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Artificial neural network-based sparse channel estimation for V2V communication systems

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Artificial neural networks (ANNs) have gained a lot of attention from researchers in the past few years and have been employed on a large scale. They have also been gaining momentum in wireless communication systems. For efficient vehicle-to-vehicle (V2V) channel communication, a sparse multipath channel issue must be studied. To minimize the multipath effect, a time reversal (TR) operation and time division synchronization orthogonal frequency division multiplexing (TDS-OFDM) have been appealing because of their fast synchronization and active spectral efficiency. To improve the transceiver's execution in a frequency-selective fading channel environment, an OFDM system is used to reduce inter- symbol interference (ISI). Simultaneous Orthogonal Matching Pursuit (SOMP) channel state estimator algorithm suffer from high computational cost and high computational complexity. The ANN algorithm has better performance than SOMP algorithm. The proposed neural network technologies have lower complexity than the SOMP algorithm. The application of ANN is capable of solving complex problems, such as those encountered in image, signal processing and have been implemented for channel estimation in OFDM. The proposed ANN outperformed the SOMP algorithm with regard to signal compensation. Overall, the ANN algorithm achieved the best performance. This study proposes an ANN-based sparse channel state estimator. Regarding the bit error rate (BER) metric, the proposed estimator outperforms the channel estimation approach based on the SOMP. The simulation results confirm the efficacy of the proposed approach.

Keywords: artificial neural networks, time reversal, orthogonal frequency division multiplexing, channel estimation, compressive sensing, simultaneous orthogonal matching pursuit

1 Introduction

The possibility of accidents resulting in severe damage and fatalities has led to an increase in the amount of interest in vehicle communication (VC) systems for both civilian and military uses. Also, V2V communication offers services like brake status updates, passenger infotainment, speed advisory, and road construction information. Authorities, automakers, and security app developers support safer driving conditions. Different vehicle types have distinct sizes and motion characteristics, making information sharing essential for efficient transportation and reducing environmental impact [1].

Road safety and traffic efficiency have increased as a result of the intelligent transportation system's (ITS) recent evolution to include driver-aid technologies. In this context, a lot of focus has been placed on developing vehicle-to-vehicle (V2V) and vehicular-to-everything (V2X) communication between individual sensor-equipped vehicles by academic researchers, the telecommunications industry, and government agencies. As a result, V2V can be used to achieve advantages including less infrastructure associated with traffic, lower logistic costs for the fleet of vehicles, and real-time, low-latency, reliable communication [2]. V2V communication is a technique that offers various services like speed advisory, passenger infotainment, brake status, and also updates the users on road construction, route planning, etc. For V2V communication, channel estimation is tedious because of the Doppler shift contributed by vehicle moving under varying speed. Further, reflection, refraction, and other disturbances caused by objects and buildings affects the communication among vehicles.V2V communications play an essential role in these pains, therefore, introducing safer, and efficient driving conditions have received strong support from both officials and car manufacturers, as well security applications.V2V communication system needs security and communications infrastructure to enable and ensure the trustworthiness of communication between vehicles, also V2V technologies will increase their liability as compared with other safety technologies. As well as V2V communication is a challenging but fast growing technology, it has the potential to enhance road safety by helping the driver to avoid collisions during basic maneuvers such as crossing street intersections, changing lanes, merging on a highway, and driving safely in blind turns.

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Using orthogonal subcarriers, orthogonal frequency division multiplexing (OFDM) efficiently decreases inter-symbol interference (ISI). Numerous communication systems rely on it, including IEEE 802.11a/g/n, IEEE 802.16, DAB, DVB, and 3-G LTE [3-4]. OFDM converts selective fading channels into flat fading channels, making it suitable for V2V communication systems with mobile transmitters and low altitude antennas [5, 6].

Time reversal (TR) systems have gained attention due to their active spectral efficiency/quick synchronization, which effectively mitigate the impact of multipath effects. TR relies on the symmetry of the linear wave equation, allowing the received sound signal to be captured at multiple locations. By reversing and retransmitting these signals, focused signals can be generated at the original source position. The TR mechanism enables the reduction of delay spread, enhancement of signal-to-noise ratio (SNR), and mitigation of fading effects by focusing on the CIR [7, 8].

To address time-varying channels, the TR technique incorporates a short pseudorandom noise (PN) sequence, specifically designed for long tap delay channels. The TDS-OFDM technique adopts a PN sequence known to both the transmitter and the receiver as a guard interval (GI) as well as a training sequence (TS) for synchronization and channel estimation. The use of PN-sequences as a prefix reduces transmission overhead, can achieve a higher spectrum efficiency with fast synchronization and provide significant BER improvement as well as energy improvement. To solve the BER performance degradation problem, thanks to TR technique assist single input multi output (SIMO) communication by converting the long tap delay channel to be impulse like channel. The impulse like channel is used to improve the TDS-OFDM BER performance and improve energy efficiency. In the TR process, at the very beginning of the communication, the transmitter transmits a probe symbol sequence that is recorded by the receiver. This recorded received probe sequence, serving as channel information and it is time reversed and transmitted back to the transmitter, in TR operations, each multipath signal sequence received convolves with the time-reversed version of its corresponding channel estimate based on this probe signal. This technique aims to convert the long tap delay channel into an impulse-like channel, effectively improving the overall performance [9-10]. Additionally, the TR method can be applied to eliminate mutual interference issues in time division synchronization orthogonal frequency division multiplexing (TDS-OFDM) systems [11].

It is crucial for research to estimate the channels in the compressed sensing (CS) area [12]. V2V channel communication systems can be estimated using the CS approach. To retrieve sparse signals from a small number of observations, CS theory is utilized. A lot of recent CS work has focused on algorithms for sparse channel estimation. Despite its complexity, the CS method achieves good results in high-data-rate transmission over multipath channels [13].

Channel state estimator based on CS can be performed using the received PN sequence, but multipath sparse techniques have high computational overhead and complexity. Analytical models created by humans are insufficient for representing channel propagation effects in situations like V2V. Vehicle motion and scattering cause rapid changes in the channel characteristics for in-car wireless communications [14-17]. Because of the car's high speed and the abundant surrounding scatters, channel parameters in vehicle wireless communications vary quickly. A channel estimator that can monitor channel variation in such an environment is required due to the channel change [18].

Simultaneous orthogonal matching pursuit (SOMP) is a conventional estimator regarding to V2V communication systems, applied to non-sparse channels [15]. SOMP method is one of the most traditional sparse signal reconstruction methods among greedy pursuit methods, requires no repeated interference deletion to separate the conditional time domain channel estimation alternately and detect the frequency domain data, and it will consider as the conventional channel estimation method in this work. Using traditional signal recovery, SOMP can retrieve a sparse signal, because of random measurements, alternating signals can be recreated with little information. Two tools for channel state estimation are Symbol-by-symbol (SBS) and Frame-by-frame (FBF), with FBF estimators improving execution accuracy. FBF estimators are typically used in high-mobility vehicular communications to improve performance accuracy.

Recently, there has been a lot of interest focused on machine learning (ML) in the communication systems industry, especially in channel estimation, equalization and detection [19-23]. ANNs are among the ML methods that are utilized the most frequently [24]. ANNs find widespread use in the solution of intricate issues, including image/signal processing. Many neurons that function in parallel and are coupled by weights make up ANNs. Because of their robust approximation/learning capabilities, numerous neural networks have been employed to estimate OFDM channels, allowing input-output pairs to accurately predict the system [25].

Numerous researches have shown how crucial ANN is to finishing estimate jobs. Regarding the channel estimate task, the authors in [13] proposed a system model-based ANN in the event of a sparse multipath channel for the OFDM system. The proposed model-based ANN provides higher performance than the conventional SOMP estimation approach. The proposed estimator performed better than the OMP and MP estimators in the comparative analysis, even with a smaller number of pilots. The authors in [25] introduced DL architectures for doubly-dispersive channel estimation. SBS and FBF channel estimators are utilized. The outcomes of the simulation indicate the recommended solution's advantage over cutting-edge CS techniques. In the current study, ANNs are used to investigate a method for channel estimation in an OFDM system that operates with sparse multipath channels. The learning power of ANN is utilized to demonstrate how to model and generate a channel estimate, which in turn enables the suggested method to provide improved performance. The study compares the performance of the SOMP algorithm with that of the suggested technique, which is widely utilized in CS literature for sparse multipath channel estimation. Compared to SOMP techniques, with its ANN-based channel estimator, the suggested BER performance is superior. SOMP is known for its high computational cost and complexity, involving iterative computations that become prohibitively expensive with large datasets or in high-dimensional signal spaces. This can hinder its real-time applicability, especially in low-latency communication systems. Moreover, SOMP's performance can significantly degrade in the presence of noise and in dynamic wireless channels affected by fading, multipath propagation, and Doppler shifts. These shortcomings highlight the necessity for alternative algorithms capable of adapting to dynamic environments and maintaining communication reliability.

ANN based sparse multipath channel estimation algorithms may have pretty much potential to be good candidates to meet better performance, smaller latency between transmitters, a low complexity ANN based channel estimation algorithm and lower computational cost.

The contributions of this study can be summed up as follows:

- We utilize an ANN estimator to improve CSE in OFDM systems operating over Rayleigh fading channels.
- The authors in [13] shown that how to model, obtain a channel estimate and how it allows the ANN proposed technique to give a better system throughput by comparing ANN to traditional LS and MMSE estimation techniques, according to the SER vs. SNR criterion.
- Evaluating the proposed ANN estimator's performance using BER vs. SNR. Additionally, we compare the proposed ANN estimator to the conventional SOMP used in [15].
- Under different GI length and number of receiver antennas, we examine the performance of the proposed ANN estimator.
- Various neural networks have been implemented for channel estimation in OFDM, on account of their strong approximation and learning ability.
- The performance of the examined estimators is tested in several simulated situations with cyclic prefix lengths in [20], and variable pilot density. Also, there is no prior channel statistics knowledge present.
- The authors in [25] study the recently proposed DL-based channel estimation techniques for doubly dispersive channels.
- Furthermore, we compare the proposed ANN estimator to other compressive sensing, including the SOMP algorithm mentioned in [26].

The remainder of this paper is structured as follows: Section 2 describes the architecture of the OFDM system used. Section 3 provides a brief overview of channel estimation, illustrates conventional estimators, and illustrates the proposed ANN-based channel estimation framework. Section 4 presents the simulation results that analyze the performance of the proposed estimator in terms of SNR and BER, compare it to other benchmarks, and assess its overall performance. Finally, this work is summarized, concluded, and future directions are discussed in Section 5.

2 System model

This section provides a quick overview of the OFDM system. For the current study, we adopted an OFDM system with a single user due to its excellent performance in resisting ISI and reducing the multipath fading effect. Figure 1 shows the model of the OFDM system based on the pilot channel estimation. OFDM used to transmit the data in parallel over these narrower sub-carriers. These narrow-band sub-carriers are mutually orthogonal and can overlap, allowing OFDM systems to use the bandwidth efficiently and be more robust against the ISI caused by multipath fading [13]. The transmitting and receiving components are identical to those used in conventional systems [19]. On the transmitter side, the chosen modulation determines how the binary data sequence is mapped and grouped according to chosen. After the conversion from serial to parallel (S/P), pilots are added to each subcarrier for a fixed amount of time or uniformly spaced out between the packets of information.

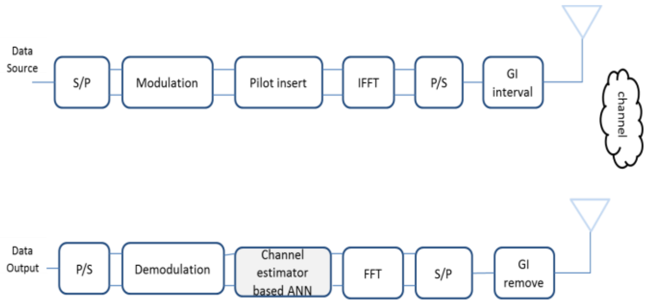

Fig. 1. OFDM system model

Pilots are placed uniformly between the information data or to all subcarriers with a specified duration. The pilot channel estimation technique begins transmission with a TS of known data symbols (pilots) and uses the received pilot signals to initially estimate the channel characteristics. The process of converting the frequency domain signals $X_i(k)$ into time domain signals $x_i(n)$is as follows:

$$x_i(n) = \frac{1}{N}\sum_{k=0}^{N-1} X_i(k)e^{j2\pi k/N} \quad n = 0, 1 \dots N-1 \quad (1)$$

where $X_i(k)$ represents the ith OFDM symbol in the kth subcarrier and in the nth symbol period, the ith OFDM symbol is represented by $x_i(n)$. N is the number of subcarriers. To prevent interference between symbols (ISI), GI is inserted. The resulting samples in the time domain are

$$x_g(n) = \begin{cases} x_i(N+n) & n = -N_G. \dots . -1 \\ x_i(n) & n = 0.1 \dots . N-1 \end{cases} \quad (2)$$

where $x_g(n)$ is a time-domain signal with GI and $N(G)$ is the number of samples in the GI. The additive white Gaussian noise (AWGN) enhanced frequency selective time-varying fading channel will then be traversed by the transmitted signals $x_g(n)$ [24]. The signal that was received was given by:

$$y_g(n) = x_g(n) \otimes h_i(n) + \omega_i(n) \quad (3)$$

where $\omega_i(n)$ is AWGN and $h_i(\mathrm{n})$ is the channel's impulse response. GI has been removed from $y_g(\mathrm{n})$ as shown below:

$$y_g(n) - N_g \le n \le N-1$$

$$y_i(n) = y_g(n+N_g) \qquad n = 0, 1, 2 \dots N\text{-}1 \quad (4)$$

Here, $y_i(n)$, received signal, is transformed into the frequency range by FFT:

$$Y_i(k) = \sum_{\mathrm{k}=0}^{N-1} y_i(n)\mathrm{e}^{-\mathrm{j}\frac{2\pi \mathrm{k}}{\mathrm{N}}}, \qquad k = 0.1 \dots . N-1 \quad (5)$$

Next, the signal that was received is shown as

$$Y_i(k) = X_i(k)\, H_i(k) + \omega_i(k), \quad (6)$$

where $Y_i(k)$ is the ith OFDM symbol of the kth sub-carrier represented in the frequency domain. $W_i(k)$ represents the FFT of $\omega_i(k)$ and $H_i(k)$ represents the complex channel coefficients ith OFDM symbol for the kth subcarrier. The pilot signals are retrieved after the FFT block, allowing for an estimation of the channel. The binary data sequences are recovered in the signal demapped block following parallel/serial (P/S) conversion.

3 Channel estimation

Concerning wireless communication, the receiver typically does not know the channel beforehand. Therefore, the channel estimation is carried out via a pilot symbol-aided modulation. Referencing pilot symbols or multiplexing reference symbols, within the data stream is the fundamental idea behind pilot symbol-aided channel estimation. Using the received known pilot symbols, the channel state information (CSI) is estimated by the receiver. In OFDM frames, either the frequency or time directions could have a scattering of the pilot symbols.

All subcarriers are assumed to be orthogonal. The diagonal matrix that follows can then be used to represent the pilot symbols for N subcarriers:

$$\mathbf{X} = \begin{bmatrix} X(0) & 0 & \dots & 0 \\ 0 & X(1) & \dots & \vdots \\ \vdots & \dots & \ddots & 0 \\ 0 & \dots & 0 & X(N-1) \end{bmatrix} \quad (7)$$

where $\mathrm{Var}[X(k)] = \sigma_x^2$ and $E[X(k)] = 0$ indicate a pilot tone at the kth subcarrier represented by symbol $X(k)$, $k = 0,1,2 \dots N-1$. As stated, a diagonal matrix provides $\mathbf{X}$, which should be noted, despite the fact that we take all subcarriers to be orthogonal. With each subcarrier k having a channel gain of $H(k)$, the received pilot signal $Y(k)$ can be expressed as:

$$\mathbf{Y} = \begin{bmatrix} Y(0) \\ Y(1) \\ \vdots \\ Y(N-1) \end{bmatrix}$$

$$= \begin{bmatrix} X(0) & 0 & \dots & 0 \\ 0 & X(1) & \dots & \vdots \\ \vdots & \dots & \ddots & 0 \\ 0 & \dots & 0 & X(N-1) \end{bmatrix} \begin{bmatrix} H(0) \\ H(1) \\ \vdots \\ H(N-1) \end{bmatrix} + \begin{bmatrix} Z(0) \\ Z(1) \\ \vdots \\ Z(N-1) \end{bmatrix} \quad (8)$$

$\mathbf{H}$ is a channel vector that is defined as $\mathbf{H} = [H(0),\ H(1) \ldots H(N-1]^{\mathrm{T}}$ and $\mathbf{Z}$ is a noise vector defined as $\mathbf{Z} = [Z(0),\ Z(1) \ldots Z(N-1)]$ with $E[Z(k)] = 0$ and $\mathrm{Var}[Z(k)] = \sigma_{\mathrm{x}}^2, k = 0,1,2,N-1$. As we talk in the discussion below, $\mathbf{H}$ represents the estimated channel H. We present neural network-based and SOMP-based channel estimation techniques. The algorithms are described as follows.

3.1 Conventional SOMP estimator

This subsection presents a dependable yet simultaneous multi-channel reconstruction strategy that combines the unique technological characteristics of TDS-OFDM with the popular signal reconstruction algorithm known as SOMP. There are many models to estimate the channel, including SOMP and other algorithm-based sparse channel estimator techniques.

The SOMP method is one of the most traditional sparse signal reconstruction methods among greedy pursuit methods. It does not require repetitive interference removal in order to identify the frequency domain data and separate the conditional time domain channel estimate alternately, and it will be considered the conventional channel estimation method in this work.

Using traditional signal recovery, SOMP can retrieve a sparse signal, and because of random measurements, alternating signals can be recreated with little information [26]. SOMP, which is derived from the popular OMP method, has received a lot of attention because of its good reconstruction quality. SOMP enquires about the number of observations and the known sparsity level S. The next equation represents the central concept of SOMP:

$$\begin{gathered} \hat{\mathrm{H}} = \arg\ \min\ \|\mathrm{H}\|_{p.q}, \\ \text{subject to } \|\mathbf{Y} - \mathbf{\Phi H}\|_{\mathrm{p.q}} \le \xi^2 \\ \mathbf{H} \in \mathrm{C}^{\mathbf{L}\times\mathbf{R}} \end{gathered} \tag{9}$$

The solution to the previous equation by chooses the observation matrices are repeatedly approximated using a limited subset of Φ's column vectors [15]. The residual value of the measuring channel $\hat{\mathrm{Y}}$ is chosen in the SOMP-based channel estimator.

Once the requirement for termination is satisfied, the iterative SOMP process will end. When the termination condition is satisfied, the iterative SOMP process will end. The following support determines what is considered common support for SOMP:

$$j^{(t)} = \arg\max \frac{\|\hat{\mathrm{Y}}^{\mathrm{H}} \phi_{\mathrm{j}}\|_2}{\|\phi_j\|_2} \tag{10}$$

$$je \notin \widehat{\mathbf{\Omega}}^{(t-1)}$$

Algorithm 1: Simultaneous OMP (SOMP) estimator

Require: $\bar{\mathrm{Y}}$ and $\mathbf{\Phi}_{\mathrm{M}} = \mathbf{P}^H \mathbf{A}_T = [\boldsymbol{\phi}_1 . \ldots . \boldsymbol{\phi}_{G\mathrm{T}}]$

1: **Initialization:** set t = 0, $\widehat{\mathbf{\Omega}}^{(0)} = \emptyset$, and $\mathbf{\Pi}^{\perp}_{\widehat{\mathbf{\Omega}}^{(0)}} = \mathbf{I}_{M_{BS}}$

2: **iterate**

3: Update the counter of iterations: $\mathrm{t} = \mathrm{t} + 1$

4: Orthogonal projection: $\mathbf{R}^{(t)} = \mathbf{\Pi}^{\perp}_{\widehat{\Omega}^{(t-1)}}\ \bar{\mathbf{Y}}$

5: Maintain the selection rule: $j^{(t)}_{SOMP} = \arg\max_{j \notin \widehat{\mathbf{\Omega}}^{(t-1)}} \|(\mathbf{R}^{(t)})^{\mathrm{H}} \boldsymbol{\phi}_{\mathrm{j}}\|_2 / \|\boldsymbol{\phi}_{\mathrm{j}}\|_2$

6: Update estimated common support: $\widehat{\mathbf{\Omega}}^{(t)} = \widehat{\mathbf{\Omega}}^{(t-1)} \cup j^{(t)}$

7: Compute orthogonal projector: $\mathbf{\Pi}^{\perp}_{\widehat{\mathbf{\Omega}}^{(t)}} = \mathbf{I}_{M_{\mathrm{BS}}} - \mathbf{\Phi}_M^{\widehat{\Omega}^{(t)}} (\mathbf{\Phi}_M^{\widehat{\Omega}^{(t)}})^{\dagger}$

8: As long as the final requirement is satisfied **provide** an estimated common support $\widehat{\mathbf{\Omega}}^{(t-1)}$

Standard OFDM systems are outperformed by TDS-OFDM, where, for all OFDM schemes, when the channel is estimated using SOMP, the channel estimator based on GI length is more effective than the pilot-based method for appropriate comparison. Whereas the GI length grows in proportion to the channel estimate accuracy. SOMP presented in Algorithm1 is applied to estimate the channel [27]. $\overline{\mathrm{Y}}$ denotes the residual of channel measurements. $\Pi^{\perp}_{\widehat{\Omega}^{(t-1)}}$ represents the orthogonal projector. Selecting the new common support involves figuring how which measurement matrix column is best correlated with the predicted residual of the channel measurements, Y. Figure 2 illustrates the flowchart of the SOMP algorithm.

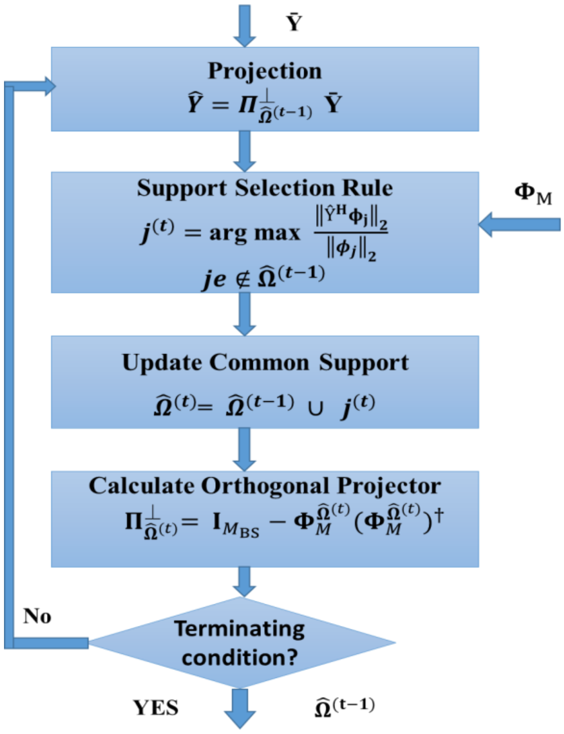

Fig. 2. Flowchart illustrating the SOMP algorithm

3.2 Artificial neural networks-based channel estimator

This part offers a thorough description of the suggested ANN-based channel estimation method's design. Next, we provide a quick overview of the training phases.

3.2.1 Proposed ANN-based channel estimator

To process data/perform artificial intelligence (AI) tasks, ANNs use a network of interconnected, adaptable, and relatively simple groupings of elements that can do very complicated computations in parallel.

To estimate channels, a three-layer feedforward neural network (FFNN) was constructed. The FFNN's architecture, which consists of an input layer, a hidden layer, and an output layer, is described in this subsection. The input layer does not require any data processing. The FFNN is built according to the following specifications: 256 inputs, there are 12 output neurons in the output layer and 85 neurons in the hidden layer. The tangent sigmoid function serves as the transfer function for every neuron. The momentum and learning rate of the network are set to 2 and 0.5, respectively. The hidden layers are activated using the Tanh function, while the output unit is activated using the sigmoid function. The training batch size is set to one hundred, and there are a total of 5,000 samples. The network is trained using the backpropagation (BP) technique with 100 iterations [28].

Data will be transferred and forwarded after the input data has successfully navigated the interface. In this work, the two inputs are the signals' real and imaginary components. The output of the hidden layer is computed inside the hidden layer and is shown as follows:

$$net_j^h = \sum I_i \, \omega_{ij} \quad j\text{=1, 2, …, 10, } i\text{= 1, 2} \tag{11}$$

where I_i represents the input-to-hidden layer weights and ω_{ij} represents the ith units' input data. Next, we were able to acquire the hidden layer output, which is shown as follows, by using the activation function:

$$O_j^h = f(net_j^h) = \frac{1}{1 + e^{-net_j^h}} \tag{12}$$

where O_j^h is the jth units' hidden layer output, and f is the activation function. We calculated the final neural network output in the output layer, which is expressed as

$$net_k^0 = \sum O_j^h \, \omega_{ij} \qquad k = 1.2 \tag{13}$$

where the weights of the hidden-to-output layer are indicated by ω_{ij}. However, this is how the output layer is expressed:

$$O_k^0 = f\,(net_k^O) \tag{14}$$

where the kth unit's output layer is denoted by O_k^0. Gradient descent is the foundation of the back-propagation learning algorithm's training phase. The goal of learning with FFNN, which is supervised learning, is to reduce the discrepancy between the network's output and the intended output values. As a result, the error function has the following definition:

$$E = \frac{1}{2} \sum (G_K - O_k^o)^2 \tag{15}$$

where the required output in kth unit is denoted by G_k Next, it updated the weights to reduce error. The definition of the weights update equation is:

$$\Delta\,\omega = -\eta \frac{\partial E}{\partial \omega} \tag{16}$$

where the learning rate, denoted by η, determines how many weights it modifies at each step. It is able to obtain the weights update equation by applying the derivation. This is the weight update for the hidden-to-output layer:

$$\Delta\,\omega_{jk} = \eta(G_b - O_b) f'\left(net_b^O\right)\; O_a^h \tag{17}$$

The input-to-hidden layer's weight update is displayed as follows:

$$\Delta \omega_{ij} = \eta \left\{ \sum \omega_{jk} \left(G_b - O_b^o \right) f' \left(net_b^o \right) \right\} \times f' \left(net_a^h \right) I_i \quad (18)$$

Upon completion of the training phase, to provide compensation, the incoming signal is sent into a neural network. Then, using the following formula, the updated weight and the old weight can be combined to get a new weight value:

$$\omega(t+1) = \omega(t) + \Delta\omega \quad (19$$

Here, $\omega(t)$ is the weight of the present data and $\omega(t+1)$ is the new weight for the data that follows. After the neural network has received the new weights, the cycle is continued until the stop condition is met or the network training is complete, which is indicated by the completion of a predetermined number of iterations. At this point, the network's parameters are the calculated channel coefficients. Ultimately, the received signal is fed into the network learning algorithm to produce the corrected signal.

Algorithm 2: proposed ANN estimator.

Number of Samples: 5000, 60% for Training and 40% for Test;
-Training Set: train_x**;**
-Label of Training Data**:** train_ y;
Construct net of ANN
-256 inputs, 1 hidden layer of 85 neurons
-1 output layer of 12 neurons
Train Neural Network:
For i = 1: numepochs
kk = randperm (m);
For l = 1: numbatches
batch_x = train_x(kk((L-1)*batchsize + 1: l*batchsize), :)**;**
batch_y = train_y(kk((L-1)*batchsize +1 : l*batchsize),:)**;**
% performs a feed forward pass
% returns a net structure with updated
nn= nnff (nn,batch_x,batch_y);
% backpropagation pass is executed
% provides an updated delta of weights for a net structure
nn= nnbp(nn);
% weights and biases are updated using computed gradients
% provides an updated net structure with weights and biases.
nn= nnapplygrads(nn) ;
End
End
Test and assess neural networks
Classify Signals and Identify Faults

3.2.2 Training of the proposed ANN model

In this work, the spare multipath channel is estimated using an OFDM system. We employ a multilayer perceptron (MLP) system with a single hidden layer. The training function of the network is the Resilient Back Propagation (R_{prop}) algorithm, which is a gradient-based batch update algorithm based on the Manhattan Update principle [13].

To produce the training and test data, we combine the received signals and transmitted pilot symbols. The function that randomly divides the training set into three subsets (train, validate, and test) is called the Divide Function. This function is used to evaluate the quality of the network's outputs.

In our approach, we estimate the channel using a feedforward neural network (FFNN). It has shown to be beneficial for wireless communication's signal processing and channel estimation [1]. Using this data, the neural network model is trained to reduce training mistakes.

Another crucial component of wireless communication is the signal-to-noise ratio, or SNR, which calculates the signal strength. Every signal that is received has a distinct SNR. At lower SNR levels, channel estimation becomes more difficult because of an increase in received signal distortion as the SNR drops.

Our proposed neural network has 85 neurons in the single hidden layer. The tangent sigmoid and linear functions are the transfer functions utilized for the output layer and hidden layer, respectively. Figure 3 illustrates the flowchart for the training strategy of the proposed ANN model. The model is trained using a batch training approach, where the weights of the neural network are shared across smaller batches of training data for testing and training purposes.

The computational complexity of artificial neural networks (ANNs) can vary significantly depending on factors such as architecture (e.g., number of layers, neurons per layer), types of activation functions, and the specific learning algorithm employed (e.g., backpropagation with gradient descent). Despite potential variations in complexity, ANNs offer advantages in performance efficiency and have gained considerable attention across diverse fields. They have been effectively utilized as channel estimators, demonstrating improved system throughput compared to traditional methods. We present an ANN-based sparse channel estimator that takes advantage of its offline training property to avoid dealing with the increased computing load during the estimate phase. the type of activation functions used, and the specific learning algorithm (e.g., backpropagation with gradient descent.

We can effectively verify the algorithm's effecttiveness, understand its computational requirements, and validate its performance for channel estimation tasks using ANN. In practice, despite the potential increase in computational complexity, ANNs have shown effecttiveness in a wide range of tasks such as image and speech recognition. Advances in hardware (like GPUs and TPUs) and algorithmic optimizations have mitigated some of the challenges posed by complexity, making ANNs practical for many real-world applications. Understanding these complexities helps in evaluating the computational demands and storage requirements of ANNs. Efficient management of these complexities is crucial for designing and deploying effective neural network models across various applications

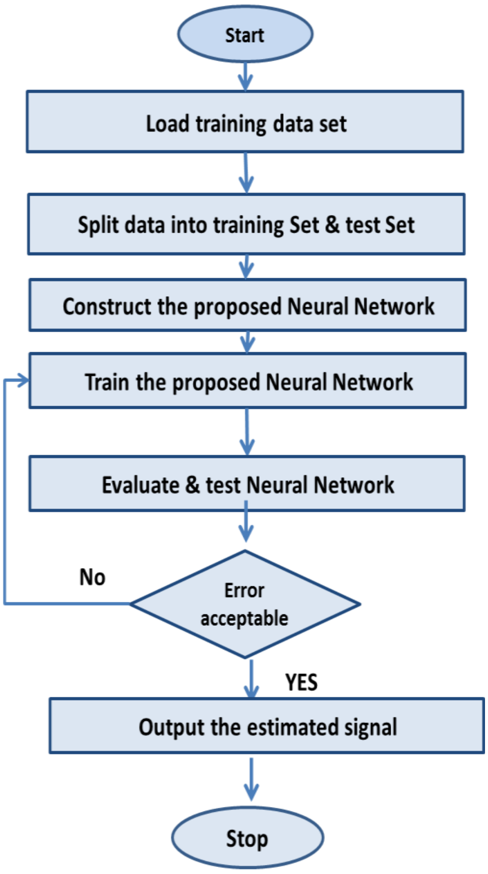

Fig. 3. The proposed ANN model flowchart

4 Simulation results

In a radio channel, the received signals are often corrupted with attenuation, reflection, and refraction. In V2V communication, the wireless channel presents significant challenges due to its dynamic and unpredictable nature. The channel is affected by attenuation, reflection, refraction, and other propagation effects, which vary rapidly over time. Unlike static environments, V2V channels are characterized by high mobility, high Doppler frequencies, and relatively low antenna heights on vehicles and roadside units. Analytical models often fail to accurately capture these dynamic propagation effects, making it difficult to track and estimate the channel reliably.

Moreover, the dynamic nature of V2V communication, where both transmitting (TX) and receiving (RX) vehicles are often in motion, exacerbates these challenges. This mobility increases the likelihood of link obstructions and introduces multipath propagation issues that further complicate channel estimation. Traditional analytic models designed for non-stationary environments can be time-consuming and costly to implement, yet they still may not adequately represent the complex real-world conditions of V2V channels. The suggested ANN estimators' performance assessment and the traditional SOMP is presented in this section, focusing on the metrics of BER and SNR. Table 1 summarizes the simulation settings that were employed in the OFDM systems. Through Monte Carlo simulations utilizing these configurations, we compare the typical SOMP estimator to the suggested ANN-based sparse channel state estimator and provide the BER and SNR performance curves for each situation. Additionally, Table 2 provides a comprehensive list of all parameters and structures that the suggested ANN sparse channel state estimator. Table 3 provides comparisons between SOMP and ANN estimator.

The BER performance of the examined estimators is compared to the SNRs with M values of 1 and 4, and the length of the GI evaluated at 16,180 respectively, in Figures 4 and 5. The results show that at low SNR ranges of 0-3 dB, the suggested ANN-based channel estimator's performance is comparable to that of the standard SOMP estimator. However, starting at 4 dB, the suggested ANN estimator performs better than the traditional SOMP estimator.

Table 1. OFDM Parameters

Parameter	Value
Number of subcarriers	1024
Modulation type	Quadrature phase shift keying (QPSK)
Sub-carrier spacing (Δ_f)	15 kHz
Channel model	Rayleigh fading
Noise model	Additive white Gaussian noise (AWGN)
Guard interval (GI) length	4, 16, 180
No. of receiver antennas (M)	1, 4
Bandwidth	10N/24K MHz
Carrier frequency (f_c)	2.5 GHz

Table 2. Parameters/structures of the proposed ANN estimator

Parameter	Value
Number of hidden layers	1
Input size	P × 2
Training function	R_{prop}
Divide function	Random
Number of hidden neurons	85
Number of Samples	5000
Performance param.	BER

Table 3. Comparison between SOMP and ANN estimator

SOMP	ANN
High computational complexity	Low complexity
High computational cost	Low computational cost
Used in compressed sensing	Resolves complex problems, such as those encountered in image and signal processing and have been implemented for channel estimation in OFDM

This improvement in performance is further enhanced by increasing the value of M. Therefore, accurate channel estimation can be attained with fewer pilots, resulting in increased spectrum efficiency.

Figures 6 and 7 compare the BER performance of the investigated estimators with SNRs of M=1 and M=4, respectively, while the duration of the GI is evaluated at 180. The results depicted in Figures 6 and 7 clearly demonstrate that the proposed ANN-based channel estimation approach consistently outperforms the traditional SOMP-based channel estimation scheme, regardless of whether M is 1 or 4. This signifies the superior performance and robustness of the proposed ANN-based estimator in various SNR scenarios.

Using Monte Carlo simulations, the coded BER performance (in the event of sufficient GI), where the GI is larger than or equal to Lc, will be tested in order to evaluate the performance of the suggested ANN. The V2V communication channel, $C_m(L)$, is created as independent, zero-mean, complex Gaussian random variables with equal variance and an order of Lc = 400. It is established as a channel tap. The system performance improves with increasing GI length due to the length of the V2V channel. Where the IBI in between the OFDM data blocks reduces as the GI lengths are sufficient.

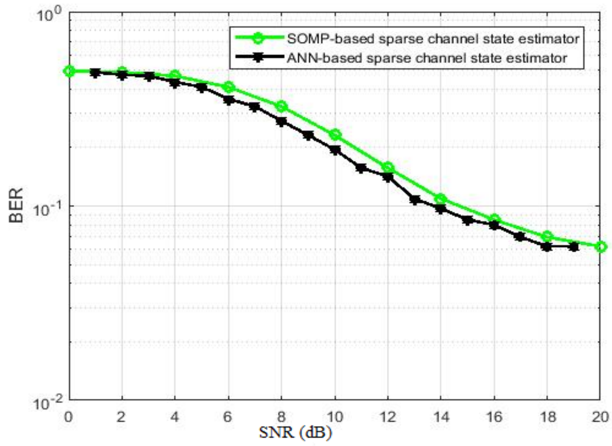

Fig. 4. Comparison of the evaluated estimators' BER performances at (M=1 and GI=16)

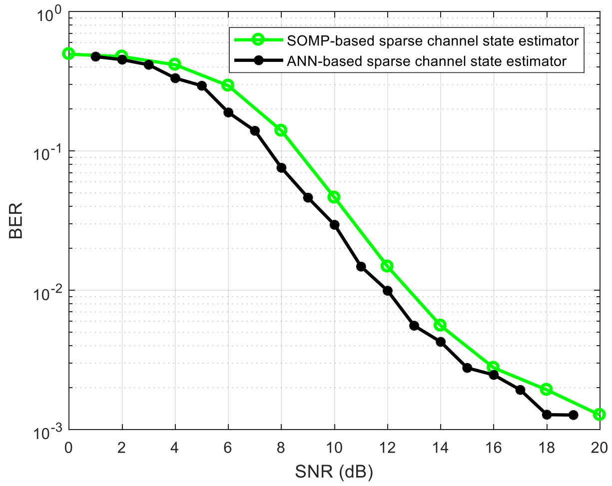

Fig. 5. Comparison of the evaluated estimators' BER performances at (M=4 and GI=16)

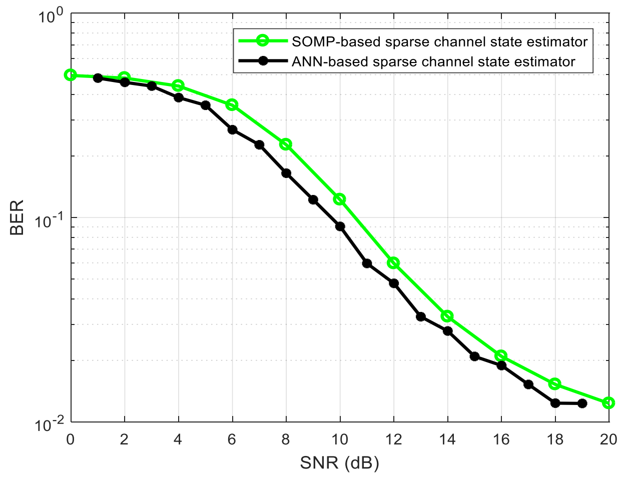

Fig. 6. Comparison of the evaluated estimators' BER performances at (M=1 and GI=180)

BER

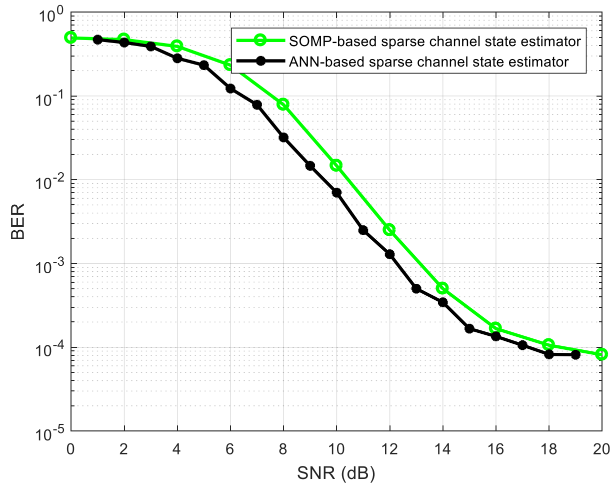

Fig. 7. Comparison of the evaluated estimators' BER performances (M = 4 and GI = 180).

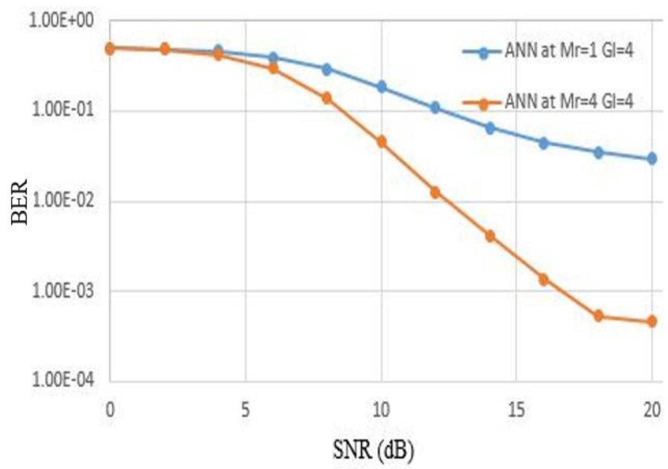

Fig. 8. Performance of the suggested ANN-based estimator at M=1 and M=4, GI=4

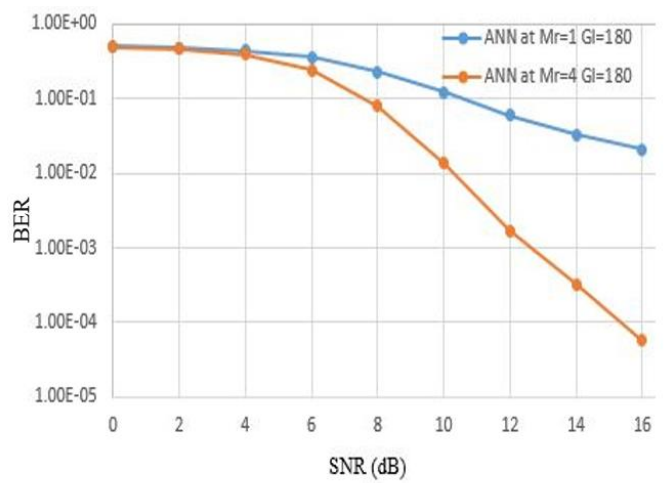

Fig. 9. Performance of the suggested ANN-based estimator at M=1 and M=4, GI=180

Figure 8 gives an overview of how well the suggested ANN-based channel estimation with varying numbers of receiver antennas (M of 1 and 4) and GI durations of 4. The results illustrate that the proposed ANN-based estimator maintains its superior performance across different numbers of receiver antennas. This demonstrates the efficiency and scalability of the suggested methodology in real-world scenarios with varying antenna configurations.

Figure 9 provides an overview of how changing the number of receiver antennas and setting the GI at 180 will affect the BER performance of the suggested ANN-based channel estimate (M of 1 and 4). The results highlight that as more receiver antennas are added, the following results improved BER performance for the proposed ANN-based estimator. This demonstrates the benefits of utilizing multiple antennas in V2V communication systems and the capability of the proposed ANN-based estimator to effectively leverage such antenna configurations.

Overall, the simulation results consistently show that the proposed ANN-based channel estimator exceeds the traditional SOMP-based estimator, particularly at higher SNR levels and with increased numbers of receiver antennas. This highlights the potential of the suggested approach to enhance the performance and efficiency of V2V communication systems.

5 Conclusions

In order not to deal with the higher computational complexity during estimation process, we propose a low complexity an ANN based sparse multipath channel estimator. ANN based channel estimation algorithm is proposed for OFDM systems operating over Raleigh fading channels. Tracking/estimating the challenging time-varying multipath channels is the main focus of the ANN-based channel estimation technique that we have proposed. The simulation outcomes showed that our suggested ANN strategy performed better than the traditional SOMP technique.

Finally, comparing with SOMP algorithms, we conclude that ANN based sparse multipath channel estimation algorithms may have pretty much potential to be good candidates to meet better performance and smaller latency between transmitters and receivers in sparse channel environment. The following research directions have been recommended by the authors:

- Assessing the suggested ANN-based channel estimation's accuracy for a more complicated system.
- Examining how applying other ML techniques affects the proposed ANN model's performance.

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