Performance Improvement in 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 systems. Making prediction of rainfall rate (RR) using Markov theory and using that prediction in an intelligent system (IS) to maintain the quality of service (QoS) in channels impacted by attenuation due to weather is the object of this paper. The paper describes the method of prediction rainfall rate (RRP) using weather collected by environment agencies and applying the predictions to gateway and ground terminal for optimal control of channel characteristics. This novel method of predicting weather characteristics using Markov theory supplies valuable data to develop an enhanced back propagation-learning algorithm to iteratively tune the IS 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.

I. INTRODUCTION

Rain attenuation (RA) and gaseous attenuation (GA) are considered dominant impairment for satellite signals. These impairments become particularly severe at high frequencies, especially above Ku band [1–3]. As such, it is extremely hard to optimally manage satellite dependent network resources that are impacted by weather attenuations. Thus, the need arises to properly predict significant attenuation factors that affect quality of service (QoS).

In fact some work has been done to study weather characteristics in satellite networks. Reference [4] articulates signal attenuation problems at high frequencies, highlighting the significance of losses not only due to rain but also due to gaseous interference. The work presented in [5] highlights these losses although it is limited to low rainfall rate (RR). And in [6], an empirical model is proposed to predict fade duration as a function of attenuation and frequency. 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 [6, 7].

Our previous method in [2, 8], where RA and GA were computed based on historical data from International Telecommunication Union-Radio Communications (ITU-R) database, provided static values of RA and GA. We also noticed that real-time predictions would yield an advanced model for weather prediction. Such models would help improve system performance by facilitating prompt adjustment of signal propagation parameters, before un-predicted events actually manifest themselves. This paper presents the solution we came up with in making real-time prediction of rain and gaseous attenuations and their use in intelligent systems (ISs).

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

Among the factors that cause propagation impairments, such as rain, gas, fog, cloud, and scintillation, the rain and the gas are 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. Therefore, determining RA and GA on a regional or individual site basis are considered important in minimizing their impact on satellite based networks through the control of channel propagation characteristics [1,3,8].

We describe a method for estimating RA and GA in weather impacted satellite networks operating at various practical frequencies up to Ka-band. The RA and GA are computed, as a function of predicted rainfall rate (RRP), which itself is predicted by using Markov theory [9] along with ITU-R models and bi-linear interpolation [10]. The method predicts RR at any location, propagation angle, and frequency. The estimated RA and GA in turn are used to adjust the control parameters and, therefore, in improving the QoS in communication channels.

A. Predicted Rainfall Rate RRP

In this section, RR is predicted by using Markov theory on weather data, which is considered a discrete random process that can assume a set of finite Classes. Further, it is assumed that the change from one Class 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 RRP, we chose to divide RRP values into five Classes 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 rain conditions into classified blocks. This classification in real-time provides a basis for the data required to apply Markov theory in RR_p.

For the purpose of modeling, different weights have been assigned to each Markov state that the RR_p measurements could assume, namely the zero order (present state), first order (previous state), and second order (previous to previous state) states. The resulting weight vector is:

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

where \( W_0, W_1, \) and \( W_2 \) represent present, previous one and two hours weight respectively.

The Markov 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 Class \( X \). In this representation, independent chains have no memory, whence called zero-order Markov chains. The transition matrix of zero-order Markov chains have no memory, whence called zero-order (previous state) states. The resulting weight vector is:

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

The Markov chain process consisting of a finite number of Classes with known probabilities \( P(X,Y) \) of transition from Class \( Y \) to Class \( X \) is considered a first order Markov Chain. The transition matrix of the first-order Markov chain is represented as follows:

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

Similarly, the transition matrix of the second-order Markov chain theory \( P(X|Z) \) for the five Classes is:

\[ P_2 = \begin{bmatrix} A & B & C & D & E \\ AA & P_{AAA} & P_{AAB} & P_{AAC} & P_{AAD} & P_{AAE} \\ : & : & : & : & : \\ AE & P_{AEA} & P_{AEB} & P_{AEC} & P_{AED} & P_{AEE} \\ BA & P_{BAA} & P_{BAB} & P_{BAC} & P_{BAD} & P_{BAE} \\ : & : & : & : & : \\ CA & P_{CAA} & P_{CAB} & P_{CAC} & P_{CAD} & P_{CAE} \\ : & : & : & : & : \\ DA & P_{DAA} & P_{DAB} & P_{DAC} & P_{DAD} & P_{DAE} \\ : & : & : & : & : \\ EA & P_{EAA} & P_{EAB} & P_{EAC} & P_{EAD} & P_{EAE} \\ : & : & : & : & : \\ EE & P_{EAA} & P_{EAB} & P_{EAC} & P_{EAD} & P_{EAE} \end{bmatrix}. \]  

The characteristics of these transition 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 the stochastic value for transition.

From the above equations, the \( RR_p \) could be periodically computed at each hour as follows:

\[ RR_{pr}(t) = W_0 P_0 + W_1 P_1(n_i,:) + W_2 P_2(n_i,:), \]  

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 \( RR_p \) values for a specific duration at a Vancouver 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 Figure 1. It was found that the Markov chain has promising application in effectively predicting the future weather result in statistical terms.

**B. Calculating RA Based on Predicted RR**

We derived the following equations from [1–3] as:

\[ A_r(f, RR_p) = \gamma_R(f, RR_p) \cdot L_E(f, RR_p) \ dB \]  

\[ A_r(f, RR_p), \] for a given value of \( RR_p \), and frequency, \( f, \) is shown in Figure 2.

Existing ITU-R methods repeat a cumbersome calculation for RA at each channel frequency as described in [2].

This method determines the predicted value of RA for any location, propagation angle, \( RR_p \), and frequency. The RA value for a given condition is then supplied to IS, to achieve intelligent control of propagation parameters for improving the performance of the system.

**C. Calculating GA Based on Predicted RR**

Thus, predicting GA requires a model that allows us to represent the specific attenuation mathematically. It can be calculated by summing the effects of all of the significant resonance lines given in ITU-R P. 676 as described below:

\[ \text{Specific Attenuation}: \]
1. The dry air attenuation $\gamma_0(f, RR_p)$ (dB/km) is:

$$
\gamma_0(f, RR_p) = \left[ \frac{7.2 r^2 \pi^2}{(3 \pi - f)^2} \right] + \ldots + \frac{0.62 r \pi^2}{(3 \pi - f)^2} + \frac{1.8 \pi}{(3 \pi - f)^2} + \frac{0.83 \pi}{(3 \pi - f)^2} \right] \cdot f^2 r^2 \rho \times 10^{-3},
$$

where $\xi_1$, $\xi_2$, and $\xi_3$ are as defined in [8].

2. The water vapour attenuation $\gamma_v(f, RR_p)$ is:

$$
\gamma_v(f, RR_p) = \left[ \frac{3.98 \eta_1 \exp[2.23(1-r_c)]}{(f-22.23)^2} + 0.49 \eta_2 \exp[6.44(1-r_c)] + 0.081 \exp[6.44(1-r_c)] + \ldots \right] + 11.96 \eta_1 \exp[6.31(1-r_c)] + 0.081 \eta_1 \exp[6.64(1-r_c)] + \ldots
$$

$$
+ \frac{3.66 \eta_1 \exp[1.6(1-r_c)]}{(f-323.9)^2} + \frac{25.27 \eta_1 \exp[1.09(1-r_c)]}{(f-323.9)^2} + \ldots
$$

$$
+ \frac{17.4 \eta_1 \exp[1.46(1-r_c)]}{(f-52)^2} + \frac{844.5 \eta_1 \exp[0.17(1-r_c)]}{(f-52)^2} + \ldots
$$

$$
\cdot f^2 r^2 \rho \times 10^{-3},
$$

where $\eta_1 = 0.955 r^2 \rho l_1^{0.68} + 0.006 \rho$, $\eta_2 = 0.735 r^2 \rho l_1^{0.68}$, and $\eta_3 = 0.35 \eta_1 - 0.035 r^2 \rho$.

3. The calculation of Total Attenuation ($A_t$):

$$
A_t(f, RR_p) = A_0(f, RR_p) + A_V(f, RR_p) + A_g(f, RR_p)
$$

4. The path attenuation for Earth-Space propagation angle between 5 and 70 degrees:

$$
A_g(f, RR_p) = A_0(f, RR_p) + A_V(f, RR_p) \left[ \frac{\sin \theta}{\sin \theta} \right] dB,
$$

where $A_0(f, RR_p) = h_0(f, RR_p) \cdot \gamma_0(f, RR_p)$ and $A_V(f, RR_p) = h_v(f, RR_p) \cdot \gamma_v(f, RR_p)$ dB.

5. The third parameter is the free space attenuation. Here, 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 [7].

$$
A_f(f, RR_p) = A_0(f, RR_p) + A_V(f, RR_p) + A_g(f, RR_p) + A_f(f, RR_p)
$$

6. The calculation of $A_W(f, RR_p)$ as per (12) is taken as a function of RA and GA. The attenuation due to fog, cloud, and scintillation were neglected as their effects were much smaller compared to RA and GA. The results of these attenuations for ranges of RR_p and frequencies are shown in Figure 2 and Figure 3.

7. The total attenuation $A_t$ is then obtained from:

$$
A_t(f, RR_p) = A_W(f, RR_p) + A_0(f).
$$

We found the prediction of total attenuation obtained in this way is respectable approximation. The $A_t$ is used to calculate SNR, which is then used by the IS in determining channel quality and subsequently adjusting satellite propagation parameters as described in the next section.

### III. AN INTELLIGENT CONTROL SYSTEM

Intelligent systems are employed in the control of satellite systems to improve signal to noise ratio (SNR) by using predicted RAs, GAs, and other factors under extreme signal-weather conditions by 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. Algorithmic Basis for SNR Calculation

The SNR estimations use parameters described in the previous section and some more parameters in the following manner. Refer to [7,8] for further explanations. Calculate thermal noise power spectral density as:

$$N_0 = K \cdot T$$

where Boltzmann constant $K = 1.38 \times 10^{-23} W s/K$ and effective noise temperature $T = T_a + T_r$. The $T_a$ is noise temperature of the antenna as represented in [8], 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 this ratio as an intermediate step:

$$\frac{C}{N_0} = \frac{C}{K \cdot T} = \frac{P_r}{K \cdot T} = \frac{P_t \cdot G_t}{A_t} \cdot \frac{G_r}{K \cdot T}, \quad (14)$$

next, obtain symbol energy ($E_s$) from $E_s = C \cdot T_s = C/R_s$, where transmission rate $R_s = (1/T_s)$.

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

$$\frac{E_s}{N_0} = \frac{C}{N_0} - R_s \text{ dB}. \quad (15)$$

Finally, combine (14) and (15) to obtain SNR as:

$$SNR(A_t, P_t) = P_t + G_t - A_t + G_r - T - K - R_s \text{ dB}, \quad (16)$$

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 $A_t$ that the method described above results in improved estimation of SNR as a direct consequence.

B. Intelligent System (IS) Architecture

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. Proposed here is 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 IS is assigned to search for different combinations of input control variables such as transmit power level, modulation schemes, channel coding, and transmission rates, with the variation of weather condition to maximize SNR. The effect is to minimize attenuations, maximize channel efficiency, and improve QoS. The method is similar to classical feedback control systems except that results for weather attenuations are far more accurate for a wide range of frequencies, propagation angles, and RRPs [11,12] thus markedly better results.

The IS architecture is depicted in Figure 5, which consists of first, second, third, and fourth control blocks that are controlled by a special module, decision support system (DSS). The DSS is to capture Service Level Agreements (SLAs) and ensure that used to maintain QoS is as per the agreement. When thresholds are reached it would trigger changes through the four control blocks the changes in satellite’s signal transmission parameters like RA, GA, propagation angle, location, and antenna gain, and adjusting signal power, transmission rate, coding, and modulation for obtaining optimal control. To achieve that a DSS would have to gather current values of controlled 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.

C. The SNR Improvement Algorithm

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

The second control block compares the differences between the predicted SNR and its threshold value set by the system’s designers. This leads to three conditions depicted as I, II, and III indicating three separate types of measures designed for normal operation, where room for fade margin exists, and other measures are to be triggered, respectively. The first outcome, for predicted SNR (P-SNR) values smaller than the threshold level, in this case the DSS increase transmit power up to a maximum limit of $-30 \text{ dB (0 dBm)}$. The second outcome, for P-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 P-SNR smaller than the threshold level even after increasing the transmit power to its maximum value; the DSS go to the next stage.

In the third control block, based on adjusted SNR value, the DSS adjusts other parameters such as data rate, frequency, modulation, and coding values as given in [2,8]. If the threshold level value can be reached by using any of the different variable combinations, then the DSS moves to the fourth stage for decision.

In the fourth control block, the DSS selects a set of modulation, coding, power, and data rate, that is optimal for the given weather condition. The feedback control system will continue iteratively as needed until a satisfactory value has been reached. This block thus maintains a reasonable SNR level that satisfies the minimum threshold level of operation as shown in Figure 6.

Our algorithm used periodically computed attenuation values to tune the IS with returned SNR values. It used the weighted modulation/codepoint values that tune with predicted weather conditions, configuration settings, and tolerance/safety margins for SLA commitment. The enhancement made over the traditionally used algorithm is apparent in that this method brings respectable results for all propagation angle and frequency range.

IV. SIMULATION RESULTS AND DISCUSSIONS

In previous sections, we computed RA and GA from RR, frequency, propagation angle, and location. The RR predicted using Markov theory and the RA and GA calculations made from it are plotted in Figures 1, 2, and 3, respectively. The results proved that Markovian prediction can statistically match the measured values. The RR calculations were based on ITU-R data and current RR.

The RA and GA obtained as above were then supplied to an IS as depicted in Figure 5 to tune satellite parameters. The IS was implemented in a simulation environment so as to understand what level of signal improvement could be made if we have a better way of predicting RA and GA as described in the previous section. The simulation was done using Matlab version 7.1 running on Intel Centrino Pentium M 1.6 GHz CPU, 512 MB RAM, and weather correlated database supplied by ITU-R. Among others, the simulated system included specific software modules including Markovian predictor for RR, RA and GA calculators, ITU-R data extractor, bi-linear interpolator for spatial data, and intelligence engine for adjusting SNR.

The object of IS was to improve end-to-end wireless communications under different weather conditions till best SNR values were achieved. The comparison between SNR achieved without the use of IS as shown in Figure 4 and by using IS as shown in Figure 6 came to demonstrate that there is a significant improvements in SNR that could be made by use of IS as described in the previous section. The SNR figures shown here consider the base case with SNR between $-44 \sim -11 \text{ dB}$ and transmission power from $-100 \sim -80 \text{ dB}$. The IS was allowed to perform as per the algorithmic logic. It was found that the IS improved SNR $(2 \sim 39 \text{ dB})$ and adjusted transmit power $(-42 \sim -59 \text{ dB})$ successfully. For both IS and no-IS cases the total attenuation considered ranged from $220 \sim 233 \text{ dB}$.

V. CONCLUSIONS

Predicting channel attenuation due to atmospheric conditions can help improve the QoS of satellite networks especially during high frequencies operations combined with high rain and gas attenuations. The mitigation planning involves adaptively selecting appropriate propagation parameters such as modulation, coding, power, frequency, and transmission rate for the given attenuation level so as to minimize digital transmission errors.

Here, Markov chain is used to predict RR and to subsequently determine RA and GA. That knowledge along with SNR are used as feedback to lower the effect of weather attenuations through the control of channel transmission parameters. The proposed method showed a distinct ability to improve QoS more than that achieved so far.

REFERENCES