Channel Estimation Methods for Frequency Hopping System Based on Machine Learning

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***Abstract*—Frequency Hopping (FH) spread spectrum system is extensively used in military and civilian fields due to its robustness against interference and efficiency in confronting radio jamming. Channel estimation is a crucial part of the FH system. However, signal processing-based channel estimation methods have some constraints, such as high computational complexity, sensitivity to noise level, and excessive overhead. To alleviate these issues, we propose a Machine Learning (ML) model for precisely estimating Narrow Band (NB) multipath fading channel parameters for a Slow Frequency Hopping (SFH) spread spectrum system. In the proposed model, we employed a Neural Network (NN) with three layers consisting of an input layer that interprets the signal's fundamental patterns, a hidden layer to extract the correlation found in the time scene, and an output layer that utilizes a linear activation function to provide the flexibility required to address the dynamic relationship between channel gain and time delay. Without prior experience, leveraging a synthetic dataset rich in complex temporal variations and channel gain nuances, the NN architecture, characterized by multiple dense layers, effectively captures complex temporal relationships. Following rigorous training and validation utilizing the Mean-Square Error (MSE) loss function, the model significantly reduced loss, emphasizing its proficiency for an accurate delay and gain estimation. A computer simulation comparison between the performance of the proposed model and previous classical models was included in this paper. Based on simulation results, the proposed ML-based estimator model significantly outperforms many classical subspace-based methods in terms of MSE, the performance improvement appears over several Signal-to-Noise Ratios (SNR). Furthermore, the proposed model provided a reasonable tradeoff between complexity and performance.**

***Keywords*—frequency hopping, time-delay estimation, channel gain, A Narrow Band (NB) multipath channel, rectified linear unit, hidden layer, machine learning, deep learning, neural networks, loss function.**

I. Introduction

Multiple strategies have been proposed to address impairments in rapidly varying radio channels. These strategies include channel coding and interleaving, adaptive modulation, antenna diversity, Fixed Channel Allocation (FCA), Adaptive Frequency Allocation (AFA), dynamic channel allocation (DCA), Cell Splitting, Resource Reuse (TDMA / FDMA), Discontinued Transmission (DTX), Power Control (PC), smart antennas, Direct Sequence (DS) and Frequency Hopping (FH) spectrum spreading [1, 2]. FH communication systems are widely utilized in anti-jamming communication primarily because of their capability to resist interception and interference [3]. As the electromagnetic environment becomes increasingly complicated, the FH communication systems' transmitters adapt by adopting more flexible frequency hopping patterns to manage interference effectively. Fast Frequency Hopping (FFH) systems are characterized by a frequency change rate that is notably higher than the information rate; this rapid variation in frequencies sustains the system's resilience against interference and fading, contributing to heightened robustness in dynamic communication environments.

On the other hand, Slow Frequency Hopping (SFH) systems operate with a frequency change rate that is intentionally comparable to or slower than the information rate. This frequency-changing approach was designed to Maximize the frequency diversity of the communication system, ensuring a strategic balance between adapting to channel conditions and maintaining reliable communication. These distinctions in frequency hopping rates allow system designers to adjust their approach based on specific requirements, environmental factors, and the desired trade-offs between the information transfer rate and the system's capacity to moderate interference. The FH system model is generally considered a Narrow-Band (NB) system; the narrow-band characteristic simplifies the modeling and analysis of the FH system, making it easier to handle in terms of signal processing and system design considerations [4].

Time-delay estimation becomes significant in an SFH system when a high data rate signal is transmitted over a frequency-selective fading channel. Blind channel estimation for FH systems refers to estimating the channel

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gain and time delays without requiring any prior knowledge of pilot symbols or training sequences. Accurate channel estimation generally leads to optimal signal detection at the receiver. This mission can be challenging due to the active nature of FH systems and the need for explicitly transmitted reference signals [5].

A Modified Discrete-Time Wigner-Ville Distribution (MDTWVD)-based blind parameter estimation technique was presented to capture the time-varying characteristics of the FH system in [6], where a low-order Chebyshev polynomial was employed as a kernel function to reduce cross-term. In [7], a blind channel parameter estimation scheme based on time-frequency diagram modification for FH signals was introduced. The technique involves transforming the observed signal into a time-frequency domain. Subsequently, an adaptive threshold-based energy detection technique was employed to modify the time-frequency diagram. The parameters of the frequency-hopping signals were then obtained from the modified spectrogram.

Subspace methods to estimate the channel parameters were examined using Estimation of Signal Parameters via Rotational Invariance Techniques (ESPRIT) [8]. An invariance structure can be extracted via the ESPRIT algorithm from the receiving FH signal. To address this issue, Hande *et al.* [9] suggested an algorithm that is like ESPRIT but exploits multiple invariances than ESPRIT. Exploiting multiple invariances results in a better estimate of the delays in an FH system.

The challenge of estimating multipath time delay parameters via the Propagator Method (PM) was tackled in references [10, 11]. Rank Revealing QR (RRQR) Factorization in [12] was employed to estimate the channel parameters in two approaches. The first approach combined the RRQR with the multiple signal classification (MUSIC) algorithm, as in [13]. In the second approach, the RR was incorporated with the eigenvalue decomposition of the projection matrix, as presented in [14]. The proposed method in [14] utilizes the null space obtained by the Rank-Revealing LU (RRLU) factorization. This factorization method offers precise information about numerical null space and rank. The proposed method decreased the computational complexity compared to RRQR methods while maintaining similar performance levels. The exploration of a noise space-based method for estimating multipath SFH channels, specifically focusing on efficient multipath time delays, was proposed in [15]. Furthermore, an algorithm for blind channel estimation was developed for SFH systems in [16] using RRQR factorization. The developed algorithm significantly improved performance compared to a Least Square incorporate with ESPRIT (LS-ESPRIT) and another method Total Least Square incorporate with ESPRIT (TLS-ESPRIT) estimators. Additionally, there was potential value in assessing the estimator performance through metrics such as Symbol Error Rate (SER).

Machine Learning (ML) has recently shown great potential in wireless communication systems [17–22]. ML can be employed as an End-to-End (E2E) system or to enhance the performance of a specific communication functional component such as modulation, channel estimations, signal detection, or channel coding. In the E2E system, the source and the receiver in the communication system can be replaced with Deep Neural Networks (DNNs) to achieve optimal overall system efficiency [17]. For example, ML approaches, such as neural networks, can be trained in channel estimation to learn the mapping between received FH signals and channel characteristics. Training datasets with known channel conditions can be used to train the model for blind estimation. ML methods were gaining attention for their ability to adapt to intricate and dynamic channel conditions [17].

An intelligent reception approach for FH sequences is introduced in [18], utilizing a combination of time-frequency analysis and Deep Learning (DL) to achieve intelligent estimations of frequency-hopping sequences. The approach involves the design of a hybrid network module, integrating a Convolutional Neural Network (CNN) with a Gated Recurrent Unit (GRU). Within this module, incorporating a Residual Network (ResNet) and squeeze-and-extraction can enhance the feature extraction and expression capabilities of the CNN network.

A hybrid Convolutional Neural Network (HCNN) system was introduced in [21], aiming to classify FH Spread Spectrum (FHSS) signals in the presence of an additive white Gaussian Noise (AWGN) and background signals. The HCNN system involves the fusion of both handcrafted and deep features. The CNN functions as a deep feature extractor, converting the Intermediate Frequency (IF) signal to a Time-Frequency Representation (TFR), which was then utilized as a Two-Dimensional (2D) input image. Concurrently, handcrafted features of the FHSS signal, such as hop frequency and hop duration, can be estimated from the TFR. The classification task was accomplished using a Three-Layer fully Connected Network (TLFCN) with a determined network structure. Furthermore, ML algorithms have been employed to enhance the efficiency of FH in wireless communication systems, optimizing frequency assignments based on real-time data and improving overall spectral utilization [22].

Although classical signal processing methods could successfully address the problem of estimating channel and signal parameters in FH-based communications, these methods still have some restrictions, especially in complex wireless environments such as 5g and beyond. Among these limitations are introducing excessive overhead in pilot-aided methods, the need for prior knowledge of channels as in blind estimation methods, and the lack of computational scalability when dealing with massive Multiple-Input and Multiple-Output (MIMO) systems.

Different channel estimation schemes based on Deep Neural Networks (DNN) were introduced in [23–27] to address issues observed in traditional channel estimation schemes. In [23], a deep learning algorithm for channel estimation using known channel parameters at pilot positions. The time-frequency response was treated as a two-dimensional image, and then deep learning techniques such as Image Restoration (IR) and image Super-Resolution (SR) were employed. Channel parameters at pilot positions were assumed to be images with low resolution. The proposed scheme presented comparable performance to Minimum Mean Square Error (MMSE) based classical estimation schemes. The proposed channel estimation scheme presented in [24] could dynamically predict Channel State Information (CSI) of time-selective fading channels without any previous knowledge about channel statistics or models. Yang *et al.* [25] suggested a deep learning channel estimation scheme for a communication system operating under time-frequency selective fading channels. The proposed scheme can utilize the previous channel estimated to predict the characteristics of channel fluctuations. Moreover, to increase the channel estimation accuracy, the DNN implicitly learns the time correlation of the time-varying channels from the preceding channel estimate. Channel estimation can be challenging in high mobility due to channel fast time fluctuation and non-stationary properties. To deal with this challenge and to obtain channel response features, a channel estimation scheme utilizing a Convolutional Neural Network (CNN) was proposed [26]. Under Weibull fading channel conditions, a deep learning channel estimation scheme was introduced in [27] for Orthogonal Frequency Division Multiplexing (OFDM) systems.

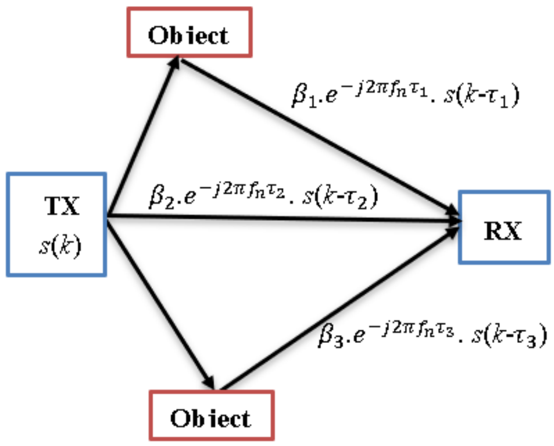

Fig. 1. The baseband model of multipath frequency hopping.

Inspired by the prospects and trends for integrating artificial intelligence in wireless communications and motivated by the potential opportunities of machine learning in addressing issues in wireless communication systems compared to solutions provided through traditional signal processing methods, we proposed a deep learning-based channel estimation scheme in a frequency hopping system.

In the proposed scheme, we used a neural network with three layers consisting of an input layer that diagnoses the signal's fundamental patterns, a hidden layer to extract the correlation found in the time scene and an output layer that employs a linear activation function to provide the flexibility required to handle the dynamic relationship between channel gain and time delay. The Mean Squared Error (MSE) acts as the loss function to measure the average squared difference between the estimated and the actual values. The simulation results indicated that the performance of the proposed model outperforms conventional channel estimation methods.

This letter is organized as follows: Section II presents the system model and problem formulation. A review of subspace-based classical methods is described in Section III. The development of the novel ML method is presented in Section IV. The performance of these methods is illustrated through MATLAB simulations in Section V. Finally, some concluding remarks and future work follow in Section VI.

II. Literation Review

A. Problem Formulation

The FH communication system operates as a multi-frequency shift keying system, comprising both a transmitting and a receiving end. The key elements of the transmitter include a transmitting antenna, frequency synthesizer, mixer, and Pseudo-Noise (PN) code generator. On the receiving end, the main components consist of the receiving antenna, synchronization circuit, PN code generator, frequency synthesizer, mixer, and filter. At the transmitting stage, the modulator is responsible for modulating the data information. Through the coordinated efforts of the pseudo-random code and local oscillator, a variable carrier frequency is generated to complete the modulation process. Carrier signals of varying frequencies are emitted at regular intervals. These carriers are then modulated with the original signals, producing an FH signal that is transmitted through a multipath fading channel. The baseband model of the multipath FH system, as shown in Fig. 1, is considered as a time-varying linear filter:

$$h(\tau,t) = \sum_{i=1}^{P(t)} \beta_i(t) e^{-j\emptyset_i(t)}\, \delta(t-\tau_i(t)) \tag{1}$$

The parameters $\beta_i(t), \emptyset_i(t)$ are r the magnitude channel gain and phase channel gain. Parameter $\tau_i(t)$ is the related time delay of the *i*-th multipath. The three parameters are assumed to be independent. The Impulse response of the NBFH multipath model is shown in Fig. 2 for a case of three paths. The received signal *y(t)* which is the output of the channel is the convolution of the input signal *x(t)* with the equivalent low-pass channel impulse response $h(\tau,t)$, i.e. $y(t)=x(t)\times h(\tau,t)$.

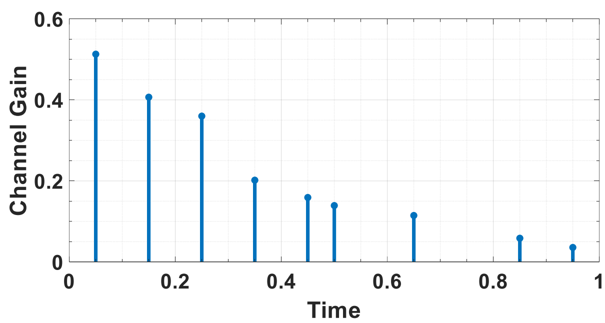

Fig. 2. The impulse response of NBFH multipath model.

The baseband model of the FH received signal in a multipath environment of the sample version form:

$$y^{(n)}(kT) = \sum_{i=1}^{P(t)} \beta_i(t) e^{-j\emptyset_i(t)} e^{-j2\pi f_n \tau_i} s(kT - \tau_i; \boldsymbol{b}_n) + w^{(n)}(kT) \quad (2)$$

where $y^{(n)}(kT)$ is the received signal in the nth hop, T is the sampling period, f_n is the frequency in the nth hop, and $\boldsymbol{b}_n$ is the sequence of the transmitted bits. $s(kT; \boldsymbol{b}_n)$ is the transmitted baseband signal and $w^{(n)}(kT)$ is the white Gaussian noise parameter. The parameter P represents the overall count of multi-paths considered in the model. The receiver is tasked with estimating the unknown transmitted bit sequence under the challenging condition of varying and unknown channel parameters. Both the transmitter and the receiver are aware of the hop frequency. Therefore, the discrete-time version of the received signal is expressed as follows:

$$y^{(n)}(k) = \sum_{i=1}^{P} \beta_i e^{-j2\pi f_n \tau_i} s_i(k) + w^{(n)}(k)$$
$$k = 1, 2, \ldots K \quad (3)$$

Here, $s_i(k)$ represents the delayed version of the transmitted signal through the i-th multipath. After capturing the signal via the antenna, the receiver initiates the process by extracting the precise phase of the transmitted FH signal through the synchronization circuit. Subsequently, it generates a local carrier frequency that is perfectly synchronized with the carrier frequency at the transmitting end. The next step implies mixing this synchronized carrier with the received FH signal, aiming to recover the original source signal.as shown in Fig. 3. The channel estimator is crucial for a receiver to adapt to varying channel conditions, mitigate the impact of impairments, and ultimately enhance the reliability and performance of communication systems. The received signal in Eq. (3) is attenuated, distorted, delayed, and phase shifted. Therefore, there is a need to provide a perfect and up-to-date estimation of the channel. The conventional channel estimator is typically a statistical model that estimates the channel's impulse or frequency response. The estimated channel response can then be used to equalize the channel's effects and improve the performance of the communication system. In recent years, increasing interest has been seen in using machine learning models to replace the conventional channel estimator. Machine learning models can be trained on large datasets of channel measurements, and they can learn to estimate the channel response more accurately than traditional statistical models. There are several potential advantages to using a machine learning model to replace the conventional channel estimator. First, machine learning models can be more accurate than traditional statistical models, especially in complex or rapidly changing channels. Second, machine learning models can be more adaptive than traditional statistical models, and they can learn to adapt to changes in the channel over time. Third, machine learning models can be used to estimate a broader range of channel characteristics than traditional statistical models, such as the channel's directional or polarization. However, some challenges are associated with using machine learning models for channel estimation. First, machine learning models can be computationally expensive to train and run. Second, machine learning models can be sensitive to the quality of the training data, and they may only perform well if the training data is representative of the actual channel conditions. Third, machine learning models can be difficult to interpret, and it can be challenging to understand how they are making their predictions. The problem tackled in this article is estimating the time delay and channel gain based on the received signal via machine learning.

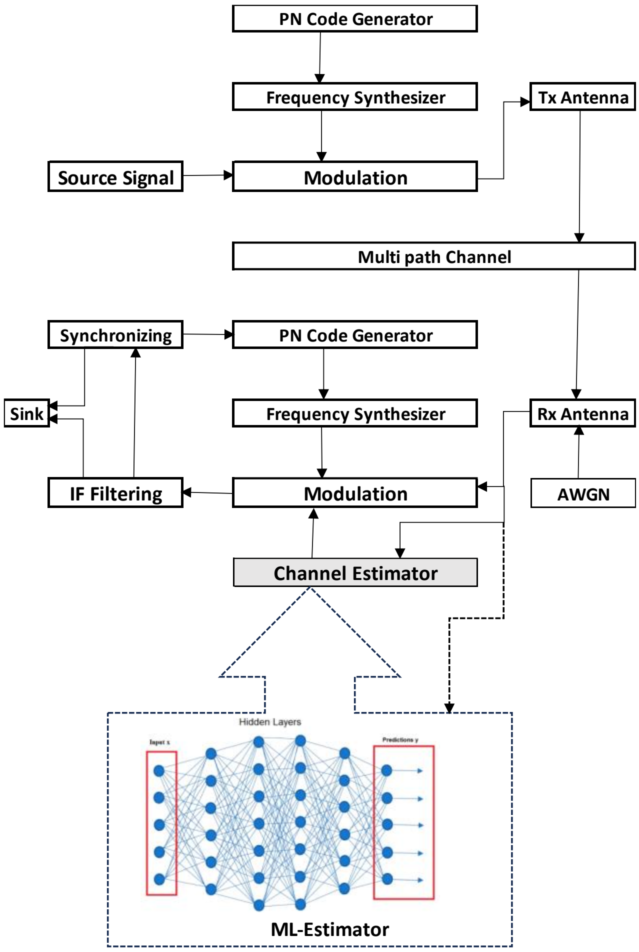

Fig. 3. FH system block diagram, the conventional channel estimator will be replaced by ML channel estimator.

B. *Review of the Classical Methods*

In this section, a review of a previous work related to this problem, based on Subspace based methods PM and RRQR is revisited. Both methods are directly applied to the received data. Let the K samples in Eq. (3) given by

$$\boldsymbol{y}_n = [y_n(0)\ y_n(1)\ \ldots\ldots y_n(K-1)] \quad (4)$$

1) Part A: estimation using PM method

Two subsets of received hop frequencies $\{f_{p_i}\}$ and $\{f_{q_i}\}$ each at least of size N are collected as $f_{p_i} = f_{q_i} + \Delta_f$, $i = 1,2, \ldots \ldots N$:

Let $\boldsymbol{Y}_p = [\boldsymbol{y}_{p1}^T\, \boldsymbol{y}_{p2}^T \ldots \ldots \boldsymbol{y}_{pN}^T]^T$ and $\boldsymbol{Y}_q = [\boldsymbol{y}_{q1}^T\, \boldsymbol{y}_{q2}^T \ldots \ldots \boldsymbol{y}_{qN}^T]^T$.

$\boldsymbol{Y}_p$ and $\boldsymbol{Y}_q$ can be written as

$$\begin{aligned} \boldsymbol{Y}_p &= \boldsymbol{AS} + \boldsymbol{W}_p \\ \boldsymbol{Y}_q &= \boldsymbol{A\Phi S} + \boldsymbol{W}_q \end{aligned} \tag{5}$$

where:

$$\boldsymbol{A} = \begin{bmatrix} e^{-j2\pi f_{p1}\tau_1} & \ldots & e^{-j2\pi f_{p1}\tau_p} \\ \vdots & \vdots & \vdots \\ e^{-j2\pi f_{pN}\tau_1} & \ldots & e^{-j2\pi f_{pN}\tau_p} \end{bmatrix}$$

$$\boldsymbol{S} = \begin{bmatrix} \beta_1 & & \\ & \ddots & \\ & & \beta_p \end{bmatrix} \begin{bmatrix} s_1(1) & \ldots & s_1(K) \\ \vdots & \vdots & \vdots \\ s_p(1) & \ldots & s_p(K) \end{bmatrix}$$

The amplitudes of the respective multipath. The sub-matrices calculated by (5) are collected matrix in **X** as

$$\boldsymbol{X} = [\boldsymbol{Y}_p\, \boldsymbol{Y}_q] + \boldsymbol{W_X} \tag{6}$$

where $\boldsymbol{W_X}$ is the related Additive White Gaussian Noise (AWGN) matrix. Matrix $\boldsymbol{A}$ is portioned into two sub-matrices $\boldsymbol{A_1}$ and $\boldsymbol{A_2}$ of size $P \times P$ and $(N-P) \times P$ respectively. A propagator matrix $\boldsymbol{P_X}$ satisfying $\boldsymbol{P_X^H A_1}=\boldsymbol{A_2}$, where $(.)^{\boldsymbol{H}}$ denotes hermitian transpose and the dimension of the matrix $\boldsymbol{P_X^H}$ is $(N-P)\times P$. Also, matrix $\boldsymbol{X}$ is divided into two sub-matrices $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ with dimensions $P \times 2K$ and $(N-P)\times 2K$ respectively. The Propagator matrix $\widehat{\boldsymbol{P}}_{\boldsymbol{X}}$ estimated by:

$$\widehat{\boldsymbol{P}}_{\boldsymbol{X}} = \arg\ \min \left\| \boldsymbol{X_2} - \widehat{\boldsymbol{P}}^{\boldsymbol{H}} \boldsymbol{X_1} \right\|^2 \tag{7}$$

Matrix $\boldsymbol{E_X}$ can be defined as $\boldsymbol{E_X} = [\widehat{\boldsymbol{P}}_{\boldsymbol{X}}^{\boldsymbol{T}} \quad -\boldsymbol{I}]^{\boldsymbol{T}}$where $\boldsymbol{I}$ is the identity $(N-P)\times(N-P)$ matrix. The orthogonal projection matrix $\boldsymbol{Q_X} = \boldsymbol{E_X}(\boldsymbol{E_X^H E_X})^{-1}\boldsymbol{E_X^H}$. Since the received hop frequencies are assembled in sets, therefore they are known at receiver. The MUSIC like search algorithm [15] is applied to estimate the multipath time delay using the function

$$\hat{\boldsymbol{\tau}}_{PM-MUSIC} = \frac{1}{\|\boldsymbol{Q_X A}\|^2} \tag{8}$$

2) Part B: Estimation Using RRQR Method

Gathering data from number of hopes and splitting the data packets into M subsets $\{F_1, F_2, \ldots, F_M\}$ of received frequencies each of at least of size N *as* $F_i = \{f_{i1}, f_{i2} \cdots, f_{iN}\}$

$$f_{ij+1} = f_{ij} + \Delta_f\ , j = 1,2 \ldots, N,\ i = 1,2, \ldots, M-1 \tag{9}$$

Two consecutive frequency sets are varied by a constant Δ_f. Let $\boldsymbol{Y}_i = [\boldsymbol{y}_{i1}^T\, \boldsymbol{y}_{i2}^T \ldots, \boldsymbol{y}_{iN}^T]^T$.It is an easy to show that M subsets can be characterized as

$$\begin{aligned} \boldsymbol{Y}_1 &= \boldsymbol{AS} + \boldsymbol{W}_1 \\ \boldsymbol{Y}_2 &= \boldsymbol{A\Phi S} + \boldsymbol{W}_2 \\ &\vdots \\ \boldsymbol{Y}_M &= \boldsymbol{A\Phi^{M-1} S} + \boldsymbol{W}_M \end{aligned} \tag{10}$$

here matrices $\boldsymbol{A}, \boldsymbol{S}, \boldsymbol{\Phi}$ already defined in part A of this section and $\boldsymbol{W}_1$, $\boldsymbol{W}_2, \ldots \boldsymbol{W}_M$ are corresponding noise matrices. The sub- matrices calculated by Eq. (10) grouped in the matrix **X** as

$$\boldsymbol{X} = [\boldsymbol{Y}_1\, \boldsymbol{Y}_2 \ldots, \boldsymbol{Y}_M] + \boldsymbol{W} \tag{11}$$

where $\boldsymbol{W}$ is the corresponding complex additive white Gaussian noise (AWGN) matrix. RRQR factorization is applied for Eq. (11)

$$\boldsymbol{X^T} = \boldsymbol{QR} = [\boldsymbol{Q_1} \quad \boldsymbol{Q_2}] \begin{bmatrix} \boldsymbol{R_{11}} & \boldsymbol{R_{12}} \\ \boldsymbol{0} & \boldsymbol{R_{22}} \end{bmatrix} \tag{12}$$

where the two matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$ are of dimensions $MK \times MK$ and $MK \times (N-M+1)$ respectively. The sub-matrix $\boldsymbol{R_{11}}$ is upper triangular full rank matrix while $\boldsymbol{R_{12}}$ is holding remaining important information with dimensions $P \times (N-M-P+1)$. Because of rank-revealing QR-factorization, it is interesting to note here is that the sub-matrix $\boldsymbol{R_{22}}$ is just about null matrix.

$$\boldsymbol{X^T} \cong \boldsymbol{Q_1}\widehat{\boldsymbol{R}} = \boldsymbol{Q_1}[\boldsymbol{R_{11}}\ \ \boldsymbol{R_{12}}] \tag{13}$$

Clearly, any vector that belongs to null space should satisfy.

$$\widehat{\boldsymbol{R}}\boldsymbol{G} = [\boldsymbol{R_{11}} \quad \boldsymbol{R_{12}}] \begin{bmatrix} \boldsymbol{g_1} \\ \boldsymbol{g_2} \end{bmatrix} = \boldsymbol{0} \tag{14}$$

So that $\boldsymbol{R_{11}g_1} = -\boldsymbol{R_{12}g_2}$. Since $\boldsymbol{R_{11}}$ is an invertible matrix, $\boldsymbol{g_1}$ can be written in terms of $\boldsymbol{g_2}$ as $\boldsymbol{g_1} = -\boldsymbol{R_{11}^{-1}R_{12}g_2}$. Then $\boldsymbol{G}$ can be written as

$$\boldsymbol{G} = \begin{bmatrix} \boldsymbol{g_1} \\ \boldsymbol{g_2} \end{bmatrix} = \begin{bmatrix} -\boldsymbol{R_{11}^{-1}R_{12}} \\ \boldsymbol{I}_{(N-M-P+1)} \end{bmatrix} \boldsymbol{g_2} = \boldsymbol{Hg_2} \tag{15}$$

Clearly, $\boldsymbol{RH} = \boldsymbol{0}$. It can be observed here that the columns of the null space $\boldsymbol{H}$ are not orthonormal. To satisfy orthonormality the orthogonal projection onto this subspace is used to improve the performance as:

$$\boldsymbol{H_o} = \boldsymbol{H}(\boldsymbol{H^H H})^{-1}\boldsymbol{H^H} \tag{16}$$

. Therefore, the MUSIC like search algorithm [16] can be applied to explore null space for unknown multipath time delay parameters using the following function:

$$\hat{\boldsymbol{\tau}}_{RRQR-MUSIC} = \frac{1}{\boldsymbol{A^H(\omega)H_o^H H_o A(\omega)}} \tag{17}$$

An alternative approach, instead of seeking peaks in Eq. (17), is to employ root-MUSIC [16]. The frequency estimates can then be derived as:

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$$D(z) = \sum_{i=0}^{N/2-1} \boldsymbol{V_i}(z)\boldsymbol{V_i^*}(1/z^*) \tag{18}$$

where $\boldsymbol{V_i(z)}$ is the z-transform of the *i*th column of a projection matrix [15].

C. Part C: Time Delay Estimation Using a Closed Form

The sub matrices calculated by Eq. (6) grouped in matrix $\boldsymbol{Y}$ as

$$\boldsymbol{Y} = \left[\boldsymbol{Y_p^T} \quad \boldsymbol{Y_q^T}\right]^{\boldsymbol{T}} + \boldsymbol{W_Y} \tag{19}$$

and partition it as $\boldsymbol{Y} = \left[\boldsymbol{Y_1^T} \quad \boldsymbol{Y_2^T}\right]^{\boldsymbol{T}}$, where $\boldsymbol{Y_1}$ and $\boldsymbol{Y_2}$ contain the first P and last $2N$-P rows of $\boldsymbol{Y}$ respectively. The solution obtained through the least squares method for the propagator using the Direct Matrix (DM) is as follows:

$$\widehat{\boldsymbol{P}}_{\boldsymbol{Y}} = (\boldsymbol{Y_1}\boldsymbol{Y_1^H})^{-1}\boldsymbol{Y_1}\boldsymbol{Y_2^H} \tag{20}$$

The matrix $\boldsymbol{E_Y}$ of size $2N \times (2N - P)$ can be defined as

$$\boldsymbol{E_Y} = [\boldsymbol{I^T} \quad \widehat{\boldsymbol{P}}_{\boldsymbol{Y}}^{\boldsymbol{T}}]^{\boldsymbol{T}} = \left[\boldsymbol{E_1^T} \quad \boldsymbol{E_2^T}\right]^{\boldsymbol{T}} \tag{21}$$

and $\boldsymbol{W}_p$ and $\boldsymbol{W}_q$ are corresponding noise matrices, and matrix $\boldsymbol{\Phi} = diag(e^{-j2\pi\Delta_f\tau_1} \ldots\ldots e^{-j2\pi\Delta_f\tau_P})$. The parameters β_i are
where $\boldsymbol{E_1}$ and $\boldsymbol{E_2}$ contain the first N and last N rows of $\boldsymbol{E_Y}$ respectively. Also,

$$\boldsymbol{E_2}(\boldsymbol{E_1^H}\boldsymbol{E_1})^{-1}\boldsymbol{E_1^H}\boldsymbol{A} = \boldsymbol{Q_Y}\boldsymbol{A} = \boldsymbol{A\Phi} \tag{22}$$

It is apparent that the P eigenvalues of $\boldsymbol{Q_Y}$ are associated with the P diagonal elements of $\boldsymbol{\Phi}$ establishing a direct correspondence. The multipath delay parameters are given by:

$$\hat{\tau}_i = \frac{-angle(\lambda_i)}{(2\pi\Delta_f)} \tag{23}$$

III. Development of ML Methods

Machine learning models in communication systems provide increased accuracy, adaptability to changing channels, and the capacity to estimate a wider range of channel characteristics. In this section, we will present the proposed ML based channel estimation scheme.

A. Datasets Generation

The first step of the research is to create a synthetic dataset that mimics the complexity of actual signal delays. A three-multipath model (P=3) is considered to compare with subspace methods. The transmission was assumed to be within the frequency range (1899 – 1929) MHz, which corresponds to the uplink frequency range for the personal communication system. A comprehensive set of 75 frequencies was considered, featuring a 400 KHz separation between carriers. The symbol period for our system is set at 4µs.A total of five thousand signals were generated, with each signal having a length of one hundred units; the time delay is taken randomly from a uniform distribution between zero and one, and the channel gain is taken as a random complex normal distribution.

B. Dataset Preprocessing

The dataset went through preprocessing procedures to guarantee consistency and make model training easier. Three components with random amplitudes and delays were combined to simulate the complex structure of real-world signals in signal synthesis. Gaussian noise was introduced to simulate the surroundings. After that, the dataset was divided into training (80%) and testing (20%) groups [28-30].

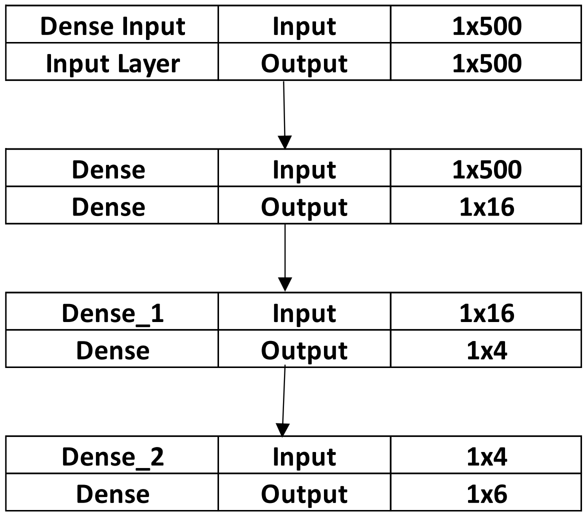

Fig. 4. ANN architecture.

C. Neural Network Architecture

The architecture of the NN employed in this study comprises three layers, each layer playing a pivotal role in capturing the intricate relationships within the synthesized signals:

1) Input layer (16 neurons)

The input layer, with 16 neurons, serves as the network gateway for the signal's temporal characteristics. Activated by the Rectified Linear Unit (ReLU) function, this layer is the initial interpreter of the signal's underlying patterns.

2) Hidden layer (4 neurons)

Nestled within the network, the hidden layer with four neurons, also employing the ReLU activation function, conceals the latent complexities associated with signal delays. It endeavors to distill the nuanced correlations embedded within the temporal landscape [31].

3) Output layer (6 neurons)

The culmination of the network lies in the output layer, housing six neurons. Each neuron corresponds to a distinct aspect of the signal, the channel gain, and the linked time delay (β_i and τ_i). Importantlyβ_i, representing the signal amplitude (channel gain), is acknowledged as a dynamic entity. While in one experiment, it may exhibit a correlation with the delay, in another experiment, this correlation may not manifest. To accommodate this variability, the output layer utilizes a linear activation function, allowing for the flexibility required to capture such experiment-specific nuances.

D. Neural Network Training Process

Activation functions in the hidden layers, employing Rectified ReLU, introduce non-linearity to discern intricate patterns, while the output layer utilizes linear activation to capture experiment-specific correlations between channel gain and time delay flexibly. The Mean-Squared Error (MSE) [32, 33] serves as the loss function, quantifying the average squared difference between predicted and actual values in this regression task.

The training loss curve and the validation loss curve for both time delay and channel gain estimator are shown in Fig. 5. The training loss curve shows how the loss on the training set evolves over epochs. In the initial epochs, the training loss tends to decrease as the model learns to capture patterns in the training data. As training progresses, the loss might stabilize, indicating improved model performance. The validation loss curve is plotted using a separate dataset that the model has not seen during training. It assesses the model's generalization to new, unseen data. The validation loss initially decreases, reaches a minimum, and then stabilizes. The training process involves the Adam optimizer for adaptive learning rates, a batch size of 32 for computational efficiency, and a carefully selected training duration of 50 epochs. Early stopping, set with a patience of 3, guards against overfitting, ensuring the model generalizes well. Hyperparameter settings were thoughtfully chosen with the default learning rate of Adam optimizer and a batch size of 32 to balance efficiency and model stability. A 50-epoch training duration, determined through convergence observations, optimizes learning. Notably, regularization techniques such as dropout layers were considered for complexity management but omitted, maintaining model simplicity in alignment with the synthetic dataset's characteristics. Hyperparameters were thoughtfully chosen with the default learning rate of the Adam optimizer and a batch size of 32 to balance efficiency and model stability. A 50-epoch training duration, determined through convergence observations, optimizes learning. Notably, regularization techniques such as dropout layers were considered for complexity management but omitted, maintaining model simplicity in alignment with the synthetic dataset's characteristics. This architectural configuration is tailored to not only to decipher temporal intricacies but also to accommodate the dynamic nature of the correlation between signal amplitude and delay across different experiments. The results of the neural network training reveal a substantial reduction in the MSE loss throughout three epochs. The initial training loss, starting at 2.3449, rapidly decreased to 0.0573 by the third epoch. Concurrently, the validation loss mirrored this trend, dropping from an initial value of 0.6402 to 0.0747. The consistent decline in training and validation losses demonstrates the model's capacity to effectively learn and generalize patterns within the data. The MSE loss metric quantifies the disparity between predicted and actual values, and the achieved low loss values indicate the model's proficiency in estimating delays. This suggests the potential utility of the developed neural network with accurate delay estimation tasks.

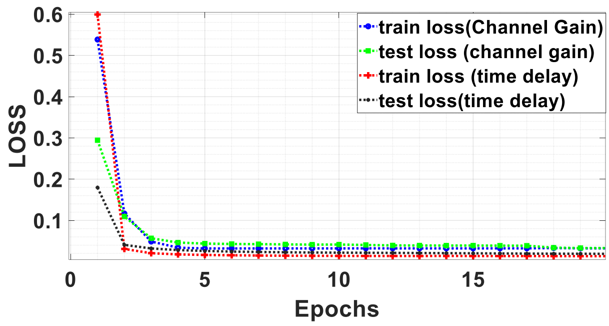

Fig. 5. Training and Validation Loss for channel gain and time delay estimators.

IV. Simulation Results

Comprehensive computer simulations were conducted to validate the existing methods and assess the performance of the newly proposed ML-based estimator. In the initial experiment, illustrated in Fig. 6, the multipath delays were configured as 0.1, 0.4, and 0.9 µs in the subspace methods. In contrast, the proposed model featured randomly chosen time delays within the range of [0, 1]. The channel gain parameter is assumed to be a complex random variable in all methods. As depicted in the figure, the proposed method demonstrates outstanding performance in comparison to all subspace reference methods. To assess the proposed system's performance compared to other classical systems, we can compare the normalized MSE at a specific SNR. The lower the MSE values, the better the system performance. For instance, at a fixed SNR of 15dB, the normalized MSE for the proposed ML-based channel estimation method equals 0.00677, and it is much lower than the normalized MSE of the QR-MUSIC method (MSE=0.02), which exhibits the best performance among the classical systems. Notably, the proposed method surpasses all subspace methods, including LS-Esprit, TLS-Esprit, RRQR-root-MUSIC, and RRQR-MUSIC, across various SNR levels.

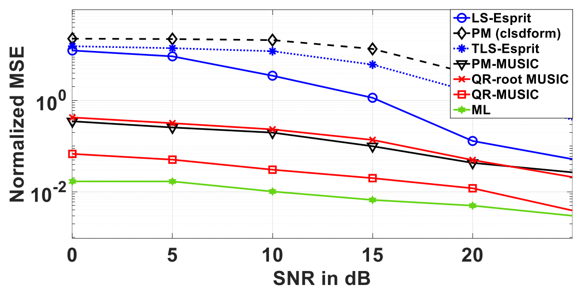

Fig. 6. Normalized MSE as a function of SNR over a normal multipath fading.

In the second experiment, depicted in Fig. 7, consistent parameter assumptions were retained from the first experiment, with the exception that the multipath gain parameters exhibited an exponential decay pattern. Moreover, the scenario was examined across one thousand distinct realizations. In this setting, the PM method, coupled with MUSIC, exhibits robustness against random multipath channel conditions. Nevertheless, the ML method outperforms other techniques in terms of performance.

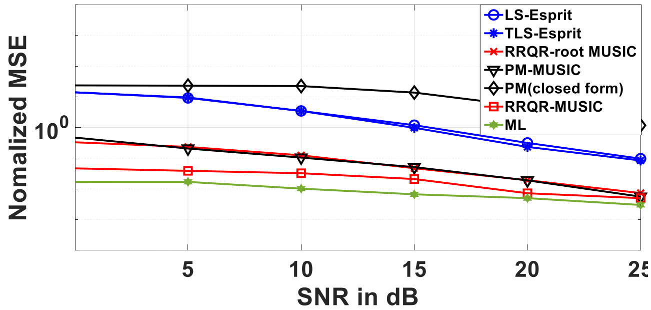

Fig. 7. Normalized MSE as a function of SNR over an exponential multipath fading.

V. Conclusion

In this paper, we proposed an ML technique to accurately estimate NB multipath channel parameters for SFH, leveraging a synthetic dataset rich in intricate temporal variations and channel gain nuances. The Neural Network architecture, characterized by multiple dense layers, effectively captured intricate temporal relationships. Following rigorous training and validation utilizing MSE loss function, the model significantly reduced loss, underscoring its proficiency in accurate delay estimation. Furthermore, we provided computer simulations to validate the effectiveness of the proposed system compared to previous work using subspace-based methods. The proposed ML estimator outperformed the classical subspace-based methods and demonstrated effectiveness over different SNRs. The proposed system will be extended in future work to build an end-to-end ML-based frequency hopping signal detection.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Mahmoud Qasaymeh is the primary author of this paper, and he has written the entire paper, compiled all necessary information, and presented it in an understandable manner. Ahmad Aljaafreh and the primary author have developed the machine learning code. Ali Alqatawneh has provided the literature review and the paper revision. all authors had approved the final version.

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