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Comparative Study of 5G Signal Attenuation Estimation Models

Md Anoarul Islam[1], Manabendra Maiti[1], Judhajit Sanyal[1*], Quazi Md Alfred[2]

[1].Department of Electronics and Communication Engineering, Techno International New Town
[2].Department of Electronics and Communication Engineering, Aliah University

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Abstract

Wireless networks functioning on 4G and 5G technology offer a plethora of options to users in terms of connectivity and multimedia content. However, such networks are prone to severe signal attenuation and noise in a number of scenarios. Significant research in recent years has consequently focused on establishment of robust and accurate attenuation models to estimate channel noise and subsequent signal loss. The identified challenge therefore is to identify or develop accurate computationally inexpensive models implementable on available hardware for generation of estimates with low error and validate the solutions experimentally. The present work surveys some of the most relevant recent work in this domain, with added emphasis on rain attenuation models and machine learning based approaches, and offers a perspective on the establishment of a suitable dynamic signal attenuation model for high-speed wireless communication in outdoor as well as indoor environments, presenting the performance evaluation of an autoregression-based machine learning model. Multiple versions of the model are compared on the basis of root mean square error (RMSE) for different orders of regression polynomials to find the best-fit solution. The accuracy of the technique proposed in the paper is then compared in terms of RMSE to corresponding moderate and high complexity machine learning techniques implementing adaptive spline regression and artificial neural networks respectively. The proposed method is found to be quite accurate with low complexity, allowing the method to be practically applicable in multiple scenarios.

Keywords: 5G; estimation; attenuation models; machine learning; dynamic model; autoregression.

1- Introduction

The present era has seen rapid advancement in the field of wireless communication technology, with extremely high data rates allowing users access to high quality multimedia content as well as streaming media services. In particular, the advent of 5G technology presents hitherto-unseen possibilities in the domain of wireless communication services. In such a scenario, reliability and Quality-of-Service (QoS) are two critical parameters that must be at acceptable levels to ensure user satisfaction.
The viability of 5G wireless communications was established in a seminal paper presenting different facets of millimeter wave wireless communication technology [1]. Corresponding attenuation models for 5G wireless communication signals have been reviewed in literature in recent times [2][3]. Diverse 5G-based applications have been proposed and established, in domains as diverse as agriculture [2] and security [4]. In all cases, the establishment and use of accurate attenuation models are critical to the success of proposed schemes. Other recent research establishes the impact of rain on channel noise and signal attenuation [5][6]. The present paper reviews recent techniques and models employed for estimation of rain attenuation, with focus on machine learning based approaches. The major contributions of the paper are as follows.

- Extensive review of recent literature documenting novel approaches to the problem of estimation of wireless communication (especially 5G) signal attenuation.
- Identification of novel solutions based on machine learning (ML) approaches, to improve model accuracy.
- Proposal of an adaptive autoregression-based estimation model to achieve suitably low root mean square error (RMSE) at low computational complexity, compared to other ML and non-ML-based techniques.
- Verification of effectiveness of proposed model through real-world experiments in low, moderate and high mobility scenarios.

The rest of the paper is organized in the following manner. Section 2 presents a survey of recent literature in the domain of attenuation modelling and estimation of wireless communication signals, with significant emphasis

✉ **Judhajit Sanyal**
judhajit.sanyal.2019@gmail.com

on machine learning based techniques employed. Section 3 presents the inferences drawn from the previous section and offers a basic conception of dynamic modelling which can help in improvement of the accuracy of estimation. Section 4 concludes the paper.

2- Literature Survey

The possibility of widespread commercial wireless communication in the millimeter wave bands has been explored some years back in a seminal work [1]. The challenges faced by wireless networks (up to 4G networks) have been extensively highlighted here, as well as the corresponding benefits offered by millimeter wave networks [1]. Following this paper and others in the same vein, extensive examination of attenuation models for 5G wireless signals have been carried out in recent years, due to noise and attenuation being critical limiting factors in the efficacy of modern wireless communication networks [2].

2-1- Attenuation Models

A number of established channel models have been examined in [2] in the context of their suitability for modelling the propagation of millimeter wave communication signals of a wide range of frequencies through free space. The authors in [2] have made extremely important contributions to the field by examining propagation of signals below 6 GHz as well as at 28 GHz and above, which are relevant for different classes of 5G communication networks. 5G D2D communications have been extensively surveyed in [3], and the benchmark measures for various aspects of such communication networks have been discussed here, inclusive of specific attenuation models for D2D networks. Heterogeneous access scenarios for 5G D2D networks have been examined in [4], with the models employed linking to the security aspects of such networks [4].

Rain attenuation is significant for millimeter wave signals, to the extent of around 7 dB per kilometer along the slant path in the 28 GHz band [2]. As a consequence, accurate estimation of the attenuation of communication signals affected by rain has been the focus of many researchers in recent times [5][6]. Terrestrial attenuation models in particular are specifically relevant for terrestrial 5G communication [5]. Rain statistics for K band (25.84 GHz) and E band (77.52 GHz) signals have been observed on a yearly basis to generate accurate estimates for short-range fixed links [6]. The work outlined in [6] allows for compensation of the wet antenna effect. The effect of rain is most pronounced in the tropical regions, as a consequence of which region-specific models are often used for achieving appreciable accuracy in such scenarios [7]. The effects of rainfall and knife-edge diffraction are examined in detail for fixed millimeter wave systems, in [8]. Attenuation models for multiple frequencies are often used in practical scenarios. However, in inclement weather conditions, such models may fail to generate accurate estimates and, in such cases, alternative means for generation of estimates can be considered [9]. Additionally, short-range terrestrial communication systems are affected by parameters such as the distance factor which affects the estimate of signal strength as well as overall link budget for both K (25 GHz) and E (75 GHz) bands [10]. In arid climates, dust storms may also severely hamper link capacity through random and anomalous diffraction of millimeter wave signals [11]. Recent researchers have also shown interest in the presently-unlicensed V band (60 GHz) for 5G backhaul networks, spanning both Line-of-Sight (LoS) and Non-LOS scenarios [12]. Significant variation in link performance is observed for both sub-6 GHz as well as 26/28 GHz bands in tropical locations, due to extensive rainfall [13]. Attenuation models for both outdoor [14] as well as indoor locations have been explored by researchers in recent times [15]. Indoor environments present an array of challenges due to diffraction as well as absorption by organic and inorganic obstacles, especially human body-based absorption [15]. The effects are significant at 28 GHz, as observed in [15]. A recent approach has also explored dynamic modelling for an indoor millimeter wave link (28-30 GHz), with favourable results [16].

Rain attenuation has also been studied by various researchers in recent years with the application of modified channel models such as the shadowed Rician fading model, which allows for accurate bit error rate (BER) and signal to noise ratio (SNR) estimation for satellite to land systems, and additionally identifies the effect of estimation error on the capacity of the satellite communication system under observation [17]. One recent significant work in the domain proposes a unified approach which allows for estimation of rain attenuation both on the slant or vertical path as well as the horizontal path [18]. Location specific attenuation models for slant path have also been proposed in [19] and [20], for specific tropical locations, which significantly outperform existing standard models such as ITU-R, Karasawa and DAH models, but may not be able to produce acceptably accurate results in other regions. Worst-month statistics are also a reflection of the accuracy of such models, and established models such as ITU-R have been found to come up short in regions with greater meteorological diversity, such as tropical locations [21]. In this context, one recent paper clearly delineates the characteristics of microwave and millimeter wave channels which allows the accurate characterization of such channels in a variety of environments [22]. Machine learning based approaches have also emerged as important tools in this context, for different frequency bands [23][24].

Indoor attenuation models have also grown in importance from a commercial context during recent years. Consequently, researchers have sought to focus on multi-frequency model (for 14 and 22 GHz) establishment in indoor environments [25]. The significant 28 GHz band has also been examined using LoS and NLoS models as well as using X-band signal [26]. Path loss models are critical to the successful implementation of 5G communication systems, and researchers in [27] have extensively examined the comparative performance of different path loss models in estimation of path loss for sub-6 GHz 5G networks, with emphasis on both indoor as well as outdoor urban and industrial environments. Though generalized models for macroenvironments have been proposed in context of 5G networks, indoor performance of such models can be significantly improved [28]. One recent work however has achieved excellent results in terms of elevation of RAN bottlenecks in indoor and outdoor environments [29]. Another interesting work has illustrated the effects of low-emissivity glass on 5G signal in indoor environments [30].

2-2- Machine Learning Based Approaches

Among the different approaches employed by researchers to generate accurate attenuation predictions, machine learning techniques have increased in popularity. Supervised learning methods have been established to be effective in [5]. Such models are especially effective in scenarios where traditional models are unable to accurately predict signal attenuation [9]. Machine learning techniques can also be used in conjunction with different LoS and Non-LoS channel models to predict link performance in a wide range of network scenarios and mobility conditions [12][13]. They also allow integration of multiple factors, such as antenna geometry [14] and the generation of accurate estimates in dynamic network conditions with significant diffraction and attenuation [15][16]. Thus, such approaches can be effectively leveraged to increase the efficacy and robustness of a proposed attenuation model.

Among different machine learning based approaches, low complexity techniques have gained in popularity due to their ease of use and integrability into communication infrastructures at low costs. For example, spline-based machine learning approaches have been found to achieve greater accuracy than other regression-based methods in estimation of rain attenuation [23][24]. Similar techniques have also been applied to predict LoS and NLoS path losses in indoor environments with suitably low complexity and low root mean square error (RMSE) [26]. Other supervised machine learning techniques have also been found to yield appreciable accuracy in outdoor environments [5][9] as well as indoors [15][16][27] for different network configurations and scenarios. The techniques outlined in [15] and [16] are especially important considering the fact that consistently accurate estimates have often been proved to be difficult to generate in dynamic indoor environments which often allow more complex propagation scenarios to exist compared to corresponding outdoor implementation environments. Unsurprisingly, therefore, most proposed techniques and models are found to perform better in one or a few types of scenarios and locations. Other popular methods include ray-tracing for establishment and testing of multi-frequency indoor and outdoor models [31]. Wall correction factor-based modelling has also borne fruitful results for researchers, since such structures may lead to diverse fading scenarios and can significantly affect the estimates generated by models not compensating for fading and signal attenuation events engendered by such indoor and outdoor structures [32]. However, outdoor models are vulnerable to inclement meteorological phenomena, but otherwise achieve higher network performance [33]. Another innovative approach uses machine learning algorithms to offset environmental losses through accurate tracking of received signal strength [34]. Another recent paper has looked at machine learning based beam quality estimation for improvement of SNR through the application of deep neural networks [35]. Attenuation map-based positioning systems have been presented in [36] with the help of a deep learning architecture. A low-complexity pilot assignment algorithm presented in [37] allows the mitigation of channel state errors and noise for massive-MIMO systems. A graph-colouring based algorithm is presented for channel estimation in massive-MIMO D2D underlay systems for optimal pilot assignment, for improvement of parameters such as SNR [38]. A deep learning-based channel estimation approach is also presented in [39], for generation of estimates from received omni-beam patterns, in the context of vehicular communication. Another relevant recent work presents an ensemble prediction system for nowcasting of attenuation data for highly accurate prediction of attenuation events such as heavy rainfall [40]. Other ML-based techniques have also proved to yield excellent results in diverse fields such as in the health monitoring of electrical systems, employing a combination of the Continuous Wavelet Transform (CWT) and Convolutional Neural Network (CNN)-based approaches [41]. Residual Neural Network (ResNet)-based approaches have also yielded accurate results in sleep-stage detection through examination of EEG signals, and such approaches are expected to be effective in time-series based prediction of signal attenuation [42]. A feature extraction methodology based on fractal analysis can also be effective for implementing feature extraction for a given time-series [43], which is another approach towards a high-accuracy solution for prediction of signal attenuation.

The survey of recent relevant literature indicates the presence of a significant research gap in terms of proposal of a suitable dynamic signal attenuation model for 5G communication with compensation for different meteorological events inclusive of rain, in different geographies around the world. The present work consequently stems from a need to address these issues in view of the great potential 5G communication possesses as well as the significant challenges posed to its effective implementation, which can be alleviated through the investigation of suitable models which can guarantee acceptably accurate performance in practical scenarios.

3- Proposed Model

On inspection of the recent research in the establishment of attenuation models for 5G millimeter wave communication signals, two major challenges are found to emerge. First, the attenuation of a 5G signal varies significantly due to meteorological phenomena such as rain, as well as the micro-environment of the network (for example, diffraction due to sand storms in arid regions). Second, attenuation models for indoor and outdoor environments are found to vary to a significant extent, and lack dynamicity to a certain degree.

In such a scenario, the application of suitable machine learning techniques allows for design and establishment of dynamic models which can adapt to changes in the network conditions and can therefore generate estimates with greater accuracy than typically used attenuation models. It is also to be kept in mind that adaptive machine learning based model are more robust in the face of significant meteorological variations, further increasing the usefulness of such models in the present context. As a consequence, a dynamic machine learning based model which accounts for both LoS and NLoS signal propagation would seem to be ideal in the given scenario.

The present work therefore proposes an autoregression-based machine learning model for generation of attenuation estimates which can be applied for real-time as well as non-real-time time series data. The basic system model is illustrated in the following Figure 1.

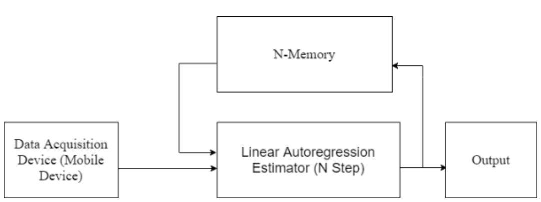


Fig. 1 N-Step Autoregression Estimator

The autoregression model generates regression estimates based on the previous N values of the signal attenuation and adjusts the weight of the values based on the estimation error. The estimation results are presented in the following section. The corresponding relations for autoregression estimation are expressed in equation 1 which follows, with F being the autoregression function, Y being the estimated output, X being the independent attenuation variable, C being the associated coefficient weight, and t being the instant of time.

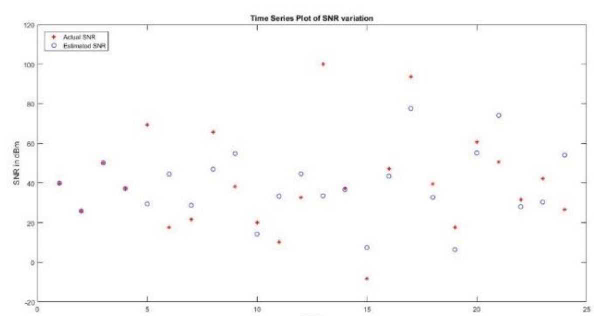
$$Y(t+1) = F_t\{\sum_1^k X_i^k(t) C_i(t)\} \quad (1)$$

The corresponding path loss attenuation model applied for simulation of the scenario is the standard 3GPP urban microenvironment model [2] with attenuation X being dependent on distance d as well as constants α, β and γ, as shown in equation 2.

$$X = \alpha + \beta \log_{10} d + \gamma \quad (2)$$

4- Results and Conclusions

Five different types of ML based autoregression estimation techniques are used to generate attenuation estimates in this study. The techniques are: forward-backward technique, least-squares estimation, Yule-walker technique, Burg's Method and Geometric Lattice Technique. The individual results are obtained for statistical samples generated over 1000 test runs each, for polynomials of order 4, 6 and 8 respectively. The corresponding results are presented in Figures 2 to 6, which follow.



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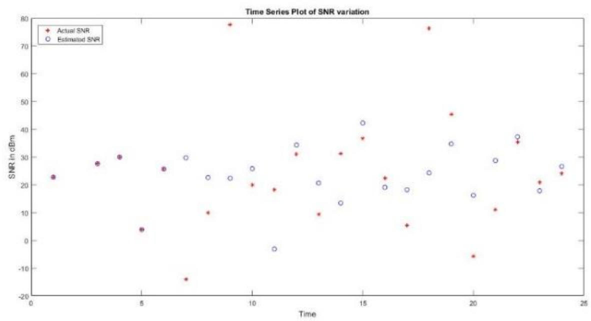

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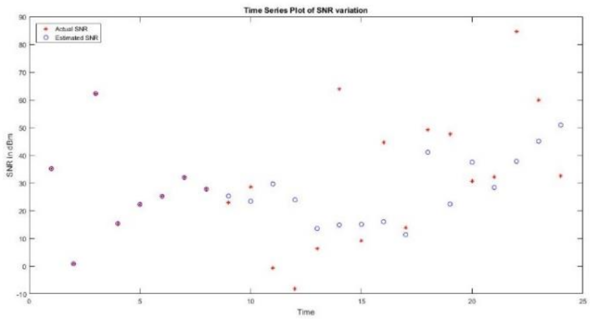

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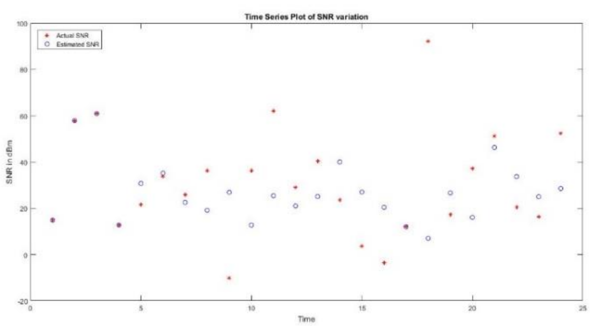
Fig. 2 Forward-Backward Method: (a) 4th order polynomial (b) 6th order polynomial (c) 8th order polynomial



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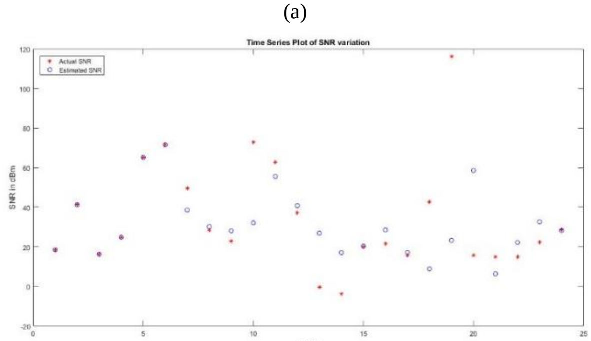

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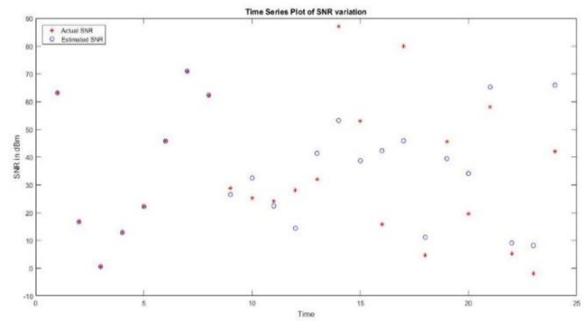

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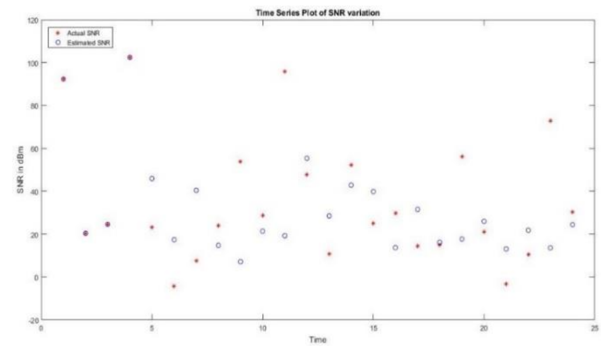
Fig. 3 Least-Squares Method: (a) 4th order polynomial (b) 6th order polynomial (c) 8th order polynomial



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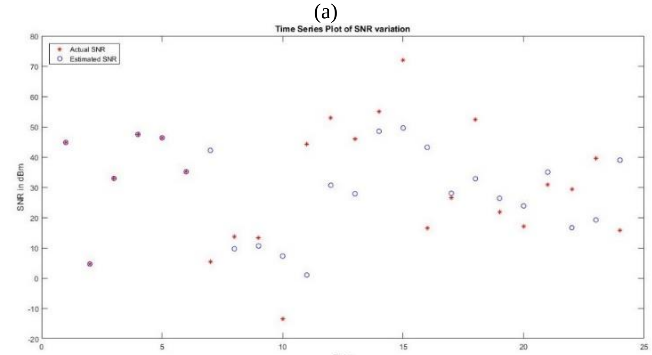

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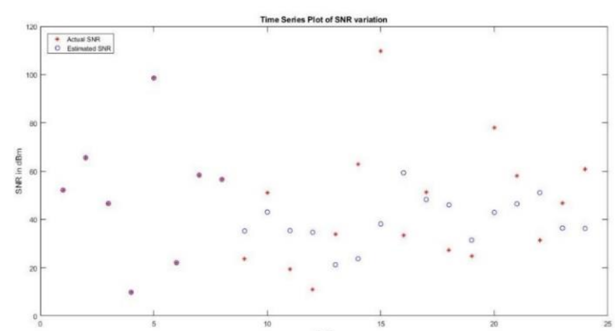

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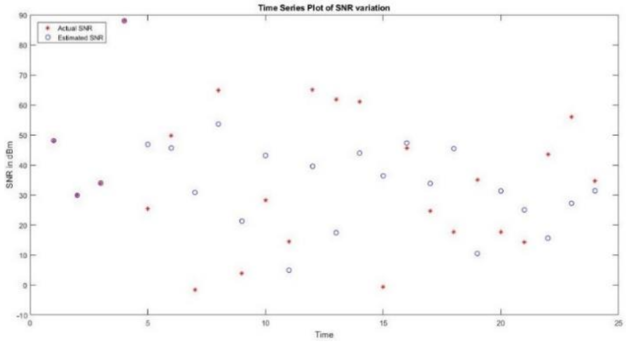
Fig. 4 Yule-Walker Method: (a) 4th order polynomial (b) 6th order polynomial (c) 8th order polynomial



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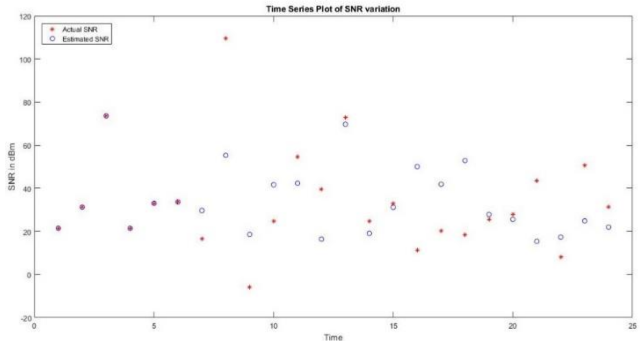

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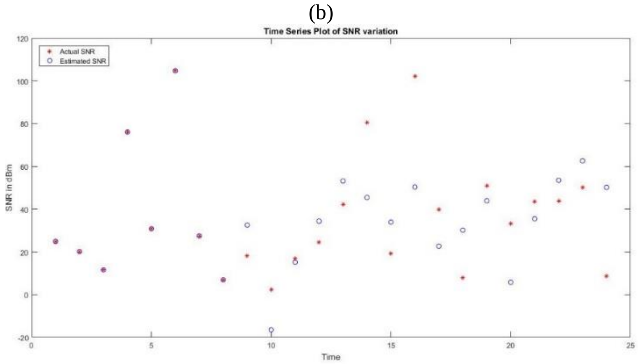
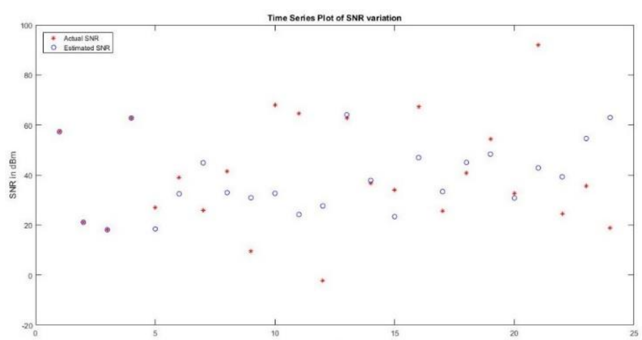


(c)

Fig. 5 Burg's Method: (a) 4th order polynomial (b) 6th order polynomial (c) 8th order polynomial



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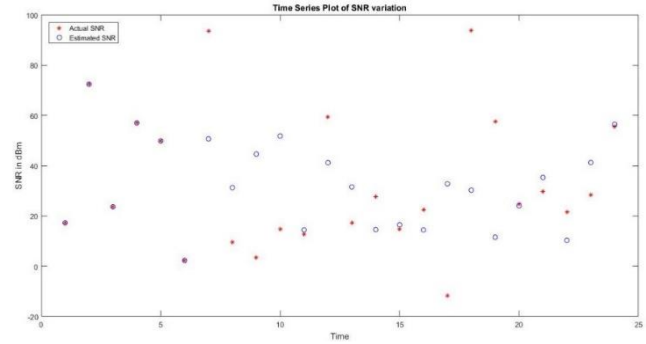

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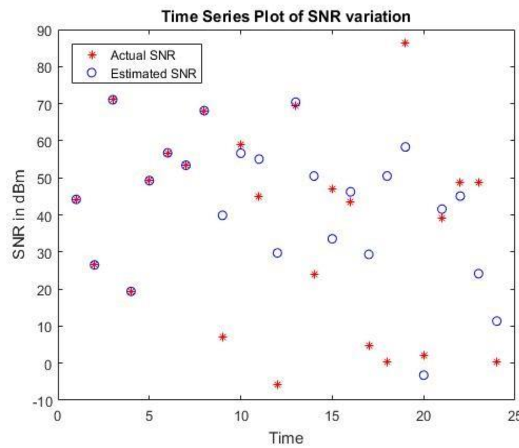

(c)

Fig. 6 Geometric Lattice Method: (a) 4th order polynomial (b) 6th order polynomial (c) 8th order polynomial

The RMSE or root mean square error metric is used to evaluate the accuracy of the estimated attenuation values in this work. The various techniques are therefore compared according to both the error as well as the RMSE metrics in the present work. The RMSE is measured due to the fact that the metric is statistically more significant than the mean error in terms of representation of the dataset, since it is less prone to bias than mean error metric. The corresponding values for each technique are presented in Table 1.

Table 1. Comparison of RMSE

Technique	***RMSE for Polynomial Order***		
	4	**6**	**8**
Forward-Backward	0.7758	1.2751	10.2541
Least-Squares	2.0739	20.9429	1.2008
Yule-Walker	1.8334	1.5183	0.5932
Burg's Method	12.4825	1.2436	2.1097
Geometric Lattice	2.8168	2.6201	39.9316

From Table 1, it is seen that even though the Forward-Backward or Burg methods may sometimes generate marginally more accurate estimates, they are prone to fluctuation of accuracy with polynomial order. The Yule-Walker method is optimal in the sense that it generates agreeably correct estimates even for higher order polynomial models and does not suddenly decrease in accuracy for any of the polynomials. The comparative RMSE performance of all techniques is shown in the following Figure 7, which validates the abovementioned inference.

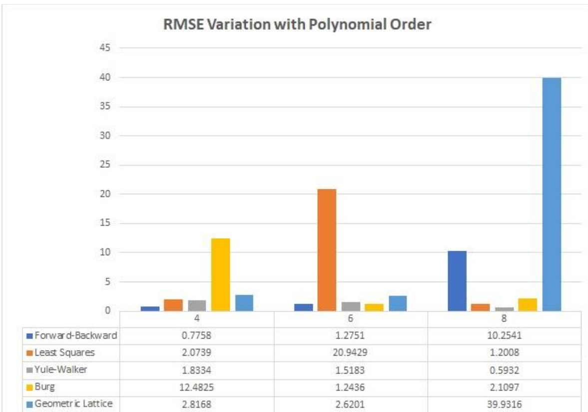

Fig. 7 Comparative RMSE Performance of Techniques

The autoregression-based machine learning technique is compared to corresponding artificial neural network (ANN) based method [39] and adaptive spline regression-based method [25]. The RMSE metric is used to compare between the three methods. The corresponding Table 2 presents the comparative results observed.

Table 2. Comparison of Autoregression, ANN and Adaptive Spline Regression Methods

Technique	***RMSE***	***Complexity***
Autoregression	0.5932	Low
ANN	0.0713	High
Adaptive Spline Regression	0.9811	Moderate

The complexity of the proposed method can be estimated in the following manner. Assuming the application of the Yule-Walker method, the power spectral density of the time series is repeatedly computed and adjusted using a small set of k samples (among a possible N samples). Assuming the worst-case convergence of the technique, that is, after N cycles, the worst-case time complexity of the proposed technique is $O(kN) << O(N^2)$, and considering the small set of samples k examined to generate estimates at each step, $k<<N$, which allows the worst-case complexity of the technique to be estimated as $O(N)$. This complexity is significantly lesser than the $O(N^2)$ complexity of the adaptive spline technique and the $O(N^r)$ for $r>2$ complexity of the ANN method.

The comparative results show that the autoregression based technique achieves suitably low RMSE at low complexity, compared to the other techniques, allowing this proposed technique to be easily implementable in practical scenarios. Another important fact that must be kept in mind is that the RMSE is not extremely low, which indicates that the model does not suffer from significant overfitting error, which in turn allows the proposed model to be more dynamic.

Next, the proposed technique is compared to the ANN and adaptive spline-based methods for different mobility scenarios, ranging from 1 m/sec (low mobility) to 30 m/sec (high mobility), with respect to the same RMSE parameter. In all cases, the transmitters are considered to be fixed while the devices receiving the signal are made mobile. The experiments are repeated to generate 1000 sets of results, which are then averaged to generate the results, for each of the techniques. The results achieved by the three techniques compared in the present work are illustrated in the following Table 3.

Table 3. Comparison of Autoregression, ANN and Adaptive Spline Regression Estimates for different Mobility Scenarios

Technique	***RMSE***	***Mobility***
Autoregression	0.61	Low (1m/sec)
ANN	0.09	Low (1m/sec)
Adaptive Spline Regression	0.93	Low (1m/sec)
Autoregression	0.69	Moderate (15m/sec)
ANN	0.11	Moderate (15m/sec)
Adaptive Spline Regression	1.31	Moderate (15m/sec)
Autoregression	0.89	High (30m/sec)
ANN	0.23	High (30m/sec)
Adaptive Spline Regression	1.75	High (30m/sec)

The comparative results are illustrated graphically in the following Figure 8.

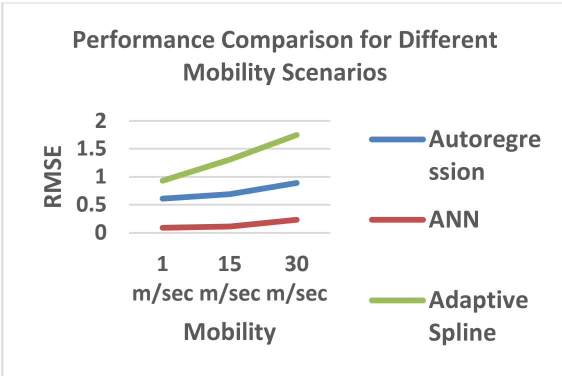

Fig. 8 Comparative RMSE Performance of Techniques in different Mobility Scenarios

From the results obtained through experiments and illustrated in Figure 8, a continuous increase of RMSE is observed for each of the three compared techniques, which is expected due to the fading conditions expected in the different mobility scenarios. However, the proposed technique, which maintains an RMSE value much lower than the adaptive spline method, has the slowest change in RMSE among the three methods, which indicates its stability in a dynamically changing mobility scenario. Such a stability may be attributed to the comparatively low-complexity approach that the proposed autoregression-based method takes in comparison to the other two techniques. The experimental results achieved consequently show that the proposed autoregression-based technique achieves acceptable performance in practical scenarios, which is a basic requirement that must be met for the model to be able to generate accurate estimates in significantly dynamic environments. Additionally, a neural network-based technique can also be used in conjunction with the proposed method in order to reduce the RMSE while restricting the overall complexity of such a hybrid technique to moderate levels. On the other hand, if reduction of complexity is a more significant issue for a particular implementation scenario, a linear spline regression method can be used in conjunction with the proposed autoregression technique to allow for low-complexity model design without significant loss in model accuracy.

5- Conclusions

On inspection of the recent research in the establishment of attenuation models for 5G millimeter wave communication signals, two major challenges are found to emerge. First, the attenuation of a 5G signal varies significantly due to meteorological phenomena such as rain, as well as the micro-environment of the network (for example, diffraction due to sand storms in arid regions). Second, attenuation models for indoor and outdoor environments are found to vary to a significant extent, and lack dynamicity to a certain degree. In such a scenario, the application of suitable machine learning techniques allows for design and establishment of dynamic models which can adapt to changes in the network conditions and can therefore generate estimates with greater accuracy than typically used attenuation models. It is also to be kept in mind that adaptive machine learning based model are more robust in the face of significant meteorological variations, further increasing the usefulness of such models in the present context. As a consequence, a dynamic machine learning based model which accounts for both LoS and NLoS signal propagation can be designed, as shown in this work, allowing optimization of RMSE of predictions at suitably low complexity, which in turn ensures that such a solution can be cheaply and easily implemented in practical scenarios for estimation of signal attenuation for 4G and 5G networks.

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