SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V13I11P118

Volume 13 Issue 11, 300-315, November 2026
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Original Article

Probabilistic Time Series Prediction of Wireless Signal Strength using Bayesian Neural Networks

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Received: 30 June 2026 Revised: 31 October 2026 Accepted: 05 November 2026 Published: 27 November 2026

Abstract - *Estimating the quality of the communication channel involves a process to determine the characteristics of efficient and reliable communication between the transmitter and receiver. For RSSI prediction, machine learning techniques including Random Forests, Decision Trees, and Gaussian Process models can also be used; the latter may provide the highest accuracy. This research involves modeling the wireless signal strength using a supervised learning technique that trains a regression model on time series wireless channel strength derived from various network and communication standards for predicting the wireless channel strength. For time series analysis, Bayesian Neural Networks (BNNs) have a number of benefits, especially where uncertainty and data scarcity are issues. BNNs are probabilistic neural networks that consider weights and biases as probability distributions, and they are able of modeling complex, nonlinear relationships between variables. In wireless networks, an efficient prediction of the channel quality is essential to improve the throughput of the network by reducing packet drops, increasing the overall lifetime of the network, reduced transmission link expiry and improved reliability. The predicted wireless signal strength shall enable selection of an optimal transmission channel from a set of available channels to be used for transmission of the data packets.*

Keywords - *Channel quality, Received Signal Strength Indicator, Wireless signal strength, Wireless Sensor Networks, Bayesian Neural Networks.*

1. Introduction

In the domain of wireless communications and networking research, modelling and precise forecasting of wireless channel quality such as received signal strength has gained momentum. The potency of the wireless channel is expressed in dBM and it is a vital component in understanding the performance of the wireless network. A reliable transmission can be achieved when the strength of the wireless network is close to -30 dBm, and a weak channel with a channel strength of -90 dBm can cause various connectivity problems. RSSI - Received Signal Strength Indicator represents the potential level of the received signal [1].

RSSI is useful for figuring out how close a device is to a signal source, but it does not give specific details about the signal's quality. Wireless signal strength is a determination of the received signal's power, although it is not a direct pointer of the wireless channel's overall quality. The physical properties of the wireless medium, interference, noise, and signal strength are some of the variables that affect wireless channel quality. Even when a signal strength is high, it may be vulnerable to interference, which could result in poor channel quality [2]. When the radio energy within the channel falls under a specific threshold, a wireless networking device can use RSSI internally to determine when it is safe to transmit (CTS). An information packet can be issued as soon as the card is approved for transmission. The parameters that represent the physical characteristics of the network have no standardised relationship with the RSSI measurement. Wireless communication protocols like Bluetooth and ZigBee frequently employ RSSI to calculate the distance between nodes [3]. This estimation is crucial for indoor localisation and is frequently chosen since it is straightforward and does not require timestamping or synchronisation, which are necessary for other approaches like Time of Arrival (TOA) [4].

RSSI is used in majority of localization techniques, such as anchor-based systems. Anchor-based algorithms determine the position of an unknown node with the help of nodes with known positions, so-called anchors. These methods estimate the distance among the known and unknown nodes by using the Time of Arrival (TOA) and Angle of Arrival (AOA) of the signal, and their precision is improved by using extensive known nodes. Signal interference, obstructions and the number of nodes in the vicinity are all factors that can influence the accuracy of these algorithms, however. The RSSI value of the wireless device was calibrated to provide a relative measure of signal strength. The RSSI measurements


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may not be directly comparable between devices, as different hardware vendors might calibrate differently. The signal quality estimation is based on calibrated RSSI value using a mapping function [5]. This mapping may be vendor-specific or standardized, depending on wireless technology in use. The mapping function transforms the RSSI value into a useful statistic, like a signal strength indicator. WLAN systems typically set criteria for signal quality levels to group signals into different categories. These cutoff points are a way to test the reliability and usability of the wireless connection. The RSSI signal strength is based on the attenuation properties of wireless signals during propagation [6]. As wireless signals travel further, they encounter more obstructions and multipath effects, which degrade the signals. The robustness of the incoming signal is estimated to indirectly determine the distance and the relative position relationship between the signal source and the receiving site. Information from RSSIs is significant in the construction and optimization of wireless transmission networks [7]. RSSI is an important metric for assessing signal quality, but it has drawbacks. RSSI by itself does not consider other aspects like noise, interference, and packet errors, so it does not represent the complete characteristics of the wireless link quality. For a more precise evaluation of signal quality in WLAN networks, RSSI is sometimes combined with other metrics or error rates observed in the physical layer [8]. There are certain critical factors (dynamic changes in the channel, interference, faults in the transceiver) that impact signal quality. Developing an analytical model that takes all these parameters into account cannot be adopted in a real-time scenario owing to highly dynamic characteristics of transmission channels.

Devices in wireless transmission networks must share scarce spectrum resources. The network system can select the optimal channel for transmission to prevent co-channel interference and channel congestion with the aid of RSSI signal strength. In contrast, a channel with a low RSSI value is comparatively idle and appropriate for data transmission; a high RSSI value suggests that the signal strength on that channel is significant and that there may be interference or congestion. The system can dynamically change the channel allocation methods by monitoring the variations of the RSSI signal intensity, so as to achieve a smooth and efficient data transmission. The complex and diverse network architecture poses a great challenge for the management and maintenance of large-scale wireless transmission networks. The RSSI can be a useful tool in troubleshooting and optimizing the network topology. A network topology graph to find bottlenecks and failure points in the network can be created by comparing the RSSI values for different nodes. For example, a very low RSSI value of a node can indicate a problem or a bad quality of the connection between the node and its neighbors. The trend and pattern of changes in RSSI values can be further analyzed to locate the exact source of the problem and take corrective measures to restore and optimize it.

The transmit power is one of the main factors affecting the coverage range and the distance of signal transmission in wireless transmission. In addition to increasing wireless transmission's energy efficiency ratio, this dynamic power control technology can lower running expenses and prolong the device's lifespan. Also, for precise positioning and location tracking in wireless transmission networks, RSSI signal strength can be paired with other positioning technologies. In this paper, time series prediction of RSSI values has been experimented with using a Bayesian technique [9], since the real-time data was noisy or ambiguous. This makes it possible to forecast future RSSI values with increased accuracy when compared to conventional techniques, particularly in complex or dynamic contexts.

1.1. Study Motivation and Contribution

The recent advancement of wireless networks has created the necessity for precise and effective prediction of wireless channel quality in dynamic settings. RSSI is mainly applied for channel selection, link management, network optimization, and localization. Moreover, they are highly impacted by unwanted interference, noise, obstructions, multipath propagation, and other environmental conditions. Hence, immediate RSSI measurements cannot effectively indicate future channel conditions. Traditional prediction approaches have major challenges in exhibiting the nonlinear and uncertain temporal variations of RSSI. To overcome these limitations, this study presented a Bayesian Neural Network (BNN)-based approach for accurate prediction of wireless channel strength from historical RSSI data. This approach learns nonlinear temporal patterns and prediction uncertainty, thereby allowing proactive channel selection for consistent and effective wireless communication. The major contributions are as follows:

- Design a supervised learning framework to model and predict wireless channel strength employing historical RSSI measurements. The structure helps integrate data from different wireless communication and networking systems.
- Integrate a Bayesian Neural Network (BNN) to capture intricate and non-linear relations in RSSI data. The probabilistic method also accounts for uncertainty and noise in wireless measurements.
- Utilize predicted RSSI values to classify suitable transmission channels. This helps reduce interference and congestion whereas supporting consistent packet transmission.
- Precise RSSI prediction helps minimized packet drops, link failures, and retransmissions. It also enhances throughput, reliability, and efficient use of network resources.
- Evaluate the proposed framework using numerous performance metrics on time-series RSSI data. Compare its performance with traditional regression and prediction methods.

2. Related Work

The wireless channel quality is decided by the following design parameters: link layer, technology used in the physical layer, and physical characteristics of the channel. Thus, the wireless channel quality is strongly influenced by a series of network layers and operations being performed in each layer. In most of the literature, a reliable and efficient transmission of data packets is ensured by the [11] Link Quality Estimation (LQE) approach using the various parameters of the radio link. Using LQE, an optimal channel for transmission or more reliable channel for re-transmission of data packets can be selected. The application of machine learning methodologies in LQE has promise for greatly enhancing wireless network performance. These ML-based predictions are more resilient, flexible, and agile. Additionally, ML approaches could be used to gain a higher level and more general understanding of wireless networks [10]. More specifically, an autonomous and intelligent system for evaluating wireless networks of any standard or transceiver can help improve the way increasingly diverse networks operate today. Application of ML techniques enables creation of efficient, reliable and resilient networks with less human intervention. Various encoding/ decoding techniques, error correction codes, and radio propagation techniques have been used, and they depend on the link quality indicators estimated based on the network parameters. ML models depend on measured data parameters which reflect the characteristics of the network in different scenarios.

When the proportional distance among the sending and receiving devices changes, the respective RSSI value will also change [12], however, their values are influenced by other factors. RSS is associated with the Signal-to-Interference-Plus-Noise Ratio (SINR) [13], which consists of noise from other nodes. Consequently, on actual WiFi networks in a variety of settings, RSSI values show significant spatial and temporal diversity. In theory, if the moving device receives low RSSI values, it means that it is far away from the emitting device. This indicates that it most likely has a brief window of time to leave the service region. This indicates that the ability to predict RSSI values is very helpful in preventing WiFi device communication errors. Because of this, it is crucial to accurately forecast future RSSI values while accounting for recent historical received values. In general, RSSI prediction can be applied to a variety of other domains, such as device localisation mechanisms [15], estimation of distance between sender and receiver [14], adaptive transmission of power and data [16], estimation of wireless link quality [17], terminal connectivity indication to Access Points (AP), and when the link is predicted to degrade [18].

The work presented in [19] proposed a predictor for applications, which must predict RSSI values hundreds of milliseconds ahead of time. Its geographic independence is an advantage. A regression model using smoothed recent historical RSSI values serves as the foundation for the approach. By fitting an 8-degree polynomial over a window of N raw RSSI data, the work in [20] predicts the subsequent RSSI value by merely comparing that polynomial with the most recent raw RSSI sample. The aforementioned tasks do not take into account the difficulty of real-world wireless connections, the variety of devices available on the market, methods for determining RSSI, or the intricacy of Wireless Network Interface Card (WNIC) drivers.

Wireless signal strength time series prediction is a significant research area in wireless connections to improve network reliability, optimize resource allocation and facilitate adaptive protocols. In [24], a notable paper developed DL technique for predicting signal strength. In [25], the authors propose a method based on 3D map and DL for predicting spatial signal strength in urban environments. Their approach does not require knowledge of transmitter locations or side-channel information and is applicable to various applications, including UAV placement optimization and dynamic spectrum access networks.

In [26], a detailed survey was proposed to compare the machine learning techniques for RSSI prediction. They pointed out the challenges of the stochastic nature of wireless signals and emphasized the need of choosing proper models according to specific network scenarios. In [27], AI-driven channel prediction in Device-to-Device (D2D) links was presented, and deep learning models like LSTMs and GRUs were evaluated. The results show that GRUs and LSTM are better at capturing the temporal dependencies than other models, especially when the dependencies are within the coherence time of the channel.

The work in [28] studied real-world enormous MIMO channel prediction by integrating DL with Neural Prophet, a time series model with statistical components. Their hybrid framework was shown to have a higher prediction accuracy and robustness in dynamic environments. [29] Classical statistical models like ARIMA are used for time series forecasting in wireless sensor networks. However, recent studies show that machine learning techniques can improve the accuracy of predictions, especially in complex and non-linear scenarios.

Murugan et al. [30] proposed a wavelet-based time series forecasting method for WSNs, which can effectively capture temporal dynamics. This approach allows data compression, with reduced data storage and transmission bandwidth requirements. The proposed system an exponential smoothing approach for improving the reliability of predicting sensor data, thus making it a useful tool for time series examination in WSNs. In the area of wearable wireless sensor systems, [31] proposed a new SCNN-LSTM model to predict the confidence interval of SNR. This model solves the problems of real-time data transmission, energy management and data integrity, which are relevant for applications such as medical monitoring and sports training.

Wright et al. [32] propose Bayesian techniques for enhancing communication variables to attain optimal network characteristics. This framework highlights the complication and computational demands of conventional network imitations. Shivakumar et al. [33] present an innovative architecture, which leverages GNN for online learning to execute outlier identification. GNNs are utilized to capture the complex features among sensors and to classify irregularities.

These studies collectively highlight the trend of adopting advanced computational techniques to develop the prediction of wireless signal strength, in response to the emerging needs of wireless communication systems. For linear time series, the ARIMA model performs well; unfortunately, it is incapable of processing nonlinear time series. BNNs were initially proposed in [21] and have since been expanded upon by several authors. This work uses the Monte Carlo approach for BNN training and applies BNN to time series analysis. Additionally, rather than using hidden units as other authors have done, a prior on network connections has been employed for the selection of BNN models. This enables us to handle the input variable selection and hidden unit selection consistently. The model is contrasted with other rivals, such as Bayesian ARIMA and Bayesian Dynamic Linear Model. In order to create a posterior probability distribution, Bayesian procedures begin with an assumption about the patterns in the data (prior probability), gather evidence (such as additional time series data), and then update that assumption over time. For modeling time series data, traditional Bayesian techniques such as Gaussian Processes (GPs) and structural time series are often utilized. A neural network having a probability distribution across weights, as opposed to a predetermined collection of weights, is known as BNN. This captures the uncertainty in the forecasts by causing a distribution over outputs. Advantages of BNNs over GPs are that classical training procedures scale with the cube of the data points counts in the time series, and training large Gaussian Processes (GPs) is computationally expensive.

Bayesian Neural Networks (BNNs) are advantageous as they can model intricate, non-linear relationships and quantify uncertainty in predictions and are very useful in time series prediction of wireless signal strength. In wireless systems such as WiFi and Wireless Sensor Networks (WSNs), signal strength measurements such as RSSI are often affected by a variety of unpredictable factors, including environmental changes, interference and mobility. BNNs overcome these issues by embedding probability distributions within the model parameters, enabling them to produce not only predictions, but also credible intervals that reflect the model's uncertainty and the noise in the data. This is especially useful in applications that require robust and risk-aware decision-making, such as handoff management, energy-efficient routing or signal coverage optimization. In addition, BNNs are regularized by priors, which reduce overfitting on noisy or sparse data, common in real-world wireless networks. They have the capacity to capture heterogeneous data sources and make them well suited to form the complex temporal dynamics characteristic of wireless signal behavior.

3. Bayesian Neural Network Architecture

Deep neural networks can have extensive model parameters; they are referred to as powerful function approximators. Gradient-based optimization can be used to learn parameter values from data. Neural networks' great adaptability has a drawback: they are especially susceptible to overfitting. The conventional neural network learns to map input-output ($y \approx f(x, w)$) using a network f with weights w. For model training, a dataset of samples with respective labels $D = (x_i, y_i)$ with the objective of minimizing the objective function represented as $L(D, w)$. This is equivalent to maximize the log probability of the dataset D and w.

$$L(D, w) := \sum_{x_i, y_i \in D} (y_i - f(x_i, w))^2 + \lambda \sum_d w_d^2 \quad (1)$$

$$\log p(D, w) := \sum_{x_i, y_i \in D} \log N(\,(y_i | f(x_i, w), l^2) + \sum_d \log N(w_d | 0, \frac{1}{\sqrt{\lambda}}) \quad (2)$$

Where $log\ p(D, w)$ represents the log-likelihood of the data samples for the model, first part of the right-hand side represents the log-probability of the output variable, which follows a normal distribution with mean represented by the output of the network and variance 1, the second part is the prior belief about weights, given by log-probability of weights following a gaussian distribution with zero mean and variance controlled by hyperparameters 1.

The system comprises an input stage corresponding to the RSSI feature space, after those multiple hidden layers with Bayesian inference utilized to the biases and weights. Instead of deterministic parameters, the network learns probabilistic weight distributions by variational inference, allowing uncertainty-aware predictions. Every hidden layer is configured with nonlinear activation functions to acquire complex temporal and spatial dependencies in the input signals. The output layer produces a probabilistic prediction reflecting both the mean estimate and associated uncertainty. Training is performed under optimizing the Evidence Lower Bound (ELBO), balancing data likelihood and prior regularization, which enhances robustness under noisy and dynamic wireless environments.

The model is trained on set of samples represented as D_{train} and the model is validated using the set D_{test}. The objective function for the train and test sets is represented as follows $log\ p(D_{train})$ and $log\ p(D_{\text{test}})$. Overfitting is a state where the performance of the model for the weights w is good

for log p(Dtrain) and poor for log p(Dtest). When more layers are added, the problem of overfitting gets worse. Bayesian neural network overcomes the problem of overfitting by modeling the weights' uncertainty.

As per the following mathematical expression of bayes rule, the posterior is computed as;

$$p(w|D) = \frac{p(D|w)p(w)}{p(D)} = \frac{p(D \mid \mathrm{w})p(\mathrm{w})}{\int_{\mathrm{w}'} p(D \mid \mathrm{w}')p(\mathrm{w}')\, d\mathrm{w}'} \quad (3)$$

Estimated posterior will be used to generate probabilistic predictions by representing a distribution over predicted output *y'* as a function of input *x*.

$$p(\hat{y}(x)|D) = \int_{\mathrm{w}} p(\hat{y}(x)|w)p(w|D)dw = E_p(w|D)[p(\hat{y}(x)|w)] \quad (4)$$

This distribution can be expressed as the network's likelihood under posterior $p(w|D)$. The predictive distribution can be interpreted as an infinite ensemble of networks, with the posterior likelihood of each weight of network that given the training data weighting its contribution to the overall prediction. Using a single network with weights w randomly selected from the posterior is comparable to approximating the predictive distribution using just one Monte Carlo sample.

One advantage of defining distributions over the parameters of the model and predictions is that their variance may be estimated, allowing the model's uncertainty to be calculated. When learning from small datasets, this is particularly important because, for the reasons mentioned above, standard neural net training will overfit, but Bayesian inference will determine the best representation for the model parameters provided the available data, which usually have a high degree of uncertainty. Having a concept of model uncertainty is useful since the inferred distributions get sharper and start to approach the solutions from normal training when the dataset size significantly exceeds the number of neurons. This limit is not achieved in reality for contemporary networks. *Kullback-Liebler divergence* (or KL-divergence) can be used to represent dissimilarity between two variables, which is expressed as

$$d_{KL}[q_\phi(w)||p(w|D)] \coloneqq \int_{\mathrm{w}} q_\phi(w)\, log\, \frac{q_{\phi(w)}}{p(w|D)} = E_{q\theta(w)}\left[log q_{\phi(w)} - log p(w|D)\right] \quad (5)$$

Where $w_i \sim p(w|D)\, \alpha p(D|w)\, p(w)$ are samples extracted from posterior distribution. Samples are to be extracted from the non-normalized posterior using MCMC techniques like Hamiltonian Monte Carlo, as the normalizing constant is intractable. A deep bayesian neural network can be defined with gaussian priors on the weights; $p(\theta) = N(0, 5.||)$. MCMC is used in the implementation of the deep Bayesian neural network to get posterior samples. After computation, the predicted distribution is plotted. The network architecture that is utilized is as follows: There are three hidden layers and 128 hidden units with activation function as $RELU$. The BNN learning process uses Bayesian inference with Gaussian priors and posterior estimation through MCMC-based sampling. During optimization, the KL divergence term regularizes the model, thereby improving generalization and uncertainty estimation.

Algorithm: BNN-based RSSI Prediction for Wireless Channel Quality Estimation

Input: RSSI time-series dataset $D = \{(x_t, y_t)\}$from WiFi / WSN / heterogeneous wireless networks

Output: Predicted RSSI values $\hat{y}$, channel quality estimate, performance metrics

Step 1: Data Acquisition

Collect RSSI measurements from wireless environments (WiFi, WSN, LTE, etc.) and construct a time-series dataset representing transmitter–receiver signal variations.

Step 2: Data Preprocessing

- Handle missing/noisy RSSI values
- Normalize RSSI values
- Transform time-series data into supervised learning instances utilizing sliding window or lag features

Step 3: Dataset Splitting

Divide dataset into training and testing sets or apply K-fold cross-validation for performance evaluation.

Step 4: Model Initialization (BNN)

Initialize Bayesian Neural Network with:

- Layer architecture (input, hidden, output layers)
- Prior distributions over weights and biases
- Hyperparameters (learning rate, batch size, epochs)

Step 5: Training Phase

For each epoch:

- Perform forward propagation using probabilistic weights
- Compute loss function = negative log-likelihood + regularization (KL divergence)
- Apply variational inference to approximate posterior distribution
- Optimize Evidence Lower Bound (ELBO) using gradient-based optimization

Step 6: Prediction Phase

Feed test samples into trained BNN and obtain:

- Predictive mean RSSI value
- Predictive uncertainty (variance distribution)

Step 7: Channel Quality Estimation

Use predicted RSSI values to assess wireless link quality and determine channel reliability for communication.

Step 8: Performance Evaluation

Compute evaluation metrics:

- MAE

- MSE
- RMSE
- R^2

Compare results with baseline models such as BARIMA and Bayesian Dynamic Linear Models (BDLM).

Step 9: Output Results

Return predicted RSSI values, channel quality classification, and evaluation performance metrics.

End Algorithm

4. Wireless Channel Model

The received signal varies from the emitted signal as a result of the radio signal changing as it travels over a communication channel from the emitter side to the receiver side. The primary factors influencing the received signal are noise, shadowing, Doppler shift, path loss, and fading brought on by multiple path arrivals. A model is used to represent the channel for better comprehension. A mathematical representation of a wireless channel represents the transition of the given input to the desired output and the functional relation between them. A simple mathematical model of a wireless channel with reference to the baseband signal is shown in Figure 1. The wireless channel is represented as a tapped delay line filter of length M. The following mathematical expression represents the relation between the input and output;

$$y(n) = \sum_{n=0}^{M-1} h(m) * x(n-m) + w(n) \qquad (6)$$

Here, n represents instance time, $x(n)$ represents the input, $y(n)$ represents the output, and $w(n)$ signifies additive white Gaussian Noise measured at time n, and $h(m)$ is the co-efficient of the Mth channel.

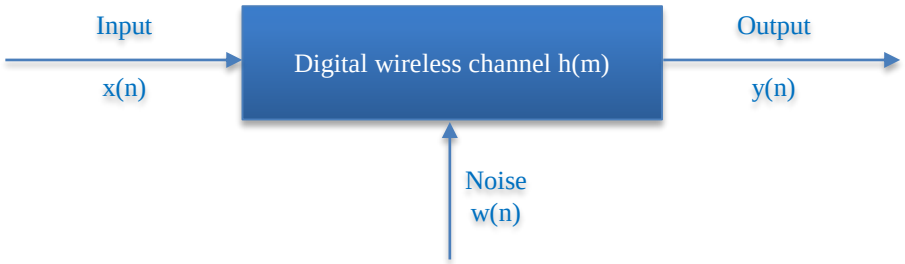

Fig. 1 Schematic view of wireless channel method

The quality of a wireless channel can vary depending on various factors, which pose a challenge in designing a universal framework for prediction. This work proposes an ML-based approach capable of calculating the channel quality irrespective of dynamic changes in the network and transmission rate. Various factors generate unexpected differences in the wireless channel quality, thereby introducing difficulties in designing a generalized system for this prediction task. In this study, Bayesian-based prediction models are developed, which can precisely forecast wireless channel variations. Wireless signal strength is inherently noisy and variable (due to fading, interference, mobility). Bayesian methods provide predictive distributions, thus enabling us to estimate confidence intervals on signal strength forecasts. Signal strength data may be incomplete or inconsistent across time and devices. Bayesian priors can regularize estimates, improving robustness to missing data or sparse sampling. MCMC and variational inference can be slow, especially for high-frequency or large-scale wireless data. The applicability of these algorithms to forecast and predict purposes, in which the goal is to foresee the future given prior time series data, has been shown in recent work [7].

The dynamic characteristics of wireless signal strength are decided by different nature of operating environments and network behaviors of WiFi and Wireless Sensor Networks (WSNs). The signal strength in WiFi networks, commonly represented as RSSI, is very volatile because of the users' mobility. This causes frequent and sudden changes in the distance between devices and access points. Furthermore, multipath fading has a big impact on the WiFi signals. The signal reflections from walls, furniture and other obstacles will lead to constructive or destructive interference, which causes rapid fluctuations of the signal strength even over a short distance. Other electronic devices and overlapping WiFi channels also cause interference and contribute to signal variability, particularly in dense urban or indoor settings.

Dynamic and often non-linear changes in the signal quality are also caused by human presence, environmental obstacles and usage patterns. On the other hand, WSNs generally consist of static low-power sensor nodes deployed in structured or ad hoc topologies. This results in relatively more stable signal behavior. However, WSNs are still affected by slow environmental changes like temperature and humidity, irregularities in terrain and variation in hardware characteristics of nodes. In WSNs, the power limitations often require nodes to run in duty-cycled modes, causing intermittent data transmission and temporal gaps, which can be seen as fluctuations in signal strength.

5. Experimental Results & Discussion

5.1. Experimental Setup

The presented architecture was evaluated using RSSI time-series datasets collected from different wireless communication environments, including WiFi and WSN networks. The dataset was divided into Training (TRANP) and Validation (VALIDN) splits, where the first 2500 samples were utilized for TRANP and the remaining samples for validation. The proposed system was compared with existing Bayesian forecasting methods under the same experimental settings. Performance was assessed using standard statistical and probabilistic forecasting metrics. Table 1 demonstrates the parameter settings used in the experiments.

Table 1. Parameter settings of the proposed model

Model	Hyperparameters	Values
Data Preparation	Window Size	20
	Sequence Length	20
Bayesian Neural Network (BNN)	Hidden Layers	3
	Hidden Neurons	128
	Activation Function	ReLU
	Prior Distribution Std. Dev.	1.0
	Posterior Samples	50
	Dropout Rate	0.2
Variational Inference	KL Divergence Weight	0.01
	Monte Carlo Samples	30
Adam Optimizer	Learning Rate	0.001
	$Beta_1$	0.9
	$Beta_2$	0.999
Training Configuration	Batch Size	32
	Epochs	50
	Early Stopping Patience	15
	Validation Split	20%

5.2. Dataset Description

The dataset utilized in this paper consists of Received Signal Strength Indicator (RSSI) measurements gathered from heterogeneous wireless network circumstances, comprising 4G LTE, WiFi, Zigbee, WiMAX, and industrial wireless sensor network WSN environments. The WiFi-based RSSI datasets are derived from Herath et al. [22], whereas measurements were collected utilize ng a Motorola G5 smartphone on a campus network under pedestrian mobility conditions, covering both indoor and outdoor environments. These datasets include two sampling rates of 1-second and 2-second intervals, with every recording session lasting approximately 50 minutes. Additionally, the WSN-based RSSI data are attained from Seetharam et al. [23], which include multiple mobility scenarios: indoor pedestrian, outdoor pedestrian, and vehicular movement. Each dataset records RSSI values at a 1-second resolution, with durations of approximately 38 minutes for indoor pedestrian, 26 minutes for outdoor pedestrian, and 10 minutes for vehicular mobility traces. These integrated datasets allow evaluation under varying mobility patterns, transmission conditions, and network dynamics, thus providing a comprehensive benchmark for predictive performance assessment.

5.3. Results and Analysis

The empirical findings highlight the robustness and broad applicability of the Bayesian-based deep learning model. The proposed framework performs single-step-ahead RSSI forecasting, where the next RSSI observation is predicted using previous sequential observations. The first 2500 observations were used for model training, while the remaining 690 observations were used for validation and testing. The Root Mean Squared Error (RMSE), which measures the error of the absolute prediction, is the primary evaluation metric. The RMSE can be mathematically denoted as

$$RMSE = \sqrt{\frac{1}{h}\sum_{i=1}^{h}(\hat{y}_i - y_i)^2}$$

For comparative result analysis, two baseline models are used, namely Bayesian Dynamic Linear Models (BDLM) and Bayesian ARIMA (BARIMA). BDLM is a state-space model that explicitly models the latent processes driving the data (e.g. level, trend, seasonality), allowing parameters to evolve over time. They often use Bayesian updating, e.g., the Kalman filter, to update predictions adaptively. BDLMs are flexible and well suited for time series with time-varying dynamics, structural breaks or missing data. BDLMs can handle both univariate and multivariate series, can easily include exogenous variables, and naturally perform online forecasting unlike Bayesian ARIMA. In time series prediction, the use of a 95% confidence interval (more accurately called a 95% prediction interval in forecasting) is crucial for conveying the uncertainty associated with future values. Rather than relying solely on point estimates, which can be misleading in dynamic or noisy time series, the 95% interval provides a range within which future observations are expected to fall with 95% confidence. This range accounts for both model's uncertainty and the inherent variability in the data. 95% prediction intervals enhance the interpretability and reliability of forecasts by presenting a more realistic and probabilistic view of future behavior, rather than a deceptively precise single-value prediction. Figures 1-3 presents the time series representation of predicted and actual values along with 95% prediction confidence interval. Bayesian ARIMA (BARIMA) combines the traditional ARIMA model with Bayesian inference to model time-series data while accounting for parameter uncertainty. Bayesian ARIMA assumes a fixed structure and does not adapt well to changes over time, making it more suitable for stationary or slowly evolving series with relatively stable patterns.

The performance of the BNN model was compared with Bayesian ARIMA and Bayesian Dynamic Linear Model. Although both BARIMA and BNN are probabilistic models, their characteristics and uses are different. While BNNs are a form of neural network that employs Bayesian inference to express uncertainty in their predictions, BARIMA is a particular kind of time series model used for analysing and forecasting data that varies over time. The parameters of an ARIMA model are estimated using a Bayesian technique in BARIMA models. This indicates that rather than assuming fixed values, the model takes into account a probability distribution over the model parameters. BNNs are less likely to overfit, a typical issue with neural networks that occurs when the networks memorize training material rather than identifying patterns that may be applied to other situations. Compared to conventional neural networks, BNNs are more adaptable, enabling them to represent intricate correlations in the data. Because of their relative rigidity, ARIMA models necessitate meticulous model parameter definition. They may find it difficult to assimilate new knowledge or adjust to shifting data patterns. In order to improve their predictions over time, BNNs can additionally take into account past information and opinions regarding the data.

The data samples are split into two portions. The first 2500 data points are used to train the model. The following 690 observations are used to validate the model. We tried different numbers of layers, M = 3, 4, 5, versus number of hidden units, H = 20, 25, 35, 40 and 45 for all cross configurations. The model performance indicates that the DL approach outperforms in all performance metrics. The DL strategy is better than the other models in improving the performance for the network configurations with high signal strength variability and lower seasonality. The representational power of the technique is leveraged by the number of layers of the Bayesian Neural Network (M) and the number of hidden units (H). As the network depth increases, the BNN can learn more complex hierarchical and nonlinear temporal dependencies in wireless RSSI time series data, which can improve predictive capability and uncertainty-aware forecasting in highly dynamic wireless environments.

However, increasing the depth of the network or the number of hidden units also increases the model complexity and computational cost and the difficulty of the posterior estimation in Bayesian inference. Model with more layers or a larger number of hidden units may overfit or lead to unstable posterior distributions or uncertainty in parameter estimation when not sufficiently regularized. Therefore, several combinations with different numbers of hidden layers (M=3, 4, 5) and hidden units (H=20, 25, 35, 40, 45) were experimentally evaluated. The study is not aimed at an independent optimization of the network architecture, but rather at evaluating the effectiveness of Bayesian deep learning for probabilistic RSSI time series prediction under different wireless communication environments.

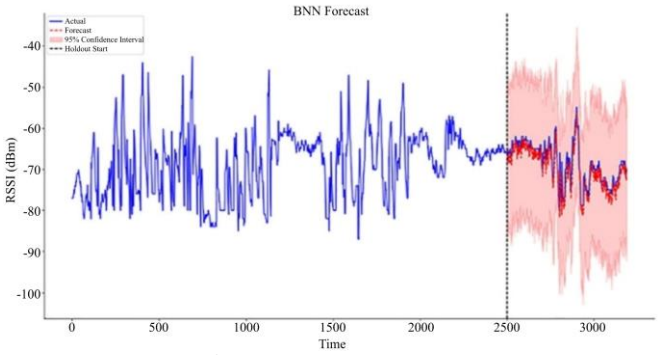

Fig. 2 Plot of predicted vs actual time series (BNN)

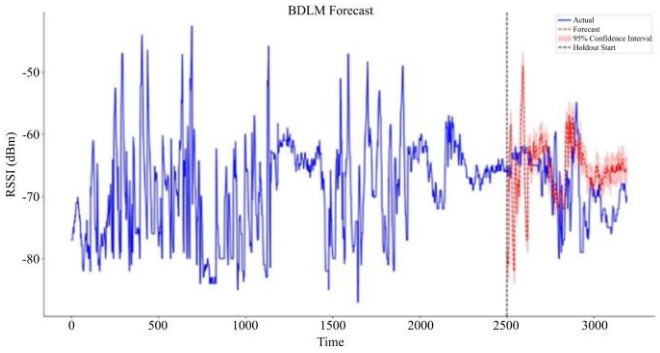

Fig. 3 Plot of predicted vs actual time series (BDLM)

Utilizing scatter plots presented in Figures 4-6, specifically "predicted vs. actual" plots, the performance of the regression methods was assessed. By plotting the model's predicted values against the actual values, the model's ability to capture the relationship among variables is assessed. The density plots reflect that the BARIMA model is not learning anything from the past patterns. As the time series has a linear trend, while predicting the signal strength using the ARIMA model, the differencing makes it flat, and the difference data becomes almost constant.

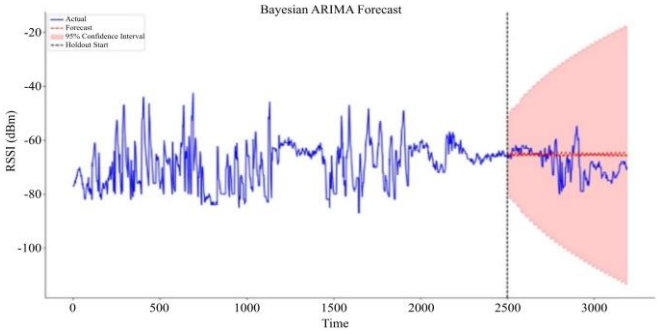

Fig. 4 Plot of predicted vs actual time series (BARIMA)

The time series prediction of bayesian ARIMA resembles a few identical steps. The results tabulated in Table 2 state that the bayesian ARIMA model is performing worse than a naive baseline, specifically, worse than simply predicting the mean of the observed values. This is evident from the R^2 value estimated from the experimental results.

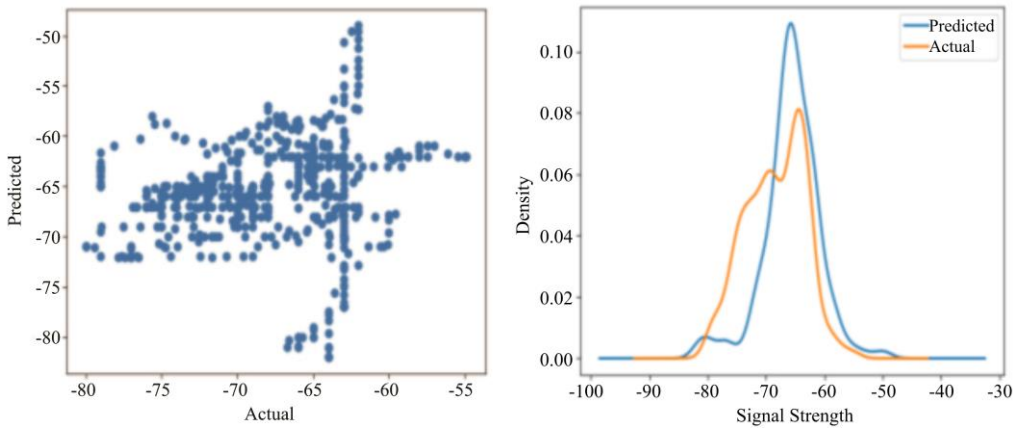

Fig. 5 Performance evaluation of BDLM model

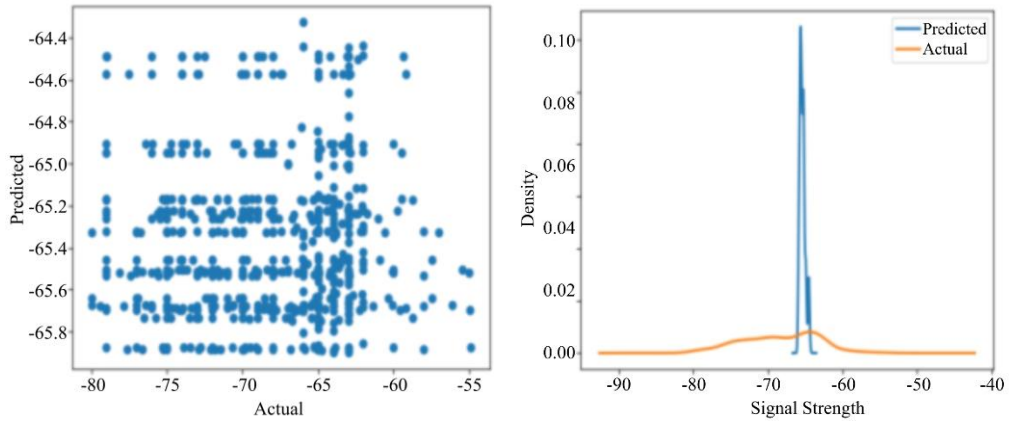

Fig. 6 Performance evaluation of BARIMA model

Bayesian ARIMA is simpler and more interpretable for stable, well-behaved time series, while BDLM provides a more flexible, adaptive framework ideal for dynamic or complex forecasting scenarios. For short-term forecasting in a stationary context, Bayesian ARIMA may perform well. BDLM is suitable for adaptive time-series forecasting; however, in this study it showed poor predictive performance, as indicated by a negative R^2 value, suggesting its inability to effectively capture the underlying data patterns. In contrast, PatchTST and GATTSF models perform more stable and consistent results than other methods. BDLM is an interpretable state-space model for time-series forecasting, whereas BNN is a flexible Bayesian deep learning approach capable of capturing complex non-linear patterns with uncertainty estimation.

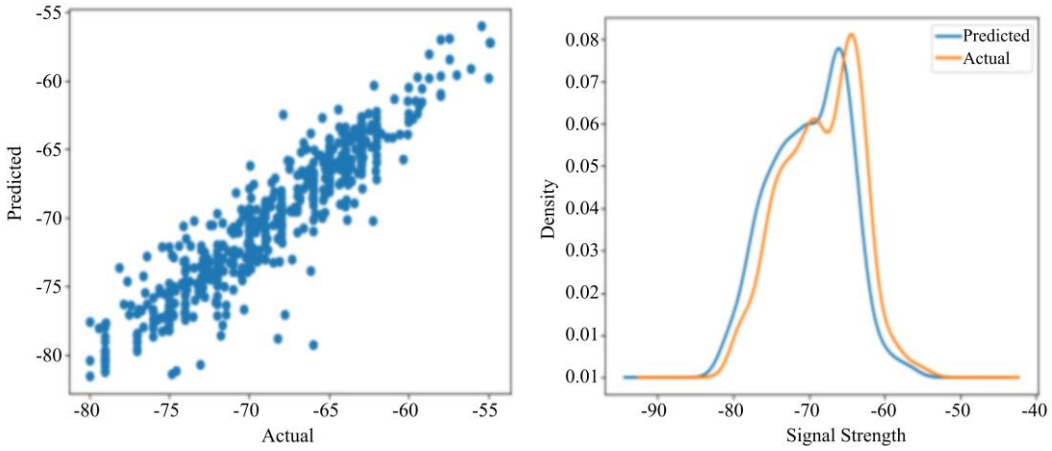

Fig. 7 Performance evaluation of BNN technique

Table 2. Summary of performance metrics of wifi network

Methods	MAE	MSE	RMSE	RMSLE	R2	CCC	rRMSE
BARIMA	4.600	34.600	5.800	1.700	-0.300	0.001	0.003
BDLM	5.700	49.200	7.010	1.940	-0.920	0.130	0.004
PatchTST [35]	2.740	9.180	3.030	1.020	0.610	0.704	0.002
GATTSF [35]	2.510	8.240	2.870	0.970	0.655	0.742	0.002
BNN	1.800	5.500	2.300	0.850	0.780	0.890	0.001

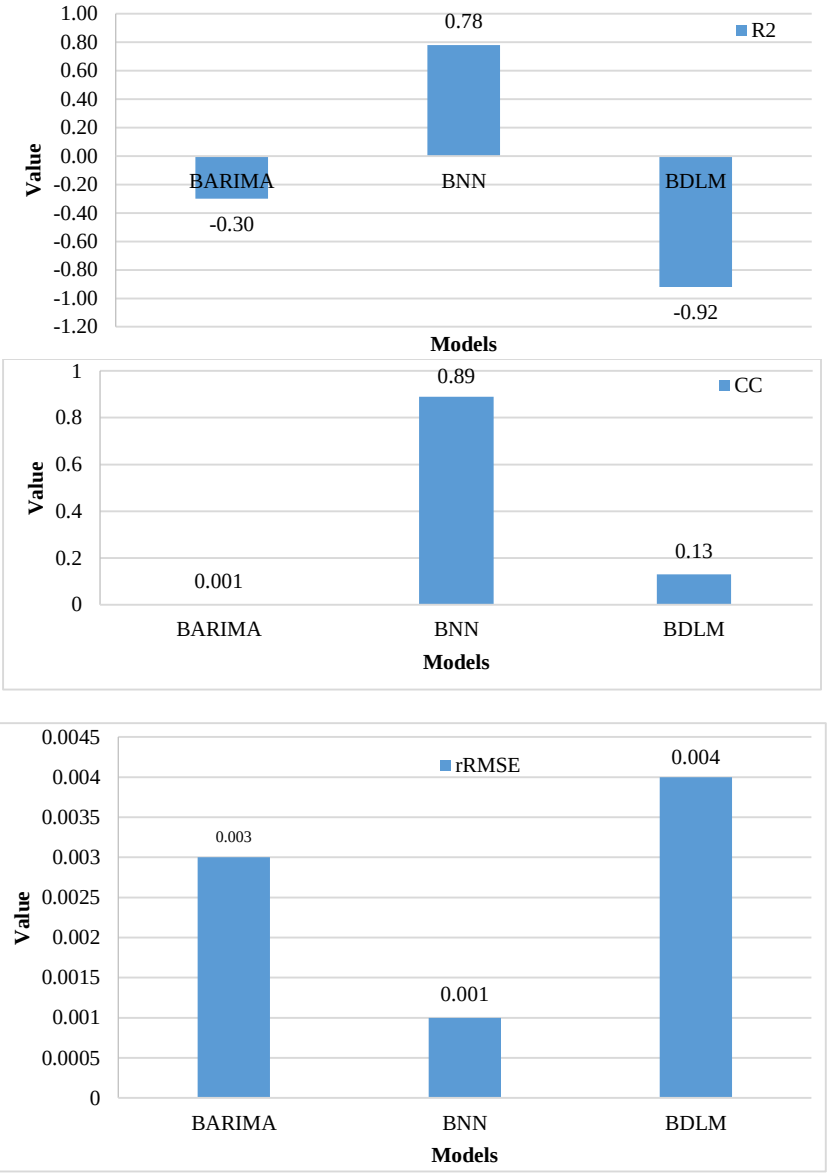

Fig. 8 Plot of performance metrics for wifi network (R^2, CCC, rRMSE)

The assessment of Bayesian models using traditional point-wise error metrics may be inaccurate and insufficient for time series prediction. These metrics aim to quantify the accuracy of point estimates and do not account for the predictive uncertainty inherent to the Bayesian paradigm. One of the big advantages of Bayesian models is that they can provide predictions in the form of probabilities (i.e., distributions of possible future outcomes), rather than just single-value predictions. Metrics such as MAE and MSE only measure the mean of the prediction and do not consider the confidence intervals and uncertainty estimates at all. These are important for applications where risk or confidence in the predictions matters.

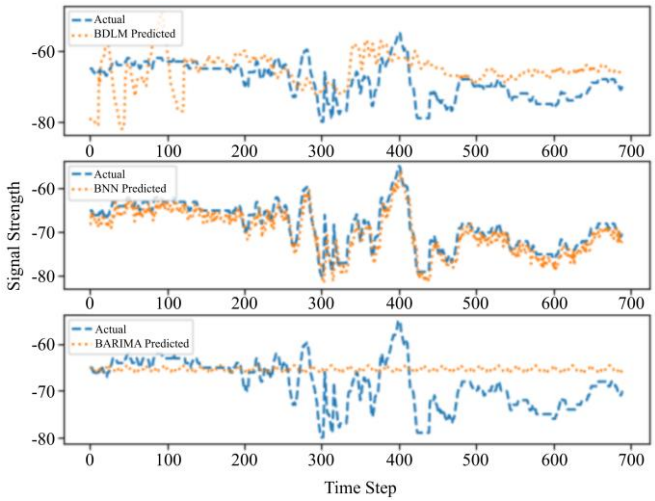

Fig. 9 Actual vs predicted time series of wireless signal strength in a wi-fi network

BNNs are capable of learning complex non-linear time series representations including long-term trends and repeating seasonal cycles without the need to define these components explicitly. They generalize well and provide uncertainty estimates over predictions with proper training and regularization.

Relative Root Mean Squared Error (rRMSE) is used to measure and compare the accuracy of models when the absolute RMSE values are hard to interpret due to different magnitudes in the data. In terms of the relative rRMSE, the minimum rRMSE value was achieved by the BNN model with 0.001277, the next lowest was the BARIMA model with 0.003428, and the highest rRMSE value was obtained by the BDLM model with 0.004059. These values suggest that the BNN model had the most accurate predictions with the smallest errors relative to the scale of the actual time series data. The low rRMSE indicates that BNN successfully captures the underlying structure of the time series, including any complex, nonlinear or dynamic patterns. The BDLM model had the largest prediction error relative to the data magnitude (i.e., highest rRMSE), indicating that the model may have underfitted the data or missed important time-varying components. Overall, based on rRMSE values, BNN outperformed both BARIMA and BDLM in delivering precise point forecasts for the given time series.

In time series prediction, when evaluating the performance of the BARIMA and BDLM models using both relative Root Mean Squared Error (rRMSE) and the Concordance Correlation Coefficient (CCC), we gain insight into both the accuracy and agreement of the models with the actual data. The BARIMA model shows a lower rRMSE value of 0.003428, indicating that its prediction error is relatively small compared to the scale of the observed values. However, its CCC value is very low at 0.001573, suggesting poor agreement between the predicted and actual time series values, despite the small error magnitude. In contrast, the BDLM model has a slightly higher rRMSE of 0.004059, indicating slightly less accurate predictions than BARIMA in terms of error size, but a significantly better CCC of 0.132247, showing better consistency and correlation between its predictions and the actual time series (values summarized in Table 3). The predictions of the BARIMA might be numerically closer to the true values, but the temporal dynamics of the actual and predicted series do not match.

BDLM, although it has higher errors, better fits the shape or structure of the series over time. Thus, BDLM might be a better model in preserving the time series pattern compared to BARIMA. BARIMA is more concerned with minimizing absolute prediction error. PatchTST and GATTSF algorithms achieve coverage prediction value of 0.9078 and 0.9255, respectively, demonstrating more balanced results.

Table 3. Summary of metrics to evaluate the accuracy of forecasts for wifi network

Methods	Coverage Prediction Interval (95%)	Continuous Ranked Probability Score	log-likelihood
BARIMA	0.1174	3.3450	2219.79
BDLM	0.9870	4.0015	2328.51
PatchTST [35]	0.9078	1.7826	1786.42
GATTSF [35]	0.9255	1.6413	1712.86
BNN	0.9507	1.3219	1635.80

The performance models in terms of both 95% prediction interval coverage and Continuous Ranked Probability Score (CRPS) can be analyzed to derive key insights with respect to the uncertainty calibration and probabilistic accuracy of each of these models. The 95% prediction interval coverage is the proportion of true time series points that are inside the 95% interval that is predicted. Ideally, this should be close to 0.95, indicating that the model's uncertainty estimates are well calibrated. Here, BDLM achieves a coverage of 0.986957, BNN achieves 0.950725, and BARIMA only 0.117391. These results indicate that BNN and BDLM provide well-calibrated uncertainty estimates, while BARIMA significantly underestimates the uncertainty, with only about 12% of the true observations falling into its interval, which can be interpreted as overconfidence or too narrow intervals.

The lower value of CRPS indicates better performance. BNN has the lowest CRPS at 1.321940, indicating the best overall probabilistic forecasting ability. It provides well-calibrated uncertainty. BARIMA, with a CRPS of 3.344951, and BDLM, with the highest at 4.001515, perform poorly in terms of probabilistic forecast quality, despite BDLM having strong interval coverage.

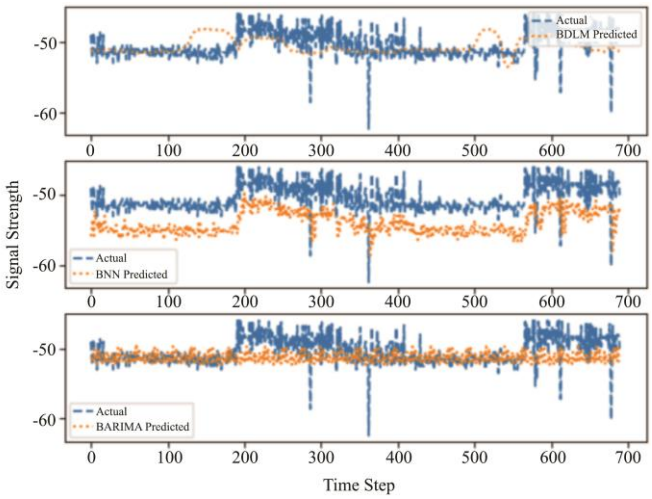

Fig. 10 Actual vs predicted time series of wireless signal strength in wsn network

Table 4. Summary of performance metrics of WSN network

Methods	MAE	MSE	RMSE	RMSLE	R2	CCC	rRMSE
BARIMA	1.600	5.000	2.200	0.800	-0.300	0.004	0.001
BDLM	3.600	15.300	3.900	1.300	-3.000	0.181	0.002
PatchTST [35]	1.740	4.960	2.227	0.754	0.105	0.082	0.001
GATTSF [35]	1.650	4.720	2.173	0.731	0.151	0.096	0.001
BNN	1.500	4.500	2.100	0.700	0.190	0.104	0.001

As shown in Table 4, it can be summarized that

- BNN provides the best balance of accuracy and uncertainty calibration—high coverage with low CRPS.
- BDLM is very cautious, providing wide and inclusive intervals (possibly too wide), leading to high CRPS despite good coverage.
- BARIMA is overconfident—it produces narrow intervals that fail to capture most actual outcomes, and its higher CRPS confirms poor probabilistic performance.
- PatchTST and GATTSF records 1.740, and 1.650 MAE values which enhance the regression metrics.

Table 5. Summary of metrics to evaluate the accuracy of forecasts for WSN network

Methods	Coverage Prediction Interval (95%)	Continuous Ranked Probability Score	log-likelihood
BARIMA	0.5986	1.2310	1545.22
BDLM	0.5507	2.7552	2848.78
PatchTST [35]	0.9046	1.0847	2410.76
GATTSF [35]	0.9283	1.0315	2678.34
BNN	0.5986	1.1737	1498.86

As shown in Table 5, it can be summarized that BNN stands out as the most reliable model in both point prediction and uncertainty quantification, while BDLM trades accuracy for overly conservative intervals, and BARIMA underestimates uncertainty, making it the least dependable of the three in a probabilistic forecasting context. However, PatchTST and GATTSF algorithms reach better coverage rates of 0.9046 and 0.9283, respectively. Signal strength can vary due to environmental conditions, mobility, interference or hardware limitations in both WiFi and Wireless Sensor Network (WSN) environments.

However, the properties of these two systems are rather different, which affects the effectiveness of different Bayesian models. BNNs are especially suited for modeling complex and non-linear relationships. This type of characteristic is common in WiFi environments because of the dynamic nature of user mobility, multipath propagation and interference from multiple devices.

BNNs allow us to quantify uncertainty via posterior distributions on the weights of the model, including uncertainty due to the data and uncertainty due to the model uncertainty. This makes them suitable for real-time prediction of RSSI in highly volatile scenarios.

Table 6 depicts the computational efficiency of presented model with other techniques [34]. Based on Latensify, the proposed method provides a lower value of 8.46ms, Flops of 11.05G and memory of 0.027GB, while the PatchTST, iTransformer, TimesNet, and FEDformer approaches obtain higher times of 14.820ms, 16.470ms, 19.350ms, and 22.610ms, respectively.

Table 6. Computational efficiency of the presented methodology

Methods	Latency (ms)	Memory (GB)	FLOPs (G)
PatchTST [35]	14.820	0.064	18.730
iTransformer	16.470	0.071	21.460
TimesNet	19.350	0.083	24.870
FEDformer [35]	22.610	0.097	28.540
Proposed BNN	8.460	0.027	11.050

Table 7 represents the K-fold cross-validation of the proposed technique's performance. The MAE values ranged from 2.599 to 5.600, while the MSE values varied between 7.130 and 12.530. The RMSE values were observed in the range of 2.670 to 3.540, and the RMSLE values ranged from 0.280 to 5.500. The Coefficient of Determination (R^2) values varied from 0.453 to 0.682 across the folds. Similarly, the CCC values ranged between 0.516 and 0.853, whereas the rRMSE values were recorded between 0.012 and 0.054. Among all folds, Fold-9 achieved the highest R^2 value of 72.104, while Fold-7 showed the highest CCC value of 0.853. The lowest MAE value of 2.599 was obtained in Fold-4, and the minimum rRMSE value of 0.012 was observed in Fold-3.

Table 7. K-Fold cross-validation of the proposed model

K-Fold Cross Validation	MAE	MSE	RMSE	RMSLE	R2	CCC	rRMSE
Fold-1	2.816	12.530	3.540	2.110	0.486	0.541	0.046
Fold-2	3.262	8.060	2.839	0.330	0.656	0.538	0.034
Fold-3	5.524	7.130	2.670	2.855	0.651	0.584	0.012
Fold-4	2.599	9.430	3.071	3.443	0.682	0.516	0.032
Fold-5	4.057	7.550	2.748	5.500	0.665	0.803	0.035
Fold-6	3.806	7.400	2.720	1.450	0.453	0.795	0.027
Fold-7	5.600	9.700	3.114	0.280	0.456	0.853	0.054
Fold-8	5.435	7.140	2.672	2.394	0.491	0.732	0.036
Fold-9	4.605	8.020	2.832	2.874	0.721	0.756	0.033
Fold-10	3.322	9.900	3.146	2.941	0.603	0.654	0.030

5.4. Analysis of Model Performance for WSN

The performance evaluation of models in WSN network based on four key metrics, namely, R^2, Concordance Correlation Coefficient (CCC), Coverage of the 95% Prediction Interval, and Continuous Ranked Probability Score (CRPS), provides important insight. The best performance was achieved by the BNN model with an R^2 equal to 0.19985, where R^2 is the percentage of variance explained by the model. The R^2 of the BDLM was significantly negative (-3.0732), suggesting a high degree of model misfit, possibly due to wrong assumptions about latent states or inability to capture changes in signal. CCC metric considers both precision and accuracy. Interestingly, BDLM had the highest CCC (0.18191), which showed that the model was in better agreement between the predicted and observed values, despite the poor R^2. BNN predicted with a CCC of 0.10456, while BARIMA performed poorly (CCC = 0.00479), almost providing a random guess. This shows that BDLM is not good at capturing variance. Regarding the prediction interval coverage, BARIMA and BNN shared the same 95% coverage (0.59855), which implies that approximately 60% of the true observations fall within the prediction interval of their respective models, significantly lower than the 95% coverage, indicating underestimated uncertainty. BDLM had slightly worse coverage at 0.55073. The CRPS, a proper scoring rule that considers both the sharpness and the calibration of the predictive distribution, helps further to understand the ability of the models in time series prediction. Lower CRPS means better predictive ability. The best CRPS was obtained by BNN (1.17368), followed by BARIMA (1.23095), whereas BDLM exhibits poor performance with CRPS value of 2.75517. This proves that predictive distributions of BDLM were both poorly centered and too dispersed when compared to actual observations.

The excellent performance of the proposed BNN method can be attributed to its capacity to learn the temporal, nonlinear, and uncertain features of RSSI measurements. The Bayesian framework allows the model to address uncertainty resulting from interference, noise, multipath propagation, and dynamic channel conditions. Compared to existing methods, BNN can capture intricate patterns from historical RSSI data. Furthermore, the temporal learning capacity supports the model in adapting to dynamic changes in wireless signal strength. The probabilistic prediction offers consistent uncertainty assessment with point predictions. These features allow the model to attain reliable and accurate performance over various wireless environments. The incorporation of

deep nonlinear learning with Bayesian uncertainty modelling creates the BNN, which is appropriate for consistent RSSI predictions and proactive wireless channel selections.

6. Conclusion

In summary, although the Bayesian ARIMA (BARIMA) models have advantages over classical ARIMA in terms of uncertainty modeling and a priori knowledge, the BNN is more flexible and has greater predictive power for complex wireless signal strength prediction problems. BNNs are well suited for modeling nonlinear temporal dependencies, high-dimensional data and uncertainty-aware predictions, making them highly applicable to dynamic wireless communication environments. Unlike BDLMs that depend on pre-specified trend and seasonal structures, BNNs can automatically learn complex temporal variations and abrupt signal fluctuations directly from data without extensive manual feature engineering. Experimental evaluation on both WiFi and WSN datasets proved that the proposed BNN model consistently outperformed BARIMA and BDLM. The BNN achieved the lowest prediction error with an MAE of 1.5, MSE of 4.5, and RMSE of 2.1, compared to BARIMA (RMSE = 2.2) and BDLM (RMSE = 3.9). The BNN obtained the highest Coefficient of Determination (R^2=0.19) and improved concordance correlation coefficient (CCC = 0.104). This indicates better agreement between predicted and actual RSSI values. In contrast, BDLM exhibited significantly poorer predictive capability with negative R^2 values (−3.0). This reflects its limitations in capturing highly dynamic wireless signal behavior.

A negative R^2 value shows that the BDLM performed worse than a naive baseline predictor that outputs the mean of the observed RSSI values. This behavior is likely due to the model's inability to adapt to abrupt nonlinear fluctuations in wireless signal strength. Also, it is sensitive to state-space parameter initialization and process noise estimation. In highly dynamic wireless RSSI environments, the latent state assumptions of BDLM cannot sufficiently capture complex temporal variations and nonlinear dependencies present in the data. The strength of BNNs lies in combining representational ability of neural networks with Bayesian inference, enabling accurate prediction along with uncertainty quantification.

The improved R^2 and improved CCC values indicate that the proposed model effectively captures nonlinear variations, sudden signal transitions, and irregular temporal fluctuations commonly observed in wireless communication channels. BNNs require higher computational resources and careful regularization to avoid overfitting. The higher predictive accuracy and robustness make them suitable for reliable channel quality estimation and optimal channel selection in next-generation wireless communication systems. The predicted RSSI and its uncertainty support periodic handoff, selection of MCS, adaptive channel assignment, and system-level networking decisions. It allows periodic and uncertainty-aware network management while enhancing link reliability and resource utilization.

6.1. Limitation

This study focuses on predicting wireless channel strength using supervised learning methods according to time-series wireless signal data gathered from multiple communication standards. Variations in environmental conditions, user mobility patterns, interference sources, and network configurations might influence the normalizability of the techniques in real-world implementations. Additionally, the study mainly evaluates channel robust estimation and does not consider other network performance metrics like latency, energy consumption, or spectrum utilization. The computational complexity related to BNN might also limit their applicability in resource-constrained wireless devices.

6.2. Future Work

Future work will emphasize verifying the proposed BNN framework by utilizing real-time RSSI datasets collected from various wireless devices and environments. Zero-shot cross-vendor assessment will be carried out to evaluate generalization through devices with multiple RSSI calibration features. Furthermore, this model can be analysed through non-stationary mobility shifts, including transitions from static indoor scenarios to high-speed vehicular environments. Additional parameters, such as interference levels, SNR, and mobility information, will be integrated to enhance prediction accuracy. In addition, DL-based methods like GRU, LSTM, and Transformer-based methods will be supported for comparative assessments. Lightweight BNN implementation on edge and IoT devices will be further analysed with adaptive channel-selection models to enhance consistency, accuracy, and effectiveness in dynamic wireless settings.

Data Availability

The data that support the findings of this study are available on request from the corresponding author

Declarations

Ethical Approval

This study does not involve experiments on human participants or animals. All experiments were conducted using publicly available datasets and simulation environments. Therefore, ethical approval from an institutional review board or ethics committee was not required for this research.

Consent to Participate

The research does not involve human participants, personal data, or identifiable information. Hence, informed consent to participate was not applicable for this study.

Consent to Publish

The research does not contain any individual person's data in any form. All authors have reviewed the manuscript and consent to its publication.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

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