An Intelligent QoS Control System for Satellite Networks Based on Markovian Weather Prediction

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Abstract—Prediction of channel characteristics can be of immense value in improving the quality of signals in high frequency satellite communication channels. Making prediction of rainfall rate (RR) using Markovian theory is the object of this paper. The paper also describes an intelligent system (IS) that uses the predictions made from Markovian model to maintain the Quality of Service (QoS) in channels impacted by rain attenuation (RA). The paper describes the method of prediction of RR using weather correlated database supplied by International Telecommunication Union-Radiocommunications (ITU-R) and applying the predictions to gateway and ground terminal for optimal control of channel characteristics. The proposed method of predicting weather characteristics using Markovian theory supplies valuable data to develop an enhanced back propagation-learning algorithm to iteratively tune the intelligent system to adapt to changing weather conditions. The effectiveness of the algorithm was tested on a simulated model for activating the weighted modulation and codepoint control. It demonstrated marked improvements in channel parameter tuning and signal quality.

Index Terms—Decision Support System (DSS), Intelligent System (IS), International Telecommunication Union-Radiocommunications (ITU-R), Quality of Service (QoS), Rain Attenuation (RA), Rainfall Rate (RR), Service Level Agreements (SLA), Signal to Noise Ratio (SNR).

I. INTRODUCTION

It is extremely hard to optimally manage satellite dependent network resources that are impacted by weather attenuations. The dominant cause of the adverse impacted is Rain attenuation (RA). And, the RA for satellite signals becomes particularly severe at high frequencies, especially above Ku band [1]–[4]. Thus, the need arises to properly identify and predict significant attenuation factors that affect quality of service (QoS).

A number of prediction models are available for estimating individual attenuation components. However, methodologies that attempt to combine them in a cohesive manner have seen limited success. Authors of [5] propose a method for RA prediction for low rain intensities in satellite links. Based on statistical measurements at Ku and Ka bands, an empirical model is proposed in [6] to predict fade time as a function of attenuation, frequency, and fade duration.

Despite the fact that some work has been done to study rain fade characteristics in satellite networks, most of the existing work is limited to low rainfall rate (RR) and predictions based on historical data [7]. It is also considered a difficult task to optimally manage the available satellite network resources that are impacted by rain fade. To the best of our knowledge, QoS provisioning in weather impacted satellite networks for reliable satellite communications is currently not available in the literature. Lately, the research thrusts in QoS over satellite links are shifting towards intelligent prediction methods. The effectiveness of the intelligent method could be further enhanced by computationally efficient techniques that take into account the propagation environments and predict parameters that affect the performance of communications systems and networks [6], [8].

Our previous method in [2], [7], [9], where RA was computed based on fifteen years of historical data from International Telecommunication Union-Radio Communications (ITU-R) database, provides a static value of RA that can be used to tune intelligent systems (IS). This paper, on the other hand, proposes not only an advanced dynamic model for weather prediction but also an intelligent control system that capitalizes those predictions for enhancing network performance. Thus, based on the current weather at any location, network and signal properties could be adjusted before detrimental events actually manifest, so that end-to-end QoS requirements could be met.

This paper is presented in five sections. Section II describes prediction of channel characteristics. Description of intelligent weather systems for satellite networks is presented in Section III. Section IV, presents simulation results and discussions. Finally, conclusion of the study and a brief description of future work is provided in Section V.

II. PREDICTION OF CHANNEL CHARACTERISTICS

This section describes the behavior of RA at high frequency and proposes a method for better estimating channel attenuation in weather impacted satellite networks. The RA is computed, based on RR, which itself is predicted by using Markovian theory [10] along with ITU-R models and bilinear interpolation [11]. The method predicts RR at any location on earth, for a wide range of propagation angles and frequencies. The RR values are then used to adjust the control parameters and, therefore, help improve the QoS in communication channels.

A. RR Prediction

Predictability and randomness are inherent traits of natural phenomena including weather. That is the reason why from
importance to current condition. The Markovian chain theory shown in Fig. 2 and previous and previous-to-previous time slot respectively as where \( W \) resulting weight vector is denoted as:

\[
W = \begin{bmatrix} W_0 & W_1 & W_2 \end{bmatrix}
\]  

(1)

ancient humans to the most sophisticated civilizations plan certain activities in certain times of the year, month or day and under certain characteristic conditions. Governments are spending much resources in weather forecasting primarily because the predictability of weather is found to be statistically significant. In this section, RR is predicted by using Markovian theory on weather data, where weather is considered a discrete random process that can assume a set of finite states. Further, it is assumed that the change from one state to another is random discrete step with certain transition probability, whose value is derived from statistical properties of the system. For the purpose of Markovian modeling of RR, we chose to divide RR values into five classes starting from zero mm/hr up to any value as follows:

1) Class A: from zero up to but less than 1 mm/hr
2) Class B: from 1 up to but less than 4 mm/hr
3) Class C: from 4 up to but less than 8 mm/hr
4) Class D: from 8 up to but less than 14 mm/hr
5) Class E: values greater than 14 mm/hr.

The approach in grouping total RR into classified blocks at different stations where the weather is tracked is shown in Fig. 1. This classification in real-time provides a basis for the data required to apply Markovian theory in RR prediction.

For the purpose of modeling, different weights have been assigned to each Markovian state that the RR measurements could assume, namely the zero order \( P_0 \): present state), first order \( P_1 \): previous state), and second order \( P_2 \): previous to previous state) as defined in Markovian chain theory. The resulting weight vector is denoted as:

\[
W = \begin{bmatrix} W_0 & W_1 & W_2 \end{bmatrix}
\]  

(1)

where \( W_0, W_1, \) and \( W_2 \) represent the weight of present, previous and previous-to-previous time slot respectively as shown in Fig. 2 and \( W_0 > W_1 > W_2 \) to give higher importance to current condition. The Markovian chain theory works with a set of finite number of states that are denoted as \( P(x) \), where \( P(x) \) is the probability of being in state \( x \). In this representation, independent chains have no memory, whence called zero-order Markov chains. The transition matrix of zero-order Markovian chain theory \( P_0 \) for the five presented classes is represented as follows:

\[
P_0 = \begin{bmatrix} P_A & P_B & P_C & P_D & P_E \end{bmatrix}.
\]  

(2)

The Markov chain process consisting of a finite number of states with known probabilities \( P(x,y) \) of transition from state \( y \) to state \( x \) is considered a first order Markovian Chain. The transition matrix of the first-order Markovian chain for the five classes mentioned before is represented as follows:

\[
P_1 = \begin{bmatrix} A & B & C & D & E \\
A & P_{AA} & P_{AB} & P_{AC} & P_{AD} & P_{AE} \\
B & P_{BA} & P_{BB} & P_{BC} & P_{BD} & P_{BE} \\
C & P_{CA} & P_{CB} & P_{CC} & P_{CD} & P_{CE} \\
D & P_{DA} & P_{DB} & P_{DC} & P_{DD} & P_{DE} \\
E & P_{EA} & P_{EB} & P_{EC} & P_{ED} & P_{EE} \end{bmatrix}.
\]  

(3)

Similarly, the transition matrix of the second-order Markovian chain theory \( P(xy|x) \) for the five classes is:

\[
P_2 = \begin{bmatrix} A & B & C & D & E \\
A & P_{AAA} & P_{AAB} & P_{AAC} & P_{AAD} & P_{AAE} \\
B & P_{ABA} & P_{ABB} & P_{ABC} & P_{ABD} & P_{ABE} \\
C & P_{CA} & P_{CAB} & P_{CAC} & P_{CAD} & P_{CAE} \\
D & P_{DA} & P_{DAB} & P_{DAC} & P_{DAD} & P_{DAE} \\
E & P_{EA} & P_{EAB} & P_{EAC} & P_{EAD} & P_{EAE} \end{bmatrix}.
\]  

(4)

The characteristics of these matrices is such that the entries for each column vectors in (2), (3), and (4) are positive.
numbers. The sum of the elements of each row in the matrices is one. The columns represent probability vectors, which are nothing but the stochastic value for transition. And the matrices are, therefore, called transition matrices.

From the above equations, the predicted RR ($R_{pr}$) could be periodically computed at each hour as follows:

$$R_{pr}(t) = W_0 \cdot P_0 + W_1 \cdot P_1(m_i,:) + W_2 \cdot P_2(n_i,:)$$  \hspace{1cm} (5)

where $m_i$ ranges from 1 to 5, and $n_i$ ranges from 1 to 25 according to the previous weather state.

Taking a set of RR values for a specific duration and relate this data to Atlin Station - Canada and applying our methodology to predict the future state, we found that the prediction closely matches with the measured results as shown in Fig 3. It was found that the Markovian chain has promising application in effectively predicting the future weather result in statistical terms. Notice that, the weights and transition matrices values are selected initially based on historical field data and are refined iteratively over time by the system through feedback control.

B. Calculating RA Based on Predicted RR ($R_{pr}$)

Among the factors that cause propagation impairments, such as rain, fog, cloud, and scintillation, rain is the most dominant, often misunderstood, and complicated phenomenon. This is specifically so in high frequencies where the signal absorption and scattering of incoming signal becomes heavily impacted by rain than other factors. Therefore, determining RA on a regional or individual site basis is considered important in minimizing its impact on communication channels through the control of channel characteristics [1], [7], [12].

These parameters and their calculations are not described here for brevity. Given the attenuation data measured at any specific frequency, the adjusted empirical formulas shown in (6) provide predicted RA. In the equation the RA is calculated given the propagation angle, predicted RR, effective path length, and frequency coefficient.

$$A_r(\theta, R_{pr}) = \gamma_R(\theta, R_{pr}) \cdot L_E(\theta, R_{pr}) \text{ dB}$$  \hspace{1cm} (6)

We derived the above equation from [1], [2], [12] to extract RA value from the predicted RR, which would be determined using the Markovian theory. where $A(\theta, R_{pr})$ represents RA for a given value of predicted RR, $R_{pr}$, and propagation angle, $\theta$, as shown in Fig. 4.

This method determines the predicted value of RA at any desired location, for different propagation angles, predicted RR, and channel frequency. The RA value for a given condition is then supplied to intelligent system, which is described below, to achieve intelligent control of propagation parameters for improving the performance of the system.

III. ISS FOR SATELLITE NETWORKS

Intelligent systems are employed in the control of satellite systems to improve signal to noise ratio (SNR) by using the knowledge of predicted RAs and other factors under extreme signal-weather conditions in adjusting signal power, modulation and coding schemes. Therefore, in this section, we describe how ISs calculate SNR and use it to markedly reduce bit error rate (BER) in transmissions above 10 GHz.

A. SNR Calculation

The SNR estimations uses parameters described in the previous section and some more parameters in the following manner. SNR is primarily contributed by rain and free space. First, RA is obtained from (6). Second, the free space loss $A_0$ is calculated as: $A_0 = (4 \cdot \pi \cdot d/\lambda)^2$, where $d$ is the distance between transmitter and receiver, and $\lambda = c/f$ is the wavelength. Note that a free space is space with nothing at all in it but because such phenomenon does not exist in the known universe we assume interstellar space as a good approximation [8]. Then the total attenuation is obtained from:

$$A_t = A_r(\theta, R_{pr}) + A_0 \text{ dB.}$$  \hspace{1cm} (7)

That $A_t$ is obtained, we are set to calculate SNR as follows. Refer to [7], [8] for further explanations. Calculate thermal noise power spectral density as: $N_0 = K \cdot T$, where Boltzmann constant $K = 1.38 \cdot 10^{-23} Ws/K = -228.6 dBW/s/K$ and effective noise temperature $T = T_a + T_r$. The $T_a$ is noise temperature of the antenna as represented in [7], and $T_r$ is noise temperature of the receiver represented as $T_r = (10^{N_r/10} - 1) \cdot 290$, with noise figure of low-noise amplifier, $N_r \approx 0.7 \sim 2 \text{ dB}$.

Now, calculate the following ratio:

$$\frac{C}{N_0} = \frac{C}{K \cdot T} = \frac{P_r}{K \cdot T} = \frac{P_t \cdot G_t}{A_t} \cdot \frac{G_r}{K \cdot T}$$  \hspace{1cm} (8)

Next, obtain symbol energy ($E_s$) from $E_s = C \cdot T_s = C/R_s$, where transmission rate $R_s$ is inversely equivalent to symbol duration $T_s$.

Next, obtain energy-to-noise power density per symbol:

$$\frac{E_s}{N_0} = \frac{C}{N_0} - R_s \text{ dB.}$$  \hspace{1cm} (9)

Finally, combine (8) and (9) to obtain the formula for determining SNR, which is:

$$SNR(A_t, P_t) = P_t + G_t - A_t + G_r - T - K - R_s \text{ dB}$$  \hspace{1cm} (10)

where $P_t$ and $P_r$ are transmitter and receiver power, and $G_t$ and $G_r$ are antenna gain at transmitter and receiver sides respectively. It should be noted that the improved estimation
of $A_t$, described above, results in improved estimation of SNR shown in Fig. 5 as a direct consequence.

B. An Intelligent System for SNR Improvement

What an IS offers in satellite communication is the control of signal characteristics (frequency, modulation, amplitude, coding, and queuing) in a manner that availability of links, SNR and system’s throughput are improved. In this section, we propose a new type of IS which brings much noticeable improvements in the control compared to ISs that we have come to know thus far.

The proposed IS is based on an adaptive intelligent model that is specialized to incorporate weather knowledge in decision making. The role of IS is to proficiently search for different combinations of input control variables such as transmit power level, modulation schemes, channel coding, and transmission rates, to minimize estimated attenuations effect and maximize channel robustness and efficiency by improving SNR using the technique presented in Fig. 6. This improves QoS by providing enhanced results for atmospheric attenuations for a wide range of frequencies, propagation angles, and RRs [13]–[15].

The IS proposed here consists of first, second, third, and fourth control block that are controlled by a special module, decision support system (DSS), as shown in Fig. 6. Here, the DSS is used to maintain QoS and Service Level Agreements (SLA) by adaptively adjusting satellite’s signal at precarious weather conditions, utilizing parameters like RA, propagation angle, location, and antenna gain, and adaptively adjusting signal power, transmission rate, coding, and modulation for obtaining optimal control. To achieve that a DSS would have to gather current values of control parameters, compare them with thresholds, and use that knowledge to control SNR values in communication channels to keep the system operations within agreed upon SLA.

The first control block compares estimated SNR (E-SNR), which is a function of signal parameters, such as predicted atmospheric attenuation, frame size, frequency, propagation angle, transmit power, and refresh duration with the actual outcomes of SNR values of the system.

The second control block compares the differences between the E-SNR and its threshold value set by the system’s designers, which will lead to one of three different outcomes: The first outcome, for E-SNR values smaller than the threshold level, in this case the DSS will decide to increase transmit power up to a maximum limit of $-30 \text{ dB} (0 \text{ dBm})$. The second outcome, for E-SNR values equal to or greater than the threshold level, the DSS will be satisfied and will jump to the last stage. The third outcome, for E-SNR smaller than the threshold level even after increasing the transmit power to its maximum value; the DSS will decide to go to the next stage.

In the third control block, based on adjusted SNR value, the DSS will decide to adjust other parameters such as data rate, frequency, modulation, and coding values as given in [2], [7], [9]. If the threshold level value can be reached by using any of the different variable combinations, then the DSS will decide to move to the fourth stage for decision.

In the fourth control block, the DSS will compromise among different SNR achieved outputs and will make the optimum decision based on the intelligent controller according to available parameters and requirements. The feedback will keep looping when needed, according to DSS decision, until a satisfactory value is reached.

In the model, the DSS is the window to the user space. It is integrated with the rest of the blocks through especially constructed algorithms, which require special writing outside the scope of this paper. In brief, the DSS takes experienced based decision inputs, especially the limits and expected values of selected parameters, from the user so that they could be factored in decision-making activities. Those mentioned user inputs include QoS and SLA parameters that are to be honored by the system. The trigger to back-propagation learning algorithm is also controlled by the DSS.

Thus, the IS will have the ability to modify controlled parameters, such as transmit power, data rate, frame size, coding, and modulation, in order to improve SNR with the change in weather conditions. IS proficiently searches for a blend of the controlled parameters for maximizing the network performance. For that it relies in maintaining a reasonable SNR level that would satisfy the minimum threshold level of operation as shown in Fig. 7. Due to space constraint, the combination of the controlled parameters used to achieve these results are presented in [7].
In this paper, we presented schemes to improve SNR and to solve rain fade problem due to different weather conditions. Using this scheme, we are able to markedly lower the effect of rain attenuation by using the RA predictions to control channel parameters. The proposed method is able to improve QoS by providing better estimates for any weather behavior that leads us to adjust SNR outputs in lieu of a wide range of weather attenuations, transmit power, modulation, coding, propagation angle, frequency, transmission rate, and location.

The results demonstrate how an enhanced tuning algorithm could use periodically computed attenuation values to iteratively tune the IS with returned SNR values. Our algorithm uses the weighted modulation/codepoint optimal values that tune with predicted weather conditions, configuration settings, and tolerance/safety margins for SLA commitment. The resulting IS helps to control various combinations of satellite’s signal parameters for all angles, and for any frequency, in order to maximize satellite system’s throughput as well as QoS under variant weather conditions.

Future work is in progress to consider the different impacts on QoS in the presence of other atmospheric conditions, as well as applying enhanced methodologies to improve satellite systems by considering other options.

**References**


