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TOPICAL REVIEW

A Topical Review of Quantum and Classical Machine Learning Approaches to Disaster Escape Routing Problems

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ABSTRACT The pathfinding problem in a graph has been solved using several classical algorithms, notably Dijkstra's and A* algorithms. However, most classical algorithms are most effective on static graphs. They either cannot be adapted to dynamic graphs or become computationally expensive. The challenge of processing dynamic graphs, which demands significant computational resources, can be addressed using Classical and Quantum Machine Learning methods. For this review, we consider a dynamically changing graph representing a disaster-stricken city. Our problem, termed the Disaster Escape Routing problem, aims to find the optimal path within this dynamic graph. We review and analyze an existing hybrid quantum-classical machine learning model alongside classical machine learning models specifically for this problem. We also explore Variational Quantum Circuits and Encoding Methods. Our study suggests that hybrid quantum-classical machine learning, Graph Neural Networks, and Temporal Graph Networks offer high performance in terms of path prediction and accuracy in finding the optimal path. This review also identifies Kolmogorov Arnold Networks as a promising approach to solving escape routing problems. Additionally, an integrated approach combining strengths of all the models has been hypothesized to enhance emergency escape route planning.

INDEX TERMS Machine learning, quantum computing, vehicle routing.

I. INTRODUCTION

In today's rapidly evolving world, technological innovation has driven scientific advancement. The increasing complexity of data and the demand for more sophisticated solutions to complex problems necessitate greater computational power. While classical computing has long been the dominant paradigm, it struggles with certain tasks, such as simulating molecular dynamics, modeling graph networks, and predicting protein folding. To address these limitations, alternative computing models are emerging, with quantum computing being one of the most promising.

Building on this, our focus in this paper is the graph-based escape routing problem, where we analyze both classical and quantum solutions. By doing so, we aim to demonstrate how quantum computing, particularly Quantum Machine Learning (QML), can offer significant improvements in solving such dynamic and computationally intensive problems. We begin by defining key concepts, including Quantum Computing (QC), QML, Escape Routing (ER), and the application of Quantum Machine Learning to the Escape Routing (QML in ER) problem.

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A. KEY CONCEPTS

1) QUANTUM COMPUTING

QC is a field at the intersection of Computer Science and Physics. It represents a fundamentally different approach to classical computing methods. QC leverages the fundamental principles of quantum mechanics, namely entanglement, superposition, and quantum parallelism, to perform quantum computations. It has been proposed that a Quantum Computer will help solve problems that are intractable or unsolvable by classical computers. As Feynman said:

Nature isn't classical, dammit, and if you want to make a simulation of nature, you'd better make it quantum mechanical [14].

Thus, one of the aims of QC is to simulate quantum systems such as molecules. Scientists are striving to find quantum solutions to problems that will offer an exponential speedup, the holy grail of Computer Science, over classical solutions. Additionally, quantum computers are being developed to tackle problems that are beyond the reach of even the most powerful supercomputers. This milestone is known as Quantum Advantage. One example of quantum advantage is factoring large integers using Shor's algorithm on QCs in sub-exponential time complexity [16]. QML is another such application where the processing power of a QC can be harnessed to handle vast amounts of data and solve intricate machine learning problems in real-time.

2) QUANTUM MACHINE LEARNING

Quantum Machine Learning (QML), a cutting-edge research area at the intersection of QC and machine learning, aims to leverage QC to solve machine learning problems. The capabilities of machine learning algorithms are fundamentally tied to the hardware they run on. The success of modern Deep Learning (DL), for example, relies heavily on the parallel processing power of GPU clusters. QML extends this pool of hardware for complex machine learning algorithms to QCs. From a modern perspective, QCs can be used and trained like neural networks [17]. This review studies an innovative application of a hybrid QML model for ER and evacuation mapping.

3) ESCAPE ROUTING

ER is a class of problems in graph theory that involves finding optimal paths between two nodes in a graph. ER algorithms play a significant role in modern industry. They are used to find optimal routing on printed circuit boards (PCBs), plan paths for autonomous vehicles, enhance disaster management through large-scale evacuation planning, and much more.

Disaster management teams utilize ER algorithms for large-scale evacuation planning in emergencies like floods or earthquakes. By analyzing population density, terrain, and infrastructure damage, these algorithms predict potential bottlenecks and suggest optimal evacuation routes for entire communities, potentially saving lives during critical situations.

4) QML IN ER

ER algorithms on large graphs, such as those encountered in disaster management and evacuation problems, demand significant computational power to be practical. Moreover, dynamically updating graphs necessitate multiple iterations to account for parameter variations and generate new optimal paths in real-time. The need for higher computational speed intensifies with the scale of application.

QML offers an innovative solution to this challenge. By applying the principles of quantum mechanics, we can exponentially increase the speed of computation. Furthermore, a hybrid network comprising both quantum and classical neural networks can be employed to run ER algorithms, yielding results of comparable accuracy and optimality to those obtained from classical algorithms like Dijkstra's or A*, but with significantly increased computational speed.

II. RESEARCH QUESTIONS

This study will specifically focus on presenting Quantum and Classical approaches along with supplementary techniques for the following goal:

Predicting the most optimal path in a graph of a disaster-hit city.

The study addresses the following research questions:

1) What do the new quantum and classical solutions offer for solving this problem?
2) What challenges have been reported in implementing these classical and quantum solutions?
3) What success factors have been reported for implementing these classical and quantum solutions?

Most existing reviews focus on the routing problem in general. We specifically target the Escape Routing problem in the domain of traffic routing during an earthquake. Therefore, if a researcher or practitioner is using this study to examine the challenges and success factors in the disaster Escape Routing problem, they will find the relevant issues.

III. ABBREVIATIONS

Table 1 lists the abbreviations and their full forms used in this text.

IV. PAPERS USED

In this review, we have mainly analyzed ideas from the following papers:

- A supervised hybrid quantum machine learning solution to the emergency escape routing problem (Haboury et al. [1])
- Graph Neural Networks for Optimal Pathfinding: Uncovering the Shortest Distance (Neyigapula [2])
- Temporal Graph Networks for Deep Learning on Dynamic Graphs (Rossi et al. [3])
- Quantum Neural Networks and Their Potential in Traffic Prediction (Moskvin et al. [4])
- Efficient Encodings of the Travelling Salesperson Problem for Variational Quantum Algorithms (Schnaus et al. [5])
- Kolmogorov-Arnold Networks (KANs) for Time Series Analysis (Vaca-Rubio et al. [7]).

TABLE 1. List of abbreviations.

Abbreviation	Term
QC	Quantum Computing
QML	Quantum Machine Learning
ER	Escape Routing
VQC	Variational Quantum Circuit
FiLM	Feature-wise Linear Modulation
PHN	Parallel Hybrid Network
HQNN	Hybrid Quantum Neural Network
GNN	Graph Neural Network
QGNN	Quantum Graph Neural Network
QAOA	Quantum Approximate Optimization Algorithm
VQE	Variational Quantum Eigensolver
QUBO	Quadratic Unconstrained Binary Optimization
HOBO	Higher-order Binary Optimization
TGN	Temporal Graph Network
QNN	Quantum Neural Network
DL	Deep Learning
MLP	Multilayer Perceptron
KAN	Kolmogorov Arnold Network

V. STRUCTURE OF THE PAPER

The remainder of this paper is structured as follows. Section VI describes our search and selection strategy for the reviewed papers. This is followed by Section VII on results and analysis of HQNN, GNNs, TGNs, VQCs, Encoding Methods, and KANs. Finally, Section X gives the conclusion to the review.

VI. PAPER SEARCH AND SELECTION STRATEGY

Suitable keywords were identified using synonyms. The search terms were:

- "Disaster escape routing machine learning"
- "Quantum machine learning escape routing"
- "Graph neural network escape routing"
- "Temporal graph learning"
- "KANs for time series analysis"

The search terms were organized into two groups. In the first group, we included the most directly related papers to the research questions. The second group included papers that were supplementary to the research questions and also presented the latest research in the field. In total, we used six papers that were most relevant to answer the research questions.

VII. MODELS AND METHODS

This section provides an overview of the Quantum and Classical solutions to the ER problem.

A. HYBRID QUANTUM-CLASSICAL MODEL

An effective QML approach to solving the problem of finding an optimal path in a dynamic graph is the hybrid quantum-classical Feature-wise Linear Modulation (FiLM) model. This section provides a concise summary of the Hybrid Quantum-Classical model proposed in [1].

Emergency response (ER) routing during natural disasters, such as earthquakes, can be represented as a dynamically evolving graph routing problem. In this context, it is essential to identify the shortest path from an arbitrary starting point to predefined, fixed exit points. Traditional graph algorithms, such as Dijkstra's Shortest Path algorithm, perform well on static graphs but require adaptability to dynamic graphs to be applicable to ER scenarios. The Hybrid Quantum Neural Network (HQNN) introduced in [1] incorporates a novel quantum FiLM network in parallel with a classical FiLM network, aiming to emulate the node-wise functionality of Dijkstra's algorithm while accessing only a limited portion of the graph. Outputs from the node-wise Dijkstra's algorithm are utilized to train the HQNN, enhancing its performance on dynamic routing tasks.

The proposed circuit architecture integrates a PHN model with a Feature-wise Linear Modulation (FiLM) model, forming a composite structure that includes both a classical FiLM neural network and a quantum neural network. Inputs to this model consist of earthquake coordinates, starting and ending points, and data on the immediate neighbors of each node. Both the classical and quantum networks process these inputs independently. Following processing, the outputs from each network are combined linearly and passed through a fully connected layer, reducing the output to five values. These five values serve as a logit layer (raw output) for the node classifier, where the neighboring node with the highest score is selected as the next node. Fig. 1 illustrates the architecture of the PHN FiLM model, which effectively identifies the next node in the optimal path solution.

It is important to recognize that the model considers only earthquake coordinates, start-end nodes, and immediate neighbors when determining the optimal path. While promising, this approach does not account for factors such as elevation or real-time traffic conditions. Elevation may be negligible on plains but is critical in mountainous areas susceptible to landslides, which could significantly affect route optimization. Similarly, real-time traffic conditions are vital for identifying the most efficient path. Including these variables would make the model more robust and applicable to a broader range of scenarios. However, acquiring post-disaster data presents unique challenges [1]. Further research is necessary to develop reliable methods for obtaining such data.

Once reliable data becomes available, comprehensive modeling and data analysis are essential to avoid overfitting. For example, a model trained solely on data from one region may lack generalizability, potentially performing poorly in different areas with distinct environmental conditions, which could lead to incorrect escape route recommendations.

Although QC offers speed and efficiency advantages over classical computing, it remains a developing field with limited hardware availability. This hybrid approach, combining quantum and classical machine learning,

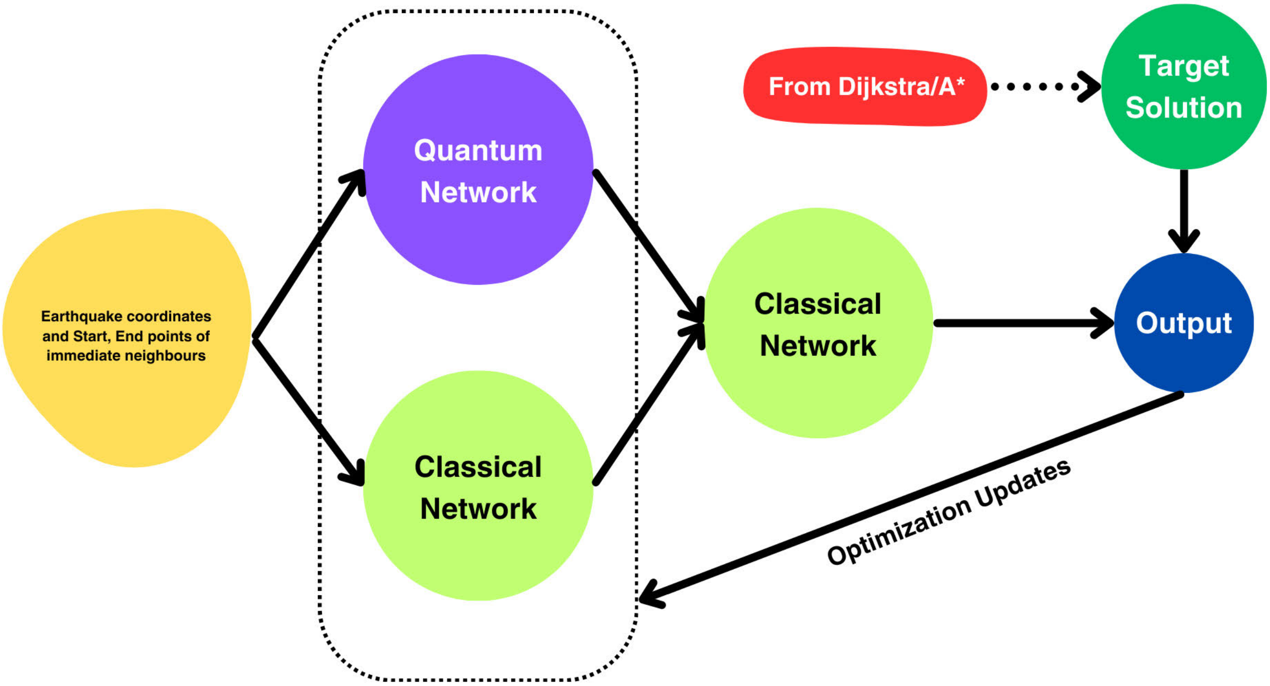

FIGURE 1. Representation of the PHN FiLM Model [1].

seeks to address the ER problem by harnessing the strengths of both. Given the critical importance of efficient ER and evacuation mechanisms during emergencies, continued exploration, development, and enhancement of these methods are vital to improving existing infrastructures and achieving faster, more reliable outcomes.

B. GRAPH NEURAL NETWORK MODEL

A second approach to shortest pathfinding in graphs is proposed by [2], which explores the application of Graph Neural Networks (GNNs) for optimal pathfinding. This framework combines the strengths of GNNs with efficient algorithms such as Dijkstra and A*.

The core strategy leverages GNNs' expressive capabilities to learn correlations within the graph structure. These learned representations are then incorporated into a pathfinding algorithm to identify the shortest path effectively. This research highlights GNNs' potential to capture complex correlations within graph structures, a significant challenge for traditional pathfinding algorithms.

As graph size and complexity increase, classical algorithms often struggle to meet the demands of pathfinding tasks. In contrast, GNNs demonstrate promising results in capturing complex relationships within graph data. GNNs are a specialized class of neural networks tailored for graph-structured data, operating primarily through the aggregation of information from neighboring nodes to create meaningful representations that encode the underlying graph structure.

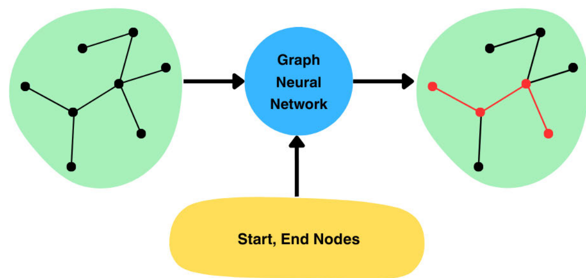

FIGURE 2. Representation of a GNN model for pathfinding. The predicted path is colored red.

GNNs can capture both local and global graph structures, consider node features, and adapt to various types of graphs. However, they still face challenges such as scalability to large graphs, robustness against noisy or incomplete data, and interpretability of learned representations. Interpretability, in this context, refers to the ability to understand and explain the embeddings generated by GNNs during training. Fig. 2 illustrates a GNN model designed for pathfinding applications.

Traditional pathfinding algorithms, such as Dijkstra and A*, depend on heuristics or explicit graph exploration, which can be computationally expensive. In contrast, GNNs adopt a data-driven approach to pathfinding by learning to capture and propagate information across nodes and edges. Two critical components in this learning process are *Graph Representation* and *Feature Engineering*.

Graph Representation schemes encode the connectivity of the graph, while Feature Engineering represents node-specific attributes. Additionally, Graph Adjacency Matrices, Node Embeddings, and feature aggregation mechanisms enable GNNs to capture both structural and semantic information [2].

However, despite these advantages, challenges persist in effectively leveraging GNNs for pathfinding. The model's reliance on high-quality training data introduces potential vulnerabilities, particularly when real-world datasets contain noise or inconsistencies. Moreover, applying GNNs to dynamic graphs—such as those encountered in ER scenarios—requires adaptations that traditional architectures may not fully support. Addressing these limitations may involve exploring alternative GNN architectures and incorporating additional graph features, such as edge weights or temporal data, to enhance model performance and versatility.

C. TEMPORAL GRAPH NEURAL NETWORKS

Temporal Graph Networks (TGNs) offer a flexible and efficient framework for deep learning on dynamic graphs modeled as time-stamped events. TGNs outperform earlier approaches in both performance and computational efficiency by combining memory modules with graph-based operators. In this model, a dynamic graph is represented as a sequence of time-stamped events, such as additions or modifications to nodes or interactions between nodes at discrete intervals. Node deletion is also modeled as an event when a node loses all connections [26].

The core modules of TGNs support real-time processing on dynamic graphs. The Memory Module maintains the state and interaction history of each node, effectively serving as a historical record. Upon each event, the memory of the affected nodes is updated, and an optional global memory tracks the graph's evolution to improve predictive accuracy. The Message Function generates messages for each event—one for the source node and another for the target node—capturing the nodes' updated states. TGNs also incorporate a Message Aggregator that enhances network efficiency by handling multiple node events simultaneously, using strategies such as Mean Message or Most Recent Message to avoid redundant updates. Finally, the Message Updater uses these messages to refresh the states of the source and target nodes within the memory module [27].

A critical feature in TGNs is the Embedder module, designed to address node staleness—when inactive nodes miss updates due to inactivity—by employing embedding algorithms that refresh their state [28]. Originally created to model social interactions on networking platforms, TGNs can also be adapted for escape routing scenarios by customizing the message function. Additionally, dynamic graph data derived from real-world events, like earthquakes, can train the network to replicate optimal solutions provided by Dijkstra's algorithm. TGNs thus present a promising approach to meet the computational speed requirements essential during natural disasters [29].

D. COMPARATIVE ANALYSIS

This section compares the performance of three neural network models—Classical NN, GNN, and HQNN—in the context of disaster escape routing. Fig. 3 presents their results across key evaluation metrics:

- **Average Accuracy (Purple):** Measures the overall correctness of the model's path predictions.
  - GNN achieves 98% accuracy.
  - HQNN follows with 94%.
  - Classical NN records 87%.
- **Path Prediction Success (Green):** Represents the proportion of correctly identified safe evacuation routes.
  - HQNN achieves 95%.
  - GNN reaches 93.4%.
  - Classical NN records 92%.
- **Dijkstra Path Alignment (Yellow):** Evaluates how closely the model's predicted paths align with those generated by Dijkstra's algorithm.
  - HQNN aligns with Dijkstra's paths 30% of the time.
  - GNN achieves a 28% match.
  - Classical NN records 24%.
- **Improved Path Prediction (Orange):** Measures the proportion of cases where the model identifies an alternative path that is potentially more efficient than the standard routes.
  - HQNN predicts improved paths in 25% of cases.
  - GNN achieves 20%.
  - Classical NN records 15%.
- **Failure Rate (Red):** Indicates the proportion of instances where the model fails to provide a viable evacuation path.
  - HQNN has a 5% failure rate.
  - GNN records 6%.
  - Classical NN has the highest failure rate at 8%.

Disaster Routing Insights:

1) **Performance Trends in Advanced Models:** The results indicate that GNN and HQNN offer notable improvements in disaster escape routing compared to traditional neural networks.
   - Higher accuracy and path prediction success suggest increased reliability in emergency evacuation planning.
   - Better alignment with Dijkstra's algorithm indicates improved pathfinding efficiency.
   - Lower failure rates demonstrate greater robustness in high-risk scenarios.
2) **Implications for Emergency Management:** The performance improvements translate into practical advantages:
   - Reduced failure rates enhance the reliability of evacuation strategies.
   - Higher path prediction accuracy ensures more dependable route recommendations.

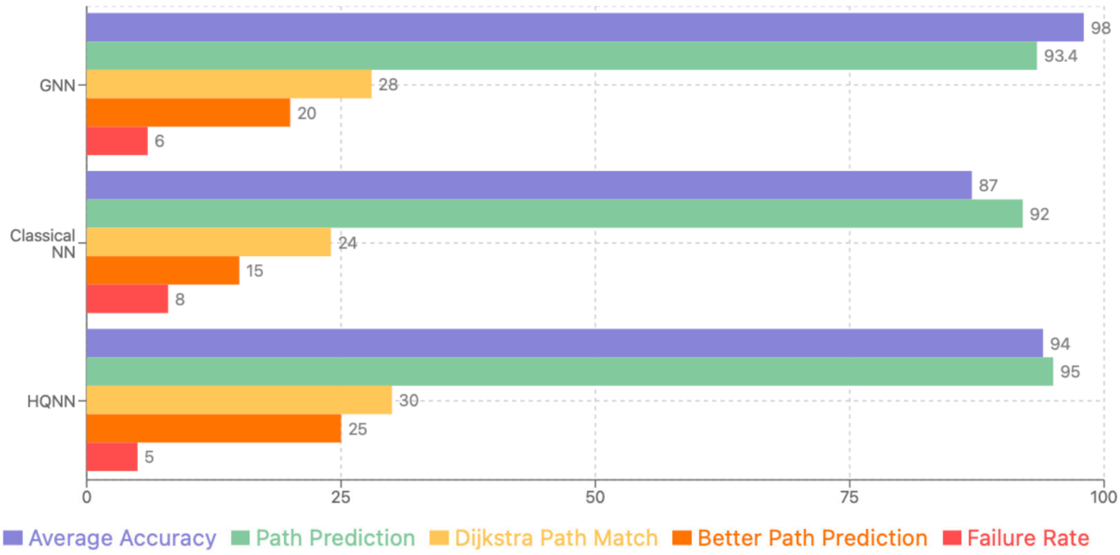

FIGURE 3. Performance comparison of different neural network approaches for disaster escape routing.

- The ability to identify improved routes may optimize evacuation efficiency under dynamic conditions.

3) **Computational Adaptability:** The evaluated models exhibit key strengths in:
   - Handling dynamic and complex disaster environments.
   - Adapting to real-time changes in evacuation scenarios.
   - Enhancing decision-making through improved route optimization.

These insights reinforce the role of advanced neural network architectures in improving disaster escape routing, highlighting their potential to enhance evacuation effectiveness and overall emergency response efficiency.

E. SUPPLEMENTARY CONCEPTS

1) VARIATIONAL QUANTUM CIRCUIT

The HQNN model discussed earlier integrates a quantum component. Although the HQNN circuit appears complex in terms of parameter equations, it operates on the fundamental principle of optimizing the parameter θ. This section introduces a simplified version of the quantum component in the HQNN circuit, known as the VQC.

Ref. [4] presents a straightforward solution utilizing a VQC to implement a QNN. Although the paper does not directly address the ER problem, examining its approach to traffic prediction offers insights into the application of VQCs.

The circuit comprises five qubits, upon which a series of angle-parameterized quantum gates are applied. These parameters are iteratively updated to optimize a cost function. In this case, the cost function is the Mean Squared Error (MSE), though alternative functions can be employed.

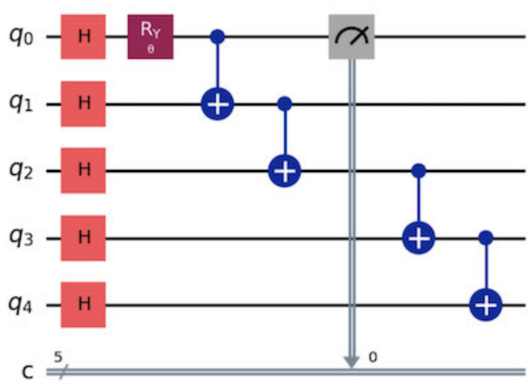

FIGURE 4. Variational quantum circuit.

The model is trained and evaluated on traffic data, and upon demonstrating reliable performance, it can be deployed for real-time traffic prediction. Fig. 4 illustrates the quantum circuit as described.

The primary focus is to introduce angle-parameterized quantum gates within a quantum circuit, followed by the application of a classical optimization algorithm to adjust hyperparameters for optimizing the cost function.

However, it is important to note that this approach does not guarantee convergence to the global optimum. Since the method involves selecting an initial guess for the parameters, the solution is highly sensitive to the choice of these initial values. Furthermore, the model's performance is influenced by the selected optimization algorithm and the complexity of the cost function landscape. Despite these limitations, this approach demonstrates how a straightforward Quantum-Classical optimization model can be implemented.

2) ENCODING STRATEGIES FOR ROUTING PROBLEMS

ER problems can be framed as well-known optimization challenges, such as the Travelling Salesperson Problem (TSP). The complexity of these problems grows significantly with the number of cities or nodes, rendering optimal solutions computationally expensive for classical algorithms. This difficulty arises due to the exponential increase in possible solutions, which classical methods struggle to handle efficiently. Quantum algorithms, especially those utilizing permutation encoding, present promising approaches to overcoming these challenges. Notable methods, such as the QAOA and the VQE, have shown potential in addressing NP-hard problems like TSP.

The study in [5] on encoding schemes for the TSP is especially relevant to QML solutions in ER applications, as the choice of encoding directly affects the efficiency and scalability of quantum algorithms. In ER scenarios, where real-time dynamic optimization is critical, encoding techniques like QUBO, HOBO, and permutation encoding determine how effectively quantum circuits can manage complex routing scenarios. By minimizing qubit requirements and ensuring solution feasibility, as demonstrated with Permutation encoding, quantum algorithms offer the potential for faster and more accurate pathfinding solutions for large-scale emergencies, which classical methods may struggle to resolve optimally.

Understanding the impact of these encoding schemes on quantum algorithms is essential. Below, we briefly outline QUBO, HOBO, and permutation encoding, emphasizing their advantages and limitations in optimizing ER problems with QML.

1) **QUBO Encoding:** This method presents a natural formulation for the TSP within quantum computing, where each route is represented by a binary matrix. Binary variables denote whether a specific city is visited at a particular time step. However, a key disadvantage of this approach is its vulnerability to infeasible solutions, as it can produce states that violate TSP constraints (e.g., visiting multiple cities simultaneously). Additionally, the solution space expands rapidly with increasing problem size, meaning only a small fraction of feasible solutions exists within the total solution space.

   When applied to disaster ER, QUBO encoding has distinct strengths and weaknesses. On the positive side, QUBO allows for the mapping of ER optimization tasks onto quantum hardware, with the potential for accelerating complex computations. Its binary matrix format offers a structured way to represent decisions on location visits, and the quadratic objective function can accommodate multiple variables and interactions—making it suitable for considering various routing criteria.

   However, significant challenges persist. QUBO encoding is prone to generating infeasible solutions, such as scenarios where multiple locations are visited simultaneously, which must be avoided in disaster situations. Moreover, QUBO faces scalability limitations; the solution space grows exponentially with the number of cities, complicating real-time decision-making. QUBO is also a static formulation, struggling to adapt to dynamic ER conditions like road closures or the emergence of hazards. Enforcing strict constraints, such as avoiding dangerous areas, is difficult, and balancing multiple objectives—such as optimizing for both safety and speed—adds further complexity. Although QUBO shows promise theoretically, its application to disaster ER requires improvements in constraint handling and adaptability to dynamic conditions for practical viability.

2) **HOBO Encoding:** HOBO encoding enhances QUBO by minimizing the number of qubits required and increasing the ratio of feasible solutions. Unlike the one-hot encoding approach, HOBO employs a binary representation for each node, allowing for better scalability in larger graphs. This representation enables more efficient use of quantum resources compared to QUBO.

   Despite these improvements, HOBO encoding still faces limitations concerning solution feasibility. While it reduces the likelihood of generating infeasible solutions compared to QUBO, challenges remain in ensuring that all generated solutions comply with the problem constraints. Additionally, HOBO often necessitates deeper quantum circuits to accommodate its encoding structure, which may pose challenges for implementation on near-term quantum devices, where circuit depth can impact coherence times and overall performance.

3) **Permutation Encoding:** Among the three encodings, permutation encoding is the most efficient, as it ensures that every quantum state corresponds to a valid TSP solution, thereby eliminating infeasibility issues. This encoding requires fewer qubits and can be effectively integrated with classical methods within hybrid quantum-classical algorithms like the VQE. However, the absence of an efficient Hamiltonian construction for permutation encoding limits its applicability in purely quantum approaches.

   In the experimental setup outlined in [5], the authors demonstrate that permutation encoding consistently outperforms both QUBO and HOBO in terms of solution feasibility and closeness to optimal routes. Nonetheless, its computational advantages are primarily observed in small problem sizes, as larger-scale instances may introduce new challenges that necessitate further investigation.

   These findings highlight the critical role of encoding strategies in quantum optimization algorithms, particularly in the context of escape routing for complex earthquake scenarios. While permutation encoding shows distinct advantages for small-scale problems,

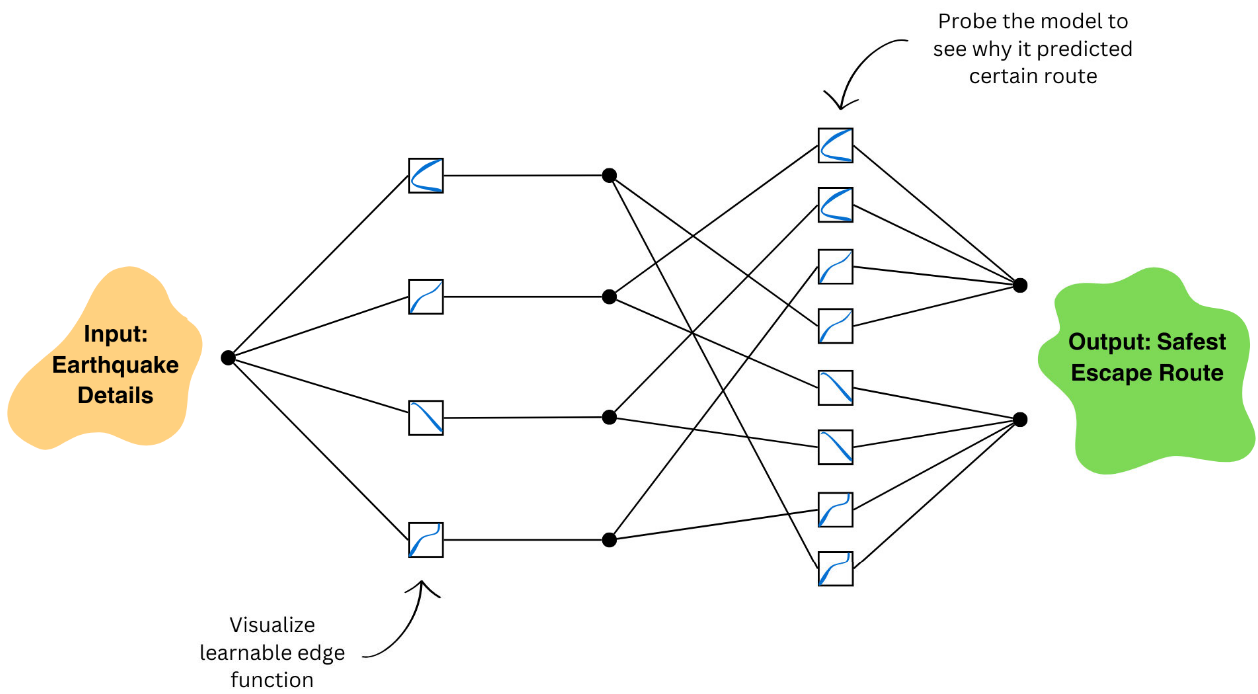

FIGURE 5. Kolmogorov Arnold Network (KAN) with learnable edge functions and simple summation at nodes.

its scalability to larger, real-time dynamic environments remains a concern due to exponential growth in problem complexity, quantum resource limitations, and challenges in maintaining real-time responsiveness. Addressing earthquake-related escape routing problems, where rapid decision-making is essential, will require ongoing refinement of these quantum techniques to effectively manage evolving conditions. Therefore, continued research is crucial to unlocking the full potential of quantum algorithms in tackling such high-stakes, real-world challenges.

F. KOLMOGOROV ARNOLD NETWORKS

Until now, the models we have discussed have been fundamentally based on Multilayer Perceptrons (MLPs), which serve as the foundational architecture for traditional deep learning. While we can certainly enhance existing models and innovate new architectures based on MLPs to achieve higher performance, it is also essential to explore the fundamental architecture itself. This is precisely the focus of Kolmogorov-Arnold Networks (KANs), a recently proposed alternative to MLPs widely used in deep learning. For more detailed information on KANs, readers can refer to [6].

In the context of traffic prediction problems, experiments conducted in [7] suggest that KANs effectively capture rapid fluctuations in traffic volume, whereas MLPs sometimes tend to overpredict or underpredict these changes. This ability to adapt to quickly evolving scenarios positions KANs as a superior choice for dynamic traffic routing applications. Further analysis indicates that KANs exhibit robustness and high performance in environments characterized by variable and intense traffic conditions.

One of the proposed advantages of KANs is their **interpretability**, which mitigates the *black-box* nature typical of MLP models. This transparency allows for visualization of the network's learning and decision-making processes. Interpretability is a crucial aspect of machine learning, as AI-based systems increasingly play a pivotal role in making critical decisions within society. In MLP models, users cannot ascertain why the AI made a particular decision over others. By contrast, KANs appear to offer potential for deeper interrogation, allowing questions such as *Why did the AI choose this specific route?*, *What precisely did it learn that influenced this choice?*, and *Could it have made a better decision given an alternative learning approach?*. Current MLP-based black-box models are unable to address these questions, whereas KANs present promising possibilities in this area. Fig. 5 shows the KAN model and its application in the ER problem.

KANs require fewer parameters than MLPs to achieve comparable or superior performance, making them simpler and faster models [6]. They are grounded in a robust theoretical framework, providing them with an intrinsic advantage in modeling complex, non-linear patterns typical of traffic systems. Their consistent performance across diverse environments also suggests that KANs possess strong generalization capabilities, which are crucial for applications in geographically varied locations with differing traffic dynamics. However, [6] notes that KANs have primarily been evaluated on small toy datasets, where they have either outperformed or matched MLPs. The dynamic ER problem introduces a different level of complexity, requiring KANs to identify the shortest path in graphs with at least a thousand nodes. Thus, investigating the development of larger KANs and integrating them with Graph Neural Networks (GNNs) to address such complex scenarios could be beneficial, allowing for performance comparisons with traditional MLPs.

KANs offer several key features that make them particularly well-suited for handling the complex, nonlinear systems required in escape routing (ER) problems, such as disaster evacuations. These features include:

1) DECOMPOSITION OF MULTIVARIATE FUNCTIONS

One of the primary features of KANs is their ability to represent multivariate continuous functions as a sum of simpler univariate functions. Specifically, KANs break down a complex, high-dimensional problem (such as a disaster evacuation scenario) into a set of low-dimensional problems, each involving a simple, continuous function of one variable. For example, in disaster evacuation, multiple factors influence routing decisions, such as traffic flow, road closures, crowd density, and weather conditions. KANs can allow these complex interactions to be represented as a combination of simpler, one-dimensional components. This decomposition may help the network capture nonlinear relationships without requiring large numbers of parameters, enhancing computational efficiency while maintaining accuracy.

2) FLEXIBLE NONLINEAR REPRESENTATION

Traditional neural networks typically rely on activation functions like ReLU or sigmoid to introduce nonlinearity, but these functions are global and lack the interpretability that KANs provide. KANs, however, represent complex dependencies using a combination of piecewise univariate activation functions—enabling them to model nonlinear relationships at a granular level. For disaster evacuation, this means that dynamic systems—such as how crowd behavior affects traffic patterns during evacuations—can be captured more precisely. Traffic flow on specific routes might follow nonlinear behavior depending on crowd density and available shelter capacity. KANs can represent these subtle nonlinear effects efficiently by using univariate functions across different variables.

3) MODELING TEMPORAL DEPENDENCIES

Evacuation routes must adapt in real-time based on changing conditions (e.g., updated information on road closures, ongoing traffic incidents, or real-time weather conditions). KANs could model time-dependent functions, which is essential in scenarios where events evolve over time and affect escape route decisions dynamically. KANs' ability to represent complex, time-varying functions gives them an advantage in handling dynamic, real-time changes in traffic flow or emergency responses. By capturing the underlying temporal structure, KANs could provide an adaptive system capable of adjusting evacuation routes as conditions shift.

4) EFFICIENT HIGH-DIMENSIONAL DATA REPRESENTATION

Escape routing often involves high-dimensional data, including spatial and temporal variables like geospatial mapping (of roads, obstacles, and shelters), traffic flow data, weather forecasts, and communication from emergency services. Traditional neural networks may require enormous amounts of data or overly complex architectures to model these relationships, whereas KANs reduce dimensionality by representing multi-dimensional functions as sums of lower-dimensional functions. This makes KANs exceptionally suited for high-dimensional routing problems that involve multiple sources of input data, such as real-time traffic and weather. For example, in evacuations through an urban area, KANs could efficiently represent traffic conditions on every possible route, crowd density on roads, and the capacity of infrastructure without requiring massive computational resources.

5) INTERPRETABILITY IN NONLINEAR SYSTEMS

KANs are particularly valuable because they generate more interpretable models, which are crucial in domains like disaster escape routing, where emergency responders need to understand the decision-making behind routing choices. Traditional deep neural networks, especially those with many layers and parameters, can become black boxes. However, KANs use a combination of univariate, continuous functions, making it possible to break down and interpret how each factor (e.g., weather, crowd behavior, or road blockage) influences the final decision. In disaster response scenarios, KANs can allow for the explicit tracking of how changes in weather or a newly closed road directly influence the predicted evacuation route, helping decision-makers trust and adapt the system's recommendations. This transparency ensures that routing systems are not only accurate but also accountable and explainable.

By leveraging these features, KANs provide an ideal solution for modeling complex, nonlinear, time-sensitive environments like disaster evacuation routing, where numerous factors influence the outcome, and the dynamics of the system evolve rapidly. However, research is still ongoing in the development and application of KANs for large-scale and dynamic ER problems. Ongoing efforts to integrate KANs with Graph Neural Networks (GNNs) and Quantum Computing could potentially unlock more advanced and scalable solutions for real-world applications in escape routing challenges.

Despite KANs showing promise, they have primarily been evaluated on small datasets. As stated in [6], larger datasets and complex environments, such as the dynamic ER problem, require further investigation of KANs integrated with GNNs, which could better handle large-scale systems. Additionally, the application of QC (as explored in [11]) could further enhance the scalability and performance of KANs in practical ER scenarios.

Despite the theoretical potential of KANs in solving complex routing problems, our literature review revealed a notable absence of empirical studies applying KANs specifically to disaster escape routing scenarios. This research gap presents a limitation in our comparative analysis, as we lack concrete performance metrics and experimental validation that would enable direct comparison with other approaches. The scarcity of such studies may be attributed to the relatively recent emergence of KANs in the optimization domain, coupled with the inherent complexity of implementing these networks for large-scale routing problems where real-time performance is critical. Consequently, while we can discuss the theoretical foundations and potential advantages of KANs, we cannot present quantitative benchmarks or empirical evidence of their effectiveness in disaster escape routing applications at this time.

VIII. OVERALL ANALYSIS

In this section, we reflect on our efforts to address the research questions outlined in Section II.

A. HQNN MODEL

The HQNN model addresses the research questions by presenting a hybrid supervised learning framework for tackling ER problems. It **offers** a novel approach by training the Quantum FiLM model to emulate the node-wise Dijkstra's algorithm, effectively combining classical optimization techniques with quantum computing. This integration aims to enhance routing efficiency and decision-making in dynamic environments, showcasing potential **success factors** such as improved performance and adaptability. However, despite the HQNN's notable performance, it faces **challenges** in its reliance on earthquake coordinates, start-end nodes, and immediate neighbors for determining optimal paths. This limited approach overlooks critical factors such as elevation and real-time traffic conditions, which can significantly impact route optimization. Including these variables would enhance the model's robustness and applicability, but acquiring post-disaster data poses unique challenges, necessitating further research to develop reliable data-gathering methods.

B. GNN MODEL

The GNN model **provides** a graph-centric approach that focuses on learning the correlations within the graph structure, which is crucial for modeling the intricate interactions among various nodes. This relationship between nodes is particularly significant in dynamic disaster scenarios, where node dependencies are prevalent and the number of nodes can increase to levels that classical machine learning strategies struggle to manage.

However, the ability of GNNs to model such complex interactions can be **limited**, as traditional GNNs are not inherently designed to handle dynamic environments. Furthermore, the presence of noise in the data complicates the task of accurately identifying node correlations. This presents a substantial challenge for conventional GNN approaches when applied to escape routing problems, highlighting the need for more robust methodologies that can effectively address these limitations.

C. TGN MODEL

The TGN model **addresses** the shortcomings of traditional GNNs in dynamic escape routing environments. Unlike GNNs, which struggle to adapt to changing node interactions, TGNs are designed to manage time-varying graphs, facilitating real-time updates of node states based on time-stamped events. This capability is essential for dynamic situations where conditions can change rapidly.

TGNs leverage memory mechanisms to preserve interaction histories, effectively reducing node staleness and improving predictive accuracy. Moreover, they exhibit greater robustness to noise and can integrate temporal information along with additional graph features. This combination enhances their ability to capture complex relationships in rapidly evolving scenarios, making TGNs a more suitable choice for tackling the challenges presented by dynamic escape routing problems.

D. KAN MODEL

Kolmogorov Arnold Networks (KANs) present a compelling alternative to Multilayer Perceptrons (MLPs) in deep learning, particularly for tasks involving complex graph structures. KANs utilize fewer parameters while achieving comparable or superior performance, which facilitates the development of simpler and faster models—attributes that are especially beneficial for larger graphs.

As the complexity of graphs increases, KANs capitalize on their robust theoretical foundation to effectively model intricate, non-linear patterns characteristic of traffic systems. This efficiency positions KANs to perform well even under demanding computational constraints, making them particularly suited for applications that require scalability and robustness, such as dynamic escape routing scenarios.

Further research into larger KAN architectures could significantly enhance their ability to tackle complex tasks, thereby solidifying their role as a leading alternative to traditional MLPs. Such advancements would also expand their applicability to large-scale escape routing problems, further demonstrating the potential of KANs in real-world scenarios.

IX. INTEGRATING DIVERSE MODELS FOR COMPREHENSIVE ESCAPE ROUTING SOLUTIONS

While each model discussed brings unique strengths to addressing real-world ER challenges, combining them can lead to a more robust and scalable solution for solving complex ER problems. Below, we illustrate how the HQNN, GNN, TGN, and KAN can complement each other:

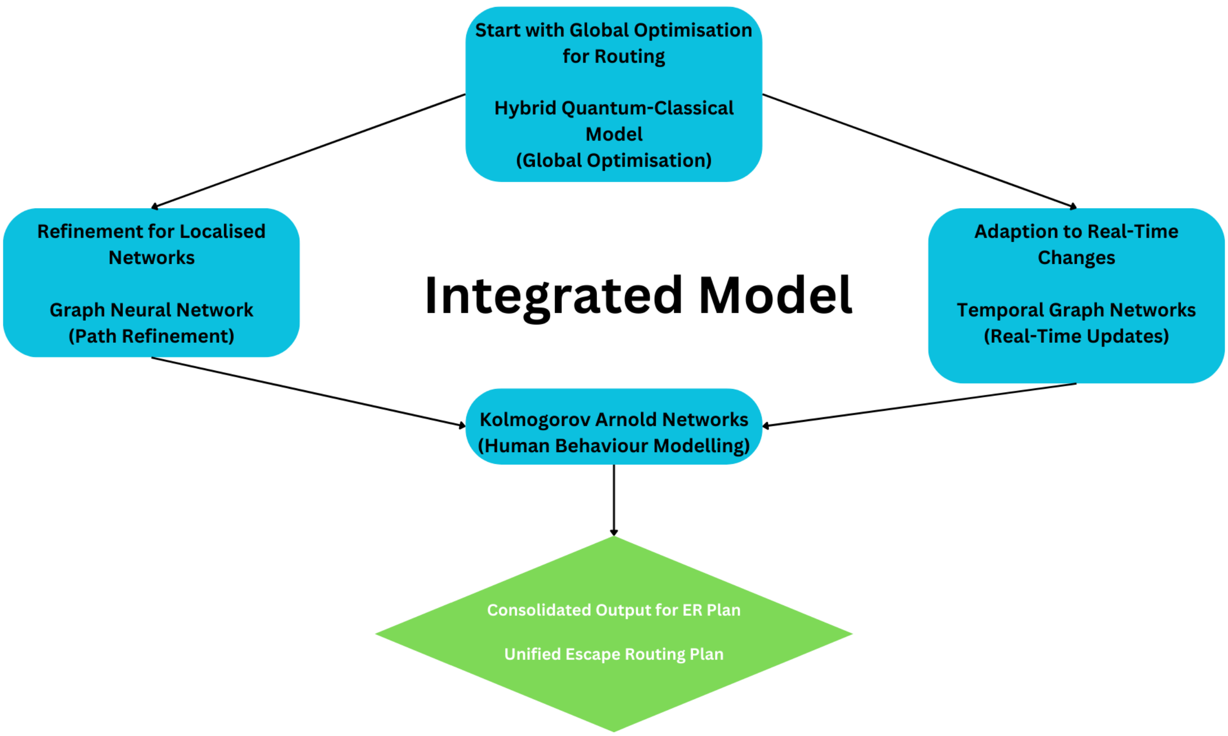

FIGURE 6. Block diagram illustrating the integration of Hybrid Quantum-Classical Model, Graph Neural Network, Temporal Graph Networks, and Kolmogorov Arnold Networks in addressing the dynamic ER problem. Each model contributes to specific tasks: global optimization, localized path refinement, real-time adaptation, and human behavior modeling, respectively, culminating in a unified escape routing plan.

A. HYBRID QUANTUM-CLASSICAL MODEL FOR GLOBAL OPTIMIZATION

The Hybrid Quantum-Classical model is highly suited for solving global optimization problems involving exponentially large solution spaces. For ER, it can compute the most efficient evacuation pathways on a macro level, accounting for constraints such as total evacuation time and road or traffic capacities across multiple regions. These global solutions serve as the foundational input to other models, which refine them further based on dynamic and localized factors.

B. GRAPH NEURAL NETWORK (GNN) FOR NETWORK-WIDE PATH REFINEMENT

GNNs process graph-structured evacuation networks to refine routes identified by the Hybrid Quantum-Classical model. By encoding edge-level details, such as road conditions, traffic capacity, and vehicle types, GNNs ensure compliance with localized constraints. They can also model interactions within the network, such as cooperative or competitive behaviors among evacuees, enhancing the system's adaptability to regional variations.

C. TEMPORAL GRAPH NETWORKS (TGN) FOR REAL-TIME ADAPTATION

TGNs address the dynamic nature of ER scenarios by incorporating temporal updates, such as road accessibility changes, evolving traffic conditions, or fluctuating weather patterns. By refining the evacuation strategy continuously, TGNs adapt routes in real time to prevent bottlenecks and address disruptions, ensuring a high level of responsiveness to dynamic scenarios.

D. KOLMOGOROV ARNOLD NETWORKS (KAN) FOR HUMAN BEHAVIOR MODELING AND INTERPRETABILITY

KANs are particularly suited for modeling nonlinear dependencies, such as crowd behavior and psychological responses during emergencies. By focusing on tasks like predicting panic-induced deviations or estimating evacuation times for pedestrians, KANs add a critical layer of human-centric modeling. Moreover, their interpretability provides insights into the evacuation plan, enabling decision-makers to identify and address potential weak points effectively.

E. COLLABORATIVE WORKFLOW OF MODELS

The synergy between these models can be illustrated through the following workflow:

1) **Initialization:** The Hybrid Quantum-Classical model generates an optimized global evacuation plan by solving for macro-level constraints, such as evacuation time and regional risks.
2) **Refinement and Adaptation:** GNNs refine the global plan, ensuring localized compliance with road conditions, traffic capacities, and individual evacuee behaviors.

3) **Dynamic Updates:** TGNs monitor evacuation operations, dynamically rerouting evacuees based on live data, such as traffic congestion, road blockages, or hazard zones.
4) **Behavior Analysis and Decision Support:** KANs model human behavior dynamics and provide interpretable insights, enabling further evaluation and improvement of the evacuation plan.

F. UNIFIED DEPLOYMENT FOR ER SCENARIOS

By leveraging the complementary strengths of these models, a dynamic system can be constructed to handle ER challenges. The integration ensures scalability across diverse geographical contexts while adapting dynamically to real-time crises, bridging global optimization, localized refinement, real-time updates, and interpretable outcomes. Fig. 5 shows the block diagram representation of the integrated model.

To the best of our knowledge, there are no existing studies that have implemented this combined approach, as indicated by our comprehensive review of the literature. This observation highlights a gap in current research. By leveraging the distinct strengths of each model, we hypothesize that their integration could lead to improved outcomes. Testing this hypothesis through rigorous experimentation is beyond the scope of this study and is proposed as future work.

X. CONCLUSION

This review enhances the understanding of research conducted on both Quantum and Classical solutions to the Disaster Escape Routing (ER) problem. We reviewed the HQNN Model, GNN Model, and TGN Model as responses to the research questions outlined earlier. Additionally, we provided insights into Variational Quantum Circuits (VQCs) and Encoding Strategies for routing problems, which contribute to a deeper understanding of these solutions.

We also discussed the latest developments in deep learning, particularly Kolmogorov Arnold Networks (KANs), highlighting their performance in the context of traffic routing problems. Our analysis suggests that while individual models show promise, a more comprehensive approach integrating multiple models could provide superior results. The proposed integration framework combines HQNN's global optimization capabilities, GNN's network-wide refinement, TGN's real-time adaptation, and KAN's human behavior modeling to create a more robust and adaptable system for disaster response.

This study primarily focused on disaster traffic ER issues, making it a relevant resource for researchers in this specific field. However, other researchers may also find value in the latest trends, such as KANs and the integrated approach, for broader ER applications. The integration framework proposed in this study opens new avenues for research in combining quantum and classical approaches for enhanced emergency response systems.

Given the niche nature of our research topic, we concentrated on papers directly related to Quantum Machine Learning (QML) and Machine Learning (ML) solutions for disaster ER problems. Consequently, this study may overlook other effective QML/ML solutions applicable to general ER challenges. Future research could expand on these solutions and the proposed integration framework, providing a more comprehensive exploration of the capabilities of quantum and classical approaches in tackling diverse ER problems. Testing and validating the integrated approach through practical implementations remains an important direction for future work.

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