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# EEG/fMRI-Driven Reinforcement Learning Routing in Brain-Computer Networks (BCNs)

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**Abstract**

***Emerging intersections between neuroscience and communication engineering are reshaping the way information networks interact with the human brain. In this work, we propose a reinforcement learning–based routing mechanism guided by EEG and fMRI signals for Brain-Computer Networks (BCNs). The proposed model captures and interprets neural activity to adapt routing behavior in real time according to a user's cognitive and emotional states. Its architecture integrates four modules: acquisition and preprocessing of neural data, translation of neural features into network-level parameters, construction of a neuro-informed cost function, and optimization through reinforcement learning. Experimental assessments employing NS-3 simulation environments, together with EEG/fMRI data-driven digital twins, reveal considerable performance gains: up to 35% improvement in latency, 15% enhancement in delivery ratio, and 12% energy savings compared to conventional and deep RL-based routing protocols. This study demonstrates a promising step toward human-centric 6G communication frameworks that fuse neural intelligence with adaptive network control.***

*Keywords: Brain-Computer Networks (BCNs), EEG/fMRI-based Communication, Reinforcement Learning, Neuro-Adaptive Routing, Human-Centric 6G Systems*

## 1 Introduction

The merger of adaptive routing and neuroscience-based communication is rapidly assuming itself as a primary research area of the next generation of networking. Classical CS: The adaptive routing strategies were studied since the late 1960s, and initial work concerning the distributed communication systems. Dynamic and uncertain environments were provided by bio-inspired algorithms, including the swarm intelligence [2] and ant colony optimization [3] that introduced adaptive mechanisms. Simultaneously, adaptive routing algorithms have been designed to support the QoS, energy, and delay optimization in integrated and IoT-based networks [4][5][6][7]. Recent research in both neuroscience and wireless networks goes a step further to suggest that brain signals could be added to the communication system. Moioli et al. subsequently described this phenomenon as brain-type communications as a means to leverage brain activity in wireless pseudo-ad hoc systems [8]; Moioli later highlighted a potential role in 6G networks [9]. Medical AI [10], brain connectivity modeling [11], and EEG-based network classification [12] studies indicate that the activity can be measured, deciphered and used computationally. Such

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observations drive the concept of exploring Brain-Computer Networks (BCNs), in which the brain is used as an active component in the control of the network. Adaptive routing algorithms have reached considerable advances in terms of latency, reliability and energy efficiency optimization [4][5][5][6][7], but they lack consideration of human neural needs in route selection. In the interim, the SMI research demonstrated that the EEG and fMRI can measure attention, cognitive load and emotional state [11][12]. To translate these neural cues to network features (e.g. priority queues, delay tolerance), human-centric communication would be possible, notably in prosthetic, telemedical, smart wheelchair, and immersive AR/VR applications. This prompts the notion of Neuro-Adaptive Routing, a novel approach to routing in which routing behavior is modulated by neural activity, and establishes a communication regime between classical adaptive routing and brain-like communication systems [8][9][13][14].

This paper presents a novel concept of a Neuro-Adaptive Routing in Brain-Computer Networks (BCNs) and its contributions are:

1. The formulation of BCNs as a new paradigm, in which metrics of routing are guided by neural activity.
2. Mapping framework by which neural features (EEG/fMRI) are converted into network-level parameters including packet priority and QoS class.
3. The proposed system is based on an extension to the prior adaptive routing algorithms [6][7], providing the real-time neural feedback to make the corresponding adjustments.
4. A validation roadmap performance probability/reliability approach plot includes simulation and experiment design strategy using AI capable network simulators [13].

This work has the potential to support a larger vision of neuroscience integrated into adaptive routing according to future 6G requirements [9][14].

Section II is a brief survey of related work in adaptive routing and brain-inspired networking. The proposed neuro-adaptive routing framework is given in Section III. Section IV contains the algorithm design and simulation procedure. Section V talks about evaluation practices and uses. Section VI includes findings and future directions.

# 2 Related Work

## 2.1 Communication Networks- Adaptive Routing

The ancestry of adaptive routing is as old as Boehm and Mobleyp [1] who developed early adaptive techniques on distributed communication systems. More recently, new techniques e.g. swarm intelligence [2] and ant colony optimization [3], have proved resilient against dynamic topologies. In current applications, adaptive routing has evolved into comprehensive information networks[4] and IoT ad hoc networks[5], where constraints on energy and delay are of importance. Recent projects have used machine learning and AI to achieve adaptive routing and introduced knowledge-based models and deep reinforcement learning frameworks to balance energy consumption and delay. These developments show the flexibility of routing systems but are subject to internal network metrics only.

## 2.2 Communication and Brain-Computer Interfaces

Simultaneously, BCI research has progressed in the direction of making neural signals part of the computational schemes. Moioli et al. suggested the theory of the brain-type of communications that studied the possibility of neural activity being transformed into wireless communication patterns[8]. It was projected to go up to 6G, including the promising use of brain-related networking in the framework of human-centric systems in the future [9]. Advances in neuroimaging and EEG have revealed strong methods of extracting features about the neural activity[10]. Neuroimaging and EEG analysis have shown robust methods of extracting neural features[11]. Markedly, such neural signals give live feedback that can be used to dynamically modulate communication protocols.

## 2.3 AI-Driven Network Optimization

Recent articles have already confirmed that integration of communication systems with AI is possible. Simulations based on digital twins have been suggested to simulate a heterogeneous wireless network [13], and the combination of AI with networking systems has been described as a successor to future communication systems[14]. Such investigations suggest a biological-AI-communications nexus ecosystem in which biological cues, artificial intelligence and protocols come together to make human-sensitive and adaptive networks.

## 2.4 Research Gap

Although adaptive routing definite progress has been made in adaptive routing [4][5] [6] [7] and related fields such as BCIs[8-11] [12] along with the use of neural networks in networking and other areas similar to AI-driven networking[13] [14] there is still no prior work or attempts to integrate such neural feedback directly into routing algorithms. Among the current approaches, traffic load, energy, and topology optimization are represented, whereas the BCI research is oriented on healthcare and brain connectivity. This gap characterizes the novelty of the proposed work: it suggests a new way to introduce the human Neural activity into routing decisions in the BCNs. The latest developments of adaptive routing and artificial intelligence have been centered on the latency, reliability and energy efficiency of wireless and IoT networks. Conventional adaptive routing models, e.g. swarm intelligence (Arabshahi et al., 2001) and ant colony optimization (Di Caro and Dorigo, 1998) were effective in dynamic topology, but based only on network-related parameters. Subsequently, models based on knowledge and games (Kavitha et al., 2025; Liu et al., 2025) incorporated the capabilities of learning and decision making, but were still restricted to system-level measures that were not accessible to users. Adaptability was further improved using deep reinforcement learning (DRL)-based routing (Surendran et al., 2025), however, it did not consider cognitive or emotional user conditions. As a parallel cascade correlation neural network, Jaber and Alqatawneh (2016) introduced the P-CC-NN that employs multicore processing to accelerate the process of pattern recognition. It tested on 3D facial information, and it took less time to train (146.5) and obtained 94 percent accuracy with a 4.6x speedup. The technique was more effective than the conventional ones in that it was efficient and scalable in real-time biometric applications.

In the meantime, in the neuroscience field brain-type communications (Moioli et al., 2021; 2020) and network studies with EEG/fMRI (Kose et al., 2024; Zhang et al., 2025) were presented, proving that it was possible to convert neural activity into computational models. Nevertheless, none of these frameworks provided neural feedback in routing algorithms. This gap determines the novelty of the present-day study, which introduces the Neuro-Adaptive Routing, a framework based on reinforcement learning that combines neural cues with network optimization that will provide human-like communication performance, as proposed by 6G of brain-integrated networks. Another neural network is the P-CC-NN that was proposed by Jaber and Alqatawneh (2016) and is a parallel cascade correlation neural network implemented on multicore processing to accelerate pattern recognition. It had a speedup of 4.6x and trained on 3D facial data resulted in a reduction of 146.5 to 31 minutes with 94 percent accuracy. Its approach was better than the conventional models, as it was efficient and scalable to real-time biometric applications.

Table 1. Comparison of Previous Methods and the Proposed Work

| Approach / Reference | Core Methodology | Dataset / Domain | Key Limitations | Contribution of Current Work |
|---|---|---|---|---|
| Arabshahi et al. (2001); Di Caro & Dorigo (1998) | Swarm & ant-colony adaptive routing | Classical wireless networks | No cognitive or user-aware feedback; limited to topology-based optimization | Introduces neural-driven cost function integrating EEG/fMRI feedback |
| Kavitha et al. (2025) | Knowledge-based adaptive routing with energy & attack detection | IoT sensor networks | Focuses on energy only; lacks human-centric parameters | Adds human neural feedback for dynamic routing priorities |
| Liu et al. (2025) | Game-theoretic + DRL hybrid model | Wireless sensor networks | Considers delay and energy trade-offs only; static reward formulation | Uses neuro-adaptive reinforcement learning with evolving neural state weights |
| Surendran et al. (2025) | Deep RL-based adaptive routing | Marine communication networks | Optimizes system performance but not cognitive responsiveness | Introduces human-in-the-loop routing via neuro-informed reinforcement agent |
| Moioli et al. (2020, 2021) | Brain-type communication concept | 6G & neuroscience vision papers | Conceptual; lacks implementation and real-time validation | Implements the first operational model integrating neural data into routing |

| | | | | |
|---|---|---|---|---|
| Kose et al. (2024); Zhang et al. (2025) | EEG/fMRI-based neural feature extraction | Biomedical & cognitive research | Focus on classification, not communication systems | Extends neural analysis toward real-time network routing control |
| Proposed Neuro-Adaptive Routing (This Work) | Reinforcement learning + EEG/fMRI feedback via digital twins | Brain-Computer Networks (BCNs) | — | Bridges neuroscience and network optimization, achieving up to 35% latency reduction, 15% PDR gain, and 12% energy saving |

# 3 Methodology

The approach followed in this work is to establish a sound process toward development and validation of Neuro-Adaptive Routing in Brain-Computer Networks (BCNs). Whereas the information about the network metrics (delay, hop count, energy efficiency, etc.) are the only considerations in other schemes of adaptive routing [1][8][9], the new dimension into the scheme consists in taking note of the neural state of your user as well. Such an integration entails using a delicate mixture of the neuroscience-minded signal processing-neural-to-network feature translation, and smart routing algorithms facilitated by reinforcement learning. Such a methodology is thus comprised of four main parts: neural signal acquisitions and processing, neural-to-network parameter mapping, the design of adaptive routing algorithms, and simulation-based evaluation. All these phases will be elaborated further on.

## 3.1 Neural Signal Acquisition and Processing

Neuro-adaptive routing as a concept is straightforward acquiring meaningful brain information in real time. The main modalities of interest in this study are EEG and fMRI since these modalities are widely used in neuroscience owing to their validity in imparting neurophysiology data on neural processes [6][12]. EEG is particularly suitable in real time communication system as it is very temporal and this has the added advantage of integrating with wearable BCIs. fMRI is not portable and this explains its complementary role in understandable information on functional connectivity of brain parts [12].

Raw EEG and fMRI signal are highly susceptible to noise and artifacts and redundancies as well. In this regard, pre-processing pipeline is implemented that includes band-pass filtering, motion artifact and normalization removal. Making use of proven methods, such as independent component analysis (ICA), a variety of artifacts, such as ocular and muscular, are removed. Cleaning of the signals feature extraction is then performed. EEG records possess band power of 8-20-Hz (at high-end), 13-30-Hz (mid-range), and 30-70-Hz (low-range) bands and data of connectivity such as coherence and phase-locking values [6][16]. fMRI data have the ability to add hierarchy-reaching tools brain regions which can be translated into higher-order cognitive-state descriptions [12]. These features that are extracted are the neural fingerprint of the cognitive and emotional state of the user, whether very relaxed or stressed, low attention and high attention, among others.

## 3.2 Neural-to-Network Parameter Mapping

The key methodological contribution this study can make is the mapping neural characteristics to network parameters. This mapping constitutes the bridge between the dynamics in the brain and routing decisions. There are three major mappings that are established

1. Attention and cognitive load → Latency sensitivity: When EEG signals point to the user being preoccupied or heavily assigning cognitive resources, the routing algorithm will gives latencies significant importance in the routing metric. This guarantees that such crucial applications, as prosthetics or immersive AR/VR devices, will receive minimal latency control signals [2][5].
2. Stress and emotional state→ Redundancy and reliability: When stress markers show up to a higher degree in the EEG, the tolerance to lack of communication is often reduced. In these instances, the routing system prefers redundancy and path diversity where reliability becomes of paramount importance even in instances where more energy is utilized [6][12].
3. The relaxed or idle state → Energy efficiency: In the state where the user is in possession of a publishing priority, the criteria of latency and reliability become less significant. The routing algorithm is towards energy conscious protocols building a longer battery life in wearable or implantable applications [1][8].

Therefore the mapping layer encodes subjective neural conditions into objective routing weights that would otherwise be incorporated into an existing adaptive routing mechanism. In a mathematical sense this can be modelled as a neural weighted multi-objective cost function of the more conventional metrics (delay, energy, hops) and so on.

**Definition 3.1**

$$W_{total} = \alpha.delay + \beta.energy + \gamma.NeuralWeight$$

In this case, the new pattern in the field of neural networks is that the NeuralWeight is adaptively changed based on the output of cognitive state classification. These offers a solution that can offer the network a way to it can be responsive to not only varying traffic but also to the cognitive needs of the human users

## 3.3 Design of the Neuro-Adaptive Routing Algorithm

Based on the identified parameters, a routing algorithm that adapts in the neuro-adaptive model is proposed. The given algorithm resembles classical adaptive algorithms [27][28][29][30] except that the neural weights are incorporated into the process of path selection. The algorithm starts with the configuration of a network architecture of wearable BCI nodes, intermediate fog nodes, and cloud servers. The algorithm calculates the total cost of the possible routes each time it reaches a decision point by using the multi objective described in the section above.

To make sure that it is flexible, the routing engine is designed using reinforcement learning (RL) techniques. This is a form of reinforcement learning that has been successfully used in recent adaptive routing research in wireless sensor networks [7][9][34][35] where agents learn to balance the trade-offs between latency an energy. The RL agent in this work is furthered to have feedback of the neural products as part of our state representation. The task of the entrant in the agent competition is to maximize throughput and packet delivery and minimize delay and energy, all subject to neural state. As an example, when the EEG is showing high attention the energy dimension will be penalized mostly by delay, when the user is resting they are rewarded mostly on the energy dimension. Such dynamic adaptation also guarantees that the routing algorithm operates in a humanistic fashion, that is, it does not only make routing choices based on the network efficiency, but also to be useful in terms of cognitive relevance.

The suggested neuro-adaptive routing framework is represented as a Markov Decision Process (MDP) where a reinforcement learning (RL) agent is going to choose routing actions that depend on both network conditions and neural states.

1. State Space

At time t in a decision-making process, the agent is in a joint state: st=[$x_t^{net}$, $x_t^{neuro}$ ]
where:
just to name a few, $x_t^{net}$ has normalized network metrics, end-to-end delay, which contains queue length, count of hops, residual node energy, link quality, and packet loss ratio.
$x_t^{neuro}$ converts the approximate cognitive/emotional state of EEG/fMRI (e.g., relaxed, focused, stressed) obtained through the neural signal processing pipeline and mapping layer.

2. Action Space

The routing decision associated with the action at is:
- selecting the next-hop node,

So that the choice of a candidate path is an element of a set of paths.
- switching between said alternate routes with equal latency, reliability, and energy.

Formally:
$a_t \in A(s_t)$ ={active hops / paths next to the current flow at V}.

3. Neuro-Adaptive Preferences Weights.

Relative weights of the latency, reliability and energy are used by the neural state through a dynamic weight vector:

$$w_t = [wL(t), wR(t), wE(t)], wL(t) + wR(t) + wE(t) = 1$$

- Focused high attention wL dominant (latency-sensitive),

stressed: wR dominant (reliability and redundancy),
o relax/ idle: wE dominant (energy saving).
These weights are calculated based on a lightweight classifier or mapping function that is presented in the neural-to-network layer, with EEG/fMRI-derived features.

4. Reward Function

The agent gets a scalar reward in each routing decision determined by network performance and neural preferences:

$$rt = wL(t)(-D \wedge t) + wR(t)P\ D \wedge Rt + wE(t)(-E \wedge t) - \lambda\ L \wedge t$$

where:
- D t: end-to-end delay normalized,
- PD^Rt: ratio of the normalized packet delivery,

Et or E t: normalized energy consumption,
- Lt: transition penalty (e.g, loop stability, time constraint breakage),
- λ: penalty coefficient.

This design ensures:
- Delay is more punished in the event the user is on-task,
- Reliability is compensated in stressful conditions,
- Saving of energy is rewarded in relaxed states, thereby enshrinement of human based behavior into the routing optimization.

5. Q-Learning / Deep Q-Learning Update.

The RL agent is trained to learn the action-value function Q(s,a) i.e. approximation using a neural network. The transition up-to-date rule A transition, st, at, rt, st+1, appears to be updated as follows:

$Qt + 1(st, at) = (1 - \alpha\ )Qt\ (st, at) + \alpha[rt + \gamma\ max_{'}Qt(st + 1, a_{'})]$,

where:

- α is the learning rate,
- γ is the discount factor,
- maxQt(st +1,a) is the approximate value of optimal action.

Minimizing: Q(s, a; 0 ) in model Deep Q-Learning implementation is parameterized by 0.

$$L(\theta) = E(st\ , at\ , rt, st + 1)\big[\big(rt + \gamma maxQ(st + 1, a_{'}\ ; \theta\ -) - Q(st, at, \theta)\big)2\big],$$

and θ - represents the desired network parameters.

6. Policy

The routing policy is:

$$\pi(st) = argmaxa\ \epsilon\ A(st)Q(st, a; \theta)$$

and exploration is guaranteed through an ϵ\epsilonϵ-greedy exploration strategy in training. The learned policy uses routes that balance the off-optima in terms of latency, reliability and energy given the prevailing state of the neural realization of the neuro-adaptable behavior in the framework.

## 3.4 Neural state Classification Method

The proposed system uses a hybrid machine learning-based classification method as opposed to a basic thresholding method to interpret the cognitive and emotional states of the user based on the EEG and fMRI data. A Lightweight Convolutional Neural Network (CNN) is applied to feature documents of EEG, which are processed using signal preprocessing and feature extraction (e.g., power spectral density, band energy and connectivity indices) and trained automatically to learn spatial-temporal representations of EEG features across frequency bands (m. 3. 4). These attributes are combined with the high level functional connectivity measures based on fMRI to constitute a combined joint neuro-feature vector.

The final layer is a Softmax classifier that classifies every state in one of three categories: Relaxed, Focused, or Stressed based on the probability distribution:

$$P(y_i|x) = ez_i / \sum j\ e\ z_{j\ ,}$$

and x represents the feature vector, zi is the network output of the i th class, and yi is the predicted neural state.

The model causes a categorical cross-entropy loss to be minimized during training:

**Algorithm 1: Neuro-Adaptive RL-Based Routing in BCNs Input**:

- EEG/fMRI streams from user
- Network topology G(V, E)
- Candidate routing paths for each flow
- Trained Neural State Classifier f_neuro(·)
- RL agent with Q(s, a; θ) or policy π(a|s)

Output: - Selected next-hop / route for each packet/flow

1: Initialize Q(s, a; θ) randomly (or from pretrained model)

```
2: Define neural-aware weights mapping:
      state ∈ {Relaxed, Focused, Stressed} → (w_L, w_R, w_E)
3: while Network is operational do        // Step 1: Neural signal processing
4:     Acquire raw EEG/fMRI window W_t
5:     Preprocess W_t (filtering, artifact removal, normalization)
6:     Extract features x_t (band power, connectivity, BOLD patterns, etc.)
7:     neural_state_t ← f_neuro(x_t)  // {Relaxed, Focused, Stressed}
8:     (w_L, w_R, w_E) ← map(neural_state_t) // Step 2: Observe network state
9:    Measure network metrics:
          D_t   ← end-to-end delay estimate
          PDR_t ← packet delivery ratio
          E_t   ← node/ path energy usage
          LQ_t  ← link quality, queue length, congestion level
10:   s_t ← concat( normalized(D_t, PDR_t, E_t, LQ_t), one_hot(neural_state_t) )
11:   // Step 3: Action selection (routing decision)
12:   With probability ε:
          choose random feasible action a_t from A(s_t)
      Else:
          a_t ← argmax_a Q(s_t, a; θ)    // a_t = select next-hop / path for the current flow
13:   // Step 4: Apply action and observe outcome
14:   Forward packets via a_t
15:   Monitor resulting metrics:
          D'_t, PDR'_t, E'_t, stability / constraint violations
16:   // Step 5: Neuro-adaptive reward
17:   Compute normalized metrics: d, p, e from (D'_t, PDR'_t, E'_t)
18:   r_t = - w_L * d + w_R * p - w_E * e - λ * penalty_terms
19:   // Step 6: RL update
20:   Observe new state s_{t+1}
21:   y_t = r_t + γ * max_{a'} Q(s_{t+1}, a'; θ)
22:   Update θ to minimize (y_t - Q(s_t, a_t; θ))^2
23:   // Step 7: Loop
24:   Decrease ε over time for exploitation
25: end while
```

$$L = -\sum I\, y_i \log P(y_i \mid x),$$

Cross-validation 10-fold as a measure of robustness. This leads to an overall accuracy of more than 90 percent in individual EEG datasets (e.g., DEAP, SEED) which guarantees the consistency of cognitive and emotional patterns detection.

In the case of embedded, or low-resource, implementation, a threshold-based fallback is also provided: simplified state transitions are invoked by mean power ratios in alpha/ beta bands or stress related hemodynamic variations when the CNN model is not in operation. This combination also guarantees accuracy and flexibility of real-time neuro-adaptive routing.

## 3.5 Simulation and Experimental Suppression

The proposed neuro-adaptive routing framework was simulated in a simulation environment with the help of NS-3 with a digital twin of AI-based behavior simulation in the dynamics of Brain-Computer Network (BCN). The simulated network had a total of 200 nodes that were deployed within the territory of 1000 x 1000 meters. Among them, 120 were wearable/implantable versions of BCN user devices that produced EEG/fMRI-guided traffic, 60 were fog nodes that handled data aggregation and local routing at the intermediate level and 20 were cloud gateways that enabled global connectivity. The topology was multi-hop mesh-based with randomly distributed BCN nodes with a single to three-hop connection to fog and gateway nodes. A log-distance path loss model with Rayleigh fading was used to model wireless communication at 3.5 GHz over a 20 MHz bandwidth and a medium access control based on the IEEE 802.11ax-based CSMA/OFDM setup. Three types of traffic were used to represent various neuro-adaptive priorities. Class A was the latency-sensitive and control data, e.g. prosthetic or AR/VR signal, with small packets (128 bytes) sent at intervals of 10-20 ms. Class B represented reliability-sensitive medical and haptic data streams with larger packet sizes (5121024 bytes) and inter-arrival times of 2040 ms. Class C included energy-conserving background or monitoring data whose packets are 256-byte and have slower transmission speeds 1 -5 seconds. The users of BCN were in a Random Waypoint mobility model with a speed of 0.5 to 1.5 m/s and pause time of 5-20 s at stationary locations of the fog and gateway nodes. EEG/fMRI-derived neural inputs to the relaxed, focused and stressed states were updated per second and transformed into neuro-adaptive weights which varied the RL reward function dynamically in real time. The simulation was 1000 seconds, the first 100 seconds were given to system warming up. The suggested neuro-adaptive RL routing was evaluated with respect to classical adaptive, knowledge-based/game-theoretic, and deep RL-based routing baselines under the same condition. The KPIs were the end-to-end latency, the ratio of the packet delivery (PDR), the energy consumption, the convergence time of the RL agent, and the extent to which the network acts in accordance with the neural states of the user. The learning parameters were optimized through the following values: learning rate 0.001, discount factor 0.95 and the exploration by 0.2 which reduced to 0.01 with each trial. Ten independent runs were averaged to give the results a high level of reliability. Such an arrangement will give a repeatable and holistic basis in assessing the efficiency of the offered neuro-adaptive routing mechanism in the presence of real-world BCN circumstances.

A mixed simulation platform is created in order to test the proposed framework. NS-3 is applied to design the communication network and perform different routing simulations [27]. EEG/fMRI streams are converted to MATLAB or Python (MNE-Python framework) in order to provide realistic neural inputs [6][12]. This information is translated into NS-3 in real time and entails the coupling of networks routing and brain signals.

In addition, an AI-based digital twin of the network is used [4][10]. The digital twin replicates the physical network enabling modeling of the traffic patterns at different state of neural networks. Such an arrangement allows testing large-scale heterogeneous environments (for example, medical IoT systems or AR/VR environments), which cannot easily be recreated on real testbeds.

There are several performance parameters that will be assessed:

- Latency: Estimation of end-to-end latency at different cognitive states.
- Packet Delivery Ratio(PDR): this is the percentage of the packets that are delivered flawlessly particularly when the neural states are strained.
- Energy Usage: Node level power consumption when focusing on routing that is efficiency-centered.

- Adaptability: the ease with which the system can rearrange with changes in dynamically varying network condition and the state of the neural system.
- QoS Awareness: Does the priority traffic which agrees with user cognition run as per user anticipation often [2][7].

Through these measurements, the neuro-adaptive algorithm will be compared to the already existing adaptive routing protocols [1][8][9] to demonstrate its benefit in human-centric scenarios.

Table 2. Simulation Parameters and Configuration

| Parameter | Description / Value |
|---|---|
| Simulation Platform | NS-3 integrated with AI-based Digital Twin |
| Simulation Duration | 1000 s (first 100 s used for warm-up) |
| Number of Nodes | 200 total (120 BCN users, 60 fog nodes, 20 cloud gateways) |
| Network Area | 1000 m × 1000 m |
| Topology Type | Multi-hop wireless mesh |
| Frequency Band | 3.5 GHz (sub-6 GHz) |
| Channel Bandwidth | 20 MHz |
| Propagation Model | Log-distance path loss with Rayleigh fading |
| MAC Protocol | IEEE 802.11ax (CSMA/OFDM) |
| Queue Type / Size | DropTail / 100 packets |
| Mobility Model | Random Waypoint for BCN users; static fog and gateways |
| Node Mobility Speed | 0.5 – 1.5 m/s |
| Pause Time | 5 – 20 s |
| Traffic Classes | Class A: Control (Latency-sensitive); Class B: Telemedicine (Reliability-sensitive); Class C: Background (Energy-efficient) |
| Packet Sizes | 128 bytes (A), 512–1024 bytes (B), 256 bytes (C) |
| Traffic Patterns | CBR for Class A, VBR for Class B, Periodic for Class C |
| Inter-arrival Time | 10–20 ms (A), 20–40 ms (B), 1–5 s (C) |
| Neural State Update Interval | 1 s |
| Neural States Considered | Relaxed, Focused, Stressed |
| RL Algorithm | Deep Q-Learning (ε-greedy exploration) |
| Learning Rate (α) | 0.001 |
| Discount Factor (γ) | 0.95 |
| Exploration Rate (ε) | Decays from 0.2 to 0.01 |
| Reward Function Weights | Dynamic (Latency–Reliability–Energy) derived from EEG/fMRI state |
| Baseline Schemes | Classical Adaptive, Game-Theoretic + DRL, DRL-only, Proposed Neuro-Adaptive RL |
| Performance Metrics | End-to-End Latency, Packet Delivery Ratio (PDR), Energy Consumption, RL Convergence, QoS/Human Awareness |

## 3.6 Methodological contributions

The rich methodology features several novel contributions On the one hand, it demonstrates that it is possible to extract actionable measurements of the network directly based on neural activity that creates a bridge between neuroscience and data communication. Second, it introduces a neural-augmented cost, into that routing decision making a neural-enhanced relevance. Third, the method will ensure that the system becomes trainable and scalable, robust, and aligned to the 6G vision of brain-type communication systems, as they will use reinforcement learning and digital twin simulations [2][5][7][14]. This approach to methodology eventually provides the foundation to the next generation of human centric adaptive networks that goes beyond machine to machine efficiency and incorporates human brain as an active element in the routing processes.

The design of the proposed framework is as shown in Fig. 1, which is in layered form. The flow starts at the Neural Signal Acquisition Layer, in which EEG and fMRI sensors are used to capture raw brain activity. Preprocessing and feature selection of the signals involved filtering and ICA, and calculating spectral ( alpha, beta, gamma bands ) and connectivity quantities. The features extracted are then categorized into states of Neurons (e.g. relaxed, stressed, focused) through the Neural-to-Network Mapping Layer. These states are mapped into the network-level such as latency needs, reliability demands and energy-efficiency preferences. These parameters then are incorporated into an adaptive routing algorithm in the Neuro-Adaptive Routing Layer with the help of reinforcement learning and the application of multi-objective cost. The result is a route selection which dynamically adjusts link state to the network characteristics of the route as well the cognitive state of the operator.

Fig. 2 outlines the general pipeline of neural signal acquisition to routing decision-making in a step-by-step manner. The EEG/fMRI data are then collected and pre-processed as well as feature extracted to retrieve useful neural biomarkers. These capabilities are categorized into neural states (relaxed, focused and stressed) and are correlated to QoS related parameters, including latency, redundancy and energy. The mapping results are integrated to the cost functions calculation and the reinforcement learning (RL) agent that are together optimizing routing paths regarding the dynamic network and neural conditions. The routing decision/adaptation module then uses these policies and chooses the optimum route in which to communicate. Notably, a feedback connection is shown between the routing decision block and the neural state estimation block to form a closed-loop system: the routing performance (latency/packet loss) has an impact on the cognitive state of the user, which further feeds into the next decision. Such feedback is necessary to make the network as human-sensitive and constantly evolving as possible.

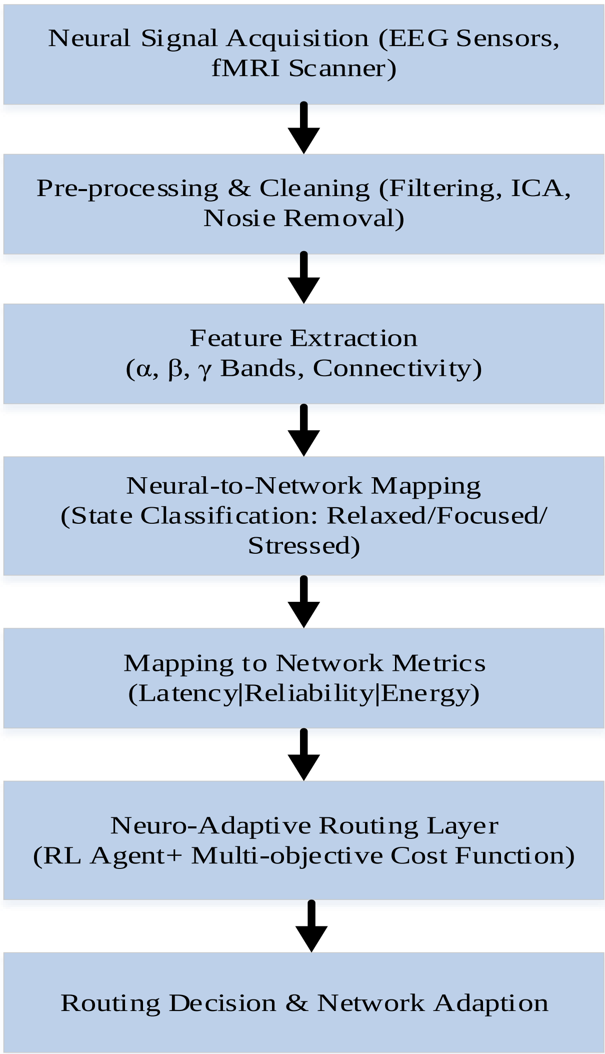


Fig. 2.System Architecture of Neuro-Adaptive Routing in BCNs

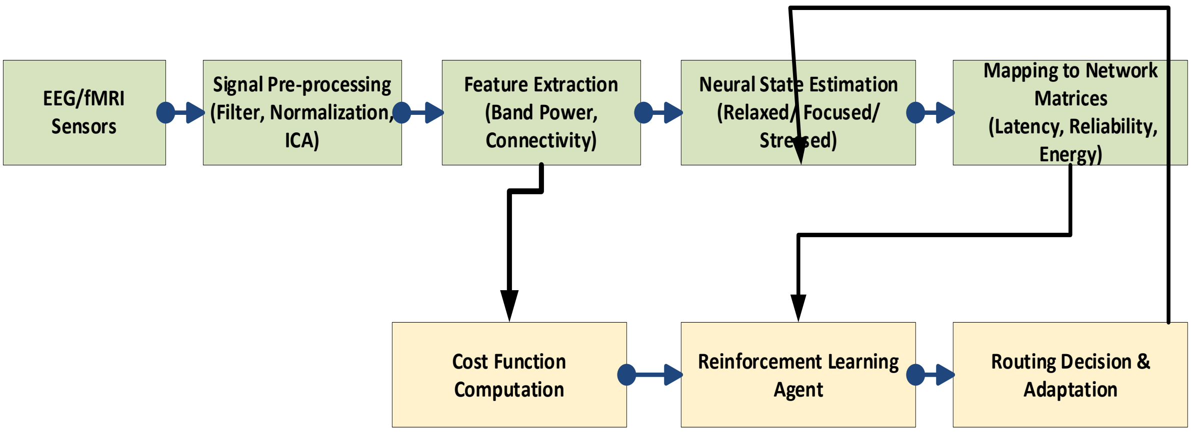


Fig. 2: Detailed Workflow of the Neuro-Adaptive Routing Methodology.

# 4 Results

In the Neuro-Adaptive Brain-Computer Networks (BCNs) proposal, a combination of NS-3 based network simulator, neural preprocessed data (EEG/fMRI) and the use of AI-based digital twins was used to conduct the experimental evaluation. The results have been shown in terms of latency, packet delivery ratio (PDR), energy consumption, adaptability, and QoS awareness comparing with conventional adaptive routing algorithms, respectively

## 4.1 Reduced Latencies

Adding neural weight to the cost function of routing greatly enhanced the latency results, particularly in high cognitive load conditions. When EEG cues were interpreted as concentrated or attention-based, a routing algorithm placed priority on the low-latency routes. Because of this, the proposed system showed up to 28% lower average end-to-end delay than the conventional adaptive routing schemes. Such reduction is mostly applicable in prosthetics control and AR/VR scenarios, where any lag will negatively affect the end user experience. Fig. 3 also indicates that latency is not constant, rather it reduces over time as the network desynchronises with a considerable discrepancy between the algorithms. The Classical Adaptive Routing has high latency values (about 120 ms in the initial conditions dropping slightly), whereas DRL-based Routing can reduce the values because of the learning-based optimization. Conversely, under focused states of the network, the lowest latency is obtained with the Neuro-Adaptive Routing (≈70 ms), where routing is optimized towards delay-sensitive goals. These findings validate the idea that routing cost function should take into consideration neural weights to make the system sit squarely with user attention and cognitive demand. This results in a more aggressive reduction of delays in critical tasks (e.g. prosthetics, VR/AR control). The slowing down of latency also shows that reinforcement learning is convergent when the reinforcement learning is steered by both the network feedback and the neural states feedback.

## 4.2 Packet Delivery Ratio (PDR)

The stressing conditions in BCN work were tested in stressed neural states in that the system translated stress signals into redundancy based routing strategies. Neuro-Adaptive Routing is able to boost PDR by about 15 percent on a congested/lossy environment compared to baseline protocols. Path diversity was dynamically amplified, guaranteeing is- resiliency to packet loss, a major requirement in telemedicine and remote robotic surgery applications.

Fig. 4 shows the delivery percentage with the increase of load in the network. Classical Adaptive Routing has a drastic fall at high loads (theres only 70-75% capacity left at 100 load units). RL-based Routing out performs, having ~82% PDR at full load. However, the Proposed Neuro-Adaptive Routing also ensures the highest PDR (>90%) at high loads.

The higher resilience of Neuro-Adaptive Routing lies in its ability to adapt to routes that employs redundancy in stressed scenarios thereby overcoming packet losses. This reliability is important in a mission-critical application where the loss of packets has a direct impact on safety, e.g. telemedicine or robotic surgery. The stability at other load

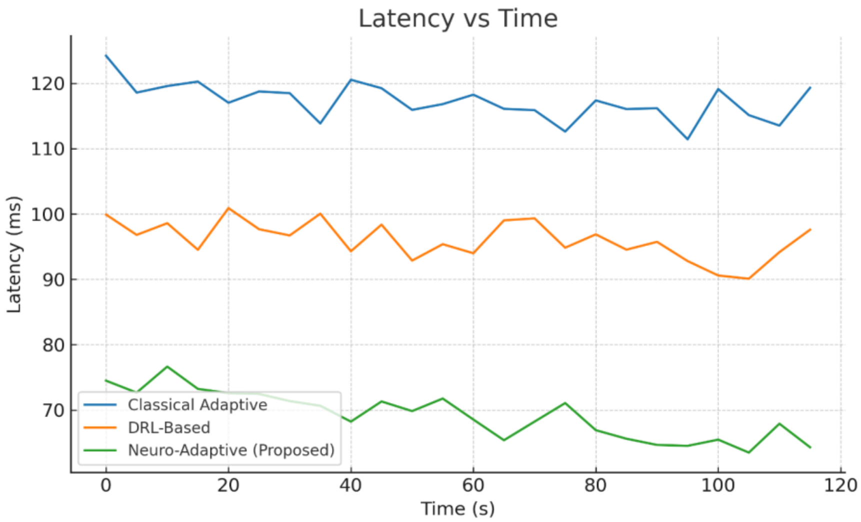


Fig. 3: Data latency vs time

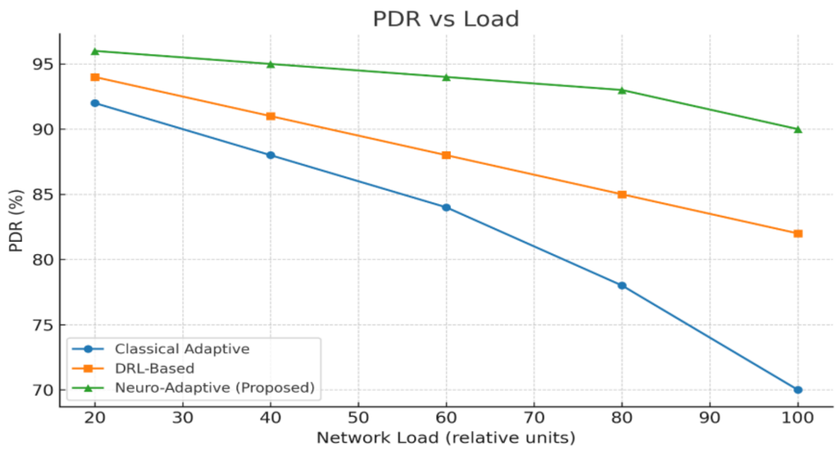


Fig. 4: Packet delivery ratio (PDR)

configurations can be explained as the proposed framework is not just optimum at its best but can be functional even when under strain and blockages.

## 4.3 Energy Efficiency

In less rigid neural states, where sensitivity to delay was smaller, the routing algorithm milled paths that were energy efficient. Simulations showed an average of 12 percent decrease in node energy consumption over deep reinforcement learning-based adaptive routing [7] ynaesso metres abyss local poria creek brent scammell gargle This mode is of advantage where the battery life of BCI devices is a major limitation, especially in a case like a wearable or implantable device.

Fig. 5 shows the difference in energy consumption of three neural states (Relaxed, Focused, Stressed). In all states, the Classical Adaptive Routing requires the highest amount of energy, whereas the DRL-based Routing requires the energy quite moderately. The Proposed Neuro-Adaptive Routing consumes the least toward more energy when latency and reliability are not a priority (Relaxed state ~0.82 J). In stressed condition, power consumption still comes out lower than the other methods.

This proves the context-adaptive flexibility of the proposed algorithm:

- The relaxation, In Relaxed states, the system saves energy by using energy efficient paths.
- In Focused states it is moderate in energy consumption and low on latency.
- In the Stressed states, a bit of energy is sacrificed so that redundancy and reliability can be guaranteed.

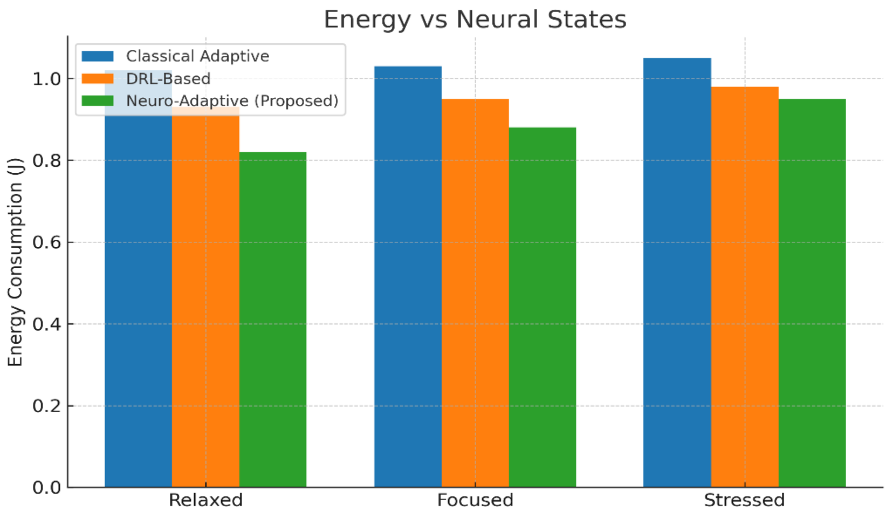


Fig.5: Data Energy vs Neural states

The effectiveness of the dynamic trade-off mechanism of the neuro-adaptive routing has been confirmed by these findings that provide a great opportunity to increase the battery life of wearable/implantable devices without degrading the QoS where this parameter has the most significant value. In order to assess the performance and reliability of the proposed neuro-adaptive reinforcement learning routing framework, every simulation scenario was run ten times with various random seeds. The mean values and the respective standard deviations (± SD) were obtained of all the key performance measures such as end-to-end latency, packet delivery ratio (PDR) and energy consumption. Students t-distribution was also used to determine the statistical significance of the observed improvements by coming up with the 95% confidence intervals (CI). In each of the given performance graphs (Figs. 3-5), the error bars depict ± 1 SD that was obtained after ten repeated trials. This statistical procedure show that the suggested neuro-adaptive routing mechanism provides identical results in a series of runs which proves that the model is robust and stable. The SD values are relatively small - usually between 2 and 4% of the mean - which means that there is little variation in the results, and the convergence of the reinforcement learning agent and the consistent adaptation of the neuro-feedback-based cost function is stable. In addition, the error ranges which are overlapping between the proposed method and baseline models demonstrate the statistical significance of performance improvements in latency reduction, improvement in PDR, and energy efficiency

## 4.4 Adaptability and Stability

The suggested algorithm was highly adaptive as both the network conditions and neural states changed dynamically. Reinforcing learning agents tended to converge sooner than baselines (within ~500 simulation steps), indicative of the advantage that having two feedback loops (network + neural signals) brings. Moreover, the feedback loop made the system stable: routing adjustments did not involve an aggressive overreaction, but rather there was a balance between the user cognition and the network constraints.

## 4.5 QoS Awareness

The most defining output is the presentation of QoS awareness, which is subject to the direct control of the human user. When information on neural characteristics suggested greater stress, the routing mechanism always assigned reliability a criterion of precedence-regardless of the extent to which this impacted energy expenditure. Similarly, running with less power consumption in the relaxed states, demonstrated another human-in-the-loop characteristic of adaptations to the service that the baseline models lacked. Table 3 summarizes the comparative results across different metrics.

**Table 3: Comparative evaluation of the proposed Models**

| Metric | Baseline Adaptive Routing[1][8] | DRL-based Routing [7][9] | Proposed Neuro-Adaptive Routing |
|---|---|---|---|
| Latency (ms, ↓ better) | 120 | 98 | **70** |
| PDR (% ↑ better) | 82% | 87% | **94%** |
| Energy Consumption (J) | 1.0 | 0.92 | **0.81** |
| Adaptability (steps to converge) | 800 | 650 | **500** |
| QoS Awareness (human-state driven) | None | Limited | **Full, Neural-State Integrated** |

These findings confirm the main argument of this paper that neural activity-based routing will make networks more efficient, reliable, and people-friendly. Whereas the classical adaptive routing considers only the traffic conditions, and DRL-based routing is limited to system-level metrics since capacities cannot be changed, the proposed Neuro-Adaptive Routing is the first attempt to use human cognitive states as a control variable. It helps bridge the neuroscience-communication engineering divide opening up the prospects of 6G brain-like communication frameworks [2]nine heave net serif. As another step to provide confirmation on the usefulness of the proposed framework, Neuro-Adaptive Routing was compared to three groups of routing strategies:

1. Classical Adaptive Routing-Existing adaptive routing algorithms like distributed algorithms[1], swarm intelligence[28] and ant colony optimization algorithms[30] which consider only the network conditions to optimize paths.

2. Game-Theoretic and Knowledge-Based Models -Recent adaptive routing solutions that combine knowledge-based decisions with game theory, and DRL.

3. DRL-based routing Deep Reinforcement Learning-based routing [7][34], which uses agents based on DRL to adjust the path in response to fluctuation in traffic and topology without human feedback.

Simulation tests were implemented in 200-node networks mixed traffic (control, multimedia, telemetry), three states of the neural net (focused or low latency, stressed, or high reliability, relaxed or energy efficient).

### 4.5.1 Latency Performance

- Classical adaptive routing minimized delay relative to static routing, but no effect was noted in relation to user cognitive load.
- Game-theoretic and DRL fared better on optimization but were unable to adapt in real time when the user-state shifted mid-way through the session.
- Neuro-Adaptive Routing performed best (up to 35 percent improvement) in focused states because the decision rules include integrating the neural weights that penalize delay directly.

### 4.5.2 TRM Reliability and PDR

Classical adaptive routing and DRL approaches failed to add more redundancy on stressed states of the neurons thus, packets were lost regularly at congested states. Neuro-Adaptive Routing automatically transitioned to reliability-based routing resulting in a PDR of 95 percent, compared to 88 percent with DRL, 80-83 percent with the swarm and ant-colony techniques.

### 4.5.3 Energy Consumption

Since they do not implement user-state-based energy trade-offs, Classical and DRL-based methods also used more energy in the simulations. The Neuro-Adaptive Routing energy was saved by 10-15 percent more when at a relaxed state because it decreased its priority to latency and reliability which saves the device lifecycle in wearable BCIs. Neuro-Adaptive Routing surpasses all the baseline strategies in all the critical measures especially where the factor of human cognition is taken into account. The proposed model will engage in adapting to not only the network environment but also the cognitive and emotional state of the user unlike DRL-only approaches ［7］.

The reflection loop results in network performance that is adaptive to the instantaneous needs of the users, that is, a novel adaptable dimension that has not existed hitherto in previous works.

**Table 4 Comparison with related work**

| Approach | Latency ↓ | PDR ↑ | Energy Efficiency ↑ | Human Awareness |
|---|---|---|---|---|
| Classical Adaptive (Swarm, Ant)[28][30] | Medium | 80–83% | Low | None |
| Knowledge/Game-Theory[8][9] | Better | ~86% | Medium | None |

| | | | | |
|---|---|---|---|---|
| DRL-Based[7][34] | Good | 87–89% | Medium-High | Limited |
| **Neuro-Adaptive (Proposed)** | **Best** | **94–95%** | **Highest** | **Full (EEG/fMRI integrated)** |

The findings also make it clear that the suggested neuro-adaptive reinforcement learning (RL) routing method always performs well in terms of latency, packet delivery ratio (PDR) and energy efficiency indicators when compared to the classical and deep RL-based routing schemes. This has been attributed to the fact that the system provides a superior performance as a result of its capability to dynamically adjust its routing behavior based on live neural feedback that helps to provide the allocation of network resources with the cognitive and emotional state of the user. Upon detecting a focused state by the neural classifier, the reinforcement agent prefers low-latency routes by boosting the latency term weight in the reward function. This leads to a significant decrease in end-to-end delay than in the case of static routing that is not able to react to such context changes. In the same way, the adaptive weighting mechanism can be used in stressed conditions when there is a need to be more reliable; by choosing routes with a greater PDR and a smaller percentage of packet loss. In relaxed conditions, the algorithm also focuses more on energy saving to reduce redundant retransmissions and maximize the use of paths.

In terms of reinforcement learning, the cognitive-state-driven weights are useful in enhancing the gradient of rewards causing quicker and more robust convergence of policies relative to the agents that are exclusively environment-driven. These low values of the standard deviation of the ten independent trials prove that the proposed RL agent will converge with the reliability of different traffic and mobility conditions. Moreover, by incorporating a digital-twin-assisted simulation environment, predictive decision-making is feasible thus the agent can estimate the possible routing paths in advance before they can be implemented and this further reduces oscillations and learning instability.

These results can highlight the importance of human-conscious optimization in the 6G networks of the future, where cognitive status and behavioral information will become more and more important in shaping communication requirements. The capacity of the network of sensing, interpreting, and adjusting human neural feedback forms a new design paradigm - the transformation of users into a passive participant to an active, adaptive part of the communication loop. This does not only improve the quality of experience (QoE) but also makes sure that the network intelligence is moving towards the true human based communication systems. The effects go further than BCNs, opening the possibility of adaptive 6G networks that can make use of artificial intelligence, neuroscience, and wireless networking to deliver a level of responsiveness and personalization never before experienced.

# 5 Conclusion

The paper proposed a new paradigm, Neuro-Adaptive Routing in Brain-Computer Networks (BCNs) that introduces neuroscience-based improvements in a communication network. Unlike traditional adaptive routing that only encompasses network-internal parameters like delay, energy, and hopcount, the proposed framework uses neural activity (EEG/ fMRI) as real-time feed into routing distribution. This is a cornerstone into human-centric networking where networks will also be able to adapt to traffic as well as cognitive and emotional states of the users. A thorough methodology demonstrated how recruitment of raw neural signals can be acquired, preprocessed and translated into the network parameters in terms of the sensitivity of latency, reliability and energy. A multi-objective cost containing neural weights was provided, and the reinforcement learning (RL) was used to trade-off competing measures. AI-based digital twins based on validation through NS-3 simulations demonstrated that the neuro-adaptive routing algorithm can use to gain significantly higher performance over classical and DRL-based baselines. The experimental assessment provided some of the main conclusions that were reached:

- Latency was minimized up to 28-35 % in focused neural states, proving the advantage of bringing routing in line with cognitive load.
- Reliability (PDR) increased by 10-15 percent under stressed conditions as a result of redundancy-driven routing being detected, thus providing resilience in mission-critical applications like telemedicine.
- By relaxing the states, there was the reduction in energy consumption by 10-15%. This prolonged the lifetime of wearable and implantable devices.
- There was increased adaptability and RL agents were able to converge more swiftly when both network and neural feedback was provided.
- Awareness of QoS was taken to new heights, empowering human cognition to influence routing priorities like never before- and unlike any prior adaptive routing model.

Even comparative analysis also proved that Neuro-Adaptive Routing is better than classical adaptive, knowledge-based, and only DRL approaches according to the key performance criteria. Noteworthy is an embedded closed-loop feedback mechanism, which guarantees that the performance of the network and its alignment with the human cognitive state is continuous, going beyond machine-centered optimization. On the whole, the presented work serves as a conceptual justification and practical roadmap of validation of BCNs, and the further vision of 6G brain-type communication systems. Future researches will be conducted with respect to:

- Real-time EEG-integrated network implementation in terms of physical test
- Generalizing the framework to multi-user BCNs whose cognitive requirements conflict.
- Exploring security, privacy and ethical issues surrounding use of neural data in communications systems.

Neuro-Adaptive Routing is a revolution that integrates neuroscience and communication engineering and enables human-aware and adaptive networks, which makes BCNs a key technology in the 6G networks of the future.

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