Int J Adv Manuf Technol (2004) 23: 586–593
DOI 10.1007/s00170-003-1776-x

ORIGINAL ARTICLE

C.-C. Hsu · C.-T. Su

A neural network-based adaptive algorithm on the single EWMA controller

Received: 13 January 2003 / Accepted: 14 April 2003 / Published online: 6 December 2003

Abstract The single EWMA controller has been proven to have excellent performance for small disturbances in the run-to-run process. However, incorrect selection of the EWMA parameter can have the opposite effect on the controlled process output. An adaptive system is necessary to automatically adjust the controller parameters on-line in order to have better performance. In this study, a simple and efficient algorithm based on neural networks (NN) is proposed to minimise the inflation of the output variance on line. The authors have shown that the sequence of EWMA gains, generated by a NN-based adaptive approach, converges close to the optimal controller value under IMA (1, 1), step and trend disturbance models. The paper also shows that the NN-based adaptive EWMA controller has a superior performance than its predecessors.

Keywords EWMA · Neural networks · Adaptive · Autocorrelation · Inflation factor

1 Introduction

Quality is an important issue in the competitive manufacturing industry. The traditional statistical process control (SPC) is a tool in which the process output is monitored in order to detect assignable causes and eliminate them. This has been successfully used in discrete parts manufacturing. Most SPC techniques assume that the process data are statistically independent observations and that they fluctuate around a constant mean. However, continuous processes such as chemical and process industries exhibit correlated process outputs which violate these assumptions of traditional SPC techniques. To address this, an approach widely known as engineering process control (EPC) is used containing manipulating variables that can be adjusted to keep the process on target.

Lately, a run-by-run feedback control method called EWMA controller has become popular in semiconductor manufacturing, particular in chemical mechanical polishing (CMP) and plasma etching processes. The performance of such a closed loop system is dependent on setting the EWMA controller parameter. Misidentifying the EWMA gain will result in the inflation of the output variance. Thus, an adaptive algorithm for optimising the EWMA gain on line is necessary to reduce the inflation of the output variance.

Based on this principle, previous research used the neural network as an approximation function [1] which maps the magnitudes of noises and drifts in order to obtain the optimal EWMA controller gain. However, estimating the slopes of drifts was a problem. Patel and Jenkins [2] provided a statistic-based adaptive approach to updating the EWMA controller parameter in accordance with the signal-to-noise (SN) ratio, which involves estimating the mean of the output and the mean square of the output. In other words, it implies that additional parameters should be chosen at first to estimate them.

In this study, a simple approach based on neural networks (NN) was developed to tune the EWMA gain on-line. This method has taken advantage of estimating the autocorrelation correlation function (ACF) only. ACF is a well known tool to identify the order of the moving average (MA) process in time series models that is easily estimated through the sample ACF (SACF). Another way of looking at the ACF is that it is a function of time series parameters, so, the tendency of the ACF is different under different parameters. With this view in mind, a NN-based adaptive algorithm is developed to estimate EWMA gains by identifying the SACF patterns. The proposed methodology was compared to the Patel and Jenkins adaptive system. Examples showed that the proposed methodology had a superior performance to their system under common disturbance models including step, trend and IMA (1, 1)

C. -C. Hsu · C. -T. Su (✉)
Department of Industrial Engineering and Management,
National Chiao Tung University, Hsinchu, Taiwan
E-mail: ctsu@cc.nctu.edu.tw

disturbance models. Thus, this research provided a simple and efficient method of updating the EWMA controller parameter on-line.

This paper is laid out as follows: Sect. 2 reviews the EWMA controller and specifies the results of incorrectly setting the EWMA gain. Section 3 introduces an adaptive algorithm which was proposed by Patel and Jenkins [2]. Section 4 briefly introduces neural networks techniques and Sect. 5 presents the structure of the proposed approach. Here the idea of using the SACF to estimate the EWMA gain will be demonstrated in more detail. Section 6 exhibits the result of the off-line trained neural network and implements it on-line via three simulation examples, including the commonly encountered disturbance model. Finally, conclusions and future work are discussed in Sect. 8.

2 The EWMA controller

The EWMA statistic, sometimes called a geometric moving average (GMA), was suggested by Roberts [3]. This statistic was used extensively in time series forecasting [4, 5] and process monitoring [6, 7, 8, 9, 10]. Most recently, the EWMA controller has been used widely in semiconductor manufacturing [11, 12, 13, 14]. EWMA controller related research is available from Ingolfsson and Sachs [15], Del Castillo and Hurwitz [16], Del Castillo [17], Pan and Del Castillo [18], Del Castillo [19] and O'Shaughnessy and Haugh [20].

The EWMA controller is similar to the SPC in that it monitors process parameters such as removal rate and the non-uniformity in the CMP (chemical mechanical planarisation) process. However, the run-to-run process control does not like SPC techniques; it makes continual changes to the process recipe in order to compensate for drifts and shifts in the process output. Consider a closed-loop system for which all the effects of a change in the compensating variable are realised at the output in one time interval. Such a system will be called a responsive system [9] i.e. the process can be expressed by the following model:

$$e_t = \alpha + \beta u_{t-1} + N_t \tag{1}$$

where e_t is the observed output deviation from target, α is the process offset, β is the process gain, u_t is the manipulated variable and N_t is the disturbance model which can be modelled by the time series model such as the IMA (1, 1) process. An IMA (1, 1) process is used widely for modelling the drift in discrete manufacturing [5, 9] and can be expressed as:

$$N_t = N_{t-1} + \varepsilon_t - \theta\varepsilon_{t-1} \qquad |\theta| \leqslant 1 \tag{2}$$

where θ is the moving average parameter, and $\{\epsilon_t\}$ are independent, identically distributed, random variables with mean zero, and variance σ_ε^2. In the EWMA controller, the estimator of β is estimated off-line and denoted as b. The single EWMA scheme can be expressed as follows:

$$u_t = -\frac{a_t}{b} \tag{3}$$

where

$$a_t = \lambda(e_t - bu_{t-1}) + (1-\lambda)a_{t-1} \cdot (0 \leqslant \lambda \leqslant 1) \tag{4}$$

is an estimate of the offset and is computed recursively based on the EWMA statistic with the last measurement data and the previous estimate a_{t-1}, and λ is the controller parameter which can be adjusted to achieve a desired output. Substituting Eq. 1 and 2 into 3 as follows:

$$a_t = \lambda \sum_{j=-\infty}^{t} e_j \tag{5}$$

thus, the adjustment at each run is proportional to the present output deviation, that is:

$$\nabla u_t = -\frac{\lambda}{b} e_t \tag{6}$$

A discrete PI controller is well-known as follows:

$$u_t = k_P e_t + k_I \left(\frac{1}{1-B}\right) e_t \tag{7}$$

from Eq. 5, it is easy to observe that the EWMA controller is a pure integral controller which is a particular case of the PI controller with parameter $K_p = 0$, $k_I = -{}^{\lambda}/_{b}$.

Substituting Eq. 5 and 2 into 1,the controlled process is changed as follows:

$$(1 - (1 - \lambda\xi)B)e_t = (1 - \theta B)\varepsilon_t \tag{8}$$

where $\xi = {}^{\beta}/_{b}$ is a bias of the gain estimate. It is evident that the controlled process exhibits an ARMA (1, 1) process and the stable condition is $|1 - \lambda\xi| \leqslant 1$. The variance of the controlled process is as follows:

$$\sigma_e^2 = \left[1 + \frac{(1 - \lambda\xi - \theta)^2}{1 - (1 - \lambda\xi)^2}\right]\sigma_\varepsilon^2 \tag{9}$$

Assume the process gain is known, that is $\xi = 1$; Fig. 1 shows the inflation factor $\left({}^{\sigma_e^2}/_{\sigma_\varepsilon^2}\right)$ versus λ and θ.

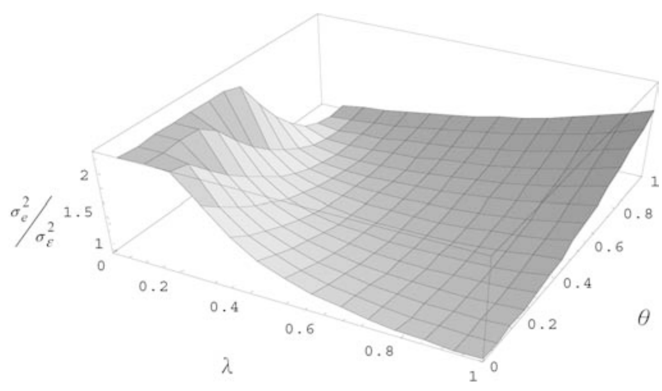

Fig. 1 Inflation factor versus λ and θ

If the disturbance model is a white noise process that is $\theta = 1$ in Eq. 2, which means that the process is in a statistical control condition and that it will not drift off target, so no adjustment to manipulate variable is necessary. If the full adjustment to Eq. 5 is used at each run, say $\lambda = 1$, then the variance of the controlled process will be inflated twice as much than if there were no adjustment. This is what Dr. Deming meant by "tampering with the process". From Fig. 1, the optimal controller parameter is found to be:

$$\lambda^* = 1 - \theta \tag{10}$$

If the optimal controller is used to control the process, then the controlled process will be a minimum mean square error (MMSE) controlled process as expected. In fact, the disturbance parameter may change with time and if the controller parameter is set incorrectly, then the variance of the controlled output will be inflated. For this reason an adaptive technique should be used to recursively estimate the controller parameter on-line in order to provide a better control performance.

3 The recursive algorithm

Sastri [21] proposed an adaptive estimation approach, based on the least squares estimation theory for sequential parameter-detection and revision of the moving average parameter in the IMA (1, 1) time series model. Luceño [22] used the maximum likelihood estimate algorithm and presented a computer program to choose the EWMA parameter. Smith and Boning [1] ran the Monte Carlo simulations and then utilised a neural network function to map the optimal weight surface via a neural network. In this section, a recursive algorithm will be introduced that was proposed by Patel and Jenkins [2]; their objective was to design an automated scheme for optimising the numerical parameter of the EWMA controller. Figure 2 shows an adaptive EWMA controller block diagram, where a tuner tunes the EWMA parameter (λ_t) to provide better control performance.

Consider the following system:

$$\begin{aligned} \mu_{t+1} &= \mu_t + \tau_t(e_{t+1} - \mu_t) \\ \zeta_{t+1} &= \zeta_t + \tau_t\left(e_{t+1}^2 - \zeta_t\right) \\ \lambda_t &= \frac{\delta^2 + 4\mu_t^2}{\delta + \mu_t^2 + \zeta_t} \end{aligned} \tag{11}$$

$\{\mu_t\}$ are the estimates of the mean of the output. $\{\zeta_t\}$ are estimates of the mean square value of the output. The initial conditions (μ_0, ζ_0) satisfy $0 \leqslant \mu_0^2 \leqslant \zeta_0$. δ is a constant with a very small value which satisfies $0 < \delta < 1$, and $\{\tau_t\}$ is a sequence such that $0 \leq \tau_t < 1$ and satisfies (1) $\lim_{t\to\infty} \tau_t = 0$, (2) $\sum_{t=0}^{\infty} \tau_t = \infty$, (3) $\sum_{t=0}^{\infty} \tau_t^2 < \infty$. The form of λt in Eq. 11 intuitively provides a measure of the signal-to-noise (SN) ratio which satisfies $0 \leq \lambda_t \leq 2$. Similar to Eq. 5, an adaptive EWMA control equation can be written as follows:

$$\nabla u_t = -\frac{\lambda_t}{b} e_t \tag{12}$$

where the adaptive tuner λ_t is expressed in Eq. 11.

4 Neural networks

The neural network is an approach to information processing that does not require algorithm or rule development. The three essential features of a neural computing network are the computing units; the connections between the computing units; and the training algorithm used to find values of the network parameters. Neural networks are trained by two main types of learning algorithms: supervised learning and unsupervised learning. In general, supervised learning can be used in prediction or mapping problems and the clustering problem usually makes use of unsupervised learning.

Neural networks can be classified into two different categories: feed forward and feedback networks [23]. In this study, we utilized the feed forward network because it has been found to be an effective system for learning distinguishing patterns from a body of examples. As

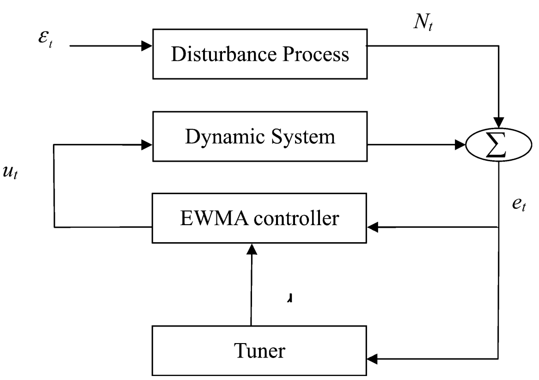

Fig. 2 Structure of adaptive tuning controller

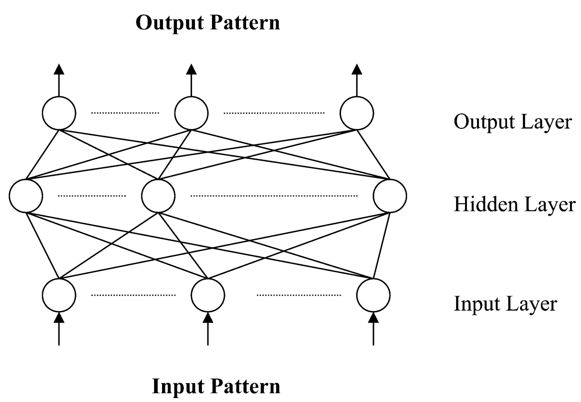

Fig. 3 Multi-layer feed forward neural network

shown in Fig. 3, a feed forward network is composed of several layers: an input layer, one or more hidden layers, and an output layer. Neurons in the feed forward network receive inputs only from the previous layer and feeds outputs only to the next layer. Multilayer feed forward neural networks are used for the modelling of many manufacturing processes which are typically trained through a back-propagation algorithm [24]. The back-propagation algorithm involves a forward pass and a backward pass. The purpose of the forward pass is to obtain the activation value, and the purpose of the backward pass is to adjust weights according to the difference between the desired and actual network outputs. The above statement can be explained by the following mathematical equations:

4.1 Forward pass

The net input to node i for pattern p is

$$net_{pi} = \sum_j w_{ij} a_{pj} + b_i \tag{13}$$

$$a_{pj} = \frac{1}{1 + e^{-net_{pj}}} \tag{14}$$

where w_{ij} is the weight from unit j to unit i, b_i is a basis associated with unit i, and a_{pj} is the activation value of unit j with sigmoid function for pattern p.

4.2 Backward pass

The sum of squares error function is as follows:

$$E_p = \frac{1}{2} \left\| t_p - o_p \right\|_2^2 \tag{15}$$

where t_p is the target output for the pth pattern and o_p is the actual output for the pth pattern. By minimising the errors E_p using the gradient decent method, the weights can be updated using as the following equation:

$$\Delta_p w_{ij} = \eta \delta_{pi} a_{pj} \tag{16}$$

where

$$\delta_{pi} = \begin{cases} \left(t_{pi} - o_{pi}\right) o_{pi} \left(1 - o_{pi}\right) & \text{if unit is an output unit} \\ opi\left(1 - o_{pi}\right) \left(\sum_k \delta_{pk} w_{ki}\right) & \text{if unit is a hidden unit} \end{cases} \tag{17}$$

and η is the learning rate. In general, a larger learning rate will increase the training speed, however it may oscillate widely. One way to increase the learning rate without oscillating is to modify Eq. 16 to the following equation:

$$\Delta_p w_{ij} = \eta \delta_{pi} a_{pj} + m \Delta_{p-1} w_{ij} \tag{18}$$

where m is the momentum coefficient ($m \in [0, 1]$) that determines the effect of past weight changes on the current direction of movement in weight space. There is no principle to determine the parameters of η and m; they are chosen by the neural network trainer via trial and error.

5 Proposed approach

A methodology was developed under the framework of neural networks to conduct on-line tuning of the parameters of the EWMA controller. The input feature of the neural structure is the sample autocorrelation function (SACF) and the output unit is an estimator of the EWMA controller parameter at run t. The theoretical autocorrelation function (ACF) at lag h is defined as follows:

$$\rho(h) = \frac{Cov(e_t, e_{t+h})}{\sigma(e_t)\sigma(e_{t+h})} \tag{19}$$

Equation 19 is estimated by the SACF:

$$\hat{\rho}(h) = \frac{\gamma_h}{\gamma_0} \tag{20}$$

where $\gamma_h = \frac{\sum_{i=1}^{n-h} (e_i - \bar{e})(e_{i+h} - \bar{e})}{n}$, n is the sample size, and $\bar{e}$ is the sample mean.

The idea of selecting the SACF to be the input feature in the neural network can be described simply in Fig. 4. Figure 4a is the family of SACF patterns given that the controller parameter is 0.1, and Fig. 4b is the family of SACF patterns given that the controller parameter is 0.9. On the one hand, one can see that the SACF behaves (in Fig. 4b) similar to exponential decay, which implies that the more non-stationary the process, the larger the value of the controller parameter will be in order to compensate the process. On the other hand, the tendency of the SACF behaves similarly when the controller parameter has a specific value (say $\lambda = 0.1$ or 0.9). So, the objective is to estimate the controller parameter through the tendency of the SACF pattern.

The structure of the proposed adaptive neural-based EWMA controller is shown in Fig. 5. At first the controlled process output was sent to the SACF block to calculate the $\hat{\rho}(h)$, and then the SACF pattern over lag h was fed into the trained NN model block to estimate the controller parameter. After estimating the parameter, the EWMA controller parameter was updated with time to provide a better control performance. The proposed methodology was implemented in Sect. 7 and compared to the Patel and Jenkins method, which was introduced in Sect. 3.

6 Implementation

6.1 Training the neural network

The training data sets were generated by simulating the environment under Eq. 1–4. At each simulation, 50 runs were simulated with values of λ_0 and λ_1, where λ_0

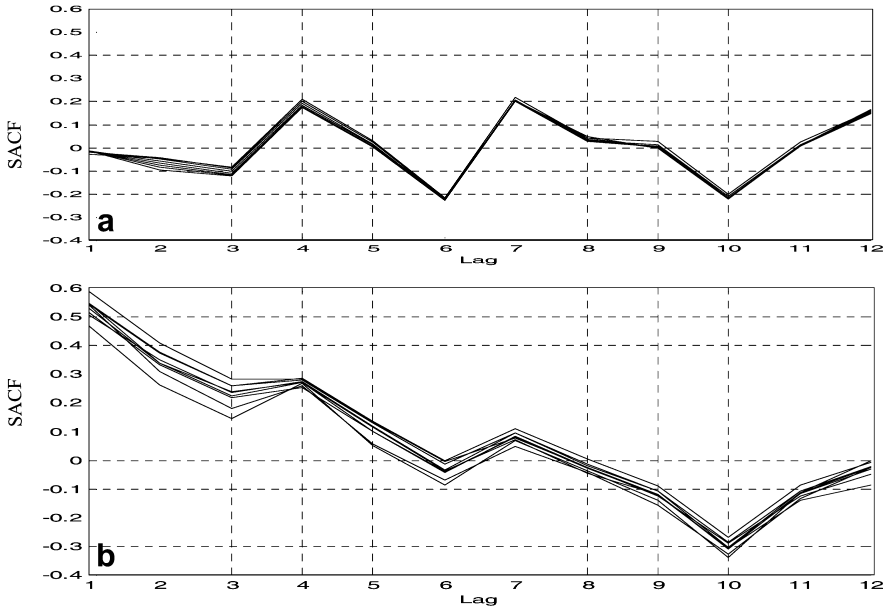

Fig. 4a,b The parameter with: **a** $\lambda = 0.1$, **b** $\lambda = 0.9$

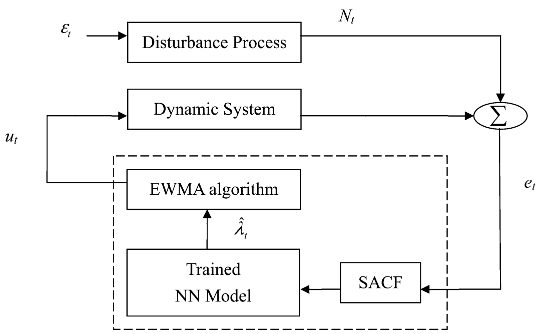

Fig. 5 NN-based EWMA controller

($\lambda_0 = 1 - \theta_0$) was the optimal controller parameter, and λ_1 was the value used to control the process. There were a total of 121 data sets which implied there was a total of 121 SACF patterns. 30 data sets were used as the testing data and the remainder were the training data. A useful guide was provided by Box-Jenkins [1, 2], who suggested that the size of time series (t) be at least 50 and lags (h) to analyse the series at most $t/4$. Thus, the number of lags in a SACF pattern used was 12, which was equivalent to the input nodes in the training network.

The learning rate we set to train the neural network was 0.15, and the momentum coefficient was 0.9. The summary of the training result is shown in Table 1. The 12-17-1 network was the best network for the data sets, because of the lower training and testing RMSE (root mean square error). Thus, the 12-17-1 network structure was utilised to implement the NN-based EWMA controller on line in the following examples.

6.2 Examples

The Matlab/Simulink version 3.0 package was used to implement the Patel-Jenkins method and the proposed NN-based adaptive EWMA controller. A comparison was then made between them. Three examples will be shown, each under a different disturbance model; including step disturbance, IMA (1, 1) disturbance and trend disturbance, which are commonly encountered in practice.

Table 1 Summary of the training results

Structure	Training RMSE	Testing RMSE
12-15-1	0.0191	0.0213
12-16-1	0.0183	0.0210
12-17-1	0.0166	0.0198
12-18-1	0.0175	0.0220
12-19-1	0.0182	0.0232

6.2.1 Example 1

First the example from Patel and Jenkins [2] was considered. The step disturbance model can be expressed as follows:

$$N_t = \begin{cases} L & t \geqslant t_s \\ 0 & t < t_s \end{cases} \tag{21}$$

where L is the level of the step change disturbance and t_s is the time of the disturbance introduced into the process. The tuner parameters in the Patel-Jenkins system (Eq. 11) were set to be the same as their simulation example. They were $\sigma_\varepsilon^2 = 1$, $\mu_0 = 0.1$, $\zeta_0 = 1$, $\delta = 10^{-4}$, $\tau = 0.005$, and the step disturbance is introduced at run 50 with $L = 10$. Figure 6a shows the controlled process output and Fig. 6b plots the EWMA gain λ_t through 800 runs. On the other hand, the trained network structure 12-17-1, which was implemented on-line to tune the EWMA controller gain under the step disturbance, was also introduced at run 50 with magnitude 10.

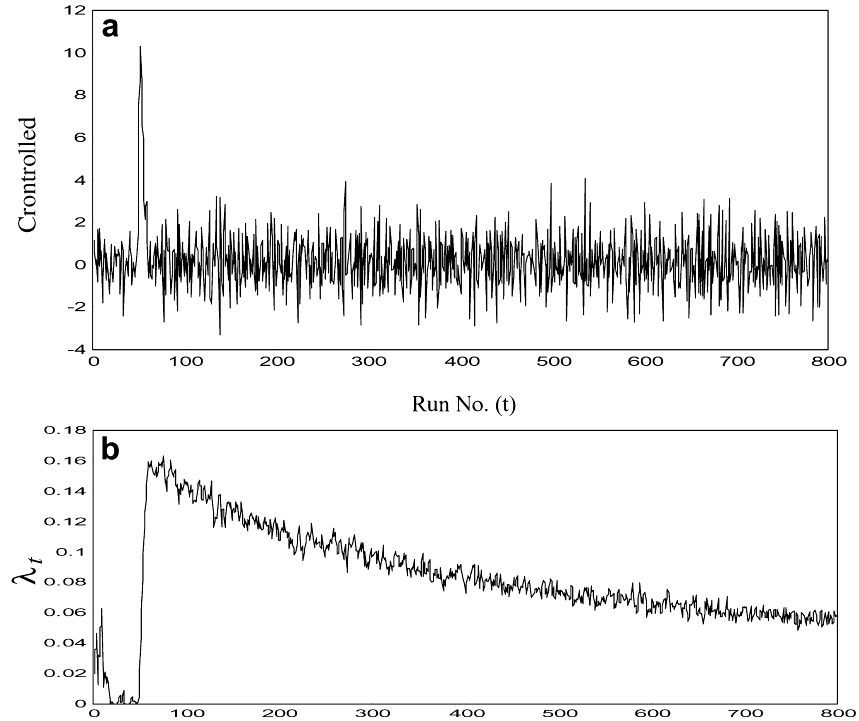

Fig. 6a,b Patel Jenkins adaptive method: **a** controlled output, **b** EWMA gain

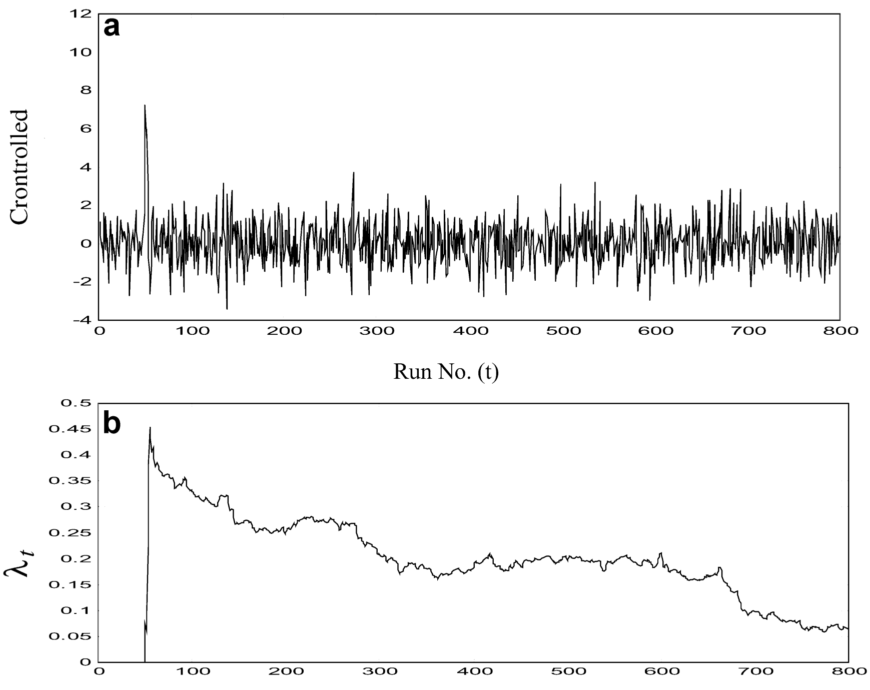

Fig. 7a,b NN-based adaptive method: **a** controlled output, **b** EWMA gain

Figure 7a shows the NN-based controlled process output and Fig. 7b plots the NN-based EWMA gain λ_t through 800 runs. As expected, λ_t increased on a shift, and decreased to a small number. The uncontrolled inflation factor $\left(\hat{\sigma}_e^2/\hat{\sigma}_\varepsilon^2\right)$ was 5.2795, and the controlled inflation factor under the Patel-Jenkins method was 1.8521, and 1.4401 in the NN-based EWMA controller. Thus, the performance of the NN-based controller was superior.

6.2.2 Example 2

In this example, a IMA(1, 1) disturbance model was considered in Eq. 2 with a moving average parameter $\theta = 0.2$ and $\sigma_\varepsilon^2 = 1$. From Eq. 10, it was apparent that the optimal controller parameter was $\lambda^* = 1 - \theta$. Assume the IMA (1, 1) disturbance model was introduced at run 50 over 800 runs. Figure 8 shows the EWMA gain under NN-based adaptive controller. The value of λ_t tended to

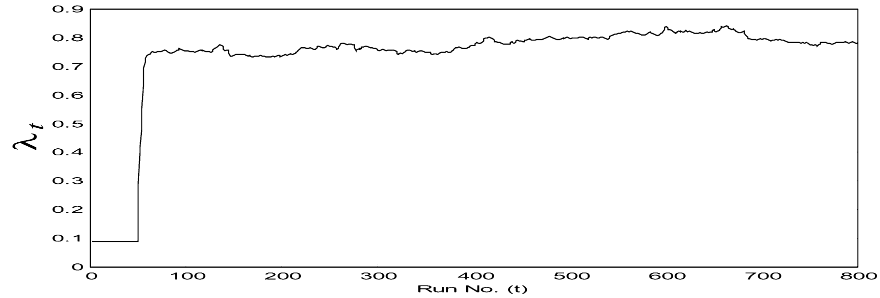

Fig. 8 NN-based adaptive EWMA gain under IMA (1,1)

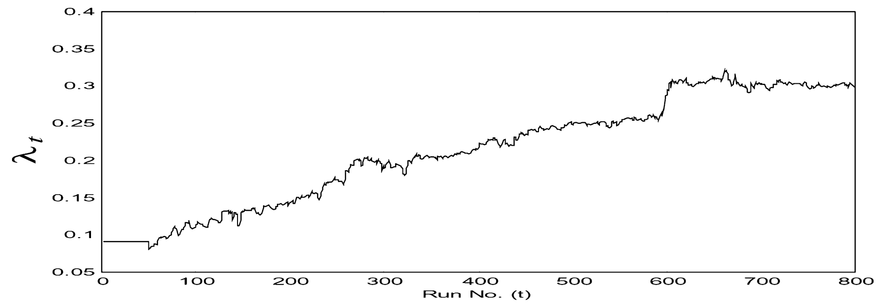

Fig. 9 NN-based adaptive EWMA gain under trend disturbance

0.7846 (taking the sample mean of the last 100 runs). This was close to the optimal controller parameter of 0.8. The NN-based adaptive controlled inflation factor after 50 runs was 1.025, which implies that the increased standard deviation (ISD) was 2.4672% and the ISD under Patel-Jenkins adaptive algorithm was 6.5762%. Thus, the NN-based adaptive algorithm produces a lower inflation in the controlled process.

6.2.3 Example 3

The chemical mechanical planarisation (CMP) is a very critical step for very large scale integrated (VLSI) manufacturing. The objective of CMP is to obtain global within-wafer planarisation. It is well known that the polish pad tends to wear-out with use, leading to a trend process in remove rate which needs to be compensated for. Therefore, this example will simulate the environment of the CMP process and apply the proposed approach to control it.

Consider the trend disturbance model which can be expressed as:

$$N_t = \begin{cases} S(t - t_s) & t \geqslant t_s \\ 0 & t < t_s \end{cases} \tag{22}$$

where S is the trend rate. The optimal EWMA controller parameter under trend disturbance can be solved by the following equation:

$$\sigma_\varepsilon^2 \lambda^3 - S^2\lambda^2 + 4S^2\lambda - 4S^2 = 0 \tag{23}$$

Assuming the trend disturbance with $S = 0.1$and $\sigma_\varepsilon^2 = 1$ was introduced at run 50. Figure 9 shows the EWMA gain under NN-based adaptive method. Taking the sample mean of the last 100 runs, the value of λ_t tended to 0.3057 which was very close to the optimal value of 0.3061, which was obtained by solving Eq. 23. The NN-based controlled inflation factor was 1.5919, and 2.0914 under Patel-Jenkins adaptive algorithm.

7 Conclusion

The effect of improperly setting the EWMA controller parameter would inflate the controlled process output variance has been demonstrated in this study. The authors have shown that the NN-based adaptive approach possesses better performance than the Patel-Jenkins adaptive algorithm on the controlled process output. Furthermore, the proposed system has been shown to be a stable system. From example 1, as was expected, the NN-based EWMA gain tended to a small value with time when a step disturbance model was introduced to the process. Examples 2 and 3 showed the EWMA gain behaving close to the optimal controller parameter when the IMA (1,1) and trend disturbance existed in the process.

The proposed methodology could update the EWMA gain automatically, which would reduce the needs for operators to tune recipes in the process. Although the proposed methodology was implemented via simulation, nevertheless it is anticipated to improve the performance of the EWMA controller on an actual process. Further research can extend the proposed methodology to the double EWMA controller that compensates for the severe drifts, such as the random walk with drift (RWD) disturbance model.

References

1. Smith T, Boning D (1997) A self-tuning EWMA controller utilizing artificial neural network function approximation techniques. IEEE Trans Compon Pack Tech 20:121–132
2. Patel N, Jenkins S (2000) Adaptive optimization of run-to-run controllers: the EWMA example. IEEE Trans Semiconduct Manuf 13:97–107
3. Roberts SW (1959) Control chart tests based on geometric moving averages. Technometrics 1:97–101
4. Box GEP, Jenkins GM (1976) Time series analysis, forecasting and control. Holden-Day, Oakland
5. Box GEP, Jenkins GM, Reinsel G (1994) Time series analysis, forecasting and control, 3rd edn. Prentice Hall, Englewood Cliffs
6. Lucas JM, Saccucci MS (1992) Exponentially weighted moving average control schemes: properties and enhancements. Technometrics 32:1–29
7. Box GEP, Kramer T (1992) Statistical process monitoring and feedback adjustment—a discussion. Technometrics 34:251–285
8. Montgomery DC (1996) Introduction to statistical quality control, 3rd edn. Wiley, New York
9. Box GEP, Luceño A (1997) Statistical control by monitoring and feedback adjustment. Wiley, New York
10. Chen A, Elsayed EA (2002) Design and performance analysis of the exponentially weighted moving average mean estimate for processes subject to random step changes. Technometrics 44:379–389
11. Sachs E, Hu A, Ingolfsson A (1995) Run by run process control: combining SPC and feedback control. IEEE Trans Semiconduct Manuf 8: 26–43
12. Wang X, Mahajan RL (1996) Artificial neural network model-based run-to-run process controller. IEEE Trans Compon Pack 19:19–26
13. Smith T, Boning D (1997) Artificial neural network exponentially weighted moving average controller for semiconductor processes. J Vac Sci Tech A 15:1377–1384
14. Moyne J, Del Castillo E, Hurwitz A (2000) Run-to-run control in semiconductor manufacturing. CRC Press
15. Ingolfsson A, Sachs E (1993) Stability and sensitivity of an EWMA controller. J Qual Tech 25:271–287
16. Del Castillo E, Hurwitz A (1997) Run-to-run process control: literature review and extensions. J Qual Tech 29:184–196
17. Del Castillo E (2001) Some properties of EWMA feedback quality adjustment schemes for drifting disturbance. J Qual Tech 33:153–166
18. Pan R, Del Castillo E (2001) Identification and fine tuning of closed-loop processes under discrete EWMA and PI adjustments. Qual Reliab Eng Int 17:419–427
19. Del Castillo E (2002) Closed-loop disturbance identification and controller tuning for discrete manufacturing processes. Technometrics 44:134–141
20. O'Shaughnessy P, Haugh L (2002) EWMA-based bounded adjustment scheme with adaptive noise variance estimation. J Qual Tech 34:327–339
21. Sastri T (1988) An adaptive estimation. IIE Trans 20:176–185
22. Luceño A (1995) Choosing the EWMA parameter in engineering process control. J Qual Tech 27:162–168
23. Cheng B, Titterington DM (1994) Neural networks: a review from a statistical perspective. Stat Sci 9:2–54
24. Lee KK, Brown T, Dagnall G, Bicknell-Tassius R, Brown A, May GS (2000) Using neural networks to construct model of the molecular beam epitaxy process. IEEE Trans Semiconduct Manuf 13:34–45