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Separation identification of a neural fuzzy Wiener–Hammerstein system using hybrid signals

Key words: Wiener–Hammerstein system; Neural fuzzy network; Correlation analysis technique; Hybrid signals; Separation identification

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Motivation

1. Nonlinear modeling methods based on a linear combination of basis functions show weak approximation ability when describing discontinuous or complex systems.

2. The issue that the intermediate variables of the system cannot be measured is the major difficulty for Wiener–Hammerstein system identification.

3. In view of the redundant parameters in Wiener–Hammerstein system synchronization identification, the separation identification of each block of system is considered for improving the identification accuracy.

Main idea

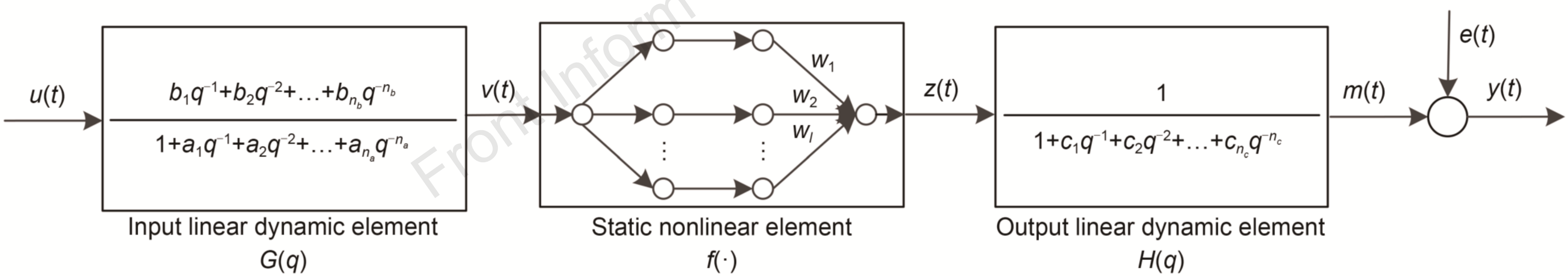
1. The presented method separates parameter identification of the nonlinear element from that of the linear elements using designed hybrid signals, which avoids decomposing parameter product terms in synchronous identification and improves identification accuracy.

2. A correlation analysis technique, involving the autocorrelation function of input and cross-correlation function of input and output, is used, which ensures that the identification procedure is realized.

3. The zero-pole match technique is adopted to acquire the parameters of the two linear elements without parameter redundancy.

Framework

The nonlinear Wiener–Hammerstein system considered consists of a model with an input linear dynamic element $G(q)$ in cascade with a static nonlinear element $f(\cdot)$ with an output linear dynamic element $H(q)$. The following figure shows the Wiener–Hammerstein system with ARX-NFN-AR interfered by output noise.



Wiener–Hammerstein system with ARX-NFN-AR interfered by the output noise

Method

Theorem 1 Assume that the input of the Wiener–Hammerstein system is a zero mean white Gaussian process. Then, there is a constant b_0 that has the following relationship:

$$R_{yu}(\tau)=b_0G(q)H(q)R_u(\tau)=b_0G_H(q)R_u(\tau),$$

where $R_{yu}(\tau)$ is the cross-correlation function of input and output, $R_u(\tau)$ is the autocorrelation function of input, and $G_H(q)$ indicates a product of two linear elements.

Method

1. The correlation analysis technique is used to estimate the input linear dynamic element $G(q)$ and output the linear dynamic element $H(q)$.

$$\theta = R\Phi^{\mathrm{T}}(\Phi\Phi^{\mathrm{T}})^{-1}, \tag{26}$$

where

$$\theta = \left((\overline{ac})_1, (\overline{ac})_2, \cdots, (\overline{ac})_{n_a+n_c}, \tilde{b}_1, \tilde{b}_2, \cdots, \tilde{b}_{n_b}\right),$$

$$R = \left(R_{yu}(1), R_{yu}(2), \cdots, R_{yu}(P)\right),$$

$$\Phi = \begin{bmatrix} -R_{yu}(0) & -R_{yu}(1) & -R_{yu}(2) & \cdots & -R_{yu}(P-1) \\ 0 & -R_{yu}(0) & -R_{yu}(1) & \cdots & -R_{yu}(P-2) \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & -R_{yu}(P-n_a-n_c) \\ R_u(0) & R_u(1) & R_u(2) & \cdots & R_u(P-1) \\ 0 & R_u(0) & R_u(1) & \cdots & R_u(P-2) \\ \vdots & \vdots & \vdots & & \vdots \\ 0 & 0 & 0 & \cdots & R_u(P-n_b) \end{bmatrix}.$$

Method

2. To configure the zeros and poles correctly, for each set of zeros and poles, when the error between the actual output and the estimated output is the lowest, the zero-pole configuration is correctly configured.

The number of zeros generated by the product element is n_b-1, and the number of poles is n_a+n_c. Thus, when $n_a=i$, $n_b=j$, $n_c=m$, there are $(j-1)C_{i+m}^{2}$ possible configuration methods.

Method

3. Based on random signals, the clustering algorithm is used to estimate center c_l and width σ_l. Then, the recursive least-squares method is used to calculate the weight w_l.

$$\hat{\theta}_1(t)=\hat{\theta}_1(t-1)+L(t)\left[y_1(t)-(\varphi(t))^{\mathrm{T}}\hat{\theta}_1(t-1)\right], \quad (33)$$

$$L(t)=\frac{P(t-1)\varphi(t)}{1+(\varphi(t))^{\mathrm{T}}P(t-1)\varphi(t)}, \quad (34)$$

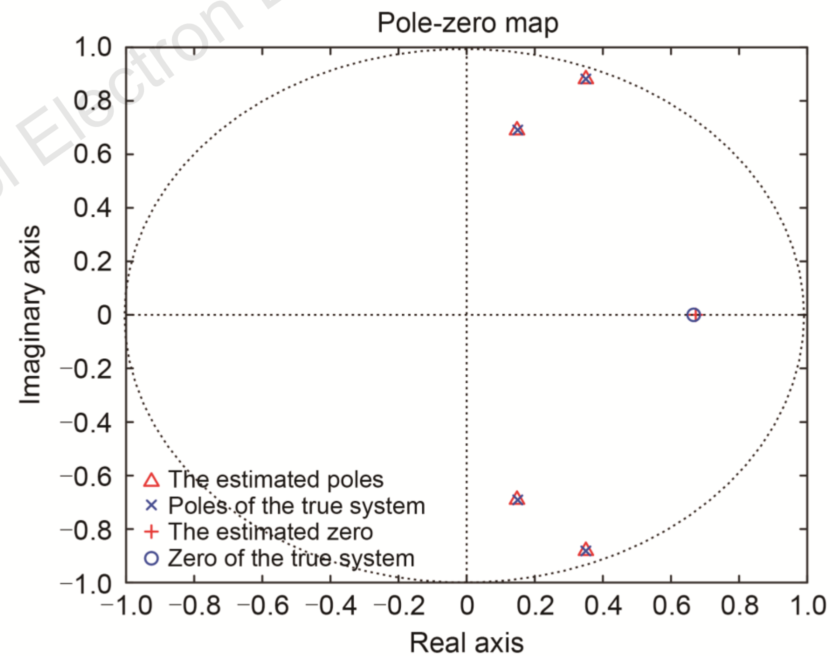
$$P(t)=\left[I-L(t)(\varphi(t))^{\mathrm{T}}\right]P(t-1). \quad (35)$$

$$\varphi(t)=\left[-y_1(t-1),\ -y_1(t-2),\cdots,\ -y_1(t-n_c),\right.$$
$$\left.\phi_1\left(\hat{v}_1(t)\right),\phi_2\left(\hat{v}_1(t)\right),\cdots,\phi_L\left(\hat{v}_1(t)\right)\right]^{\mathrm{T}},$$
$$\theta_1=\left[c_1,c_2,\cdots,c_{n_c},w_1,w_2\cdots,w_L\right]^{\mathrm{T}}.$$

Major results

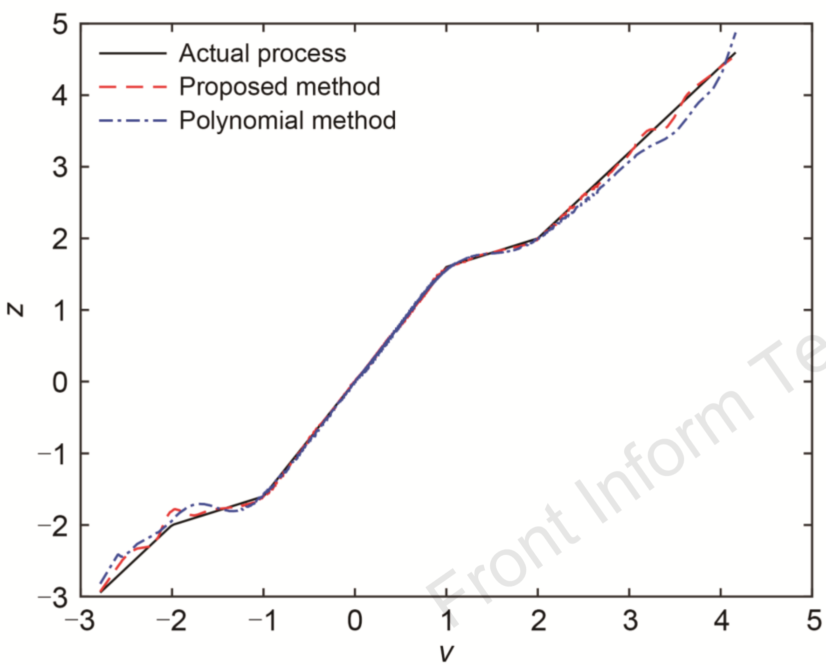
Table 1 Output error comparisons under different zero-pole configurations

Sequence	Zero-pole configuration	MSE
1	*G*(zero, pole1, pole2), *H*(pole3, pole4)	1.5136
2	*G*(zero, pole1, pole3), *H*(pole2, pole4)	0.6569
3	*G*(zero, pole1, pole4), *H*(pole2, pole3)	0.6566
4	*G*(zero, pole2, pole3), *H*(pole1, pole4)	1.1539
5	*G*(zero, pole2, pole4), *H*(pole1, pole3)	0.1657
6	*G*(zero, pole3, pole4), *H*(pole1, pole2)	0.0140

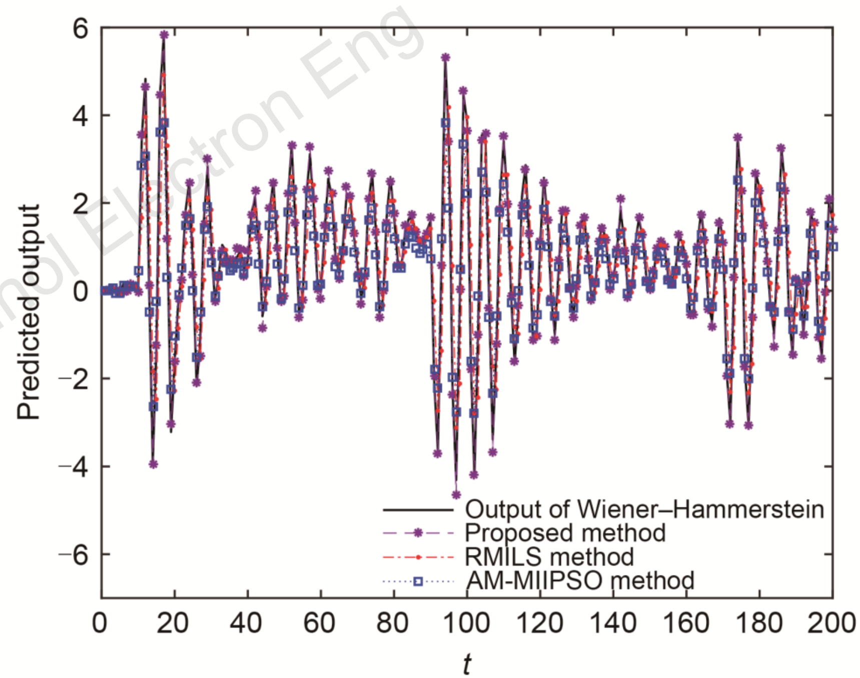


Identification results for the two linear elements

Major results



Nonlinearity approximation using two models



Comparisons of the predicted output using different methods

Conclusions

1. Based on the characteristic that Gaussian signals do not excite the linear element, the parameters of the two linear elements and the nonlinear element are identified independently using the designed hybrid signals, which simplifies the identification process and reduces complexity.

2. The correlation analysis technique is used for Wiener–Hammerstein system estimation, thereby solving the problem that the intermediate variable information cannot be measured, and the interference of the output noise is handled.

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