Research Article

A Method for Parameter Identification of Combined Integrating Systems

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This manuscript presents a novel structure of combined integration in the process industry and proposes an efficient method for identifying its parameters. Combined integrating processes are delay-time processes that widely exist in the industry. Conventional identification methods have a low-identification accuracy, a large vibration amplitude of the identification curve, and a poor effect for this kind of process. In this paper, a new variable forgetting factor recursive least squares method was adopted to ameliorate this problem. The method could quickly track the mutation of the ideal parameters of the process and accurately identify which of the parameters have high precision, small oscillation, and a smooth curve. The simulation results indicate that the proposed method is a significant improvement compared to the ordinary recursive least squares method and the recursive least squares with a fixed forgetting factor method, and a concise program can be verified. The experimental simulation based on the actual cut tobacco rebaking industrial process shows that the proposed method has improved identification precision and the best following effect.

1. Introduction

In the process industry, especially in tobacco temperature control areas, the chemical industry, and other industrial fields, industrial control processes often show a first-order or high-order delay-time element that contains the integrating process. The essence of an integrating process is open-loop stability, and the process model has specific properties. Generally, a graphic method or an approximate method is used to determine model parameters. However, it is not possible to carry out open-loop experiments in the actual process industry [1]. A relay-feedback identification method applies a repetitive switching PID controller to collect multiple system diagnostic messages to ensure that the system is working near the stable point. A repetitive switching PID controller easily causes system oscillation and influences the control effect. Therefore, the method of relay-feedback identification cannot be employed to accurately identify the controlled object that contains the integrating element.

Extensive efforts have been directed toward the creation of a new method to solve the problem. Gauss proposed the least squares (LS) method in the study of the orbital motion of stars in 1795. Under the application of batch processing and recursion, the recursive least squares (RLS) method has been generated for systems with constant unknown parameters. Usually, the RLS method is used in adaptive filters and identification systems. Its advantages are good convergence and a small mean square error (MSE). However, slowly changing parameters cannot accomplish the parameter estimation. It is difficult to extend the method to a complex nonlinear system. Fortescue et al. [2] and Jung [3] proposed a RLS method with a forgetting factor (FFRLS), but in an unstable system, the system parameter changes and the forgetting factor remains unchanged. The unstable system cannot obtain satisfactory performance, and a burst emerges in the covariance of the parameter estimation error. In 2000, Song et al. [4] developed the RLS with the variable forgetting factor RLS (VFFRLS), which solves the abovementioned
problem. VFFRLS can be implemented in dynamic systems, static systems, linear systems, nonlinear systems, etc. Many scholars have amended VFFRLS. So et al. [5] proposed the gradient variable forgetting factor RLS (GVFF-RLS) to improve MSE analysis for dynamic equations. Shi et al. [6] proposed a novel algorithm that can realize unbiased estimates under color noise and improve the tracking effect of time-varying parameters. Zhang and Yan [7] designed a method by training the weight coefficients of the multidimensional Taloy network (MTN) online with VFFRLS, and they provided an identification method for nonlinear time-varying systems. Goel and Bernstein [8] applied a forgetting factor to build target VFF to overcome covariance divergence for low-dimensional problems. Kang et al. [9] first obtained low-frequency signals, then used the adaptive filter on RLS to pre-estimate delay time, and finally, obtained locally accurate delay-time estimate.

However, the combined integrating processes that exist in many industrial environments have not attracted the attention of researchers. This paper proposes combined integrating process and discretizes the combined integrating process for the first time. Based on a conventional identification method, we modified the variable forgetting factor function to identify parameters. Ultimately, we hope to obtain an accurate identification effect for the combined integrating process, and the identification effect of the proposed method is confirmed according to a real industrial tobacco redrying process.

In this paper, a new system and a novel identification method are proposed to implement the identification of an integrating system by training the forgetting factor. This paper is organized as follows. In Section 2, based on the analysis of a complex industrial process, we define the combined integrating process. In Section 3, VFFRLS is built to recognize the parameter of the combined integrating process and an example is given for verification and comparison. In Section 4, we discretize the combined integrating process. In Section 5, we take a tobacco redrying process as a real example and use VFFRLS as a novel method to identify the parameters. Finally, Section 6 concludes this work.

2. Definition of Combined Integrating Process

Many complex industrial processes are composed of different integrating delay-time elements, which can be approximated as first-order elements under some conditions. Through the mechanism analysis and modelling establishment of an industrial production process, we get a new kind of process and define this process as a combined integrating process, as described by the following equation [10]:

$$P(s) = \sum_{i=1}^{n} \frac{k_i}{sG_i(s)} \left(1 - e^{-\tau_i s}\right)e^{-\tau_i s},$$  \tag{1}

where $1/G_i(s)$ represents a stable component without integrating terms, $k_i$ represents the gain coefficient, and $\tau_{1i}$, $\tau_{2i}$ represents the delay time.

A combined integrating process has the following characteristics:

1. Each term of the combined integrating system has the term $(k/s) \left(1 - e^{-\tau_i s}\right)$, which guarantees the open-loop stability of the system.
2. $\tau_{1i}$ and $\tau_{2i}$ must adhere to $\tau_{2i} = \tau_{2i-1} + \tau_{1i-1}$. In this case, the open-loop response of the system is continuous and does not exhibit a periodic jumping output.
3. The combined integrating process not only contains the poles of the nonleft half plane but also contains the zeros of the nonleft half plane; thus, it has the characteristics of both the integration and non-minimum phases [10].

Without a loss of generality, the existing combined integrating objects can be divided into several different types according to their structures and characteristics in the actual industrial control process. A combined integrating process is obtained through mechanism analysis and modelling of the industrial production process, which has two common forms. The process transfer function is expressed as follows [10]:

$$G_p(s) = \frac{k}{\tau_1 s} \left(1 - e^{-\tau_1 s}\right) e^{-\tau_2 s} (a),$$

$$G_p(s) = \frac{k}{\tau_1 s (Ts + 1)} \left(1 - e^{-\tau_1 s}\right) e^{-\tau_2 s} (b),$$  \tag{2}

where $T$ represents the sampling period.

The combined integrating process has good response performance. The rising process of the system output is relatively smooth and can reach a steady state without overshoot. At the same time, since the link $G_p(s) = \left(1 - e^{-\tau_1 s}\right)/rs$ is, essentially, a mean-filtering link between the time $[t - \tau, t]$, the combined integrating process itself has a certain ability to resist noise.

3. System Identification Method

3.1. Recursive Least Squares Estimation. System identification, which was first introduced many years ago by L. A. Zadeh, is a strategy that can be used to obtain a production-controlled object model by monitoring its input output data in industrial production. The definition of system identification is to determine a model equivalent to the measuring system based on the input and output data from a given set of model classes. The common system identification method is the least squares method; thus, the actual value is subtracted from the estimated value to find the minimum square of the difference for optimization. Based on the algorithm mentioned above and recursive thinking, an RLS algorithm, which is a classical identification algorithm widely applied in practice, is generated in a system of constant unknown parameters. RLS uses the new measurement data to estimate the previously estimated result in the identified system. With the update of new data, the new parameter estimation values are updated until the estimated value achieves the desired effect [11].
The RLS algorithm is summarized as follows; a new estimate vector \( \hat{\theta}(k) \) is an old estimated vector + a correction term. Thus, the new estimate value is based on the old value, and new observations are used to correct the old estimate value [11]; \( k \) implies the \( k \)th time.

The algorithm is deduced simply as follows. Assume batch least squares estimation at time \( k \) [11],

\[
\hat{\theta}(k) = (Y_k R_k)^{-1} Y_k \phi_k.
\]

Let
\[
Y_k = \begin{bmatrix} \gamma_y \end{bmatrix}, \quad \phi_k = \begin{bmatrix} \phi_{k-1} \\ \phi_k \end{bmatrix},
\]

\( \hat{\theta}(k) \) represents least squares estimation of system parameters at \( k \) times, and its initial value is 0. \( Y_k \) represents the data vector matrix at time \( k \). \( \phi_k \) represents the data output vector matrix at time \( k \). \( r_k \) represents an input signal vector at time \( k \). \( \phi_k \) represents the object expected output value at time \( k \). Vectors of parameter estimations are assumed to be \( \hat{\theta} \), then, the estimated output of the observation at time \( k \) is obtained as follows [5]:

\[
\hat{\phi}(k) = r_k^T \hat{\theta}(k).
\]

The difference between the actual output and the estimated output of the controlled object is \( e(k) \); then [5],

\[
e(k) = \varphi(k) - \hat{\varphi}(k) = \varphi(k) - r_k^T \hat{\theta}(k).
\]

Let
\[
p(k) = (Y_k \cdot Y_k)^{-1} = \left[ Y_k^{-1} r_k + r_k^T r_k \right]^{-1},
\]

\( p(k) \) represents the inverse matrix of the input signal autocorrelation matrix. The initial value of \( p(k) \) is \( p(0) = \varepsilon I \), where \( \varepsilon \) is a constant bigger than 100 (usually bigger than 1000). \( I \) is the identity matrix.

The expression of least squares estimation at time \( k \) is denoted as follows [11]:

\[
\hat{\theta}(k) = P_k \cdot Y_k^T \phi_k
\]

\( = \theta_{k-1} + K(k) [ \phi_k - r_k^T \hat{\theta}_{k-1} ] \).

Here,
\[
K(k) = P_k r_k = \frac{P_{k-1} r_k}{I + r_k^T P_{k-1} r_k},
\]

where \( K(k) \) represents the gain vector [5]. Thus,
\[
P_k = \left[ P_{k-1} + r_k^T r_k \right]^{-1} = P_{k-1} - P_{k-1} r_k \left[ I + r_k^T P_{k-1} r_k \right]^{-1} r_k^T P_{k-1}.
\]

Then, the recursive formula is expressed as follows [11]:

\[
\hat{\theta}(k) = \hat{\theta}_{k-1} + K(k) [ \phi_k - r_k^T \hat{\theta}_{k-1} ],
\]

\[
K(k) = \frac{P_{k-1} r_k}{I + r_k^T P_{k-1} r_k},
\]

\[
p_k = \frac{I}{\lambda} \left[ I - K(k) r_k^T \right] p_{k-1}.
\]

3.2. Recursive Least Squares Method with Fixed Forgetting Factor. The RLS algorithm is well known to possess fast convergence and small MSE, especially for highly correlated input signals. However, it is easy to generate the “data saturation” phenomenon in systems with slowly varying parameters. To solve these conflicting requirements, the RLS algorithm needs to be modified and RLS with forgetting factor algorithms (FRLS) is introduced. The \( \lambda \) is determined at every step of identification. Based on the understanding of \( \lambda \), the modified function is proposed and FFRLS is obtained [12]:

\[
J = E \left[ \lambda^k \left[ \phi_k - r_k^T \hat{\theta}(k-1) \right] \right]^2.
\]

\( J \) is performance indicators, the sum of the squares of the residuals.

The recursive formula is shown as follows:

\[
\hat{\theta}(k) = \hat{\theta}_{k-1} + K(k) [ \phi_k - r_k^T \hat{\theta}_{k-1} ],
\]

\[
K(k) = \frac{P_{k-1} r_k}{\lambda + r_k^T P_{k-1} r_k},
\]

\[
p_k = \frac{1}{\lambda} \left[ I - K(k) r_k^T \right] p_{k-1},
\]

where \( \lambda \) denotes the forgetting factor (0 ≤ \( \lambda \) ≤ 1) that is used to estimate the effect of the new data on the RLS algorithm. To reflect the time-variance of the system, the role of new data should be strengthened and that of old data should be reduced. At this point, the forgetting factor \( \lambda \) plays an important role in the behavior of the RLS algorithm in terms of convergence, misalignment, and stability. \( \lambda \) is fixed in the classical FFRLS algorithm, usually called the fixed forgetting factor (FFF), and its value ranges from 0 to 1 [13]. It is known that if \( \lambda \) is close to 1, then the algorithm achieves faster convergence but with reduced tracking ability. When the measured signal changes, the fixed value \( \lambda \) makes it difficult to quickly track the variation of the wave form. At the same time, a fixed value of \( \lambda \) causes the convergence speed to slow [14]. Usually, \( \lambda \) is not less than 0.9. If the system is linear, then \( \lambda \) takes the value of 0.95 to 1. However, if \( \lambda = 1 \), then VFFRLS degenerates into RLS. For slow-time-varying parameters, \( \lambda \) should take bigger values. \( \lambda \) is usually chosen based on experience and experimentation.
3.3. Recursive Least Squares Method with Variable Forgetting Factor. In control systems with time-varying parameters, we track the change in the dynamic parameters of the control system. The method of reducing the weight of old data can be adopted in a database, which not only reduces computational complexity but also improves the speed of identification. At the same time, reducing the weight of old data can increase the speed of identification and the simulation effect. This method is appropriate for the parameter identification of time-varying processes [15]. A smaller \( \lambda \) can quickly track changes in time-varying parameters, but it has an obvious defect because it is more sensitive to noise and large steady-state error. The ability to track time-varying parameters decreases along with increasing \( \lambda \), but it is not sensitive to noise, and the estimation error of the parameters at the time of convergences is small [15]. A proper VFF has been proven to influence system recognition, convergence rate, and performance of the learning algorithm.

Based on the learning of \( \lambda \), we take the VFF as the following form:

\[
\lambda(n) = \begin{cases} 
\lambda_0, \\
\lambda_1 + (\lambda_0 - \lambda_1) \sin \left( \frac{\pi}{2} \cdot \frac{k}{10^4} \right),
\end{cases}
\]

where \( e(n) \) represents the prior error and round \( [e(n)]^3 \) is an integer representing the nearest value to \( e(n) \).

If round \( [e(n)]^3 = 0 \), then \( \lambda(n) = \lambda_0 \) (while the estimation error is small).

If round \( [e(n)]^3 \neq 0 \), then \( \lambda(n) = \lambda_1 + (\lambda_0 - \lambda_1) \sin \left[ \pi / 2 \cdot (k/10^4) \right] \) (while the estimation error is large).

To verify the identification accuracy, convergence speed, and steady-state error of the VFFRLS, consider the following system [11, 16]:

\[
\begin{align*}
\hat{\theta}(k) &= \hat{\theta}_{k-1} + K(k) \left[ \varphi_k - r_k^T \hat{\theta}_{k-1} \right], \\
K(k) &= \frac{P_{k-1} r_k}{\lambda + r_k^T P_{k-1} r_k}, \\
P_k &= \frac{1}{\lambda} \left[ I - K(k) r_k^T \right] P_{k-1}, \\
\lambda(n) &= \begin{cases} 
\lambda_0, \\
\lambda_1 + (\lambda_0 - \lambda_1) \sin \left( \frac{\pi}{2} \cdot \frac{k}{10^4} \right),
\end{cases}
\end{align*}
\]

3.4. Simulation Verification. To verify the identification accuracy, convergence speed, and steady-state error of the VFFRLS, consider the following system [11, 16]:

\[
y(k) + a_1 y(k-1) + a_2 y(k-2) = b_0 e(k-3) + b_1 e(k-4) + \xi(k),
\]

where \( y(k) \) represents the sampling current output, \( e(k) \) represents the sampling current input, \( \xi(k) \) is the white noise, and the variance is equal to 0.1. The parameter of the tobacco redrying process is slowly changing, which corresponds to slow time-varying parameters. This paper takes tobacco redrying as an example. Assume the objects are the time-varying parameter \( \theta(k) = [a_1, a_2, b_0, b_1]^T = [-1.4, 0.7, 1.6, 1.0]^T \), taking the initial value \( P(0) = 10^6 I, \theta(0) = 0 \). The RLS algorithm is adopted to identify the parameter, and the simulation result is shown in Figure 1.

Figure 1 shows that when \( k = 400 \), the parameter estimation is \( a_1 = -1.389, a_2 = 0.6928, b_0 = 1.583, \) and \( b_1 = 1.039 \). This identification result is better for time-invariant systems, but has a poor effect under the conditions of parameter changes.

To accelerate the speed of the identification of parameters and decrease identification errors, an improved method usually called FFFRLS is used [16]. Considering the
object time-varying parameters $\theta(k) = [a_1, a_2, b_0, b_1]^T = [-1.4, 0.7, 1.6, 1]^T$, when the data length is greater than 501, the object time-varying parameters change to $\hat{\theta}(k) = [\hat{a}_1, \hat{a}_2, \hat{b}_0, \hat{b}_1]^T = [-1.0, 4, 1.7, 0.9]^T$. While the parameters change, taking $\lambda = 0.9$ and $\lambda = 0.99$ as FFF separately, the simulation result is shown in Figures 2 and 3.

The differences are compared by tabulating in Table 1.

A comparison between the true value and the identification value is shown in Table 1. Comparing Figure 2 with Figure 3 shows that the identified velocity changes and the system oscillations are significantly reduced when the forgetting factor $\lambda$ increases. The identification value can follow the true value better, but this process is slow to go after. The oscillation of the system is larger, and the error still exists. To solve the problem addressed above, this paper presents a VFFRLS and does the same experiment. The simulation result is shown in Figure 4.

The VFFRLS can converge effectively with relatively high precision [17]. In addition, there is good stability and small oscillation. The identification values enable fast tracking of the real values, and the identification effect is obviously better.

A comparison of the identification value and true value of VFFRLS is provided in Table 2.

Comparing Table 1 with Table 2, it is further observed that although the deviation exists in VFFRLS, the errors are much smaller than those of FFFRLS.

**4. Discretization of Combined Integrating Process**

Combined integrating processes have an element $(1 - e^{-r_1k})e^{-r_2k}$ that contains two delay-time factors, $r_1$ and $r_2$, where $r_1$ and $r_2$ influences the output response of the combined integrating system. In the practical industrial field, such as in the control of temperature or moisture, the transfer function of control variables can be obtained according to experience to calculate the lag factors. Using VFFRLS to identify system parameters can improve the tracking speed and stability error.
4.1. Discretization of the Combined Integrating Process of Type (a). According to the structural characteristics of the combined integrating process, the combined integrating of type (a) with a zero-order keeper is discretized. The zero-order keeper uses constant extrapolation and holds the sampling value \( u(kT) \) at the moment \( kT \) to \( u((k+1)T) \). Meanwhile, the sample value changes from \( u(kT) \) to \( u([k+1]T) \) and obtains a stepped output signal that contains higher harmonics. With increasing frequency, the amplitude of the zero-order keeper decays; thus, the zero-order keeper possesses the characteristics of low-pass filtering [13]. Discretizing the combined integrating process of type (a),

\[
Z[G_h(s) \cdot G_p(s)] = Z\left[ \frac{1 - e^{-Ts}}{s} \cdot \frac{k}{\tau_1 s} \cdot (1 - e^{-\tau_1 s}) e^{-\tau_1 s} \right].
\]

Here, the transfer function of the zero-order keeper is \( G_h(s) = \left( 1 - e^{-Ts} \right)/s \), and the difference equation is obtained through the \( Z \) transformation. The final result is displayed as follows:

\[
y(n) - y(n-1) = \frac{kT}{\tau_1} e\left( n - 1 - \frac{\tau_2}{T} \right) - \frac{kT}{\tau_1} e\left( n - 1 - \frac{\tau_1 + \tau_2}{T} \right),
\]

where \( T \) is the sampling period.

Letting \( b_1 = (kT/\tau_1), b_2 = -(kT/\tau_1), \) and \( a_1 = -1 \), (18) becomes

\[
y(n) + a_1 y(n-1) = b_1 e\left( n - 1 - \frac{\tau_2}{T} \right) + b_2 e\left( n - 1 - \frac{\tau_1 + \tau_2}{T} \right),
\]

(19)

4.2. Discretization of the Combined Integrating Process of Type (b). Simultaneously, discretizing the combined integrating process of type (b),

\[
Z[G_h(s) \cdot G_p(s)] = Z\left[ \frac{1 - e^{-Ts}}{s} \cdot \frac{k}{\tau_1 s(Ts + 1)} \left( 1 - e^{-\tau_1 s} \right) e^{-\tau_1 s} \right].
\]

Simplify and get the result as follows:

\[
y(z) = \frac{kT_0}{\tau_1} \cdot \frac{Az^{-((\tau_1 s)^T)/T} + Bz^{-((\tau_1 s + 2\tau_2)/T)} - Cz^{-((\tau_1 s + \tau_2)/T)} - Dz^{-((\tau_1 s + 2\tau_2)/T)}}{1 - \left( 1 + e^{-T/\tau_1} \right) z^{-1} + e^{-(T/\tau_1)} z^{-2}},
\]

(21)

| Parameters | \( a_1 \) | \( a_2 \) | \( b_0 \) | \( b_1 \) |
|------------|---------|---------|---------|---------|
| True value \((k < 501)\) | -1.0 | 0.5 | 1.0 | 0.4 |
| True value \((k \geq 501)\) | -0.5 | 0.3 | 1.5 | 0.2 |
| Identification value | -0.563 | 0.312 | 1.509 | 0.234 |
| Deviation | 0.063 | 0.012 | 0.009 | 0.034 |

Table 2: Comparison of identification value and true value of VFFRLS.
where

\[
A = e^{-(T/T_0)} + \frac{T}{T_0} - 1,
\]
\[
B = 1 - \frac{T}{T_0} e^{-(T/T_0)} - e^{-(T/T_0)},
\]
\[
C = 1 + e^{-(T/T_0)} - \frac{T}{T_0},
\]
\[
D = 1 - \frac{T}{T_0} e^{-(T/T_0)} - e^{-(T/T_0)}.
\]

Subtract and get the final result:

\[
y(m) - \left(1 + e^{-(T/T_0)}\right)y(m - 1) + e^{-(T/T_0)} y(m - 2)
= \frac{kT_0}{\tau_1} \left[ A e\left(m - \frac{\tau_2 + T}{T}\right) + B e\left(m - \frac{\tau_2 + 2T}{T}\right) 
- C e\left(m - \frac{\tau_2 + \tau_1 + T}{T}\right) - D e\left(m - \frac{\tau_2 + \tau_1 + 2T}{T}\right) \right].
\] (23)

5. Simulation Example

The combined integrating process is widely used in the rebaking of tobacco leaves, electroslag furnace remelting, and other complex industries. In particular, the redrying process of the tobacco leaves and the regaining process both contain a combined integrating process. In the actual redrying process of tobacco leaves, the control mode of the outlet moisture content of tobacco leaves is a typical combined integrating process. Using traditional PID and lag compensation control can preserve the outlet moisture content at \(\pm 0.5\%\), but the control speed and system stability are poor. If the outlet moisture content is controlled below \(\pm 0.3\%\), then the benefits can be increased by nearly 10 million.

The moisture content of raw tobacco is reduced from 80% \~ 90% to 15% \~ 20% after baking. The moisture content is still at a relatively high level, which can easily cause mildew, grease, and other adverse problems [18]. Therefore, it is necessary to perform rebaking to improve the quality of tobacco leaves. The rebaking process includes a drying process, a cooling process, and a regaining process.

The drying cylinder for the cut tobacco dryer leans 1.5 \~ 2.0° the horizontal plane, and the antechamber is higher than the posterior chamber. The cut tobacco leaves enter the roller from a feeding inlet. Simultaneously, with the roller rolling from the high location to the lower location because of gravity, the tobacco leaves go out from the posterior chamber.

The wind is heated by a resistance wire, and the blower is used to blow hot air into the front antechamber. The hot wind goes into the roller from the antechamber to the posterior chamber. The cut tobacco leaves rotate with the roller and contact the hot wind. The embossed metal plate becomes embedded in the inner wall of the roller to heat the cut tobacco leaves and to tumble and sprinkle to increase the contacting surface of the cut tobacco leaves. This method can enhance the drying rating of hot air [18]. Meanwhile, the cut tobacco leaves run from one side to another. Due to the heat, the moisture of cut tobacco leaves diffuses toward the surroundings.

To prevent condensation in the posterior chamber because of the low temperature, the evaporating gas is drawn from the dust extraction box. At the same time, the upper blower prevents the dust from entering the posterior chamber. Under this condition, part residual steam and condensate water effuse from the pipe [19].
The drying method used in this way can make the tobacco leaves warm and humid, and the tobacco piece becomes soft and loose. Increasing the antimachinability of tobacco sheet leaves results in large delay-time characteristics for the moisture and temperature-control processes of rebaking [19]. The cut tobacco drying process is shown in Figure 5, and the regain outlet moisture content of the rebaking [19]. fQ_he cut tobacco drying process is shown in Figure 6.

The moisture-control process of the cut tobacco redrying outlet has a model that possesses the combined integrating process structure mentioned above (a). When the matrix dimension increases, it burdens the arithmetic and storage of the computer, which makes tracking the change of the parameter in real time impossible. To reduce the calculation and storage of the computer, VFFRLS is adopted.

We can assume that the moisture control transfer function \( G(s) = (2/(10s^2 + 1))(1 - e^{-10s})e^{-15s} \), as described above, for the difference discretization, we get the following equation:

\[
y(k) = (1 + e^{-1/2}) y(k - 1) + e^{-1/2} y(k - 2)
\]

\[
= 0.4 \left[ e^{-1/2} \frac{u(k - 16) + (1 - \frac{3}{2}) e^{-1/2} u(k - 17)}{1 + e^{-1/2}} \right] + (1 - \frac{3}{2}) e^{-1/2} u(k - 26) - \left( 1 - \frac{3}{2} e^{-1/2} \right) u(k - 27),
\]

\[
a_1 = -(1 + e^{-1/2}) \approx -1.607,
\]

\[
a_2 = e^{-1/2} \approx 0.607,
\]

\[
b_0 = 0.4 \left( \frac{1}{2} + e^{-1/2} \right) \approx 0.043,
\]

\[
b_1 = 0.4 \left( 1 - \frac{3}{2} e^{-1/2} \right) \approx 0.036,
\]

\[
b_2 = -0.4 \left( \frac{1}{2} + e^{-1/2} \right) \approx -0.443,
\]

\[
b_3 = -0.4 \left( 1 - \frac{3}{2} e^{-1/2} \right) \approx -0.036.
\]

The identification simulation that uses FFFRLS is shown in Figure 9.

A comparison of the identification value and true value of the combined integrating process of type (b) of VFFRLS is provided in Table 5.
From Figures 9 and 10, it is obvious that the effect of VFFRLS is better than that of FFFRLS, as the deviation decreases very fast and the estimated value is closer to the true value.

A comparison of the identification value and true value of the combined integrating process of type (a) of VFFRLS is provided in Table 3.

| Parameter                     | $a_1$ | $b_0$ | $b_1$ |
|-------------------------------|-------|-------|-------|
| True value ($k < 1001$)       | −1.0  | 0.2   | −0.2  |
| True value ($k ≥ 1001$)       | −0.5  | 0.6   | −0.6  |
| Identification value $\lambda = 0.98$ | 0.510 | 0.595 | 0.612 |
| Deviation                     | 0.010 | 0.005 | 0.012 |

Table 4: The comparison of the identification value and true value of the combined integrating process of type (a) of VFFRLS.

| Parameter                     | $a_1$ | $b_0$ | $b_1$ |
|-------------------------------|-------|-------|-------|
| True value ($k < 1001$)       | −1.0  | 0.2   | −0.2  |
| True value ($k ≥ 1001$)       | −0.5  | 0.6   | −0.6  |
| Identification value $\lambda = 0.98$ | 0.491 | 0.605 | 0.599 |
| Deviation                     | 0.009 | 0.005 | 0.001 |

From Figures 9 and 10, it is obvious that the effect of VFFRLS is better than that of FFFRLS, as the deviation decreases very fast and the estimated value is closer to the true value.
each parameter from the graph and table. The deviation of the partial parameter that used FFFRLS for estimation is less than 1%, and for another part, it is greater than 1%. The overall identification effect is worse than that of VFFRLS. At the same time, VFFRLS works better in terms of stability by observing the identification graph under the same conditions.

5.1. Comparative Performance of VFFRLS with Other Identification Methods. The performance of the VFFRLS algorithm is compared with those of the two algorithms described in [9, 11], which are called the recursive extended least squares algorithm (RELS) and the recursive stochastic Newton algorithm (RSNA), respectively. In Figures 11 and 12, the curves of these identification methods are compared. In the simulation, three different methods are used to identify the combined integrating process (a) under the same parameter mentioned before.

By comparing Figures 8, 11, and 12, we clearly find that the tracking capability of VFFRLS is stronger than those of RELS and RSNA. Especially when the parameter changes occur suddenly, the tracking performance is even more obvious.

A comparison of the identification value and true value of the combined integrating process of type (b) of RELS and RSNA is provided in Tables 7 and 8.

By comparing Tables 4, 7, and 8, we clearly find that the deviation of identification of VFFRLS is smaller than those of RELS and RSNA. This is very important for the industrial process.

In this paper, a new structure is proposed that uses VFFRLS to identify the combined integrating process parameters. The stability and quick response of the combined integrating system cannot be guaranteed due to the delay time that exists in the integrating process. The parameters are recognized under the given model by using VFFRLS, and the rationality is verified via simulation. The VFFRLS method can quickly track the true value, and system identification has a relatively high accuracy when the system parameters change [21–25]. It is useful for a system to see the parameters. At the same time, VFFRLS works better in terms of stability by observing the identification graph under the same conditions.

Table 5: The comparison of the identification value and true value of the combined integrating process of type (b) of FFFRLS.

| Parameter | $a_1$  | $a_2$  | $b_0$  | $b_1$  | $b_2$  | $b_3$  |
|-----------|--------|--------|--------|--------|--------|--------|
| True value ($k < 1001$) | -1.6   | 0.6    | 0.04   | 0.036  | -0.44  | -0.036 |
| True value ($k \geq 1001$) | -0.8   | 0.3    | 0.02   | 0.018  | -0.22  | -0.018 |
| Identification value $\lambda = 0.99$ | -0.798 | 0.322  | 0.023  | 0.066  | -0.245 | -0.222 |
| Deviation | 0.002  | 0.012  | 0.003  | 0.048  | 0.025  | 0.042  |

The identification simulation that uses VFFRLS is shown in Figure 10.

Table 6: The comparison of the identification value and true value of the combined integrating process of type (b) of VFFRLS.

| Parameter | $a_1$  | $a_2$  | $b_0$  | $b_1$  | $b_2$  | $b_3$  |
|-----------|--------|--------|--------|--------|--------|--------|
| True value ($k < 1001$) | -1.6   | 0.6    | 0.04   | 0.036  | -0.44  | -0.036 |
| True value ($k \geq 1001$) | -0.8   | 0.3    | 0.02   | 0.018  | -0.22  | -0.018 |
| Identification value $\lambda = 0.99$ | -0.793 | -0.309 | 0.015  | 0.011  | -0.221 | -0.011 |
| Deviation | 0.007  | 0.009  | 0.005  | 0.007  | 0.001  | 0.006  |

Figure 10: The estimation of combined integrating process parameter of type (b) of VFFRLS.
time, this method provides a standard for workers to use to regulate operations. In addition, this method is applicable to a multivariate system with a combined integrating element.

**6. Conclusion**

The combined integrating process comes from the understanding of a practical industrial process, such as, the dual...
frequency quenching machine control process and moisture control process in tobacco leaf production. The combined integrating process is regarded as a delay-time process because of different equipment and material reaction times. The integrating links and parameters vary with the changes in the internal industrial processes or external environmental factors. Regardless of how the model of the controlled objects is set up in theory, certain errors exist in the identification of model parameters [26].

In this paper, a modified VFFRLS method is proposed for combined integrating system identification. The simulation result indicates the superior performance of the new method through the practical tobacco redrying example. The combined integrating process parameters are proved to be identified accurately. The method in this paper has relatively high identification accuracy and obtained improved results, as verified through comparison with simulation results.

Data Availability
The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest
The authors declare no conflicts of interest.

Authors’ Contributions
Zhiping F, Zhengyun R, and Angang C conceptualized the study; Zhiping F, Zhengyun R, and Angang C worked on the methodology; Zhiping F, Zhengyun R, and Angang C validated the study; Zhiping F wrote and prepared the original draft, Wenbin W. financially supported the study; Xue F validated the study; Zhiping F, Zhengyun R, and Angang C worked on the integrating process. The final edition check was carried out by Zhiping F. Zhiping F, Zhengyun R, and Angang C financially supported the study; Xue F validated the study;

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