Graph Neural Networks as Industrial X-Ray Vision

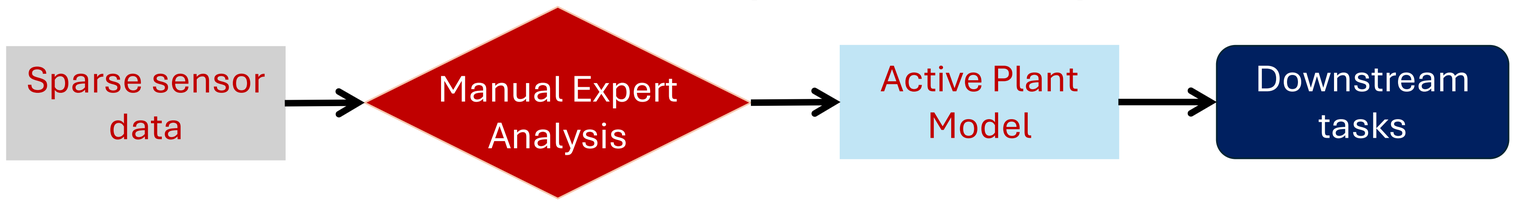
C Lokesh Reddy[a], Soham Mangesh Virkar[b], Vishnu Swaroopji Masampally[a], Venkataramana Runkana[a]

[a]TCS Research, Tata Research Development & Design Centre, Tata Consultancy Services Limited, Pune 411057.
[b]Department of Aerospace Engineering, Indian Institute of Technology, Madras, Chennai, Tamil Nadu 600036.

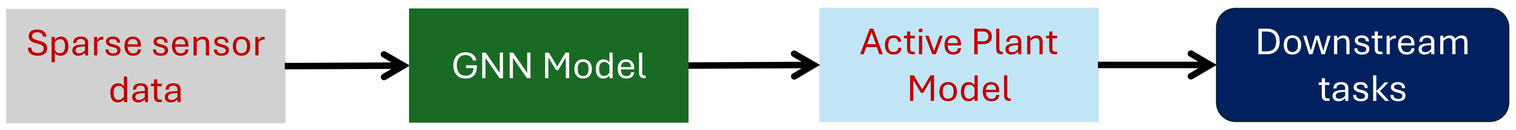
The Industrial Bottleneck

- All critical downstream tasks (optimization, control, simulation) depend on an accurate plant model
- Industrial process plants operate dynamically
- They never have 100% sensor coverage
- Identifying the active network is a big challenge

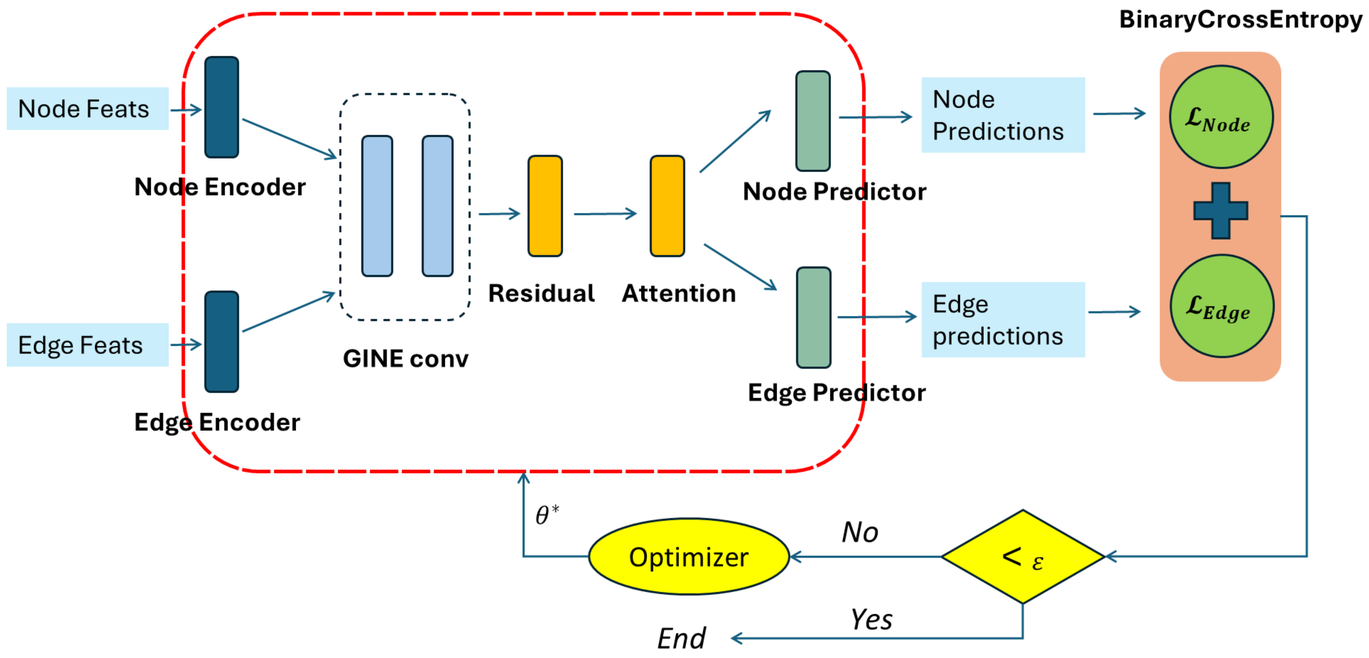
Current State (Manual & Slow)



Our Approach (Automated & Fast)



Our Solution: The GNN Pipeline



The GINEConv architecture designed to predict node & edge states from encoded features

- We frame the problem as graph completion task to infer the operational state of full network
- GINEConv model was chosen for its ability to effectively leverage edge features
- Our 3D feature vector was critical to solving data ambiguity

Unambiguous 3D Feature Vector

Sensor state	Feature 1: Sensor	Feature 2: Status	Feature 3: Unknown
Absent (Unknown)	0	0	1
Present & Active	1	1	0
Present & Inactive	1	0	0

Results & Key Takeaways

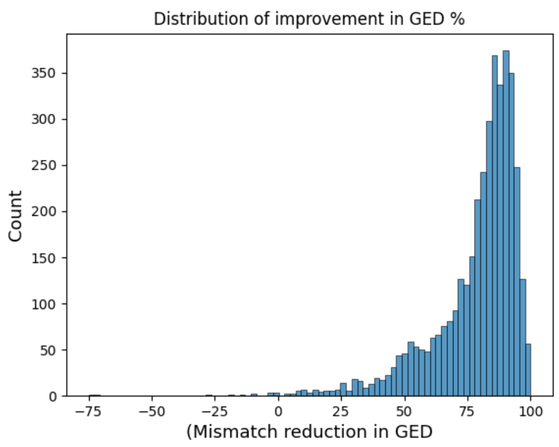
❖ Classification Accuracy

F1 score	
Nodes – 0.93	Edges – 0.89

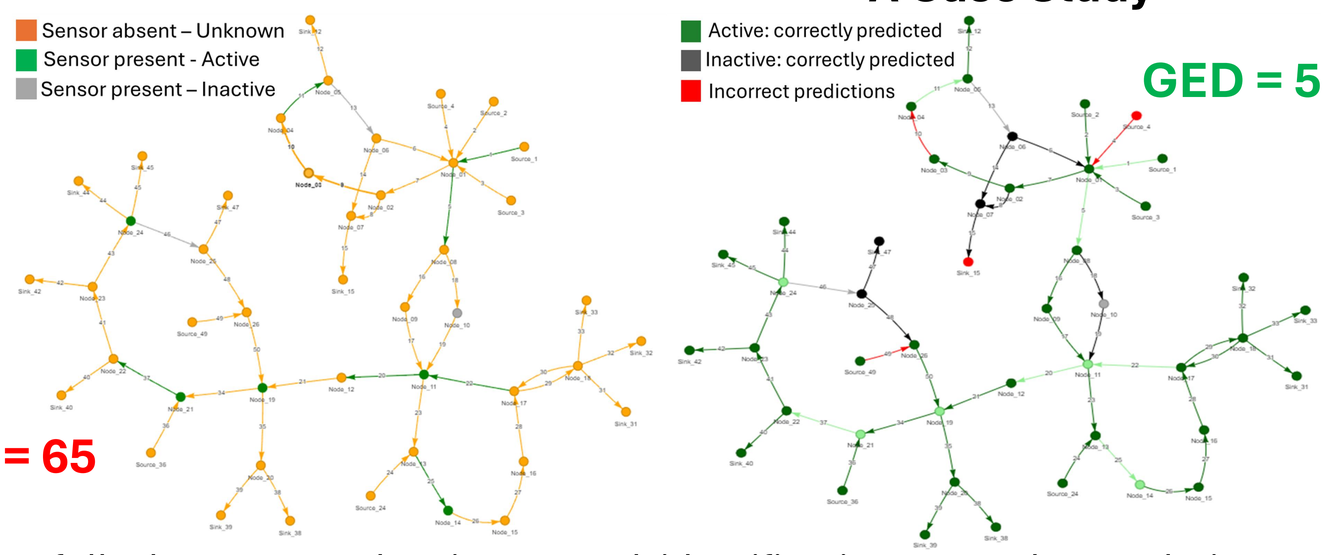
❖ Structural Reconstruction

78.45% average improvement in Graph Edit Distance (GED)

Reduced the average error from GED 59 to GED 7



❖ From Sparse to Complete: A Case Study



- Successfully demonstrated active network identification as graph completion task.
- Our GNN model accurately and automatically reconstructs the full plant topology using ONLY sparse sensor data and plant's structural graph.
- Achieved high performance (78.45% GED improvement). Further improvement can be obtained by providing process-rich information.
- This study provides the foundational, real-time plant model necessary for all downstream tasks.

References

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