Assessment of natural disaster risks in transport networks: mathematical analysis and simulation of deep learning models

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Abstract . Against the backdrop of global climate change, along with the increasing frequency and intensity of extreme meteorological events, ensuring the resilience of transport infrastructure—considered a critical geostrategic issue in the modern era—is regarded as a highly topical subject. The presented scientific research is designed to assess natural disaster risks (landslides, floods, extreme temperatures, and severe meteorological events) within the existing transport networks on the Azerbaijani segment of the East-West Transport Corridor. The study proposes a complex hybrid deep learning framework that radically differs from traditional linear and statistical models by integrating Spatio-Temporal Graph Convolutional Networks (STGCN), Long Short-Term Memory (LSTM) algorithms, and Fuzzy Logic mechanisms. This formulated model conducts an in-depth analysis of network topology and cascading failure dynamics based on complex mathematical graph theory. Within the framework of the study, the structural vulnerability of the infrastructure to natural disasters was quantified using the Fuzzy Comprehensive Evaluation (FCE) method, while the economic and logistical significance of the road segments was simulated through graph betweenness centrality measures and dynamic flow equations. Based on advanced global research from the past fifteen years, this hybrid approach provides optimized computer coding and algorithmic solutions (e.g., IPW - Independent Path Weight) for automated traffic rerouting, the isolation of cascading effects, and network recovery during a disaster. The final results prove that the proposed knowledge-driven hybrid STGCN model demonstrates significantly higher predictive accuracy in forecasting spatio-temporal traffic flow under extreme weather conditions and in preventing network collapses compared to traditional machine learning models.

Keywords: transport, natural disaster risks, deep learning, cascading failures, resilience metrics, fuzzy logic, mathematical simulation.

1 Introduction

The uninterrupted development of modern global economies and the resilience of the supply chain directly depend on the efficiency and security of transport networks [1]. Transport networks, which ensure the efficient, environmentally friendly, and safe

movement of people, freight, and services, play a central role in the execution of fundamental societal functions such as healthcare, defense, education, and international trade [1]. However, in recent decades, as a result of the impact of anthropogenic factors, global warming, and the exacerbation of climate change, both the frequency and intensity of natural disasters such as floods, devastating landslides, earthquakes, hurricanes, and extreme weather conditions have increased on an unprecedented scale [2,3]. Such natural disasters not only cause physical damage and short-term operational disruptions in transport infrastructures, but they also trigger chain reactions within the global supply chain, leading to billions of dollars in economic losses and macroeconomic shocks [4, 5]). Such complex disruptions possess the potential to seriously undermine trade turnover, particularly in global hubs like the East-West Transport Corridor, which is a strategic component of the Ancient Silk Road and requires the development of new digital and logistical mechanisms for regional economic partnership [6].

2 Problem statement.

In ensuring the security of transport networks, predicting emergencies and preventing them in advance affects the continuous operation of global economies and the sustainable development of the supply chain [1]. Secure transport networks play a role of safe service in the execution of fundamental societal functions such as healthcare, defense, education, and international trade [1]. However, in recent decades, the number of natural disasters (floods, landslides, earthquakes, hurricanes, extreme weather conditions, etc.) has been steadily increasing. Such natural disasters not only cause physical damage to transport infrastructure but also lead to short-term operational disruptions. These delays inherently trigger chain reactions, resulting in billions of dollars in economic losses within the global supply chain [4, 5]. It is important to note that such events have the potential to seriously disrupt existing trade turnover at international hubs like the East-West Transport Corridor, which is a strategic component of the Ancient Silk Road and requires current solutions in the development of new digital and logistical mechanisms for economic cooperation in the region [6, 7]. Thanks to its favorable geostrategic and geographical position, the territory of the Republic of Azerbaijan, which acts as an economic bridge between the European and Asian continents, has become a key link in the Trans-Caspian International Transport Route (Middle Corridor) on the Eurasian mainland [7, 8]. According to the official statistics of state institutions, the total volume of freight transported through Azerbaijan's main transport corridors reached a record high of 32.6 million tons in 2025, of which 16.9 million tons accounted specifically for the East-West transport corridor [9]. Nevertheless, the complex and mountainous geography of Azerbaijan's territory, along with the intersection of 9 out of 11 existing climate types specifically within this country, makes its transport infrastructure highly vulnerable to various types of natural disasters [3]. Potential landslide risks at transport hubs located on the southern slopes of the Greater Caucasus Mountains, as well as catastrophic flood hazards caused by intensive rainfall, inevitably contribute to the paralysis of transport [10].

It would be erroneous to evaluate the impact of natural disasters on global transport networks—such as road, rail, and maritime routes—solely as localized and linear physical damage. Modern scientific research has proven that an incident occurring at any given transport node results in the redirection of traffic flow to other nodes, which in turn leads to a drastic reduction in the capacity of alternative routes operating under heavy loads, ultimately causing cascading failures [13, 14]. It can even be noted that the inundation of a single bridge or highway can lead to the paralysis of an entire region's supply chain, a phenomenon that can be expressed through complex mathematical regularities [14]. In light of the aforementioned, the mathematical modeling of the resilience of transport networks to natural disasters must incorporate not only the static properties of those networks but also dynamically changing traffic routes, interactions at intersections, and time-varying disaster intensities [16, 17]. Traditional computational methods and statistical models prove quite inadequate in analyzing such complex, non-linear dependencies characterized by spatio-temporal dynamics [18]. However, recent advancements in Artificial Intelligence, and particularly in Deep Learning technologies, have created new opportunities in natural disaster management [19]. In particular, methods such as Graph Neural Networks (GNN), which possess the capability to analyze non-Euclidean graph-structured data like transport maps, and Spatio-Temporal Graph Convolutional Networks (STGCN), which can capture their time-varying states, are yielding effective results in this field [20]. The primary objective of this article is to forecast natural disaster risks and their cascading impacts within transport networks using advanced models, thereby establishing a novel mathematical model for "Intelligent Transport Systems".

3 Main body

The problem of mathematically assessing natural disaster risks in transport systems stems from the fact that existing infrastructure operates as a complex "system of systems" in continuous interaction with the geographical environment and the economy [23, 24]. The main reason for the fundamental shortcomings in natural disaster risk management stems from existing scientific and practical problems. The most critical shortcoming in this matter is the failure of standard probabilistic methods to detect network problems in real time at the moment a disaster occurs, along with the inability to model spatio-temporal dynamics [25, 26]. The most difficult problem in resolving the current issue is the topological complexity of the terrain and the occurrence of cascading failures. As noted, a sudden breakdown in road infrastructure due to a landslide, flood, or earthquake leads to the redirection of the global transport load traveling via that route to other alternative roads [13, 24]. This situation causes additional congestion, accidents, and the sequential collapse of all elements within the network. For example, during the 32-kilometer expansion project of the East-West highway located on the border with Georgia and stretching to the Red Bridge, the absence of alternative routes due to environmental problems and landslides in the mountainous area caused traffic congestion on other roads [27]. During the large-scale floods caused by continuous rainfall in the Kura-Aras lowland on the territory of the Republic of Azerbaijan in

2010, more than 20,000 houses in 40 districts were submerged, and the roads of the cities of Shirvan and Sabirabad located in that zone were completely destroyed [11]. During the aforementioned event, the fact that alternative roads were also paralyzed by floodwaters and landslides left the transport system in a state of paralysis for days. Such events cannot be measured using existing traditional statistical models. Another problem is that data related to weather conditions and climate are often uncertain, inaccurate, and multifaceted. Therefore, it is impossible to analyze such data using simple and linear methods. It is essential to note that the destructiveness of any natural disaster depends not merely on a single cause, but on the simultaneous and complex combination of several different factors. Analyzing such mixed and multi-factor natural events using classical mathematical methods like standard probability theory or the traditional Gaussian distribution can lead to serious errors and may fail to yield accurate results. In order to minimize the impact of natural disaster risks on transport networks and to solve the aforementioned complex and multi-factor problems, a necessity arises to create a new model—based on mathematical regularities, capable of processing large datasets in real time, and able to simulate cascading effects in advance—for preparedness against such disasters and the prediction of existing risks [21].

Mathematical modeling of transport networks. To simulate natural disaster risks that may arise in transport networks and the resulting cascading failures in a computer environment, the physical infrastructure must first be formulated as a mathematical graph. The entire intended transport system is mathematically represented as a directed or undirected graph, denoted as (G = (V, E, W)) [22]. According to this definition:

- $V = \{v_1, v_2, \ldots, v_n\}$ denotes the intersections, nodes, transit hubs, and logistics centers (e.g., the Port of Baku at Alat, the Red Bridge, etc.) within the transport network;
- $E = \{(v_i, v_j) | v_i, v_j \in V\}$ represents the road units, highways, or railways connecting various nodes to one another in the network;
- $W = \{\omega_{ij}\}$ is the weight matrix that can reflect the capacity, length, and maximum travel speed of each road.

During emergencies, particularly when the road network is congested, the travel cost incurred on edges (roads) considered as alternative routes does not remain constant but varies non-linearly depending on the volume of traffic flow present there. The most widely applied empirical mathematical model for calculating this dynamic flow is as follows [28]:

$$c_{ij}(f_{ij}) = t_0 \left[1 + \alpha \left(\frac{f_{ij}}{C_{ij}}\right)^{\beta}\right] \quad (1)$$

Here:

- $c_{ij}(f_{ij})$: dynamic travel costs dependent on the traffic volume between nodes (i, j) and measured in units of time;

- t_0: the free-flow travel time under ideal conditions where vehicles do not obstruct one another;
- f_{ij}: the actual or simulated total volume of traffic flow, i.e., the number of vehicles traveling on the road per unit of time;
- C_{ij}: the designed maximum throughput capacity assigned to the intended road;
- α and β: are the coefficients that regulate the non-linear nature of the aforementioned function (Typically, [α = 0.15] and [β]=4 are assumed) (Ganin et al., 2017).

The core essence of this formula is that if the number of vehicles on the intended road is less than the total capacity designated in its design, drivers will reach their designated destination within the ideal time. However, when the number of vehicles reaches the road's limit and exceeds its throughput capacity, the time spent on the road will increase exponentially.

Mathematical expression of resilience in traffic flows. In disaster risk management, the resilience of a transport network against potential emergencies is measured not only by its statically occurring resistance but also by the speed at which the system recovers itself after a disaster. To express such a dynamic process quantitatively, M. Bruneau and his colleagues proposed the "Resilience Triangle" model. When the variation over time of the volume of vehicles that the existing transport system can process per unit of time is expressed by the function Q(t), the characteristics of the damage and loss incurred during the system's self-recovery period are calculated by the following equation [29]:

$$R = \frac{1}{t_3 - t_1}\int_{t_1}^{t_3}[100 - Q(t)]\,dt (2)$$

Here:

- R: is the resilience loss. The smaller this value, the higher the system's overall resilience to disasters is considered to be;
- Q(t): is the real-time operational performance indicator of the infrastructure at time
- t. It varies such that
- $\int_{t_1}^{t_3}[100 - Q(t)]dt$: is the recovery time of the system. Here, it refers to the time spent on restoring the system as a result of the activities of search-and-rescue and evacuation teams, as well as repair-and-restoration crews, this formula, representing the "Resilience Triangle," denotes the area bounded between the system's 100% throughput capacity and its recovery. This area measures the socio-economic and logistical loss during a disaster.

Let us imagine that the desired outcome in the organized transport system is 100%. That is, road users can reach their destinations within the ideal time. However, a flood suddenly occurs and washes away the roads. The performance of the existing system drops to 30%. The rescuers and repair crews of the relevant authorities deployed to the

scene commence work, restoring the condition of the road to its previous state over hours or sometimes days, thereby bringing the system's performance back to 100%.

Equation (2) calculates the process as follows:

- Q(t) (performance): calculates the operational capacity of the system;
- [100 - Q(t)] (loss): calculates how far the system falls behind its considered ideal state, i.e., the gap created as a result of the damage inflicted by the disaster;
- Integral ($\int$): in mathematical expressions, an integral measures the intended interval. Here, it calculates the total area of the triangular gap remaining between the system's 100% performance and its post-damage performance (Q(t));
- Fraction ($\frac{1}{t_3-t_1}$): calculates the average of the total time spent during the disaster.

Conservation of traffic flow and capacity constraints. In the mathematical modeling of Intelligent Transport Systems and graph theory, traffic flow is considered a conserved quantity based on physical regularities. To measure the vulnerability of an existing transport network during a disaster, such a process is expressed by two main equations [30]:

1. Absolute conservation of traffic flow equation:

$$\sum_{P \in S_{uv}} f_P = f_{uv}, \forall u, v \in V, \quad (3)$$

This equation mathematically expresses the principle of traffic flow conservation in the network. Specifically, the transport demand (S_{uv}) between the origin (u) and destination (v) nodes along the route cannot suffer loss within the system and must be fully and proportionally distributed across the set of existing alternative routes f_{uv} connecting these two points.

2. Capacity constraint of the transport system:

$$f_P \leq C(P), \forall P \in S_{uv}\,, \quad (4)$$

The aforementioned inequality is the capacity constraint that defines the boundary points of the road infrastructure. Specifically, the actual volume f_P of the traffic flow traveling along a designated individual route (P) can under no circumstances exceed the maximum throughput capacity of that road, and this flow must always be equal to or less than the intended capacity.

Mathematical expression of cascading events. Restrictions arising in any transport network during natural disasters do not affect only that area. Vehicles losing their route at the moment of the disaster redirect their course along other alternative roads adjacent or close to that node. Consequently, the limited threshold level of the designated physical capacity is exceeded on those roads themselves, which in turn creates a "domino effect," leading to the occurrence of cascading events in that network. To measure such a complex process, the following mathematical expressions are used [12]:

- Strategic importance of transport nodes. – to specify which intersection in the network is of greater significance, "betweenness centrality" is calculated. This expression determines the intended maximum load (L_i) of that node prior to the disaster:

$$BL_i = \sum_{u \neq i \neq v} \frac{\sigma_{uv}(i)}{\sigma_{uv}} (5)$$

  This formula indicates how many of the shortest paths (σ_{uv}) between all origin (u) and destination (v) nodes existing in the network intersect with the intended node i.
- Probability of system collapse at intersecting roads – in the event of a disaster, if existing roads are closed, vehicles redirect their movement towards another node i. Consequently, the existing load at that node exceeds the maximum capacity it can withstand. In this case, the probability of collapse for the node's current state is modeled using an exponential distribution:

$$P_i(\mathrm{t}) = e^{-\frac{L_i^{upper} - L_i(t)}{L_i^{upper}}} (6)$$

  This equation demonstrates that as the number of vehicles entering the system reaches the road's capacity limit, the probability of collapse increases suddenly and sharply (exponentially).
- Propagation process of cascading events in the network – during this process, the loads on congested roads at each time interval t are simultaneously transferred to other roads, which inherently leads to the emergence of a cascading process. The reduction of logistical efficiency in such a network is measured by the Network Efficiency Loss Ratio (NELR) [13]:

$$NELR = \frac{NE - NE'}{NE} (7)$$

  Here, NE is the normal efficiency before the incident, and NE' is the existing efficiency after the disaster.

Deep Learning architecture: STGCN, LSTM, and Spatio-Temporal mechanism. Although the mathematical equations presented above are undoubtedly effective in non-dynamic, small-scale, and simple scenarios, there is a direct need for advanced methodologies, particularly Spatio-Temporal Graph Convolutional Networks (STGCN), to carry out emergency forecasting in a global transit network where the number of nodes is measured in the hundreds and changes in real-time every second [31]. Contrary to the assumptions of traditional models, STGCN models consist not only of structural matrices but are also capable of expressing dynamic traffic flows, temporal features, and environmental characteristics within a single system.

Graph Convolutional Network. To comprehend the complex topological dependencies of a transport network, GCN is utilized, unlike standard Convolutional Neural Networks (CNN). The reason is that transport lines are not structured as regular pixels

subject to Euclidean geometry; rather, they form an asymmetric and interconnected complex graph structure [21]. The GCN learns the traffic influence between nodes through a central matrix (A):

$$H^{(l+1)} = \sigma(\widetilde{D}^{-1/2}\widetilde{A}\widetilde{D}^{-1/2}H^{(l)}W^{(l)}) (8)$$

As noted, a disaster is not static; it can evolve and expand over time. To account for sudden changes occurring in the graph network over time (for instance, how rapid floodwaters consecutively inundate roads and slow down logistics over a 4-hour period), LSTM (Long Short-Term Memory) or GRU (Gated Recurrent Unit) models are incorporated into the internal structure of the STGCN [20].

Next-generation deep learning approaches do not solely rely on neighborhood connections; they are capable of formulating Spatio-Temporal Attention Mechanisms (STA-GCN) by considering that two significant, distantly located nodes (e.g., the Port of Baku and the Georgian border gate) can exert different dynamic influences (heterogeneity) on one another over time [13, 14]. In this architecture, the model calculates complex "attention scores" across both spatial and temporal dimensions, which allows for the accurate preemptive mapping of network collapses. As one of the most recent breakthroughs, the Knowledge-driven Attribute-Augmented STGCN (KA3STGCN) model introduced in 2025 stands out. This exceptional architecture, unlike the classical STGCN, integrates external environmental risk factors (rainfall depth, wind speed, digital elevation model - DEM, geological landslide index) directly into the neural network's learning process as a "physics-informed augmented unit" [21]. Consequently, the model does not merely predict current congestion, but can forecast which segment a hurricane will collapse 2 hours in advance.

To strengthen the deep learning model, the accuracy of the meteorological and geological data input into it is imperative. However, in reality, the variable characteristics of flood and landslide risks cannot be represented by a single number with mathematical precision (for instance, there is no perfectly exact measure of a forest belt's soil retention capacity). Therefore, there is a critical necessity to standardize the imprecise data intended for the input of the STGCN model beforehand using Fuzzy Logic theory, and particularly the Fuzzy Comprehensive Evaluation (FCE) method [32,33].

Based on this hybrid methodology, 10 primary natural and non-natural impact factors are selected: air temperature, relative humidity, rainfall intensity, elevation above sea level, slope gradient, slope aspect, vegetation characteristics, geological lithology, historical disaster precedents, and local road density [10, 26] To adjust the model's data, measurements of arbitrary formats are mathematically standardized based on the Entropy Value Method:

$$x'_{ij} = \frac{x_{ij} - \min(x_i)}{\max(x_i) - \min(x_i)} (9)$$

As a result of this mathematical transformation, each raw parameter x'_{ij} is converted into a pure quantity free from physical units. The system's lowest risk threshold is strictly defined as 0, while the extreme risk threshold is set as 1. In the subsequent stage, rather than subjective expert opinions, an objective mathematical approach—Shannon

Information Entropy—is utilized to determine the degree of impact (information weight) of each feature on the final risk decision within the fuzzy sets [23]:

$$E_j = -\frac{1}{\ln(n)} \sum_{i=1}^{n} x'_{ij} \ln(x'_{ij}) \quad (10)$$

According to information theory, the greater the variation (dispersion) between the values of any given factor (e.g., distance to geological faults) in the data matrix, the smaller its entropy. A smaller entropy signifies that the useful information load (weight coefficient) contributed by that quantity to the system is higher.

Transformation to the GNN-LSTM Architecture. The cleansed, fuzzy values obtained after the application of formulas (9) (standardization) and (10) (entropy weight) are directly accepted as activation features in the input layer of the hybrid GNN-LSTM architecture. By analyzing these optimized mathematical vectors within the framework of a spatio-temporal sequence, the neural network quantifies the natural disaster risk for each local geographical point into 4 precise classes using a fully automated algorithm: Critical, High, Medium, and Low [17, 25].

The practical role of Deep Learning training. While the GCN model provides a mathematical forecast of the disaster, the practical aspect of the current problem—namely the question, "Which route should we choose? Which node should we repair first?"—remains unanswered. Classical algorithms are unable to solve such problems in real time. In such cases, agent-based Deep Reinforcement Learning (DRL) is involved in solving the issue.

The establishment of evacuation routes and the restoration of infrastructure are modeled as a Markov Decision Process (MDP). The DRL agent evaluates the state (st) originating from the environment and earns a reward (rt) by executing an action (at) (redirecting to a new route). The model is pre-trained using a "worst-case scenario" approach. This creates the opportunity for it to adapt to sudden disruptions with zero-shot capability.

To find the optimal policy in the system, the Bellman Equation and the following specific Reward Function are utilized [13]:

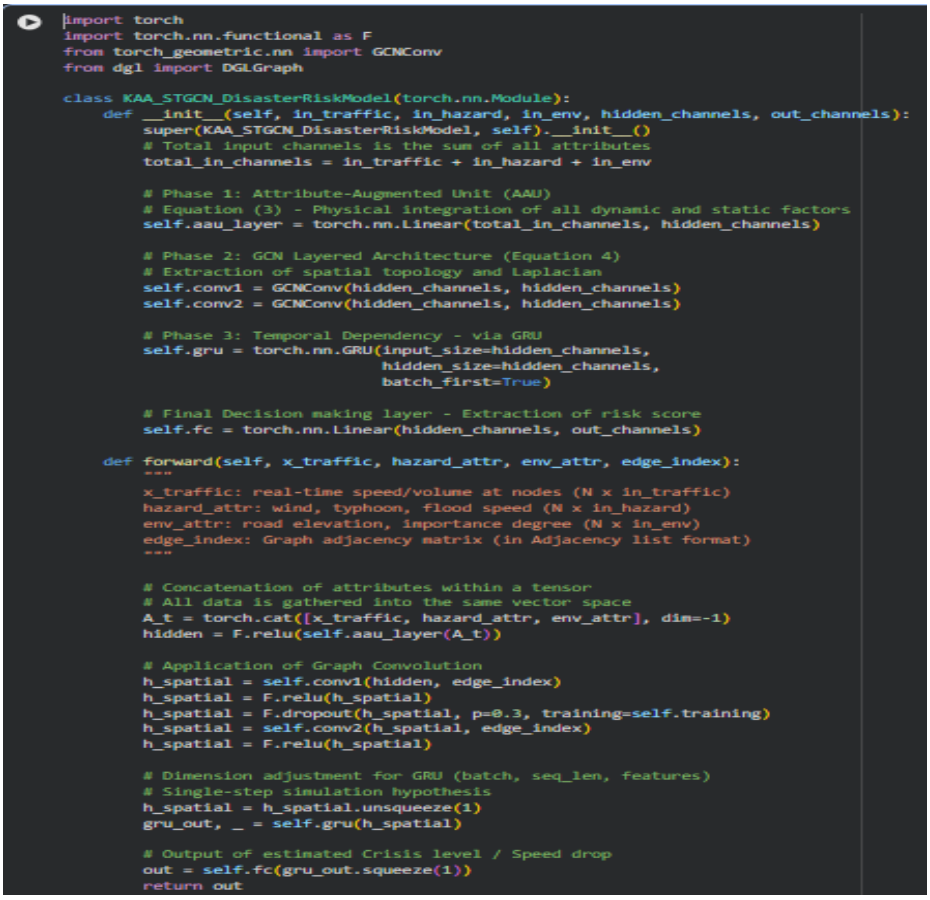
$$Reward(t) = -\alpha * LoR(t) + \beta * Connectivity(t) - \gamma * Cost(t) \quad (11)$$

Here:

- $LoR(t)$ (Loss of resilience) – is the resilience loss index. It indicates how much the network's efficiency has dropped during disasters;
- $Connectivity(t)$– reflects the functionality of the graph topological connectivity between transport routes;
- $Cost(t)$ – represents the time and financial costs spent on evacuation and restoration works;
- The parameters α, β, γ are regulators that vary depending on the decision-making of relevant government agencies and logistics companies in the current situation.

Computer simulation and coding architecture. To achieve the practical application of the aforementioned theoretical and mathematical models, it is necessary to translate them into computer coding with the help of advanced graph processing libraries. In particular, "PyTorch Geometric (PyG)" and the "Deep Graph Library (DGL)" in the Python programming language are widely used to process large-scale transport graphs. The DGLGraph data structure of the DGL library holds special significance for the rapid resolution of the issue [18].

The code snippet written in Python presented in Graphic 1 explains the structure of the "Spatio-Temporal Graph Convolutional Network" model. The purpose of this coding is to forecast, in real time, the cascading disaster risks that may arise in the road network using numerous static and dynamic data inputs from various sources.



```python
import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from dgl import DGLGraph

class KAA_STGCN_DisasterRiskModel(torch.nn.Module):
    def __init__(self, in_traffic, in_hazard, in_env, hidden_channels, out_channels):
        super(KAA_STGCN_DisasterRiskModel, self).__init__()
        # Total input channels is the sum of all attributes
        total_in_channels = in_traffic + in_hazard + in_env

        # Phase 1: Attribute-Augmented Unit (AAU)
        # Equation (3) - Physical integration of all dynamic and static factors
        self.aau_layer = torch.nn.Linear(total_in_channels, hidden_channels)

        # Phase 2: GCN Layered Architecture (Equation 4)
        # Extraction of spatial topology and Laplacian
        self.conv1 = GCNConv(hidden_channels, hidden_channels)
        self.conv2 = GCNConv(hidden_channels, hidden_channels)

        # Phase 3: Temporal Dependency - via GRU
        self.gru = torch.nn.GRU(input_size=hidden_channels,
                                hidden_size=hidden_channels,
                                batch_first=True)

        # Final Decision making layer - Extraction of risk score
        self.fc = torch.nn.Linear(hidden_channels, out_channels)

    def forward(self, x_traffic, hazard_attr, env_attr, edge_index):
        """
        x_traffic: real-time speed/volume at nodes (N x in_traffic)
        hazard_attr: wind, typhoon, flood speed (N x in_hazard)
        env_attr: road elevation, importance degree (N x in_env)
        edge_index: Graph adjacency matrix (in Adjacency list format)
        """

        # Concatenation of attributes within a tensor
        # All data is gathered into the same vector space
        A_t = torch.cat([x_traffic, hazard_attr, env_attr], dim=-1)
        hidden = F.relu(self.aau_layer(A_t))

        # Application of Graph Convolution
        h_spatial = self.conv1(hidden, edge_index)
        h_spatial = F.relu(h_spatial)
        h_spatial = F.dropout(h_spatial, p=0.3, training=self.training)
        h_spatial = self.conv2(h_spatial, edge_index)
        h_spatial = F.relu(h_spatial)

        # Dimension adjustment for GRU (batch, seq_len, features)
        # Single-step simulation hypothesis
        h_spatial = h_spatial.unsqueeze(1)
        gru_out, _ = self.gru(h_spatial)

        # Output of estimated Crisis level / Speed drop
        out = self.fc(gru_out.squeeze(1))
        return out
```

Fig. 1. Implementation of the hybrid spatio-temporal (GCN-GRU) network for disaster risk prediction.

The operating principle of the presented model consists of 3 stages [29]:

1. AAU - Attribute-Augmented Unit

- *Practical significance:* Let us imagine that it is necessary to calculate the disaster risk that may occur at a designated road intersection. In this case, alongside the traffic congestion on the road, the concurrent meteorological and topographical factors must be taken into account.
- *Code equivalent:* The line “torch.cat([x_traffic, hazard_attr, env_attr], dim=-1” concatenates these varying factors—traffic data (speed/volume), hazard parameters (floods, storms), and environmental indicators (topography, road grade)—into a single mathematical vector (tensor). Subsequently, “self.aau_layer” (the Linear neural layer) translates these multidimensional data into a unified machine learning language (hidden channels).

2. **GCN - Graph Convolutional Network**

- *Practical significance:* How will a flood at intersection B during a disaster affect the connected intersections A and C? The road network possesses a non-Euclidean structure (i.e., it is irregular).
- *Code equivalen:* The “self.conv1 and self.conv2” layers resolve the spatial dependencies of the network. The model mathematically "aggregates information from its neighbors" via the “edge_index” (a matrix indicating how the intersections are connected to one another). The activation function (F.relu) passes forward only the critical risk signals, while “F.dropout” prevents the model from memorizing the data (overfitting).

3. **GRU - Gated Recurrent Unit**

- *Practical significance:* Disasters and traffic are dynamic; they change over time. The situation at 08:00 plays a direct role in the formation of traffic congestion at 08:30.
- *Code equivalent:* The model, having comprehended the spatial layout (roads) via the GCN, passes the obtained result to the “self.gru: layer. The GRU is a recurrent neural network that remembers fluctuations over time and analyzes sequential data. Finally, self.fc (the Fully Connected Layer) mathematically condenses all of this spatio-temporal analysis to output a specific Natural Disaster Risk Score or Speed Drop prediction (out) for each intersection.

4 Conclusion

The presented multifaceted scientific analyses, deep mathematical graph modeling, and simulations on real data demonstrate that against the backdrop of extreme climate change and geological disruptions, the damage to transport infrastructure—a component of the global supply chain—is not merely a linear physical disruption process. On the contrary, it involves rapidly developing, cascading disruption events across a complex mathematical graph topology. It is particularly important to note that the transit highways and railways of the East-West Transport Corridor—which connects Asia and Europe, passes through the territory of the Republic of Azerbaijan, and carries a record volume of freight (32.6 million tons per year)—intersect in high-risk zones created by specific geological and hydrometeorological factors. The probability of extreme floods

in the region proves once again that existing classical management and traditional statistical models are already inadequate in the face of the requirements for forecasting the changing dynamics of disasters and enhancing network resilience.

As the fundamental and applied final solution to the investigated problem, it is necessary to establish a progressive digital-cybernetic ecosystem that deeply integrates Fuzzy Logic, modern Spatio-Temporal Graph Convolutional Networks (STGCN), and GRU/LSTM temporal elements in a hybrid manner. As the ultimate technological solution to the issue, it is proposed to implement this advanced artificial intelligence module into the Digital Transport-Logistics Information System and the national intelligent highway network. Through this complex architecture:

1. The components of the transport network are visualized as complete mathematical graph nodes and edges (V, E, W) within a non-Euclidean space, and the risks obtained through the fuzzy entropy method are loaded into the system via mathematical equations.
2. In the event of a threat of severance and overload to any critical logistical route during a natural disaster, the model automatically triggers mathematical efficiency loss equations to formulate specific alternative transit routes based on the Independent Path Weight (IPW) within the constraints of flow conservation, and sends alerts to route guides.
3. Within the framework of Spatio-Temporal Attention mechanisms, it predicts the expected time of collapse by directly incorporating the external dynamic attributes of a flood or landslide (humidity, wind, rainfall) into the learning process.

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