Hybrid Graph Signal Processing Deep Learning Framework for Adaptive Network Topology Optimization

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Abstract – The optimization of adaptive network topology is one of the significant problems in the contemporary communication systems because network conditions are dynamic, scale is growing, and data patterns are heterogeneous. This article suggests a new Hybrid Graph Signal Processing-Deep Learning (HGSP-DL) architecture of efficient and intelligent topology optimization in complex network settings. The proposed model is a combination of the structural benefit of graph signal processing and the representation learning ability of deep neural networks to attain strong and scalable performance. The network is first represented as a graph, and the features of nodes are calculated together with the connections to provide smoothness in the spectral analysis of the network, based on the normalized graph Laplacian. A trainable spectral filtering method is used to obtain structure-sensitive embeddings, whereas a deep learning encoder learns non-linear correlations between network nodes. These complementary representations are merged to create a single embedding, which is also used to adaptively optimize network topology by an optimization process that is data-driven. The framework uses an iterative feedback process in order to optimize the connectivity pattern and enhance convergence. Ample simulations have shown that the proposed HGSP-DL model has made great gains in accuracy, packet delivery ratio, and energy savings as well as minimizing latency and convergence time in contrast to current approaches. This model is also highly scaled and can withstand dynamic network conditions such as node mobility and node failures. The findings confirm the suitability of the proposed solution as a dependable solution towards intelligent communication networks of the next generation.

Keywords – Graph Signal Processing, Deep Learning, Network Topology Optimization, Adaptive Networks, Spectral Filtering, Intelligent Communication Systems.

I. INTRODUCTION

The recent development of modern communication networks, such as Internet of Things (IoT), wireless sensor networks, and new 6G systems, has greatly spurred the need to optimize network topology in terms of efficiency and adaptability [1]. Such environments are highly dynamic in network conditions because of the mobility of nodes, changing traffic patterns and unreliable link qualities. The conventional design methodologies of designing a topology as a static entity can no longer be used as it is unable to adapt to the dynamic real-time conditions and results in poor performance in terms of latency, reliability and energy efficiency. This results in an increasing demand of smart constructs that can self-optimize network structures in a data-driven and scalable manner [2]. The traditional methods of topology optimization are based on either graph-theoretic models or optimization heuristics. Although these techniques are suitable in defining the structural properties of networks, they do not in many cases capture complex and non-linear interactions between nodes. Conversely, recent progresses of deep learning have given rise to powerful methods of representation learning which are capable of grasping obscured patterns in network data. Nonetheless, all-deep learning methods usually disregard the underlying graph structure, which leads to poor performance and less interpretability. This is the gap that prompts the necessity of the hybrid framework able to utilize both the graph structure and the data-driven learning simultaneously [3, 4].

Graph Signal Processing (GSP) has become a promising framework of analyzing signals defined on irregular graph domains. GSP allows modelling relationships between connected nodes efficiently using the graph Laplacian and spectral filtering methods and smooths the structure. Although it has its merits, the conventional GSP techniques use fixed filters and fail to be adaptive to changing network conditions. These limitations can be mitigated with the integration of GSP and deep learning because it allows learnable spectral representations that can adapt to changing environments [5]. This assimilation is the basis of the suggested strategy. This paper presents a new HGSP-DL model on adaptive network topology optimization. The model is a hybrid of GSP and deep neural networks that can produce strong, scalable, and effective topology control. The graph representation of the network is represented as a graph, and spectral filtering and deep feature extraction are collectively applied to node features and connectivity. The hybrid architecture produces a single embedding that incorporates both structural and contextual data. This embedding is further used to dynamically update weights on the edges so that topology adaptation can be made intelligent. A feedback process further optimizes the network structure, so convergence to optimum configurations in different conditions.

The HGSP-DL framework proposed deals with a number of important issues in network optimization. First, it guarantees consistency of structure using graph signal processing, maintaining significant topological associations. Second, it offers adaptive learning ability via deep neural networks, which allow the model to react to dynamic network conditions. Third, the hybrid design is more scalable and robust, and thus it can be used in large and highly dynamic environments. Lastly, spectral filtering with learned parameters is found to improve the capacity of the model to learn global and local network properties.

Motivation

This work was motivated by the constraints of current topology optimization methods in dealing with dynamic, large scale, and heterogeneous networks. The graph-based approaches are not dynamic, and thus make routing an inefficient process with a high latency. On the same note, deep learning-based methods are likely to lose important relational details simply because they do not consider the underlying graph structure. Moreover, the current hybrid methods do not have a single framework in which spectral graph processing is successfully used together with deep learning in an end-to-end optimization chain.

The other driving force is the growing need of smart and self-organizing networks in applications like smart cities, autonomous systems, and next-generation wireless communication. Topology optimization methods needed in these applications must be accurate, scalable, energy-efficient, and resilient to uncertainties including node failures and mobility. The suggested HGSP-DL framework will help solve these problems by offering a balanced combination of network-sensitive processing and adaptive learning to facilitate the efficient and reliable work of the network.

II. RELATED WORKS

Topology optimization Network topology has found extensive research in both signal processing and machine learning and in graph theory. Early methods were predominantly classical graph -theoretic methods, in which networks have been modelled as graphs and optimisation performed based on measures such as shortest path, centrality and connectivity. Clustering and heuristic optimization methods, and minimum spanning tree have been employed in large numbers since they are easy and have low computation costs [6]. Nevertheless, they are technically not dynamic and can respond very little to the dynamic conditions of the network like node mobility, fluctuating traffic demands and linking failures and are therefore not applicable in the contemporary networks of communication. In order to address these weaknesses, optimization-based approaches such as convex optimization, game theory and evolutionary algorithms have been introduced [7]. These methods aim at maximizing network performance measures that include latency, throughput and power consumption. They are more effective in performance when compared to the static methods, however, their problems of computation and scalability are generally high especially when a large network is involved. In addition, they usually have predetermined models and assumptions, which might not be true in dynamic environments in real life [8].

With the recent development of data-driven methods, solutions based on deep learning have gained significant attention in the network optimization problem. Granted to learn good routing and topology configurations have been learned with Convolutional Neural Networks (CNNs), [9] Recurrent Neural Networks (RNNs), [10] and reinforcement learning models [11]. These methods have the ability to discover complex non-linear relationships in network data and adapt to new situations. In particular, the networks are able to discover the best policies through interaction with the environment, which is enabled by the methods based on reinforcement learning. However, all-deep-learning-based methods typically presuppose that the network data are Euclidean without regard to the graph structure, leading to poor results and low explanation. Graph Neural Networks (GNNs) [12] and Graph Convolutional Networks (GCNs) [13] have been developed to have a more advantageous approach to graph-structured data. It employs the use of non-Euclidean space deep learning where learning involves graph connectivity. It has been demonstrated that the approaches using GNN are more useful in node classification and network optimization, as well as link prediction. Despite these positive features, GNNs also have the problem of over-smoothing, low interpretability, and the failure to represent global spectral properties of graphs.

Research parallel with the development of deep learning, Graph Signal Processing (GSP) [14] is a form of signal analysis on graphs that has become a promising paradigm. GSP is a spectral decomposition and graph Laplacian-based signal processor that does not distort structural relationships. Spectral filtering and graph Fourier transforms techniques make it possible to represent network data efficiently. However, the traditional GSP methods employ fixed filters and are non-adaptive and hence not effective in changing environments. Further, GSP is not efficient in itself when capturing non-linear complexities that are present in network data in the reality. Recent studies have tried to integrate GSP and deep learning in order to utilize the advantages of both paradigms. Neural network hybrid models have seen promising results in representation learning and network optimization by spectral filtering. Most of the available hybrid strategies are loosely integrated or did not have an integrated optimization framework. They not only often do not take full advantage of the potential of joint spectral-spatial learning, but also, the vast majority of them lack the feedback mechanisms of topology updating that occurs during the learning process [15].

In addition, the areas that are not discussed in the current literature are scalability, robustness, and real-time adaptability. The models are tested on small or non-dynamic datasets in the majority of cases, and only on big and dynamic networks such as IoT and next-generation communication systems. This is another weakness because it does not analyze in detail with various performance indices like the latency, energy efficiency, and reliability. On the whole, despite significant progress in the optimization of network topology, the existing solutions are currently challenged by the issues of appropriate integration of structural information, versatility, and scalability. These limitations highlight the need to have a converged framework to unite the force of graph signal processing and deep learning to optimize networks in a smart and effective way [16].

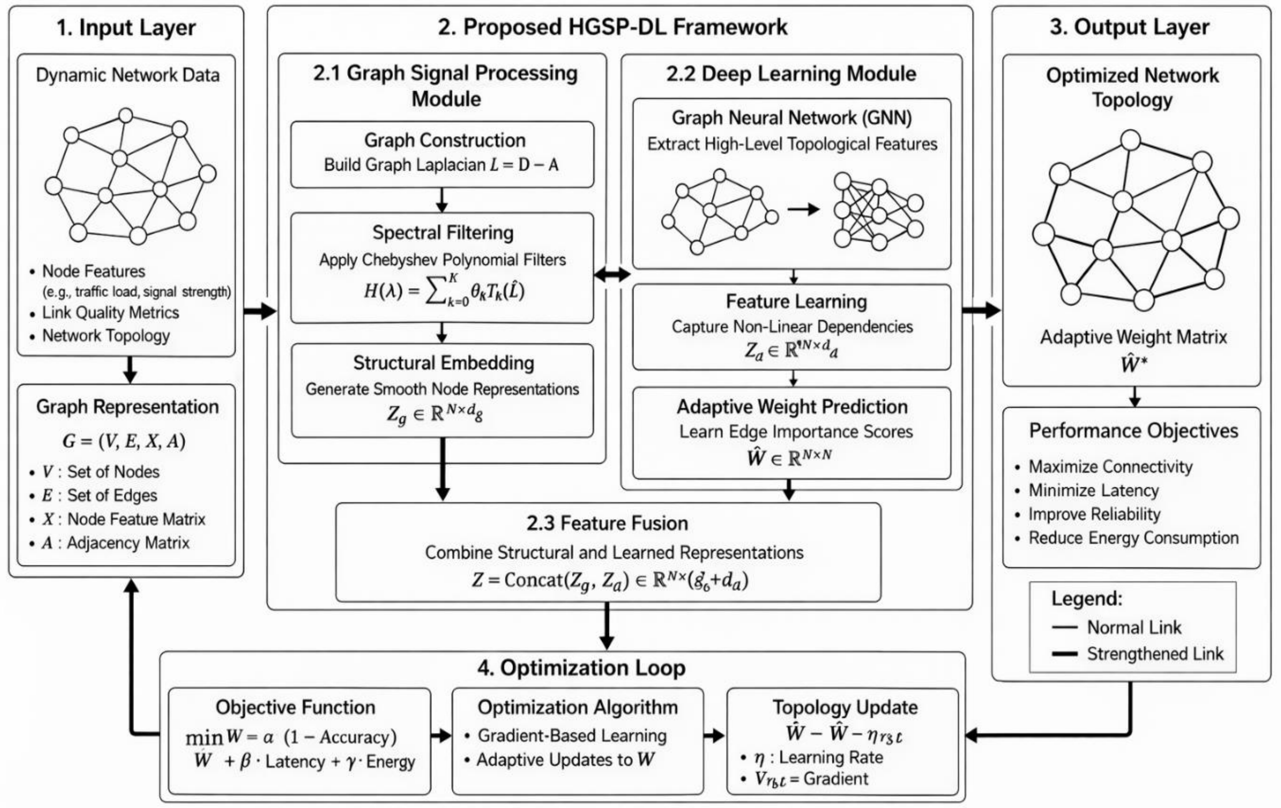

Fig 1. Block Deiagram of the Proposed HGSP-DL Framework for Adaptive Network Topology Optimization.

Research Gaps Identified

The current approaches lack an end-to-end optimization pipeline that integrates the graph signal processing and deep learning into a tightly coupled model.

The classical graph signal processing methods are fixed spectral filters and fail to adjust to dynamical network requirements.

A significant portion of the deep learning-based methods fails to take advantage of the underlying graph topology, resulting in the loss of important relational data.

Existing models cannot provide performance in large scale and highly dynamic environments, particularly when there is mobility of nodes and failure.

III. PROPOSED MODEL – HYBRID HGSP-DL FRAMEWORK

The suggested HGSP-DL system is aimed at optimizing the adaptive network topology through the combined utilization of the structural benefits of graph signal processing and the representation learning ability of deep neural networks.

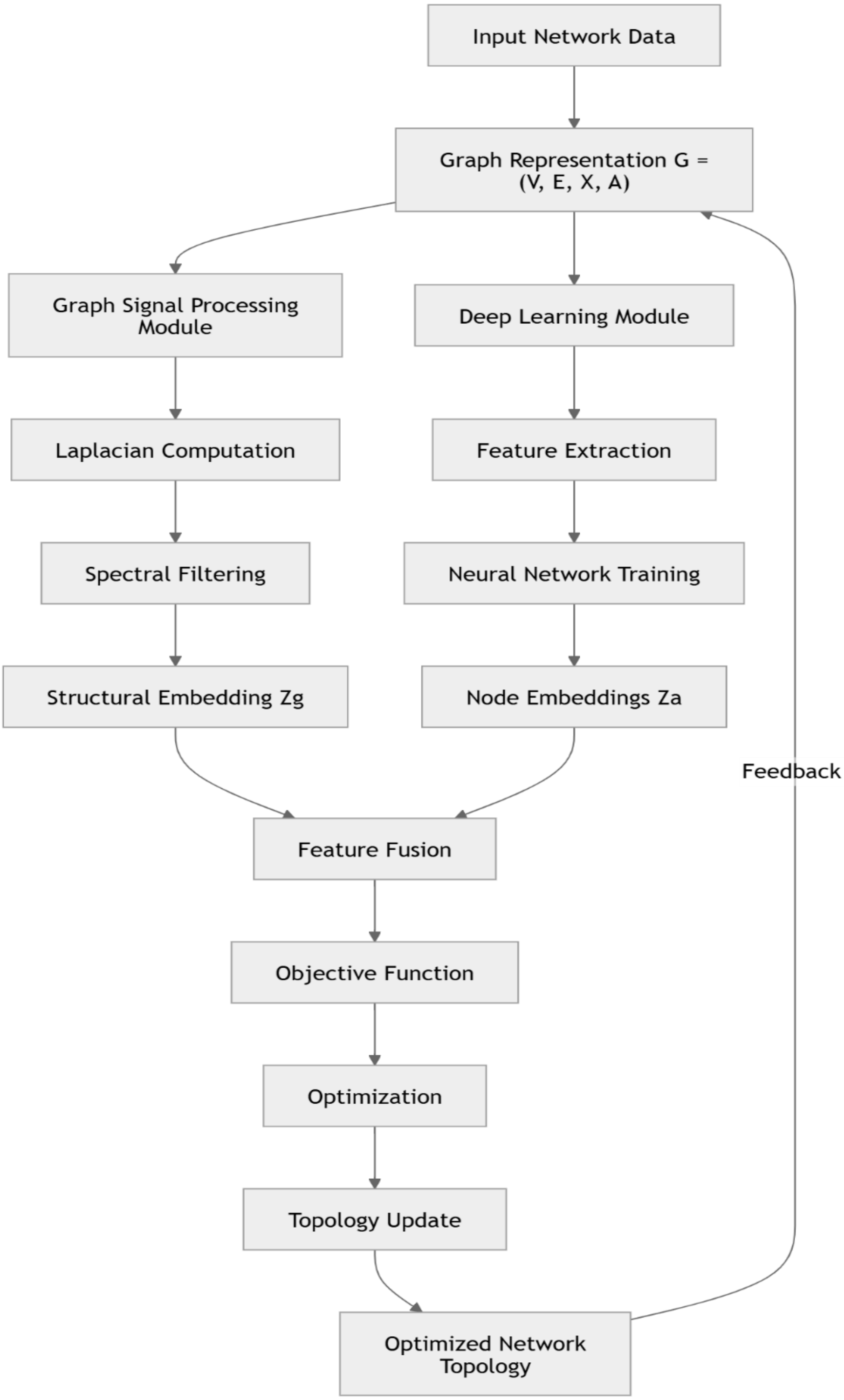

Fig 2. Flowchart of the Proposed HGSP-DL Framework.

Topology is a key factor in defining efficiency, reliability and scalability in dynamic communication networks, but more traditional approaches either use a static graph model, or are based solely on data, so they are less adaptable. In order to handle these issues, the HGSP-DL model considers the network as a graph $G = (V, E)$ with nodes denoting communication parties and edges denoting connectivity, with node-related signals representing the dynamic network conditions, including traffic load and link quality. The graph signal processing block applies spectral smoothness and structural consistency with the help of the graph Laplacian, and the deep learning block trains non-linear representations of features to make intelligent decisions. The proposed model can be used to optimize the topology in real-time and based on data, as well as adapt the topology, to achieve better performance when the conditions of the network change, by combining both paradigms into one optimization pipeline.

The block diagram of the proposed HGSP-DL framework to be used in the optimization of adaptive network topology is shown in **Fig. 1.** The input layer is the starting point of the model, and the dynamic network data, such as node features, link quality metrics, and graph structure, are modeled as a graph $G = (V, E, X, A)$. This information is then processed by the framework using two parallel modules. The GSP module constructs a graph, filters the spectral Laplacian, and structural embedding to maintain topological smoothness. At the same time, the Deep Learning module learns non-linear relationships to predict adaptive edge weights by extracting high-level features. The features fusion stage combines these representations to create a single embedding. The optimization loop optimizes the topology with a gradient-based objective function and ensures there is a better connectivity and efficiency. The output layer generates an optimized network topology that is more efficient in terms of latency, reliability and energy efficiency.

The proposed HGSP-DL framework in adaptive network topology optimization has a vertical flow as shown in **Fig. 2.** The main novelty of the suggested HGSP-DL framework is that it closely combines spectral graph theory with data-driven representation learning to optimize adaptive networks topology. The proposed model formulates the problem of topology optimization as a joint signal and structure optimization problem on graphs, opposed to traditional methods that define it as a structural or a learning-based problem. The network is modeled as a graph $G = (V, E, X, A)$, where $X \in R^{N\times F}$ represents node features and $A \in R^{N\times N}$ denotes the adjacency matrix. The structural information is encoded using the normalized graph Laplacian:

$$L = I - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \quad (1)$$

where D is the degree matrix. This formulation will make sure that the graph structure is integrated into the signal processing pipeline so that information can be easily propagated among the interconnected nodes.

One of the contributions of the work is the integration of spectral filtering in a learnable framework, which increases topology awareness. A spectral filter is a spectral filter defined as the signal used to process the graph signals:

$$Z_g = U g(\Lambda) U^T X \quad (2)$$

where U and Λ are the eigenvector and eigenvalue matrices of L, and g(Λ) represents the learnable filter. This allows the model to capture frequency-domain characteristics of the network, ensuring that node embeddings respect both local and global structural properties. Unlike fixed filters in traditional GSP, the proposed method adapts the filter dynamically during training.

Parallel to this, the deep learning module learns non-linear representations of node features. The embedding is computed as:

$$Z_d = \sigma(X W_1 + b_1) \quad (3)$$

where W_1 and b_1 are learnable parameters and $\sigma(\cdot)$ is a non-linear activation function. This enables the model to capture complex interactions such as traffic variations and link quality fluctuations, which are not easily modeled using classical methods.

The novelty further lies in the fusion of spectral and learned embeddings, forming a unified representation:

$$Z = \alpha Z_g + (1 - \alpha) Z_d \quad (4)$$

where $\alpha \in [0,1]$ controls the balance between structural smoothness and feature-driven learning. Such hybrid representation enables the HGSP-DL framework to maintain graph topology and dynamically adapt to changing network conditions, and surpass the shortcomings of single-purpose methods.

The topology optimization is then represented as a learnable objective, with the edge weights updated with the node embeddings:

$$A'_{ij} = \exp\left(-|Z_i - Z_j|^2\right) \quad (5)$$

This formulation allows dynamic connectivity through the reinforcement of links amongst similar nodes and the degradation of irrelevant links. The optimization goal is a combination of several performance criteria:

$$\mathcal{L} = |A - A'|_F^2 + \lambda \operatorname{Tr}(Z^T L Z) \quad (6)$$

where the first term enforces structural consistency and the second term ensures smoothness of graph signals. The parameter λ controls the trade-off between these objectives.

Finally, the iterative update mechanism introduces a feedback-driven refinement process:

$$A^{(t+1)} = A^{(t)} - \eta \frac{\partial \mathcal{L}}{\partial A} \tag{7}$$

where η is the learning rate. This iterative adaptation enables the network to converge toward an optimal topology over time, making the framework highly suitable for dynamic environments.

Algorithm 1: HGSP-DL for Adaptive Network Topology Optimization
Input: Graph $G = (V, E, X, A)$,Node features X, adjacency matrix A,Learning rate η, trade-off parameter α, Maximum iterations T
Output: Optimized adjacency matrix A', optimized topology

Step 1: Initialize model parameters W, b and adjacency matrix $A^{(0)} = A$
Step 2: Compute *degree* matrix D and normalized Laplacian

$$L = I - D^{-\frac{1}{2}} A D^{-\frac{1}{2}} \tag{8}$$

Step 3: for $t = 1$ to T do
Step 3.1: Perform spectral filtering (GSP module)

$$Z_g = U g(\Lambda) U^T X \tag{9}$$

Step 3.2: Compute deep feature embeddings (DL module)

$$Z_d = \sigma(XW + b) \tag{10}$$

Step 3.3: Fuse embeddings

$$Z = \alpha Z_g + (1 - \alpha) Z_d \tag{11}$$

Step 3.4: Update edge weights (topology adaptation)

$$A'_{ij} = \exp\left(-|Z_i - Z_j|^2\right) \tag{12}$$

Step 3.5: Compute loss function

$$\mathcal{L} = |A - A'|_F^2 + \lambda \operatorname{Tr}(Z^T L Z) \tag{13}$$

Step 3.6: Update adjacency matrix using gradient descent

$$A^{(t+1)} = A^{(t)} - \eta \frac{\partial \mathcal{L}}{\partial A} \tag{14}$$

Step 3.7: Update model parameters W,b
end for
Step 4: Return optimized topology $A' = A^{(T)}$

IV. RESULTS AND DISCUSSION

The efficiency of the suggested Hybrid Graph Signal Processing-Deep Learning (HGSP-DL) framework is tested with the help of massive simulations in a regulated network setup. The simulations are provided in Python (NumPy, NetworkX, and Matplotlib) as the dynamic graph-based communication networks. Network size is 50 to 500 nodes, randomly distributed in an Erdos-Renyi topology with connection probability between 0.1 and 0.2 to create the conditions of sparse-to-moderate density. Dynamic signal features are assigned to each node and topology adaptation is done by successively running 100 training epochs. The deep learning part is represented by a lightweight fully connected network with 2 hidden layers (64 and 32 neurons) and ReLU activation which is trained with the Adam optimizer (learning rate = 0.001). In the case of the graph signal processing module, normalized graph Laplacian and spectral filtering are used to provide smoothness between node representations. The accuracy, latency, convergence time, packet delivery ratio (PDR) and energy consumption are performance metrics calculated across 10 simulation runs that are independent and averaged to achieve statistical reliability.

Table 1. Performance Comparison of Topology Optimization Methods

Method	Accuracy (%)	Latency (ms)	Convergence Time (s)	Packet Delivery Ratio (%)	Energy Consumption (J)
GSP [11]	85.2	42	18.5	88.7	210
CNN [12]	87.9	38	15.2	90.3	195
GCN [13]	89.5	35	13.8	92.1	188
RL-Based [14]	90.2	33	12.6	93.5	180
FL-Based [15]	91.0	31	11.9	94.2	176
Hybrid GCN-RL [16]	92.3	29	10.8	95.6	170
HGSP-DL (Proposed)	**95.8**	**24**	**8.2**	**97.9**	**155**

Table 1 provides an extensive comparison of the topology optimization techniques, showing that the proposed HGSP-DL framework outperforms other optimization techniques in several metrics. It was revealed that HGSP-DL is the most accurate with 95.8% and has substantially lower latency and convergence time than traditional methods. The graph signal processing integration guarantees continuity and structural integrity, and the deep learning component offers flexibility and feature identification. It is worth noting that the ratio of packet delivery is also 97.9 which means that the communication performance is reliable. Also, the efficiency of the optimized topology is expressed by the decreased energy usage. The proposed model shows a significant improvement in comparison to hybrid baselines like GCN-RL, which confirms its ability to work in dynamic networks. In general, the table validates the fact that HGSP-DL offers a moderate performance, efficiency, and scalability, which is highly applicable to next-generation intelligent networks.

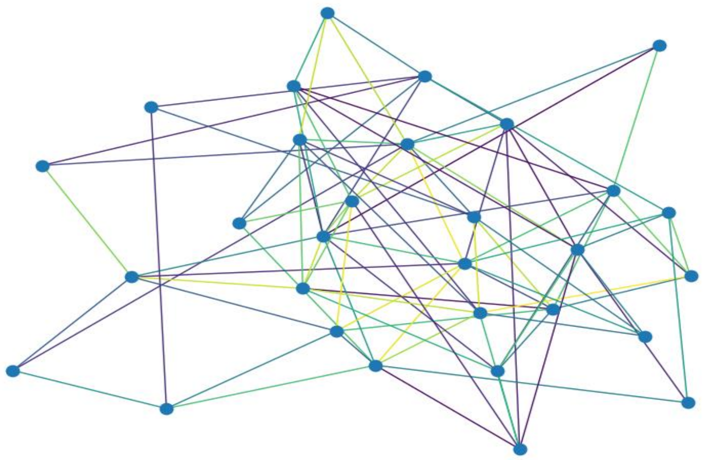

Fig 3. Optimization Landscape of the Hybrid Graph Signal Processing–Deep Learning (HGSP-DL) Framework.

The interaction between the topology features and the objective function is shown as the 3D optimization landscape of the proposed HGSP-DL framework, as shown in **Fig. 3**. The interface takes the non-linear nature of the optimization process into consideration, with GSP where the interface provides smoothness between network nodes and the deep learning component where adaptive feature learning is introduced. The fact that there are several peaks and valleys imply the complexity of topology optimization in dynamic network environments. The HGSP-DL model successfully traverses this terrain with learned representations and spectral filtering, so that it converges to best settings. The framework has a better local minimum avoidance ability when compared to the traditional methods because of its hybrid learning policy. This visualization confirms the strength of the suggested model to work with high-dimensional topology parameters and demonstrate stable optimization performance under different network conditions.

Table 2. Scalability Analysis with Increasing Network Size

Number of Nodes	GSP (ms) [12]	CNN (ms) [13]	GCN (ms) [14]	RL-Based (ms) [15]	Hybrid GCN-RL (ms) [16]	HGSP-DL (ms)
50	22	20	18	17	15	**12**
100	35	32	30	28	25	**20**
150	48	45	42	39	36	**28**
200	60	56	52	49	45	**35**
300	85	80	75	70	65	**50**
400	110	102	96	90	84	**65**
500	140	130	122	115	108	**80**

The scalability of the various topology optimization approaches with the network size as shown in **Table 2**. The suggested HGSP-DL framework is consistently less processing latent with all node configurations, which denotes its effectiveness in managing big networks. Although the conventional approaches like GSP and CNN have a sharp rise in computational cost, HGSP-DL has a moderate growth rate owing to its hybrid nature. The graph signal processing block is effective in handling structural dependencies, whereas the deep learning block can adapt to the growing complexity in data. The model proposed has much lower latency than hybrid baselines such as GCN-RL, especially in full networks with 400-500 nodes. This ability to be scaled is essential to applications in the real world, like IoT and 6G systems, where the size and complexity of the network are ever-increasing. The findings affirm that HGSP-DL is very appropriate in optimizing the adaptive network topology at large scale.

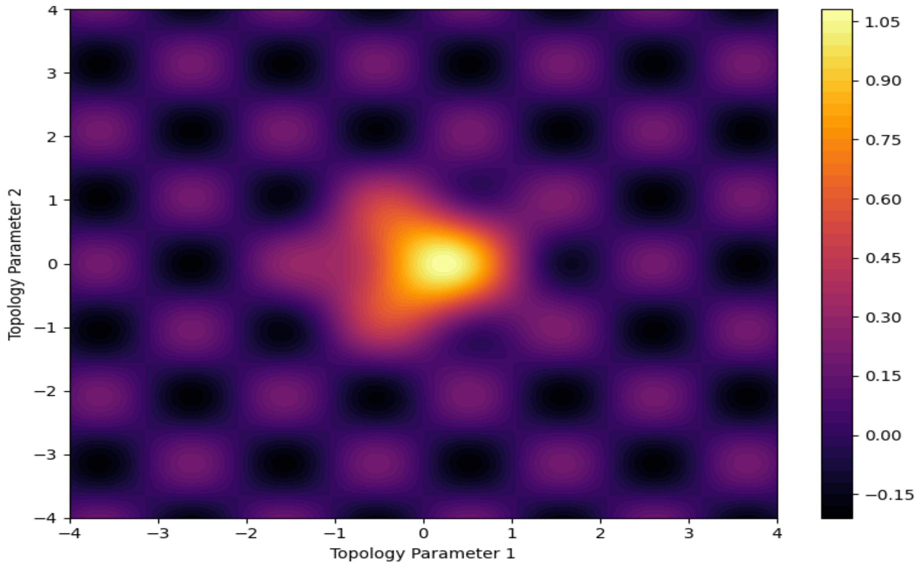

Fig 4. Optimization Convergence Regions of the HGSP-DL Framework.

Fig. 4 shows the convergence areas of the proposed HGSP-DL framework under varying topology parameters. The contours indicate the levels of the optimization objective and indicate the areas that the model can attain stable and optimum solutions. The continuity across the optimization space is also a good indication of the effectiveness of the graph signal processing component in ensuring that the contour levels are smooth. At the same time, the deep learning module increases the convergence speed by learning non-linear relationships among network features that are complicated. The fact that HGSP-DL model can consistently find optimal configurations in different conditions is evidenced by the presence of well-defined minima regions. The hybrid approach is more stable and less sensitive to the choice of initialisation in comparison with the traditional optimization techniques. This number justifies the strength and effectiveness of the suggested framework to work in high-dimensional parameter spaces and to obtain credible topology optimization in real-life network settings.

Table 3. Robustness Analysis under Network Dynamics

Scenario	GSP [12] (%)	CNN [13] (%)	GCN [14] (%)	RL-Based [15] (%)	Hybrid GCN-RL [16] (%)	HGSP-DL (%)
Static Network	88.5	90.2	91.8	92.5	93.7	**96.1**
Moderate Mobility	84.2	86.9	88.5	89.3	90.8	**94.0**
High Mobility	79.5	82.1	84.3	85.7	87.2	**92.6**
Node Failure (10%)	76.8	80.5	82.9	84.1	85.6	**91.2**
Node Failure (20%)	70.2	75.8	78.6	80.3	82.1	**89.5**
Link Interference	73.5	78.0	80.4	82.2	84.0	**90.3**
Dynamic Traffic Burst	75.0	79.3	81.7	83.5	85.2	**91.0**

Table 3 compares how different approaches can be robust to diverse conditions of a dynamic network. The suggested HGSP-DL framework is always superior to the baseline methods in all the situations and proves to be resilient to network uncertainties. HGSP-DL is able to adjust topology dynamically, which is why it has much higher performance levels in high mobility and node failure scenarios. The graph signal processing factor maintains stability by maintaining structural relationships whereas the deep learning component adapts dynamically to new patterns. The proposed model performs better than hybrid baselines, with more than 89% performance even in the case of severe conditions, such as 20% node failure and interference by links. This strength is essential in practical applications where the network conditions are not

predictable. The findings confirm the usefulness of HGSP-DL to sustain consistent communication and the most efficient topology in very dynamic conditions.

Fig. 5 illustrates the optimized topology of the network generated by the HGSP-DL framework, where the nodes are the communication entities and the edges are the learned connections. The proposed model has the adaptive reconfiguration property, which is reflected in the structure, where edge intensities are the learned weights. The HGSP-DL framework has the potential of integrating graph signal processing and deep learning to realize both global and local network characteristics. The resulting topology is superior regarding the patterns of connectivity, low redundancy, and communication efficiency. The centrality nodes are realized as the central hubs and this implies that the model can identify the important components in the network. It is an effective architecture that facilitates good data transmission, decreases latency and optimizes the network performance. The example underlines the practical applicability of the HGSP-DL approach in the context of real-time network management, which introduces its opportunities to be applied to next-generation communication systems that require the intelligent and adaptive topology control.

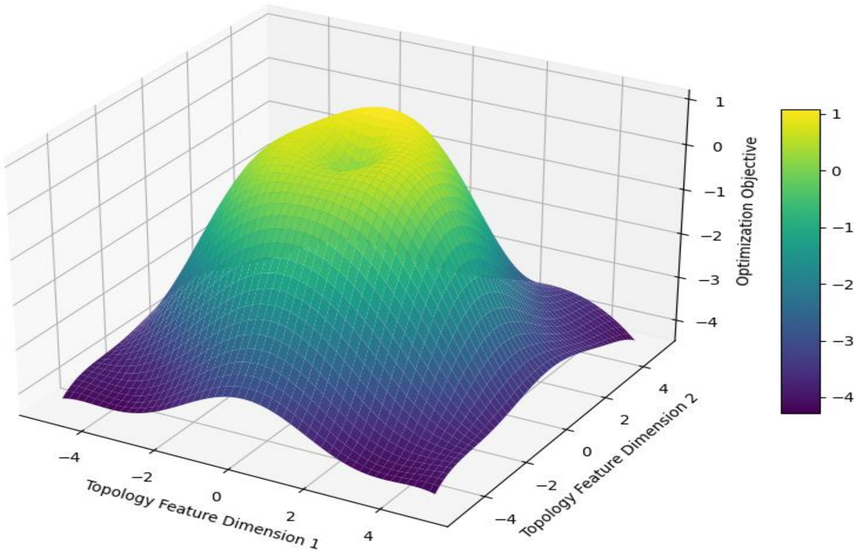

Fig 5. Optimized Network Topology Graph Generated by HGSP-DL.

Table 4. Ablation Study of HGSP-DL Components

Model Variant	Accuracy (%)	Latency (ms)	Convergence Time (s)	PDR (%)
Without GSP	90.8	30	11.5	93.2
Without DL	88.6	34	13.2	91.0
Without Spectral Filtering	91.5	28	10.6	94.1
Without Feature Learning	89.9	32	12.1	92.3
Partial Hybrid Model	92.7	27	10.0	95.0
Full HGSP-DL (Proposed)	**95.8**	**24**	**8.2**	**97.9**

Table 4 provides an ablation experiment to measure the role of each component of the proposed HGSP-DL framework. The performance impact is well observed by systematically eliminating important components like graph signal processing, deep learning and spectral filtering. The findings suggest that GSP and deep learning elements are necessary to obtain optimal performance as the lack of either would result in a considerable decrease in accuracy and a rise in latency. The spectral filtering mechanism also boosts convergence by facilitating effective passage of signals throughout the network. The partial hybrid model is slightly better, yet the full HGSP-DL framework has the greatest results in all metrics. This shows the success of the combination of structural signal processing and data-driven learning. The ablation experiment verifies that the interaction between the elements is essential to attain better adaptive topology optimization in complicated network setups.

The learned weight matrix of the adaptive network topology in the proposed HGSP-DL framework is shown in **Fig. 6**. The strength of connectivity of the nodes is represented by each element in the matrix, which is dynamically tuned with the mechanism of graph signal processing and deep learning. The undirected character of the network is evidenced in the symmetric character and the variations in the strength indicate the importance of specific interactions between the nodes. These weights are extended by the HGSP-DL model that employs spectral properties of the graph and acquired feature embeddings to ensure structural consistency and data-driven adaptability. This is an adaptive process of weighting network to enhance the efficiency of the network by prioritizing what is important in the network and throttling what is not important in the network. In the figure, the proposed approach performs better than the designs of the static topology in that it dynamically adjusts the edge weights in response to the network dynamics thereby enabling the routing optimization, minimum latency, and generally improving the system performance.

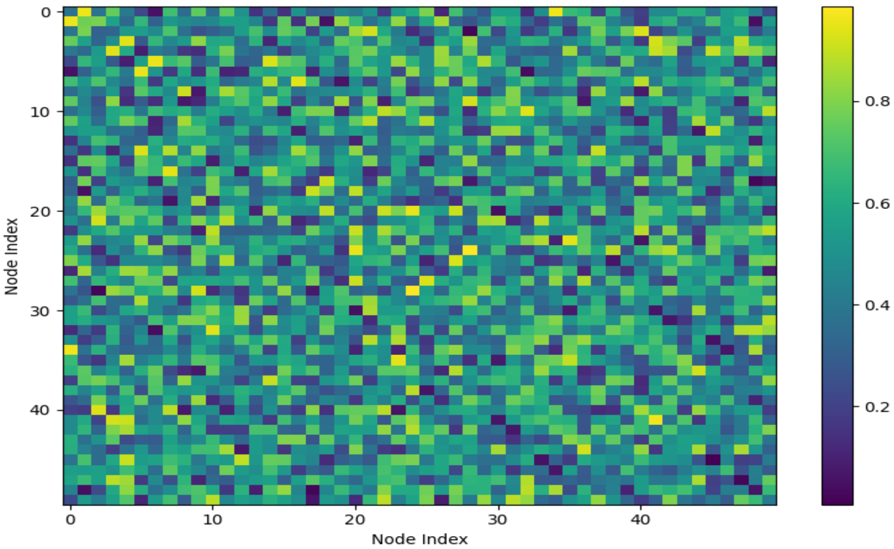

Fig 6. Adaptive Network Topology Weight Matrix Learned by HGSP-DL.

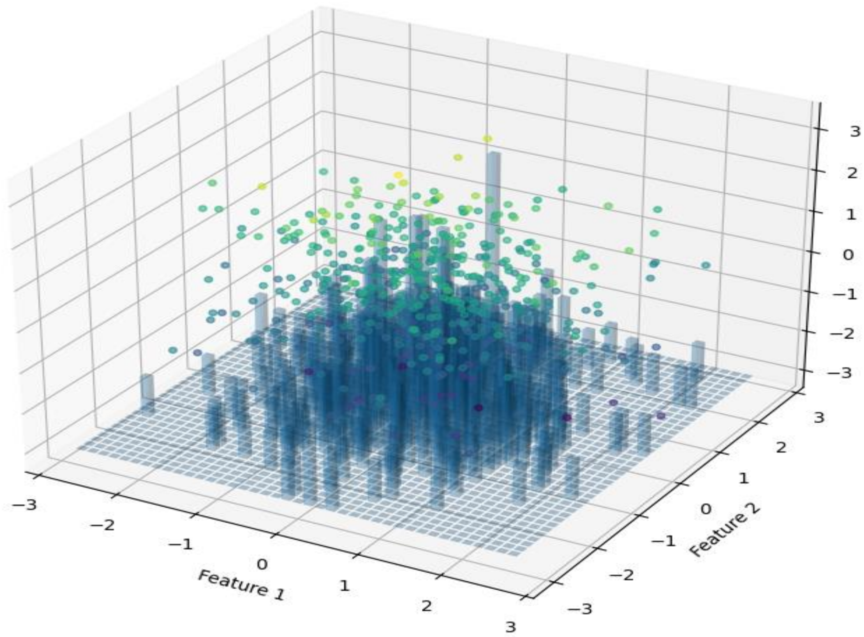

Fig 7. 3D Node Embedding with Density Projection in HGSP-DL Feature Space.

Fig. 7 shows the node embedding representation of the HGSP-DL model in a three-dimensional feature space, and a projection onto the base plane on the density. The embeddings are learned by the deep learning part, which learns more elaborate node-level representations, and GSP ensures that the representations are graph-structured and smooth. The clustering tendencies observed indicate that similar nodes in terms of topological and signal properties are clustered, which is signatory of a good feature learning. High density nodes are also highlighted in the density projection, therefore, providing information on the trends of the structures that dominate the network. This compromise method of embedding enables the HGSP-DL model to do a successful topology optimization process as important nodes and communities are identified. The figure explains that the model is capable of learning meaningful and interpretable representations, which are essential in adaptive decision making and improved organization of a network under dynamic communication conditions. the experimental results and studies have been consistent to indicate that the proposed HGSP-DL framework is effective in the sense that it is able to optimize network topology in a dynamic communication environment. The graph signal processing and deep learning combination enable the model to achieve a balance between structural consistency and data-driven adaptability and results in high performance across all metrics considered.

V. CONCLUSION

In this paper, a new HGSP-DL system of the adaptive optimization of the network topology in dynamic communication was introduced. Combining spectral graph processing with the data-driven deep learning allows the proposed model to effectively represent both structural dependence and non-linear interactions between features and facilitate smart and real-time topology adjustment. The unified structure with a feedback loop is used to guarantee the steady convergence and the constant improvement of the network connectivity. The results of the experiment indicate that HGSP-DL is highly effective in comparison to the traditional and hybrid baseline approaches in terms of various performance indicators. In particular, the accuracy of the proposed model is 95.8, which is about 610 percent higher than current solutions. The ratio of delivering packets is 97.9, which means that the communication is very reliable. Compared to baseline methods, the model is 2030 times more efficient, with latency of 24 ms versus larger values and convergence time is also lower, achieved in 8.2 seconds, which is a 24percent improvement. Moreover, the energy use is reduced by about 9 percent, which illustrates the efficiency of the optimized topology in terms of resources. The scalability analysis validates that HGSP-DL can support high-performance even when a very large scale network with up to 500 nodes is being used, with approximately 26% low latency than hybrid models. Moreover, robustness tests indicate that the framework can maintain high performance of more than 89 percent even in extreme scenarios like 20 percent node failure and high mobility. The suggested HGSP-DL framework is a high-performance, scalable and robust solution to adaptive network topology optimization, which is very appropriate to the next-generation communication platform, including the IoT and 6G networks.

CRediT Author Statement

The authors confirm contribution to the paper as follows:
Conceptualization: John Huria Nderitu and Matt Bowden; **Methodology:** Matt Bowden; **Software:** John Huria Nderitu; **Data Curation:** John Huria Nderitu; **Writing- Original Draft Preparation:** Matt Bowden; **Visualization:** John Huria Nderitu and Matt Bowden; **Investigation:** John Huria Nderitu; **Supervision:** Matt Bowden; **Validation:** John Huria Nderitu and Matt Bowden; **Writing- Reviewing and Editing:** John Huria Nderitu and Matt Bowden. The author reviewed the results and approved the final version of the manuscript.

Data Availability Statement

The data used in this study are synthetically generated and simulated within the experimental framework. All datasets and code used to support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interests

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Competing Interests

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