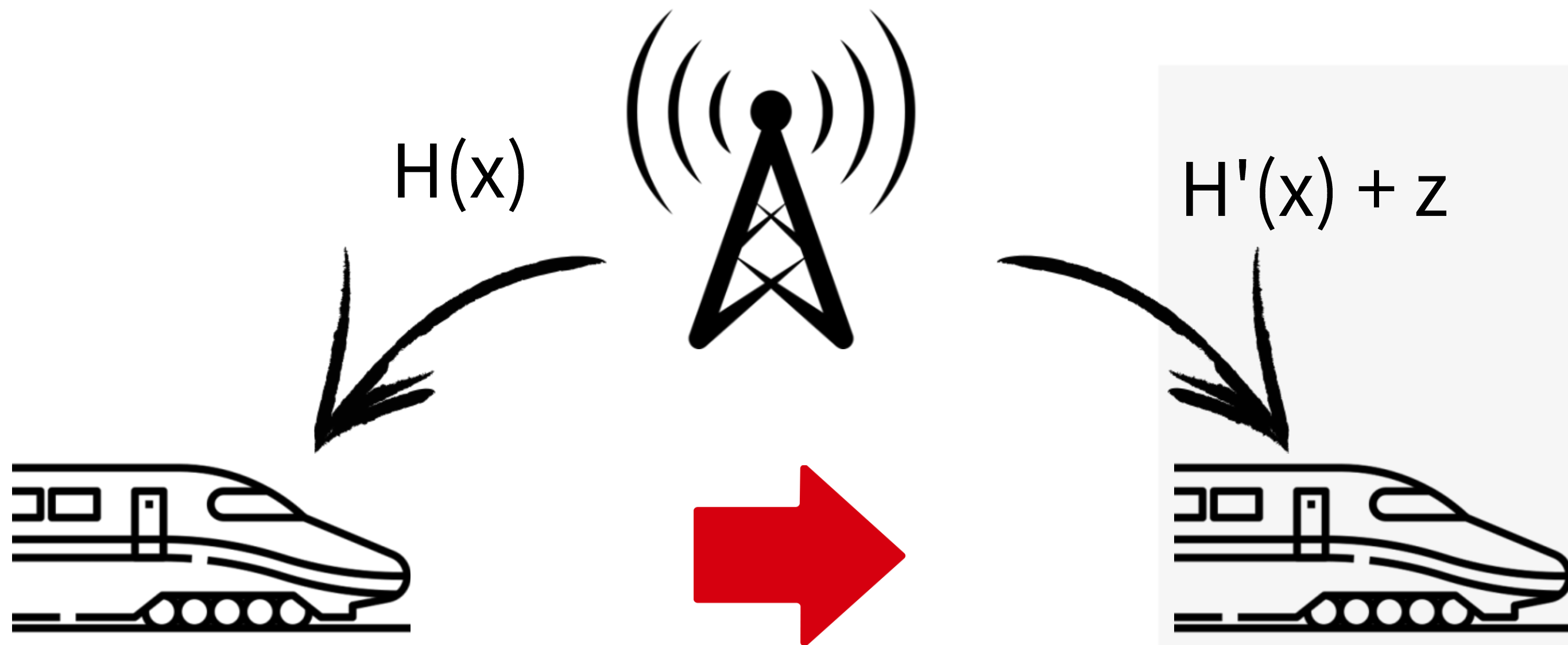


거대 무선 채널 기반 미래 채널 예측 및 통신 환경 분류 연구

지도교수님 | 양희철 교수님
컴퓨터융합학부 | 이호윤 | 202002541
인공지능학과 | 김가현 | 202202469

01

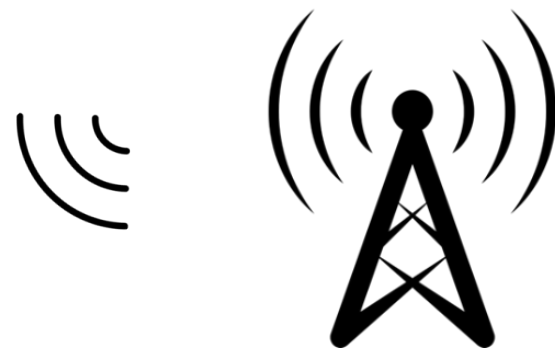
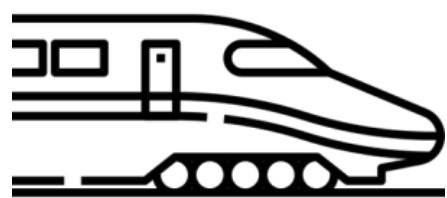
동적 시나리오에서의 통신 예측



표본 : 57명

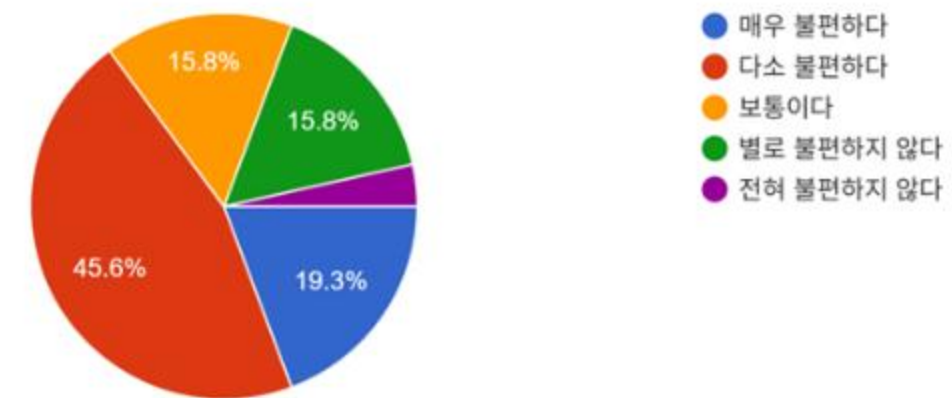
기차에서 인터넷 끊김 경험: 72%

기차에서 인터넷 끊김 불편함: 65%



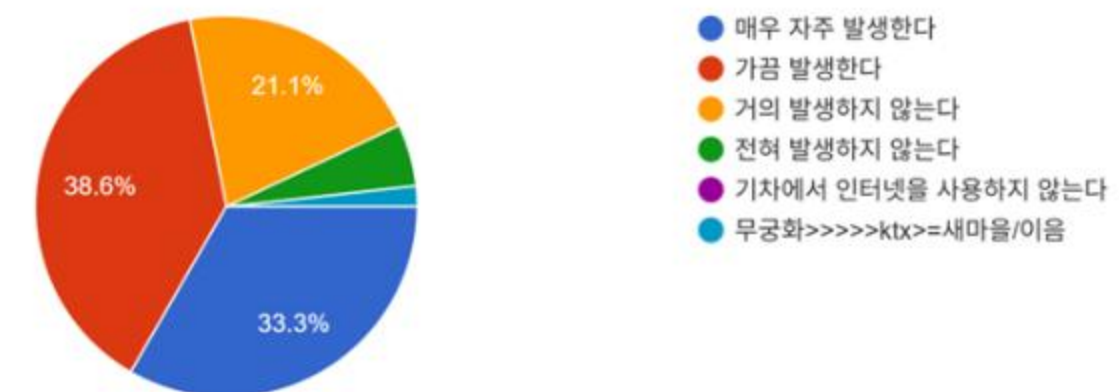
7. 기차 내에서 인터넷이 끊기는 문제가 얼마나 불편하다고 느끼십니까

응답 57개



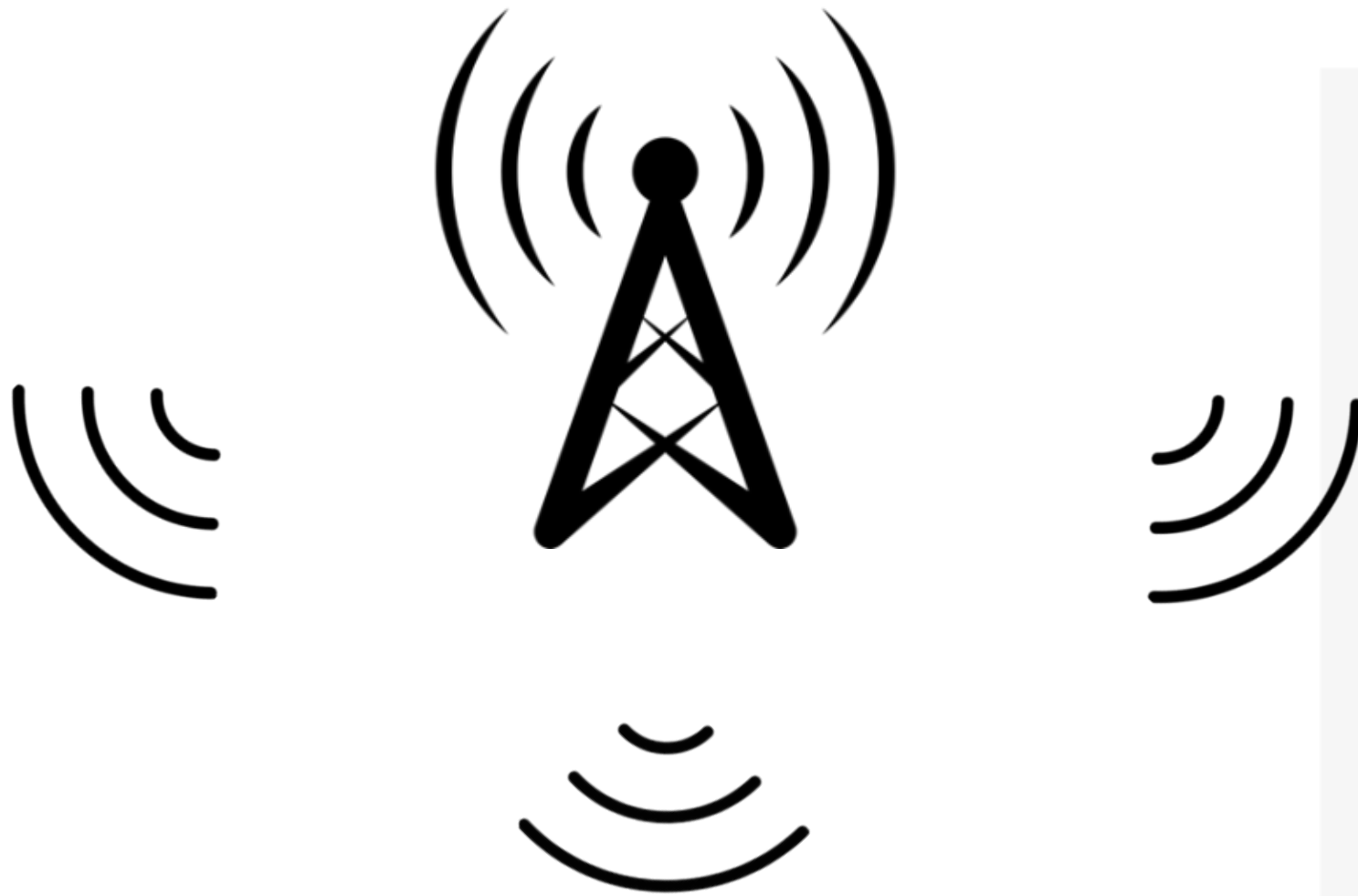
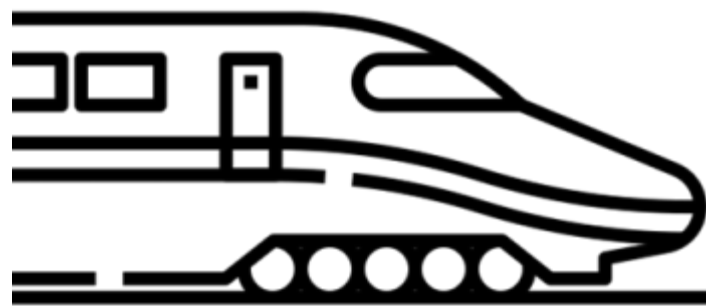
1. KTX 또는 일반 기차를 이용할 때 인터넷(와이파이 또는 모바일 데이터) 연결이 끊긴 경험이 있습니까?

응답 57개



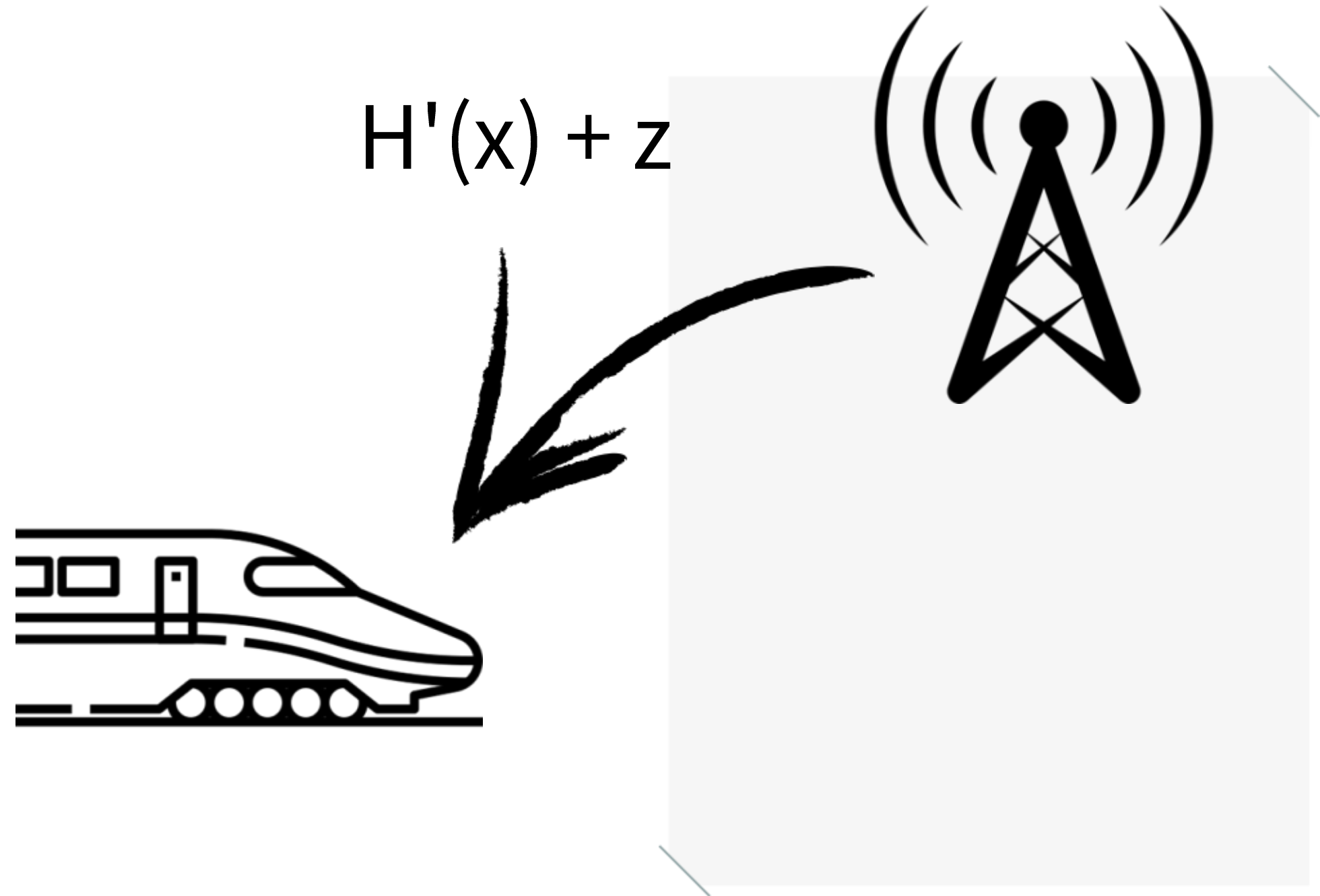
03

기차의 인터넷이 끊기는 이유



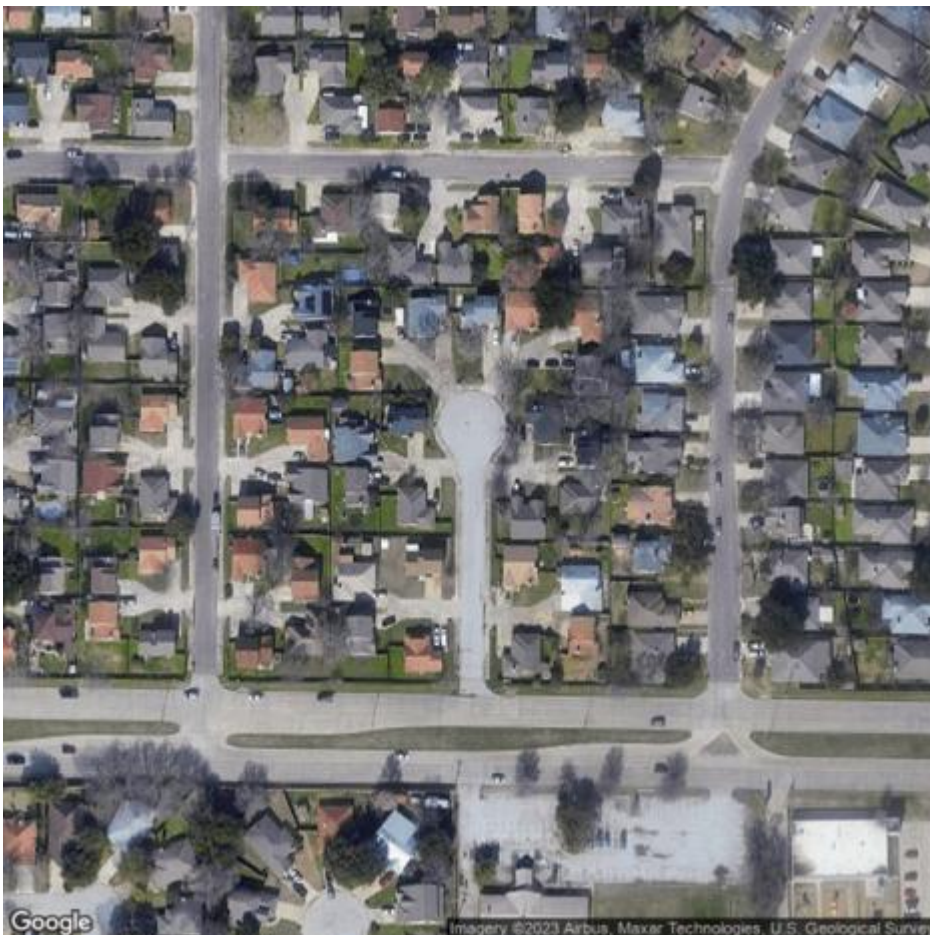
1. 빔포밍 예측

2. LoS/NLoS 분류

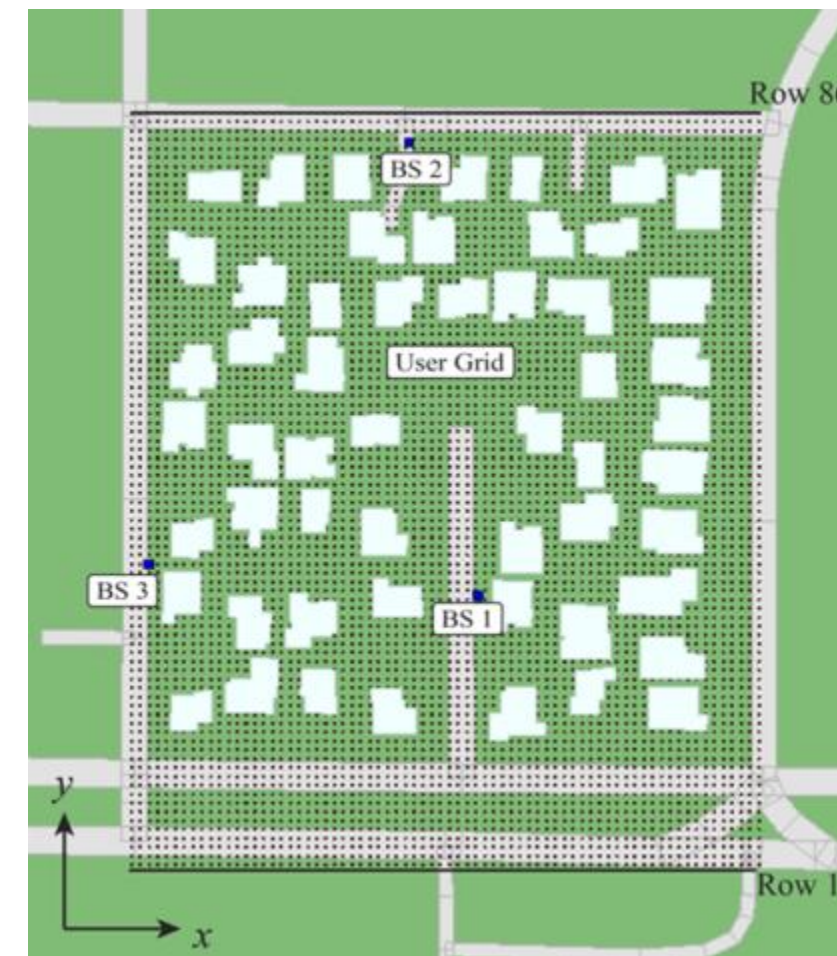


빔 포밍이란?

빔포밍(BeamForming): 기지국의 전파를 특정방향으로 집중시켜 보내는 기술



Fort Worth 위성사진



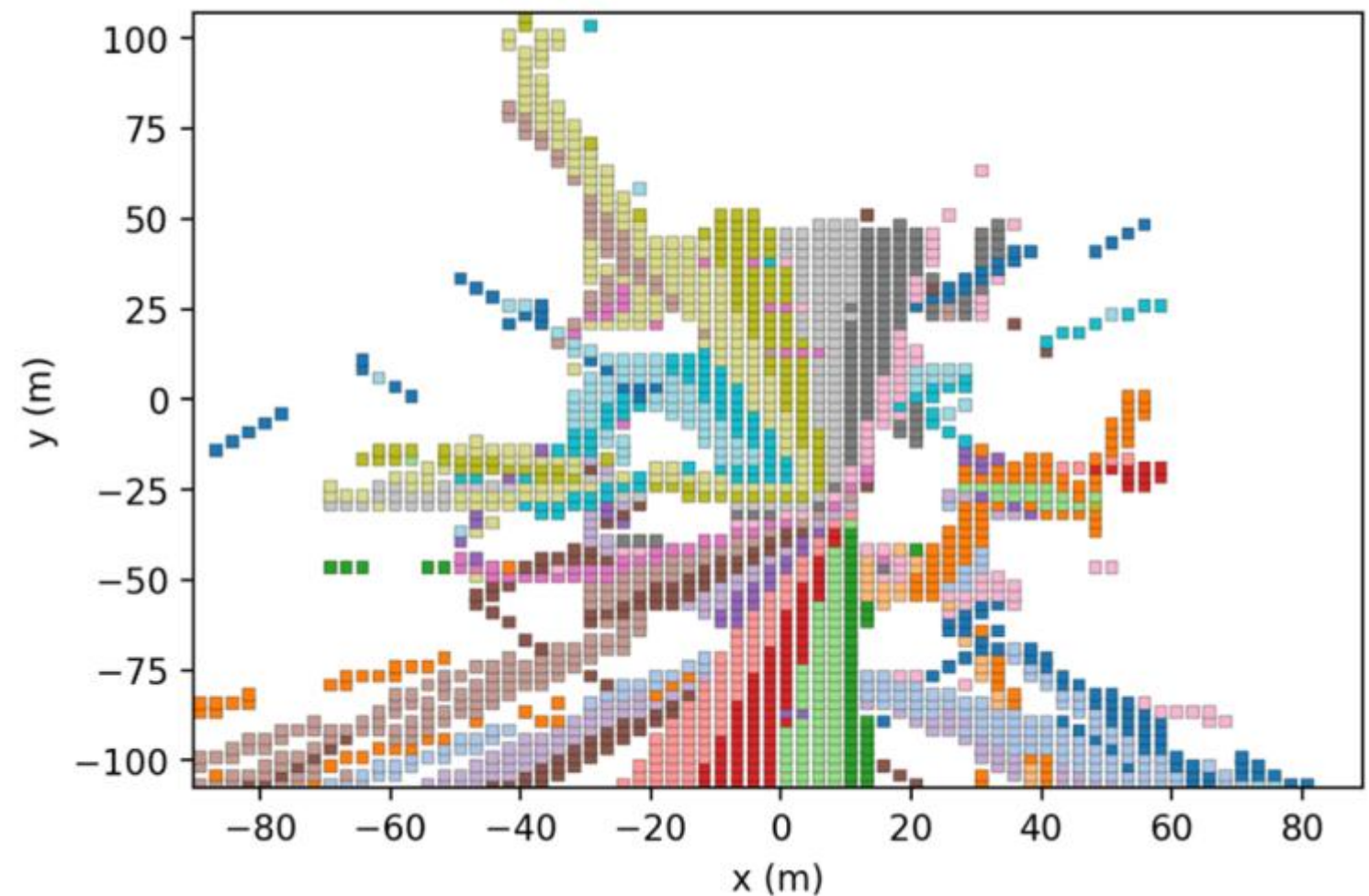
Fort Worth 모델링 사진

빔포밍(BeamForming): 기지국의 전파를 특정방향으로 집중시켜 보내는 기술

기지국: BS1

채널 수: 64

기대효과: 빔포밍 예측을 통해
사용자의 위치 변화에 따라
최적의 전파 방향을 미리 결정함으로써
더 빠르고 안정적인 무선 통신이 가능해집니다.



Fort Worth 빔 예측

07

LoS/NLoS 분류

LoS(Line of Site)



직선 경로로 신호 전달

NLoS(None Line of Site)

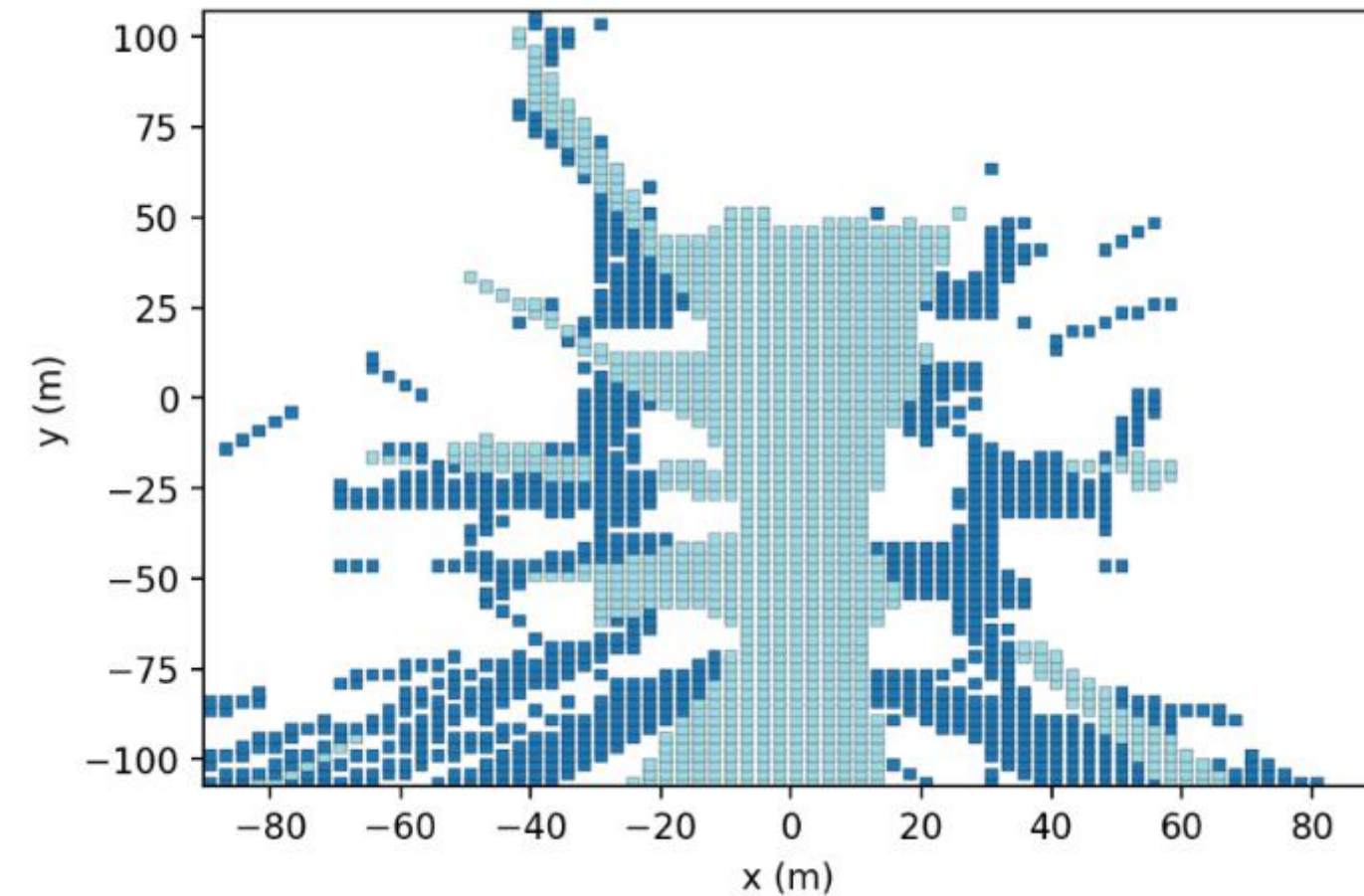


신호가 건물 벽 등에 반사되어 전달

기지국: BS1

채널 수: 64

기대효과: LoS와 NLoS를 구분하면,
환경에 맞는 통신 전략을 적용할 수 있어
신호 품질 향상, 예측 정확도 증가,
자원 효율 최적화에 도움이 됩니다.



Fort Worth LoS/NLoS

Transfer Learning and Meta Learning-Based Fast Downlink Beamforming Adaptation

Yi Yuan[✉], Gan Zheng[✉], *Senior Member, IEEE*, Kai-Kit Wong[✉], *Fellow, IEEE*, Björn Ottersten[✉], *Fellow, IEEE*, and Zhi-Quan Luo[✉], *Fellow, IEEE*

I. INTRODUCTION

Abstract—This article studies fast adaptive beamforming optimization for the signal-to-interference-plus-noise ratio balancing problem in a multiuser multiple-input single-output downlink system. Existing deep learning based approaches to predict beamforming rely on the assumption that the training and testing channels follow the same distribution which may not hold in practice. As a result, a trained model may lead to performance deterioration when the testing network environment changes. To deal with this task mismatch issue, we propose two offline adaptive algorithms based on deep transfer learning and meta-learning, which are able to achieve fast adaptation with the limited new labelled data when the testing wireless environment changes. Furthermore, we propose an online algorithm to enhance the adaptation capability of the offline meta algorithms in realistic non-stationary environments. Simulation results demonstrate that the proposed adaptive algorithms achieve much better performance than the direct deep learning algorithm without adaptation in new environments. The meta-learning algorithm outperforms the deep transfer learning algorithm and achieves near optimal performance. In addition, compared to the offline meta-learning algorithm, the proposed online meta-learning algorithm shows superior adaption performance in changing environments.

Index Terms—Deep transfer learning, meta-learning, online learning, beamforming, MISO, SINR balancing.

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Björn Ottersten is with the Interdisciplinary Centre for Security, Reliability and Trust (SeRT), University of Luxembourg, 1559 Luxembourg City, Luxembourg (e-mail: bjorn.ottersten@uni.lu).

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Accurate Channel Prediction Based on Transformer: Making Mobility Negligible

Hao Jiang[✉], *Student Member, IEEE*, Mingyao Cui, *Student Member, IEEE*, Derrick Wing Kwan Ng[✉], *Fellow, IEEE*, and Linglong Dai[✉], *Fellow, IEEE*

Abstract—Accurate channel prediction is vital to address the channel aging issue in mobile communications with fast time-varying channels. Existing channel prediction schemes are generally based on the sequential signal processing, i.e., the channel in the next frame can only be sequentially predicted. Thus, the accuracy of channel prediction rapidly degrades with the evolution of frame due to the error propagation problem in the sequential operation. To overcome this challenging problem, we propose a transformer-based parallel channel prediction scheme to predict future channels in parallel. Specifically, we first formulate the channel prediction problem as a parallel channel mapping problem, which predicts the channels in next several frames in parallel. Then, inspired by the recently proposed parallel vector mapping model named transformer, a transformer-based parallel channel prediction scheme is proposed to solve this formulated problem. Relying on the attention mechanism in machine learning, the transformer-based scheme naturally enables parallel signal processing to avoid the error propagation problem. The transformer can also adaptively assign more weights and resources to the more relevant historical channels to facilitate accurate prediction for future channels. Moreover, we propose a pilot-to-precoder (P2P) prediction scheme that incorporates the transformer-based parallel channel prediction as well as pilot-based channel estimation and precoding. In this way, the dedicated channel estimation and precoding can be avoided to reduce the signal processing complexity. Finally, simulation results verify that the proposed schemes are able to achieve a negligible sum-rate performance loss for practical 5G systems in mobile scenarios.

Index Terms—Channel prediction, error propagation, transformer, attention mechanism, machine learning.

I. INTRODUCTION

MILLIMETER-WAVE (mmWave) massive multiple-input multiple-output (MIMO) has been a key technique for the fifth-generation (5G) wireless communications [1]. Equipped with an array with a large number of

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antennas, massive MIMO can achieve orders of magnitude increase in the achievable sum-rate [2] through different advanced precoding designs [3].

In fact, effective real-time precoding highly depends on the quality of the estimated instantaneous channel state information (CSI). According to the 5G standard [4], each frame in the time-division duplex (TDD) mode contains multiple slots, and the instantaneous CSI is estimated only in the first slot of each frame by using the predefined sounding reference signal (SRS). Then, the subsequent slots within the same frame can only utilize the estimated channel in the first slot for the precoding design.

Since the channel coherence time is inversely proportional to the carrier frequency and user speed, it is possible that the channel coherence time [5] is shorter than the channel estimation period, i.e., the SRS period [4], in mobile scenarios. For example, when the carrier frequency of 28 GHz and the user speed of 60 km/h, the channel coherence time is roughly 0.32 ms, while the smallest SRS period is 0.625 ms according to the 3GPP standard [4]. In such a typical scenario, the actual channels for the second half of the slots in the same frame are likely to have significant changes. This phenomenon is known as channel aging [6], which could result in about 30% achievable sum-rate performance loss with the user speed of 60 km/h [7]. Consequently, channel aging is an essential issue that has to be addressed for mmWave MIMO in mobile scenarios.

A. Prior Works

To alleviate the performance loss caused by channel aging, channel prediction techniques have been extensively studied to predict the future channel by exploiting the temporal correlation between the historical CSI and the future channel [7]–[15]. Specifically, the channel prediction techniques are utilized to predict channels in the next several frames. Since the second half of the slots in the current frame are in the channel coherence time of the predicted channel in the next frame, these slots could perform precoding design according to the predicted channel in the next frame. Furthermore, due to the significant baseband processing delay, which aggravates the channel aging issue, the prediction of the future channels in the next several frames is required. The existing channel prediction methods could be generally divided into two categories, i.e., the model-based methods and the neural network-based methods.

For the model-based methods [7]–[11], several models have been considered to characterize the time-varying channels with

Real-Time Massive MIMO Channel Prediction: A Combination of Deep Learning and NeuralProphet

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²Laboratoire des Signaux et Systèmes, CentraleSupélec, CNRS, University of Paris-Saclay, France.

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Abstract—Channel state information (CSI) is of pivotal importance as it enables wireless systems to adapt transmission parameters more accurately, thus improving the system's overall performance. However, it becomes challenging to acquire accurate CSI in a highly dynamic environment, mainly due to multi-path fading. Inaccurate CSI can deteriorate the performance, particularly of a massive multiple-input multiple-output (mMIMO) system. This paper adapts machine learning (ML) for CSI prediction. Specifically, we exploit time-series models of deep learning (DL) such as recurrent neural network (RNN) and Bidirectional long-short term memory (BiLSTM). Further, we use NeuralProphet (NP), a recently introduced time-series model, composed of statistical components, e.g., auto-regression (AR) and Fourier terms, for CSI prediction. Inspired by statistical models, we also develop a novel hybrid framework comprising RNN and NP to achieve better prediction accuracy. The proposed channel predictors (CPs) performance is evaluated on a real-time dataset recorded at the Nokia Bell-Labs campus in Stuttgart, Germany. Numerical results show that DL brings performance gain when used with statistical models and showcases robustness.

Index Terms—AI/ML, channel prediction, CSI, massive MIMO, NeuralProphet, 6G.

I. INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) are the defining technologies of next-generation wireless networks, called sixth-generation (6G). It is expected that AI/ML will play a pivotal role in the design phase of 6G wireless networks [1], [2]. In this regard, standardization of ML has also begun [3]. Specifically, it is expected that ML, together with massive multiple-input multiple-output (mMIMO), disruptive technology of fifth-generation (5G), can improve, for instance, precoding gain [1], [3]. Furthermore, the validity of ML algorithms in a real-time environment has opened up a new horizon for the consideration of ML in 6G [4].

A mMIMO system can improve signal-to-noise ratio, as well as throughput, by utilizing diversity and multiplexing techniques, respectively [5]. However, accurate channel state information (CSI) is indispensable to get expected gain. In a highly dynamic wireless communications environment, it is hard to acquire accurate CSI, e.g., due to reporting compressed CSI to base station (BS) by user-equipment (UE), and feedback/processing delays [6].

To acquire accurate CSI, researchers have started exploiting an *active* approach, known as channel prediction [4] as it can improve the accuracy of CSI without requiring extra radio resources. The key idea of channel prediction is to forecast CSI realizations that can mitigate, e.g., compressed CSI and induced delays. Recently, its application to reduce mMIMO CSI feedback overhead and accuracy improvement of acquired CSI at BS have opened new doors for its consideration [3], [6].

The study of channel prediction has been considered by a few researchers in the literature [4], [7]–[10], which is mainly divided into statistical models and ML. For example, auto-regression (AR) and parametric models have been studied in [7] and [8], respectively. However, the downside of statistical models is their iterative re-estimation of parameters that can expire quickly in a dynamic environment. And due to manipulation of matrices, parameters re-estimation can be costly [8]. In contrast, ML has the capability of making multi-step prediction, as well as can provide huge gains in a diverse environment. To this end, [9] and [10] evaluated the performance of a recurrent neural network (RNN), an ML algorithm, on a synthetic dataset. To demonstrate the effectiveness of RNN in a real-world environment, [4] evaluated the performance of RNN on compressed and uncompressed CSI.

In this paper, we evaluate the performance of various state-of-the-art deep learning (DL) models such as RNN [4] and Bidirectional long-short term memory (BiLSTM). Also, a DL inspired statistical algorithm, i.e., NeuralProphet (NP), is tested on out-of-sample data. Further, getting the inspiration from using statistical algorithm and DL together, we propose a novel hybrid framework composed of RNN and NP, which yields better prediction results than individual models. In addition to this, we employ hyperparameter tuning for each of these individual models to select only the best training parameters. We observe the performance of channel predictors (CPs) in a realistic environment.

Rest of the paper is organized as follows: Section II provides details of CPs used in our study. Section III summarizes real-time dataset. Section IV gives performance comparisons of CPs, and Section V concludes the paper.

단점 요약

CNN	대규모 데이터셋 필요, 해석 어려움
RNN	학습 시간 오래걸림, 그레디언트 소실 문제
Attention	다른 환경 일반화 어려움
Transfer learning	도메인 불일치 위험, 튜닝 어려움
Meta-learning	망각문제, 튜닝 어려움

TABLE I: Features of channel prediction approaches depending on prediction types.

Ref.	Prediction type	Method	Architecture	Advantages	Limitations
[3]	Temporal channel prediction	Model-based	AR model and Kalman filtering	✓ Simple and efficient implementation ✓ Strong theoretical foundation	✓ Limited to linear dynamic systems ✓ Performance heavily depends on initial state and covariance estimates
[13]			Parametric channel prediction	✓ High accuracy when fit model ✓ Model-based approach considers physical channel properties	✓ Complexity in parameter estimation ✓ High dependency on environmental knowledge
-			Deterministic channel model	✓ High accuracy ✓ Site-specific including geometry	✓ Not suitable for real-time applications ✓ Limited generalization to unseen environments
[5]		ML-based	MLP	✓ Enable complex nonlinear relationships ✓ Adaptive to various conditions	✓ Dependent on large datasets ✓ Careful selection of hyper-parameters
[6]			CNN	✓ Spatial feature recognition ✓ Automatic feature extraction	✓ Dependent on large datasets ✓ Difficult to interpret
[7]			RNN	✓ Temporal dependency modeling ✓ Variable sequence length handling	✓ Gradient vanishing problem ✓ Learning time and resources
[8]			Attention	✓ Focus on important information ✓ Learn long-range dependencies	✓ Increased resource consumption ✓ Generalization issue
[9]	Environmental adaptation	ML-based	Transfer learning	✓ Efficient pre-trained model utilization ✓ Reduced learning time	✓ Risk of domain mismatch ✓ Difficulty in parameter tuning
[10]			Meta-learning	✓ Quick domain adaptation ✓ Improved generalization	✓ Catastrophic forgetting ✓ Difficulty in parameter tuning
[11]			Data augmentation	✓ Increased data diversity ✓ Reduced labeling costs	✓ Physical consistency issue ✓ Domain discrepancy
-			Environmental feature-aware NN	✓ High adaptability ✓ Efficient integration of data	✓ Incorrect feature selection ✓ Require large datasets

TABLE II: Practical guidance and model selection.

Practical guidance	Simple and predictable environment	Complex and non-linear environment	Sequential or time-series data	Require quick adaptation	Lack of sufficient data
Model selection	Model-based methods	MLP, CNN, or Environmental feature-aware NN	RNN or Attention mechanism	Transfer learning or Meta-learning	Data augmentation

Machine Learning for Future Wireless Communications: Channel Prediction Perspectives
Hwanjin Kim, Member,

왜 LWM을 사용해야 할까?

POINT. 01

한정된 데이터로도 좋은 성능

자기지도 학습으로 대규모 데이터 사전학습
기존 CNN/RNN 보다 학습 데이터 의존도 낮음

POINT. 02

노이즈와 불완전한 채널에 대한 강건성

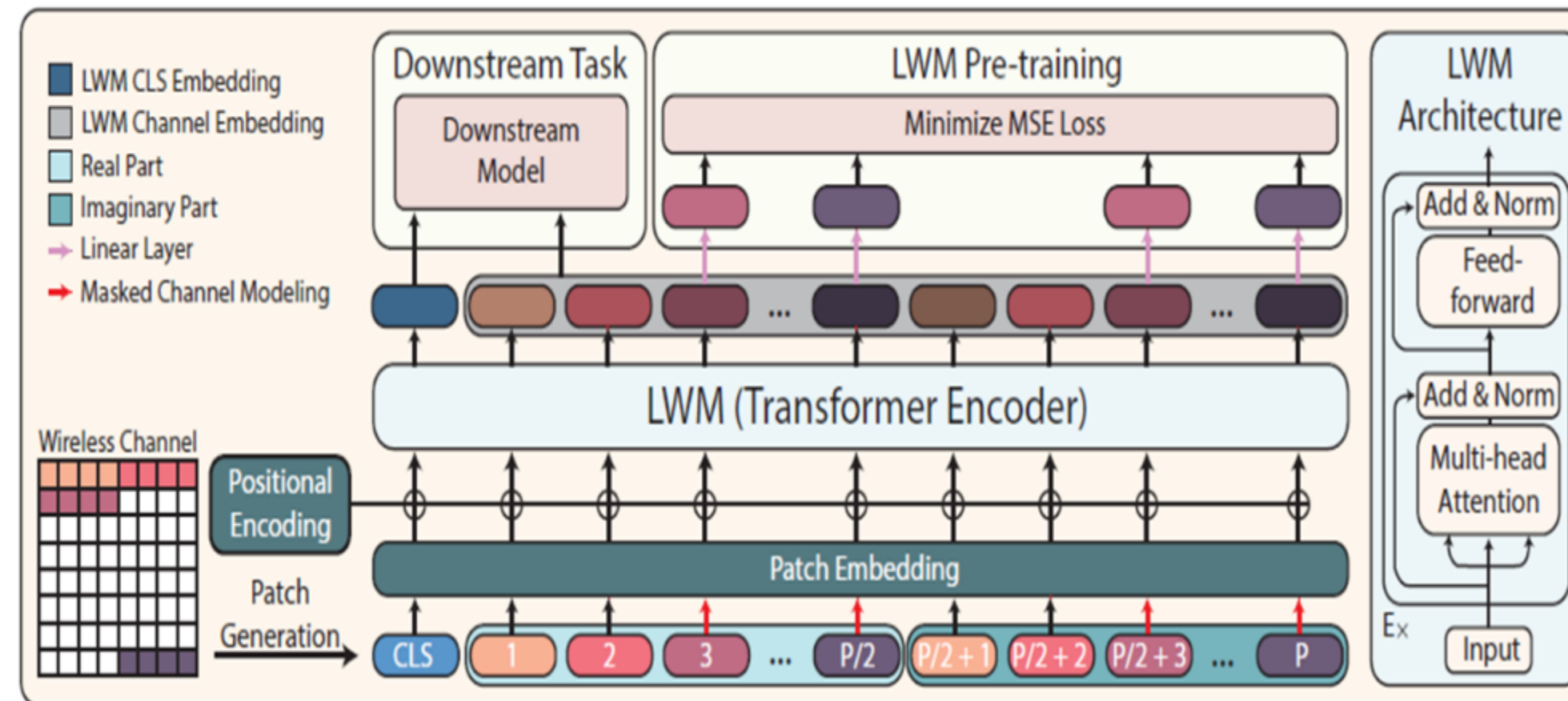
MCM(Masked Channel Modeling)방식으로 학습
자기어텐션을 활용해 주변 패치 정보 바탕으로 복원가능
실제 채널에 노이즈, 손실이 있어도 맥락적으로 정확히 추론

POINT. 03

범용성과 다양한 다운스트림 작업지원

하나의 모델로, 빔 예측, LoS/NLoS 분류 등
다양한 무선 통신 과제 적용 가능
패치 임베딩, CLS 임베딩을 통해 전역/국소 정보 모두 제공

LWM architecture



입력: 무선 채널 데이터를 패치로 분할 후 임베딩 + 위치 인코딩 적용
 Patch Embedding은 허수 패치와 실수 패치로 임베딩한다.
 마스킹된 채널 복원을 통해 MSE Loss 최소화
 다운 스트림 작업에 적용 (빔 예측, LoS/NLoS 등)



앞으로는 DeepMIMO의 동적 시나리오 데이터를 활용하여 빔포밍 정확도를 향상시키고 LoS/NLoS 여부를 고려한 성능 개선을 목표로 할 예정입니다.

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<input type="checkbox"/> O2_dyn_3p5.2.DoD.mat	2025-03-24 오후 6:20	MAT 파일	3,064KB
<input type="checkbox"/> O2_dyn_3p5.2.LoS.BSBS.mat	2025-03-24 오후 6:20	MAT 파일	1KB
<input type="checkbox"/> O2_dyn_3p5.2.LoS.mat	2025-03-24 오후 6:20	MAT 파일	5KB
<input type="checkbox"/> O2_dyn_3p5.2.PL.BSBS.mat	2025-03-24 오후 6:20	MAT 파일	1KB
<input type="checkbox"/> O2_dyn_3p5.2.PL.mat	2025-03-24 오후 6:20	MAT 파일	653KB
<input type="checkbox"/> O2_dyn_3p5.BSBS.params.mat	2025-03-24 오후 6:20	MAT 파일	1KB
<input type="checkbox"/> O2_dyn_3p5.BSBS.RX_Loc.mat	2025-03-24 오후 6:20	MAT 파일	1KB
<input type="checkbox"/> O2_dyn_3p5.BSBS.TX_Loc.mat	2025-03-24 오후 6:20	MAT 파일	1KB

기차 통신을 위해 추가적으로 고려할 사항

POINT. 01

고속 이동 중 무선 통신 예측 어려움

고속열차와 같은 빠른 이동 시나리오에서의
무선 통신 품질 예측이 어려워,
핸드오버 실패나 통신 끊김 등의 문제가 발생할 수 있음

POINT. 02

기차 내 와이파이 VS 모바일 데이터 사용 고려

사용자가 기차 내에서 와이파이를 사용할지, 혹은
모바일 데이터를 사용할지를 고려하여
최적의 연결 방식 설계가 필요함

POINT. 03

터널 구간에서의 통신 품질 저하

터널 내부에서는 인터넷 연결이 끊기거나 지연되는 문제가
자주 발생하므로, 이에 대한 대응 기술 및 백업
연결 방안이 요구됨

감사합니다.