Graph Neural Network and Particle Swarm Optimization hybrid model for the optimization of the IEEE 14-bus network reactive power

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***Abstract*— In this work, Graph Neural Network (GNN) and Particle Swarm Optimization (PSO) hybrid model for the optimization of the IEEE 14-bus network reactive power is presented. This hybrid strategy is particularly designed to integrate the topological learning capacity of GNNs with the population-based search capability of PSO, aimed at reducing systemic deviations across active and reactive power mismatches. The results showed that the GNN + PSO hybrid model shows notable improvements over the standalone GNN model, with substantial reductions in Bus 1 active mismatch; dropping from 147.750 MW to 128.174 MW. The Q_mismatch profile also benefits from the hybrid approach. Bus 1 exhibits a mismatch of 48.841 MVAR, a reduction from 56.095 MVAR in the standalone GNN case. Across the board, reactive mismatches fall within a narrow band: between +4.494 MVAR (Bus 8) and −17.901 MVAR (Bus 14). This uniformity suggests that reactive support mechanisms (e.g., capacitor banks or tap-changing transformers) could be better coordinated using this hybrid setup. Also, the hybrid model exhibits notable improvements in energy loss reduction over the standalone GNN model, primarily driven by the PSO layer's fine-tuning of line parameters.**

Keywords—Graph Neural Network (GNN), IEEE 14-bus network, Particle Swarm Optimization (PSO), Reactive Power Optimization, GNN + PSO Hybrid Model

1. Introduction

Across the globe, electric power transmission networks are generally used to transfer the generated energy from the generator system to the distribution point or a long distance [1,2,3]. The transmission network therefore has much impact on the quality of the power that get delivered to the end user [4,5,6]. Notably, the power transmission network has both active and reactive power and a proper balance of the reactive and the active power is required to ensure good quality and efficient delivery of the power delivered to the load [7,8]. Ensuring the optimal balance of the active and reactive power in a transmission network has attracted several researches [9,10]. In recent times, Artificial Intelligent (AI) models has been used for the power system studies [11]. The AI models has consistently demonstrated superior results when compared with the typical analytical models-based solution [12,13].

Hence, in this work, the Graph Neural Network and Particle Swarm Optimization hybrid model is employed to optimize the reactive power flow in IEEE 14-bus network [14,15]. The hybrid model hybrid aims to mitigate the shortcomings of standalone GNNs, which tend to underperform in precision-based optimization tasks due to limited reward shaping and exploration diversity.

2. Methodology

The hybrid model approach is presented for the optimization of the IEEE 14-bus network reactive power. Specifically, the Graph Neural Network (GNN) and Particle Swarm Optimization (PSO) hybrid model is used for the reactive power control in the IEEE 14-bus network. This hybrid strategy is particularly designed to integrate the topological learning capacity of GNNs with the population-based search capability of PSO, aimed at reducing systemic deviations across active and reactive power mismatches.

2.1 Development of Particle Swarm Optimization for Reactive Power Optimization

In this work, the Particle Swarm Optimization (PSO), inspired by the social behaviour of birds and fish schools, is used in conjunction with GNN model to optimize reactive power dispatch by minimizing network power losses, voltage deviations, and/or cost functions under the constraints of electrical network operations.

The PSO is applied as a metaheuristic optimizer to enhance voltage stability, minimize active power losses, and ensure feasible operation of a smart grid through reactive power compensation, tap changer control, and capacitor switching. The flow diagram of a generic PSO model for reactive power optimization is shown in Figure1. Now, let the optimization goal be to minimize a multi-term objective function $J(x)$, where x is the decision variable vector; then the objective function is defined as:

$$\min_x J(x) = \lambda_1 \cdot P_{loss}(x) + \lambda_2 \cdot V_{dev}(x) + \lambda_3 \cdot C_{switch}(x) \quad (1)$$

Where, x is the decision variable vector, λ_1, λ_2, λ_3 are trade-off weights, C_{switch} is a penalty function for switching operation, P_{loss} and V_{dev} functions are defined in Equation 2 and Equation 3, respectively.

$$P_{loss} = \sum_{(i,j)\in\mathcal{L}} R_{ij}\left(\frac{P_{ij}^2+Q_{ij}^2}{V_i^2}\right) \quad (2)$$

Where, $\mathcal{L}$ is a set of lines, P is active power, Q is reactive power, V is the bus voltage, and R is the line reactance.

$$V_{dev} = \sum_{i\in B}(V_i - 1)^2 \quad (3)$$

The decision matrix variable is defined as:

$$x = [Q_{c1}, Q_{c2}, \dots, Q_{cn}, T_1, T_2, \dots T_m, S_1, \dots S_p] \quad (4)$$

Where, Q_{ci} denotes the reactive power injected by capacitor bank i, T_j is tap position of transformer j, S_k is the switch status (on or off) for capacitor k. Some constraints are outlined for the objective function as follows:

$$\left.\begin{array}{c} Voltage\ Limits:\ V_i^{min} \le V_i \le V_i^{max},\ \ \forall i \in B \\ Reactive\ Power\ Limits:\ Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max} \\ Tap\ Settings:\ T_j \in \{T_j^{min}, \dots T_j^{max}\} \\ Thermal\ Limits:\ |I_{ij}| \le I_{ij}^{max},\ \ \forall (i,j) \in \mathcal{L} \end{array}\right\} \quad (5)$$

Where, B is a set of buses, $\mathcal{L}$ is a set of lines, and I_{ij} is the line current magnitude. Each particle i in the swarm represents a candidate solution x_i. The swarm evolves by updating the position and velocity of each particle based on local and global best solutions. If there are n particles in the swarm, each particle i is initialized with position $x_i^0 \in R^d$, velocity $v_i^0 \in R^d$. Personal best position is defined as:

$$p_i = x_i^0 \quad (6)$$

Global best position is defined as:

$$g = arg\min_i J(p_i) \quad (7)$$

At each iteration t, each particle updates its velocity and position using the following expressions;

$$v_i^{t+1} = w \cdot v_i^t + c_1 r_1 (p_i - x_i^t) + c_2 r_2 (g - x_i^t) \quad (8)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (9)$$

Where, w is the inertia weight (exploration vs exploitation), c_1, c_2 are acceleration coefficients (personal vs social), r_1, $r_2 \sim U(0,1)$ are random scalars for stochasticity. To ensure feasible solutions, infeasible solutions are penalized using a high cost and projection methods are applied to map x_i back into feasible set: $x_i \leftarrow clip(x_i, x^{min}, x^{max})$. PSO is integrated with Newton-Raphson load flow (Figure 2) solver for computing power losses and voltages after each particle's configuration.

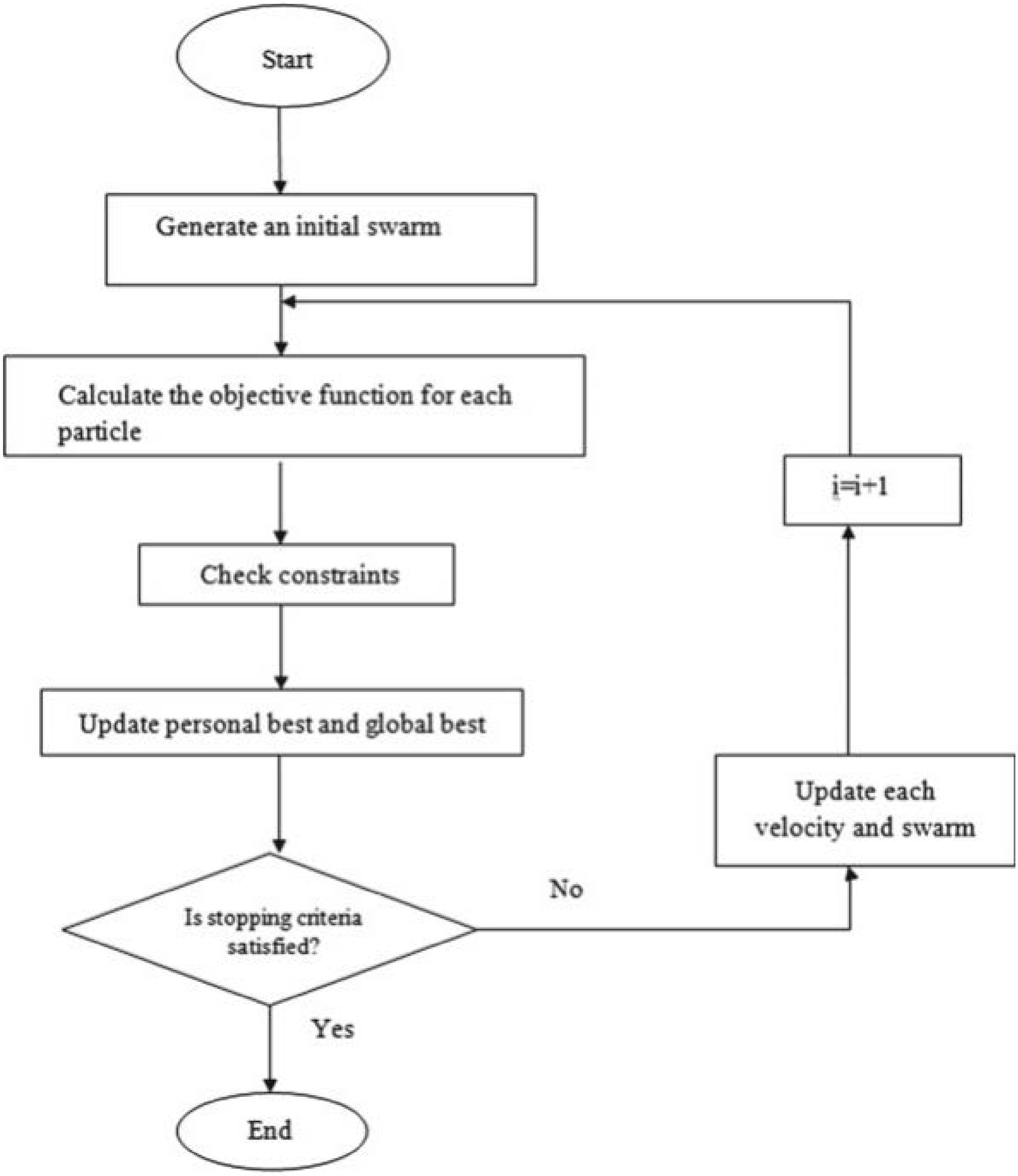

Figure 1 The flow diagram of a generic PSO model for reactive power optimization [16]

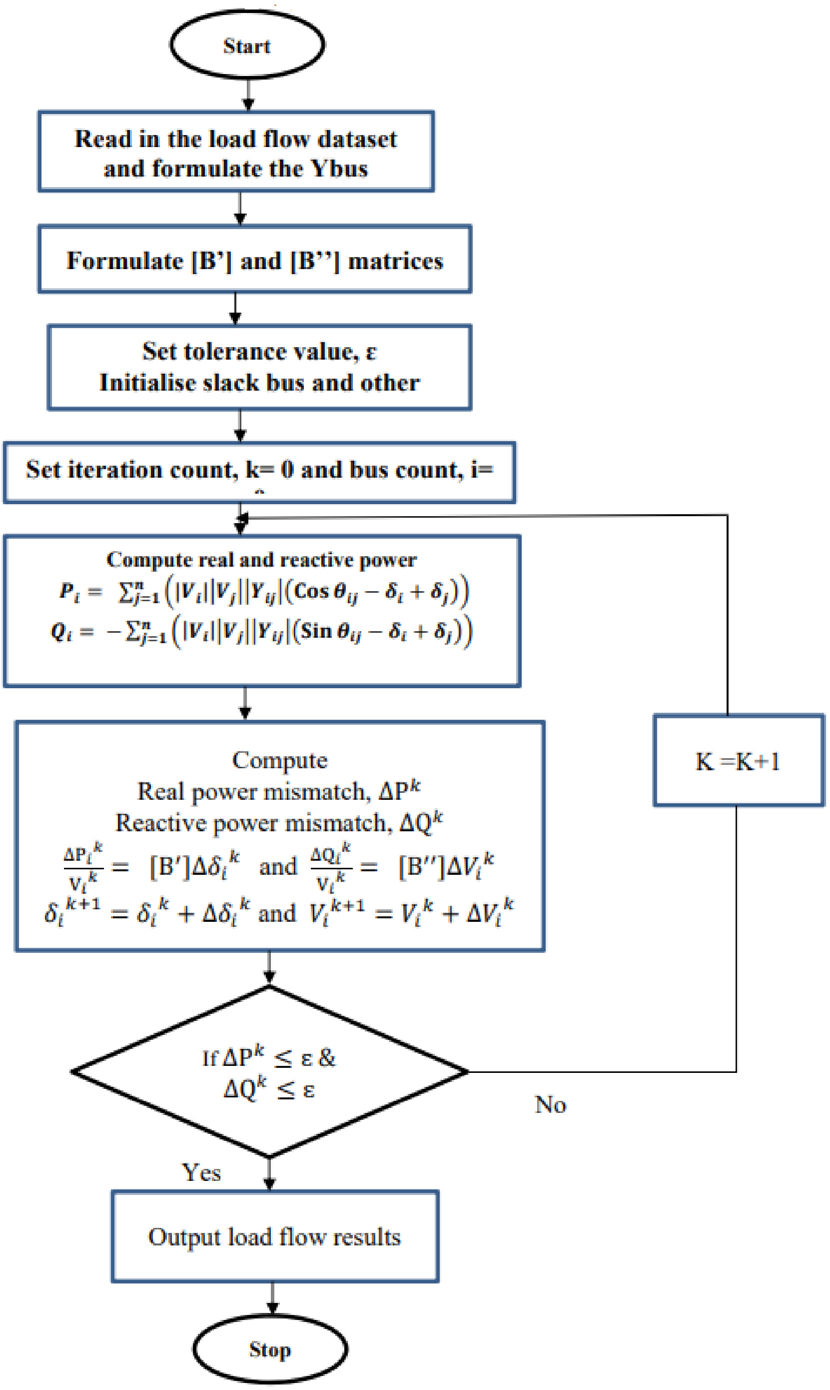

Figure 2 The flowchart of the Newton Raphson Load Flow Model [17]

2.2 The hybrid GNN + PSO model

In this work, the Graph Neural Network (GNN) is the base model for optimization of the IEEE 14-bus network reactive power while the PSO is used to enhance the performance of the GNN model. The architecture of a generic the GNN model is presented in Figure 3 while the flow diagram of the reactive power flow optimization model based on the GNN model is shown in Figure 4.

Figure 3: The architecture of a generic the GNN model. [18]

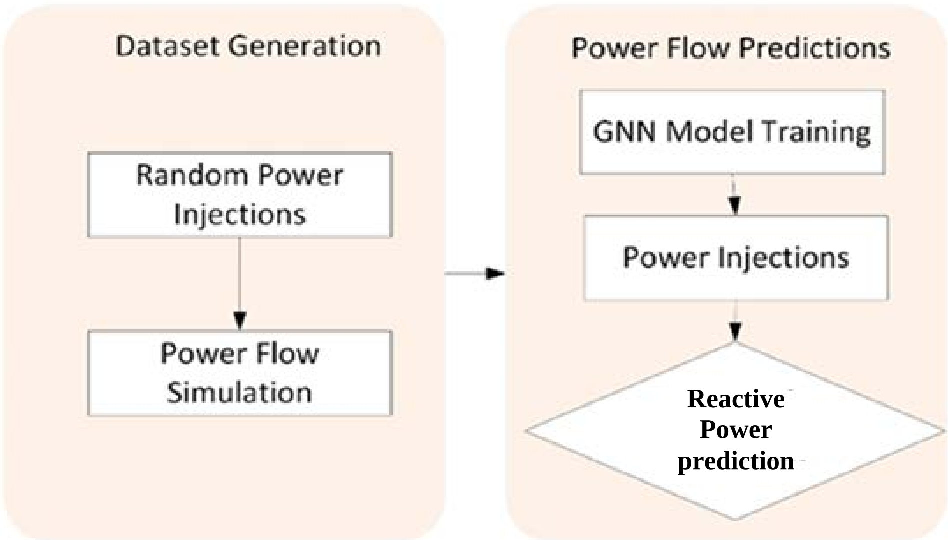

Figure 4 The flow diagram of the reactive power flow optimization model based on the GNN model [19]

By blending PSO into GNN, PSO leverage grid topology (nodes = buses, edges = lines) for spatially coordinated control of voltage/reactive flows. GNN model maps $\hat{V} = f_{GNN}(\mathcal{G}, X, \theta)$, where $\mathcal{G}$ is the graph (IEEE 14-bus), X is node-wise input, and θ is hyperparameters. PSO is used to: optimize graph signal Qc(capacitor settings), tune node-wise input weights and adjacency thresholds and select GNN architecture (depth, aggregation rules). The optimization function is formulated as:

$$\min_{Q_c} J = \lambda_1 \cdot \left\| \hat{V} - V_{ref} \right\|^2 + \lambda_2 \cdot GNN_{loss} \quad (10)$$

Each particle represents a set of node level Q_c^i values to inject or absorb reactive power. This hybrid GNN + PSO enables graph-structured control, ensuring coordinated decision-making across spatially distributed buses with minimal communication latency. The single line model of the IEEE 14-transmission network is presented in Figure 5.

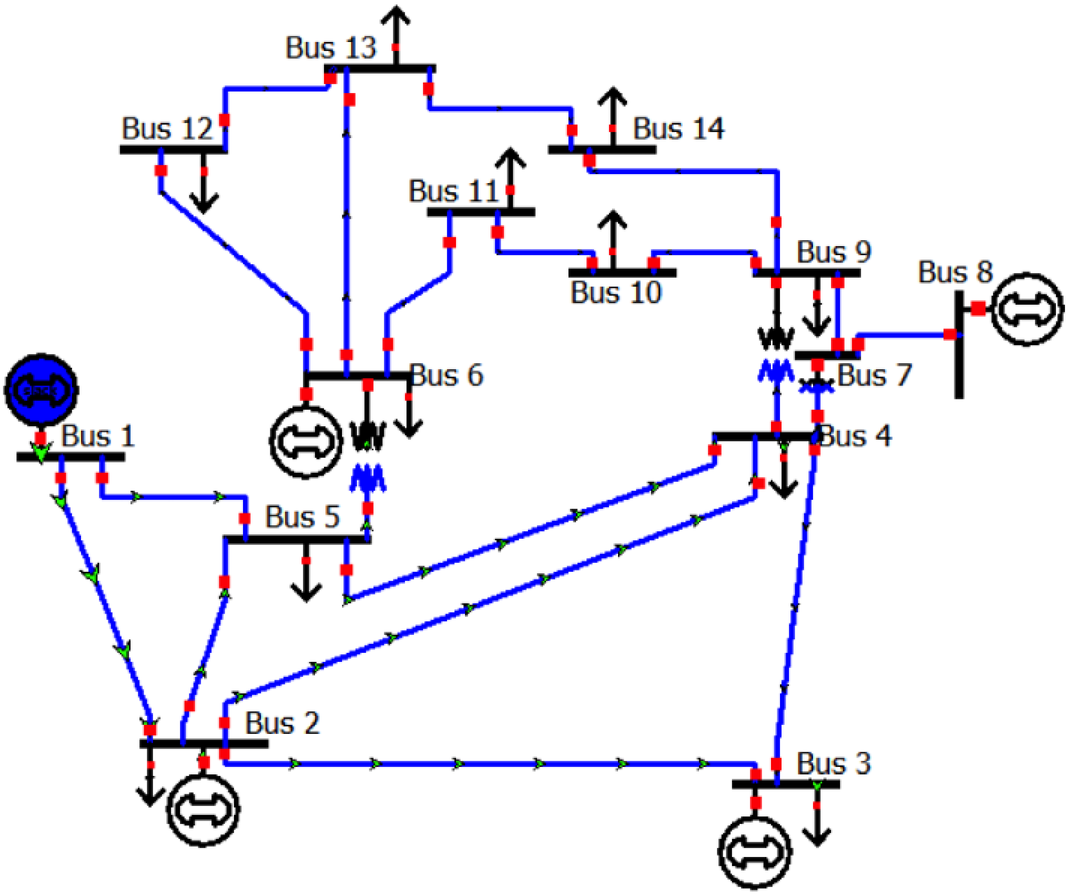

Figure 5 The single line model of the IEEE 14-transmission network [20]

3. Results and discussion

The power mismatch data result from the GNN + PSO model are presented in Table 1 and visualized in Figure 6. The results offer in-depth view into the behavior of the Graph Neural Network (GNN) model when enhanced with the Particle Swarm Optimization (PSO) algorithm for load flow refinement. The GNN + PSO hybrid model shows notable improvements over the standalone GNN model, with substantial reductions in Bus 1 active mismatch; dropping from 147.750 MW to 128.174 MW.

Table 1: Per-Bus Power Mismatch (GNN + PSO Hybrid)

Bus ID	P_mismatch (MW)	Q_mismatch (MVAR)
1	128.174	48.841
2	62.283	19.227
3	54.133	15.700
4	-41.151	-17.731
5	-40.315	-17.809
6	45.895	11.872
7	-40.947	-17.814
8	46.023	4.494
9	-40.753	-17.745
10	-41.150	-17.807
11	-40.983	-17.667
12	-40.738	-17.681
13	-40.583	-17.806
14	-40.890	-17.901

The Q_mismatch profile also benefits from the hybrid approach. Bus 1 exhibits a mismatch of 48.841 MVAR, a reduction from 56.095 MVAR in the standalone GNN case. Across the board, reactive mismatches fall within a narrow band: between +4.494 MVAR (Bus 8) and −17.901 MVAR (Bus 14). This uniformity suggests that reactive support mechanisms (e.g., capacitor banks or tap-changing transformers) could be better coordinated using this hybrid setup. The relatively flat profile seen in Figure 6 supports this conclusion. The bar chart in Figure 6 graphically depicts the active and reactive mismatches per bus, clearly reflecting the structured power balancing strategy induced by the GNN + PSO model: The blue bars (active mismatch) and red bars (reactive mismatch) are nearly symmetric. The fluctuations across buses are moderate and consistent, especially when compared to the raw GNN model. This visual evidence supports the idea that PSO has effectively guided GNN's learned weights toward lower-cost mismatch configurations, despite GNN's known limitations in numeric convergence.

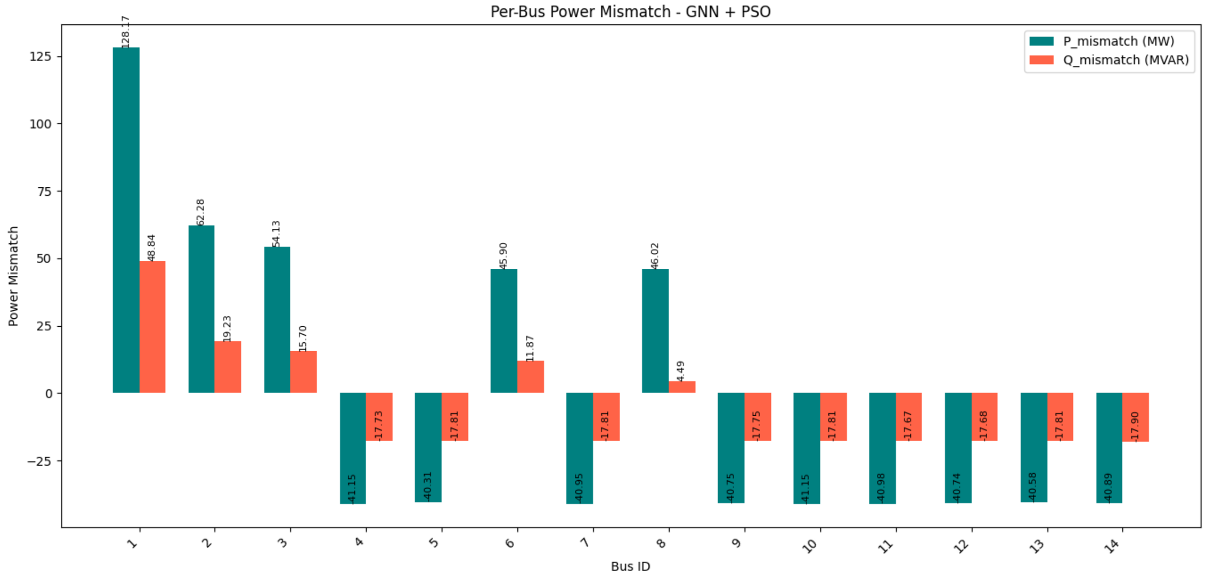

Figure 6: Per-Bus Power Mismatch (GNN + PSO Hybrid)

The results from Table 2 indicate that the GNN + PSO model successfully allocates load across major transmission corridors. Notably, the heaviest load paths include:

i. Line 1–5 with an active flow of 216.207 MW,
ii. Line 2–4 with 130.114 MW, and
iii. Line 6–11 with 113.412 MW.

Peripheral lines such as 4–7, 4–9, and 7–9 still maintain nominal flow levels, suggesting appropriate reactive distribution to fringe buses. Mid-network lines like 2–5, 3–4, and 6–12 also reflect steady power movement, confirming that the GNN has correctly learned the topological influence of each bus on regional dispatch. Figure 7 visually supports these findings by mapping directional active and reactive power across the grid with balanced gradient intensities, affirming the network's operational stability.

The hybrid model exhibits notable improvements in energy loss reduction over the standalone GNN model, primarily driven by the PSO layer's fine-tuning of line parameters:

i. The line with the highest total loss is again 1–5, recording 12,447.800 MVA, a clear reduction compared to the pure GNN model (13,238.815 MVA in Table 4.12).
ii. Major improvements are observed in: Line 2–5: reduced to 3408.504 MVA, Line 6–12: now at 3802.265 MVA, and Line 6–13: optimized to 1976.095 MVA.
iii. Low-voltage, low-load lines, such as 7–9, 9–10, and 13–14, continue to display negligible losses, supporting the efficiency and fidelity of power routing even at the distribution tails.

These patterns are clearly illustrated in Figure 8.

Table 2: GNN + PSO based line flow demand and loss

From–To	Active Power Flow (MW)	Reactive Power Flow (MVAR)	Active Power Loss (MW)	Reactive Power Loss (MVAR)	Total Power Loss
1–2	82.591	36.004	140.315	479.001	498.155
1–5	216.207	84.221	2860.770	12010.203	12447.800
2–3	8.934	4.103	5.012	21.084	22.462
2–4	130.114	46.334	1110.411	3402.118	3525.379
2–5	128.951	47.031	1071.323	3293.401	3408.504
3–4	119.915	42.406	1098.018	2883.199	2999.608
4–5	-1.011	0.096	0.013	0.041	0.045
4–7	-0.261	0.105	0.000	0.015	0.015
4–9	-0.497	0.020	0.000	0.129	0.129
5–6	-112.810	-37.781	0.000	3580.613	3580.613
6–11	113.412	37.660	1358.001	2863.303	3021.304

6–12	113.090	37.800	1745.110	3652.312	3802.265
6–13	112.981	38.066	934.019	1855.789	1976.095
7–8	-112.096	-28.235	0.000	2421.701	2421.701
7–9	-0.227	-0.081	0.000	0.006	0.006
9–10	0.491	0.072	0.008	0.021	0.023
9–14	0.136	0.203	0.008	0.016	0.018
10–11	-0.212	-0.185	0.006	0.015	0.017
12–13	-0.189	0.160	0.014	0.013	0.018
13–14	0.360	0.136	0.026	0.053	0.059

Figure 7: GNN + PSO based line flow demand

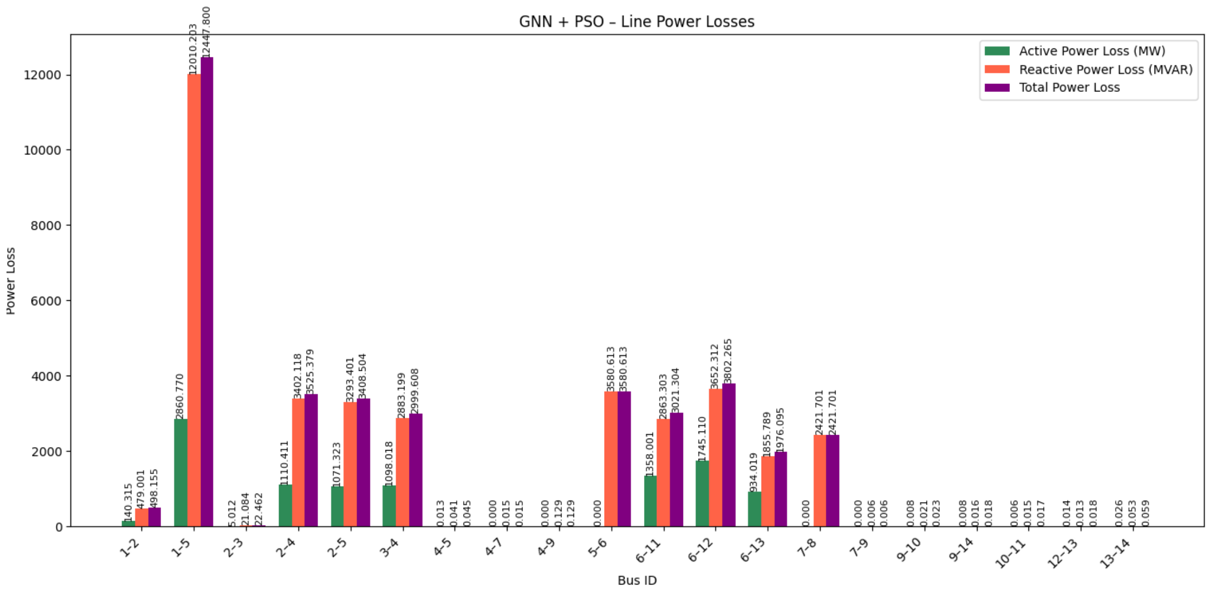

Figure 8: GNN + PSO based line losses

4 Conclusion

A hybrid model approach for the optimization of the IEEE 14-bus network reactive power is presented. Specifically, the Graph Neural Network (GNN) and Particle Swarm Optimization (PSO) hybrid model is used for the reactive power control in the IEEE 14-bus network. The combination of Graph Neural Networks (GNNs) with Particle Swarm Optimization (PSO) brings together two complementary paradigms; GNNs for spatial feature learning over topologically structured grid data, and PSO for global exploration of parameter configurations that minimize network inefficiencies. This hybrid aims to mitigate the shortcomings of standalone GNNs, which tend to underperform in precision-based optimization tasks due to limited reward shaping and exploration diversity. The results show that the GNN + PSO hybrid model shows notable improvements over the standalone GNN model, with substantial reductions in Bus 1 active mismatch; dropping from 147.750 MW to 128.174 MW. Also, the hybrid model exhibits notable improvements in energy loss reduction over the standalone GNN model, primarily driven by the PSO layer's fine-tuning of line parameters.

References

1. Gönen, T., Ten, C. W., & Mehrizi-Sani, A. (2024). *Electric power distribution engineering*. CRC press.
2. Singh, R., & Powar, V. (2024). The Future of Generation, Transmission, and Distribution of Electricity. In *The Advancing World of Applied Electromagnetics: In Honor and Appreciation of Magdy Fahmy Iskander* (pp. 349-383). Cham: Springer International Publishing.
3. Von Meier, A. (2024). *Electric power systems: a conceptual introduction*. John Wiley & Sons.
4. Adewumi, O. B., Fotis, G., Vita, V., Nankoo, D., & Ekonomou, L. (2022). The impact of distributed energy storage on distribution and transmission networks' power quality. *Applied Sciences*, *12*(13), 6466.
5. Ma, S., Chou, Y. C., Zhao, H., Chen, L., Ma, X., & Liu, J. (2023, May). Network characteristics of leo satellite constellations: A starlink-based measurement from end users. In *IEEE INFOCOM 2023-IEEE Conference on Computer Communications* (pp. 1-10). IEEE.
6. Gönen, T., Ten, C. W., & Mehrizi-Sani, A. (2024). *Electric power distribution engineering*. CRC press.
7. Razmi, D., Lu, T., Papari, B., Akbari, E., Fathi, G., & Ghadamyari, M. (2023). An overview on power quality issues and control strategies for distribution networks with the presence of distributed generation resources. *IEEE access*, *11*, 10308-10325.
8. Rehman, A., Koondhar, M. A., Ali, Z., Jamali, M., & El-Sehiemy, R. A. (2023). Critical issues of optimal reactive power compensation based on an HVAC transmission system for an offshore wind farm. *Sustainability*, *15*(19), 14175.
9. Mehbodniya, A., Paeizi, A., Rezaie, M., Azimian, M., Masrur, H., & Senjyu, T. (2022). Active and reactive power management in the smart distribution network enriched with wind turbines and photovoltaic systems. *Sustainability*, *14*(7), 4273.
10. Kumar, C., Lakshmanan, M., Jaisiva, S., Prabaakaran, K., Barua, S., & Fayek, H. H. (2023). Reactive power control in renewable rich power grids: A literature review. *IET Renewable Power Generation*, *17*(5), 1303-1327.
11. Alhamrouni, I., Abdul Kahar, N. H., Salem, M., Swadi, M., Zahroui, Y., Kadhim, D. J., ... & Alhuyi Nazari, M. (2024). A comprehensive review on the role of artificial intelligence in power system stability, control, and protection: Insights and future directions. *Applied Sciences*, *14*(14), 6214.
12. Mansouri, S. S., Sivaram, A., Savoie, C. J., & Gani, R. (2024). Models, modeling and model-based systems in the era of computers, machine learning and AI. *Computers & Chemical Engineering*, 108957.
13. Wei, Y. (2024). Development of novel computational models based on artificial intelligence technique to predict liquids mixtures separation via vacuum membrane distillation. *Scientific Reports*, *14*(1), 24121.
14. Al Butti, O. S. T., Burunkaya, M., Rahebi, J., & Lopez-Guede, J. M. (2024). Optimal power flow using PSO algorithms based on artificial neural networks. *IEEE Access*, *12*, 154778-154795.
15. Abdel-Basset, M., Mohamed, R., Hezam, I. M., Sallam, K. M., Alshamrani, A. M., & Hameed, I. A. (2024). Artificial intelligence-based optimization techniques for optimal reactive power dispatch problem: a contemporary survey, experiments, and analysis. *Artificial Intelligence Review*, *58*(1), 2.
16. Manasvi, K., Venkateswararao, B., Devarapalli, R., & Prasad, U. (2020). PSO Based Optimal Reactive Power Dispatch for the Enrichment of Power System Performance. In *Recent Advances in Power Systems: Select Proceedings of EPREC 2020* (pp. 267-276). Singapore: Springer Singapore.
17. Ukut, U. I., Okpura, N., & Umoette, A. T. (2023). Comparison Of Load Flow Analysis On IEEE 33 Bus System Based On Newton Raphson And Fast Decoupled Methods. *Science and Technology Publishing (SCI&TECH)*, *7*(2).
18. Hansen, J. B., Anfinsen, S. N., & Bianchi, F. M. (2022). Power flow balancing with decentralized graph neural networks. *IEEE Transactions on Power Systems*, *38*(3), 2423-2433.
19. Tuo, M., Li, X., Zhao, T.-Q. (2023): Graph neural network-based power flow model. 2023 North American Power Symposium (NAPS), 1–5 (2023) https://doi.org/10.1109/NAPS58826.2023.10318768
20. Talebi, S., & Zhou, K. (2025). Graph Neural Networks for Efficient AC Power Flow Prediction in Power Grids. *arXiv preprint arXiv:2502.05702*.