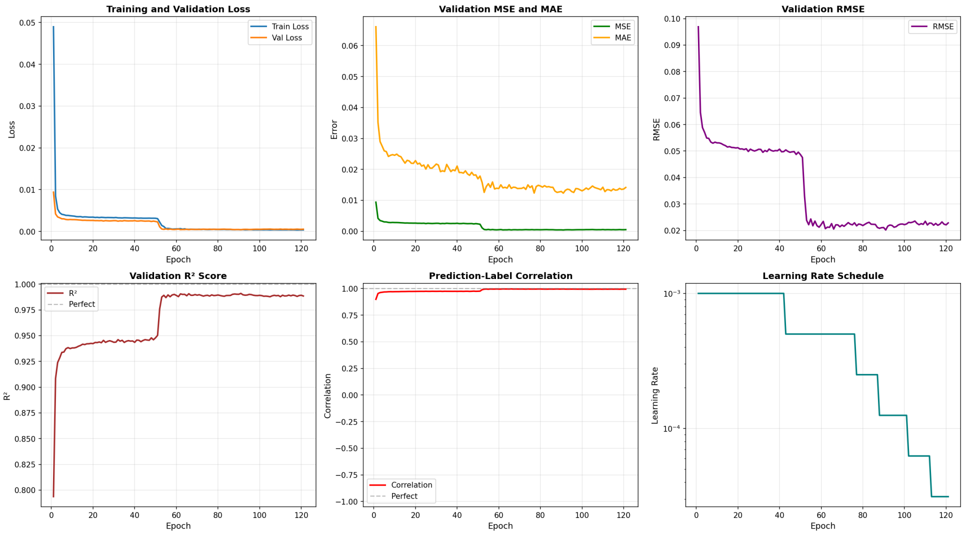

Figure 1.3: Training dynamics showing loss convergence and R^2 improvement.

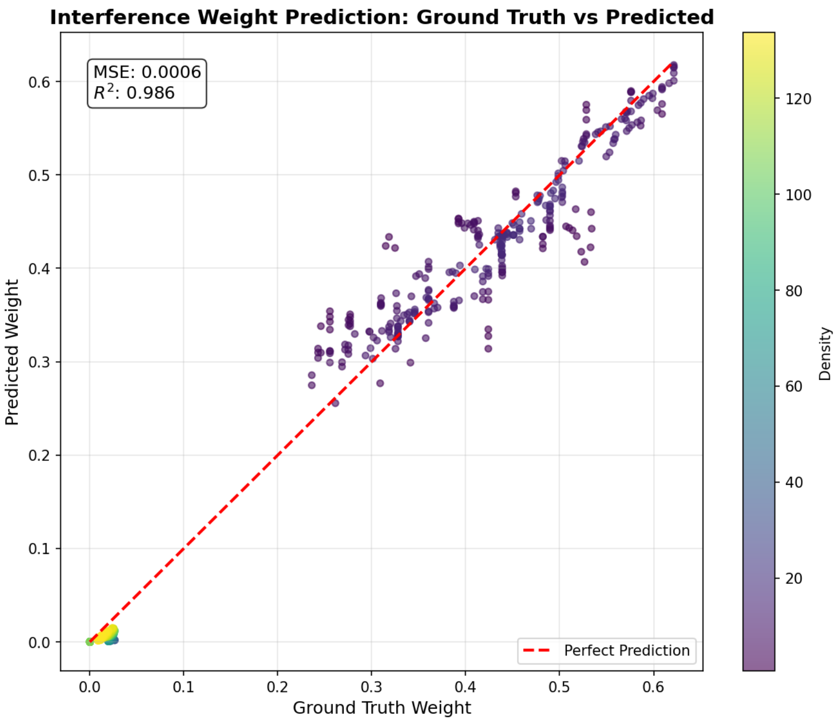

Figure 1.4: Scatter plot of Ground Truth vs. Predicted Interference Weights. The model maintains high accuracy ($R^2 = 0.986$) even with diverse interference conditions ranging from 0.0 to 0.7.

1.5 Conclusion

The proposed Edge-Aware GNN effectively approximates complex interference simulations. By leveraging 11 key RF and operational features, it provides accurate, real-time interference estimates, enabling dynamic and responsive wireless network management.