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DYNAMIC ROUTING METHOD IN MOBILE SOFTWARE-DEFINED NETWORKS USING ARTIFICIAL INTELLIGENCE

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Introduction

The rapid development of wireless technologies and the increasing number of mobile terminals (including unmanned aerial vehicles, vehicles, and Internet of Things devices) require new approaches to building computer networks. Implementing the Software-Defined Networking (SDN) paradigm in mobile environments allows for separating the control plane from the data plane, ensuring flexibility, programmability, and centralized monitoring of the infrastructure [1, 2].

However, when utilizing SDN in a mobile environment, classical protocols and centralized algorithms designed for a quasi-static topology prove inefficient due to the persistent necessity to recalculate routes upon connection loss or node relocation [3, 4]. In mobile networks, nodes are constantly moving, leading to regular link breaks and new connection establishments. Using classical routing protocols (e.g., OSPF, ECMP) under such conditions is inefficient. Every topology change generates a significant amount of control traffic to the central controller, which is forced to constantly recalculate flow tables to restore routes. This inevitably leads to controller overload, increased latency, packet loss, and general degradation of Quality of Service (QoS).

The main challenge of mobile SDN lies precisely in the temporal variability of the network graph. The network state at time t almost never coincides with the state at time $t+\Delta t$, and routing decisions made "here and now" often become obsolete by the time they are installed in the flow tables. Classic reactive approaches force the controller to respond to events post-factum, leading to bursts of control traffic, increased latency, and degraded QoS.

Artificial intelligence-based methods, such as multilayer perceptrons (MLP), reinforcement learning (RL), or graph neural networks (GNN), predominantly involve the analysis of static metrics (throughput, latency, packet loss) without profoundly accounting for the spatiotemporal evolution of the network. This necessitates the development of methods that integrate the modeling of the network's topological graph structure with the analysis of its temporal evolution.

The objective of this study is to develop a conceptual architecture for a dynamic routing method in mobile SDN networks, utilizing temporal graph neural networks (T-GNN), capable of simultaneously considering the spatial structure of the network graph and its temporal dynamics for proactive route establishment.

Review of Existing Solutions

Both classical and intelligent approaches are widely used in contemporary routing and load balancing research. Classical methods extensively applied in SDN include shortest path algorithms (Dijkstra, OSPF-like implementations in controllers), as well as mechanisms for uniform traffic distribution, particularly Equal-Cost Multi-Path (ECMP) [1]. While these approaches ensured predictable behavior, they relied on a fixed or slowly changing set of link weights, usually derived from current throughput measurements or administratively assigned metrics. The major drawback of this approach is that routes are established based on the network state snapshot without considering its change trend. Consequently, a node failure triggers a computationally expensive full or partial recompilation of the flow tables, and uniform distribution (ECMP) does not account for non-uniform actual load and packet loss on wireless channels. Overall, these limitations demonstrate that in highly mobile scenarios, the convergence time of such algorithms often exceeds the lifetime of the route itself.

Transitioning to artificial intelligence, a significant portion of work on intelligent routing in SDN relied on fully connected neural networks (multilayer perceptrons, MLP) and supervised learning methods [7]. A typical input vector for such a model included aggregated metrics: current channel bandwidth, latency, packet loss rate, and queue occupancy, where the MLP output formed recommendations for path selection or weights for a subsequent classical routing algorithm.

A separate direction explored Deep Reinforcement Learning (DRL) methods, which formulated the routing problem as a Markov Decision Process [5, 6]. In mobile environments (UAV, MANET, VANET), adapted versions of QoS-oriented and DRL routers were applied [11].

To address topological unawareness, specific research utilized classical Graph Neural Networks (GNN) for SDN modeling and optimization, particularly the RouteNet architecture and its extensions [8, 9, 10]. These models successfully accounted for the spatial structure of the graph, i.e., topological interdependencies between links.

Despite a diversity of approaches, the predominant majority of the analyzed methods conceptualize the network as a static snapshot at a discrete point in time. As noted, MLP models receive a metric vector without explicit topology representation; classical GNN models consider the graph but ignore its evolution; and DRL agents mainly operate under the assumption of a quasi-stationary environment. Together, these studies indicate that none of these architectures are fundamentally capable of predicting precisely how the load or connectivity will change in the coming seconds, which is critically important specifically for mobile SDN networks.

This observation motivates a paradigm shift toward models that explicitly integrate graph structures with temporal dynamics, specifically temporal graph neural networks (T-GNN).

T-GNN Based Routing Method

To overcome the limitations of existing approaches, this study proposes a predictive routing method founded on temporal graph neural networks. The core idea is to change the paradigm: from reactive route computation based on the current state to proactive traffic engineering based on predicting the network's spatio-temporal evolution.

Within the T-GNN-based routing method, the SDN controller forms the network state not as an isolated set of metrics, but as a time-ordered sequence of graphs

$$G = \{G_{t-k}, G_{t-k+1}, \dots G_{t-1}, G_t\},$$

where each graph $G\tau = (V\tau, E\tau, X\tau, W\tau)$ describes the network state at a discrete moment in time τ:

$V\tau$ – the set of vertices (SDN switches, access points, mobile hosts).

$E\tau$ – the set of edges (active communication links between nodes).

$X\tau$ – the vertex feature matrix (geographic location, node type, buffer size, etc.).

$W\tau$ – the edge feature matrix (bandwidth, latency, packet loss, signal level, current load).

This representation naturally captures the key feature of mobile networks – that the set of vertices, edges, and their weights changes dynamically. The SDN controller, having a global view, is capable of forming this sequence based on periodic telemetry measurements.

A Temporal Graph Neural Network (T-GNN) is a class of models that combines two complementary mechanisms:

- Graph Convolutions (Graph Convolutional Networks, GCN) – responsible for extracting spatial (topological) dependencies. They aggregate information from neighboring nodes within a single graph $G\tau$. This allows obtaining local representations (embeddings) that account for the topological context: load on neighboring channels, degree of connectivity, and node position in the graph [8, 9].

- Recurrent mechanisms (e.g., GRU or LSTM) – responsible for extracting temporal dependencies. They analyze the history of graph state changes at previous time steps and identify trends: for example, gradual degradation of connection quality due to the mobile node moving away.

Formally, if $H_\tau = GCN(G_\tau)$ is the graph embedding at time τ, then the temporal module computes the prediction

$$\hat{Y}_{t+1} = f_\theta(H_{t-k}, H_{t-k+1}, \dots, H_t),$$

where $\hat{Y}_{t+1}$ are the predicted channel characteristics in the next time step (expected load, expected latency). The parameters θ are trained on historical telemetry data.

Thanks to the synergy of these mechanisms, the T-GNN module is capable of predicting the state of the network graph for subsequent time intervals with high accuracy. Upon receiving such a prediction, the SDN controller gains the ability to proactively calculate alternative routes and update the flow tables on the switches even before the active communication link is broken. The technical novelty of this approach for mobile environments lies in the system's ability to work proactively, allowing for truly continuous routing, minimization of packet loss, and a radical reduction of signaling load on the SDN controller.

The key advantage of this approach is the transition from reactive to predictive routing. Instead of recalculating routes after an event occurs (link break, queue overload), the controller uses the forecast $\hat{Y}_{t+1}$ as input for the decision-making module, which:

- Preemptively redistributes flows from channels that are highly likely to become overloaded.
- Avoids establishing routes through links for which a break is predicted due to node movement.
- Considers the route's lifetime by selecting paths with a more stable predicted topology.

System Architecture

The lifecycle of the predictive routing system in a mobile SDN network is based on a continuous feedback loop between the data plane and the intelligent controller. The general logic of component interaction is shown in Fig. 1 and consists of the following sequential stages:

1. Telemetry Collection: obtaining primary data from network devices.
2. Graph Formation: transforming raw data into a time sequence of graph structures.
3. Analysis in the T-GNN Module: extracting topological and temporal dependencies.
4. Generation of Predictive Decisions: updating flow tables based on the forecast.
5. Feedback and Retraining: evaluating effectiveness and adapting the model.

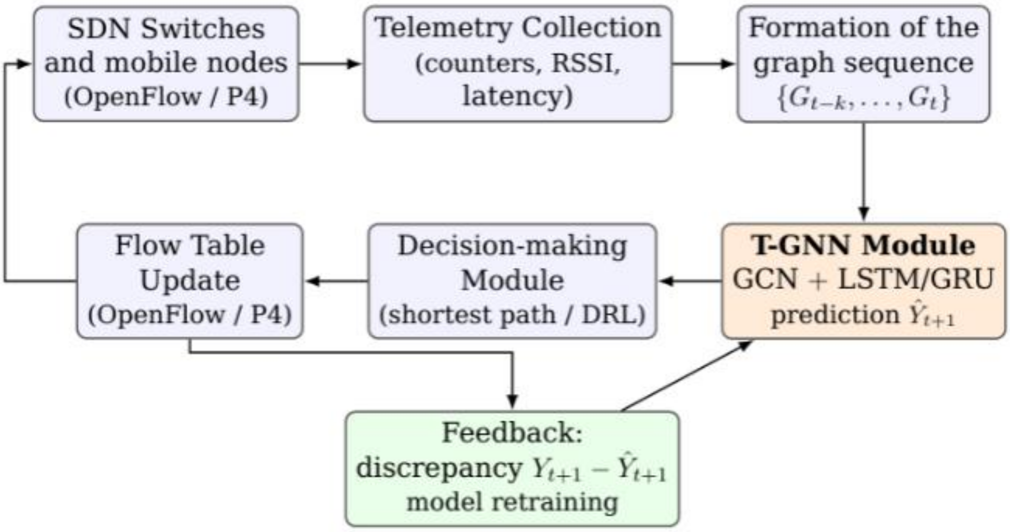

Fig. 1. Architecture of the dynamic routing system based on T-GNN.

The data plane is formed by SDN switches and mobile nodes managed via OpenFlow or P4 interfaces. The controller periodically (with an interval Δt, typically from hundreds of milliseconds to seconds) polls network devices and receives:

- Byte and packet counters on each port.
- Latency and jitter estimates.
- Signal levels (RSSI), SNR, and current transmission speed on wireless interfaces.
- Information about neighboring nodes and their movement parameters (coordinates, vectors) if relevant localization data is available.

A specialized controller module converts the raw telemetry data into a graph structure $G_\tau = (V_\tau, E_\tau, X_\tau, W_\tau)$. The sequentially formed graphs are accumulated in a ring buffer of a specified length $k+1$, forming a sliding time window. This representation is the single unified format for data exchange between the controller and the AI module.

The formed sequence of graphs for the observation window is fed into the T-GNN neural network module. Graph convolutional layers extract topological dependencies of the current state, while recurrent blocks analyze the temporal dynamics of these changes. At the output, the module generates a prediction graph $\hat{Y}_{t+1}$ – the expected network topology for the next time step with predictive weighting coefficients for each edge, which is used as input for the routing decision-making module.

The decision-making module is implemented through one of the following approaches:

- A classical shortest path algorithm applied to the predicted weights.
- A multi-path routing algorithm with QoS constraints.
- A DRL agent that uses the T-GNN output as an observation of the environment state [6, 10].

Based on the predicted graph, the SDN controller's routing module calculates optimal paths for active data flows. If the forecast indicates an inevitable degradation or break of a specific connection, the controller proactively forms new routing rules and sends them to the switches before the actual failure occurs. This ensures smooth traffic switching without session interruption.

The measured metric values at time $t+1$ are compared with the prediction $\hat{Y}_{t+1}$. The discrepancies (errors) are used for:

- Online monitoring of model quality.
- Periodic fine-tuning of the T-GNN module (in the background or on a separate computational resource).
- Adaptation of hyperparameters (length of the time window k, frequency of telemetry polling).

Consequently, the system operates on the principle of a self-regulating closed loop, consecutively executing telemetry data collection, graph representation, T-GNN prediction, and adaptive route correction, thereby ensuring the continuous optimization of network flows. It is this closed-loop and predictive nature of decision-making that distinguishes the proposed architecture from classical reactive SDN solutions.

Conclusions

This work substantiates the conceptual architecture of a dynamic routing method in mobile Software-Defined Networks based on Temporal Graph Neural Networks. It is shown that classical static algorithms (ECMP, OSPF) and basic neural network models (MLP, static GNN, DRL agents) interpret the network as a snapshot of its state and are therefore fundamentally incapable of adequately accounting for the temporal evolution of topology, which is characteristic of mobile environments.

The proposed concept involves representing the network state as an ordered sequence of graphs that combine spatial structure (nodes, links, metrics) and temporal dynamics. Integrating the T-GNN module into the SDN controller's control plane allows for a transition from reactive to predictive routing: path decisions are made based on the forecast of channel status, not post-factum after events occur. The closed operational cycle of the system is described – from collecting telemetry via OpenFlow or P4 to updating flow tables and fine-tuning the model based on prediction discrepancies.

The main advantage of the proposed method is its capacity for anticipatory operation, which facilitates the realization of uninterrupted routing and the substantial minimization of packet loss. Through the preemptive calculation of alternative routes and the advance updating of switch flow tables prior to actual link disconnection, seamless traffic migration is achieved without the disruption of network sessions. Furthermore, transitioning to a proactive management paradigm facilitates a reduction in control traffic volume, thereby mitigating the issue of SDN controller signaling overload in highly dynamic mobile environments.

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DYNAMIC ROUTING METHOD IN MOBILE SOFTWARE-DEFINED NETWORKS USING ARTIFICIAL INTELLIGENCE

The article examines the problem of ensuring effective routing and load balancing in mobile Software-Defined Networks (SDN), which are characterized by high node mobility and frequent topology changes. Existing solutions based on classical static approaches or basic artificial intelligence models (for example, multilayer perceptron) have a significant drawback: they analyze the network state as a snapshot at a fixed moment in time and are unable to capture temporal changes and the evolution of the topology graph. This leads to SDN controller overload and reduced Quality of Service (QoS) due to constant link breaks. To solve this problem, a conceptual architecture for a predictive routing system based on Temporal Graph Neural Networks (T-GNN) is proposed. The suggested approach allows for modeling spatio-temporal dependencies in the network, predicting the future state of connections based on historical data, and establishing routes proactively, which significantly reduces the load on the control plane.

Keywords: *artificial intelligence, software-defined networks, SDN, T-GNN, mobile networks, dynamic routing, predictive routing, QoS.*

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МЕТОД ДИНАМІЧНОЇ МАРШРУТИЗАЦІЇ В МОБІЛЬНИХ ПРОГРАМНО-КОНФІГУРОВАНИХ МЕРЕЖАХ З ВИКОРИСТАННЯМ ШТУЧНОГО ІНТЕЛЕКТУ

У статті розглядається проблема забезпечення ефективної маршрутизації та балансування навантаження в мобільних програмно-конфігурованих мережах (SDN), що характеризуються високою динамікою переміщення вузлів та частими змінами топології. Існуючі рішення, що базуються на класичних статичних підходах або базових моделях штучного інтелекту (наприклад, багатошаровий перцептрон), мають суттєвий недолік: вони аналізують стан мережі як миттєвий зріз у фіксований момент часу і не здатні вловлювати часові зміни та еволюцію графа топології. Це призводить до перевантаження SDN-контролера та зниження якості обслуговування (QoS) при постійних обривах каналів зв'язку. Для вирішення цієї проблеми запропоновано концептуальну архітектуру системи предиктивної маршрутизації на основі часових графових нейронних мереж (Temporal Graph Neural Networks, T-GNN). Запропонований підхід дозволяє моделювати просторово-часові залежності в мережі, прогнозувати майбутній стан з'єднань на основі історичних даних та прокладати маршрути на випередження, що суттєво знижує навантаження на площину керування (control plane).

Ключові слова: *штучний інтелект, програмно-конфігуровані мережі, SDN, T-GNN, мобільні мережі, динамічна маршрутизація, предиктивна маршрутизація, QoS.*

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