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Energy Efficiency Improvement of RF Power Amplifiers for Agricultural Small Base Stations in Aksu Region through Fuzzy Logic Control

Junfei Yang[1], Zhiqun Cheng[2,*] and Song Qian[1]
[1] Information Engineering School, Xinjiang Institute of Technology, Aksu, Xinjiang, 843100, China
[2] Electronic Information College, Hangzhou Dianzi University, Hangzhou, Zhejiang, 310018, China
Corresponding authors: (e-mail: 13579140507@163.com).

Abstract As an important agricultural production area, Xinjiang Aksu region faces the problem of low energy efficiency of its agricultural small base stations. The traditional RF power amplifier has the disadvantages of high energy consumption and low spectral efficiency, which affects the construction of agricultural informationization. This study proposes an optimization method of RF power amplifier energy efficiency for agricultural small base station in Aksu area based on fuzzy logic control. The Sugeno fuzzy model is used to construct an adaptive fuzzy neural inference system, which is combined with the orthogonal least squares method to screen the polynomial coefficients, and an ant colony algorithm to find the optimal weight configuration. The experimental results show that the fuzzy logic control algorithm is outstanding in energy efficiency optimization, and its energy efficiency is 38% higher than the SIC algorithm and 88% higher than the OMP algorithm when the number of RF links is 2. The energy efficiency is 71% higher than the SIC algorithm when the maximum transmitting power is 60 dBm. The spectrum efficiency is 9% higher than the SIC algorithm and the energy efficiency is 66% higher than the SIC algorithm when the number of transmitting antennas of the base station reaches 200. At the same time, the energy efficiency is improved by 66%. In addition, after adding fuzzy logic control, the power spectrum output is closer to the input signal, the maximum difference is only 60dBW, and the BER is significantly reduced to about 0.2. The study proves that the fuzzy logic control can effectively solve the RF amplifier nonlinearity problem of agricultural small base station, and significantly improve the energy efficiency while guaranteeing the spectral efficiency, which provides an effective solution for the construction of agricultural communication infrastructure in Aksu region.

Index Terms Fuzzy logic control, RF power amplifier, Energy efficiency, Spectral efficiency, Agricultural small base station, Orthogonal least squares method

I. Introduction

Agriculture is the foundation of China's national economy, and China has also raised the agricultural power to an unprecedented height in the report of the 20th National Congress. At present, China's agriculture has gone through three stages of traditional, mechanized, and information-based agriculture, and is gradually moving towards smart agriculture [1]. Among them, a large number of Internet of Things (IoT) technologies have been applied in smart agriculture, and the application of IoT technologies in agriculture greatly enhances the efficiency of agricultural production, while reducing the consumption of resources and improving the quality of agricultural products [2]-[5]. Common applications of IoT in agriculture include smart farmland management, livestock monitoring and management, smart irrigation systems, traceability of agricultural products, smart greenhouse management, and monitoring and management of agricultural machinery [6], [7]. The implementation of all these applications requires timely and efficient wireless communication technology to enable the nodes to communicate with the base station to ensure that the base station can receive accurate data in real time from the growth status of the crops being monitored by the sensor nodes [8]-[10]. Based on these collected data, it is possible to accurately adjust the amount of irrigation water, the type of fertilizer and the amount of pesticide, to improve the growth efficiency of the crops, and thus to increase the total amount of food production in China [11]-[13].

With the full-scale use of agricultural small base stations, in order to meet the needs of high gain, high efficiency, wide bandwidth, high power, and miniaturization, the RF power of the base station puts forward higher application requirements [14], [15]. RF power amplifier as the core device in the wireless communication base station system, its performance index affects the working performance of the whole wireless communication system [16]. Therefore, it is of great significance to design a good performance RF power amplifier for the working frequency band of agricultural small base station.

The application of communication technology in the field of agriculture is becoming more and more widespread, and agricultural small base stations, as an important communication infrastructure, play a crucial role in the construction of agricultural informationization. However, agricultural small base stations are usually distributed in remote areas with limited power supply, and energy efficiency has become a key factor restricting their development. As a core component in the base station, the energy efficiency of RF power amplifier directly affects the performance of the whole communication system. Traditional RF power amplifiers face problems such as high energy consumption, poor linearity and low spectral efficiency, which seriously limit the communication quality and coverage of small agricultural base stations. In order to solve this problem, various optimization methods have been proposed by academics in recent years, such as digital pre-distortion technique, envelope tracking technique and matching network optimization, etc. However, it is often difficult for these methods to take into account both energy efficiency and linearity improvement at the same time. Fuzzy logic control has been successfully applied in many fields due to its ability to effectively deal with the uncertainty and nonlinear characteristics of the system. Introducing fuzzy logic control into the energy efficiency optimization of RF power amplifiers is expected to break through the limitations of traditional methods and realize the synergistic optimization of energy efficiency and linearity. Especially for the Xinjiang Aksu area, which is an agricultural area with complex geography and variable climate, it is of more practical significance to improve the energy efficiency of RF power amplifiers for small base stations. It can not only reduce the energy consumption and extend the service life of the base station, but also improve the communication quality and provide more reliable information service support for agricultural production.

This study will focus on the optimization of RF power amplifier energy efficiency of agricultural small base station in Aksu area, using Sugeno fuzzy model to establish an adaptive fuzzy neural inference system, and fuzzy logic control to achieve power amplifier energy efficiency improvement. The study firstly introduces the basic theory and modeling method of fuzzy logic system, and then combines the orthogonal least squares method to optimize the RF power amplifier behavioral model, and further introduces the ant colony algorithm to realize the collaborative optimization of multi-base stations. Aiming at the geographic characteristics and agricultural demands of Aksu area, the performance of fuzzy logic control algorithm under different parameter conditions is analyzed through simulation experiments, including the total power of base station, energy efficiency, spectral efficiency and other indexes. Finally, the power spectrum and BER changes before and after the fuzzy logic control are compared and analyzed to verify the effectiveness and practicability of the proposed method, which provides theoretical basis and technical support for the optimization of the communication system of agricultural small base stations in Aksu area.

II. Fuzzy logic control based RF amplifier energy efficiency improvement strategy

II. A. Fuzzy logic modeling theory

II. A. 1) Fuzzy logic systems

The basic structure of the fuzzy logic system is shown in Figure 1 [17]. The following introduces the four important components of the fuzzy logic system: Fuzzification maps precise input to corresponding fuzzy input. For precise input, single-point fuzzification is generally adopted. There is a rule base that contains a series of fuzzy rules such as (if x is Athen y is B), and an inference engine that, for a specific input, obtains reasonable output and conclusion through rules that can activate the rule base to varying degrees. Deblurring, which is exactly the opposite of the blurring process, converts the fuzzy output into an exact output. Common methods include the center of gravity method and the area center method, etc.

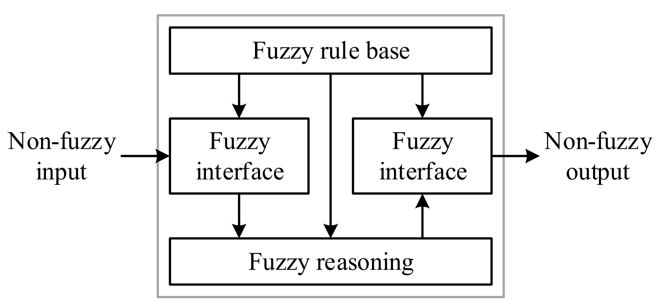


Figure 1: Basic Structure of the Fuzzy Logic System

It can be shown that the essence of a fuzzy logic system is a system that defines a mapping relationship between input and output variables, i.e., given precise inputs and outputs, a fuzzy inference system is capable of realizing a nonlinear mapping between inputs and outputs. The core of the mapping is a set of fuzzy rules, each of which describes the local behavior of the mapping. The three main fuzzy models commonly used in fuzzy logic systems are Sugeno model, Mamdani model, and Tsukamoto model. Considering that Sugeno model is more convenient to apply, this paper subsequently uses Sugeno model, which is briefly introduced here.

Sugeno fuzzy model is a nonlinear model, easy to express the dynamic characteristics of the system, is the most commonly used fuzzy inference model, which was firstly proposed by Takagi and Sugeno in 1985.Sugeno model mainly has the following advantages:

(1) It can represent highly nonlinear complex systems with fewer fuzzy rules.

(2) It is easy to generalize to multi-input and multi-output fuzzy systems, and it is convenient to adjust the parameters.

(3) Quantitative extraction of qualitative knowledge of the system using input and output data of the system

(4) Local linear models are easy to design controllers and system analysis.

The typical fuzzy inference rule of Sugeno fuzzy model is:

$$\text{If } x \text{ is } A \text{ and } y \text{ is } B \text{ Then } z = f(x, y) \tag{1}$$

where, a and b are fuzzy sets in the antecedent part and $z = f(x, y)$ is the exact number in the conclusion. Usually $z = f(x, y)$ is a polynomial in x and y. When $f(x, y)$ is a first order polynomial, the model is called a first order Sugeno fuzzy model.

Since each rule has an exact output, the overall output can be obtained by weighted averaging, thus avoiding the time-consuming defuzzification process required by the Mamdani fuzzy inference system.The Sugeno fuzzy model does not require time-consuming and mathematically unanalyzable defuzzification computations. Therefore, it is by far the most commonly used method in fuzzy modeling based on sample data. For simplicity, the system is assumed to be two-input, single-output with only two rules.

Rule 1: If x is A_1 and y is B_1, then $z_1 = p_1 x + q_1 y + r_1$

Rule 2: If x is A_2 and y is B_2, then $z_2 = p_2 x + q_2 y + r_2$

where x, y are the two input variables, $[A_1, A_2], [B_1, B_2]$ are their corresponding fuzzy sets, respectively, and $z_i (i = 1, 2)$ is the conclusion part of the rule.

In order to realize the learning process of the Sugeno fuzzy inference system, it is generally transformed into an adaptive network, i.e., an adaptive fuzzy neural inference system, as shown in Fig. 2 [18], [19].

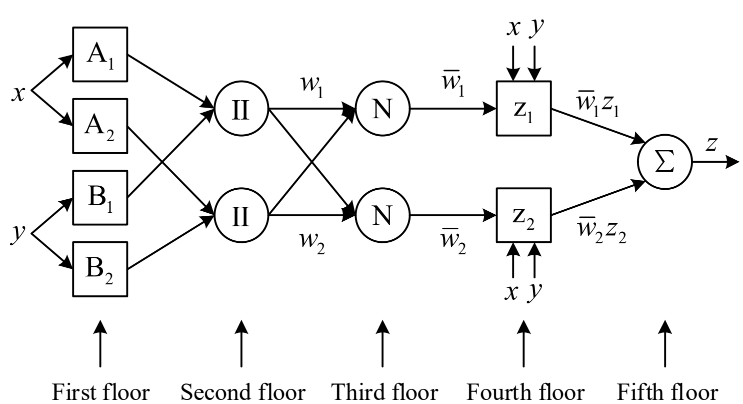


Figure 2: Structure of the Adaptive Fuzzy Neural Reasoning System

This adaptive network is a multilayer feedforward network which can be divided into five layers in which square nodes are required for parameter learning. These five layers are described below.

Layer 1: Calculate the matching degree of the input variables, i.e., the fuzzification process. Assuming a Gaussian function for the fuzzy set, the output of this layer (O_i^j denotes the i th output of the j th layer) is [20]:

$$O_i^1 = \mu_{A_i}(x) = \exp\left(-\frac{(x - c_i)^2}{2\sigma_i^2}\right), i = 1, 2 \tag{2}$$

For the calculation of y in the same way, c_i, σ_i denote the center and width of the Gaussian function, respectively, which are the parameters to be regulated in the fuzzy rule antecedents.

Layer 2: Calculate the excitation strength of the current input to each rule, using a product operation on the affiliation of each fuzzy variable in the antecedent part of the rule, i.e.:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), i = 1,2 \tag{3}$$

Layer 3: Normalization of incentive intensity:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \tag{4}$$

Layer 4: Compute the output of each rule; the output of a rule is the product of the strength of the incentive for that rule given the input and the thesis part of Junction (5):

$$O_i^4 = \overline{w}_i z_i = \overline{w}_i(p_i x + q_i y + r_i), i = 1,2 \tag{5}$$

Layer 5: Calculate the output of the fuzzy system, where the total output is the sum of all rule outputs:

$$O^5 = z = \sum_i \overline{w}_i z_i = \frac{\sum_i w_i z_i}{\sum_i w_i} \tag{6}$$

It follows that this fuzzy logic system defines a mapping from x, y to z:

$$z = (x, y) \tag{7}$$

The relationship between the variables can be accurately portrayed by careful selection of the parameters in the fuzzy rules.

II. A. 2) Initial modeling

From the above, the initial model for building a fuzzy logic system needs to decide:

(1) The fuzzy sets corresponding to the input variables and their affiliation functions

(2) The fuzzy sets corresponding to the output variables and their affiliation functions

(3) Fuzzy rules

Determining the corresponding fuzzy sets of the input variables is actually deciding the partition of the input space, the simplest and most commonly used method is the average partitioning method, for the input variables to first decide the number of fuzzy subsets corresponding to each input variable, and then average partitioning in space. When the definition domain of the input variable is not clear in advance, the corresponding maximum value $(x_{\max})$ and minimum value $(x_{\min})$ can be found according to the given sample, and then $[x_{\min}, x_{\max}]$ is taken as the definition domain. Another commonly used method is fuzzy clustering.

Deciding the output variables corresponding to fuzzy sets is importantly based on the following two methods: the pre-set method and the set method based on input/output samples. The former is based on the pre-set number of fuzzy subsets (n_y) of the output variables and the affiliation function $B_j(i = 1,2,...,n_y)$, and equipartition the value domain of the output thus determining the affiliation function. The latter method usually involves obtaining both the affiliation function and the fuzzy rules for the output variables, and this is the method used for the fuzzy subset of input variables with Gaussian affiliation functions, which will be utilized later in this paper.

The third step is to determine the fuzzy rule base after obtaining the fuzzy set (affiliation function) of each variable. The fuzzy rule base generation method commonly used in modeling is described below.

(1) The input variables are each taken as a corresponding fuzzy subset (represented by the affiliation function), which constitutes the antecedent part of the rule, i.e.:

If x_1 is A_{ir}, x_2 is $A_{2r}, \ldots$, and x_n is A_{nr}.

(2) For all samples, compute:

$$\mu_k(x^k) = \prod_{i=1}^{n} \mu_{A_r}(x_i^k) \tag{8}$$

where k denotes the k th sample, $x^k = (x_1^k, ..., x_n^k)^T$, and μ_{A_r} is a representation of the affiliation function of A_{i} ,.

(3) The output fuzzy set B of the conclusion part of each rule is taken as a polynomial in the input variables, i.e:

$$y_k = \alpha_1 x_1^k + \alpha_2 x_2^k + \ldots + \alpha_n x_n^k + \alpha_0 \tag{9}$$

All are zero except $y = y_0$ which is $\mu = 1$. The value of y_0 is determined this way:

$$y_0 = \frac{\sum_k \mu_k(x^k) \times y^k}{\sum_k \mu_k(x^k)} \tag{10}$$

where y_k denotes the system output value of the k th sample, the resulting rule can be expressed as follows:

If x_1 is A_1, x_2 is $A_{2r}, \ldots,$ x_n is A_{nr}, then y is y_0

(4) Repeat (1) to (3) until all initial fuzzy rules are obtained.

II. B.Modeling process

In this thesis, the modeling will be done using the Adaptive Fuzzy Logic Inference tool that comes with MATLAB, whose main function is ANFIS.The essence of modeling with this is to learn from the given input-output data using either the back-propagation algorithm or the least-squares back-propagation algorithm, so as to adjust the shape parameter of the affiliation function of the variables. The backpropagation method as well as the least squares propagation algorithm are well developed algorithms in neural networks. Fuzzy inference system based on adaptive neural network algorithm in MATLAB is generally used in the case where a large number of inputs and outputs that are desired to be used for modeling have already been obtained, so ANFIS is a modeling method based on the existing data, and then the ability of the model built to simulate these data well is the best criterion to test this method.

II. B. 1) Modeling process

The main process of modeling is divided into two steps, the first step is to select the circuit to be modeled and add excitation signals to the circuit, such as single-tone signals, two-tone signals, modulated signals, etc. Simulate and record the data required for modeling such as voltage, frequency, harmonic terms, mixing products etc. The second step is to import the obtained excitation and response data into MATLAB and use the toolbox or a self-written program for modeling. Typically the voltage or current and the differential of voltage and current with respect to time are chosen as variables to construct the model.

II. B. 2) ANFIS model learning

The basic idea of an adaptive neural network fuzzy system is very simple; it provides a learning method for the process of fuzzy modeling that is able to extract the appropriate information (fuzzy rules) from the data set. This kind of learning is very similar to the learning method of neural network, through which the best parameters of the affiliation function can be effectively calculated, so that the designed Sugeno-type fuzzy inference system can best simulate the hoped-for or actual input-output relationship, so ANFIS is a modeling method based on existing data. Whether the results of the established fuzzy system model can simulate these data well is the best criterion to test this algorithm.

II. C.RF amplifier energy efficiency optimization model for small agricultural base stations

This chapter first introduces the recursive polynomial-based macro model of RF amplifier behavior, illustrating its advantages. Next, a model identification algorithm, orthogonal least squares, is introduced and it is shown how the algorithm can be applied to the modeling of recursive polynomial models. By using orthogonal least squares, the proper model structure is selected from the initial model, i.e., the most useful of all the polynomial terms for modeling, and those that are not useful or contribute less are deleted, resulting in a more streamlined model.

II. C. 1) Orthogonal least squares method

The polynomial coefficients are linearly related and can be expressed as a linear equation. To harmonize with the previous notation, equation (11) is first expressed as:

$$d(t) = \sum_{j=1}^{M} p_i(t)\theta_j + e(t) \tag{11}$$

where $d(t)$ is the system output i.e. $y(k)$, the unknown parameters θ_j are the respective coefficients of the polynomials, $p_j(t)$ is a monomial of each order consisting of $x(k-q), y(k-q)$, and e is the possible model error.

For a given set of input-output sequences, i.e., $\{x(1).....x(N), y(1)....x(N)\}$, Eq. (12) from t=1 to N can be written in the following matrix form:

$$D = P\theta + E \tag{12}$$

where $d=[d(1)...d(N)]^T, P=[p_i...p_M], p[_i=\{p_i(I)...p_i(N)]^T, \theta=[\theta_i...\theta_M]^T$, $E=[\varepsilon(1)...\varepsilon(N)]^T$. D is the column vector consisting of $y(k)$ in Eq. (11), P is the matrix consisting of the monomial terms of each order in Eq. (11), containing both linear and nonlinear terms, θ is the vector of coefficients, and E is the model error.

The starting point for the orthogonal least squares (OLS) method is to consider that $P\theta$ can be viewed as a projection of D onto a space consisting of basis vectors. In other words, the square of the projection $P\theta$ is the sum of the output energies of the individual vectors, but in due to the existence of correlation components between the columns of vectors of P, the contribution of each vector to the output energy is not easy to see. For this reason, the set of vectors P is converted into a set of orthogonal basis vectors using orthogonal least squares, thus making it possible to calculate the contribution of each vector individually to the output energy

First, the matrix P is decomposed into:

$$P = WA \tag{13}$$

where A is an M × M upper triangular matrix with 1's on the diagonal and 0's all down the diagonal:

$$A = \begin{bmatrix} 1 & \alpha_{12} & \alpha_{13} & \dots & \alpha_{1M} \\ 0 & 1 & \alpha_{23} & \cdots & \alpha_{2M} \\ 0 & 0 & & \ddots & \vdots \\ \vdots & & \ddots & 1 & \alpha_{M-1M} \\ 0 & \cdots & 0 & 0 & 1 \end{bmatrix} \tag{14}$$

W is an N × M matrix consisting of orthogonal columns ω_i:

$$W^T W = H \tag{15}$$

where the diagonal of H consists of element h_i:

$$h_i = \omega_i^T \omega_i = \sum_{i=1}^{N} \omega_i(t)\omega_i(t), \quad 1 \le i \le M. \tag{16}$$

The space consisting of the set of orthogonal basis vectors ω_i is the same as the space consisting of the set of vectors p_i. Thus equation (13) can be rewritten in the following form:

$$d = Wg + E \tag{17}$$

The orthogonal least squares solution $\hat{g}$ is given by the following equation:

$$\hat{g} = H^{-1} W^T d \tag{18}$$

Or:

$$\hat{g}_i = \omega_i^T d / (\omega_i^T \omega_i), \quad 1 \le i \le M. \tag{19}$$

The parameters $\hat{g}$ and $\hat{\theta}$ satisfy the following triangular system:

$$A\hat{\theta} = \hat{g} \tag{20}$$

The classical Grunschmidt algorithm and the modified Grunschmidt algorithm can be derived from Eq. (20) to compute the required coefficients $\hat{\theta}$. It is also possible to decompose P into orthogonal form using a similar Haushold transformation method. As an illustration, an example of using the well-known classical Grunschmidt algorithm to orthogonalize P to obtain a column of an A matrix is as follows: at step k, the orthogonal column of k needs to be added to the previous $k-1$ orthogonalized well-posed columns, and for $k=2,...,M$, the operation needs to be repeated and the computational procedure can be expressed as:

$$\left.\begin{aligned} & w_1 = p_1 \\ & \alpha_{ik} = w_i^T p_k / (w_i^T w_i), \quad 1 \le i < k \\ & w_k = p_k - \sum_{i=1}^{k-1} \alpha_{ik} w_i \end{aligned}\right\} k = 2,...,M \tag{21}$$

Orthogonal least squares has superior numerical performance compared to ordinary least squares. Using orthogonal least squares it can be used to select subsets, i.e., column vectors of the matrix P that contribute significantly to the output energy.

The OLS algorithm works in a forward regression manner. Since the matrix W is column orthogonal, the sum of the energies or squares of D is:

$$D^T D = \sum_{i=1}^{M} g_i^2 \omega_i^T \omega_i + E^T E \tag{22}$$

Here, the error ratio caused by the i st column in the matrix is righteous:

$$[err]_i = g_i^2 \omega_i^T \omega_i / (D^T D) \tag{23}$$

This ratio forward regression approach provides a simple and efficient way to find subsets from a large number of column vectors. By using the classical Gram-Schmidt transformation, the regression term selection process is as follows:

In the first step, for $1 \le i \le M$, compute:

$$\left.\begin{aligned} & \omega_i^{(i)} = p_i \\ & g_i^{(i)} = (\omega_i^{(i)})^T d / ((\omega_i^{(i)})^T \omega_i^{(i)}) \\ & [err]_i^{(i)} = (g_i^{(i)})^2 (\omega_i^{(i)})^T \omega_i^{(i)} / D^T D \end{aligned}\right\} \tag{24}$$

Find out:

$$[err]_1^{(i_1)} = \max\{[err]_1^{(i)}, 1 \le i \le M\} \tag{25}$$

Then choose:

$$\omega_1 = \omega_1^{(i_4)} = p_{i_1} \tag{26}$$

At step k, where $k \ge 2$, for $1 \le i \le M, i \ne i_1, ..., i \ne i_{k-1}$ calculated:

$$\left.\begin{aligned} & \alpha_{jk}^{(i)} = \omega_j^T p_i / (\omega_j^T \omega_j), \quad 1 \le j < k \\ & \omega_k^{(i)} = p_i - \sum_{j=1}^{k-1} \alpha_{jk}^{(i)} \omega_j \\ & g_k^{(i)} = (\omega_k^{(i)})^T d / ((\omega_k^{(i)})^T \omega_k^{(i)}) \\ & [crr]_k^{(i)} = (g_k^{(i)})^2 (\omega_k^{(i)})^T \omega_k^{(i)} / (d^T d) \end{aligned}\right\} \tag{27}$$

Find out:

$$[err]_k^{(i_k)} = \max\{[err]_k^{(0)}, 1 \le i \le M, i \ne i_1, ..., i \ne i_{k-1}\} \tag{28}$$

Then choose:

$$\omega_k = \omega_k^{(i_k)} = p_k - \sum_{j=1}^{k-1} \alpha_{jk} \omega_j \tag{29}$$

where $\alpha_{jk} = \alpha_{jk}^{(i_k)}, 1 \le j < k$.

The process will end at step M when:

$$1 - \sum_{j=1}^{M_s} [err]_j < \rho \tag{30}$$

where $0 < \rho < 1$ is a selectable tolerance. This selects a subset of M_s regression terms.

After the selection of useful terms, the number of coefficients in the previous model is greatly reduced. The coefficients needed for the model can be found simply by solving a system of linear equations. Here, an ant colony optimization algorithm can be introduced to find the optimized coefficients for RF amplifier energy efficiency.

II. C. 2) RF power amplifier energy efficiency optimization model for agricultural base stations

Assuming the weight combination configuration of N agricultural small base stations in the Aksu region, the objective is to find the optimal solution for the joint adjustment of each agricultural small base station, i.e., $I = [I_1, I_2, ..., I_N]$ (I_i denotes the weight configuration of the i th small agricultural base station) the optimal solution can be searched according to the following 5 steps.

Step 1: Initialization parameter setting. Initialize the parameters such as the number of ants m , the maximum number of iterations $iter\_\max$, the pheromone volatility factor ρ , the information heuristic factor α , the expectation heuristic factor β , etc., e.g., $m = 100, iter\_\max = 80$.

Step 2: Initialize position update. Based on the beam weight combination candidate set output from step 1, randomly select one weight of any small agricultural base station as the initial position of an ant.

Step 3: Weights update selection. This step is the most critical step of the algorithm, each agricultural small base station in the selection of the weight value, mainly based on the weight value selection probability, the expression is:

$$P_i^k = \frac{\tau_i(t)^{\alpha} \eta_i(t)^{\beta}}{\sum_{i \in I} \tau_i(t)^{\alpha} \eta_i(t)^{\beta}} \tag{31}$$

where P_i^k denotes the probability that ant k selects weight i , $\tau_i(t)$ denotes the pheromone concentration on weight i at moment t , and $\eta_i(t)$ denotes the degree of expectation on weight i at moment t . If the pheromone concentration $\tau_i(t)$ and the degree of expectation $\eta_i(t)$ on weight i are higher, the higher P_i^k is, and the more likely that weight i will be selected. In the initial calculation of P_i^k , the initial pheromone concentration is denoted as τ_0 , the initial value of expectation is denoted as η_0 , and the initial value of the selection probability of each weight is 1/M (M is the number of optional weighting schemes for a single small agricultural base station).

(1) Predicting RSRP based on the road loss model. The Fries transmission formula in antenna theory has:

$$P_r = P_t \frac{G_t G_r \lambda^2}{(4\pi R)^2} \tag{32}$$

where P_r is the received power, P_t is the transmitted power, G_t is the gain at the transmitter end, G_r is the gain at the receiver end, λ is the wavelength of the transmitted electromagnetic wave, and R is the distance from the transmitter to the receiver. After taking logarithmic calculations for both sides, the level of a particular link can be expressed by equation (32).

where P is the reference signal transmit power, G_{TX} is the antenna gain, and L is various losses including path loss, building penetration loss, etc. G_{RX} is the terminal antenna receiving gain. Since only the path loss and line loss are considered in this paper, and the line loss and terminal receiving gain remain unchanged during the optimization process, if L_P is the path loss between the grid and the antenna.The calculation of RSRP can be simplified as:

$$RSRP = P + G_{TX} - L_P \tag{33}$$

The MDT data contains the RSRP of the serving small agricultural base station and the neighboring small agricultural base station measured by the terminal.The RSRP of the small agricultural base station arriving at each raster can be known by casting the MDT sampling points into the raster and calculating the average value of the RSRP of all the sampling points in the raster.Let the actual measured RSRP of the small agricultural base station i in the raster j be $RSRP_0$, and then the path loss L_p can be estimated as $L_P = P + G_{TX} - RSRP_0$. For a certain fixed grid, during the iterative optimization process, its and the antenna's position and propagation environment are unchanged, and it can be assumed that the path loss is also unchanged. Let the RSRP predicted in the t th iteration be:

$$RSRP(t) = P(t) + G_{TX}(t) - L_P \tag{34}$$

where, the antenna gain $G_{TX}(t)$ can be calculated by combining the antenna azimuth, downward inclination, and the orientation of the grids relative to the antenna based on the antenna orientation maps of different scenarios. After obtaining the RSRP value of the agricultural small base station reaching each grid, the average RSRP value of the agricultural small base station is calculated and used as the iterative objective function.

(2) The expected value $\eta_i(t)$ is associated with RSRP in a way. Do normalization on RSRP, map RSRP to (0, 1] data, and assign the mapped data to the expectation value $\eta_i(t)$.

Step 4: Pheromone update. The ant colony algorithm is characterized by the fact that after the ants pass through a certain path to release the pheromone, the accumulated pheromone on that path will be volatilized according to a certain degree. Corresponding to the weight optimization in this paper, the pheromone volatilization factor accumulated in each weight history is ρ. When all ants complete a weight search, the following updates will be done for each weight pheromone of each agricultural small base station:

$$\begin{cases} \tau(t+1) = (1-\rho)\times\tau(t) + \Delta\tau \\ \Delta\tau = \sum_{k=1}^{N} \Delta\tau_k \end{cases} \tag{35}$$

where $\Delta\tau_k$ denotes the pheromone concentration released by the k th ant at that weight:

$$\Delta\tau_k = \begin{cases} Q\times\eta, & \text{The ant selects this weight} \\ 0, & \text{The ant did not choose this weight} \end{cases} \tag{36}$$

where Q is a constant for the pheromone increase strength coefficient, η is the expectation value, $\Delta\tau$ denotes the sum of the pheromone concentrations released by all ants at that weight, and $\Delta\tau_k$ is updated based on the Ant Cycle System model, which is updated after the ants have gone through the whole journey using global information.

Step 5: Judge the convergence. Judge whether the termination condition is satisfied, i.e., the maximum number of iterations is reached. If the termination condition is satisfied, then end the search process and output the combination of MIMO weights for agricultural small base stations, if not, then continue the iterative optimization.

III. Energy Efficiency Analysis of Radio Frequency Amplifiers for Small Base Stations for Agriculture in Arkansas Land

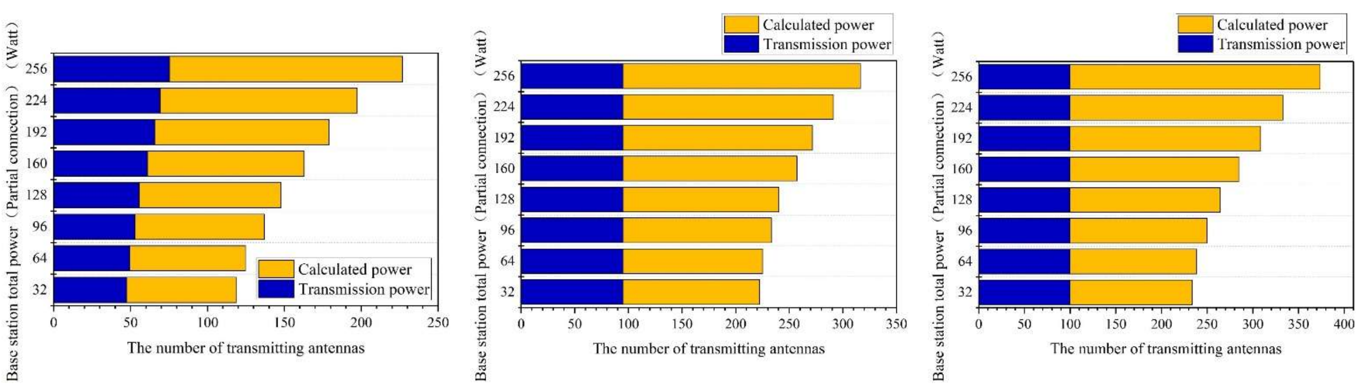
III. A. Geographic overview of the Aksu region of Xinjiang

The study area is 1 city and 8 counties in Aksu region of Xinjiang, which are Aksu city, Wensu county, Kuqa county, Shaya county, Xinhe county, Baicheng county, Wush county, Awati county and Koping county. Aksu region is rich in land resources, with a total land area of 132500 hm². the terrain is high in the north and low in the south, tilting from northwest to southeast, with Tomur Peak at an altitude of 7443.8m as the highest point in the territory, and the Tarim River with a length of 1020km as the lowest point in the territory, with the terrain on both sides of the Tarim River being relatively flat and the soil deep. The climate type belongs to the typical warm temperate continental climate, with dryness and little rain throughout the year, vigorous evaporation and scarce precipitation. The total solar radiation is 5340~6220 MJ/m², which is one of the regions with more solar radiation in the country, and the annual sunshine time of the whole region reaches 2750~3029 h, which is much larger than that of the same latitude in eastern China. The study of climate change cycles in the plain area of the Aksu River Basin in Xinjiang over the past 50 years has yielded an increasing trend in temperature and precipitation in Aksu. The Aksu region grows a variety of melons and fruits, cotton (early-maturing long-staple cotton versus medium- and early-maturing land cotton), and a variety of grains, such as corn, rice, and wheat, and is an important agricultural production area in Xinjiang. In recent years, the Aksu agro-ecosystem has been affected to a certain extent by the growing population size and economy, the expanding area of reclaimed agricultural land, and the frequent occurrence of extreme weather.

III. B. Simulation experiment results and performance analysis

III. B. 1) Algorithmic performance of fuzzy logic control

The relationship between the total power of the base station and the number of transmitting antennas at the base station end is shown in Fig. 3. Fig. 3(a) shows the total power of the base station using fuzzy logic control algorithm, Fig. 3(b) shows the total power of the base station using SIC algorithm, and Fig. 3(c) shows the total power of the base station using OMP algorithm. In the traditional RF power amplifier for small agricultural base stations, the transmission energy consumption is basically unchanged with the increase in the number of antennas, while in the actual system, the transmission energy consumption increases with the increase in the number of transmitting antennas, which indicates that the traditional model is not accurate enough. When the fuzzy logic control algorithm is utilized, both the transmission power and the computational power of the base station increase with the increase in the number of transmitting antennas, and the transmission power is increased from 47 W to 75 W, while the computational power is increased from 71 W to 151 W. This is more in line with the actual system. After comparison, it is found that the computational power and transmission power of the base station of the traditional model using OMP algorithm and SIC algorithm are higher than those of the base station of the energy-efficient model based on the efficiency of the segmented linear amplifier using the fuzzy logic control algorithm, which indicates that the fuzzy logic control algorithm can effectively reduce the computational and transmission energy consumption of the system, which is due to the fact that the fuzzy logic control algorithm realizes the joint optimization of computational power and transmission energy consumption. This is due to the fact that the fuzzy logic control algorithm achieves the joint optimization of computational power and transmission energy consumption.



(a) Fuzzy logic control (b)SIC (c)OMP

Figure 3: The relationship between total power and the number of antenna antennas

III. B. 2) Energy efficiency analysis

Fig. 4 shows the relationship between energy efficiency and the number of RF links. The number of transmitting antennas at the base station end is set NT = 128. The energy efficiency of all three algorithms decreases with the increase in the number of RF links in the agricultural small base station RF amplifier. This is because although the increase in the number of RF links increases the spectral efficiency of the system, the total energy consumption of the base station also increases with the increase in the number of RF links, mainly due to two reasons: firstly, the increase in the number of hardware of the RF links makes the transmission energy consumption of the system increase, and secondly, the computational energy consumption of the system increases continuously, and the increase in the total energy consumption is far more than the increase in the degree of spectral efficiency. When the number of RF links is the same, the energy efficiency of the fuzzy logic control algorithm proposed in this chapter for the partially connected structure is higher than that of the OMP algorithm for the fully connected structure and the SIC algorithm for the partially connected structure. The system energy efficiency model based on segmented linear amplifier efficiency in this chapter is more in line with the actual system, and the calculated power and transmitted power are analyzed separately, so the energy saving effect of the fuzzy logic control algorithm is more obvious. With the increase in the number of RF links, the energy efficiency of the fuzzy logic control algorithm decreases faster than the other two algorithms' energy efficiency, which is due to the fact that the increase in the number of RF links leads to a decrease in the power on each RF link, and thus the efficiency of the power amplifier on the RF link decreases, and the total power consumed by the power amplifier increases. Therefore the fuzzy logic control algorithm is more superior when the number of RF links is less. When the number of RF links is equal to 2, the energy efficiency of the fuzzy logic control algorithm is improved by 38% over the energy efficiency of the SIC algorithm, which is also a partially connected structure, and 88% over the energy efficiency of the OMP algorithm, which is a fully connected structure.

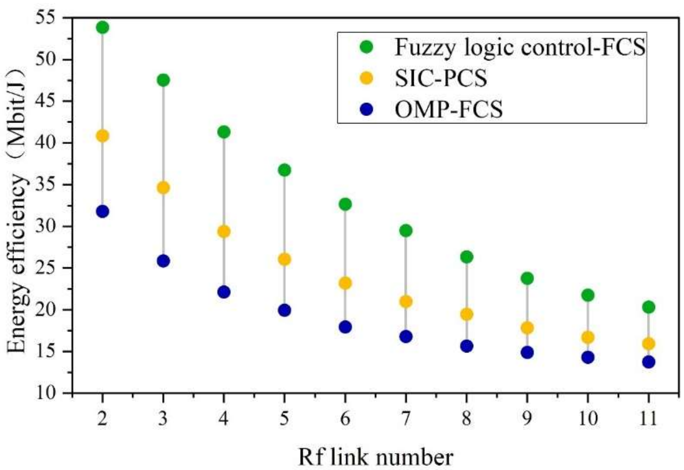


Figure 4: The relationship between energy efficiency and the number of rf links

Fig. 5 shows the relationship between spectral efficiency and the number of RF links. The number of transmitting antennas at the base station end is set NT=128. In the agricultural small base station RF amplifier, the spectral efficiency of all three algorithms rises with the increase in the number of RF links. This is because the increase in the number of RF links leads to an increase in the equivalent channel dimension, and the antenna array gain also increases, and the spectral efficiency naturally rises. When the number of RF links is certain, the spectral efficiency of both the fuzzy logic control algorithm and the SIC algorithm of the partially connected structure is lower than that of the OMP algorithm of the fully connected structure, which is due to the fact that each RF link in the partially connected structure is connected to only a single antenna, and therefore its spectral efficiency is lower than that of the fully connected structure. When the number of RF links is 2, the spectral efficiency of the fuzzy logic control algorithm is 20% higher than that of the SIC algorithm with the same partially connected structure. Although the fuzzy logic control algorithm reduces the spectral efficiency by 5.8% compared to the OMP algorithm for the fully-connected structure, it is exchanged for an 88% improvement in energy efficiency.

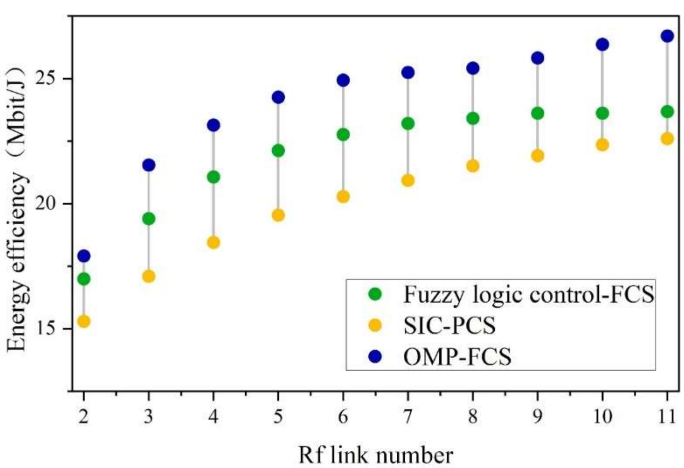


Figure 5: The relationship between spectral efficiency and rf link number

Fig. 6 shows the relationship between energy efficiency and maximum transmit power. The number of transmitting antennas at the base station end is set NT=128, and the number of RF links is set NRF=6. In the agricultural small base station RF amplifier, the energy efficiency of the three algorithms first rises with the increase of the maximum transmitting power, and then decreases after reaching a certain threshold, while the energy efficiency of the fuzzy logic control algorithm proposed in this chapter decreases in the most gentle trend. When the maximum transmit power is less than 20 dBm, the energy efficiency of the fuzzy logic control algorithm is smaller than that of the SIC and OMP algorithms. This is because in the hybrid precoding system model based on segmented linear amplifier efficiency, when the transmit power is very low, less power is allocated on each RF link, resulting in a small output power of the amplifier. According to the characteristics of amplifier efficiency, the amplifier efficiency is low, so the ratio of energy wasted by amplifier losses to the total energy consumed by the amplifier increases. In order to ensure the quality of service for users, the maximum transmit power is usually not set very low, so there is no need to worry about the application of fuzzy logic control algorithms to produce low energy efficiency. When the maximum transmit power is equal to 60 dBm, the energy efficiency of the fuzzy logic control algorithm is 71% higher than that of the SIC algorithm with the same partially connected structure, and 414% higher than that of the OMP algorithm with the fully connected structure.

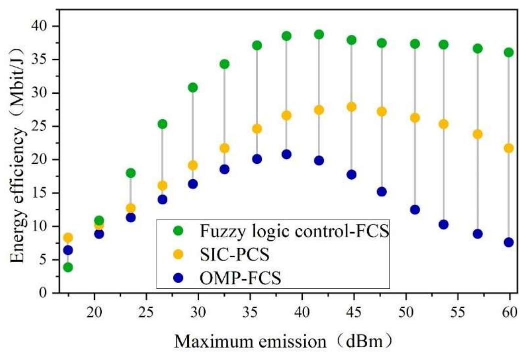


Figure 6: The relationship between energy efficiency and maximum emission power

Fig. 7 shows the relationship between spectral efficiency and maximum transmit power. The number of transmit antennas at the base station end is set NT = 128, and the number of RF links NRF = 6. The spectral efficiency of all the three algorithms increases with the increase of the maximum transmit power in the RF amplifier of the agricultural small base station. When the maximum transmit power is less than 22 dBm, the spectral efficiency of the fuzzy logic control algorithm is less than that of the SIC algorithm, which is also a partially connected structure. This is because in agricultural small base station RF amplifiers, the spectral efficiency decreases as the amplifier efficiency decreases. When the maximum transmit power is small, the amplifier output power is small, and the efficiency of the amplifier becomes smaller with the amplifier output power, at this time, the spectral efficiency of the fuzzy logic control algorithm is lower than the spectral efficiency of the SIC algorithm and the OMP algorithm. When the maximum transmit power is greater than 22dBm, the spectral efficiency of the fuzzy logic control algorithm is higher than that of the SIC algorithm, which is also a partially connected structure. When the maximum transmit power is equal to 60dBm, the spectral efficiency of the fuzzy logic control algorithm is 12.5% higher than that of the SIC algorithm with the same partially-connected structure, and although it is 48% lower than that of the OMP algorithm with the fully-connected structure, the energy efficiency has been improved tremendously, by 414%.

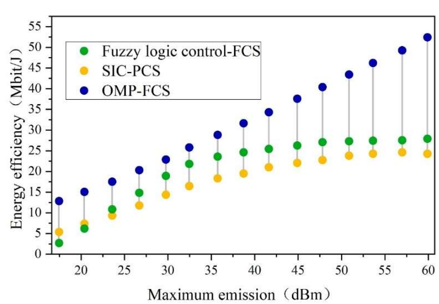


Figure 7: The relationship between spectral efficiency and maximum emission power

Fig. 8 shows the relationship between energy efficiency and the number of transmit antennas at the base station end. The number of RF links is set NRF = 6. In the agricultural small base station RF amplifier, the energy efficiency of all three algorithms decreases with the number of transmitting antennas, and the rate of decrease gradually slows down and eventually stabilizes. The energy efficiency of the OMP algorithm for fully connected structures decreases the fastest, so the study of hybrid precoding for partially connected structures is important to improve the energy efficiency of the system. The energy efficiency of the fuzzy logic control algorithm proposed in this chapter is significantly higher than that of the SIC algorithm and the OMP algorithm, and with the increase in the number of transmitting antennas, the more superior the energy efficiency indexes of the fuzzy logic control algorithm, which indicates that the fuzzy logic control algorithm is suitable for the agricultural small base station RF amplifier. When the number of base station transmitting antennas is 200, the energy efficiency of the fuzzy logic control algorithm is 66% higher than that of the SIC algorithm with the same partially connected structure, and 100% higher than that of the OMP algorithm with the fully connected structure.

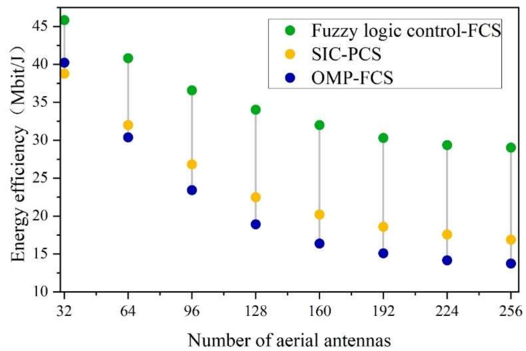


Figure 8: Energy efficiency and the number of antenna antennas on the base station

Fig. 9 shows the relationship between the spectral efficiency and the number of transmitting antennas at the base station end. Setting the number of RF links NRF = 6. In the agricultural small base station RF amplifier, the spectral efficiency of all three algorithms increases with the increase of the number of transmitting antennas, and that of the fuzzy logic control algorithm proposed in this chapter is higher than that of the SIC algorithm, which is also a partially connected structure, but lower than that of the OMP algorithm, which is a fully connected structure. When the number of transmitting antennas at the base station end is 200, the spectral efficiency of the fuzzy logic control algorithm is 9% higher than that of the SIC algorithm with the same partially-connected structure, and 11% lower than that of the OMP algorithm with the fully-connected structure, but the energy efficiency is 100% higher.

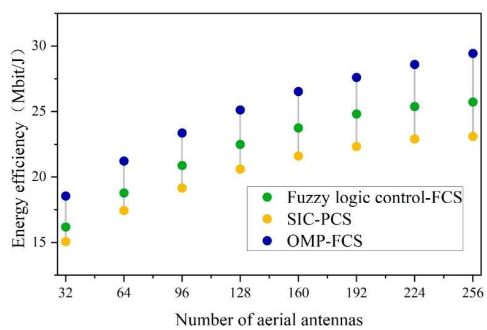


Figure 9: Spectrum efficiency and the number of aerial antennas on the base station

III. C. Modeling results based on fuzzy logic control

III. C. 1) Analysis of modeling results

Firstly, the schematic diagram of the RF amplifier is built in ADS and the simulation of this circuit schematic is carried out to get the sample data of the input and output voltage waveforms. Then the program about fuzzy logic control modeling is written in MATLAB to determine the type of affiliation function, the number of fuzzy sets, the number of fuzzy rules, and the number of iterations, and next the training data obtained from the simulation is imported into the MATLAB program to generate the initial model.

Finally, the test data are imported into the program, and the output voltage is calculated with the established initial model, and the fit degree of the model calculated results is compared with the simulation results of ADS software, which is used as a criterion to test the accuracy of the established model. The parameters of the model were adjusted using the least squares method to improve the accuracy of the model.

Figure 10 shows the steady-state output voltage, and the corresponding scatter curves in the figure correspond to the steady-state period waveforms of the output voltage with input powers of 5.6 dBm and 19.5 dBm, respectively, from which it can be seen that the results of the simulation and the results calculated by the model are in good agreement.

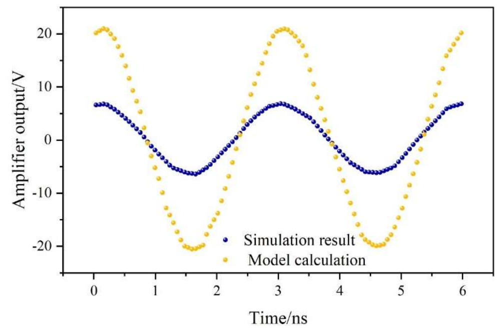
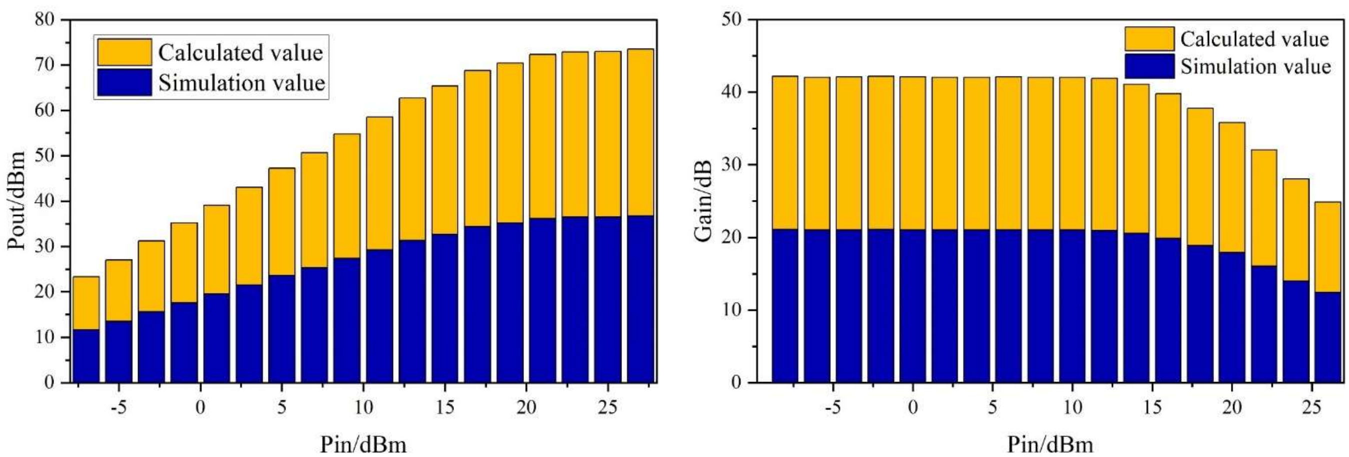


Figure 10: Steady state output voltage

Figure 11 shows the simulation and calculation of compression, Figure (a) is the power, Figure (b) is the gain compression, the model calculated P_{1dB} output power is about 30dB m, and the simulation results are very consistent. The simulated and calculated values can fall very accurately on the gain compression characteristics of the data above, the maximum value of the gain is about 20dB, that is to say, the fuzzy logic model calculation results and the amplifier circuit model simulation results are very well fitted.



(a)Power compression as well (b)Gain compression

Figure 11: Simulation and computational compression

III. C. 2) Power spectrum

Figure 12 shows the comparison of power spectrum output results, the blue line represents the input signal, the yellow line represents the output signal without fuzzy logic control device, and the green line represents the output signal after adding fuzzy logic control. The signal after adding the fuzzy logic control device is closer to the input curve, especially in the [-40,-15] and [18,38] two frequency bands, the maximum difference between the two signal power spectra output is only about 60dBW, the improvement effect is more obvious.

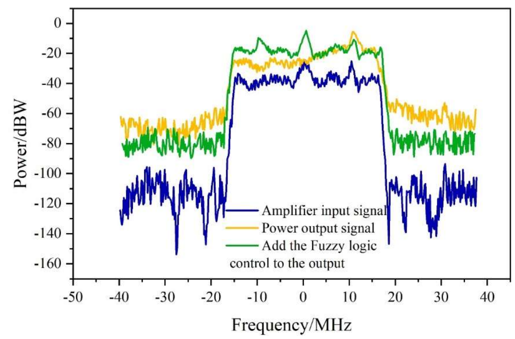


Figure 12: The output of the power spectrum is compared

III. C. 3) BER

Fig. 13 shows the SNR-BER, where the BER of the nonlinear channel decreases more slowly as the SNR increases. However, after fuzzy logic control, the BER of the nonlinear channel decreases sharply with increasing SNR. This indicates that although the amplifier has a nonlinear characteristic that can lead to a high BER, the BER can be effectively reduced by adding fuzzy control, and the BER is finally controlled at about 0.2.

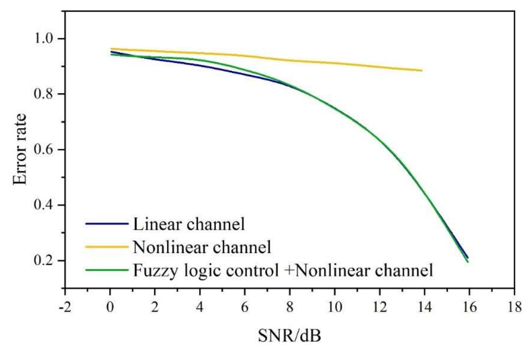


Figure 13: Signal-to-noise ratio - error rate

IV. Conclusion

Fuzzy logic control demonstrated significant results in optimizing the energy efficiency of RF power amplifiers for agricultural small base stations in Aksu region. Accurate modeling of a nonlinear RF power amplifier system is achieved by establishing a Sugeno fuzzy model and screening polynomial coefficients by orthogonal least squares. Experiments demonstrate that the fuzzy logic control algorithm improves the energy efficiency by 38% over the SIC algorithm and 88% over the OMP algorithm when the number of RF links is 2. The fuzzy logic control algorithm improves the spectral efficiency by 9% over the SIC algorithm while the energy efficiency is improved by 66% when the number of antennas in the base station is 200. The power spectrum analysis shows that the output signal after adding the fuzzy logic control device is closer to the input signal, and the power spectrum difference in the key frequency band is controlled within 60dBW. The BER test shows that the fuzzy logic control can effectively improve the nonlinear channel characteristics and reduce the BER to about 0.2. These results fully prove that fuzzy logic control can not only solve the nonlinear problem of RF amplifier in agricultural small base station, but also significantly improve the energy efficiency under the premise of ensuring signal quality, which provides a technical guarantee for the sustainable development of agricultural communication infrastructure in Aksu area, and is of great value in promoting the digital transformation of agriculture.

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Data Availability

All data generated or analysed during this study are included in this published article.

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