A novel accurate and low-complexity behavior model for IMUX-HPA-OMUX of LEO satellite based on iterative compensation of cascade modeling errors

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Abstract Next generation satellite communications (NGSC) evolved by 5G NR combination is the hot issue in recent researches. For the conditions of new frequency (Ku/Ka/Q/V) and much more broadband (>100 MHz) for satellite mobile communications, the obvious nonlinearity by Input Multiplexing (IMUX) filter, High Power Amplifier (HPA), and Output Multiplexing (OMUX) filter will cause serious signals degradation. Traditional behavioral modeling methods of IMUX filter, HPA, and OMUX filter (IHO) are relatively independent of each other, which is difficult to quantitatively evaluate intrinsic modeling errors and cumulative modeling errors. That makes modeling errors of IHO cannot be compensated accurately. In this paper, we are the first to exploit a quantitative evaluation of cascade modeling errors for IHO. A novel accurate and low-complexity behavior model for IHO of LEO satellite based on the iterative compensation of cascade modeling errors (ICCE-IHO) is proposed. Based on the normalized least mean square (NLMS) algorithm, the ICCE-IHO model realizes accurate modeling and low-complexity. Experimental results show that the ICCE-IHO model can achieve a maximum 0.67 dB improvement in Normalized Mean Square Error (NMSE), a maximum 2.24 dB improvement in Adjacent Channel Error Power Ratio (ACEPR), and the hardware resource consumption is reduced by 28%.

Keywords: next generation satellite communications, behavioral modeling, nonlinearity, input multiplexing filter, high power amplifier, output multiplexing filter

Classification: Microwave and millimeter-wave devices, circuits, and modules

1. Introduction

International standardization organizations such as the 3rd Generation Partner Project (3GPP) and International Telecommunications Union (ITU) regard the satellite communication system as one of the important scenarios in researches of the next generation communication system. And satellite communications have been included in researches of non-terrestrial networks (NTN) and 6G [1, 2, 3]. Different from terrestrial mobile networks and existing narrowband satellite networks, next generation satellite communications (NGSC) will be combined with 5G communication systems [4, 5, 6, 7, 8]. NGSC will realize the global coverage of high-frequency (Ku/Ka/Q/V) and broadband (>100 MHz) services. However, the obvious nonlinearity of specific satellite channel components such as Input Multiplexing (IMUX) filter, High Power Amplifier (HPA) and Output Multiplexing (OMUX) filter will lead to serious signals degradation. Therefore, accurate behavioral modeling of IMUX-HPA-OMUX (IHO) is the most important technology of NGSC design and its efficiency improvement [9, 10, 11, 12, 13]. Traditional independent behavioral modeling methods of IHO are difficult to quantify intrinsic modeling errors and cumulative modeling errors. In [14, 15, 16], the link-level simulation method of the linear additive IHO model is adopted. But modeling errors of these methods are serious. For this method, it will cause more than a 15% deviation of parameters for time-frequency synchronization. To reduce modeling errors of the linear additive method, the band-limited function is used to reduce frequency domain errors of satellite components [17, 18, 19]. And the complexity of band-limited models such as the band-limited memory polynomial (BLMP) model, the band-limited envelope MP (BLEMP) model, and the band-limited orthogonal MP (BLOMP) model are compared [20, 21, 22, 23, 24]. But cumulative errors caused by satellite components cannot be quantified. Based on canonical piecewise-linear function or wavelet basis, modeling errors of each part of IHO components can be discretely and partially compensated [25, 26, 27, 28, 29, 30, 31, 32]. But it difficult to realize continuous and global compensation.

In this paper, we focus on the scheme to quantify the IHO cascade modeling errors, which can effectively compensate for modeling errors and reduce model complexity. The main contributions of this paper are summarized as follows:

• A new, accurate, and low-complexity behavior model for IMUX-HPA-OMUX of LEO Satellite at Ku-band based on iterative compensation of cascade modeling errors (ICCE-IHO) is first constructed. And the ICCE-IHO model realizes the quantification of cascade modeling errors.

• The iterative compensation of cascade modeling errors is based on the normalized least mean square (NLMS) algorithm, which can improve modeling accuracy. Furthermore, we propose the centralized cascade distribution of function modules, which reduces model complexity.

• We construct the measurement and test platform of the
ICCE-IHO model. Experimental results show that the ICCE-IHO model can achieve a maximum 0.67 dB improvement in Normalized Mean Square Error (NMSE), a maximum 2.24 dB improvement in Adjacent Channel Error Power Ratio (ACEPR), and the hardware resource consumption is reduced by 28%.

2. System architecture

2.1 ICCE-IHO model

Since the traditional model is difficult to realize continuous and global compensation of modeling errors of satellite IHO, we propose the ICCE-IHO model based on iterative compensation of cascade modeling errors. First, we propose the ICCE-IHO model and the construction of model parameter sets. Then we realize the quantitative evaluation of cascade modeling errors. At last, cascade modeling errors are iteratively compensated by the NLMS algorithm.

The cascade modeling errors and the ICCE-IHO model construction scheme are shown in Figure 1. Considering the influence of lighting effect on IHO measurement, the construction of model parameter sets. Then we realize the quantitative evaluation of cascade modeling errors. At last, cascade modeling errors are iteratively compensated by the NLMS algorithm.

The cascade modeling errors and the ICCE-IHO model scheme are shown in Figure 1. Considering the influence of lighting effect on IHO measurement, the construction process of the ICCE-IHO model is also carried out under lighting conditions (visible light 390~760nm). We find that the performance difference of the ICCE-IHO model under dark and lighting conditions in the Ku band is obvious, which is consistent with the conclusion in [33, 34, 35].

1) Construction of ICCE-IHO model

In this paper, we propose the ICCE-IHO model and the construction of model parameter sets. The expression of the ICCE-IHO model is given by:

\[
y(n) = \sum_{t=1}^{T} \sum_{m=0}^{M-1} \sum_{p=1}^{P} h_{mp} \omega(k)x(n-m-k-t) - |x(n-m-k-t)|^{p-1} \omega^2(t)
\]

where \( \omega(.) \) is the band-limited function of IMUX filter with the order \( K \). \( \omega(.) \) is the band-limited function of OMUX filter with the order \( T \). The modeling of HPA is based on the memory polynomial model (MP), \( h_{mp} \) is coefficient of polynomials, \( M \) is memory depth, \( P \) is the order of polynomials. \( x(n) \) is the input signal. \( y(n) \) is the output signal. \( W \) is parameter sets of IMUX filter, \( H \) is parameter sets of HPA, \( W^\prime \) is parameter sets of OMUX filter. Parameter sets are updated by the factors \( \delta(n) \), which are \( \delta_{I}(n) \), \( \delta_{H}(n) \), and \( \delta_{O}(n) \). \( W(n+1) = W(n) + \Delta W(n) = W(n) + \delta_{I}(n)W(n) \), \( H(n+1) = H(n) + \Delta H(n) = H(n) + \delta_{H}(n)H(n) \), \( W^\prime(n+1) = W^\prime(n) + \Delta W^\prime(n) = W^\prime(n) + \delta_{O}(n)W^\prime(n) \).

2) Quantitative evaluation of cascade modeling errors

The quantitative evaluation of intrinsic modeling errors and cumulative modeling errors in the ICCE-IHO model is realized. The calculation methods of the total modeling errors (intrinsic modeling errors and cumulative modeling errors) of each modeling component are \( Er_I(n) = y_I(n) - y_I(n), Er_H(n) = y_H(n) - y_H(n), Er_O(n) = y_O(n) - y_O(n) \). \( y_I(n), y_H(n), y_O(n) \) are the measured signal output results for each component of ICCE-IHO. \( \hat{y}_I(n), \hat{y}_H(n), \hat{y}_O(n) \) are simulation signal output results for each component of ICCE-IHO. The intrinsic modeling errors of the IMUX filter model are the same as the total modeling errors \( Er_I(n) \). To calculate the intrinsic modeling errors of HPA \( Er_H(n) \), the cumulative modeling errors generated by the former stage should be removed from the total modeling errors \( Er_O(n) \) as follows \( Er_H(n) = Er_I(n) - Er_O(n)H \). To calculate the intrinsic modeling errors of OMUX \( Er_O(n) \), the cumulative modeling errors generated by the former stage should be removed from the total modeling errors \( Er_O(n) \) as follows \( Er_O(n) = Er_I(n) - Er_H(n)W^\prime \). At last, the intrinsic modeling errors and the total modeling errors of model components are the input parameters of the NLMS algorithm.

3) Iterative compensation of cascade modeling errors

Cascade modeling errors are iteratively compensated by the NLMS algorithm to minimize the intrinsic modeling errors and cumulative modeling errors. Intrinsic modeling errors, cumulative modeling errors, and simulation output values are taken as parameters of the NLMS algorithm. The iterative formula is as follows,

\[
\alpha(n) = \frac{\rho(n)}{\varepsilon(n)}
\]

\[
\beta(n) = \frac{\alpha(n)}{|\hat{y}(n)|^2 + c}
\]

\[
\delta(n) = \beta(n)\rho(n)\hat{y}(n)
\]

where \( \rho(n) \) is the intrinsic modeling errors, \( \varepsilon(n) \) is the total modeling errors, \( \alpha(n) \) is step length factor. \( \hat{y}(n) \) is the simulation signal output result for each component of ICCE-IHO. \( c \) is a fixed constant (to ensure the effectiveness of non-zero values). \( \beta(n) \) is a variable step function, \( \delta(n) \) is update factor. Since \( \rho(n) \leq \varepsilon(n) \) the step size factor can always satisfy the convergence condition \( 0 < \alpha(n) < 2 \) of the NLMS algorithm. In the iterative process, the updating factor \( \delta(n) \) is used to update the model parameter sets to compensate for modeling errors. The iterative process adopts a variable step-size function \( \beta(n) \), which can efficiently select the step size and reduce the number of iterations.

2.2 Complexity analysis

The computational complexity can be classified into identification complexity and running complexity.

Identification complexity: Compared with traditional models, the ICCE-IHO model has many types of parameters and needs to measure a variety of performance indicators. Mainly includes 1) IMUX/OMUX filter amplitude-frequency response and group delay characteristics; 2) AM-AM and AM-PM characteristics of HPA. In this paper, we built the general measurement platform as in [22, 25, 26, 31] to measure the required data. Since the ICCE-IHO model consists of multiple boxes, a single-step least squares (LS) algorithm cannot solve all the model coefficients. To obtain
Fig. 1 Cascade modeling errors and ICCE-IHO model scheme.

![Diagram](image)

Table I Number of FLOPs for different operations.

| Operation             | FLOPs |
|-----------------------|-------|
| Conjugate             | 0     |
| Delay                 | 0     |
| Real addition         | 1     |
| Real multiplication   | 1     |
| Complex addition      | 2     |
| Complex-real multiplication | 2   |
| \(|P\)|                | 3     |
| Complex-complex multiplication | 6   |
| Square-root           | 6~8   |

Fig. 2 The fitting process time and FLOPs of the traditional model and the ICCE-IHO model.

The complexity of the ICCE-IHO model is related to the memory depth \(M\), nonlinear order \(P\), IMUX filter order \(K\), and OMUX filter order \(T\). The model complexity expression is as follows,

\[
C_{\text{ICCE-IHO}}(P, M, K, T) = P + 8\left(\frac{P + 1}{2}\right)(M + 1) + 2(K + T) + 6
\]  

The fitting process time (identification complexity) and FLOPs (running complexity) of the traditional model and the ICCE-IHO model are compared in Figure 2.

It can be seen from Figure 2 that the ICCE-IHO model significantly reduces running complexity, but it has a longer fitting time (higher identification complexity). Since the identification of the behavioral model is typically done offline, this complexity is normally not a major issue.

3. Experimental results and analysis

The ICCE-IHO model measurement setting connection diagram and hardware test platform diagram are shown in Figure 3. Under the synchronous control of the controller, the signal generator transmits RF signals, which pass through the IMUX-HPA-OMUX device to be tested, and then RF sig-
nals are sent back to the spectrum analyzer to achieve model identification through IQ data. The digital signal processing of the ICCE-IHO model is implemented on the FPGA board.

The analysis method of the behavior model should include in-band performance (NMSE) and out-of-band performance (ACEPR). In this paper, we choose the BLMP model, the BLEMP model, the BLOMP model, and the ICCE-IHO model as references. For the above models, a band-limiting function \( K = T = 12 \) with a filter order of 12 is fixed. Test data are set to contain 40,000 symbols. To smooth the curve, we interpolate some of the data in Figure 4 and Figure 5.

First, the NMSE performances of behavior models with different memory depth \( (M) \) and memory order \( (P) \) are shown in Figure 4. The BLMP model with configuration \( (P = 9, M = 7) \) has the minimum NMSE value \(-34.55\) dB. The BLEMP model with configuration \( (P = 7, M = 8) \) has the minimum NMSE value \(-34.66\) dB. The BLOMP model with configuration \( (P = 7, M = 9) \) has the minimum NMSE value \(-34.9\) dB. The ICCE-IHO model with configuration \( (P = 9, M = 6) \) has the minimum NMSE value \(-35.22\) dB. Then, the ACEPR performances of behavior models with different memory depth \( (M) \) and memory order \( (P) \) are shown in Figure 5. The BLMP model with configuration \( (P = 9, M = 3) \) has the minimum ACEPR value \(-34.31\) dB. The BLEMP model with configuration \( (P = 8, M = 4) \) has the minimum ACEPR value \(-35.3\) dB. The BLOMP model with configuration \( (P = 9, M = 4) \) has the minimum ACEPR value \(-34.7\) dB. The ICCE-IHO model with configuration \( (P = 8, M = 6) \) has the minimum ACEPR value \(-36.55\) dB.

Behavior Models with different memory depths and nonlinear order configurations occupy different FLOPs. The experimental results of the relationship between hardware complexity (FLOPs) and model accuracy (NMSE, ACEPR) are shown in Figure 6 and Figure 7.

According to the simulation results in Figure 6, the BLMP model, the BLEMP model, and the BLOMP model have similar NMSE when occupying similar FLOPs. The ICCE-IHO
model has the maximum NMSE gain of 0.67 dB. For ACEPR in Figure 7, the BLEMP model is better than BLMP model and BLMP model. The proposed ICCE-IHO cascade model has a maximum ACEPR gain of 2.24 dB. When the model dimension (represented by hardware occupancy complexity FLOPs) increases excessively, the performance of the four models deteriorates to varying degrees, which is caused by the overfitting problem. But ICCE-IHO model has the lowest degree of deterioration and better robustness.

Based on the complexity analysis of the above behavior model, we implement the above model structure on the hardware module PXIe-7915. FPGA platform is based on Xilinx KU060, the total number of LUT is 331680 and DSP48 is 2760. The FPGA resources’ utilization is shown in Table II. According to the results of FPGA resources’ utilization, the hardware resource occupation of the ICCE-IHO model is reduced by 28%.

### 4. Conclusion

In this paper, a quantitative evaluation of cascade modeling errors for IHO is proposed for the first time. We propose a novel accurate complexity-reduced ICCE-IHO model for behavior model for IMUX-HPA-OMUX of LEO Satellite at Ku-band. Based on the NLMS algorithm, the ICCE-IHO model realizes the iterative compensation of cascade modeling errors and reduces model complexity. Experimental results show that the ICCE-IHO model can achieve a maximum NMSE gain by 0.67 dB, a maximum ACEPR gain by 2.24 dB, and the hardware resource consumption is reduced by 28%.

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### Table II FPGA resources’ utilization.

| Models | Resource | Utilization | Available | Occupation(%) |
|--------|----------|-------------|-----------|---------------|
| BLMP   | Flip-Flop| 48701       | 663360    | 7.34          |
|        | LUT      | 41797       | 331680    | 12.6          |
|        | BRAM     | 91          | 1080      | 8.43          |
|        | DSP48    | 104         | 2760      | 3.77          |
| BLEMP  | Flip-Flop| 37581       | 663360    | 5.67          |
|        | LUT      | 32240       | 331680    | 9.72          |
|        | BRAM     | 59          | 1080      | 5.46          |
|        | DSP48    | 89          | 2760      | 3.22          |
| BLOMP  | Flip-Flop| 48012       | 663360    | 7.24          |
|        | LUT      | 41788       | 331680    | 12.6          |
|        | BRAM     | 99          | 1080      | 9.17          |
|        | DSP48    | 108         | 2760      | 3.91          |
| ICCE-IHO| Flip-Flop| 35100       | 663360    | 5.29          |
|        | LUT      | 30080       | 331680    | 9.07          |
|        | BRAM     | 77          | 1080      | 7.12          |
|        | DSP48    | 72          | 2760      | 2.61          |

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