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Genetic Algorithm Based BER Aware Channel Selection Using Break Point Technique For Next Generation Milli-Meter (mm) Wave Communication Systems

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ABSTRACT- Due to exponential increase in communication speed when shifting from 4th Generation 4G to 5G networks, there is a requirement to redesign equipment to support spectrum ranges from 450 MHz to 52.6 GHz, which makes them operate at very high speeds. In order to maintain good communication performance while operating at this bandwidth, millimeter waves (mmWaves) are used. As communication radius increases, the BER also increases linearly, which limits range of these equipment's, thereby incurring higher deployment costs. In order to reduce these costs, and design mmWave communication components to work for larger areas, this text proposes a Genetic optimization architecture that uses intelligent channel modelling and selection. The architecture is designed in order to reduce BER during communication when threshold breakpoint occurs, thereby improving communication speed, and overall throughput. It exploits long-ranged loopback communications in order to automatically tune internal transmission parameters for supporting larger areas with minimum packet loss. The underlying model is tested on various channel types, different network scenarios, and under different noise conditions. It is observed that the proposed model outperforms original mmWave communication models in terms of BER reduction by 8% and in terms of communication coverage by 6%, thereby making it applicable for wider geographical areas. This results in reduced deployment costs, and better communication quality of service (QoS), thereby assisting in better network design.

General Terms: Wireless Communication, Millimeter Wave, Artificial Intelligence, Machine Learning, Algorithms et. al.
Keywords: mm waves; Genetic optimization; BER; Breakpoint; Geography; Machine Learning.

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1. INTRODUCTION

Bit error rate (BER) is one of the primary metrics involved during trans-receiver design for any wireless communication network. A trans-receiver with minimum BER is recommended, even if its other parameters like energy consumption, memory utilization, delay of communication, etc. are moderately affected. Millimeter wave (mmWave) communication circuit design principles [1] also recommend use of low BER based trans-receiver, which assists in improving temporal communication performance. Due to low BER, number of faults in the network are also reduced, because number of invalid packet injections are minimized. Moreover, low BER indicates that the network can communicate at higher data rates without compromising on communication quality. In order to achieve this, mmWave communication circuits use digital pro-coders, analog beamforming circuits, and channel modelling (H) techniques as observed from *figure 1*.

Due to advances in VLSI (Very Large-Scale Integrated circuits) technology, and digital signal process modelling, the designs for pro-coders, and beamforming circuits are highly optimized. Due to which their optimization has limited scope of research at application level. Thus, researchers have designed various channel modelling techniques, which assist in reducing BER by making the transmitted signal fault proof. In order to perform this task, a wide variety of system models are developed and deployed by researchers & system designers over the years. A survey of these models is done in the next section, which gives a brief idea about them, and indicates their nuances, advantages, limitations and characteristics. It is observed that most of these models do not consider exhaustive system parameters (like number of channels, maximum signal to noise ratio, sampling frequency of noise, *etc.*) for channel modelling, which limits their overall system performance. Thus, the BER performance of these models is limited. In order to improve this performance, a Genetic optimization model is proposed after the literature review section. This model considers a wide number of parameters including threshold BER, Maximum number of channels, Maximum SNR for the channel, and Maximum sampling frequency for the system for designing a

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comprehensive channel model. The designed model is tested under various network communication conditions, and results for BER, and delay of modelling are evaluated. These results are compared with various state-of-the-art models, and it is observed that the proposed model outperforms existing models in terms of both BER and delay of modelling. Finally, this text concludes with some interesting observations about the proposed model, and recommends methods to improve its performance.

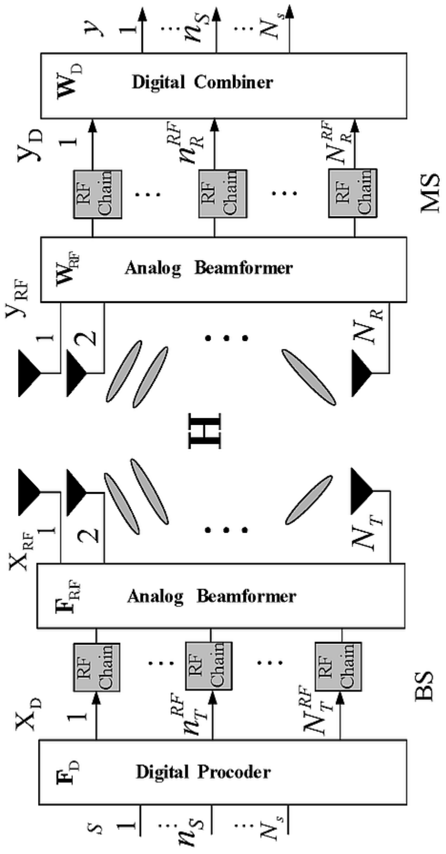

Figure 1: Design of a typical mmWave communication system

2. LITERATURE REVIEW

Designing a channel modelling technique for mmWave network communication requires estimation of a wide variety of parameters. These parameters include, signal-to-noise ratio (SNR), end-to-end delay, sampling frequency, etc. The work in [2] uses Gaussian-less random variables for estimation of these parameters via in-phase and quadrature phase components. This improves BER reduction capabilities, along with high-performance communication in the network. Similar methods are described in [3, 4, 5, 6] wherein, beam squint effect analysis with off-grid delays, off-grid angles, & complex gains for multipath channels, 3D space time non-stationary model, link & budget aware model, and channel sounding with ray tracing are used for reducing BER, but these models use an iterative process for BER reduction, which increases overall end-to-end delay of the network. The channel modelling process can be reconfigured using dynamic designs as suggested in [7, 8, 9], wherein dual-polarized mmWave MIMO models, hybrid mmWave MIMO models, and wideband dynamic mmWave models are described. These models assist in improving deployment capabilities via large-scale testing for the multiple scenarios. Models that assist in ergodic capacity estimation [10], generalized approximate message passing [11], angles of arrival (AoAs) based frequency-division duplex (FDD) mmWave massive MIMO OFDM models [12], hybrid model design using calibration-based ray tracing [13], blockage models with path loss, coverage range, non-stationarity, & spatial consistency [14] are discussed. These models aim at solving a specific task during estimation of channel behaviour in the network. Due to which their performance is good under specific conditions, but can be improved via deep learning methods [15] for other general purpose network scenarios.

Upon estimation of channel models, efficient measurement of BER is also necessary. The work in [16] proposes such a model, wherein industrial environments are used for estimation of channel effects, and evaluation of BER with high accuracy. These high efficiency BER estimation models are used to improve channel modelling capabilities of algorithms like Beaulieu-Xie model [17], joint sparse & low-rank structures [18], expectation maximization (EM) based sparse Bayesian learning [19], space time & frequency correlation function (STFCF) with doppler power spectral density [20], and Fisher information matrix [21]. These models work with general purpose network, and have low BER performance, but this performance is limited by BER estimation capabilities, which can be improved by the work in [16], where channel effects are considered during BER estimation. Other generalized models like 3D non-stationary 5G channel model [22], linear-minimum-mean-square-error (LMMSE) minimization using low-precision analog to digital converters [23], uniform circular antenna array for channel capacity bound estimation [24], block sparse & low rank time varying channel estimation [25], stochastic geometric coverage analysis [26], and Neyman-Pearson criterion based-Detector [27], are discussed. These models assist in improving channel capacity estimation for a wide variety of general-purpose network conditions, which enables designers to deploy highly efficient channel modelling algorithms for low BER performance. Other models as described in [28, 29, 30, 31, 32, 33] aim at application specific mmWave channel modelling scenarios, which includes, railway networks, transmitter impaired conditions, blockage prediction for 6 GHz channels, hovering fluctuation consideration for unmanned aerial vehicles (UAVs), mobile to mobile (M2M) mmWave models, and urban microcell environments. On Similar models are discussed in [34, 35, 36, 37, 38, 39] where BER optimizations are proposed for different scenarios. While the work in [40, 41, 42, 43] proposes use of compact wideband antenna for 5G applications, along with improvement of QoS with routing protocols.

Deep learning-based fish swarm optimization algorithm is proposed with MIMO system for faster and accurate signal detection for optimizations in BER levels. Based on the characteristics of these models, it can be observed that soft computing which is used for optimization of systems, is minimally used for channel modelling. Thus, the next section proposes a Genetic optimization soft computing model for BER aware channel modelling.

3. PROPOSED GENETIC OPTIMIZATION MODEL FOR BER AWARE CHANNEL MODELLING

Channel modelling for mmWave communication systems is a multistep task, which involves signal processing, noise estimation, signal mutation, and received signal correction. Each communication interface has a transmitter (T) and receiver (R) pair. Let the signal transmitted be **x**, and the noise in the channel be **n**, then the signal received at the receiver side **y** is represented using the following *equation 1*,

$$\mathbf{y} = \mathbf{x} + \mathbf{n}(\mathbf{x}) \tag{1}$$

For modelling the effect of this noise, it is recommended that noise should be incorporated into the signal itself. This process is termed as channel modelling, and it modifies the signal **x** using *equation 2*,

$$\mathbf{x}' = \mathbf{x} + \mathbf{n}'(\mathbf{x}) \tag{2}$$

After transmitting this signal, the received signal is now modified as per *equation 3*,

$$\mathbf{y} = \mathbf{x} + \mathbf{n}'(\mathbf{x}) + \mathbf{n}(\mathbf{x}) \tag{3}$$

For effective channel modelling, the equations for **n** & **n′** must be implemented such that they minimize their effect on signal **x**. In order to perform this task, a Genetic optimization-based channel modelling technique is designed. The proposed technique uses the following design steps for channel modelling,

- Input
  - Number of iterations (N_i)
  - Number of solutions (N_s)
  - Learning factor (L_r)
  - Threshold BER (BER_T)
  - Maximum number of channels (Max_C)
  - Maximum SNR for the channel (Max_S)
  - Maximum sampling frequency for the system (Max_F)
- Output
  - Optimum channel model for the given network scenario
- Algorithm,
  - Initially mark all solutions as '*to be updated*'
  - For each iteration in 1 to N_i
    - For each solution in 1 to N_s
    - If the solution is marked as '*not to be updated*', then go to next solution
    - Find a random channel selection number (C_{sel}) using *equation 3*,

$$C_{sel} = random(2, Max_c) \tag{4}$$

    - For each value of C_{sel}, select a random channel from the list of channels. Let these selected channels be, $C_1, C_2, C_3, \ldots\ C_{sel}$
    - Evaluate the value of SNR to be used (SNR_{used}) and sampling frequency to be used (F_{used}), using *equation 5*,

$$SNR_{used} = random(1, Max_s), F_{used} = random(1, Max_F) \tag{5}$$

    - Select a predefined sequence (S), and transmit it over the network, while looping it back to the same node.
    - This sequence should be modelled as per equation 6, wherein noise estimates are already added to the transmitted signal.

$$S_{tx} = S + \sum_{i=1}^{Csel} C_i(S) \tag{6}$$

    - Receive the sequence on the same device, and use the following equation to evaluate effect of channel,

$$S_{rx} = S_{tx} - \sum_{i=1}^{Csel} C_i(S_{tx}) \tag{7}$$

    - Now, evaluate BER between S and S_{rx}, and evaluate fitness function,

$$F_s = BER(S, S_{rx}) \tag{8}$$

    - If, this fitness is more than BER_T, then re-evaluate this solution, else accept it for further processing.
    - Repeat this process for all solutions, and evaluate the fitness threshold,

$$F_{th} = \frac{\sum_{i=1}^{Ns} F_{si}}{Ns} * Lr \tag{9}$$

  - For all solutions, where fitness is more than F_{th}, mark them as 'to be updated', mark all other solutions as 'not to be updated'
  - Repeat this for all iterations, and accept the solution with minimum value of fitness.

The solution consists of the following channel parameters,
- Selected channels
- SNR for each channel
- Sampling frequency for each channel

While transmission of sequences, use these selected parameters for modifying input signal, and making is resilient to channel noises. Due to this exhaustive selection process, overall BER, and delay of communication are reduced. Estimation of these parameters for different channel types, and different input sequence length can be observed from the next section.

4. BREAKPOINT SELECTION TECHNIQUE

Identify the break point using the BER algorithm is as shown in *figure 2.*

- Select -Training Phase
- Apply the channel models for current scenario to evaluate the current BER and the fitness value
- Repeat the step for number of iterations and solutions

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After the final iteration compare the fitness value and current BER with previous value.

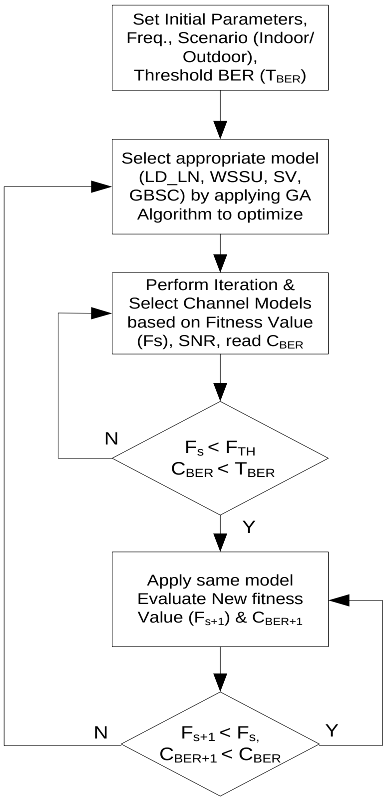

Figure 2: Breakpoint Selection algorithm based on threshold BER

- If the current BER is less than previous value, then retain the same model and continue the iterations.
- If the current BER is greater than the previous value (break point occurred), then apply the other models and evaluate the new fitness value and new BER.

5. RESULT ANALYSIS

The proposed protocol aims at selecting best possible channel parameters for the given channel configuration. From the protocol design, it can be observed that individual channel parameters are estimated in order to reduce BER values, to obtain, low error communications. Performance of the proposed model is compared against [14], and [24] under the following multiple input multiple output (MIMO) network parameters as shown in *table 1*.

Based on these network parameters, input size is varied between 1000 bits to 100k bits, and performance values for BER and computational delay are estimated. Estimation of BER performance can be observed from *figure 3*, wherein Saleh-Valenzuela channel was used as a communication interface.

Table 1: Network parameters used for performance estimation

Parameter	Value
Configuration of MIMO	3 x 3
Channel types in the network	Saleh-Valenzuela Model, Log-distance Path Loss Model with Log-normal Shadowing, Wide-Sense Stationary Uncorrelated Scattering Model, Geometry-based Stochastic Channel Model
Number of nodes	50
FFT Size	64
Number of carriers	4
Quadrature Amplitude Modulator (QAM) type	64 QAM
Guard Time	1 sample
Guard Type	Circular guard
Window Type	Hamming
Input frequency	30 GHz
mmWave iterations for communication	8

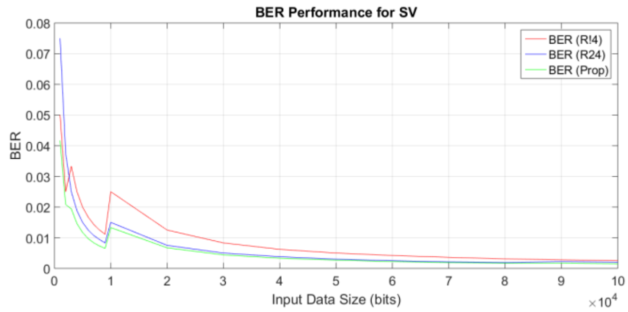

Figure 3: BER performance for Saleh-Valenzuela channel model

It can be observed that a BER reduction of 10% is achieved when compared with [24], and 15% when compared with [14] is obtained for this channel. The performance visualized in *figure 3* indicates that the proposed model is useful for high-performance and low error rate communications for this channel model.

Similar estimation of BER performance for Log-distance Path Loss Model with Log-normal Shadowing can be observed from *figure 4*.

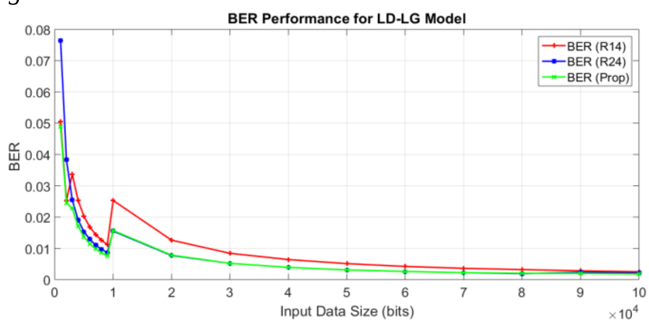

Figure 4: BER performance for Log-distance Path Loss Model with Log-normal Shadowing channel model

It can be observed that a BER reduction of 8% is achieved when compared with [24], and 10% when compared with [14] is obtained for this channel. The performance indicates that the proposed model is useful for high-performance and low error rate communications for this channel model. Similar estimation

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of BER performance for Wide-Sense Stationary Uncorrelated Scattering Model can be observed from *figure 5* as follows,

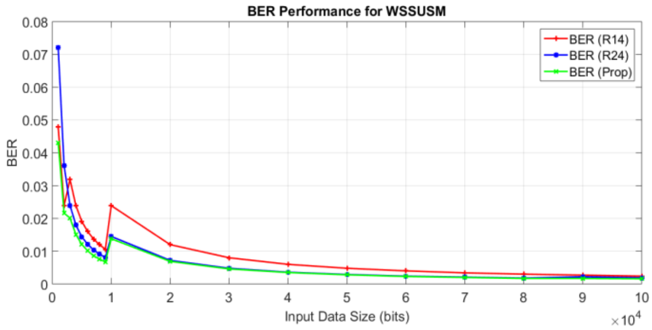

Figure 5: BER performance for Wide-Sense Stationary Uncorrelated Scattering Model

It can be observed that a BER reduction of 15% is achieved when compared with [24], and 20% when compared with [14] is obtained for this channel. The performance indicates that the proposed model is useful for high-performance and low error rate communications for this channel model. Similar estimation of BER performance for Geometry based Stochastic Channel Model can be observed from *figure 6* as follows,

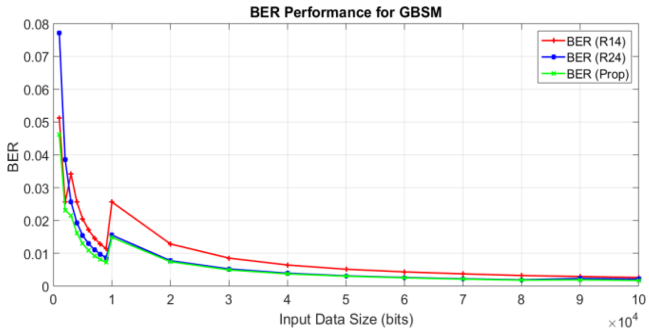

Figure 6: BER performance for Geometry based Stochastic Channel Model

It can be observed that a BER reduction of 18% is achieved when compared with [24], and 25% when compared with [14] is obtained for this channel. The performance indicates that the proposed model is useful for high-performance and low error rate communications for this channel model. Similar estimation was done for communication & computational delay incurred while using these models. Estimation of delay performance can be observed from *figure 7*, wherein Saleh-Valenzuela channel was used as a communication interface.

It can be observed that an end-to-end delay reduction of 28% is achieved when compared with [24], and 30% when compared with [14] is obtained for this channel.

The performance as observed from *figure 7* indicates that the proposed model is useful for high-speed communications for this channel model, which is due to the fact that lower error communications require less acknowledgements, thereby reducing the necessity of retransmission. This reduces overall delay of communication, thereby improving communication speed.

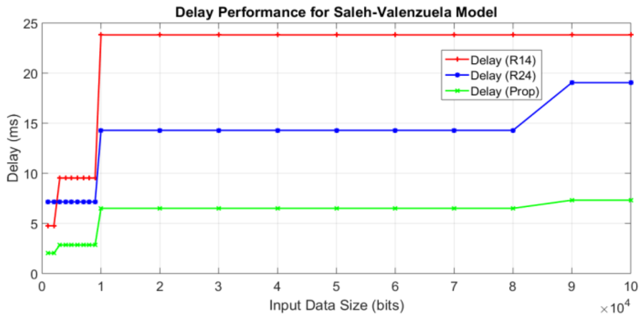

Figure 7: End-to-End delay performance for Saleh-Valenzuela channel model

Similar estimation of delay performance for Log-distance Path Loss Model with Log-normal Shadowing can be observed from *figure 8* as follows,

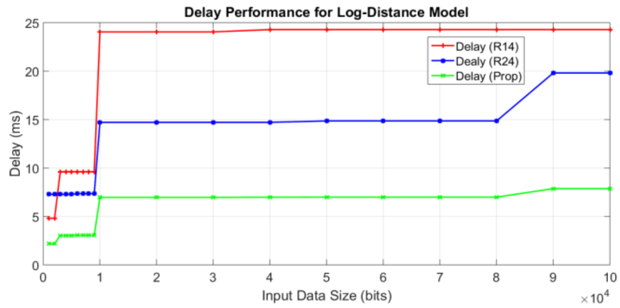

Figure 8: Delay performance for Log-distance Path Loss Model with Log-normal Shadowing channel model

It can be observed that an end-to-end delay reduction of 25% is achieved when compared with [24], and 29% when compared with [14] is obtained for this channel. The performance indicates that the proposed model is useful for high-speed communications for this channel model, which is due to the fact that lower error communications require less acknowledgements, thereby reducing the necessity of retransmission. This reduces overall delay of communication, thereby improving communication speed. Similar estimation of delay performance for Wide-Sense Stationary Uncorrelated Scattering Model can be observed from *figure 9*.

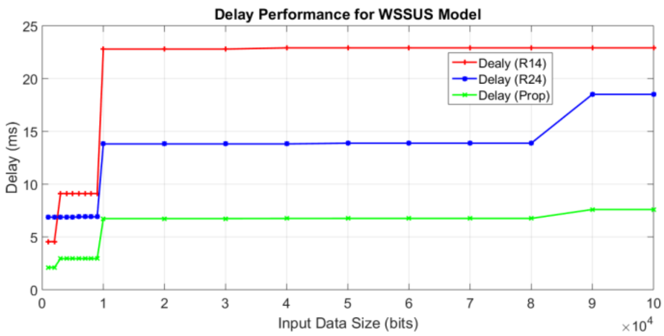

Figure 9: Delay performance for Wide-Sense Stationary Uncorrelated Scattering Model

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It can be observed that an end-to-end delay reduction of 22% is achieved when compared with [24], and 27% when compared with [14] is obtained for this channel. The performance indicates that the proposed model is useful for high-speed communications for this channel model, which is due to the fact that lower error communications require less acknowledgements, thereby reducing the necessity of retransmission.

This reduces overall delay of communication, thereby improving communication speed. Similar estimation of delay performance for Geometry based Stochastic Channel Model can be observed from *figure 10* as follows,

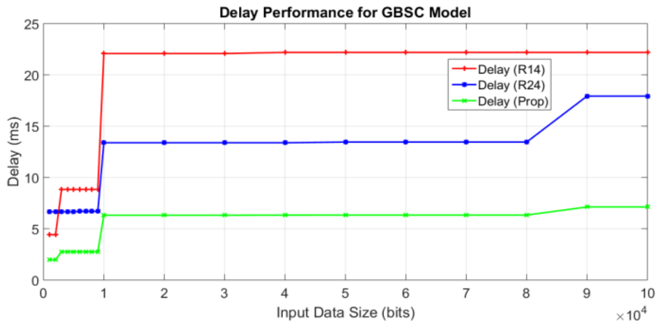

Figure 10: Delay performance for Geometry based Stochastic Channel Model

It can be observed that an end-to-end delay reduction of 29% is achieved when compared with [24], and 34% when compared with [14] is obtained for this channel. The performance indicates that the proposed model is useful for high-speed communications for this channel model, which is due to the fact that lower error communications require less acknowledgements, thereby reducing the necessity of retransmission. This reduces overall delay of communication, thereby improving communication speed. From this performance, it can be observed that the proposed model has lower BER and moderate delay when compared with [14], and [24], thereby making it suitable for real time deployment in mmWave trans-receiver designs.

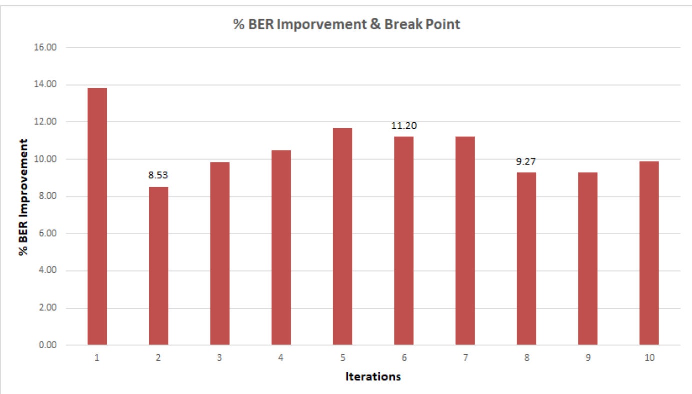

Figure 11: Breakpoint occurred and Percentage improvement in BER

It is also observed that BER based Breakpoint model selection algorithm chose the appropriate model to get better BER performance even though scenario is get changed. *Figure 11* shows average 10.5% improvement in BER with 03 breakpoint and *figure 12* gives the number of time the selection of model during 10 iterations.

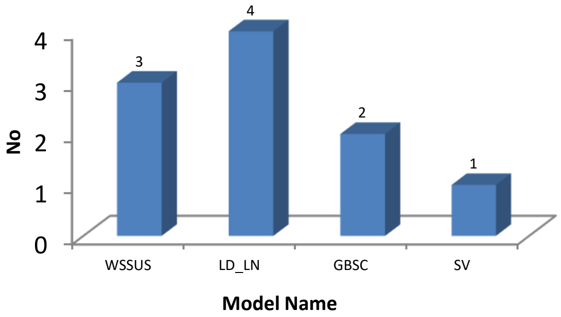

Figure 12: Channel selection during the iterations

6. CONCLUSION

Reducing BER in mmWave networks has a 2-fold advantage, which includes, reduced error communications, and optimum number of acknowledgements sent between source and receiver. Due to reduced number of acknowledgements, the delay incurred during communication is reduced, thereby improving speed of operation. Moreover, this increase in speed further assists in improving secondary parameters like network throughput, and reduced energy consumption during long ranged communications. As the proposed Genetic optimization model is focused on reducing BER values, it directly reduces end-to-end delay, thereby improving communication speed. From the result evaluation, it can be observed that a BER reduction of 18% is achieved when compared with [24], and 25% when compared with [14] is obtained for this channel. The performance indicates that the proposed model is useful for high-performance and low error rate communications for this channel model. Moreover, from delay evaluation, it can be observed that an end-to-end delay reduction of 25% is achieved when compared with [24], and 29% when compared with [14] is obtained for this channel. The performance indicates that the proposed model is useful for high-speed communications for this channel model, which is due to the fact that lower error communications require less acknowledgements, thereby reducing the necessity of retransmission. This reduces overall delay of communication, thereby improving communication speed.

The limitation of this study is that it is not applied to large-scale scenarios, thus in future, researchers can work on further reducing BER values via use of deep learning-based auto-encoders and transfer learning architectures which can adapt as per network traffic. Use of blockchain can be one of the future prospects, which will assist in improving security for mmWave networks, thereby extending its usability.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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