

HB9VQQ V0.4 – October 2025

Development of an AI Model for Predicting Long-Distance HF Radio Skywave Propagation

Table of Contents

[HB9VQQ V0.4 – October 2025](#)

[Project Goal](#)

[Background](#)

[Key Factors Influencing Skywave Long-Distance Communications on the 20-Meter Band](#)

[Project Objectives](#)

[Scope of Work \(Expert Responsibilities May Include\)](#)

[Deliverables](#)

[Target Outcome](#)

[Expertise Required](#)

[Proof of Concept \(PoC\): Single Path Prediction \(K3WRG – EA8BFK on 20m\)](#)

[Unique Aspects of This Approach and Benefits of a Data-Driven AI Model](#)

[Similar Efforts and Concepts](#)

[Why More Training Data Hurts HF Propagation Models](#)

[Current State of Work](#)

[References](#)

Project Title

AI-Driven Prediction of 20-Meter Band Long-Distance HF Radio Skywave Propagation

Project Goal

To develop a robust and accurate AI model capable of predicting the likelihood and/or signal strength of HF radio skywave communication on the 20-meter amateur radio band (approximately 14 MHz) over a minimum distance of 3000 kilometers, leveraging historical WSPR (Weak Signal Propagation Reporter) data and historical solar space weather data. A key goal is to integrate this AI model into a user-friendly web application that allows amateur radio operators to input their transmitting and receiving station details and obtain predicted signal-to-noise ratio (SNR) values over time for that path.

Background

The 20-meter band is essential for long-distance HF amateur radio communication, primarily relying on skywave propagation via the ionospheric F2 layer. This layer's ionization, influenced by solar activity and geomagnetic conditions, directly impacts propagation quality. Predicting such

propagation is valuable but complex — this project seeks to make it practical for operators through a data-driven AI model integrated into a web application.

Key Factors Influencing Skywave Long-Distance Communications on the 20-Meter Band

- Solar Activity: Measured by Solar Flux Index (SFI) and Sunspot Number.
- Ionospheric Conditions (F2 Layer): Key parameters include foF2 and MUF.
- Geomagnetic Activity: Represented by Kp and Ap indices.
- Time of Day & Season: Solar illumination patterns affect ionization.
- Path Characteristics: Distance, geometry, and geomagnetic latitude influence outcomes; multihop effects are significant for >3000 km.

Project Objectives

- Targeted Data Integration: Merge historical 20m WSPR data with solar and geomagnetic indices.
- Feature Engineering: Develop propagation-relevant features (e.g., SFI, Kp, UTC time, seasonal markers).
- AI Model Development: Train regression models to predict received SNR for >3000 km paths.
- Web Application: Build a web tool allowing operators to enter station data and view predictions.
- Integration & Deployment: Combine the trained model with the web backend for real-time use.
- Evaluation: Measure performance using RMSE and correlation metrics on test data.
- Implicit Multihop Handling: Utilize real-world WSPR data to capture these effects naturally.

Scope of Work (Expert Responsibilities May Include)

- Data acquisition from WSPRnet, wspr.live, and solar indices sources.
- Feature engineering, data cleaning, and normalization in Python.
- Model design, hyperparameter tuning, and validation (scikit-learn, TensorFlow, or PyTorch).
- Backend logic for prediction requests and model integration (Flask or Django).
- Web interface development (HTML, CSS, JavaScript, or a frontend framework).
- Application testing, documentation, and deployment.

Deliverables

- Fully documented AI model (Python code + methodology).
- Operational web application providing point-to-point 20m propagation predictions.
- Technical report detailing data sources, feature engineering, model architecture, and deployment.
- Recommendations for enhancements and retraining strategies.

Target Outcome

A web-based platform providing personalized long-distance 20m propagation forecasts, allowing operators to plan optimal contact times based on predicted SNR over time.

Expertise Required

- Deep understanding of HF propagation and ionospheric science.
- Proficiency in Python (NumPy, Pandas, scikit-learn, TensorFlow, PyTorch).
- Experience with web development and API integration.
- Knowledge of WSPR datasets and space weather data access.
- Strong analytical, programming, and RF modeling skills.

Proof of Concept (PoC): Single Path Prediction (K3WRG – EA8BFK on 20m)

Goal: Validate feasibility by predicting SNR between K3WRG (FN20, USA) and EA8BFK (IL38, Canary Island, Spain). Steps include acquiring historical WSPR data, merging it with solar indices, feature engineering, model training, and evaluation. Deliverables will include a Python PoC script and a summary report with visualization of predicted vs actual SNR.

Unique Aspects of This Approach and Benefits of a Data-Driven AI Model

- Personalized predictions for specific paths.
- Data-driven learning from real WSPR observations.
- Higher responsiveness to short-term space weather variations.
- Integration of user parameters (antenna gain, transmit power).
- Focus on 20m for optimized feature modeling and accuracy.

Similar Efforts and Concepts

- Physics-based models: VOACAP, PROPLAB Pro.
- Data-driven studies: Prior research on AI-based propagation prediction.
- Web-based tools: Existing regional HF forecast sites.
- Commercial services: Proprietary models offering generalized forecasts.

Why More Training Data Hurts HF Propagation Models

<https://claude.ai/public/artifacts/6edf88e7-2aed-4668-9cd2-1f255fdbea76>

Current State of Work

<https://claude.ai/public/artifacts/aeb85c41-f8aa-47ba-8ccc-61004d6277b9>

References

- WSPRnet Database: <https://wsprnet.org/>
- WSPRdaemon API / wspr.live: <https://wspr.live/#database-fields>
- GFZ-Potsdam Kp & SFI Indices: <https://kp.gfz-potsdam.de/en/data#c42>
- NOAA SWPC: <https://www.swpc.noaa.gov>