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An Integrated SPC-EPC Study Based on Nonparametric Transfer Function Model

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Abstract: Traditional integrated SPC-EPC studies are based on linear transfer function models to describe the relationship between the input and output variables. However, these linear models are unable to model complex nonlinear input-output relationships, which are closer to real situations. In order to solve this problem, this paper presents an integrated SPC-EPC method based on a nonparametric transfer function model to describe the input-output relationship in the system. A controller and integrated SPC-EPC control system based on this model are built. The performance of this method for checking assignable causes resulting in trend and sustained shift is analyzed using examples and simulations. The results indicate that the integrated SPC-EPC control method based on nonparametric transfer function model is effective in controlling complex nonlinear systems, which have assignable causes resulting in trend or sustained shift.

Keywords: Statistical process control, engineering process control, nonparametric transfer function model, nonparametric smoothing, time series.

1 Introduction

Statistical process control (SPC) and engineering process control (EPC) are two different techniques originated from distinct fields to guarantee the quality of products. The paths they achieve their own goals are totally different, but they have the same goal of reducing variation in the quality characteristics. Control chart is a useful tool of statistical process control. Traditional control chart assumes that the mean values of the process fluctuate around a constant value, and they are independent. Typical control charts include Shewhart control charts, EWMA control charts, CUSUM control charts and Hotelling T^2 charts for multivariate processes [1].

Engineering process control originated from process industry and it is mainly used in some continuous processes such as chemical process. Sometimes EPC is also called automatic process control (APC). The methods of EPC are based on feedforward or feedback adjustment to control the process, by tuning the input variables to reduce the deviation in the output variables in order to minimize the variation within the process. EPC assumes that the output variables are not stable, they are autocorrelated, engineers can do adjustment based on this relationship. Typical EPC controllers are MMSE controller, PID controller, EWMA controller and adaptive controller [2].

However, due to the reason that quality engineers lack the knowledge of dynamic and continuous control, control engineers lack the knowledge of statistics. The communication between them was very little for a long time. Montgomery et al [3] pointed out, “Statistical Process Control” is not an appropriate name, control chart didn’t really play the role of “control”, a more suitable name is “Statistical Process Monitoring”. Control chart only plays the role of finding the signal of assignable causes. EPC is doing some adjustment to eliminate the deviation which can be forecasted in order to keep the output close to the target value. EPC really does “control” to the process, but EPC cannot remove the reason of the deviation. Zhang [4] studied the complementary features of SPC and EPC and the new trend of modern manufacturing environment: small batch of manufacturing, frequent adjustment in the process, using sensor to collect data and so on. She pointed out that integrating SPC and EPC had many advantages, and reached the following conclusions: 1) Modern manufacturing environment resulting in the output data are highly autocorrelated, this violates the two traditional assumptions of the control chart: the data are independent and normally distributed. EPC can filtrate this autocorrelation in the data; 2) EPC can avoid some deviations caused by inner reasons which cannot be eliminated. This can reduce some fluctuations in the process; 3) Using SPC to monitor the process in order to find and eliminate assignable causes can improve the process; 4) Integrated SPC-EPC can reduce the cost of quality improvement. Because of the advantages of integrating SPC-EPC and the new need in modern manufacturing, more and more researchers are starting to be aware of these advantages.

2 Studies in Integrated SPC-EPC

Along with the development of manufacturing techniques and the mixed industries, more and more products have autocorrelationships in their manufacturing processes. So the barrier between SPC and EPC is starting to be removed. Integrated application of SPC and EPC is now considered to be an effective way to control and guarantee the quality of products. Early ideas of integrated SPC-EPC was proposed by MacGragor. He said we should remove the barrier between SPC and EPC, and he proposed the concept of “Online Quality Control” [5]; Van der Wiel et al analyzed the characteristics of APC (another name for EPC) and SPC, they proposed the concept of ASPC (Algorithmic Statistical Process Control) [6]; Box et al proposed the idea of the integration of SPC and APC. They introduced the knowledge of statistical monitoring and dynamic feedback control and gave a comparison of the two fields. They indicated that SPC was used to reduce some outside disturbance and EPC was used to compensate some deviation cannot be avoided. They also explained some criticized viewpoints on integrating SPC and EPC [7]; Messina and Montgomery et al gave a frame of SPC-EPC integration, they said we could use EPC to remove the autocorrelation in the process and use the control chart to get a complementary effect. They verified that using SPC and EPC together is better than using either alone [8-9]. In the books of Box et al, Del Castillo and Montgomery, integrated SPC-EPC was elaborated specifically [10, 1-2].

Now the studies on integrated SPC-EPC mainly use linear transfer function models proposed by Box et al [11] to describe the input-output relationships in processes [12-18]. Although linear transfer function models sometimes can be used to model some simple processes well, they have many errors and limitations when the relationships are nonlinear. Nonlinear transfer function models can be used to describe some nonlinear relationships, but modeling biases always exist in the selection of the explicit parametric nonlinear forms. To solve the problem of lacking study on the control of nonlinear input-output relationships, this paper proposes a method using nonparametric transfer function models, which do not have a specific form to describe the dynamic input-output relationships within the system and then build an integrated SPC-EPC control system based on this model. Trend and sustained shift are two typical forms of results of the assignable causes, which may happen in the process. Trend is very common in some continuous processes such as chemical processes and sustained shift is very common in some parts manufacturing processes. Using a controller alone cannot remove the assignable causes, so we need to use integrated SPC and EPC to get best control results. The research of this paper focuses on the two forms of results of assignable causes, and the integrated SPC-EPC method based on the nonparametric transfer function model.

3 Nonparametric Transfer Function Model

3.1 Introduction to Nonparametric Transfer Function Model

Linear transfer function model was proposed by Box et al [11] to describe the relationship between input and output variables. This model has been extensively and successively applied in many fields. However, linear transfer function model is only the first step to discover the relationship between input and output variables. Most applications have nonlinear features between input and output variables. An example is the effect of rainfall on the river flow [19]. These complex relationships cannot be well approximated by linear models. A direct solution for this problem is to use nonlinear transfer function models instead of linear models. Chen et al proposed a kind of nonlinear transfer function model [19]:

$$Y_t = C + f(X_{t-d}, ..., X_{t-d-p}; \theta) + N_t \qquad (1)$$

Where $f(.)$ is a parametric function assuming the Volterra series representation and N_t is a stationary ARMA process.

The problem in using nonlinear transfer function models is that it is very difficult to justify the explicit parametric functional forms. Modeling bias always exists for the selection of the parametric models. Nonparametric smoothing methods provide a more flexible alternative to model nonlinear time series. Liu et al provided a kind of nonparametric transfer function model [20]:

$$Y_t = f(X_t) + e_t \tag{2}$$

Where $f(.)$ is an unknown and smooth function. The processes $\{X_t\}$ and $\{e_t\}$ are assumed to be strictly stationary. The transfer function $f(.)$ is modeled by nonparametric smoothing and the innovation process $\{e_t\}$ is modeled as a stationary and inevitable ARMA(p,q) process:

$$\phi(B)e_t = \theta(B)\varepsilon_t \tag{3}$$

Where $\phi(B) = 1 - \sum_{i=1}^{p}\phi_i B^i$; $\theta(B) = 1 - \sum_{j=1}^{q}\theta_j B^j$; $\phi = (\phi_1, ..., \phi_p)^\tau$ and $\theta = (\theta_1, ..., \theta_q)^\tau$ are unknown parameters and $\{\varepsilon_t\}$ is a sequence of independent random variables with mean 0 and variance σ^2, $\{X_t\}$ and $\{\varepsilon_t\}$ are assumed to be independent [20].

By modeling the transfer function $f(.)$ nonparametrically, the model is flexible therefore can be used to model nonlinear relationships of unknown functional forms. By modeling $\{e_t\}$ as an ARMA(p,q) process, the autocorrelation in the data is removed so $f(.)$ can be estimated more efficiently [20].

3.2 Estimation Algorithm of Nonparametric Transfer Function Model

Liu et al [20] proposed an estimation algorithm of the nonparametric transfer function model. Assume $\{e_t\}$ is a stationary AR(p) process, model (2) can be written as

$$Y_t = f(X_t) + e_t \quad \phi(B)e_t = \varepsilon_t \tag{4}$$

Under normal assumption and with observations $\{(X_t, Y_t)\}_{t=1}^{n}$, the maximum likelihood estimation for $f(.)$ and ϕ boils down to the following optimization problem:

$$\inf_{f,\phi} \sum_{t=1}^{n}\{Y_t - f(X_t) - \sum_{i=1}^{p}\phi_i(Y_{t-i} - f(X_{t-i}))\}^2 \tag{5}$$

Where the infimum is taken over all smooth function f and $\phi \in R^p$ satisfies the stationary condition.

First obtain a preliminary estimator for $f(.)$ by local linear regression, ignoring the correlation in $\{e_t\}$. Namely, $\tilde{f}(x) = \tilde{a}_0$, and $(\tilde{a}_0, \tilde{a}_1)$ minimizes:

$$\sum_{t=1}^{n}\{Y_t - a_0 - a_1(X_t - x)\}^2 K_b(X_t - x) \tag{6}$$

Where $K_b(.) = b^{-1}K(./b)$ is a kernel function in R, and b>0 is a bandwidth.

Let $\tilde{e}_t = Y_t - \tilde{f}(X_t)$ be the initial estimate of the innovation series e_t, define:

$$X_1 = \begin{pmatrix} \tilde{e}_p & \tilde{e}_{p-1}\ldots & \tilde{e}_1 \\ \tilde{e}_{p+1} & \tilde{e}_p\ldots & \tilde{e}_2 \\ \ldots & \ldots & \ldots \\ \tilde{e}_{n-1} & \tilde{e}_{n-2} & \tilde{e}_{n-p} \end{pmatrix} \qquad Y_1 = \begin{pmatrix} \tilde{e}_{p+1} \\ \tilde{e}_{p+2} \\ \ldots \\ \tilde{e}_n \end{pmatrix} \tag{7}$$

And $W = diag\{\prod_{i=0}^{p} w(X_{t-i})\}$, where $w(.)$ is a weight function controlling the boundary effect in nonparametric estimation. The following estimation procedure is used [20]:

1. Specify an initial value $\phi = \tilde{\phi}$ defined as:

$$\tilde{\phi} = (X_1^T W X_1)^{-1} X_1^T W Y_1 \tag{8}$$

2. For given ϕ, let $\tilde{f}_j \equiv \tilde{f}(X_j) = \hat{a}_0$, where $(\hat{a}_0, \hat{a}_1)$ minimizes:

$$\sum_{t=1}^{n}\left\{Y_t - a_0 - a_1(X_t - X_j) - \sum_{i=1}^{p}\phi_i[Y_{t-i} - \tilde{f}(X_{t-i})]\right\}^2 K_h(X_t - X_j)\prod_{i=1}^{p} w(X_{t-i}) \tag{9}$$

Where $K_h(.) = h^{-1}K(./h)$, and h>0 is a bandwidth. Obviously $\hat{a}_1$ is an estimator for $\widehat{f}_j \equiv \tilde{f}(X_j)$.

3. Obtain $\widehat{\phi}$ by minimizing:

$$\sum_{j=1}^{n}\sum_{t=1}^{n}\left\{Y_t - \widehat{f}_j - \tilde{f}_j(X_t - X_j) - \sum_{i=1}^{p}\phi_i[Y_{t-i} - \tilde{f}(X_{t-i})]\right\}^2 K_h(X_t - X_j)w(X_j)\prod_{i=1}^{p} w(X_{t-i}) \tag{10}$$

Step 2 and step 3 are repeated until convergence.

3.3 Nonparametric Estimation of a Real Process

In order to test the advantage of the nonparametric transfer function model over linear transfer function models in modeling real processes, this part uses a real process to verify this.

A gas furnace was employed in which air and methane combined to form a mixture of gases containing CO_2. The air feed was kept constant, but the methane feed rate could be varied in any desired manner and the resulting CO_2 concentration in the off gases measured [11]. The input variable (gas feed rate) and corresponding output variable (CO_2 concentration) are in Fig. 1. The time intervals are 9 seconds [11].

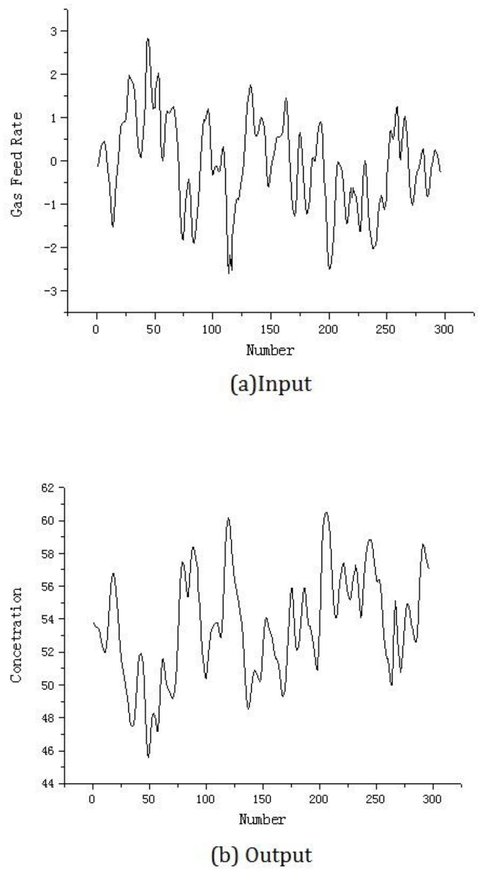


Figure 1. Input gas rate and output CO_2 concentration from a gas furnace

In the book of Box et al [11], the final form of the combined linear transfer function-noise model estimation result for the gas furnace data is:

$$Y_t = \frac{-(0.53+0.37B+0.51B^2)}{1-0.57B} X_{t-3} + \frac{1}{1-1.53B+0.63B^2} a_t \quad (11)$$

And the corresponding transfer function model is:

$$(1-0.57B)Y_t = -(0.53+0.37B+0.51B^2)X_{t-3} \quad (12)$$

The final estimation variance of the linear transfer function-noise model is 0.048.

We also use nonparametric estimation method in 3.2 to estimate the same process in Fig. 1. Assume the model is $Y_t=F(X_{t-3})$ and the noise is an AR(2) process, which is the same with the results in the book of Box et al. In step 1, the initial estimation results of ϕ are ϕ_1 =1.531630 and ϕ_2 =-0.730715. Then repeat step 2 and step 3, the convergence is achieved at about the 30th time of calculation. The results from the estimation of ϕ are ϕ_1 =0.8434287 and ϕ_2 =-0.1589558. The final estimation variance of the nonparametric transfer function-noise model is only 6.07×10^{-5}.

In the results of the two different transfer function models, the final variance of the nonparametric transfer function model is smaller than the result of the linear model. So in the estimation of this real example, the nonparametric model has better performance than the linear model, it can preserve more information about the data. So the nonparametric transfer function model is closer to real situations, it is more suitable and flexible than other linear transfer function models in modeling different kinds of complex processes.

4 Effect of Integrated SPC-EPC Control Method Based on Nonparametric Transfer Function Model

4.1 Controller Based on Nonparametric Transfer Function Model

Because the nonparametric transfer function model is more suitable in modeling real processes, this part uses a nonparametric transfer function model to build an EPC controller. A popular model that describes the dynamic behavior of the quality characteristics and noise-disturbance effects is given by Van der Wiel [6]:

$$Y_t = T(B)X_{t-1} + N_t \quad (13)$$

Where Y_t is the output of the quality characteristic, assume its target value is 0; X_t is the control action employed with transfer function $T(B)$, and B is the backshift operator; N_t is the dynamic noise of the system that can be represented by a time series model. This model is similar to model (1) and (2), transfer function $T(B)$ is unknown. In manufacturing process, if no control action is made, the output during this time is the dynamic autocorrelated noise N_t. Deviation in this output may cause the loss in quality, so we need to reduce deviation in this output. If we want to get an MMSE output, assume the form of N_t is known, we need to adjust input X_t in order to cancel the MMSE forecast of N_t, and the transfer function $T(B)$ is gotten by nonparametric smoothing:

$$T(B)X_{t-1} = \hat{N}_t \tag{14}$$

4.2 Effect of Controller Based on Nonparametric Transfer Function Model

The purpose of building a controller is to reduce the deviation in the output quality characteristics. However, in a large number of real manufacturing processes, due to some reasons, the process would have one or more assignable causes. So to study the performance of the controller under assignable causes is very necessary. Trend and sustained shift are two typical forms of the results of assignable causes, which would happen in the process. So this part will study the performance of the controller (14) and the integrated SPC-EPC method in controlling trend and sustained shift.

We generate 200 data points from (15):

$$Y_t = X_{t-1} + 0.2X_{t-1}{}^2 + 0.5X_{t-1}{}^3 + N_t \tag{15}$$

Where N_t is a AR(2) process with ϕ_1 =0.6 and ϕ_2 =-0.05, and X_t have normal distribution of mean 0 and standard deviation 5.

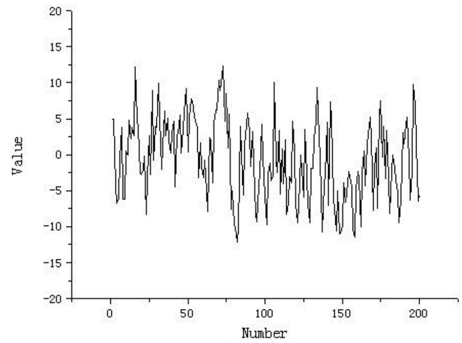
We assume the form of N_t is known and can be removed from the combined data, so we can get the relationship between X_t and Y_t without noise. We also assume how much compensation has been made by X_t is known. We use these 200 points to estimate the nonparametric transfer function. We also generate another 200 points of N_t for control.

To evaluate the effect of the controller and the integrated control method, the paper chooses the mean of the squared error as the performance measure. The smaller this value is, the better the control method. The formula is:

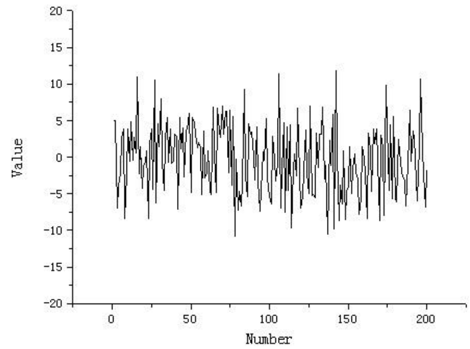
$$PM = \frac{1}{n}\sum_{t=1}^{n}(Y_t - T)^2 \tag{16}$$

Where n is the number of data points; Y is the output of quality characteristics; T is the target value, in this paper T=0.

First we assume there are no assignable causes in the process. We adjust the last 200 points using controller (14). Before adjustment, *PM*=31.31662, after adjustment, *PM*=23.68302. Results are in Fig. 2:



(a) Before

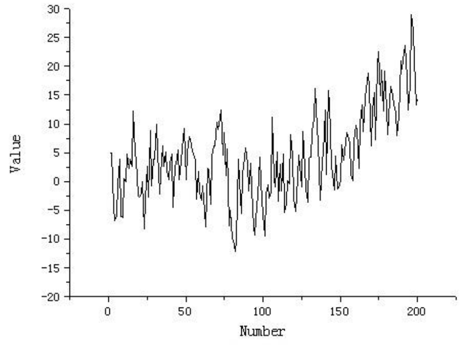


(b) After

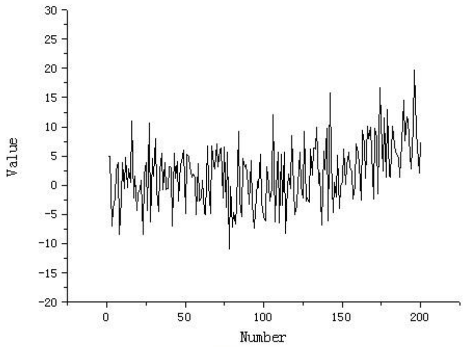
Figure 2. Process after control with no assignable causes

From the *PM* comparison and the results in Fig. 2, the EPC controller based on the nonparametric transfer function model can reduce deviation further at the output in the process which is in control.

Then we assume there are assignable causes resulting in a trend at the 101st point in the last 200 points. The trend has an increase of 0.2 per unit time point. We use controller (14) to do adjustment in the process. Before adjustment, *PM*=79.17783, after adjustment, *PM*=33.71696. Results are in Fig. 3:



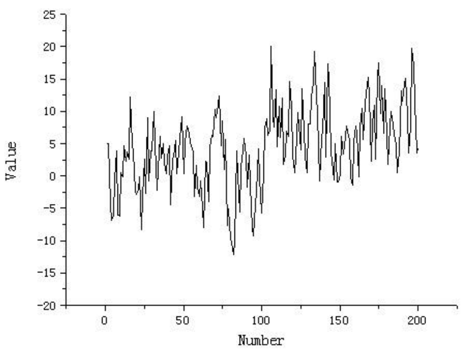
(a) Before



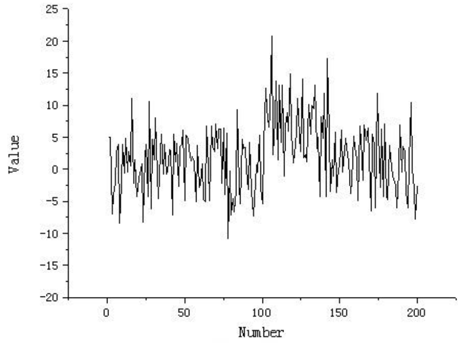
(b) After

Figure 3. Process after control with assignable causes resulting in a trend

We also assume there are assignable causes resulting in a sustained shift at the 101st point in the last 200 points. The sustained shift is an increase of 10. We use controller (14) to do adjustment in the process. Before adjustment, *PM*=58.67332, after adjustment, *PM*=33.84610. Results are in Fig. 4:



(a) Before



(b) After

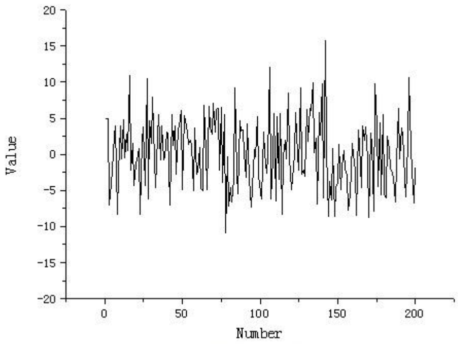
Figure 4. Process after control with assignable causes resulting in a sustained shift

In the comparison of the *PM* and the results in Fig. 3 and Fig. 4, the controller (14) can reduce a large amount of variations in the processes compared with the original processes. This demonstrates that the controller is effective in controlling processes with assignable causes resulting in the form of trend and sustained shift. However, there are still a small amount of trend and sustained shift at the output after control, so the controller (14) cannot compensate all the deviations in the processes. The reason behind this result is that the EPC controller only compensated some deviation which can be forecasted. But it cannot remove the deviation caused by the assignable causes. At this time, the assignable causes still exist within the process. So if we want to reduce the variation further, we need to use a control chart to help us remove the assignable causes.

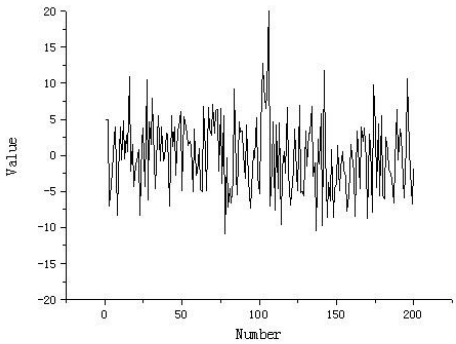
4.3 Effect of Integrated SPC-EPC Method Based on Nonparametric Transfer Function Model

From the study of the previous sections, we can see the EPC controller based on the nonparametric transfer function model is effective in controlling a nonlinear process which is in control or has assignable causes resulting in trend or sustained shift. But a small amount of deviation still exists at the output. So a method that can apply the advantages and avoid the disadvantages of EPC controller is to use integrated SPC-EPC method, that is simultaneously using controller and control chart.

In the processes of Fig. 3 and Fig. 4, we simultaneously use controller (14) and Shewhart 3σ control chart for individuals, assume the assignable causes can be removed immediately after the alarm of the control chart. The final *PM*=24.39389 for trend and *PM*=26.81842 for sustained shift. Results are in Fig. 5:



(a) Trend



(b) Sustained Shift

Figure 5. Process after integrated control based on nonparametric transfer function model

In the results of Fig. 5, the integrated SPC-EPC method has solved the problem of using the controller alone when the process is out of control. We can use a control chart to find and eliminate the assignable causes in time and use a controller to reduce the deviation which can be forecasted. The *PM*=24.39389 for trend is smaller than *PM*=79.17783 which do not control and *PM*=33.71696 of using a controller alone. The *PM*=26.81842 for sustained shift is also smaller than *PM*=58.67332 which do not control and *PM*=33.84610 of using a controller alone. If using the control chart alone, the results are *PM*=32.02090 for trend and *PM*=36.94402 for sustained shift, they both larger than the results of the integrated SPC-EPC method. So in the controlling of the complex nonlinear process, integrated SPC-EPC is better than using either alone. The total results are in Tab. 1.

Table 1. Results of different control methods

Control Method	No Control	Only Controller	Only Control Chart	Controller + Control Chart
Trend	79.17783	33.71696	32.02090	24.39389
Sustained Shift	58.67332	33.84610	36.94402	26.81842

5 Simulation Study of the Integrated SPC-EPC Method Based on Nonparametric Transfer Function Model

5.1 Simulation Study on the Assignable Causes Resulting in Trend

In order to further investigate the integrated SPC-EPC control system based on nonparametric transfer function model, we conduct a simulation study. Based on a large amount of simulations, we study the performance of the system. First we assume processes of (15) have assignable causes resulting in trend of increase 0.05, 0.1, 0.2, 0.3, 0.5 per unit time point. All these out-of-control signals happen from the 101st time point, and we assume the assignable causes can be removed as soon as it was detected by the control chart. We use controller (14) to do adjustment in these processes. We use 3 different kinds of control charts to monitor the processes. They are Shewhart chart; EWMA chart of λ=0.1 and EWMA chart of λ=0.4. The reason of chose λ=0.4 is that when λ=0.4, current and previous observations nearly have identical weights [8]. Based on 500 simulations, we check the mean of sum of squared error and average run length (ARL_1) of all these cases, we set ARL_0=370. Results are in Tab. 2 and Tab. 3

Table 2. Mean of squared error of different degree of trend

Deviation	0.05	0.1	0.2	0.3	0.5
No chart	14.23847	18.06374	37.92582	96.31947	/
Shewhart-Output	19.28803	17.50712	15.17858	15.59571	23.88990
Shewhart-Input	12.36702	12.14782	16.51118	18.88842	40.96622
EWMA-Output (λ=0.1)	14.96499	14.37515	12.78832	12.96059	15.23776
EWMA-Input (λ=0.1)	14.20630	14.27362	14.41544	14.92915	31.85255
EWMA-Output (λ=0.4)	12.63705	16.49736	13.58133	12.98117	12.94381
EWMA-Input (λ=0.4)	14.30899	17.28226	38.75358	46.73027	277.9397

Table 3. ARL of different degree of trend

Deviation	0.05	0.1	0.2	0.3	0.5
Shewhart-Output	86.04	71.52	45.71	37.02	26.72
Shewhart-Input	5.04	5.08	6.57	11.12	45.94
EWMA-Output (λ=0.1)	47.65	33.67	24.07	21.23	16.33
EWMA-Input (λ=0.1)	96.05	69.68	50.37	40.84	58.01
EWMA-Output (λ=0.4)	46.70	39.92	28.22	23.26	16.24
EWMA-Input (λ=0.4)	-	-	92.88	74.47	83.17

In the results of Tab. 2 and Tab. 3, we can see when the process has assignable causes resulting in the form of trend, only using the nonparametric controller (14) is effective when the deviation is very small, but it is not effective when the deviation is large. When the controller is used with a control chart, controller + EWMA chart can reduce the deviation in the process, and monitoring the output variable is more effective than monitoring the input variable; using the controller + Shewhart chart is better than using a controller alone, and monitoring the input is better than the EWMA chart when the deviation is small. Through the comparison of the λ values of the EWMA chart, using λ=0.1 is a little bit effective than λ=0.4, and the ARL values of this two λ values is not very large. Using Shewhart chart monitoring the input has the smallest ARL when the deviation is small. EWMA chart monitoring the output has the smallest ARL when the deviation is large. Small ARL is helpful in finding and removing the assignable causes in time.

After the analysis of this part, we can get a conclusion that if a complex process has assignable causes resulting in the form of trend, if we don't know the degree of deviation, or we know the deviation is large, we can use the controller based on nonparametric transfer function model and the EWMA control chart monitoring the output variable. When we know the deviation is small, we can use the controller based on nonparametric transfer function model and the Shewhart control chart monitoring the input variables.

5.2 *Simulation Study on the Assignable Causes Resulting in Sustained Shift*

We assume processes of (15) have assignable causes resulting in sustained shift of increase 0.5; 1; 2; 5; 10. All these out-of-control signals happen from the 101st time point, and we assume the assignable causes can be removed as soon as it was detected by the control chart. We use controller (14) to do adjustment to these processes. We use 3 different kinds of control charts to monitor the process. They are Shewhart chart; EWMA chart of λ=0.1 and EWMA chart of λ=0.4. Based on 500 simulations, we check the mean of sum of squared error and average run length (ARL_1) of all these cases, we set ARL_0=370. Results are in Tab. 4 and Tab. 5.

Table 4. Mean of squared error of different degree of sustained shift

Deviation	0.5	1	2	5	10
No chart	13.16874	12.64734	16.86644	16.23207	31.31908
Shewhart-Output	12.69791	14.82094	21.01615	15.05096	17.59686
Shewhart-Input	12.50452	12.35310	13.86978	12.44581	12.23439
EWMA-Output (λ=0.1)	12.93107	22.46007	15.94912	12.91471	14.06941
EWMA-Input (λ=0.1)	17.74330	15.57995	12.92898	15.41068	23.64010
EWMA-Output (λ=0.4)	15.76331	12.34718	12.60039	12.94052	12.99853
EWMA-Input (λ=0.4)	12.81632	12.60330	12.93822	16.61562	26.52534

Table 5. ARL of different degree of sustained shift

Deviation	0.5	1	2	5	10
Shewhart-Output	86.30	86.96	83.63	58.70	23.78
Shewhart-Input	5.67	5.58	5.17	1.91	1.33
EWMA-Output (λ=0.1)	60.91	60.08	38.05	15.09	7.05
EWMA-Input (λ=0.1)	97.83	96.05	95.51	63.17	20.37
EWMA-Output (λ=0.4)	65.75	60.45	53.02	20.69	6.31
EWMA-Input (λ=0.4)	-	-	-	-	89.62

In the results of Tab. 4 and Tab. 5, we can see when the process has assignable causes resulting in the form of sustained shift, the results of using the controller (14) alone are the same with trend. It is effective when the deviation is very small, but not effective when the deviation is large. When the controller is used with the a control chart, controller + Shewhart can reduce the deviation in the process, and monitoring the input variable is more effective than monitoring the output variable; using the controller + EWMA is not better than using Shewhart chart, and using the controller + Shewhart chart also has the smallest ARL value.

After the analysis of this part, we can get a conclusion that if a process has assignable causes resulting in the form of sustained shift, no matter the degree of the sustained shift, integrating controller based on nonparametric transfer function model and the Shewhart control chart monitoring the input variable can get the best effect.

6 Conclusion

According to all the studies above, nonparametric transfer function model can be used to model some complex nonlinear input-output relationships, which are closer to real situations. Compared with the parametric linear transfer function model, nonparametric model can preserve more information about the process, so this will give a method to achieve a more accurate control. EPC controller based on the nonparametric transfer function model can reduce a large amount of variations, if it is used together with a control chart, variation will be reduced further because the reason of variation is removed.

SPC-EPC integration is a very effective way in quality control. The integrated method includes features from both SPC and EPC and could get a complementary performance. Using the nonparametric transfer function model to describe the relationship within a system and built controllers based upon this model can result in more effective control.

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