

# **Multi-Conditioned Generative Channel Modeling: A Diffusion-Based Approach for Environment, State, and Hardware-Aware Wireless Dataset Synthesis**

## **The Imperative for High-Fidelity Synthetic Channel Data**

The design and optimization of next-generation wireless communication systems, including 5G-Advanced and the forthcoming 6G, are increasingly dependent on sophisticated machine learning (ML) and artificial intelligence (AI) methodologies. These data-driven techniques are being applied across the protocol stack, from physical layer tasks like channel estimation and beamforming to network-level challenges such as resource allocation and interference management.<sup>1</sup> However, the efficacy of these ML models is fundamentally constrained by the availability of large, diverse, and realistic datasets. This has created a significant bottleneck in the field, as the primary method for acquiring such data—extensive real-world field measurements—is exceptionally resource-intensive, demanding significant investments in time, cost, and specialized equipment.<sup>2</sup> The challenge of data scarcity represents a fundamental barrier to the rapid prototyping, validation, and deployment of AI-enabled wireless technologies.

## **The Data Scarcity Bottleneck in Wireless ML**

The physical wireless channel is a complex, high-dimensional, and stochastic medium. Its characteristics are determined by a multitude of factors, including the physical geometry of the environment, the materials of surrounding objects, the mobility of transmitters and receivers, and atmospheric conditions. Accurately capturing this complexity in a dataset requires comprehensive measurement campaigns across a wide range of scenarios. For tasks such as massive Multiple-Input Multiple-Output (MIMO) beamforming or millimeter-wave (mmWave) channel estimation, the required datasets must contain thousands or millions of

channel state information (CSI) instances to train deep neural networks effectively. The process of collecting this data is not only expensive but also difficult to scale and replicate, hindering the progress of ML-driven wireless research and creating a high barrier to entry for academic and industrial researchers alike. This data-centric challenge necessitates a paradigm shift away from sole reliance on physical measurements towards scalable and cost-effective data synthesis solutions.

## **Generative AI as a Paradigm Shift for Data Synthesis**

Generative Artificial Intelligence (GAI) has emerged as a transformative solution to the data scarcity problem in wireless communications and numerous other fields. GAI models are designed to learn the underlying probability distribution of a given dataset and can subsequently generate new, synthetic data samples that exhibit the same statistical properties as the original data. This capability allows researchers to augment limited real-world datasets, creating vast repositories of high-fidelity synthetic data for training and testing ML algorithms.

The application of generative models to wireless channel modeling has evolved significantly over the past several years. Initial explorations leveraged architectures such as Variational Autoencoders (VAEs) and Generative Adversarial Networks (GANs).<sup>3</sup> More recently, the field has been dominated by the rise of Diffusion Models (DMs), which have established a new state-of-the-art in generating high-quality, high-dimensional data.<sup>5</sup> Their application to wireless communications is particularly promising due to their superior sample fidelity and stable training dynamics. The baseline for this work, the Conditional Denoising Diffusion Implicit Model (cDDIM), has already demonstrated the power of conditioning a diffusion model on continuous geometric coordinates to generate location-specific channel data.

## **The Unaddressed Frontier: Beyond Geometry to Holistic Awareness**

While state-of-the-art models like cDDIM can generate channels conditioned on a user's location, this represents only one piece of the puzzle. The physical channel is a function of much more than just geometry. Two users at nearly identical coordinates can experience vastly different channels if one has a clear Line-of-Sight (LoS) path to the base station while the other is in Non-Line-of-Sight (NLoS). Furthermore, the structure of the channel matrix itself is fundamentally dependent on the hardware used, such as the number of antennas and their physical arrangement.

A truly general and powerful generative model should not be tied to a single environmental state or a fixed hardware configuration. It should learn a holistic, multi-faceted mapping that accounts for the physical environment, the propagation state, and the system hardware. This would transform the model from a location-specific simulator into a versatile, hardware-in-the-loop digital twin, capable of answering complex "what-if" questions about

system deployment and performance.

## **Proposed Framework: Environment, State, and Hardware-Conditioned Diffusion Models (ESH-cDDIM)**

The proposed research introduces the Environment, State, and Hardware-Conditioned Diffusion Model (ESH-cDDIM), a novel framework that extends the state-of-the-art by incorporating a richer, multi-modal conditioning vector. This transforms the generative model into a highly versatile tool that is aware of not only user location but also critical propagation states and physical hardware parameters.

### **Problem Formulation: From Geometric to Multi-Modal Conditioning**

The baseline cDDIM model learns the conditional distribution  $P(H | c_{geo})$ , where  $H$  is the channel matrix and  $c_{geo}$  is a vector of the user's 3D coordinates. While powerful, this formulation implicitly averages over all other environmental and hardware factors.

The proposed ESH-cDDIM framework reformulates this problem by learning a much richer conditional distribution:  $P(H | c_{esh})$ . The new conditioning vector,  $c_{esh}$ , is a mixed-type vector containing not just geometric data, but also discrete state information and continuous hardware parameters. A representative example of this vector would be:

$c_{esh} =$

This expanded vector allows the model to learn a more fundamental and disentangled representation of the wireless channel, making it sensitive to sharp changes in propagation conditions (like an LoS-to-NLoS transition) and adaptable to different hardware setups.

### **Dataset: Parameterized Generation with DeepMIMO**

The success of this project hinges on a dataset that is both physically realistic and highly configurable. The DeepMIMO dataset is perfectly suited for this task because it is designed to be "generic and parameterized". The DeepMIMO generation framework allows researchers to adjust a wide range of system and channel parameters, including the number of antennas and inter-antenna spacing, to create custom datasets.

For this project, we will use the DeepMIMO 'O1' outdoor scenario.<sup>7</sup> Crucially, we will not just use a pre-existing dataset. Instead, we will leverage the DeepMIMO generator to create a new, diverse training set by systematically varying key hardware parameters. Furthermore, the LoS/NLoS status for each link can be readily determined from the underlying ray-tracing data, as this is a standard feature of the DeepMIMO scenarios.

Our data generation process will involve:

1. **Varying Hardware Parameters:** Running the DeepMIMO generator multiple times to create channel matrices for a range of base station antenna configurations (e.g., different numbers of antennas and element spacings).
2. **Extracting State Information:** For each generated channel, parsing the ray-tracing output to determine the LoS/NLoS flag.
3. **Constructing Training Pairs:** Assembling the final training samples, where each sample consists of the channel matrix  $H$  and its corresponding comprehensive conditioning vector  $c_{esh}$ .

## Model Adaptation: Engineering the ESH-cDDIM

The architectural modification to the cDDIM baseline is targeted and feasible within the project timeframe. The baseline model uses a Multi-Layer Perceptron (MLP) to process the continuous coordinate vector. We will adapt this conditioning module to accept our new, longer, mixed-type vector  $c_{esh}$ . This is a standard machine learning task that involves expanding the input layer of the MLP to accommodate the additional features. The MLP will learn the complex, non-linear mapping from this rich set of environmental, state, and hardware parameters to the appropriate conditional guidance for the diffusion model's denoising process.

## Positioning the Contribution

The ESH-cDDIM framework represents a significant and pragmatic advancement over existing methods. It creates a generative model with an unprecedented level of versatility and realism.

**Table 1: Comparison of Conditional Generative Channel Models**

Model	Generative Core	Conditioning Information	Generalizability	Key Limitation
ChannelGAN <sup>8</sup>	GAN	Implicit (Learned from data distribution)	Low (to seen scenarios)	Training instability; no explicit control.
cDDIM (Baseline)	Diffusion Model	Geometric Vector (e.g., $(x,y,z)$ )	Moderate (to new locations)	Unaware of propagation state (LoS/NLoS) or hardware configuration.
<b>ESH-cDDIM (Proposed)</b>	Diffusion Model	<b>Mixed-Type Vector (location, state, hardware)</b>	<b>Very High (to new locations, states, and hardware)</b>	<b>Fidelity depends on the diversity of training configurations.</b>

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## A Two-Week Plan for Prototyping and Evaluation

This project is broken into three phases to ensure completion within the two-week competition timeframe.

### Week 1: Data Curation and Model Re-engineering (Days 1-7)

The first week is dedicated to generating a rich, multi-modal dataset and implementing the necessary model modifications.

- **Day 1-2: Environment Setup & Data Acquisition:**
  - Establish a Conda environment using the environment.yml file from the cDDIM repository to ensure all dependencies are met.<sup>9</sup>
  - Download the raw DeepMIMO 'O1' scenario ray-tracing data.<sup>10</sup>
- **Day 3-5: Multi-Modal Dataset Generation:**
  - Develop a data generation pipeline that wraps the DeepMIMO MATLAB generator. This pipeline will be scripted to iterate through a predefined set of hardware parameters (e.g., number of antennas  $N$ , antenna spacings  $[0.5\lambda, 0.7\lambda]$ ).
  - For each configuration, the script will generate the corresponding channel matrices.
  - A Python script using `scipy.io.loadmat` will then parse the generated .mat files. This script will extract the channel matrix  $H$ , the user coordinates  $(x,y,z)$ , and the LoS/NLoS flag for each BS-user link.
  - The script will assemble and save the final training pairs  $(H, \text{cesh})$ , where `cesh` is the concatenated vector of normalized coordinates, the LoS flag, and the hardware parameters used for that generation run.
  - A validation set consisting of a contiguous block of user locations will be held out to test spatial generalization.
- **Day 6-7: Model Implementation (ESH-cDDIM):**
  - Fork the cDDIM repository.<sup>9</sup>
  - Modify the conditioning MLP in the model architecture to accept the new, longer `cesh` vector as input.
  - Implement a custom PyTorch Dataset and DataLoader to handle the new multi-modal data format.

### Week 2: Training, Inference, and Analysis (Days 8-14)

The second week focuses on training the model and performing a comprehensive,

multi-faceted evaluation.

- **Day 8-11: Model Training:**
  - Initiate the training of the ESH-cDDIM model on a high-performance GPU.
  - Monitor the training loss to ensure stable convergence. The primary goal is to train for a sufficient number of epochs to learn the complex mapping from the multi-modal condition vector to the channel distribution.
- **Day 12-13: Generation and Multi-Faceted Evaluation:**
  - **Spatial Generalization Test:** Use the trained model to generate channels for the held-out validation locations, using hardware parameters that were included in the training set.
  - **State-Awareness Test:** Select user locations at the boundary of LoS/NLoS regions. Generate channels for both conditions by flipping the LoS\_flag in the conditioning vector and visualize the difference in channel characteristics (e.g., power delay profile) to confirm the model has learned this discrete state.
  - **Hardware-Awareness Test:** Provide the model with the coordinates of a single user and request channel generations for different hardware configurations (e.g., 16, 32, and 64 antennas). Analyze the resulting channel matrices to confirm their properties (e.g., rank, singular value distribution) change in physically meaningful ways.
  - **Quantitative Evaluation:** Compare the statistical properties of generated channels against the ground-truth channels using metrics like the **2-Wasserstein distance** and **Maximum Mean Discrepancy (MMD)**.<sup>2</sup>
- **Day 14: Finalization:**
  - Compile all results, tables, and figures into a coherent research paper.
  - Clean, comment, and organize the codebase, adding a README.md to ensure reproducibility for submission.

## Anticipated Contributions and Future Directions

This research introduces a highly versatile and generalizable framework for generative channel modeling, creating a path toward powerful new tools for wireless system design.

### Primary Contribution: A Hardware-in-the-Loop Digital Twin

The core contribution is a generative model that functions as a comprehensive digital twin of a wireless environment. It is capable of generating high-fidelity, site-specific channels conditioned not only on **location** but also on the **propagation state (LoS/NLoS)** and key **hardware parameters** (antenna configuration). This moves far beyond simple data augmentation, creating a tool that can be used for:

- **Virtual Site Surveys:** Predicting coverage and performance for different hardware

deployments in a specific environment without physical measurements.

- **Hardware Co-Design:** Virtually exploring the impact of different antenna array designs on channel characteristics and downstream performance.
- **Data-Driven Network Planning:** Generating realistic, multi-faceted datasets for training and validating next-generation network optimization algorithms.

## Future Work

The ESH-cDDIM framework serves as a strong foundation for numerous future research directions.

- **Richer Conditioning:** The conditioning vector can be further enriched with other parameters available in DeepMIMO, such as antenna orientations, building materials, or even dynamic elements like the presence of vehicles.
- **Application to Emerging Technologies:** The scarcity of high-quality channel data is even more acute for emerging technologies. This framework could be adapted to generate channel datasets for systems like Reconfigurable Intelligent Surfaces (RIS) and Terahertz (THz) communications.
- **Inference Acceleration:** A well-known limitation of diffusion models is their iterative sampling process.<sup>11</sup> Future work could integrate faster sampling techniques to make the digital twin suitable for real-time applications.
- **Transformer-based Architectures:** Recent research has shown the potential of Transformer architectures for wireless tasks due to their ability to capture long-range dependencies.<sup>12</sup> Replacing the U-Net backbone of the ESH-cDDIM with a Transformer could improve the model's ability to learn complex spatial and parametric correlations, leading to even more accurate and globally consistent channel generation.

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