



Optimization-Enhanced CSI-Aware Mobility Management for 5G and 6G Networks: A Structured Review

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Abstract. The mobility of current wireless networks (e.g. 5G and next-gen 6G) is far more complex than ever before with the combination of ultra-dense deployments, heterogeneous radio access technologies and strict quality of service (QoS) requirements. Many machine learning (ML) methods for predicting handover and channel state information (CSI) based decisions have been proposed. However, the optimization method of these learning methods is rarely evaluated with respect to the underlying problem structure. It is well known that most previous works rely on standard gradient approaches, and their analysis is not quite optimization-aware. Here we present a systematic optimization-aware work of CSI-based mobility management. It is shown that CSI-driven mean squared error (MSE) objectives are normally smooth, twice differentiable and locally quadratic. The latter makes them very well suited to curvature-aware methods. We compare first-order, Newton-type, and limited memory quasi-Newton optimization with respect to convergence speed, computational complexity, and numerical stability. We identify a long-standing gap between learning-oriented mobility intelligence and programmable SDN control and advanced optimization techniques. We propose L-BFGS-type methods as a principled approach for CSI-based handover learning and outline future research directions in scalable, secure, and efficient 6G mobility management.

Keywords: Mobility management, Handover optimization, Channel state information (CSI), Quasi-Newton methods, L-BFGS, 5G/6G networks, Federated learning, Software-defined networking

1 Introduction

The transformation of wireless communication systems from heterogeneous radio access networks to 5G and now to 6G architectures has raised the complexity of mobility management and handover (HO). The initial approaches were based on network system interoperability and low signaling overhead [1]. Later on, the Mobility-Driven Networks (MDN) framework defined a scalable architecture by

separating identity and locator functions [2]. Mobility scenarios were also more dynamic as LTE technology changed to 5G New Radio (NR): denser deployment, faster user speed, and more stringent QoS conditions have resulted in handover failures, ping-pong effects, and increased signaling overhead [3]. These problems are particularly acute in heterogeneous and dense environments where rule-based algorithms cannot adapt [4,5]. Machine learning (ML) approaches (supervised, unsupervised, and reinforcement learning) have been proposed to overcome this issue [4,5]. Furthermore, satellite–aerial–ground integrated networks require flexible, distributed control strategies, and Industrial IoT (IIoT) systems in which reliability and latency are severely limited [7]. Channel state information (CSI) is often regarded as a valuable tool for intelligent decision making such as improving spectral efficiency and adaptive mobility strategies [8]. Federated reinforcement learning for distributed, privacy-preserving vehicular network intelligence is currently being studied [9]. Architecturally, SDN and distributed control-plane designs can be used to make decisions about mobility automatically and programmatically [10,11]. In order to improve the training of deep learning models and distributed systems, quasi-Newton optimization methods have also been investigated [16]. Although progress has been made in recent years, most of the existing research works treat mobility prediction and optimization, distributed learning, and resource management as separate problems. This fragmentation hinders the development of cohesive, deployment-ready mobility management systems. This work fills this gap and systematically evaluates optimization-based mobility management models and AI-powered mobility management methods from theoretical standpoint to application endpoints.

1.1 Motivation: The Optimization Gap in CSI-Based Mobility Learning

Prior work on CSI-based learning models for bit error rate (BER) estimation and automatic handover decisions is well documented [8,52]. However, the selection of optimization algorithm in these models has hardly been investigated in depth. Most studies use gradient-based approaches without considering whether they suit the underlying problem structure. BER prediction from CSI involves MSE objectives that are smooth over a moderate-dimensional parameter space — a configuration in which curvature-aware methods such as BFGS and L-BFGS are expected to outperform first-order optimizers such as SGD or Adam. The benefits of these methods for mobility-aware learning have not been systematically studied, which motivates the analysis presented in this paper.

1.2 Contributions

This review makes the following contributions:

- An organized classification of mobility management research spanning classical methods, ML approaches, CSI-aware approaches, SDN-equipped paradigms, optimization-oriented approaches, and security-oriented approaches.

- A mathematical analysis of the CSI-BER objective that supports the use of curvature-aware optimizers.
- A comparison between optimizer classes (first-order, Newton-type, quasi-Newton) for CSI-based learning, with a dedicated notation table.
- A high-level flowchart of the proposed Optimization-Aware CSI Learning pipeline.
- Identification of current research challenges and future research directions for scalable, intelligent 6G mobility management.

2 Search Methodology of the Literature

A systematic search strategy was used for this structured review. We searched IEEE Xplore, ACM Digital Library, Elsevier ScienceDirect, Springer Link, and arXiv using the terms mobility management 5G/6G, handover optimization machine learning, channel state information handover, quasi-Newton wireless learning, and SDN vehicular mobility. The review spans the 2004–2026 period, with emphasis on 2019–2026. Inclusion criteria required that a paper address one or more of the following: handover decision-making, CSI-based prediction, optimization for wireless learning, SDN mobility control, or 6G network intelligence. Duplicate and non-peer-reviewed sources were excluded. The final corpus consists of 52 references.

3 Literature Review

This section reviews earlier work across six thematic areas: (i) classical mobility and handover foundations, (ii) ML-based handover optimization, (iii) SDN/MEC-enabled vehicular mobility, (iv) CSI-aware decision systems, (v) optimization and quasi-Newton methods, and (vi) 6G cross-domain intelligence. Fig. 1 shows the temporal distribution of the reviewed studies.

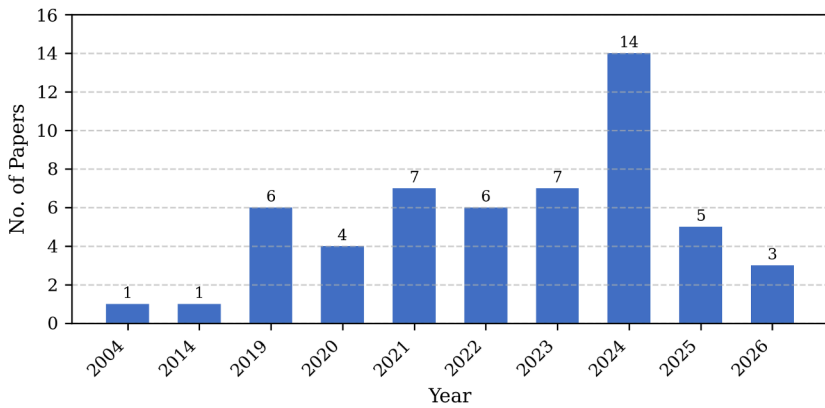


Fig. 1. Temporal distribution of reviewed mobility management papers, showing the rapid growth of learning-based research after 2020.

3.1 Classical Mobility and Handover Basics

Early work focused on reconfiguration-based mobility management systems for interoperability and to mitigate the impact of handovers. Qian et al. [1] proposed initial reconfiguration schemes. The MDN framework [2] subsequently proposed an improved scalability framework by distinguishing the roles of identity and locator. The survey by Tayyab et al. [3] documented the transition from LTE to 5G NR, identifying handover failures, latency, and ping-pong effects as canonical issues — findings that reflect the weaknesses of static, threshold-based decision mechanisms.

3.2 Machine Learning for Handover Optimization and Mobility Robustness

Mollet et al. [4] showed that handover performance in multi-dimensional settings requires multi-metric learning beyond RSS/RSRP. Thillaigovindhan et al. [5] presented a large-scale survey of ML techniques for handover optimization in 5G, identifying reinforcement learning as a particularly powerful method in changing environments. In satellite–aerial–ground integrated networks [6], ML supports flexible control of non-terrestrial nodes, while ML also helps maintain mission-critical reliability for IIoT [7]. Federated reinforcement learning for V2X communications [9] and UAV trajectory prediction [42] further extend this mobility intelligence space. Real-time deployment, generalization, and standardized benchmarking remain open challenges for these contributions.

3.3 SDN and MEC-Driven Mobility in Vehicular Networks

Separating the control plane from the data plane enables SDN-based programmable mobility. Shah et al. [10] reported distributed MEC-based architectures for reducing handover latency. Dias et al. [11] enhanced mobility-aware decision-making by integrating C-ITS messages into SDN control. Marques et al. [12] developed dynamic V2X link monitoring for efficient SDN-based network operation. Cui et al. [35] reported a reduction in handover latency using LISP-based mobility control in software-defined vehicular networks, and Abideen et al. [45] validated SDN handover strategies using a real-world Mininet-WiFi testbed. A recurring limitation is that conventional SDN methods have long relied on heuristic decision rules without optimally principled insight.

3.4 CSI-Aware Multiple Access Coexistence and Handover Switching

CSI-based approaches rely on user-specified parameters such as SNR, SINR, and path loss to drive mobility decisions. Urade and Kanthe [8] demonstrate that adaptive switching across access techniques based on CSI improves QoS across traffic scenarios, and in a follow-up study [52] show that automated CSI-assisted handover reduces BER and improves spectral quality. Song et al. [44] proposed channel-perceiving handover management for space-ground integrated networks, achieving improved performance under rapidly fluctuating channel conditions. These systems remain largely simulation-based, and their robustness to imperfect or delayed CSI, along with practical field verification, remains unresolved.

3.5 Optimization and Quasi-Newton Strategies in Wireless Learning

Training learning-based wireless control systems efficiently requires careful optimizer selection. Goldfarb et al. [16] showed that quasi-Newton methods are practical and have better convergence stability than standard first-order techniques for deep neural network training. Rafati and Marcia [17] found that L-BFGS-inspired updates speed deep reinforcement learning. Niu et al. [21] introduced a momentum-enhanced version of L-BFGS (mL-BFGS) that outperforms SGD in distributed large-scale optimization problems. Bemporad [18] implemented L-BFGS-B with ℓ_1 and group-Lasso regularization to system identification problems, leading to significantly better stability. Specifically in wireless applications, Qiao et al. [13] used an L-BFGS approach to beamforming design in IRS-assisted massive MIMO systems; Gao et al. [14] integrated BFGS with Armijo line search to find energy-efficient power allocation; Eisen et al. [25] presented a primal-dual quasi-Newton approach for distributed consensus optimization. However, quasi-Newton methods are not widely integrated in mobility-aware optimization methods.

3.6 Cross-Domain Intelligence Toward 6G Networks

In 6G, current research is also using AI, digital twins, O-RAN architectures, and federated learning. Koursioupas et al. [37] introduced context-aware AI profiling for 5G/6G resource management. Ali and Arslan [38] studied digital-twin optimization of network slicing in terrestrial and non-terrestrial networks. Wu et al. [39] used AI-based resource management in heterogeneous RF-Light networks. González et al. [47] applied federated learning and cooperative game theory to network selection in 5G-Advanced heterogeneous networks and Sroka et al. [48] proposed policy-based traffic steering for O-RAN-based V2N communications. However, integration across these areas remains scarce, which motivates the unified perspective adopted in this review.

Table 1. Representative approaches: problem, technique, metric, and key limitation.

Ref	Problem	Technique	Metric	Limitation
[3]	LTE–NR HO	Survey	Failure rate	Static thresholds
[4]	ML HO	Multi-metric ML	QoS	No benchmark
[10]	Vehicular MEC	SDN	Latency	Scalability
[8]	Access switching	CSI + DL	BER	Simulation only
[16]	DNN training	Quasi-Newton	Convergence	Compute cost
[47]	Network selection	Federated + GT	Throughput	Comm. overhead

3.7 Taxonomy and Research Distribution

The taxonomy of mobility management approaches is shown in Fig. 2 and Fig. 3 shows the distribution of the reviewed research across categories. Table 2 shows the methodology distribution and Table 3 shows the identified research gaps. Fig. 2. Classification of mobility management research in six thematic branches. Fig. 3. Distribution of reviewed papers for mobility management research categories. Table 2. Distribution of reviewed papers by methodology.

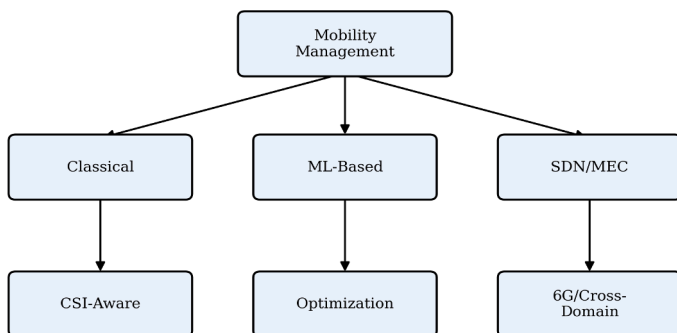


Fig. 2. Taxonomy of mobility management research, organized into six thematic branches.

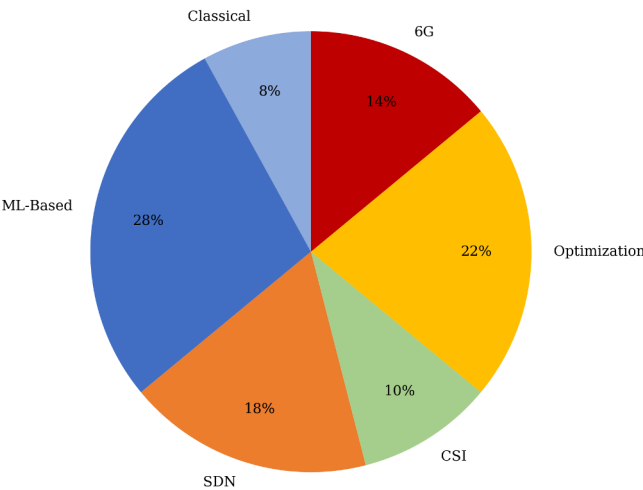


Fig. 3. Distribution of reviewed papers across mobility management research categories.

Table 2. Distribution of reviewed papers by methodology.

Methodology	Papers
Supervised Learning	12
Reinforcement Learning	10
Federated Learning	6
SDN-Based Control	9
Quasi-Newton Optimization	11
Security-Focused	6

Table 3. Key research gaps identified across mobility management paradigms.

Approach	Limitation	Required Improvement
Classical	No predictive capability	ML integration
ML-Based	No control integration	SDN coupling
SDN	No optimization intelligence	Quasi-Newton methods
Optimization	No mobility awareness	Mobility-aware design
Security	Isolated from intelligence	Integrated framework

3.8 Summary and Motivation

Even with the progress across all the paradigms, the literature has largely been created in silos. Classical approaches lack predictive capabilities, ML approaches lack programmable control integration, SDN frameworks lack optimization intelligence, optimization methods lack mobility awareness, and security mechanisms are not integrated into intelligent systems. No architecture combines CSI-aware learning,

SDN control, advanced optimization, and security. This gap motivates the analysis of the following sections.

4 Notation

Table 4 defines the mathematical symbols used throughout this paper. We use this notation to compare the optimization formulations in Sections 5 and 6.

Table 4. Mathematical notation used throughout the paper.

Symbol	Definition
$\mathbf{x}_i \in \mathbb{R}^d$	Feature vector derived from CSI for sample i
y_i	Target variable (BER, outage indicator, or QoS metric)
$\hat{y}_i$	Model prediction for sample i
$\hat{f}(\cdot; \theta)$	Parametric model (e.g., MLP with smooth activations)
$\theta \in \mathbb{R}^p$	Trainable model parameter vector
$J(\theta)$	MSE training objective
n	Number of training samples
d	Input feature dimension
p	Number of model parameters
H	Hessian matrix of J with respect to θ
B_k	Quasi-Newton approximation to the Hessian at iteration k
$\nabla J(\theta_k)$	Gradient of objective at iteration k
m	Number of correction pairs stored in L-BFGS
k	Iteration index
α_k	Step size (learning rate) at iteration k

5 Mathematical Nature of CSI–BER Optimization

Several CSI-assisted learning techniques for handover decision-making and BER/QoS estimation can be formulated within an empirical risk minimization (ERM) framework. Let $\mathbf{x}_i \in \mathbb{R}^d$ be a feature vector obtained from channel state information such as SNR, SINR, path loss, received signal strength, and pilot symbols. The target y_i is the bit error rate (BER), outage indicator, or QoS-related metric. For a parametric model $\hat{y}_i = \hat{f}(\mathbf{x}_i; \theta)$, the training objective is defined as the mean squared error (MSE):

$$J(\theta) = (1/n) \sum_i (y_i - \hat{f}(\mathbf{x}_i; \theta))^2 \quad (1)$$

Where $\hat{f}(\cdot)$ is differentiable (e.g., a multilayer perceptron with smooth activations such as tanh or GELU), the objective in (1) is smooth and twice differentiable. In the real CSI regression problem with a small feature dimension d and a small model size, the loss surface is roughly quadratic in the neighborhood of a local minimum. This local quadratic structure has direct implications for the choice of optimizer, since curvature-aware methods, which are based on second-order information about the

loss, do not solve the problem of this kind. Because the full Hessian is computationally expensive, we can use a quasi-Newton approach for this problem.

6 Why Quasi-Newton Optimization Suits CSI-Based Learning

6.1 Curvature Awareness Without Full Hessian

First-order optimizers (SGD, Adam, RMSProp) rely exclusively on gradient information. While easy to adopt and can scale well to large models, they are prone to slow convergence or oscillation on poorly conditioned objectives. Newton's method instead uses second-order information via the Hessian:

$$\theta_{k+1} = \theta_k - H_k^{-1} \nabla J(\theta_k) \quad (2)$$

which allows convergence but requires $O(p^2)$ memory to store H_k and $O(p^3)$ operations to invert it. In the case of the quasi-Newton approaches (BFGS, L-BFGS) the Hessian computation is avoided by building an approximation $B_k \approx H_k$ from accumulated gradient differences:

$$\theta_{k+1} = \theta_k - \alpha_k B_k^{-1} \nabla J(\theta_k) \quad (3)$$

This allows for curvature information to be kept but at a lower cost than full second-order methods. This makes quasi-Newton methods particularly well suited to the smooth MSE objectives in (1).

6.2 Complexity and Memory

- **Newton's method:** $O(p^2)$ memory; $O(p^3)$ cost per iteration.
- **BFGS:** $O(p^2)$ memory for the full Hessian approximation; suitable for moderate-size models.
- **L-BFGS:** It is $O(mp)$ memory and only m curvature correction pairs ($m \ll p$) are stored; the best for real-time CSI learning.

CSI features (SNR, SINR, path loss) tend to have correlated fading and channel scaling, which leads to poorly conditioned optimization landscapes. Curvature-sensitive algorithms stabilize convergence in such settings by adapting update directions to local geometry.

6.3 CSI Structure Alignment with Quasi-Newton Optimization

Because of the physics of wireless propagation, CSI parameters change smoothly. For an MSE objective, this results in a loss surface with a close to quadratic near optima

regime which is where quasi-Newton approaches become best. Unlike first-order methods that rely only on gradient magnitude, L-BFGS adapts step directions in a way that is close to the approximate curvature leading to faster and more stable convergence. This coherence suggests that L-BFGS is well matched to BER prediction from CSI for moderate model sizes with smooth objectives.

Table 5. Comparison of optimization methods for CSI-based BER learning, highlighting Adam vs. L-BFGS trade-offs for reducing CSI-based handover latency.

Optimizer	Order	Memory	Convergence	HO Latency
SGD	1st	$O(p)$	Slow / oscillatory	High
RMSProp	1st	$O(p)$	Moderate	Moderate
Adam	1st	$O(p)$	Fast (initial); noisy at fine-tuning	Moderate
Newton	2nd	$O(p^2)$	Quadratic	Low (impractical)
BFGS	QN	$O(p^2)$	Superlinear	Low
L-BFGS	QN	$O(mp)$	Superlinear; stable	Lowest

Key insight: Adam converges quickly at first but can become noisy on structured, smooth problems like CSI-based BER prediction. L-BFGS, on the other hand, utilizes curvature information to achieve superlinear convergence with the smallest memory footprint among curvature-aware methods compared, directly reducing handover-latency decisions.

6.4 Recommended Evaluation Protocol for Optimizer Selection

A systematic evaluation framework for optimizer selection in CSI-based learning systems should assess:

- Convergence speed: iterations to reach a target BER or MSE threshold.
- Computational complexity: memory usage and per-iteration cost as a function of p .
- Robustness against noisy CSI: performance with perturbations in CSI inputs.
- Numerical stability: sensitivity to hyperparameter tuning and absence of oscillatory behavior.

6.5 Findings of Convergence in Previous Work

The momentum-based L-BFGS variants outperform SGD in large-scale learning [21]. In wireless beamforming, L-BFGS is less costly than first-order methods for CSI uncertainty [13]. The hybrid Adam+L-BFGS-B methods increase both stability and final accuracy [18]. For distributed consensus optimization, quasi-Newton updates can achieve exact convergence when gradient-descent methods take a smaller amount of time. Our results together support the use of L-BFGS-like methods for the smooth MSE objectives found in CSI-based mobility learning.

6.6 Summary of Justification

Because CSI-based MSE objectives are smooth and twice differentiable, and due to the stability and efficiency requirements of real-time mobility management, L-BFGS is a principled compromise between convergence speed, numerical robustness, and memory efficiency. This holds both for CSI-based BER prediction and more general mobility management optimization tasks.

7 Optimization-Aware CSI Learning Pipeline

Fig. 4 shows a high-level flowchart of the proposed Optimization-Aware CSI Learning pipeline that includes CSI feature extraction, model training with quasi-Newton optimization, and SDN-based handover execution.

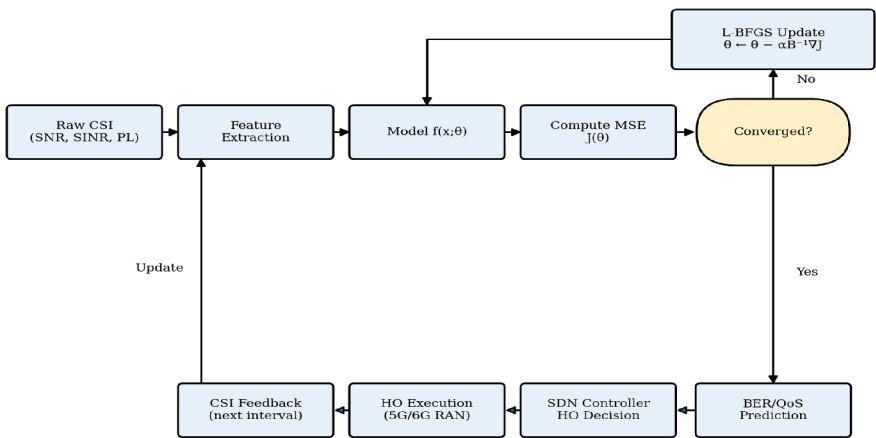


Fig. 4. Optimization-Aware CSI Learning Pipeline. Raw CSI is obtained and used to train a parametric model from L-BFGS iterations. Once convergence occurs, BER/QoS prediction is used to make the SDN handover decision, and the updated CSI feedback completes the loop.

8 Open Research Challenges

8.1 Real-Time Deployment Constraints

Learning-based handover models are computationally heavy, making edge deployment challenging. In addition, inference latency, energy consumption and

scalability are highly important, since small processing delays can degrade handover performance. Lightweight, efficient model architectures are a research challenge.

8.2 Generalization and Dataset Limitations

AI-based mobility models are typically trained on simulation or case-specific data. Models trained under fixed conditions do not generalize well to changing network conditions, and the lack of standardized benchmark datasets hinders reproducibility and systematic comparison.

8.3 Imperfect and Delayed CSI

Practical CSI is seldom perfect. Noise, feedback lag and incomplete channel information can reduce prediction accuracy. Models that are stable even under imperfect and time-evolving CSI are necessary for real-world applications.

8.4 Federated Learning Overheads

Federated learning involves communication costs, synchronization delays, and instability during model aggregation. These issues are exacerbated in large, heterogeneous networks in which many devices are capable and connected.

8.5 Security of Learning-Assisted Mobility

Learning-based mobility systems are vulnerable to adversarial inputs, model poisoning, and malicious pattern transfer. 6G networks need secure, robust learning frameworks capable of countering such threats.

8.6 Energy–Intelligence Trade-Offs

Greater intelligence requires more computing and signaling, which increases energy consumption. Finding the balance between predictive ability and energy efficiency is key to sustainable 6G deployment.

9 Future Research Directions

9.1 CSI-Aware Federated Learning

Using CSI feature extraction with federated model learning can ensure accurate mobility prediction without centralizing confidential user data. Communication

overhead and model consistency when using non-IID channel distributions must be addressed before we can make it practical.

9.2 Curvature-Aware Training Optimization

Using quasi-Newton methods such as L-BFGS in CSI-based models can improve convergence stability and training time in dynamic channel environments in contrast to first-order approaches.

9.3 Mobility-Aware Digital Twins

AI-driven digital twin models can simulate the behavior of an active network and user mobility patterns, enabling scenario testing in simulation before real-world deployment. Identifying handover strategies across different traffic and channel conditions is a high-priority direction.

9.4 Integration into O-RAN Architectures

Open Radio Access Network (O-RAN) architectures offer flexible, programmable interfaces for intelligent mobility control. Under O-RAN, AI-based decision modules can support modular, multi-vendor mobility systems with interoperable decision-making across network components.

9.5 Secure and Explainable AI for Mobility

Future mobility management systems should combine adversarial robustness with interpretable decision support. Explainability is essential for building trust in mission-critical network contexts.

10 Conclusion

This paper presents a systematic survey of mobility management research spanning classical methods, ML-centric systems, CSI-aware approaches, SDN-based network designs, optimization methods, and security techniques. The resulting taxonomy and gap analysis indicate that nearly all advances have been made in isolation: learning-based methods achieve higher adaptability and predictive ability but are rarely combined with programmable control-plane systems or principled optimization; SDN frameworks continue to rely on heuristic choices; and security is largely absent from intelligent mobility-management frameworks. Our mathematical analysis shows that CSI-based BER objectives are smooth, twice differentiable, and locally quadratic — properties that favor curvature-aware optimizers. Among the methods considered, L-BFGS offers the best trade-off between convergence speed,

numerical stability, and memory efficiency for this class of problem. The proposed Optimization-Aware CSI Learning pipeline (Fig. 4) integrates these insights within an SDN-based handover control loop. Next-generation 6G mobility management systems should pursue holistic architectures that combine CSI-driven predictive learning, federated distributed intelligence, programmable SDN control, high-performance quasi-Newton optimization, and embedded security — an integration that promises more adaptive, robust, energy-efficient mobility management for the dynamic, heterogeneous, and increasingly interdependent environments expected in next-generation wireless networks.

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