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Nonlinear Modeling and Identification of the Electro-hydraulic Control System of an Excavator Arm Using BONL Model

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Abstract: Electro-hydraulic control systems are nonlinear in nature and their mathematic models have unknown parameters. Existing research of modeling and identification of the electro-hydraulic control system is mainly based on theoretical state space model, and the parameters identification is hard due to its demand on internal states measurement. Moreover, there are also some hard-to-model nonlinearities in theoretical model, which needs to be overcome. Modeling and identification of the electro-hydraulic control system of an excavator arm based on block-oriented nonlinear(BONL) models is investigated. The nonlinear state space model of the system is built first, and field tests are carried out to reveal the nonlinear characteristics of the system. Based on the physic insight into the system, three BONL models are adopted to describe the highly nonlinear system. The Hammerstein model is composed of a two-segment polynomial nonlinearity followed by a linear dynamic subsystem. The Hammerstein-Wiener(H-W) model is represented by the Hammerstein model in cascade with another single polynomial nonlinearity. A novel Pseudo-Hammerstein-Wiener(P-H-W) model is developed by replacing the single polynomial of the H-W model by a non-smooth backlash function. The key term separation principle is applied to simplify the BONL models into linear-in-parameters structures. Then, a modified recursive least square algorithm(MRLSA) with iterative estimation of internal variables is developed to identify the all the parameters simultaneously. The identification results demonstrate that the BONL models with two-segment polynomial nonlinearities are able to capture the system behavior, and the P-H-W model has the best prediction accuracy. Comparison experiments show that the velocity prediction error of the P-H-W model is reduced by 14%, 30% and 75% to the H-W model, Hammerstein model, and extended auto-regressive (ARX) model, respectively. This research is helpful in controller design, system monitoring and diagnosis.

Key words: electro-hydraulic control system, backlash, Pseudo-Hammerstein-Wiener model, nonlinear identification, recursive least square algorithm

1 Introduction

Hydraulic excavators are versatile machines which are widely used in construction, forestry, and mining industries. They are controlled manually to finish works such as lifting, carrying, digging and ground leveling in a series of repetitive operations. So implementation of autonomous and robotic technology to this earthwork operation can benefit a lot by improving human safety, work quality, and machine efficiency[1]. However, the conventional robot control methods cannot be applied to robotic excavator directly due to the highly nonlinear dynamics of its electro-hydraulic control system[2]. Though lots of robust and adaptive control strategies were proposed to deal with this problem[3], modeling and identification of the electro-hydraulic control system is an important step for controller design.

Modeling the electro-hydraulic control system linearly under the assumption that the hydraulic actuator is moving around operating point is a popular way[4–5], but it is not a good choice to describe the electro-hydraulic control system of excavator due to the wide moving range of hydraulic cylinder[6]. LI, et al analyzed the nonlinear dynamic characteristics of electro-hydraulic control system of excavator[7], and built a nonlinear state space model for system analysis[8]. YAO, et al[9], pointed out that there were parametric uncertainties, discontinuous nonlinearities, and hard-to-model nonlinearities for the single-rod hydraulic actuator. So, modeling the electro-hydraulic control system of excavator by a flexible black-box or grey-box nonlinear model may be more appropriate.

The block-oriented nonlinear(BONL) models have been widely used in the nonlinear systems identification area[10]. KWAK, et al[11], proposed two Hammerstein-type models to identify hydraulic actuator friction dynamics, an improvement in the model accuracy, and an increased convergence speed were both achieved by incorporating a theoretical nonlinear model to the Hammerstein-type models. YAN, et al[12], adopted a Hammerstein model with a nonlinear static block containing two-segment nonlinearity to describe the electro-hydraulic control

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system of excavator, and the same model was adopted in this paper for comparison. These common BONL models consist of the interaction of linear time-invariant(LTI) dynamic subsystems and static nonlinear blocks in series, such as Hammerstein, Hammerstein-Wiener(H-W), etc. They are flexible enough to approximate most of the nonlinear dynamics with an arbitrarily high accuracy. However, they cannot describe dynamic nonlinearities such as the input and output backlash nonlinearities which usually exist in hydraulic valves, actuators and so on[13]. It is well known that the existence of backlash may cause delays, oscillations and inaccuracy, which deteriorates the performance of control systems[14]. Hence, in order to improve modeling accuracy and system performance, the effect of backlash should be considered.

Three types of parameterized BONL model are adopted in this paper, which are different form of the "data based model" constructed by GU, et al[15]. The Hammerstein model is composed of a two-segment nonlinearity followed by a LTI subsystem. The H-W model is built based on the Hammerstein model in cascade with a single polynomial nonlinear output. A novel Pseudo-Hammerstein-Wiener (P-H-W) model is developed by replacing the output nonlinear function of H-W model by a backlash function. The proposed method might be called semi-physical modeling, by which we mean using physical understanding to come up with the essential nonlinearities and incorporated these characteristics into the BONL models. The so-called key term separation principle is employed to provide special forms of BONL models which are linear-in-parameters. These models are used in a modified recursive least square algorithm(MRLSA) with iterative estimation of internal variables, enabling simultaneous estimation of all of the model parameters. The advantage of this approach is that only the input and output data are required for identifying all of the unknown parameters, i.e., no information of the internal state is demanded, which can simplify the identification process and improve the prediction accuracy by less sensors and progress noise.

2 Nonlinear Characteristics Analysis

2.1 The experiment machine

A human-operated hydraulic excavator was retrofitted to be controlled by computer in our laboratory[16]. Fig. 1 shows the prototype machine, its manual pilot hydraulic control system was replaced by electro-hydraulic proportional control system, inclinometers and pressure transducers were installed on the excavator arms for position and force servo control. Servo control and data acquisition are performed by the low level controller. The industrial PC which is connected with the low level controller provides interface and safety monitoring functionality. Block diagram of the electro-hydraulic control system is shown in Fig. 2.

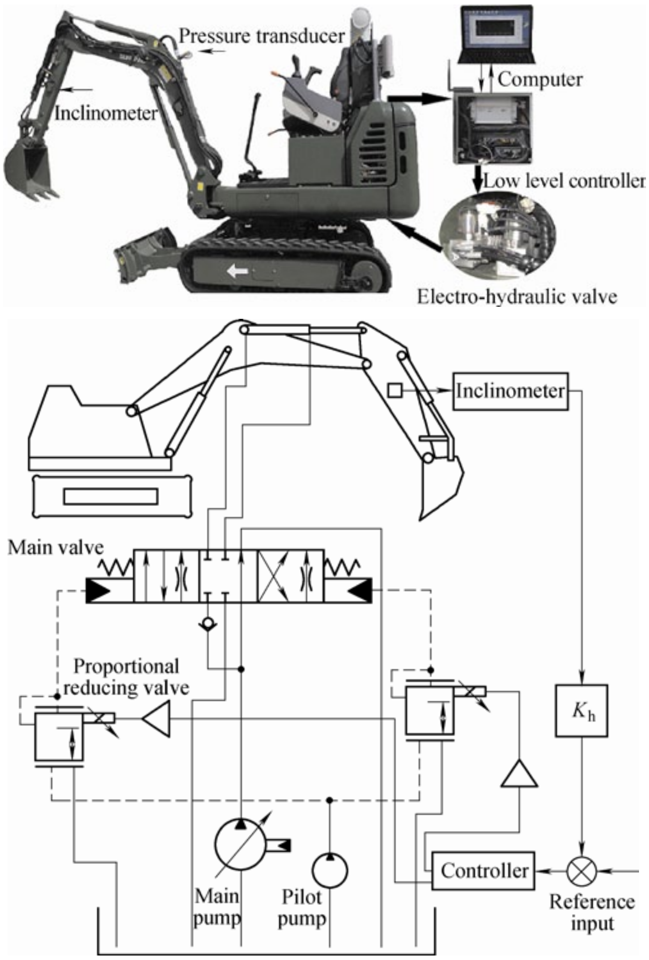


Fig. 1. Experimental prototype machine

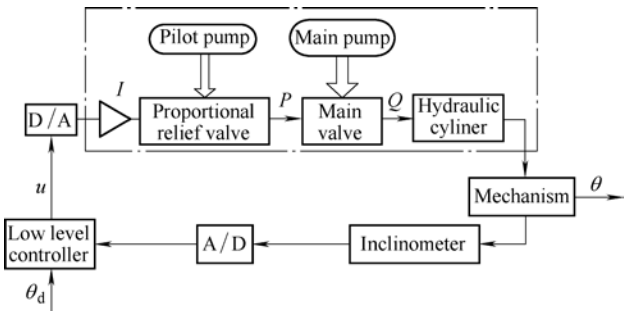


Fig. 2. Block diagram of electro-hydraulic control system

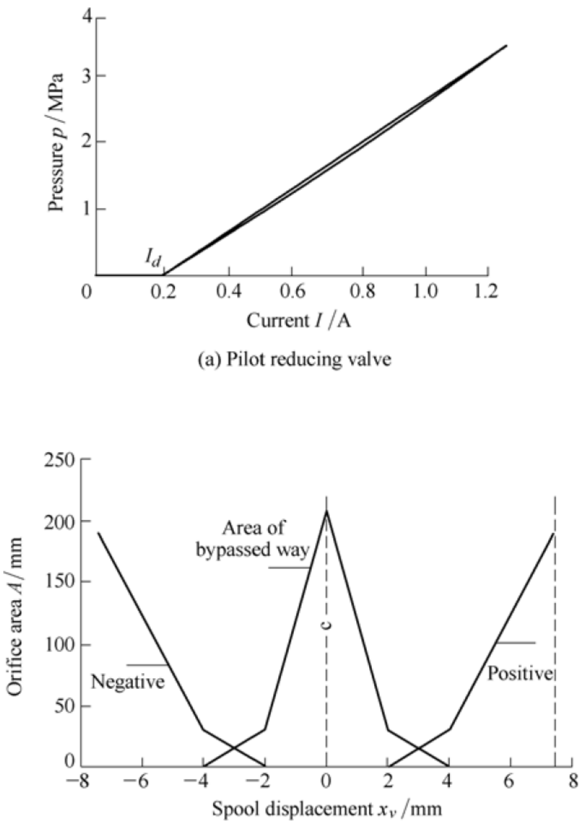
2.2 Theoretical modeling

Modeling the system by physical laws gives us a particular insight into the system's properties that will allow us to seek the parameterized models which are flexible enough to capture all kinds of reasonable system behavior. The elector-hydraulic control system of the retrofitted excavator is mainly composed of electro-hydraulic proportional valve, and valve controlled asymmetric cylinder subsystem.

The electro-hydraulic proportional control system is controlled directly by the low level controller. It consists of the pilot reducing valve and main valve, and can be modeled as a first order model as follows[7]:

$$\tau_v \dot{x}_v + x_v = k_v u_v, \tag{1}$$

where k_v is the gain of the electro-hydraulic proportional valve, τ_v is the time constant, x_v is displacement of the main valve, u_v is the effective input after dead band compensation. The dead band mainly due to the pilot reducing valve and the main valve are depicted in Fig. 3.



(a) Pilot reducing valve

(b) Dead band of the main valre

Fig. 3. Electro-hydraulic proportional system

The valve controlled asymmetric cylinder subsystem is shown in Fig. 4. In Fig. 4, h is the displacement of piston, M is the equivalent load mass, A_1 and A_2 are the areas of piston in the head and rod sides of cylinder, p_1 and p_2 are pressures inside the two chambers of the cylinder, p_s is the supply pressure, p_r is the pressure of return oil, Q_1 and Q_2 are the flows in and out of the cylinder, B_p is the viscous damping coefficient, F_f represents nonlinear friction, F_s represents nonlinear spring force, F_c represents viscous force, F_l represents uncertain load. Generally, the model of the valve controlled hydraulic cylinder is built by combining the flow equation of spool valve, the continuity equation of hydraulic cylinder, and the force equilibrium equation of hydraulic cylinder[17]. Define the state variables as $\boldsymbol{x}=[x_1,x_2,x_3,x_4,x_5]^{\mathrm{T}} \equiv [h,\dot{h},p_1,p_2,x_v]^{\mathrm{T}}$.

The entire system can be modeled as the following nonlinear state space model[8]:

$$\begin{aligned}
&\dot{x}_1 = x_2,\\
&\dot{x}_2 = \frac{A_1x_3}{M} - \frac{A_2x_4}{M} - \frac{F_f(x_2)}{M} - \frac{F_s(x_1)}{M} - \frac{F_c(x_2)}{M} - \frac{F_L}{M},\\
&\dot{x}_3 = -\frac{\beta_e A_1 x_2}{V_1} - \frac{\beta_e (C_i + C_e) x_3}{V_1} + \frac{\beta_e C_i x_4}{V_1} + \frac{\beta_e g_1(x)}{V_1} x_5,\\
&\dot{x}_4 = \frac{\beta_e A_2 x_2}{V_2} + \frac{\beta_e C_i x_3}{V_2} - \frac{\beta_e (C_i + C_e) x_4}{V_2} - \frac{\beta_e g_2(x)}{V_2} x_5,\\
&\dot{x}_5 = \frac{k_v}{\tau_v} u_v - \frac{x_5}{\tau_v},
\end{aligned} \tag{2}$$

$$\begin{aligned}
&g_1(x) = \operatorname{sgn}(\alpha-\beta) C_{d1} W \sqrt{2(\alpha-\beta)/\rho},\\
&g_2(x) = \operatorname{sgn}(\alpha+\gamma) C_{d2} W \sqrt{2(\alpha+\gamma)/\rho},\\
&\alpha = p_s(1+\operatorname{sgn} x_5)/2,\ \beta = x_3 \operatorname{sgn} x_5,\ \gamma = x_4 \operatorname{sgn} x_5,
\end{aligned}$$

where β_e is the effective bulk modulus, C_i and C_e are internal and external leakage coefficients, W is the area gradient of the valve orifice, C_{d1} and C_{d2} are flow discharge coefficients of the spool valve.

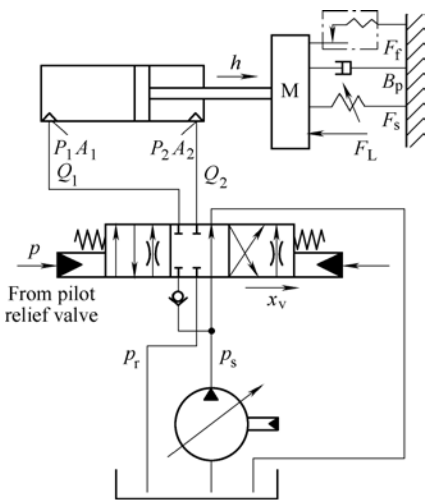


Fig. 4. Valve controlled asymmetric cylinder

Several physical phenomena have been taken into consideration in the mathematic Eq. (2), e.g., nonlinear friction F_f, nonlinear spring force F_s, viscous force F_c, uncertain load F_L, discontinuous flow discharge g_i, oil compliance, internal leakage, and external leakage. However, there are still some unmodeled dynamics like backlash, etc.

The displacement of the hydraulic cylinder is related to the manipulator angle of each excavator arm by the corresponding Jacobian relationships according to the geometrical mapping $g(\cdot)$ of the mechanism[7]. Taking this nonlinear relation into consideration, schematic diagram of the entire system could be depicted as Fig. 5.

2.3 Nonlinear behavior analysis

Open loop experiments were taken to testify the nonlinear characteristics of the electro-hydraulic control system. A group of step excitation tests and a unit of Sine excitation test were implementated on the dipper joint of the electro-hydraulic controlled excavator. The step excitations were 2.7 V, 2.65 V, and 2.6 V. Fig. 6(a) shows that the curves of the angle output are non-linear, which is mainly due to the nonlinear properties of the whole system. Fig. 6(b) shows that the response speed is not proportion to the input values, these deteriorated responses were mainly due to the nonlinear spring and nonlinear friction characteristics.

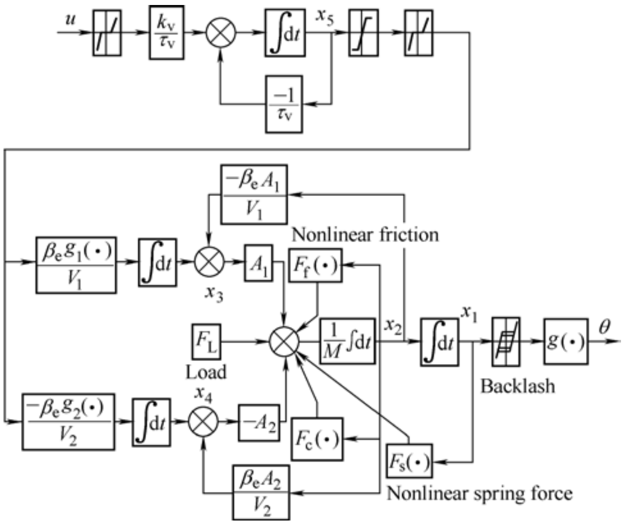
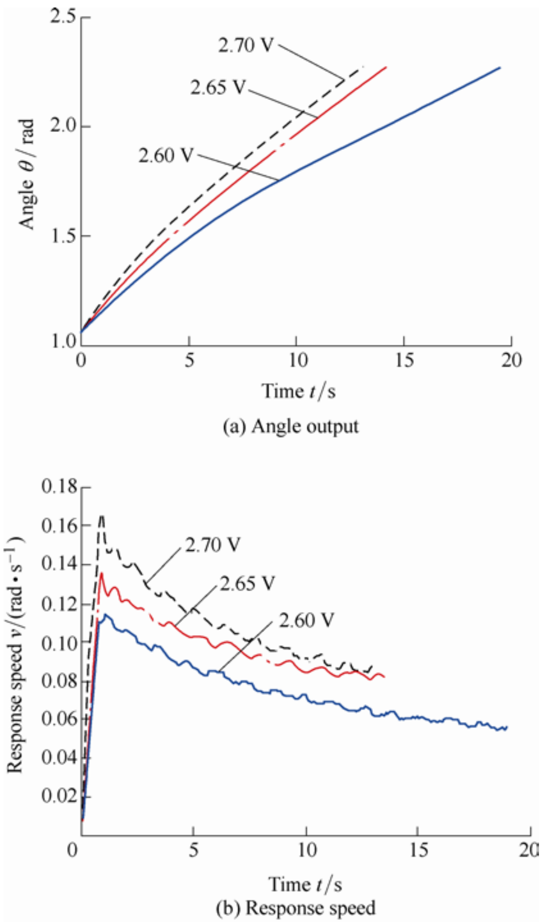


Fig. 5. Schematic diagram of the nonlinear model



(a) Angle output

(b) Response speed

Fig. 6. Comparison results of step responses

As shown in Fig. 7, the angle response to Sine excitation is trending up, i.e. the angle velocity is different at the positive and negative directions, which is mainly due to the asymmetric dynamic property of the system. The angle output is also flat-headed, this is mainly due to the dead band nonlinearity, i.e. the angle velocity is zero when input signal is around the centre point. The angle velocity is distorted which is mainly due to the nonlinear friction and other nonlinear disturbance.

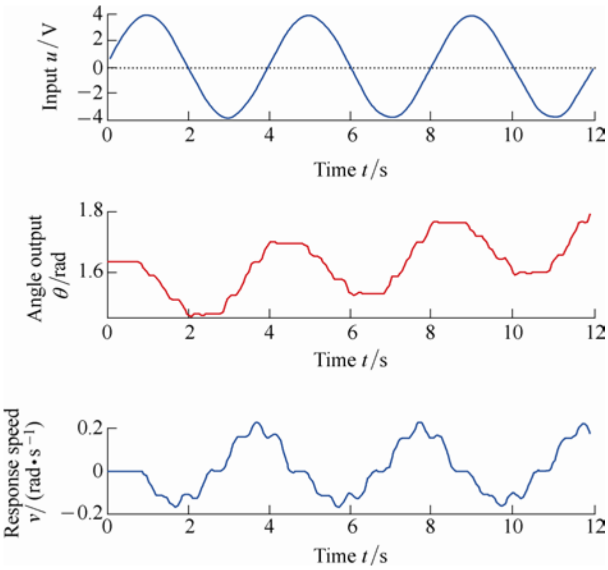


Fig. 7. Open-loop response to the Sine excitation

From the theoretical modeling and filed-test results, we can see that the electro-hydraulic control system of the excavator arm is a highly complicated nonlinear system, which contains the dead band nonlinearity, saturation, squared pressure drop, asymmetric response property, etc. There are some hard-to-model nonlinearities such as nonlinear friction, nonlinear spring force, and uncertain external disturbances, which have significant influence to the responses of open-loop excitations. There are also some unmodeled dynamics such as backlash, et al. So, modeling this system just by physical laws fails to approximate the actual system. Furthermore, identification of the unknown parameters in Eq. (2) is hard due to its demand on internal state measurement. In the following, three BONL models will be adopted to model this complex nonlinear dynamic system based both on physical insight into the actual system and flexibility of the black-box model, and only the input and output data are need for parameter identification.

3 Block-oriented Nonlinear Modeling

When the above-mentioned mathematical modeling approach is insufficient, the ‘universal’ black-box nonlinear model structures like neural networks, fuzzy models, Volterra series, etc, are used frequently[10]. However, these models have little physical insight into the nonlinear characteristics of the actual system which is important for system analyzing, monitoring, diagnosis, and controller design. Nevertheless, the BONL models possess the flexibility to capture all the nonlinear phenomena as well as the physical insight into the actual system.

In this section, the well known Hammerstein model is constructed first, and then the H-W model is built based on the Hammerstein model. Finally, a novel BONL model which we call it Pseudo-Hammerstein-Wiener (P-H-W) model is developed based on the previous two models.

3.1 Description of the Hammerstein and H-W models

The Hammerstein and H-W models are defined by Fig. 8. They are single input, single output discrete time model, so all signals $u(k)$, $w(k)$, $x(k)$, $y(k)$, and $v(k)$ are scalars.

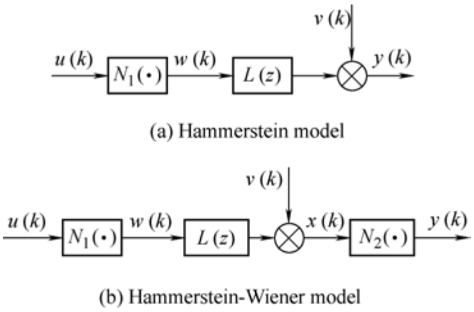


Fig. 8. Hammerstein and H-W models

According to the nonlinearities of the actual system, e.g. dead-band, saturation, nonlinear friction, nonlinear spring force, asymmetric dynamics of the cylinder, the input nonlinearity(N_1) block of the Hammerstein and H-W model are described by a two-segment polynomial nonlinearity. The two-segment nonlinearity has the advantage of describing the systems whose dynamic properties differ significantly for the positive and negative inputs[18], it has less parameters to be estimated than the one described by single polynomial and piecewise linear models. It can be written as

$$w(k)=\begin{cases} f\left(u(k)\right)=\sum\limits_{l=0}^{r} f_l u^l(k), & u(k)\geqslant 0, \\ g\left(u(k)\right)=\sum\limits_{l=0}^{r} g_l u^l(k), & u(k)<0. \end{cases} \tag{3}$$

where $u(k)$ and $w(k)$ denote the input and output of static nonlinear function N_1, respectively, f_l and g_l are unknown parameters of the two-segment polynomial function, r is the degree of the polynomial function.

Define the switching function:

$$h(u)=\begin{cases} 0, & u\geqslant 0, \\ 1, & u<0, \end{cases} \tag{4}$$

then, the relation between inputs $\{u(k)\}$ and outputs $\{w(k)\}$ of the input nonlinearity can be written as

$$w(k)=f\left(u(k)\right)+\left(g\left(u(k)\right)-f\left(u(k)\right)\right)h\left(u(k)\right)= \\ \sum_{l=0}^{r_1} f_l u^l(k)+\sum_{l=0}^{r_1} p_l u^l(k) h\left(u(k)\right), \tag{5}$$

where $p_l=g_l-f_l$.

The linear dynamic block ($L(z)$) is described by a extended auto-regressive(ARX) model as follows:

$$A\left(z^{-1}\right)x(k)=z^{-n_{\mathrm{k}}}B\left(z^{-1}\right)w(k)+v(k), \tag{6}$$

where $w(k)$ and $x(k)$ are the input and output, respectively, $v(k)$ is white noise, n_{k} represents the pure delay of the system, $A(z^{-1})$ and $B(z^{-1})$ are scalar polynomials in the unit delay operator z^{-1}:

$$A\left(z^{-1}\right)=1+a_1 z^{-1}+\cdots+a_{n_{\mathrm{a}}} z^{-n_{\mathrm{a}}}, \tag{7}$$

$$B\left(z^{-1}\right)=b_0+b_1 z^{-1}+\cdots+b_{n_{\mathrm{b}}} z^{-n_{\mathrm{b}}}. \tag{8}$$

The output of Hammerstein model is equal to the output of the linear dynamic block, i.e. $y(k)=x(k)$ for Hammerstein model. The output nonlinear block(N_2) for H-W model is described by a single polynomial as

$$y(k)=q\left(x(k)\right)=\sum_{m=1}^{r_1} q_m x^m(k), \tag{9}$$

where r_1 is the degree of the single polynomial function, q_m is unknown parameter, $y(k)$ is the output of the entire system, in this paper, it represents the angle velocity.

3.2 Backlash model and the P-H-W model

The Hammerstein and H-W models developed above cannot describe the dynamic nonlinearity of backlash which commonly occurs in hydraulic components. According to the physical architecture of the electro-hydraulic control system in this paper (Fig. 5), the output nonlinear function of the H-W model is replaced by a non-smooth backlash function. Generally, the backlash can be described by the architecture shown in Fig. 9.

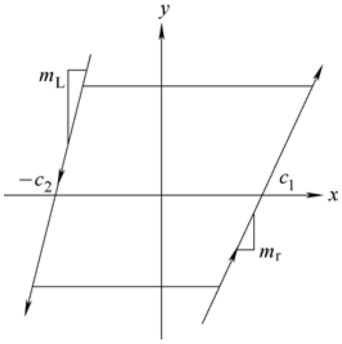


Fig. 9. Description of backlash

Note that the backlash shown in Fig. 9 is specified by the slopes m_r and m_L as well as the absolute thresholds, c_1 and c_2, where $0<m_r<\infty$, $0<m_l<\infty$, $0<c_1<\infty$, and $0<c_2<\infty$. Hence, the discrete-time model of the backlash can be described by non-smooth mapping with memory, i.e.,

$$y(k)=f\left(x(k),y(k-1)\right), \tag{10}$$

where $x(k)$ and $y(k)$ are the input and the output of backlash, respectively.

For the convenience to describe the system, the backlash is supposed to be symmetric, i.e., $m_r=m_L=m$, and $c_1=c_2=c$. In order to simplify the identification procedure, assume $m=1$. Define the internal variable i.e. $y_1(k)$ as

$$\begin{aligned}y_1(k)=x(k)-0.5c\left[\operatorname{sgn}\left(\Delta x(k)\right)+1\right]g_3(k)+\\ 0.5c\left[1-\operatorname{sgn}\left(\Delta x(k)\right)\right]g_4(k),\end{aligned} \tag{11}$$

where $\Delta x(k)=x(k)-x(k-1)$, sgn(·) is the sign function, both $g_3(k)$ and $g_4(k)$ are the switching functions, respectively, defined by

$$g_3(k)=\begin{cases}0, & y(k-1)+c\geqslant x(k),\\ 1, & y(k-1)+c<x(k),\end{cases}$$

and

$$g_4(k)=\begin{cases}0, & y(k-1)-c\leqslant x(k),\\ 1, & y(k-1)-c>x(k),\end{cases}$$

Hence, the output $y(k)$ of the backlash can be rewritten as

$$y(k)=y_1(k)+\left[y(k-1)-y_1(k)\right]\left[g_3(k)-1\right]\left[g_4(k)-1\right]. \tag{12}$$

The P-H-W model for the system can be depicted by Fig. 10.

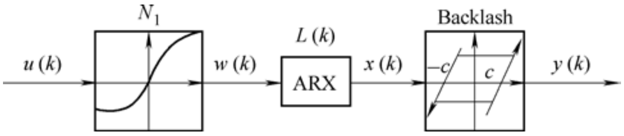


Fig. 10. Block diagram of the P-H-W model

4 Recursive Identification Method

In section 3, the static nonlinear blocks, linear dynamic block and backlash block in discrete time are developed for the Hammerstein, H-W, and P-H-W models, respectively. Combining the mathematic model of each block in series leads to composite mappings models which are strongly nonlinear both in the variables and in the unknown parameters, hence not appropriate for parameter estimation. In this section, A special decomposition technique is proposed for the composite mappings based on the so-called key term separation principle[19]. The BONL models are decomposed to be special form of models with linear coefficients combining with nonlinear variables. Hence, the parameters estimation can be treated as a quasi-linear problem using an modified iterative algorithm with internal variable estimation, similarly as in Ref[20].

The similar approach was proposed for Hammerstein and H-W models in Refs. [12], [21], respectively. However, the application of the proposed approach to P-H-W with memory hard nonlinearity is a more challenging problem. In the following, the aforementioned approach will be used to simplify the description of P-H-W model and the estimation of the corresponding model parameters.

4.1 Decomposition of the P-H-W model

According to the above-mentioned decomposition technique, and assuming that $b_0=1$(this is always possible in the given model), Eq. (6) can be rewritten as

$$\begin{aligned}x(k)=b_0w(k)z^{-n_k}+z^{-n_k}\left[B\left(z^{-1}\right)-b_0\right]w(k)+\\ \left[1-A\left(z^{-1}\right)\right]x(k).\end{aligned} \tag{13}$$

After choosing $w(k)$ as the key term, then substituting Eq. (5) only for the separated key term in Eq. (13), the output of Hammerstein model will be

$$\begin{aligned}x(k)=\sum_{l=0}^{r}f_lu^l\left(k-n_k\right)+\sum_{l=0}^{r}p_lu^l\left(k-n_k\right)h\left(u\left(k-n_k\right)\right)+\\ \sum_{i=1}^{n_b}b_iw\left(k-n_k-i\right)+\sum_{j=1}^{n_a}a_jx\left(k-j\right).\end{aligned} \tag{14}$$

By substituting Eq. (14) for the first term in the right side of Eq. (11), then substitute the new Eq. (11) into Eq. (12) to arrive at

$$\begin{aligned}y(k)=\sum_{l=0}^{r}f_lu^l\left(k-n_k\right)+\sum_{l=0}^{r}p_lu^l\left(k-n_k\right)h\left(u\left(k-n_k\right)\right)+\\ \sum_{i=1}^{n_b}b_iw\left(k-n_k-i\right)+\sum_{j=1}^{n_a}a_jx\left(k-j\right)-\\ 0.5c\left[\operatorname{sgn}\left(\Delta x(k)\right)+1\right]g_3(k)+\\ 0.5c\left[1-\operatorname{sgn}\left(\Delta x(k)\right)\right]g_4(k)+\\ \left[y(k-1)-y_1(k)\right]\left(g_3(k)-1\right)\left(g_4(k)-1\right).\end{aligned} \tag{15}$$

Up to now, the P-H-W model described by Eq. (15) is decomposed into a special forms being linear in all of the model parameters except for parameter c. To make the parameter identification adapt for least square method, define $y_c(k)$ as the adjusted output of the model:

$$y_c(k) = y(k) - [y(k-1) - y_1(k)](g_3(k)-1)(g_4(k)-1), \tag{16}$$

then Eq. (16) can be re-arranged as

$$y_c(k) = \boldsymbol{\Phi}^T(k) \bullet \boldsymbol{\theta}, \tag{17}$$

where $\boldsymbol{\Phi}(k)$ denotes the data vector, i.e.,

$$\begin{aligned}\boldsymbol{\Phi}(k) = [&1, u(k-n_k), \cdots, u^r(k-n_k), h(u(k-n_k)),\\ &u(k-n_k)h(u(k-n_k)), \cdots, u^r(k-n_k)h(u(k-n_k)),\\ &w(k-n_k-1), \cdots, w(k-n_k-i), x(k-1), \cdots, x(k-j),\\ &0.5\{(1-\mathrm{sgn}(\Delta x(k)))g_4(k) - (1+\mathrm{sgn}(\Delta x(k)))g_3(k)\}]^{\mathrm{T}},\end{aligned} \tag{18}$$

and $\boldsymbol{\theta}$ represents the parameter vector, i.e.,

$$\boldsymbol{\theta} = (f_0, f_1, \cdots, f_r, p_0, p_1, \cdots, p_r, b_1, \cdots, b_{n_b}, a_1, \cdots a_{n_a}, c). \tag{19}$$

Note that the input $u(k)$ and output $y(k)$ can be measured directly, but the internal variables $x(k)$, $w(k)$ and $y_1(k)$ as well as the switching functions $g_3(k)$ and $g_4(k)$ are not measurable which need to be estimated based on the preceding estimates of model parameters.

4.2 Modified recursive least square algorithm

The estimates of the parameter vector of Eq. (17) can be evaluated using a modified recursive least square algorithm (MRLSA) with the estimation of internal variables. Suppose the MRLSA is to minimize the following quadratic criterion:

$$\hat{\boldsymbol{\theta}}(k) = \arg\min_{\theta} \sum_{k=1}^{n} \lambda^{n-k} \left[\hat{y}_c(k) - \hat{\boldsymbol{\Phi}}^T(k)\hat{\boldsymbol{\theta}}(k-1)\right]^2, \tag{20}$$

where $0<\lambda\leqq 1$ is the forgetting factor, the data vector $\boldsymbol{\Phi}(k)$ and the adjusted output $y_c(k)$ are respectively replaced by the corresponding $\hat{y}_c(k)$ and $\hat{\boldsymbol{\Phi}}(k)$, n is the length of the date set.

The MRLSA supplemented with the internal variables estimation is summarized as follows:

$$\hat{\boldsymbol{\theta}}(k) = \hat{\boldsymbol{\theta}}(k-1) + \boldsymbol{K}(k)\left[\hat{y}_c(k) - \hat{\boldsymbol{\Phi}}^T(k)\hat{\boldsymbol{\theta}}(k-1)\right], \tag{21}$$

$$\boldsymbol{K}(k) = \frac{\boldsymbol{P}(k-1)\hat{\boldsymbol{\Phi}}(k)}{\lambda + \hat{\boldsymbol{\Phi}}^T(k)\boldsymbol{P}(k-1)\hat{\boldsymbol{\Phi}}(k)}, \tag{22}$$

$$\boldsymbol{P}(k) = \frac{1}{\lambda}\left[\boldsymbol{I} - \boldsymbol{K}(k)\hat{\boldsymbol{\Phi}}^T(k)\right]\boldsymbol{P}(k-1), \tag{23}$$

$$\hat{w}(k) = \sum_{l=0}^{r} \hat{f}_l(k-1)u^l(k) + \sum_{l=0}^{r} \hat{p}_l(k-1)u^l(k)h(u(k)), \tag{24}$$

$$\hat{x}(k) = \sum_{j=0}^{n_b} \hat{b}_j(k-1)\hat{w}(k-q-j) - \sum_{i=1}^{n_a} \hat{a}_i(k-1)\hat{x}(k-i), \tag{25}$$

$$\begin{aligned}\hat{y}_1(k) = \hat{x}(k) - 0.5\hat{c}(k-1)[\mathrm{sgn}(\Delta\hat{x}(k))+1]\hat{g}_3(k) +\\ 0.5\hat{c}(k-1)[1-\mathrm{sgn}(\Delta\hat{x}(k))]\hat{g}_4(k),\end{aligned} \tag{26}$$

$$\hat{y}_c(k) = y(k) - [y(k-1) - \hat{y}_1(k)](\hat{g}_3(k)-1)(\hat{g}_4(k)-1), \tag{27}$$

$$\begin{aligned}\hat{\boldsymbol{\theta}}(k-1) = [&\hat{f}_0(k-1), \hat{f}_1(k-1), \cdots, \hat{f}_r(k-1),\\ &\hat{p}_0(k-1), \hat{p}_1(k-1), \cdots, \hat{p}_r(k-1),\\ &\hat{b}_1(k-1), \cdots, \hat{b}_{n_b}(k-1),\\ &\hat{a}_1(k-1), \cdots \hat{a}_{n_a}(k-1), \hat{c}(k-1)],\end{aligned} \tag{28}$$

$$\begin{aligned}\hat{\boldsymbol{\Phi}}(k) = [&1, u(k-n_k), \cdots, u^r(k-n_k), h(u(k-n_k)),\\ &u(k-n_k)h(u(k-n_k)), \cdots, u^r(k-n_k)h(u(k-n_k)),\\ &\hat{w}(k-n_k-1), \cdots, \hat{w}(k-n_k-i), \hat{x}(k-1), \cdots, \hat{x}(k-j),\\ &0.5\{(1-\mathrm{sgn}(\Delta\hat{x}(k)))\hat{g}_4(k) - (1+\mathrm{sgn}(\Delta\hat{x}(k)))\hat{g}_3(k)\}]^{\mathrm{T}},\end{aligned} \tag{29}$$

where $\boldsymbol{P}(0)=\mu\boldsymbol{I}$, $0<\mu<\infty$;

$$\hat{g}_3(k) = \begin{cases} 0, & y(k-1) + \hat{c}(k-1) \geqslant \hat{x}(k),\\ 1, & y(k-1) + \hat{c}(k-1) < \hat{x}(k); \end{cases} \tag{30}$$

$$\hat{g}_4(k) = \begin{cases} 0, & y(k-1) - \hat{c}(k-1) \leqslant \hat{x}(k),\\ 1, & y(k-1) - \hat{c}(k-1) > \hat{x}(k). \end{cases} \tag{31}$$

In conclusion, the MRLSA can be presented as follows:

Step 1: Set the initial values of $x(0)$, $w(0)$, $u(0)$, $y_1(0)$, $\boldsymbol{K}(0)$ and $\boldsymbol{P}(0)$.

Step 2: Estimate the parameter $\hat{\boldsymbol{\theta}}(k)$ by Eq. (21), and calculate $\boldsymbol{K}(k)$ and $\boldsymbol{P}(k)$ by Eq. (22), Eq. (23), respectively.

Step 3: Estimate the internal variables $\hat{w}(k)$, $\hat{x}(k)$ and $\hat{y}_1(k)$, by Eq. (24), Eq. (25) and Eq. (26), respectively, using the recent estimates of model parameters $\hat{\boldsymbol{\theta}}(k)$.

Step 4: Update the values of $\hat{y}_c(k)$, $\hat{\boldsymbol{\theta}}(k)$ and $\hat{\boldsymbol{\Phi}}(k)$ by Eq. (27), Eq. (28) and Eq. (29), respectively.

Step 5: Return to step 2 until the parameter estimates converge to constant values.

5 Experiment Results

The experiments were performed on the dipper joint of the experiment excavator shown in Fig. 1. In order to obtain the steady-state characteristics of the system when changing the directions, and to obtain sufficient excitation, the multi-sine input which contained the frequency of 0.1 Hz, 0.2 Hz, 0.4 Hz, 0.5 Hz and 1 Hz was employed. The input signal and angle output were sampled at a frequency of 100 Hz for a time duration of 50s, which was good enough for the identification of electro-hydraulic system on the experimental excavator. First order low-pass filters with a cutoff frequency of 10 Hz were used to remove sensor noise. The same test was repeated 10 times, and the angle outputs were averaged, then the angle velocity output was calculated by numerical differentiation.

Note that lower forgetting factor λ is useful for reducing the influences of old date, while a value of λ close to 1 is less sensitive to disturbance. Therefore, the forgetting factor is chosen to be λ=0.98 during the first 200 samples, and λ=1 otherwise. Generally, a third-order linear dynamic model is shown to be flexible enough to approximate the electro-hydraulic servo systems moving around operation point[4]. So, we set the variables to be n_a=3, n_b=2, n_k=8, r_1=r=3. The initial variables are respectively chosen as $x(0)=0$, $w(0)=0$, $y_1(0)=0$, $y_c(0)=0$, $u(0)=0$, $c(0)=0.01$, $\boldsymbol{K}(0)=0$, and $\boldsymbol{P}(0)=10^6\boldsymbol{I}$. The identification results shown in Table 1 were obtained by applying the MRLSA to the ARX model, Hammerstein model[12], H-W model[21], and P-H-W model, respectively,

Table 1. Identification results

Parameter	Identified model			
	P-H-W	H-W	Hammerstein	ARX
b_0	1	1	1	−0.027 6
b_1	0.031 5	0.034 9	0.010 5	0.012 4
b_2	0.029 5	0.061 7	0.014 7	0.051 4
a_1	−0.035 7	−0.030 9	−0.059 6	−0.066 1
a_2	−0.035 0	−0.059 8	−0.061 3	−0.065 3
a_3	−0.040 4	−0.089 7	−0.061 0	−0.061 9
f_0	0.013 2	0.010 9	0.002 7	
f_1	−0.004 2	$-1.461\,9\times10^{-5}$	0.001 2	
f_2	−0.011 1	−0.005 0	−0.001 2	
f_3	0.008 5	0.005 2	0.004 5	
p_0	−0.012 1	−0.016 5	−0.005 5	
p_1	0.004 0	0.003 3	0.001 3	
p_2	0.005 9	0.010 4	0.003 6	
p_3	−0.006 2	−0.001 0	$-8.685\,8\times10^{-4}$	
q_1		1		
q_2		0.005 0		
q_3		$6.356\,2\times10^{-4}$		
c	0.122 6			

The identified models were used to predict the tracking velocity of a general trajectory, and the comparison results are shown in Fig. 11 and Fig. 12. Fig. 11 shows that the three BNOL models which contain the input nonlinear block with two-segment polynomial have derived satisfactory results, while the ARX model cannot approximate the real system well. The comparison of the estimation residua shows in Fig. 12 demonstrates that the P-H-W model with backlash nonlinearity has the best prediction accuracy. The mean-square error (MSE) of the identified models in Table 2 demonstrates that the prediction error of the P-H-W model is about 14%, 30% and 75% less than the H-W, Hammerstein, and ARX models.

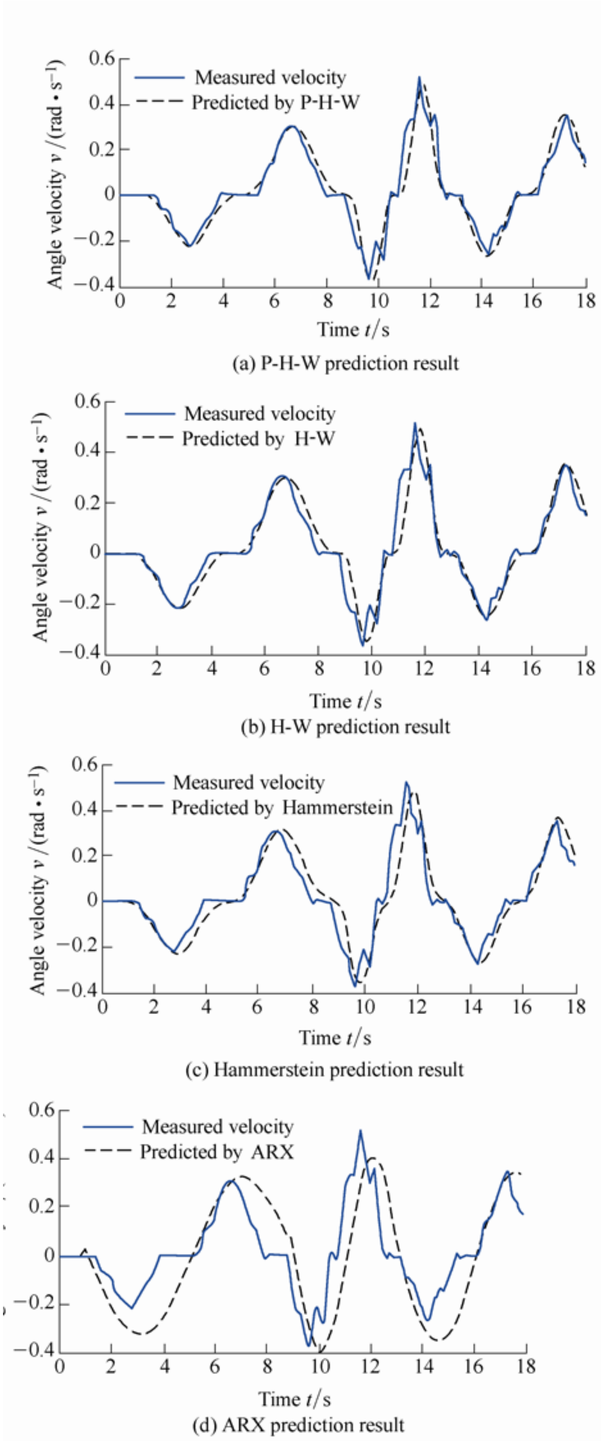


Fig. 11. Comparison results of the identified models

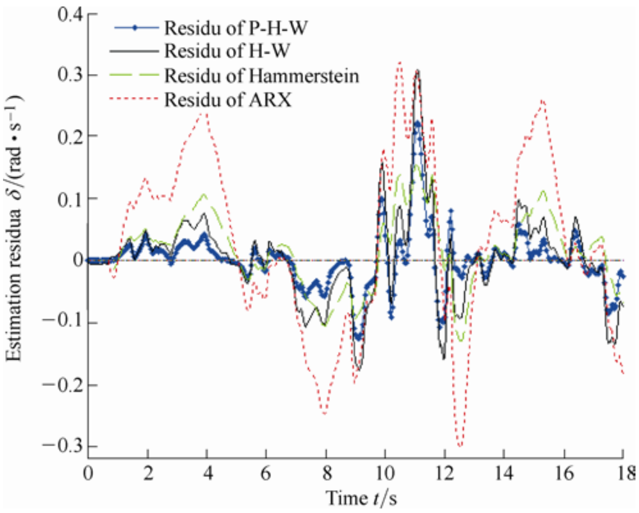


Fig. 12. Comparison of the estimation residua

Table 2. MSE of the identified models

Error	Identified model			
	P-H-W	H-W	Hammerstein	ARX
$\delta/(\mathrm{r}\cdot\mathrm{s}^{-1})$	0.028 9	0.033 4	0.041 5	0.113 6

6 Conclusions

In order to improve tracking performance, modeling and identification of electro-hydraulic control system of an excavator arm is investigated. The theoretical model is developed and filed tests are carried out to analyze the nonlinear characteristics of the system. Three BONL models are proposed to model the complex nonlinear system based on the physic insight into the actual system, and a modified least square method with internal variables estimation is applied to identify the BONL models. There are following main conclusions:

(1) The prototype system is a highly complicated nonlinear system which is hard to model. The developed state space model is hard to identify due to its demand on the measurement of state variables.

(2) The developed BONL models are given by the cascade connection of linear dynamic blocks, static nonlinearity blocks, and backlash blocks, which leads to composite mappings. The so-called key term separation principle is employed to decompose the models into linear-in-parameters structures, and then the MRLSA with internal variables estimation is employed to identify all of the model parameters simultaneously. The model parameters' estimation is carried out only with records of measured input/output data.

(3) The comparison results show that the BLON models with nonlinear static blocks containing the two-segment nonlinearity capture the nonlinear dynamics of the system well while the ARX model cannot approximate the actual system. The P-H-W model with backlash output has the best prediction accuracy, and the prediction error of the P-H-W model is about 14%, 30% and 75% less than the H-W, Hammerstein, and ARX model.

Note that iterative algorithm is applied in this paper, which can be used in algorithms of adaptive control. Our future work will concern the adaptive control of excavator arm based on the BONL models.

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