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Advancing 6G Network Performance: AI/ML Framework for Proactive Management and Dynamic Optimal Routing

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ABSTRACT As 6G networks proliferate, they generate vast volumes of data and engage diverse devices, pushing the boundaries of traditional network management techniques. The limitations of these techniques underpin the need for a revolutionary shift towards AI/ML-based frameworks. This article introduces a transformative approach using our novel Speed-optimized LSTM (SP-LSTM) model, an embodiment of this crucial paradigm shift. We present a proactive strategy integrating predictive analytics and dynamic routing, underpinning efficient resource utilization and optimal network performance. This innovative, two-tiered system combines SP-LSTM networks and Reinforcement Learning (RL) for forecasting and dynamic routing. SP-LSTM models, boasting superior speed, predict potential network congestion, enabling preemptive action, while RL capitalizes on these forecasts to optimize routing and uphold network performance. This cutting-edge framework, driven by continuous learning and adaptation, mirrors the evolving nature of 6G networks, meeting the stringent requirements for ultra-low latency, ultra-reliability, and heterogeneity management. The expedited training and prediction times of SP-LSTM are game-changers, particularly in dynamic network environments where time is of the essence. Our work marks a significant stride towards integrating AI/ML in future network management, highlighting AI/ML's exceptional capacity to outperform conventional algorithms and drive innovative performance in 6G network management.

INDEX TERMS Artificial intelligence (AI), machine learning (ML), long short-term memory (LSTM), speed-optimized LSTM (SP-LSTM), 6G networks, network management, predictive analytics, dynamic routing, reinforcement learning (RL), network congestion forecasting, resource utilization, ultra-low latency, ultra-reliability, heterogeneity management, AI/ML implementation, algorithm performance optimization, network performance optimization, proactive network strategies, next-generation networks, evolutionary network solutions.

I. INTRODUCTION

The dawn of 6G technology promises ultra-fast connectivity, vast data capacities, and an array of smart devices, but brings forth challenges in efficiently managing intricate networks [1], [2], [3]. This article identifies key challenges:

1) Traditional, rigid network management techniques are becoming obsolete [13], [4], [7].
2) Existing methods struggle to efficiently handle the data surge characteristic of 6G, leading to resource inefficiencies [5], [12].

One primary concern arising from these challenges is ensuring ultra-low latency, essential for applications such as autonomous driving and telemedicine [6]. Congestion-heavy networks further aggravate latency issues, particularly during traffic rerouting [16].

In response, we introduce an AI/ML-driven network management framework, blending predictive analytics and dynamic routing. While LSTM networks show potential in predictive analytics, they face challenges like computational demands and extended temporal dependency mapping [23], [24]. We address this with our Speed-optimized LSTM (SP-LSTM), optimized for real-time 6G requirements.

On the other side, dynamic routing adapts to live network conditions [17], and Reinforcement Learning (RL) emerges as an adaptive solution for real-time routing [18]. With RL, we integrate current network data with future predictions to develop comprehensive routing strategies, enhancing performance and reducing latency [10].

This article offers a groundbreaking approach to 6G network management with a dual-layered AI/ML framework. The central vision: AI/ML stands as the linchpin for effective 6G network management [11].

Our key contributions are:

1) *A Novel AI/ML Framework:* Designed to address 6G complexities.
2) *SP-LSTM Introduction:* Merging efficiency with predictive accuracy.
3) *Advanced Dynamic Routing:* An RL-based adaptive routing solution.
4) *Innovative AI/ML Framework:* A dual-layered design for consistent 6G performance evolution.
5) *Centralizing AI/ML:* Emphasizing its pivotal role in 6G management.
6) *Setting New Standards:* Pioneering insights that shape future research directions in network management.

Our article is organized as follows: Section II evaluates the inadequacies of conventional network management strategies for upcoming 6G networks. In Section III, we delve into the pivotal role of LSTM and SP-LSTM in AI/ML-based predictive analytics. Section IV contrasts the flexibility of RL in dynamic routing against traditional methods. Section V presents a cohesive AI/ML framework, merging predictive analytics and dynamic routing, tailored for the challenges of 6G networks. Section VI assesses the efficacy of our model, emphasizing its capability to handle 6G's anticipated data traffic demands. The conclusion encapsulates our findings and delineates avenues for future research.

II. RELATED WORK

The early days of networking revolved around static and rigid routing policies, sufficient for initial network infrastructures to maintain stable connections [2], [26]. However, with the complexities of modern-day connectivity, particularly in the 6G era, these paradigms show limitations, unable to exploit 6G's vast data avenues efficiently [21]. The advent of 6G, characterized by massive data capacities, diverse device integration, and a push for ultra-low latency, demands more robust network management solutions [1], [2]. These technical advancements pave the way for real-time applications such as remote robotic surgeries and autonomous vehicles [6]. However, they also underscore the perennial challenge of latency and the need for dynamic, intelligent routing.

Artificial Intelligence (AI) and Machine Learning (ML) have shown promise in addressing the intricacies of 6G. Notably, the LSTM networks, a subset of recurrent neural networks, have gained recognition for their capability to model complex, non-linear dependencies in network time-series data, thereby transforming predictive analytics for 6G [22], [23]. Shi et al. pioneered the use of LSTM for traffic prediction methods to assist light path reconfiguration in hybrid data center networks (DCN) [28]. In contrast, our groundbreaking work introduces the SP-LSTM, designed to comprehend 6G network dynamics comprehensively compared to others like Xiao et al. [29].

Considering the shortcomings of conventional LSTM or GRU models with attention features, we developed the SP-LSTM for time series prediction. While current models manage long-term sequences and non-linear behaviors effectively, they face challenges with inconsistent or irregular patterns [32], [33], [34], particularly in complex scenarios such as 6G networks. Our SP-LSTM tackles LSTM's overfitting vulnerabilities by embedding regularization techniques and enhanced memory mechanisms, offering efficiency in processing extended sequences.

The evolution of dynamic routing has spanned:

1) *Rule-Based Dynamic Routing:* Originating from early computer networks, these were simple but lacked adaptability. OSPF and BGP serve as examples [5].
2) *Adaptive Routing Algorithms:* Pivotal during the network's intermediate evolution, these are dynamically adjusted based on real-time conditions. RIP and EIGRP are prominent examples [27], [30].
3) *Machine Learning-Driven Routing:* Machine learning's permeation into routing led to:

- *Predictive Analytics:* ML models, notably LSTMs, became popular for network prediction tasks [22].
- *Reinforcement Learning-Based Routing:* RL algorithms like Q-learning and Deep RL began adapting in real-time, based on feedback [15], [28].

While RL's application to routing predates 6G, 6G's unique challenges necessitated advanced RL approaches. Classic research by Sutton and Barto provided foundational RL knowledge [25], with more recent works like Deng et al.'s emphasizing Deep RL for 5G networks [31]. Our research uniquely integrates SP-LSTM insights with RL's adaptability, crafting a routing strategy attuned to 6G's demands. Instead of mere reactive strategies, our method forecasts and then implements actions.

The ever-evolving nature of 6G demands models that continuously learn, ensuring they remain relevant to the network's progression [12]. Our work introduces a paradigm shift with a two-tiered AI/ML-driven architecture, uniting predictive accuracy with dynamic adaptability, specifically for 6G [11]. In the vast realm of dynamic routing literature, our research stands out, merging SP-LSTM's predictive capabilities with RL's real-time adaptability, delivering a holistic solution for 6G's challenges.

III. AI/ML FOR PREDICTIVE ANALYTICS

The potential of predictive analytics to transform the dynamics of network management has been recognized increasingly in recent years. Harnessing the power of Artificial Intelligence and Machine Learning (AI/ML) to convert vast swathes of historical network data into actionable intelligence marks a paradigm shift in network management practices. Predictive analytics enables us to forecast future network conditions, paving the way for proactive, data-driven decision-making that can significantly enhance network performance, reliability, and efficiency.

A. TRADITIONAL LSTM: BRIDGING TIME DEPENDENCIES IN PREDICTIVE ANALYSIS

In the constellation of AI/ML algorithms, Long Short-Term Memory (LSTM) networks [8], a form of Recurrent Neural Network (RNN), have emerged as particularly potent tools for predictive analytics. Characterized by their ability to capture long-term dependencies in time-series data, LSTM networks are ideally suited to address the inherent temporal patterns in network traffic [27]. This capacity to comprehend and learn from the past to predict future network congestion is indispensable for proactive network management. By forecasting potential congestion areas, LSTM-based models allow for preemptive rerouting of data traffic, thereby mitigating congestion and enhancing network throughput. Let's delve deeper into the mechanics of LSTM networks. Given a sequence of inputs $(x_1, x_2, \ldots, x_t)$, LSTM updates its internal states using the following set of equations (refer to "(1)"):

$$\begin{aligned}
\text{Forget gate:} \quad & f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
\text{Input gate:} \quad & i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
& \hat{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\
\text{Cell state update:} \quad & C_t = f_t * C_{t-1} + i_t * \hat{C}_t \\
\text{Output gate:} \quad & o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
& h_t = o_t * \tanh(C_t)
\end{aligned} \tag{1}$$

Here, σ denotes the sigmoid activation function, tanh represents the hyperbolic tangent activation function, * is element-wise multiplication, [.,.] signifies concatenation, the W terms stand for weight matrices, and the b terms refer to bias vectors.

Traditional LSTMs outperform RNNs in managing long sequences, but they face challenges:

- *Computational Complexity:* Their advanced gating increases computational demand and training time.
- *Training Challenges:* Complex structures raise the potential for gradient-related issues, although less than basic RNNs.
- *Parameter Overhead:* High parameter counts can lead to overfitting, especially with limited data.
- *Memory Constraints:* Their need for storing numerous parameters and states demands substantial memory.
- *Opacity:* LSTMs often lack clarity in decision-making, functioning as black boxes.
- *Issues with Extended Sequences:* Extremely long sequences can overwhelm LSTMs, causing data loss or distortion.

Nevertheless, LSTMs shine in tasks with sequential data. Innovations like GRUs and the Transformer model (e.g., BERT, GPT) offer alternative solutions with distinct benefits and trade-offs [35].

B. SP-LSTM: A TRANSFORMATIVE EVOLUTION OF TRADITIONAL LSTM

The traditional LSTM, while robust, has areas of potential improvement that the `Speed-optimized LSTM` (SP-LSTM) directly addresses, bringing forth a suite of innovative enhancements.

1) SIMPLIFIED ARCHITECTURE

SP-LSTM streamlines the classic four-gate LSTM design. By merging the forget and input gates into a unified `update gate`, it achieves efficiency levels akin to the Gated Recurrent Unit (GRU). This merger ensures the model retains LSTM's notable proficiency for handling long sequences.

2) ENHANCED PARALLELIZATION

One of the long-standing challenges of the LSTM is its sequential processing, which limits parallelization opportunities across time steps. SP-LSTM effectively addresses this by borrowing from the Transformer's self-attention mechanism. This inclusion allows simultaneous evaluation of all time steps, ascertaining their relevance and optimizing computational resource utilization.

3) ROBUST REGULARIZATION:

Given the LSTM's propensity for overfitting due to its considerable parameter count, the SP-LSTM integrates built-in regularization. This involves embedding dropout layers within its cells and applying efficiency-improving strategies, such as Batch Normalization. This holistic approach mitigates overfitting without compromising on performance.

4) ADVANCED MEMORY MECHANISM

Our model is fortified with an explicit memory mechanism, reminiscent of `memory networks` or the `Neural Turing Machine` framework [36], [37]. This innovation empowers the SP-LSTM to adeptly manage extensive sequences, elevating its capabilities, especially in scenarios requiring the processing of long sequential data.

5) INTRODUCING EXPLAINABILITY

A groundbreaking feature of the SP-LSTM is its intrinsic explainability. By utilizing attention mechanisms, it not only offers accurate predictions but also delivers insightful interpretations, emphasizing which parts of the input it considered crucial during its prediction phase.

Encapsulating the pivotal ideas of our work, we present the efficient and robust SP-LSTM in algorithmic form (Algorithm 1). This groundbreaking method streamlines processing and advances machine-learning algorithms to the next frontier of speed and precision. The ensuing algorithm

Algorithm 1: SP-LSTM Algorithm for Network Congestion Prediction.

```
procedure SP-LSTM
    Initialize C[0] = 0, h[0] = 0
    for each t ∈ sequence do
        Compute u[t] = σ(W_u[h[t − 1], X[t]] + b_u)
        Compute C̃[t] = tanh(W_c[h[t − 1], X[t]] + b_c)
        Update
        C[t] = u[t] ∗ C[t − 1] + (1 − u[t]) ∗ C̃[t]
        Compute a[t, i] for all i, normalize to get a[t, :]
        Compute C̃[t] = Σ_i(a[t, i] ∗ C[i])
        Compute
        o[t] = σ(W_o[h[t − 1], X[t], C̃[t]] + b_o)
        Update h[t] = o[t] ∗ tanh(C̃[t])
    return h[0], . . ., h[T] if return_sequences=True
    else h[T] only.
```

elegantly synthesizes the complexities of SP-LSTM into a digestible format, making it an invaluable tool for comprehending and implementing this powerful AI/ML paradigm in 6G network management and beyond.

Where:

- $h[t]$: The hidden state at time t.
- $x[t]$: The input at time t.
- $C[t]$: The cell state at time t.
- $u[t]$: The update gate at time t.
- $o[t]$: The output gate at time t.
- W_u, W_c, W_o: The weight matrices for the update gate, candidate memory, and output gate respectively.
- b_u, b_c, b_o: The bias vectors for the update gate, candidate memory, and output gate respectively.
- σ: The sigmoid function.
- tanh: The hyperbolic tangent function.
- $a[t, i]$: The attention score at time t for cell state i.
- $\tilde{C}[t]$: The candidate cell state at time t.
- *return_sequences:* A boolean that determines whether to return the hidden states for all time steps or just the last one.

Given the dynamic unpredictability of network conditions, simply relying on past behavior for predictions is inadequate. A blend of proactive predictions and real-time adjustments is crucial. Our approach integrates SP-LSTM-based analytics for initial routing decisions and dynamic routing for live adjustments. This approach optimally balances predictive and real-time responses, elevating network performance in varying conditions. The subsequent section explores the union of AI/ML dynamic routing and predictive analytics in network management.

IV. AI/ML FOR DYNAMIC ROUTING

Dynamic routing, known for its real-time adaptability to evolving network states, is a critical element in contemporary network management. This approach surpasses traditional static routing by providing increased flexibility to navigate complex, fast-changing networks. AI/ML technologies have been instrumental in enhancing the efficiency of routing procedures, with reinforcement learning (RL) showing significant promise for dynamic routing applications. RL, a subset of machine learning, facilitates optimal decision-making through environmental interaction, using feedback to iteratively refine actions. In a dynamic routing scenario, an RL agent continuously learns and adjusts optimal routing policies. Observing the current network state, it makes routing decisions and receives feedback based on the impact of these decisions on overall network performance. This repetitive process of action-feedback promotes the agent's progressive adjustment of routing strategy across iterations. An RL-based routing system's primary goal is to maximize a reward function reflecting desirable network conditions. This function might include metrics like latency reduction, congestion minimization, and network load balancing. For instance, the agent might earn positive rewards for reducing network latency and negative rewards for actions increasing congestion. Formally, this objective can be represented as in the following equation (refer to "(2)"):

$$\max_{\pi} \mathbb{E}_{(s,a)\sim\pi}[R(s, a)] \tag{2}$$

Here, π symbolizes the routing policy, (s, a) denotes the state-action pairs (i.e., the current network state and the corresponding routing action), and $R(s, a)$ embodies the reward function. The expectation $\mathbb{E}$ is computed over the state-action pairs generated by adhering to policy π.

This RL-based approach to dynamic routing harnesses the strength of AI/ML to create a more robust, adaptable, and efficient network management system. When integrated with SP-LSTM-based predictive analytics, it forms a potent combination capable of handling both predictable and unpredictable fluctuations in network conditions. The fusion of these AI/ML methodologies not only enhances the responsiveness and adaptability of network management but also paves the way for the realization of truly autonomous network systems. The ensuing section elucidates this integration and discusses its potential to transform network management practices.

V. REENVISIONING NETWORK MANAGEMENT: THE TWO-TIERED AI/ML SYSTEM

The proposed framework signifies a transformative approach to network management, adeptly crafted to tackle the multifaceted challenges inherent to next-generation networks. By synergistically integrating the profound predictive capabilities of SP-LSTM-based analytics with the dynamic adaptability of RL-based routing, we present a two-tiered AI/ML system. This fusion culminates in a robust solution that excels not only in efficiency but also in resilience amidst unpredictable network variations.

The first tier of our system leverages SP-LSTM networks, widely acclaimed for their proficiency in time-series data analysis. By harnessing historical network data, the

TABLE 1. Detailed Breakdown of SP-LSTM Neural Network Architecture

Component	Description
SP-LSTM Architecture	
Units	LSTM units.
Input Dimension	Input data dim.
State Size	LSTM cell state dim.
Weight Matrices and Bias Vectors for LSTM Cell Gates	
Wu, bu	Update gate (Glorot uniform, zeros).
Wf, bf	Forget gate (similar initialization).
Wc, bc	Cell input.
Wo, bo	Output gate.
SP-LSTM Layer Specifics	
Return Sequences	Return last output or full sequence.

TABLE 2. Q-Learning Architecture for Routing Decisions

Component	Description
States	Link ID, Time, 3 types of Throughput
Actions	Device pairs and Link ID
Reward	Predicted Moving Avg. Throughput
α	0.1 (Learning Rate)
γ	0.9 (Discount Factor)
ϵ	0.1 (Exploration Rate)
Convergence	Threshold at 0.001
Episodes	Max of 50
Q-Table	States x Actions, initialized to zeros

SP-LSTM model offers prescient predictions concerning imminent network conditions. This capability becomes instrumental in preempting congestion scenarios, thus allowing for insightful data rerouting and load-balancing decisions. The network architecture of the SP-LSTM is delineated in Table 1. For a comprehensive understanding, please refer to the https://github.com/pmushidi2/AI-Powered-Predictive-Analytics-and-Dynamic-Routing.git GitHub repository.

$$x_{t+1} = SP\text{−}LSTM(x_1, x_2, \ldots, x_t) \tag{3}$$

Informed by the predictions derived from SP-LSTM analytics, an initial routing strategy, grounded in the anticipated network conditions, is formulated.

Building on this foundation, the second tier employs reinforcement learning to further refine routing decisions dynamically. Our implementation utilizes the Q-learning algorithm, an RL technique that adjusts routing based on real-time network feedback.

To elucidate further, the RL framework is built upon the Markov Decision Process (MDP) paradigm. Technical details of the RL implementation can be found in Table 2 and the accompanying GitHub repository. The essence of the MDP consists of states, actions, transitions, and rewards. Within our system:

- *State Space (S):* Every state $s \in S$ is a vector representation that includes features such as Link ID, Time, and various throughput metrics. More specifically, given a network with N links, and assuming we're considering T time steps for throughput metrics, the state at any time t can be represented as $s_t = [link_{1...N}, time_{1...T}, throughput_{1...T}]$.
- *Action Space (A):* The action $a \in A$ corresponds to routing decisions made based on the current network topology. Given a device d in the network, actions can involve routing to any of the directly connected links. Thus, for a device with L connected links, the action space will have L possible routing decisions.
- *Transition Probabilities (P):* These define the likelihood $P(s_{t+1}|s_t, a_t)$ of transitioning from one state s_t to another s_{t+1} given an action a_t. In our network scenario, these probabilities can be estimated using historical data combined with real-time feedback. For instance, given the current state of the network and a chosen routing action, we can estimate the probability that a certain link will be congested in the next time step.
- *Reward Function (R):* As previously mentioned, our reward function links the predicted moving average throughput of selected links to potential rewards for respective routing actions. Mathematically, for a given state-action pair, $R(s_t, a_t)$ quantifies the benefit of routing through a particular link given the current network conditions.

$$\pi^* = \arg\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} R(s_t, a_t)\right] \tag{4}$$

The RL-based dynamic routing layer, continuously learning and adjusting based on network feedback, mitigates the inherent limitations of LSTM-based predictions. It ensures routing decisions remain effective even in the face of unexpected network changes. This fosters the deployment of advanced, anticipatory mechanisms within the 6G framework. Furthermore, RL significantly reduces signaling overhead costs by enabling autonomous learning from the network environment.

Our innovative approach introduces a sophisticated two-tiered AI/ML system, aiming to revolutionize the management of emergent 6G networks.

Fig. 1 provides an in-depth visual representation of the proposed system, detailing the workflow and interplay among its various components:

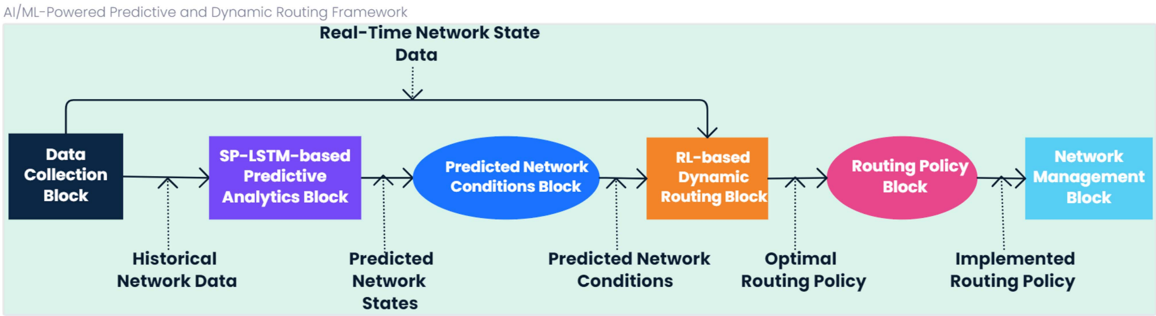

FIGURE 1. **AI/ML-powered predictive and dynamic routing system.**

- *Data Collection:* Represents the data sources, including historical network data for SP-LSTM analytics and real-time state data for RL routing.
- *SP-LSTM-based Predictive Analytics:* Utilizes historical data to forecast future network conditions.
- *Predicted Network Conditions:* Depicts the anticipated network state based on historical data.
- *RL-based Dynamic Routing:* Ingests input from both Predicted Network Conditions and real-time state data. This process adjusts the routing policy based on real-time feedback and projected conditions, emphasizing constant learning and adaptation for dynamic optimization.
- *Routing Policy:* Illustrates the output of RL Dynamic Routing, or the optimal routing policy at a given time.
- *Network Management:* The final stage that implements the derived routing policy in the network.

In the complex realm of 6G network management, our dual-layered AI/ML framework strikes a balance between foresight and adaptability. The first tier, leveraging SP-LSTM networks, harnesses historical data to predict imminent network scenarios. While it excels in proactive load management using time-series analysis, it can be vulnerable to unexpected network shifts. The second tier, anchored in reinforcement learning (RL), steps in to address this. RL adapts dynamically, learning from real-time feedback, and compensates for the occasional shortcomings of LSTM predictions. Its focus on long-term rewards sets it apart from traditional short-term models. Moreover, RL's inherent efficiency reduces signaling overheads, promoting cost-saving operations. Yet, its dependence on real-time data necessitates a solid feedback system for precision. Together, SP-LSTM provides predictive strength, while RL ensures flexibility, together catering seamlessly to 6G's fluid demands.

VI. PERFORMANCE EVALUATION

Our proposed framework exhibits a compelling use case, demonstrating the transformative potential of a proactive AI/ML system for resource optimization and network performance in 6G. By employing advanced technologies such as predictive analytics and dynamic routing, powered by SP-LSTM networks and RL, we enable intricate network pattern modeling, accurate congestion forecasting, and preemptive disruption avoidance. By utilizing real-time data and intelligent routing decisions, our solution ensures high network performance. It effectively manages the vast data volumes of 6G networks and facilitates near-instantaneous routing decisions. The complete code can be accessed on https://github.com/pmushidi2/AI-Powered-Predictive-Analytics-and-Dynamic-Routing.git GitHub.

A. NETWORK TOPOLOGY

Our network topology, designed using NetSim v13.3 [25], caters to the needs of 6G networks. Fig. 2 illustrates the topology, featuring nodes, links, and vital elements for 5G and 6G networks. These include the AMF for access and mobility management, SMF for session management and traffic optimization, UPF for handling user plane data traffic, and gNB as the base station for transmitting/receiving signals and managing radio resources. We also apply various mobility models to user equipment (UE) for realistic mobility scenarios. The topology incorporates critical 5G and 6G elements for simulating the advanced characteristics of these networks. Technologies like Massive MIMO, mmWave communications, network slicing, edge computing, SDNs, and VNFs are included. This integration allows us to evaluate the performance of network management and optimization strategies that address the unique needs and challenges of 6G networks. Our experimental setup is augmented with realistic traffic patterns and diverse traffic types for enhanced realism. These patterns emulate the traits of emerging 6G applications and services, including ultra-high-definition video streaming, IoT device communication, and mission-critical communications. These diverse traffic types allow us to evaluate the network's ability to manage the stringent requirements of varied use cases and applications.

In essence, the designed network topology seeks to represent real-world 6G networks regarding scale, heterogeneity, and connectivity. This topology is derived from current and anticipated networking technologies, noting the absence of a finalized 6G Network architecture. Our design emphasizes connectivity rather than strictly representing an L-3 topology. We utilized the full-mesh configuration as a theoretical model to highlight optimal connectivity and associated complexities.

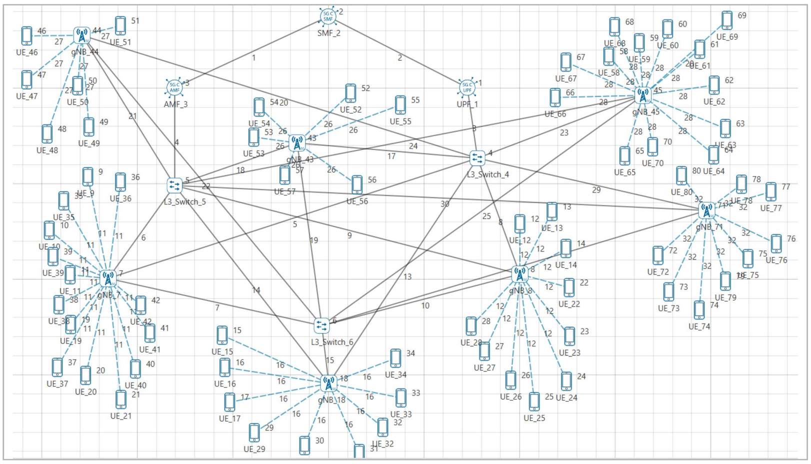

FIGURE 2. **NetSim designed topology mimicking a 6G network infrastructure.**

B. DATASET

Utilizing the meticulously crafted network topology outlined in the preceding section, we successfully generated a comprehensive dataset imbued with critical features essential for our research. The dataset encompasses crucial attributes, including `Link_ID`, `Time`, `Moving_Average_throughput`, `Instantaneous_throughput`, and `Time_average_throughput`. `Link_ID` serves as a fundamental identifier denoting the network connection between distinct nodes within the topology, thereby establishing the foundation for our subsequent analyses. Additionally, the `Time` attribute signifies the temporal aspect of the data, enabling temporal correlation investigations. Furthermore, the `Moving_Average_throughput` provides insights into the average throughput over time, while the `Instantaneous_throughput` showcases instantaneous variations in network performance. Lastly, the `Time_average_throughput` captures the time-based average throughput, offering a holistic view of network efficiency. The incorporation of these key features empowers our research with a rich dataset that facilitates in-depth exploration and analysis of network dynamics and performance.

C. RESULTS AND DISCUSSION

1) PREDICTIVE ANALYTICS AND CONGESTION ANALYSIS

We begin by loading the `Dataset.csv` which contains crucial features: `Link_ID`, `Time`, `Moving_Average_throughput`, `Instantaneous_throughput`, and `Time_average_throughput`. Preprocessing involves data normalization using MinMaxScaler and splitting it into training and testing sets. The SP-LSTM model (Table 1) is then employed to capture temporal dependencies and predict `Moving_Average_throughput`. We evaluate the model's performance using mean squared error (MSE) and assess prediction accuracy. Predicted outputs are saved as CSV files for further analysis. Additionally, we analyze link congestion levels based on `Moving_Average_throughput` before and after prediction to demonstrate the impact of our approach. Our evaluation methods provide quantitative insights into the effectiveness of our solution for optimizing latency and enhancing network performance in heterogeneous 6G environments.

2) AI/ML-BASED STRATEGIES FOR OPTIMAL NETWORK MANAGEMENT

This study unveils a new AI/ML-based network management system (Algorithm 2) and contrasts its performance with a conventional method (Algorithm 3) under the same network conditions. Algorithm 2 employs Q-learning, a Reinforcement Learning technique, that uses network topology and Predicted Moving Average throughput to determine the best data transmission path. It aims to reduce differences between predicted and actual throughput, thus improving network performance. The Q-table, updated regularly, directs the model to the best path. The system also offers visualization features like showing the optimal path and monitoring rewards and path lengths over time.

Algorithm 3 represents OSPF, a classic network management method using Dijkstra's shortest path algorithm. It builds a graph from network topology, with edge weights based on the inverse of predicted throughput to determine the best data transmission route. It also offers tools like network topology visualization and throughput analysis, although the latter two features are omitted in this article. Comparatively, while both methods find optimal paths, Algorithm 2 stands out in adaptability and performance in ever-changing network scenarios. Its ability to learn and modify strategies over time underscores the importance of AI/ML in enhancing network management.

3) ANALYSIS FOR SCALABLE NETWORK CONGESTION PREDICTION

We utilized the advanced SP-LSTM network to forecast network congestion based on past throughput metrics. Our method spans from data handling to prediction dissemination, with results summarized in Table 3. The training accuracy

Algorithm 2: Q-Learning Algorithm for Optimal Network Path.

```
procedure Q-Learningdf, topology
    Load df, topology
    Init Q_table, α, γ, ε, num_episodes, G, states
    for episode in [1, num_episodes] do
        Init state, sum_rewards, path_length
        while True do
            action ← epsilon-greedy()
            next_state ← perform_action(action)
            reward ← observe_reward()
            Q_table ← Q_table + α * (reward + γ *
            Q_table[next_state] - Q_table[state])
            state ← next_state
            if state == 'gNB_7' then break
        Store sum_rewards, path_length
        if episode % 1000 == 0 then Print progress
    Print episode values
    Compute optimal_path, total_weight
    Visualize G, optimal_path
    Plot sum_rewards, path_lengths
    Print mean(rewards), mean(path_lengths)
```

Algorithm 3: Shortest Path Calculation in Network Graph.

```
procedure ShortestPathDataset,
Predicted_Output, Topology
    ↑ pandas, networkx, matplotlib.pyplot
    df, predicted_output, topology ← CSV
    merged_data ← df ⋈ predicted_output (on
    Link_ID, Time)
    G ← Graph(), Add nodes from topology
    for row ∈ merged_data do
        link_id, predicted_throughput ← row
        devices ← topology (by link_id)
        if devices ∈ topology then
            device_name_1, device_name_2 ← devices
            G ← edge(device_name_1, device_name_2,
            weight = 1/predicted_throughput)
            start_node, end_node ← define
    if start_node, end_node ∈ G then
    path ← Dijkstra(G)
        ↓ path
```

shows the model effectively learns network dynamics, capturing over 98% of training data variance. A low Mean Squared Error (MSE) on the test set underscores its predictive strength, and an approximate prediction accuracy of 99.9988% indicates excellent performance on new data. These findings affirm the model's reliability in predicting network congestion.

TABLE 3. Training and Prediction Performance of the SP-LSTM Model

Metric	Value
Training Accuracy	0.98220
Mean Squared Error	1.04132e-07
Prediction Accuracy	0.99998

4) SP-LSTM: A SPEEDY LEAP IN 6G NETWORK ANALYSIS

Fig. 3 and Table 4 present a comparison between traditional LSTM and the upgraded SP-LSTM models, emphasizing their significance in future network management. The SP-LSTM stands out due to its fast training and prediction times, making it ideal for 6G networks. Though LSTM achieves high accuracies, SP-LSTM's speed is its game-changer, especially beneficial for real-time network tasks. Its increased speed enhances system adaptability, vital for efficient dynamic routing, and is particularly important for 6G use cases like ultra-reliable and low-latency communication (URLLC).

5) RESILIENCE ANALYSIS: UNRAVELING NETWORK PATH OPTIMIZATION AND CONGESTION FORECASTING

Comparing link orders by `Moving_Average_throughput` before and after predictions (shown in Table 5) provides valuable insights for improving network management. These changes in order hint at potential network congestion, facilitating early resource adjustments. In this scenario using a Q-learning AI/ML algorithm, we aimed to identify the best network paths for data transmission between `gNB_18` and `gNB_8`. We assessed the path efficiency using the `sum_of_rewards` and `path_length`. The `sum_of_rewards` indicates path selection efficacy, capturing both immediate and future gains. Meanwhile, `path_length` measures transmission speed and resource consumption, being crucial in time-sensitive scenarios. The findings (Fig. 4 and Table 6) showed that most episodes lacked a meaningful path discovery, indicated by zero values for rewards and path length.

During episodes 14, 28, 42, 56, 60, 67, 73, 89, and 95, the agent identified rewarding paths. Except for episode 95, all episodes had a path length of 1, indicating the algorithm's effectiveness in finding optimal paths. Episode 95, with a path length of 2 and a higher negative reward, serves as a learning cue for the agent to favor shorter routes, consistent with our second metric. Our results, shown in Fig. 5, emphasize Q-learning's proficiency in improving network path optimization.

The algorithm consistently identifies optimal routes, even when many episodes don't produce favorable paths, showcasing its robustness. Examining episodes with non-zero rewards provides a crucial understanding of the optimization process, aiding future enhancements. This introduces a groundbreaking reinforcement learning technique for optimal network path

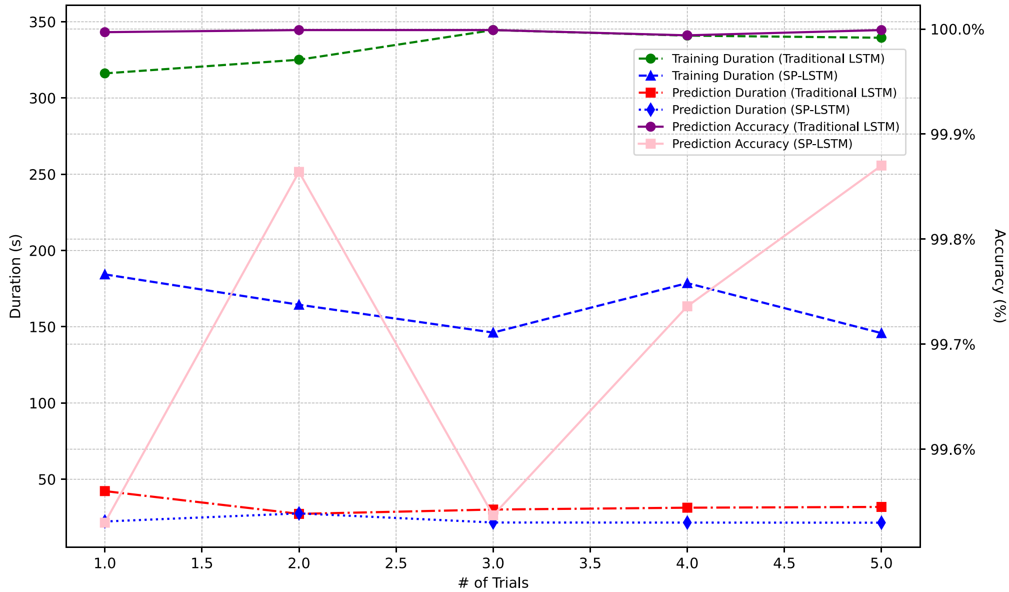

FIGURE 3. Duration and accuracy: A comparative analysis of LSTM and SP-LSTM models.

TABLE 4. Comparison Between Traditional LSTM and SP-LSTM

Model	Trial	Training Duration (s)	Prediction Duration (s)	Training Accuracy	MSE	Prediction Accuracy
Traditional LSTM	1	316.15	42.24	0.982	2.29e-07	0.99997
	2	325.11	27.28	0.982	1.06e-07	0.99999
	3	344.55	30.13	0.982	1.15e-07	0.99999
	4	340.92	31.34	0.982	4.95e-07	0.99994
	5	339.51	31.84	0.982	1.25e-07	0.99999
SP-LSTM	1	184.34	22.30	0.984	4.16e-05	0.99530
	2	164.44	27.60	0.976	1.20e-05	0.99864
	3	146.18	21.63	0.981	4.09e-05	0.99537
	4	178.62	21.58	0.983	2.33e-05	0.99736
	5	145.82	21.51	0.981	1.15e-05	0.99870

selection, crucial for improving communication networks. Its importance is highlighted in routing, network resilience, and resource distribution in telecom and cloud computing, especially with the increasing need for advanced computing and swift communication.

Table 7 unveils the Q-learning algorithm's ability in ensuring efficient resource utilization, with an optimal path total weight of approximately 0.202. This weight, stemming from individual link weights, shows the significant contributions from the `gNB_18` to `L3_Switch_4` link and the `L3_Switch_4` to `gNB_8` link.

Moreover, the average reward of -3.84470e-05 suggests the algorithm's capability in reward maximization along selected paths. Also, the average path length of 0.1 indicates the algorithm's proficiency in discovering shorter, more resource-efficient paths with fewer link traversals. These results were compared with a conventional network management strategy based on the OSPF, employing Dijkstra's algorithm. The key distinction lies in their operational principles: OSPF relies on static link costs to find the shortest path, while our AI/ML-based Q-learning dynamically adjusts weights in response to predicted congestion levels. This facilitates more adaptive network management, enabling dynamic route adjustment in line with changing network conditions. In the conventional OSPF-based network management approach, our main novelty is assigning each edge a weight, determined as the reciprocal of the forecasted moving average throughput. Consequently, higher weights are assigned to links with anticipated higher congestion (lower throughput), rendering them less attractive for shortest-path computation.

Utilizing Dijkstra's shortest path algorithm, we establish the optimal path from a designated start to the end node,

TABLE 5. Network Links Ranked From Most to Least Congested: Before and After Prediction

Rank	Link ID (Before Prediction)	Link ID (After Prediction)
1	3	8
2	5	13
3	8	15
4	13	10
5	2	14
6	4	9
7	15	-
8	1	-
9	10	-
10	7	-
11	14	-
12	9	-
13	6	-

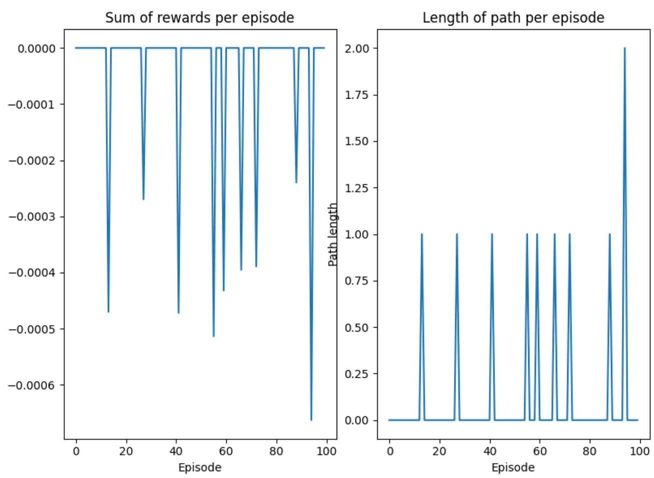

FIGURE 4. Variation of sum of rewards and length of path per episode in the Q-learning algorithm for optimal network path discovery.

TABLE 6. Episodes With Non-Zero Sum of Rewards and Path Length

Episode	Sum of Rewards	Length of Path
14	-0.000470177	1
28	-0.000269618	1
42	-0.000472024	1
56	-0.000513732	1
60	-0.000432139	1
67	-0.000395246	1
73	-0.000389049	1
89	-0.000239827	1
95	-0.000662890	2

TABLE 7. Q-Learning in Action: Streamlining Resource Utilization Through Optimal Path Selection

Metric	Value
Optimal Path	[gNB_18, L3_Switch_4, gNB_8]
Weight (gNB_18 to L3_Switch_4)	0.07692
Weight (L3_Switch_4 to gNB_8)	0.125
Total Weight	0.20192
Average reward	-3.844701e-05
Average path length	0.1

TABLE 8. Optimal Path Analysis

Parameter	Value
Optimal Path	{gNB_18, L3_Switch_4, gNB_8}
Weight (gNB_18 to L3_Switch_4)	11.22887
Weight (L3_Switch_4 to gNB_8)	4.44496
Total Weight	0.31402

shown in Tables 8 and 9. This path, bearing the smallest cumulative weight, signifies the most resource-efficient route, bypassing potential congestion spots. The computed optimal path was [`gNB_18`, `L3_Switch_4`, `gNB_8`], with corresponding weights of 11.23 and 4.44. These outcomes, comparable to those acquired via the AI/ML Q-Learning approach, endorse this path as optimal for data transmission, skirting potential congestion. These findings highlight the robustness of our dual-tiered AI/ML system, which integrates predictive analytics and dynamic routing for network path optimization and superior communication networks. Its capability to determine an optimal path with a suitable total weight, in harmony with the average reward and path length metrics, verifies the algorithm's effectiveness and applicability in real-world telecommunication situations. Insights from this study guide future strides in AI-assisted network management and optimization and lay a foundation for the practical deployment of AI/ML techniques in the 6G era.

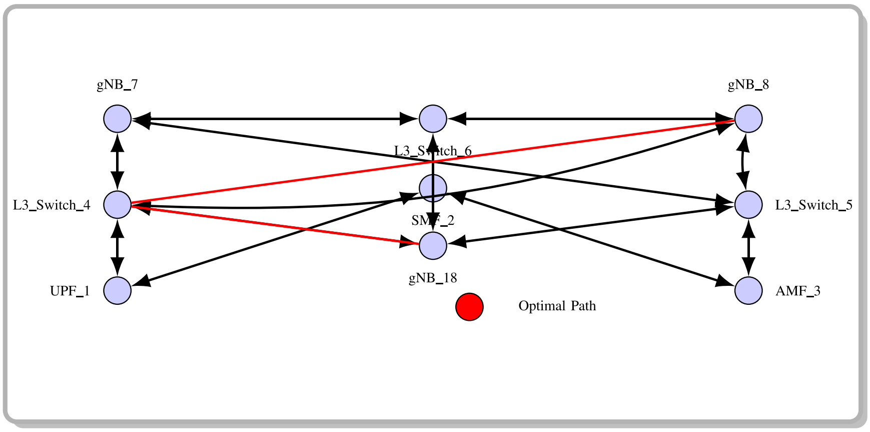

FIGURE 5. Network topology with optimal path.

TABLE 9. Alternative Paths Analysis

Path	Node 1	Node 2	Wt.
[gNB_18, L3_Switch_4, gNB_8]	gNB_18	L3_Switch_4	11.23
	L3_Switch_4	gNB_8	4.44
[gNB_18, L3_Switch_5, gNB_8]	gNB_18	L3_Switch_5	383.97
	L3_Switch_5	gNB_8	491.75
[gNB_18, L3_Switch_6, gNB_8]	gNB_18	L3_Switch_6	139.79
	L3_Switch_6	gNB_8	178.85

VII. CONCLUSION AND FUTURE WORK

This research introduces a pivotal advancement for 6G network management via a novel AI/ML system. Built upon a robust network topology that integrates crucial 5G and 6G elements, such as Massive MIMO, mmWave communications, network slicing, edge computing, SDNs, and VNFs, the proposed two-tiered system adeptly simulates the advanced nuances of these cutting-edge networks. By addressing 6G's ultra-low latency, high reliability, and multifarious management needs, this system underscores the significant contributions of predictive analytics, powered by SP-LSTM networks, and dynamic routing orchestrated by reinforcement learning (RL). The harmonious confluence of these technologies fosters a proactive and adaptive response to evolving network conditions, raising the bar above traditional methodologies.

The inherent adaptability of our system, tailored for the dynamic 6G landscape, is a testament to its capacity to manage vast data volumes and ensure expeditious routing decisions through the judicious infusion of AI/ML. With this research serving as a beacon, the 6G network management realm is poised for a transformative evolution, efficiently catering to the rigorous demands of contemporary networks.

As we gaze toward the horizon of future research endeavors, several tantalizing avenues beckon. One such avenue, inspired by the comprehensive topology of our study, is a comparative performance assessment between our proposed AI/ML framework and an alternative scheme that omits the aforementioned advanced 5G and 6G features. Such a comparison can elucidate the incremental benefits derived from technologies like Massive MIMO and mmWave communications, offering valuable insights for further optimization.

Furthermore, the metamorphosis of our two-tiered AI/ML paradigm into a multi-agent system offers an exhilarating potential to fortify 6G network management. Harnessing the duality of reactive agility and predictive foresight, this transformation can pioneer strategies to avert network congestion, accentuating advancements in traffic management, load balancing, and latency reduction. Exploiting distributed computing resources, either through edge or cloud deployments, can further amplify decision-making precision and swiftness, capitalizing on the unique advantages of each deployment strategy.

In summation, with AI/ML steering the helm, the trajectory of 6G research is set on an unprecedented path of innovation and refinement. This study, a cornerstone in its own right, not only amplifies the existing knowledge spectrum but also carves out a visionary roadmap for the future of 6G network management.

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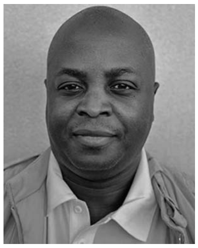

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