Swing Process Model Design of a Cutter Suction Dredger Based on RBF-ARX Model

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Abstract. The swing process of a cutter suction dredger are affected by many factors, which changed time and nonlinear. So it is difficult to describe the change law accurately. The swing process model based on RBF-ARX model is established after detailed analysis of the formation process of dredger production. The shortcomings of the traditional neural network could be overcome by this method, such as slow convergence rate, more hidden layer. After modeling, the linear and nonlinear parameters of the RBF-ARX model are identified off-line by using SNPOM (Structured Nonlinear Parameter Optimization Method). Then the errors of the output of the model and the real data are compared and analyzed by simulation. The result show that the swing process model can accurately describe the dynamic characteristics of the system in the global range, and the model output is well fitted with the real data of a cutter suction dredger.

1. Introduction

Due to advantages such as low engineering cost, high production efficiency, wide scope of application, etc., cutter suction dredger is widely used in such dredging engineering as earth reclamation, channel construction and maintenance [1]. But because its complex and variable dynamic characteristics varies with soil quality, landform and operating condition of ship, dredging operation process cannot be summarized and expressed with an accurate equation. For a long time, construction efficiency of dredger mainly depends on experience of operators, with problems such as large yield fluctuation, high energy consumption and experience difficult to copy, enormous difference between individuals, etc. In recent years, rapid development of computer technology and modern control theory creates necessary conditions for modelling and automatic control of dredger construction process which is a nonlinear system with obvious time variant characteristics.

Overseas, the research on automation of dredging operation began in 1990s, and a dredging comprehensive detection system developed by Dutch L.H.C can express dredging process information by combining text and graph [2]. Jelmer Braaksma of DELFT conducted deep research on modelling and control of trailing suction hopper dredger [3]. Domestically, related research on dredger has been conducted for nearly 10 years, but those on swing process control are few. Tang Jianzhong of Zhejiang University proposed swing speed control aiming at a steady working point [4]. Bi Yuezhi proposed inline optimization of soil and sand delivery system operating point based on the concentration process model proposed by Tang JianZhong [5]. Ni Fusheng of Hohai University conducted much research on dynamic characteristics of soil and sand delivery system, laying a foundation for research on swing process [6]. Li Zhigang proposed a swing control mathematical model of current protection under ideal...
condition [7]. Zhu Wenliang used modern control theory to resolve the modelling problem of complex parameter of swing process, proposing a spatial model of swing process state based on measured data [8].

RBF-ARX model is an emerging offline identification model proposed for dealing with nonlinear control system with a complex object [9]. It is based on linear ARX model, but the difference between them is that the model has functional factors based on RBF neural network. Based on full understanding of RBF-ARX model, by combining dynamic characteristics of swing process, directly starting from measured input/output data of the dredger, this paper identifies linear and nonlinear parameters in the model using SNPOM method to establish dredger swing process model, compares and analyses the error result of established model and real data using simulation.

2. RBF-ARX model

2.1. Basic structure of RBF-ARX model

RBF-ARX model is a composite structure of RBF neural network and linear ARX model [10], with equation as shown in (1).

\[
y(t) = \phi_y(X(t-1)) + \sum_{i=1}^{n_y} \phi_{yi}(X(t-1))y(t-i) + \sum_{i=1}^{n_u} \phi_{ui}(X(t-1))u(t-i) \\
+ \sum_{i=1}^{n_v} \phi_{vi}(X(t-1))v(t-i) + \xi(t)
\]

(1)

Where, \(y(t)\) is output; \(u(t)\) is input; \(v(t)\) is external measurable interference quantity; \(\xi(t)\) is white noise; \(X(t-1)\) is state vector which can have direct or indirect relation with the system; \(ny, nu, nv\) is the order of model; \(\phi_y(X(t-1))\) and \(\phi(X(t-1))\), \(i=1,2,...,n_i; j=y,u,v\) are state dependent functional coefficients which rely on state vector \(X(t-1)\). When state vector \(X(t-1)\) at moment \(t-1\) is decided, functional coefficient can be calculated through RBF neural network.

2.2. Identification method for RBF-ARX

The functional coefficient in RBF-ARX model is obtained by RBF neural network training and calculating offline data, its structural diagram is shown in Figure 1.

![Figure 1. Structural diagram of RBF identification of RBF-ARX model functional coefficient](image_url)

SNPOM parameter identification method was used to solve parameters of functional coefficient, the core of the method is to construct nonlinear parameter subspace and linear parameter subspace by dividing model parameters into nonlinear and linear parameters [11]. Nonlinear parameters are optimized using LMM method, linear parameter is optimized using LSM method.

First write equation (1) as:

\[
y(t) = f(\theta_y, \theta_u, X(t-1)) + \xi(t); \ y(t) = \phi(\theta_x, X(t-1))\theta_x^T + \xi(t)
\]

(2)

Where, \(\theta_y\) is nonlinear parameter space, \(\theta_y \in \mathbb{R}_{[c_y, Z_y]}^{l_y}|k=1,2,...,m; j=y,u,v\); \(\theta_u\) is linear parameter subspace. \(\theta_x \in \mathbb{R}_{[c_x, Z_x]}^{l_x}|k=1,2,...,m; i=1,2,...,n_i; j=y,u,v\}. The initial value of RBF network centre \(Z_y\) in nonlinear parameter subspace \(\theta_y\) can be given at random, to ensure steady boundedness of linear weight space, the initial value of proportion coefficient of RBF network also needs to be decided:
The initial value of linear parameter $\theta_L$ is calculated using LSM algorithm:

$$
\theta_L^0 = \left[ R(\theta_L^0)^T R(\theta_L^0) \right]^{-1} R(\theta_L^0)^T \bar{Y}
$$

(4)

Where, $R(\theta_L^0) = \begin{bmatrix} \varphi(\theta_L^0, \bar{X}(\tau)) \\ \varphi(\theta_L^0, \bar{X}(\tau+1)) \\ \vdots \\ \varphi(\theta_L^0, \bar{X}(M-1)) \end{bmatrix}$, $\bar{Y} = (\bar{y}(\tau+1), \bar{y}(\tau+2), \ldots, \bar{y}(M))$, here $\{\bar{y}(i), \bar{X}(i-1)|i = \tau + 1, \tau + 2, \ldots, M\}$ is the set of observed data, $\tau$ is the time delay of the system, $M$ is length of observed data.

After being initialized, parameters need to be optimized further. Define target function:

$$
V(\theta_L, \theta_N) = \frac{1}{2} \| F(\theta_L, \theta_N) \|_2^2
$$

(5)

Where, $F(\theta_L, \theta_N) = \begin{bmatrix} f(\theta_L, \theta_N, \bar{X}(\tau) - \bar{y}(\tau+1)) \\ f(\theta_L, \theta_N, \bar{X}(\tau+1) - \bar{y}(\tau+2)) \\ \vdots \\ f(\theta_L, \theta_N, \bar{X}(M-1) - \bar{y}(M)) \end{bmatrix}$.

So, parameter optimization is transformed into the following equation:

$$(\hat{\theta}_L, \hat{\theta}_N) = \arg \min_{\theta_L, \theta_N} V(\theta_L, \theta_N)$$

(6)

Updating strategy of nonlinear parameter $\theta_N^{k+1}$ is:

$$
\theta_N^{k+1} = \theta_N^k + \beta_k d_k
$$

(7)

Where, $d_k$ is search direction, $\beta_k$ is step size. Every iteration $d_k$ is solved by the following equation:

$$
\begin{cases}
J(\theta_L^k)^T J(\theta_L^k) + \gamma_k I & d_k = -J(\theta_L^k)^T F(\theta_L^k, \theta_N^k) \\
J(\theta_L^k) = \left( \frac{\partial F(\theta_L^k, \theta_N^k)}{\partial \theta_L^k} \right)^T
\end{cases}
$$

(8)

Where, $J(\theta_L^k)$ is the Jacobean matrix of $F(\theta_L^k, \theta_N^k)$ with respect to $\theta_L^k$; where, $\gamma_k$ controls the amplitude and search direction of $d_k$ .when $\gamma_k$ approaches 0, $d_k$ will be in Gauss-Newton direction; $\gamma_k$ approaches infinite, $d_k$ will be in max decline direction. After $\gamma_k$ is selected $d_k$ can be obtained. When next nonlinear parameter $\theta_N^{k+1}$ is determined, next linear parameter $\theta_L^{k+1}$ needs to be optimized using LSM again. During parameter optimization, $V(\theta_L^{k+1}, \theta_N^{k+1}) < V(\theta_L^k, \theta_N^k)$ needs to be ensured, otherwise optimization is over, parameter identification end.

3. Model design of cutter suction dredger swing process

3.1. Variable analysis of swing process

Production of cutter suction dredger refers to the earthwork volume delivered in pipe in unit time. When flow rate of slurry is stable, concentration variation of slurry can reflect variation of output to certain extent, so expression of slurry concentration is:

$$
C_v = f(\lambda, \eta, A, v) V_s
$$

(9)
Where, \( C_w \) is concentration of slurry(\%), \( \dot{\lambda} \) is rate of sedimentation loss, \( \eta(0 \leq \eta \leq 1) \) is slurry leakage rate, \( A_i \) is actual cutting area of cutter(\( m^2 \)), \( v \) is velocity of slurry(\( m/h \)), \( V_s \) is swing speed(\( m/min \)). During dredging construction output is expected as large as possible, but limited by the cutter power, \( A_i \) cannot be too large, nor adjustable. Slurry flow rate depends on characteristics of pump, unable to be adjusted frequently, either. So, the swing process model established uses concentration reflecting production as output, swing speed regulated most frequently as control input.

3.2. Basic structure of swing process model

Without considering external measurable interference, RBF-ARX based cutter suction dredger swing process model is as follows:

\[
\begin{align*}
C_c(t) &= \phi_k(X(t-1)) + \sum_{i=1}^{n_v} \phi_i(X(t-1))C_c(t-i) + \sum_{i=1}^{n_v} \phi_i(X(t-1))V_s(t-i) + \xi(t) \\
\phi_k(X(t-1)) &= \sum_{i=1}^{n_v} \phi_i(X(t-1))C_c(t-i) + \sum_{i=1}^{n_v} \phi_i(X(t-1))V_s(t-i) + \xi(t) \\
\phi_k(X(t-1)) &= \sum_{i=1}^{n_v} \phi_i(X(t-1))C_c(t-i) + \sum_{i=1}^{n_v} \phi_i(X(t-1))V_s(t-i) + \xi(t)
\end{align*}
\]

(10)

Where, \( C_c(t) \) is concentration of slurry, \( V_s(t) \) is swing speed, \( \xi(t) \) is white noise array, \( X(t-1) \) is state vector which contains combination of input variable of slurry concentration and output variable of swing speed; \( n_c, n_v, m, n_w \) are the orders of model; \( \phi_i(X(t-1)) \) and \( \phi_j(X(t-1)) \) are state dependent functional coefficients which are approximated by a group of RBF network respectively; \( Z^{*}_{jk}(k=1,2,...,m; j=c,v) \) is RBF network center; \( \lambda^{*}_{jk}(k=1,2,...,m; j=c,v) \) is proportion coefficient of RBF network; \( c_i^{*}(k=1,2,...,m) \), \( c_j^{*}(k=1,2,...,m;i=1,2,...,n_j; j=c,v) \) are linear weights of RBF network; \( |\cdot| \) represents vector quadratic norm. \( \tau \) is lagging time of slurry concentration.

3.3. Parameter identification of swing process model

Basic procedure of parameter identification of swing process model is shown in the following figure 2.

![Flow chart of parameter identification of swing process model](image)

Figure 2. Flow chart of parameter identification of swing process model

3.3.1. Determination of orders of swing process model

\( m \) and \( n_w \) are selected based on experience, typically \( m \) is 1-2, in this paper \( m=1, n_w \) is typically selected as 2. Then use Akaike Information Criterion, AIC:

\[
AIC = N\log V + 2d
\]

(11)
Where, V is the covariance of model, N is the length of observed data. d is the sum of numbers of all linear parameters and nonlinear parameters to be identified. Because the smaller the AIC value, the better swing process model output and actual value fit, it can be found from Figure 3 that by comparing AIC value, combining model characteristics, they can be selected $n_1 = 3$, $n_2 = 2$.

**Figure 3.** Comparison curve of AIC value of different order

### 3.3.2. Determination of linear parameter and nonlinear parameter
Next model parameters will be identified using measured data of system global input/output, the result of linear parameter and nonlinear parameter of parameter identification is shown in Table 1.

| Parameter class | Symbol | Recognition values |
|-----------------|--------|--------------------|
| Linear parameters | $\theta_i \{c_i', c_i''\}$ | $\theta_L$ |
| | $k = 1, 2, ..., m$; $i = 1, 2, ..., n_j$; | $1.20 \times 10^{-9}$ |
| | $j = y, u, v$ | $5.62 \times 10^{-6}$ |
| Linear parameters | $\theta_n \{c_n', c_n''\}$ | $\theta_n$ |
| | $k = 1, 2, ..., n_k$; $i = 1, 2, ..., n_j$; | $1.00 \times 10^{-3}$ |
| | $j = y, u, v$ | $1.20 \times 10^{-9}$ |
| Nonlinear parameters | $\lambda_j$ | $0.048$ |
| Nonlinear parameters | $n_k$ | $1.13 \times 10^{-45}$ |
| | $k = 1, 2, ..., n_k$; $j = y, u, v$ | $1.20 \times 10^{-10}$ |

### 4. Test of swing process model
To test prediction capacity of established swing process model, select the data of the same cutter suction dredger measured at another moment, with length of 4000s. Comparison diagram of swing process model prediction output and measured data is shown in figure 4.

**Figure 4.** Comparison diagram of swing process model prediction output and measured data
It can be found from figure 4 that variation of predicted value and measured value of slurry concentration have the same overall trend, prediction result is relatively accurate. But comparing with measured data, model output result of slurry concentration has a larger error at higher and lower concentration, because actual dredging process is very complex, those factors such as flow rate in pipe, cutter power and vacuum can influence slurry concentration to different extent. In this paper only swing speed is used as control input, and state variable only includes swing speed and slurry concentration itself, later such factors as flow rate, cutter power and vacuum will be included in the process of model establishment.

5. Conclusion
In the paper swing process model is established using RBF-ARX model without needing accurate parameter relation. By directly starting from the data measured by the dredger, through RBF network and SNPOM combined parameter identify algorithm, swing process modelling is transformed into solving linear ARX model of the operating point, and these models are integrated into a global model issue through functional coefficient. Through simulation the model is tested to clearly describe swing process dynamic characteristics, also laying a foundation for next design of swing controller using prediction control theory.

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