NONLINEAR SYSTEM IDENTIFICATION WITH SHORTAGE OF INPUT-OUTPUT DATA

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Abstract: A system identification method for nonlinear systems with unknown structure by means of short input-output data is proposed. This method introduces more general model structure for nonlinear systems. Moreover, based on gray-box idea and its salient feature with expanding NARMAX (Nonlinear Autoregressive, Moving Average eXogenous) modeling, this method integrates different system information. Then GMDH (Group Method of Data Handling) method is employed to obtain the model terms and parameters. Effectiveness of the proposed method is illustrated by a typical nonlinear system with unknown structure and short input-output data.

Keywords: System identification, Nonlinear system, ARMA models, Information integration, Parameter estimation.

1. INTRODUCTION

Simple linear system models are used extensively in practice, but they are limited in nonlinear system with a dominant nonlinear behaviour. As a number of systems are characterized by nonlinear behaviors, many researchers were focused on nonlinear models developments in order to improve the accuracy and performances of models of nonlinear systems. There exist several mathematical representations describing nonlinear systems, such as the Hammer-stein model (Narendra, *et al*., 1966), the Wiener model (Ljung, 1999), the feedback block-oriented model (Pottmann, *et al*., 1988), exponential time series models (Ozaki, 1985), trigonometric and rational models (Billings and Chen, 1989), etc. For highly nonlinear processes, Eykhoff (1974) introduced a general discrete time model, Kolmogorov-Gabor polynomial model. A stochastic version was developed by Leontarities and Billings (1985). Moreover, GMDH method presented by Ivakhnenko (1971) is attractive and it employs the Ivakhnenko polynomial model to identify nonlinear system. Other selection techniques of the significant terms have also been proposed in (Kortmann and Unbehauen, 1988; Pottmann, *et al*., 1993; Boutayeb, *et al*., 1998). Most identification methods (Narendra, *et al*., 1966; Ljung, 1999; Pottmann, *et al*., 1988; Ozaki, 1985; Billings and Chen, 1989; Eykhoff, 1974; Leontarities and Billings, 1985; Ivakhnenko, 1971; Boutayeb, *et al*., 1998) have the salient feature in certain condition that each of them can be used in the system with similar dynamic behaviours.

Among the above identification methods, NARMAX model (Leontarities and Billings, 1985) is the generalized nonlinear system form. However, the number of estimated parameters in NARMAX model is so large that sometimes the identification result is inaccurate. Although the identification method of nonlinear system via Boutayeb, et al. (1998) can reduce the computational requirements to some degree, it is still very time consuming. Neural networks is proposed and become universal approximators in nonlinear system identification (Qin, *et al*., 1992; Sjöberg, *et al*., 1995; Burke and Ignizio, 1997). Nevertheless, neural networks can only resolve existing problems for nonlinear function approximation (Sjöberg, et *al*., 1995; Burke and Ignizio, 1997). Schoukens, *et al*. (2003) presented a new identification method for nonlinear system with a dominant linear behavior and it can fast identify system at a low experimental cost instead of obtaining the best possible nonlinear model. Moreover, GMDH method (Ivakhnenko, 1971) is attractive for system identification, however it has the same problem with NARMAX method that has a large number of estimated parameters. Generally, although there are various identification methods for nonlinear systems with known structure (Ljung, 1999), there lack general and efficient methods for system identification with unknown system structure from short input-output data. Especially, it is necessary when a model is needed to approximate the actual system mechanism and measurements without known structure. Thus, a new identification method for nonlinear system with unknown structure by short input-output data is of importance.

The aim of this paper is to model nonlinear systems with a dominant nonlinear behavior, approximating system mechanism and at the same time obtaining good measurements approximation. In the idea of exponential-trigonometric generalization, polynomial NARMAX model is modified. And GMDH method is used to estimate the parameters of the proposed model structure. The rest of the paper is organized as follows. Section 2 is dedicated to the presentation of the proposed model structure. In Section 3 the method of structure identification and parameters estimation is described. In Section 4 the proposed method is applied to a typical nonlinear system with unknown system structure and short input-output data. Finally, we make some conclusion in Section 5.

2. MODEL STRUCTURE

According to Leontarities and Billings (1985), NARMAX structure is a general parametric form for nonlinear systems. This structure describes both the stochastic and deterministic components of a system.

A NARMAX structure (Leontarities and Billings, 1985) models the input-output relationship as a nonlinear difference equation of the form

$$y(k) = F^l(y(k-1),\ldots,y(k-n_y),u(k-d),\ldots, u(k-d-n_u+1),e(k),\ldots,e(k-n_e)) \quad (1)$$

where n_y, n_u and n_e are the maximum lags for output, input and noise terms, respectively; d is the delay measured in sampling intervals, T_s; $u(k)$ and $y(k)$ are the input and output data respectively; $e(k)$ accounts for uncertainties, possible noise, unmodelled dynamics etc; $F^l(\cdot)$ is a nonlinear function of $y(k)$, $u(k)$ and $e(k)$, and the popular function of $F^l(\cdot)$ is a polynomial-type with nonlinearity degree $l \in Z^+$.

A multi-dimensional polynomial NARMAX with output r and input s can be modelled as

$$y_t(k) = \theta_0^t + \sum_{i_1=1}^{m}\theta_{i_1}^t p_{i_1}(k) + \sum_{i_1=1}^{m}\sum_{i_2=i_1}^{m}\theta_{i_1,i_2}^t p_{i_1}(k)p_{i_2}(k) + \cdots + \sum_{i_1=1}^{m}\cdots\sum_{i_l=i_l-1}^{m}\theta_{i_1,\cdots,i_l}^t \times p_{i_1}(k)\cdots p_{i_l}(k) + e_k(k), \quad t=1,\ldots r \quad (2)$$

where

$$p_1(k) = y_1(k-1), \quad p_2(k) = y_1(k-2),\ldots \quad (3, 4)$$

$$p_{r\times n_y}(k) = y_r(k-n_y), \quad p_{r\times n_y+1}(k) = u_1(k),\ldots \quad (5, 6)$$

$$p_{r\times n_y+s\times(n_u+1)}(k) = u_s(k-n_u),\ldots \quad (7)$$

$$p_{r\times n_y+s\times(n_u+1)+1}(k) = e_1(k-1),\ldots \quad (8)$$

Here $y_t(k)$ is the output at time(or sample number) k for the tth degree of freedom, $u_t(k)$ is the input of the tth degree of freedom at time t, $e_t(k)$ is the prediction error at time t for the tth degree of freedom, and $m = (r\times(n_y+n_e) + s\times(n_u+1))$.

If a nonlinear system with dominant behaviour is modelled by (2), the values of n_y, n_u and n_e are assumed to be very large to approximate the factual system. Although computers are enough advanced to resolve the approximation, error resulted by the complex computation can lead to bad result. In order to reflect the factual system structure more accurately, the NARMAX model structure (2) is modified.

Here, nonlinear multi-input-single-output systems are considered, thus (2) becomes

$$y(k) = \theta_0 + \sum_{i_1=1}^{m}\theta_{i_1} p_{i_1}(k) + \sum_{i_1=1}^{m}\sum_{i_2=i_1}^{m}\theta_{i_1,i_2} p_{i_1}(k)p_{i_2}(k) + \cdots + \sum_{i_1=1}^{m}\cdots\sum_{i_l=i_l-1}^{m}\theta_{i_1,\cdots,i_l} p_{i_1}(k)\cdots p_{i_l}(k) + e(k) \quad (9)$$

Here, $m=(n_y+n_e+s\times(n_u+1))$. Considering only two nonlinear terms of NARMAX, (9) reduces to

$$y(k) = \theta_0 + \sum_{i_1=1}^{m}\theta_{i_1} p_{i_1}(k) + \sum_{i_1=1}^{m}\sum_{i_2=i_1}^{m}\theta_{i_1,i_2} p_{i_1}(k)p_{i_2}(k) + e(k) \quad (10)$$

And can thus be transferred to

$$y(k) = \theta_0 + \sum_{i_1=1}^{m}\theta_{i_1} g_{i_1}(p_{i_1}(k)) + \sum_{i_1=1}^{m}\sum_{i_2=i_1}^{m}\theta_{i_1,i_2} \times g_{m+i_1+2i_2-2}(p_{i_1}(k))g_{m+i_1+2i_2-1}(p_{i_2}(k)) + e(k) \quad (11)$$

where $g(\cdot)$ is the function of $y(k)$, $u(k)$ and $e(k)$; the total unknown numbers of $g(\cdot)$ are (m^2+2m).

Considering the exponential-trigonometric generalization, typical functions of $g(\cdot)$ always take the forms

$$g_i(x) \in \{a_i + \sin^{b_i}(x), \frac{a_i}{1+b_i\exp(-x)}, a_i + b_i x\} \quad (12)$$

In (10), there is a term θ_0 and corresponding coefficients. So function $g_i(\cdot)$ can be adjusted to more simple form as follows.

$$g_i(x) \in \left\{\sin(x),\ \frac{1}{1+\exp(-x)},\ x\right\} \quad (13)$$

Thus, the number of estimated parameters is reduced without changing the form of (10).

Compared with the original polynomial NARMAX model structure, the MP-NARMAX (modified polynomial NARMAX) model structure has fewer unknown parameters, which reduces identification complexity to a great extent. Therefore, good measurements approximation can be achieved. And the most important is the good approximation of system structure. As a result, the approximation ability of the factual system is improved greatly.

3. STRUCTURE IDENTIFICATION

With the obtaining of the general model structures of nonlinear system, the next step is to determine the model terms and model orders, and estimate the unknown parameters.

3.1 Integration of Information Sources

In order to obtain the best estimated model of the actual system mechanism and the system input-output behavior, different information sources are used. Four types of information sources are considered in this paper, and they are prior theory, measurements, expert experience, and researchers' extense experience.

Considering the complexity of nonlinear system with dominant behaviour, generally, prior theory is not so accurate, expert experience is also hard to collect and use. So much attention should be paid to the available measurements and our researchers' experience.

The believable degrees of information sources are suggested and given in Fig.1. The believable degree for each information source is an approximate scope, and it should be determined via simulation. According to the analysis of information sources, a more real model structure can be constructed. And it can also provide relative right measurements for structure identification.

Moreover, according to Pearson (1995), in taking the approach of nonlinear input-output data modeling, the primary focus is on goodness of fit. In practice, it is important to note that other criteria may be of equal or greater importance. For example, an extremely important related issue is the sensitivity of the model prediction errors to change in the problem formulation. This issue has two aspects: the sensitivity of the algorithms used for model identification to errors in the data, and the region of validity of the model as an approximation of some factual systems.

So, even measurements has a high believable degree, estimation is still necessary to get proper values of the unmerited data by major observation and minor induction from the believable degrees of measurements when pretreat measurements.

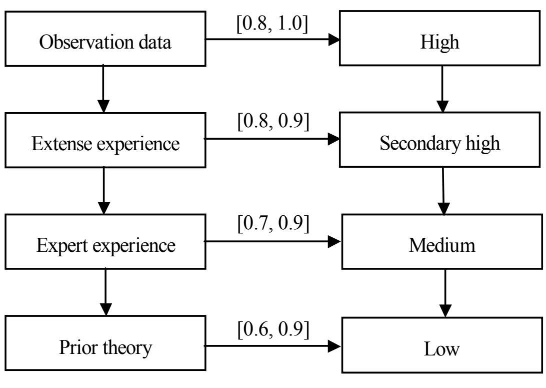


Fig.1. The believable degrees of information sources

Look for the outliers by plotting the measurements because of the complex nonlinearity and the shortage of the measurements.

Although the believable degrees of measurements are not the same, the original Least-squares (LS) method instead of weighted least-square (WLS) method is employed to identify system because of the complex nonlinearity and the shortage of the measurements.

3.2 Structure Identification

Here, GMDH (Ivakhnenko, 1971) method is used to identify MP-NARMAX model structure.

Ivakhnenko (1971) models the input-output relationship of a complex system by using a multilayered perception-type network structure. Each element in the network implements a nonlinear function of its inputs. The function is usually a second-order polynomial of the inputs and it implemented by an element in one of the layers is

$$A_2(x) = a_0 + a_1x_1 + a_2x_2 + a_3x_1^2 + a_4x_2^2 + a_5x_1x_2 \quad (14)$$

where the subscript in $\boldsymbol{A_2}$ denotes a second-order transformation of the inputs. Fig.2. illustrates the structure of the overall input-output transformation.

Here, by (14) GMDH method is used to estimate the unknown parameters in the modelled structures.

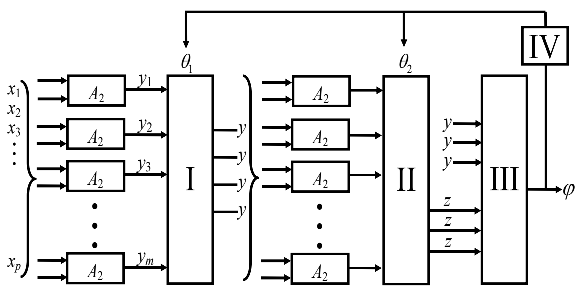
3.3 Identification Procedure

In this Section GMDH method is described to estimate the parameters of the MP-NARMAX model.

The basic steps of GMDH method to calculate the MP-NARMAX model parameters are as follows:

Step (1) Partition the data with the first N rows designated as the training set and the remaining rows as the testing set. In this paper, just assume the quadratic nonlinear terms are 1 and both the lags of the input and output of nonlinear terms are 1, since the case with shortage of measurements is considered.

From the training set, a matrix of N observations of MP-NARMAX model terms is formed like the ones in (15) shown below that ignore the prediction error terms $e(N)$ in (11).



Algorithm of GMDH method using second-degree polynomials. **I**–first threshold self-selection; **II**–second threshold self-selection; **III**–selection from all solutions; **IV**–threshold optimization.

Fig.2. The GMDH structure

$$
\begin{aligned}
&y(k) = [g_1(y(k-1)), g_2(y(k-2)), \ldots, g_{n_y}(y(k-n_y)), g_{n_y+1}(u_1(k)), g_{n_y+2}(u_1(k-1)), \ldots, \\
&\quad g_{n_y+n_u+1}(u_1(k-n_u)), \ldots, g_{n_y+(s-1)\times(n_u+1)+1}(u_s(k)), g_{n_y+(s-1)\times(n_u+1)+2}(u_s(k-1)), \ldots, g_{n_y+s\times(n_u+1)}(u_s(k-n_u)), \\
&g_{n_y+s\times(n_u+1)+1}(y(k-1)) g_{n_y+s\times(n_u+1)+2}(u_1(k)), g_{n_y+s\times(n_u+1)+3}(y(k-1)) g_{n_y+s\times(n_u+1)+4}(u_1(k-1)), \ldots, \\
&\quad g_{n_y+s\times(n_u+1)+4\times s-3}(y(k-1)) g_{n_y+s\times(n_u+1)+4\times s-2}(u_s(k)), g_{n_y+s\times(n_u+1)+4\times s-1}(y(k-1)) g_{n_y+s\times(n_u+1)+4\times s}(u_s(k-1)), \\
&\quad g_{n_y+s\times(n_u+1)+4\times s+1}(y(k-2)) g_{n_y+s\times(n_u+1)+4\times s+2}(u_1(k)), g_{n_y+s\times(n_u+1)+4\times s+3}(y(k-2)) g_{n_y+s\times(n_u+1)+4\times s+4}(u_1(k-1)), \ldots, \\
&\quad g_{n_y+s\times(n_u+1)+4\times s+1+4\times(s-1)}(y(k-2)) g_{n_y+s\times(n_u+1)+4\times s+4+4\times(s-1)+2}(u_s(k)), \\
&\quad g_{n_y+s\times(n_u+1)+4\times s+3+4\times(s-1)}(y(k-2)) g_{n_y+s\times(n_u+1)+4\times s+4+4\times(s-1)}(u_s(k-1)), \\
&g^2_{n_y+s\times(n_u+1)+8s+1}(y(k-1)), g^2_{n_y+s\times(n_u+1)+8s+2}(y(k-2)), g^2_{n_y+s\times(n_u+1)+8s+3}(u_1(k)), \ldots, g^2_{n_y+s\times(n_u+1)+8s+3+s-1}(u_s(k)), \\
&\quad g^2_{n_y+s\times(n_u+1)+9s+2+1}(u_1(k-1)), \ldots, g^2_{n_y+s\times(n_u+1)+9s+2+s}(u_s(k-1))], \qquad k = 1, 2, \ldots, N
\end{aligned}
$$

Matrix **R** (15)

Here considering the shortage of the measurements, select as much samples as possible, and these measurements selected for training need be pretreated. Also, with respect to the analysis of robustness, the remaining measurements are purposely made for test non-pretreated data.

Step (2) Take all variables in the columns of Matrix $\mathbf{R}\{g_1(y(k-1), \ldots, g_{n_y}(k-n_y), g_{n_y+1}(u_1(k)), \ldots\}$ two columns at a time and for each of these $s(s-1)/2$ combinations find the RLSE regression that best fits the observation (vector) **Y**'s. Here, s is the total number of input variables. For each of the combinations evaluate the least squares of the N data points. After evaluating N values, store these N values in the first column of a new array **Z**.

The remaining ($s(s-1)/2-1$) columns are constructed in a similar manner. The array **Z** contains the new variables, which replace the original variables. The objective is to retain those **Z**'s that best estimate the output vector **Y** and the insignificant variables. To determine which columns of **Z** replace the old variables in the matrix **R**, select the Mean Squares Errors (MSE) criteria and calculate MSE d_j

$$d_j = \sum_{i=1}^{N} (y_i - z_{ij})^2 \Big/ N, \quad j = 1, 2, \ldots, s(s-1)/2 \quad (16)$$

And order the columns of **Z** according to increasing LS by the data of testing set. One can place a restriction as to some prescribed number of new variables to replace the old variables in the matrix **R**, i.e., $d_j < M$, where M is some prescribed number.

Step (3) From Step (2) takes the smallest of the d_j. The value of d_j is smaller than the previous d_j (in the first iteration this is assumed to be true) go back and repeat steps (2) and (3). If the value of d_j is greater than the previous d_j stop the process. It is our observation, however, that the value of d_j becomes smaller than the previous d_j as the number of iterations is increased.

Step (4) Calls for LS method to find the coefficients of the retained variables.

4. AN EXAMPLE

In this Section, the proposed MP-NARMAX-GMDH method is applied to model radar-land-clutter reflectivity (RLCR). The RLCR at low grazing angle owes complex nonlinearity to its dependence on many parameters (Skolnik, 1990; Long, 1975; Barton, 1988). And the information about RLCR is hard to collect and organize. Considering the importance of RLCR model in engineering, it is necessary to model RLCR accurately.

4.1 Integration of Information Sources

- **Prior Theory**

Referring to literatures (Skolnik, 1990; Long, 1975; Barton, 1988), RLCR mainly relates to radar frequency, terrain type, grazing angle and polarization. From Barton (1988), the available RLCR data are summarized, and they can provide a good base for performance prediction of common radar. According to Blake (1980), polarization has no influence on RLCR, or it has little; RLCR ordinarily increases with the increment of radar frequency f and it depends on f between f^0 and f^1.

- **Observation data**

Highlights about RLCR data have been summarized by Nathanson, *et al.* (1991) and Skolnik (1990) while more extense information has been compiled by Long (1975) and Barton (1988). Among them, the statistical measurements in (Nathanson, *et al*, 1991) are authoritative relatively. Here, the measurements from Nathanson, *et al.*, (1991) are referenced.

- **Expert Experience**

1) CG Model

$$\sigma_l = \gamma \sin \psi$$

where σ_l is RLCR; γ is the parameter describing reflectivity of land surface; ψ is grazing angle.

2) Morchin Model

Morchin (1990) give a RLCR model

$$\sigma_l = A - 10\log\lambda + 10\log(\sin\psi) + 10\log\left\{\cot^2\beta_0 \exp\left[\frac{-\tan^2(B-\psi)}{\tan^2\beta_0}\right]\right\} + u + \sigma_c$$

where A = –29 for desert, –24 for farmland, –19 for wooded hill, –14 for mountain; u = $10\log(\sqrt{f}/4.7)$; $B = \pi/2$ for all terrains except mountain, 1.24 for mountain; $\beta_0 \approx$ 0.14 radians for desert, 0.2 for farmland, 0.4 for woodlands, 0.5 for mountain; $\sigma_c = 10\log(\psi/\psi_c)$ desert only as $\psi < \psi_c$; $\psi_c = \arcsin(\lambda/4\pi h_e)$; $h_e \approx 9.3\,\beta_0^{2.2}$.

3) GIT Model

GIT researcher Currie (1987) propose

$$\sigma_l = A(\theta + C)^B \exp(-D/(1+0.1\sigma_h/\lambda))$$

where σ_h is the surface standard deviation and related with terrain type; λ is radar wavelength; A,B,C and D are the constants obtained by experience, and related with radar frequency, and terrain type.

4) Extense Experience

To low altitude target at low angles, there has a definitely difference about the grazing angle when land-based radar is engaged in against the target. This is because the noises influence. From this it can be obtained that the data from the relatively-large grazing angle has the relatively reliable degree.

- **Integration of information sources**

Considering the complexity of RLCR system, generally, prior theory is not so accurate, expert experience is also hard to collect and use. So much attention should be paid to the available observation data and our prior extense experience.

The believable degrees of all information sources have been given in Fig. 3. Here, the general believable degree scope is used too. Observation data has a high believable degree, however, they need to be made pretreatment. And the comparison between data (Nathanson, *et al.*, 1991) and the pretreatment data are shown in Fig.3.

4.2 Structure of RLCR

According to (Skolnik, 1990; Long, 1975; Barton, 1988; Barton, 1975; Blake, 1980; Nathanson, *et al.*, 1991; Morchin, 1900; Currie, 1987), RLCR σ_l is known mainly related to radar frequency, terrain type, and grazing angle. So the proposed RLCRσ_l model can be written as

$$\sigma_l = T_l(f, \psi, \gamma) \tag{17}$$

where $f \in X_1$, X_1=(0.03,12.5); $\psi \in X_2$, X_2=(0,0.174); $\gamma \in X_3$, X_3=(0, +∞); T_l is function defined in X_1, X_2 and X_3.

RLCR ordinarily increases with the increment of f (Currie, 1987) and RLCR depends on f between f^0 and f^1 (Blake, 1980). Refrering from (Nathanson, *et al.*, 1991), it can be obtained the influences by desert and city on RLCR are the least and the most respectively. The values of γ from (Barton, 1975) are a good generalization and are used to describe the influence on RLCR by different typical terrains. With regard to the grazing angle, generally, RLCR increases with its increment according to (Barton, 1975; Blake, 1980). By CG model and Morchin model (Morchin, 1900), RLCR is known to have a linear relation with the sine of the grazing angle to a great extent. There are four typical terrain types, and they are desert, crops, hill, and mountain (or city). Here, for the limitation of paper length just desert terrain type is considered when γ is equal to 0.01. And the MP-NARMAX model of RLCR can be obtained and be written as

$$T_l(f,\psi,\gamma,k) = \theta_0 + \sum_{i_1=1}^{m} \theta_{i_1} g_{i_1}(p_{i_1}(k)) + \sum_{i_1=1}^{m}\sum_{i_2=i_1}^{m} \theta_{i_1,i_2} g_{m+i_1+2i_2-2}(p_{i_1}(k)) g_{m+i_1+2i_2-1}(p_{i_2}(k)) + e(k) \tag{18}$$

Here, the s input is 3. The reference data (Nathanson, *et al.*, 1991) are twelve groups. n_y, n_u and n_e are assumed to be 2, 2, and 2, respectively. Thus m is 13. And function $g_i(\cdot)$ is thus

$$g_i(x) \in \left\{ (\sin(x), \ \frac{1}{1+\exp(-x)}, \ x \right\} \tag{19}$$

And when p_i (i=1,2, …m) is related to γ, set g_j (j=1,2, …m^2+m) to be p_i ; when p_i is related with ψ, set g_j is sin(p_i); when p_i is related with f, set g_j to be 1/(1+exp(-p_i).

4.3 Identification of RLCR

Here, the newly-developed modified GMDH is used to identify RLCR structure.

The reference data (Nathanson, *et al.*, 1991) are 12 groups. Partition the data with the first 8 groups designated as the training set and the remaining ones as the testing set. These data selected for training are pretreated, however the remaining ones are not. Take all the variables in the columns of the Matrix $\mathbf{R}\{g_1(y(k-1),\ldots,g_{n_y}(y(k-n_y)),g_{n_y+1}(u_1(k)),\ldots\}$.

By using GMDH method, once recursion is finished, and the calculation is simplified for the nonlinear RLCR system after the general identification model structures is obtained. The final identification result of RLCR is

$$\begin{aligned}\sigma_l(k) &= (3.1e-5) + (4.5e-3)\sin(\theta(k-1)) \\ &+ (3.0\text{e-}4)(\sin\theta(k-1))^2 \\ &+ (4.5\text{e-}7)(\gamma(k-1))^2 \sin(\theta(k-1))\end{aligned} \tag{20}$$

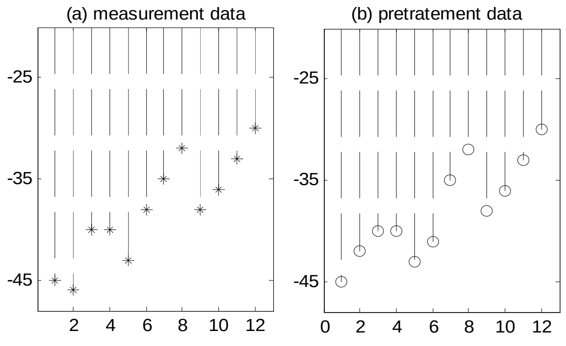
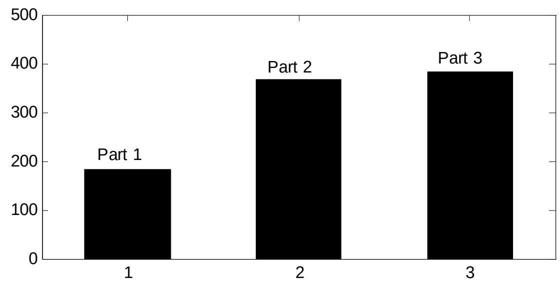


Fig.3. Comparison between data (Nathanson, *et al.*, 1991) and pretreatment data



Part 1–the error for the proposed model, part 2–for Morchin Model (Morchin, 1990), and part 3–for CG model.

Fig.4. The squares errors comparison

Table 1 Total squares errors of several methods of system identification

MP-NARMAX-GMDH	GMDH	NARMAX
183	315	—

Fig.4. shows the squares errors comparison among the commonly used RLCR models and the proposed RLCR model obtained by using MP-NARMAX-GMDH method. Table 1 shows the squares error of MP-NARMAX-GMDH, GMDH, and NARMAX. for RLCR modeling.

GIT Model (Currie, 1987) is accurate, however it is inconvenient for its variety of pertinent parameters. So in Fig. 4. GIT Model (Currie, 1987) is absent. From Fig. 4. the proposed model (20) of RLCR for desert terrain is preferable because it reflects RLCR mechanism to a great degree and fits measurements well. From Table 1, although GMDH method can obtain RLCR model, it cannot fit measurements well. According to expectation NARMAX cannot obtain RLCR model for its limitation with a large number estimated parameters.

5. CONCLUSION

In this paper a new identification method is proposed for nonlinear system with shortage of nonlinear input-output data, named MP-NARMAX-GMDH method. The method expands the application of NARMAX by means of absorbing the idea of exponential-trigonometric generalization and the identification ability and robustness of GMDH method.

The proposed method gives reasonable application of information integration of complex system with a dominant nonlinear behavior. The most important for the proposed method is combining two excellent methods of NARMAX and GMDH. As a result it can obtain the efficacy of system identification with unknown system structure and short nonlinear input-output measurements. The proposed method was verified through a typical nonlinear system with unknown structure and short input-output data.

REFERENCES

Barton, D.K. (1975). *Radars Volumes 5, Radar clutter*. Mass: Artech House, Dedham. MA.

Barton, D.K. (1988). *Modern radar system analysis*. pp.124-128. Mass: Artech House, Dedham, MA.

Billings, S.A., S. Chen (1989). Identification of nonlinear rational systems using a prediction error estimation algorithm, *Int. J. Syst. Sciences*, 20, pp.467-494.

Blake, L.V. (1980). *Radar range-performance analysis.* Lexington Books, pp.321-325.

Boutayeb, M., M. Darouach and P.M. Frank (1998). Modeling and identification for highly nonlinear processes. *Mathematics and Computers in Simulation* 46, pp.551-557.

Burke, L., J.P. Ignizio (1997). A practical overview of neural networks. *J. Intelligent Manufacturing*, 8, pp.157-165.

Craddock, R., K. Warwick (1998). Dealing with complexity: an overview of the neural network approach. *Proc. UKACC International Conference on Control '98*. 1(45), pp.705-708.

Currie. N.C. (1987). "Clutter Characteristics and Effects" in Eaves J. L. and Reedy E. K. eds., *Principles of Modern Radar*: Van Nostrand Reinhold Co, New York.

Eykhoff, P. (1974). *System Identification*, Wiley, New York.

Ivakhnenko, A.G. (1971). Polynomial theory of complex systems. *IEEE Trans. on Systems, Man, and Cybernetics*. 1(4), pp.364-378.

Kortmann. M.H. Unbehauen (1988). Two algorithms for model structure determination for nonlinear dynamic systems with application to industrial processes. *8th IFAC SISPE*, Peking, pp. 939-946.

Leontarities, I.J., S.A. Billings (1985). Input-output parametric models for nonlinear systems. Part I: Deterministic nonlinear systems. Part II: Stochastic nonlinear systems, *Int. J. Control* 41, pp.303-344.

Ljung, L.(1999). *System Identification*: *Theory for the User* (2nd ed.). Prentice Hall, New Jersey.

Long. M.W. (1975). *Radar reflectivity of Land and Sea*. Lexington Books, Lexington MA, pp.260-307.

Morchin, W.C. (1990). *Airborne early warning radar*. ch.4.Artech House, Norwood, MA.

Narendra, K.S., P.G. Gallmann (1966). An iterative method for the identification of nonlinear systems using a Hammerstein model, *IEEE Trans. Auto. Control* AC 11, pp.46-550.

Nathanson, F.E., J.P. Reilly and M. N. Cohen (1991). *Radar design Principles*: *signal processing and the environment* (2nd ed.). pp.275-319 McGraw-Hill, New York.

Pearson, R.K. (1995). Nonlinear input/output modeling. *J. Proc. Cont*. 5(4), pp.197-211.

Pottmann, M., R.K. Pearson (1988). Block-oriented NARMAX models with output multiplicities, *AIChE J*. 44, pp.131-140.

Pottmann, M.,H. Unbehauen and D.E. Seborg (1993). Application of a general multi-model approach for identification of highly nonlinear process – a case study, *Int. J .Control* 57(1), pp.97-120.

Qin, S.Z., H.T. Su and T.J. McAvoy (1992). Comparison of four neural net learning methods for dynamic system identification. *IEEE Trans. on Neural Networks*. 3(1), pp.122-130.

Schoukens, J., et al. (2003). Fast approximate identification of nonlinear systems. *Automatica*. 39, pp.1267-1274.

Sjöberg, J., et al. (1995). Nonlinear black-box modeling in system identification: A unified overview. *Automatica*, 31(12), pp.1691-1724.

Skolnik, M.I. (1990). *Radar Handbook* (2nd ed.). pp.13.1-13.35. McGraw-Hill, New York.

Ozaki,T.(1985). Nonlinear time series models and dynamical systems, *Handbook of statistics*, pp.25-83.