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Online automatic process control using observable noise factors for discrete-part manufacturing

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Robust Parameter Design (RPD) has been used as the primary technique to reduce process and product variability. The offline choice of appropriate control factor settings allows RPD to ensure that noise factors have a minimum influence on responses. In this article, an alternative methodology of automatic process control is proposed, that is, controllable factors are adjusted online based on in-process observations of noise factors. A cautious control strategy, which explicitly considers the observation uncertainty in adjusting the settings of controllable factors, makes the system performance consistently more favorable when compared with the certainty equivalence control strategy and RPD. On the other hand, RPD can be considered a special case of automatic control laws using a constant control setting during production. A case study of a sheet-metal stamping process demonstrates that the implementation of the proposed method in an industrial facility can lead to significant quality improvements.

1. Introduction

In manufacturing processes, there are many process variables that interact in a complicated nonlinear fashion. In general, these variables are classified into controllable factors $\mathbf{x}$ (variables which can be easily manipulated online) and noise, or uncontrollable, factors $\mathbf{n}$ (variables that vary randomly and are difficult to manipulate online). If y is used to denote the system response, the relationship between $\mathbf{x}$, $\mathbf{n}$, and y can be generally expressed as:

$$y = f(\mathbf{x}, \mathbf{n}) \quad (1)$$

For a discrete-part manufacturing process, the relationship in Equation (1) can often be expressed in the format of a regression model (Box and Draper, 1987). This type of regression model, usually having no input-output dynamics, mainly focuses on the description of the dependency of the process response y on the process variables ($\mathbf{x}$, $\mathbf{n}$) and their interactions.

Regression models have been widely used for process optimization and Robust Parameter Design (RPD). RPD, which was pioneered by Taguchi (1986), is considered a cost-effective tool for reducing process variability. By choosing the settings of the controllable variables, RPD minimizes the influence of noise factors on system responses. A summary and discussion of RPD can be found in the panel discussion edited by Nair (1992); more technical details are presented in Wu and Hamada (2000).

RPD is essentially an offline technique for selecting nominal settings of key parameters at the design stage. The RPD approach assumes that the distribution of noise factors is known from tolerance design or can be identified from historical data, but real-time observations of noise factors are unknown during production. However, in reality, some noise factors, although not controllable, may be measurable or can be estimated through other measurements during production. In this paper, these factors are called "observable noise factors." Examples of observable noise factors include (but are not limited to) the quench oil temperature in heat treatment processes and incoming material thickness in a sheet-metal stamping process. It is desirable to fully utilize these additional real-time observations of noise factors to regulate the levels of controllable factors accordingly. If this is achieved, a superior process performance can be expected. In a broad sense, this concept goes beyond the statistical *offline* RPD with the intention of exploring a new class of *online* Automatic Process Control (APC) using regression models.

This paper aims to develop a feedforward controller that can utilize in-process observations of observable noise factors, and thereby, adjust controllable factors online accordingly, while also taking into account the uncertainty of noise factor estimations. The paper will show that if it is

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possible to develop and implement such a controller for a process having observable noise factors, the proposed APC approach works better than simply doing offline RPD optimization (without taking advantage of the observable noise). On the other hand, if the process is already being used as opposed to being manufactured, it is impossible to add any controllers. In this case, RPD is the best choice for process variability reduction. In this situation, RPD can be considered as a special case of the automatic control laws with a constant control setting predetermined for controllable factors.

Some research work has recently been initiated, which uses information from observable uncontrollable factors to achieve a better performance in robust design (Pledger, 1996). Although the problem in that paper is solved in a similar manner to the special case of designing a certainty equivalence controller pledger do not consider observation uncertainty nor does she discuss implications in the context of APC.

This paper will develop a general APC methodology for solving RPD-like problems based on a given regression model. The paper will investigate two types of control strategies: (i) Cautious Control (CC); and (ii) Certainty Equivalence (CE) control, and compare them with RPD. Following this introduction, in Section 2, the analysis procedures for determining an optimal APC strategy are investigated. A simulation study follows to demonstrate the applicability and validity of the resulting APC strategies. Section 3 presents an industrial case study, where the proposed method for process control is implemented in a sheet-metal stamping process. Finally, the paper is summarized and conclusions drawn in Section 4.

2. The APC strategy

2.1. *Cautious and certainty equivalence control*

As we mentioned in Section 1, the APC strategy developed in this paper utilizes observable noise factors and generates control laws by explicitly considering the observation uncertainty. The concept of CC found in control theory (Stengel, 1986; Astrom and Wittenmark, 1995) will be used in our controller design. If the observation uncertainty is not considered, the controller would be designed following the principle of CE control that is widely used in control theory. We will present more detailed discussions about these two different control strategies after a general control law is developed.

In a regression model, we classify noise factors into two sets: (i) observable noise $\mathbf{e}$; and (ii) unobservable noise $\mathbf{n}$. The real-time values of the observable noise factors can be obtained either from direct sensor measurements during production or from estimations using other measurable variable(s) correlated to those observable noise factors. A general regression model can be expressed in terms of $\mathbf{x}$, $\mathbf{e}$, and $\mathbf{n}$ as:

$$y = f(\mathbf{x}, \mathbf{e}, \mathbf{n}). \tag{2}$$

We focus on the *nominal-the-best* problem, namely the response y should be controlled as close to the target or nominal value as possible. Therefore, the quadratic loss function is selected as the control objective function, i.e.,:

$$J(\mathbf{x}) = c\{\text{var}(y) + (E(y) - t)^2\}, \tag{3}$$

where $\text{var}(y)$ and $E(y)$ are the variance and expectation of y, respectively, t is the target specified by engineering design, and c is the monetary coefficient. In this paper, we assume $c = 1$ without loss of generality. The optimal setting of control factor $\mathbf{x}^*$ is defined as that which minimizes the quality loss. Because the regression model in Equation (2) is only validated within the experimental region, any setting outside of the experimental region should be treated with caution. Hence, a constraint on $\mathbf{x}$ is constructed to ensure that the proposed optimal solution is within the experimental region. Since $\mathbf{x}$ is coded as a value in [−1,1] during the experimental designs, the unit hypercube of $\{\mathbf{x}: \|\mathbf{x}^*\|_\infty \le 1\}$ constrains the coded values of control settings. Mathematically:

$$\mathbf{x}^* = \arg\min_{\mathbf{x}} \{J(\mathbf{x})\}, \qquad \text{subject to} \quad \|\mathbf{x}\|_\infty \le 1, \tag{4}$$

and the corresponding minimum quality loss is $J(\mathbf{x}^*)$.

A regression model $f(\mathbf{x}, \mathbf{e}, \mathbf{n})$ generally includes various interaction terms and is nonlinear in terms of the inputs but still linear in terms of the parameters. In this paper, we use the following second-order regression model:

$$y = \beta_0 + \boldsymbol{\beta}_1^T\mathbf{x} + \boldsymbol{\beta}_2^T\mathbf{e} + \boldsymbol{\beta}_3^T\mathbf{n} + \mathbf{x}^T\mathbf{B}_1\mathbf{e} + \mathbf{x}^T\mathbf{B}_2\mathbf{n} + \mathbf{x}^T\mathbf{B}_3\mathbf{x} + \mathbf{e}^T\mathbf{B}_4\mathbf{n} + \varepsilon, \tag{5}$$

where $\mathbf{x} \in \Re^{n\times 1}$, $\mathbf{e} \in \Re^{m\times 1}$, $\mathbf{n} \in \Re^{p\times 1}$, and other vectors and matrices are of appropriate dimensions. It needs to be clarified that the regression model used to generate the control law is a reduced model with only factors found to be significant. In this sense, we believe that factors and their interactions included in model (5) are fairly comprehensive for a reduced model in many engineering applications. Further, we make the following assumptions:

1. We assume model (5) is for a time-invariant system, that is, all model parameters (β's and $\mathbf{B}$'s) do not change over time. It is also a static model with no input-output dynamics. This model would be appropriate to represent many discrete-part manufacturing processes with slowly and smoothly changing variables
2. It is assumed that $\mathbf{e}$, $\mathbf{n}$ and ε are independent of one another with a covariance of $\boldsymbol{\Sigma}_\mathrm{e}$, $\boldsymbol{\Sigma}_\mathbf{n}$ and variance σ_ε^2, respectively. $\mathbf{n}$ and ε have a zero mean. The residual error ε is i.i.d. noise.
3. There exists an online observer for observable noise factors $\mathbf{e}$ (called the "noise observer" hereafter) that can provide an unbiased observation of $\mathbf{e}$ during real-time

production, i.e., $E[\hat{\mathbf{e}} - \mathbf{e} \mid \hat{\mathbf{e}}] = \mathbf{0}$ and $\text{cov}[\hat{\mathbf{e}} - \mathbf{e} \mid \hat{\mathbf{e}}] \equiv \boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$, where $\hat{\mathbf{e}}$ is the observation of $\mathbf{e}$, and $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$ represents the observation uncertainty.

In the above assumptions, we do not assume that the observations of noise factor $\mathbf{e}$ are independent over time in Assumption 2. Instead, we assumed that different error sources ($\mathbf{e}$, $\mathbf{n}$ and ε) are independent of one another. The dependency of noise factor $\mathbf{e}$ over time will not limit the application domain of the proposed methodology. It will affect our choice of a noise observer which will be explained in Section 2.2, but will not affect the general procedure for controller design. Assumption 3 specifies an unbiased observer for observable noise factor estimation/measurement. In the case that the observer is biased, $E[(\hat{\mathbf{e}} - \mathbf{e})^2 \mid \hat{\mathbf{e}}]$ rather than $\text{cov}[\hat{\mathbf{e}} - \mathbf{e} \mid \hat{\mathbf{e}}]$ should be used to indicate the observation uncertainty. The estimation of the observation uncertainty will also be discussed in Section 2.2.

When the observation $\hat{\mathbf{e}}$ is obtained through an online observer, the corresponding control objective function is

$$J(\mathbf{x}) = (E_{\mathbf{e},\mathbf{n},\varepsilon}[y \mid \mathbf{x}, \hat{\mathbf{e}}] - t)^2 + \text{var}_{\mathbf{e},\mathbf{n},\varepsilon}[y \mid \mathbf{x}, \hat{\mathbf{e}}], \quad (6)$$

and the constraint function is the unit hypercube $\|\mathbf{x}\|_\infty \le 1$. The subscripts on $E(\cdot)$ and $\text{var}(\cdot)$ indicate the random variables on which $E(\cdot)$ or $\text{var}(\cdot)$ operates. Based on Equations (5) and (6), the block diagram of the controller is shown in Fig. 1.

To develop the controller, we can further derive:

$$\begin{aligned} &E_{\mathbf{e},\mathbf{n},\varepsilon}[y \mid \mathbf{x}, \hat{\mathbf{e}}], \\ &\quad = E_{\mathbf{e},\mathbf{n},\varepsilon}\big[\beta_0 + \boldsymbol{\beta}_1^T\mathbf{x} + \boldsymbol{\beta}_2^T\mathbf{e} + \boldsymbol{\beta}_3^T\text{n} + \mathbf{x}^T\mathbf{B}_1\mathbf{e} + \mathbf{x}^T\mathbf{B}_2\mathbf{n} \\ &\qquad + \mathbf{x}^T\mathbf{B}_3\mathbf{x} + \mathbf{n}^T\mathbf{B}_4\mathbf{e} + \varepsilon \mid \mathbf{x}, \hat{\mathbf{e}}\big], \\ &\quad = \beta_0 + \boldsymbol{\beta}_1^T\mathbf{x} + E_{\mathbf{e}}\big[\boldsymbol{\beta}_2^T\mathbf{e} \mid \hat{\mathbf{e}}\big] + E_{\mathbf{e}}\big[\mathbf{x}^T\mathbf{B}_1\mathbf{e} \mid \hat{\mathbf{e}}\big] + \mathbf{x}^T\mathbf{B}_3\mathbf{x}, \\ &\quad = \beta_0 + \boldsymbol{\beta}_1^T\mathbf{x} + \boldsymbol{\beta}_2^T\hat{\mathbf{e}} + \mathbf{x}^T\mathbf{B}_1\hat{\mathbf{e}} + \mathbf{x}^T\mathbf{B}_3\mathbf{x}, \end{aligned} \quad (7)$$

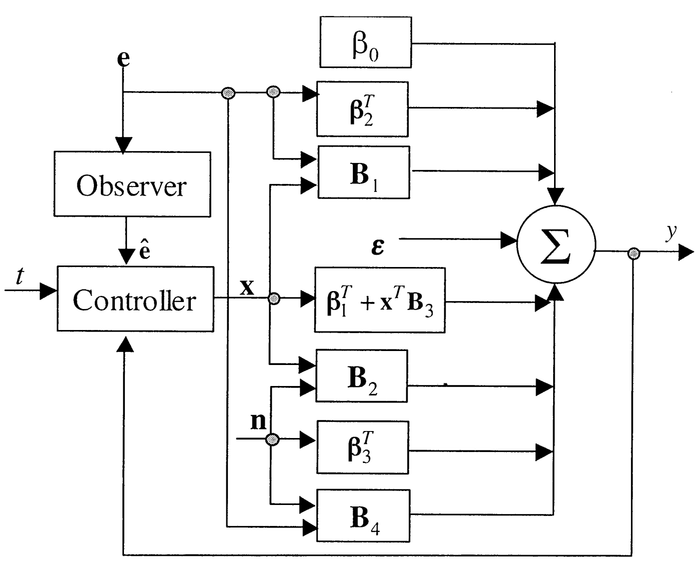


Fig. 1. Controller block diagram.

where we use the result $E[\mathbf{e} \mid \hat{\mathbf{e}}] = E[\mathbf{e} - \hat{\mathbf{e}} \mid \hat{\mathbf{e}}] + E[\hat{\mathbf{e}} \mid \hat{\mathbf{e}}] = \hat{\mathbf{e}}$.

$$\begin{aligned} &\text{var}_{\mathbf{n},\mathbf{e},\varepsilon}[y \mid \mathbf{x}, \hat{\mathbf{e}}], \\ &\quad = E_{\mathbf{n}}\{\text{var}_{\mathbf{e},\varepsilon}[y \mid \mathbf{x}, \hat{\mathbf{e}}, \mathbf{n}]\} + \text{var}_{\mathbf{n}}\{E_{\mathbf{e},\varepsilon}[y \mid \mathbf{x}, \hat{\mathbf{e}}, \mathbf{n}]\} \\ &\quad = \sigma_\varepsilon^2 + E_{\mathbf{n}}\big\{(\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x})^T \times \boldsymbol{\sigma}_{\hat{\mathbf{e}}} \times (\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x}) + (\mathbf{B}_4^T\mathbf{n})^T \\ &\qquad \times \boldsymbol{\Sigma}_{\hat{\mathbf{e}}} \times \mathbf{B}_4^T\mathbf{n}\big\} + \text{var}_{\mathbf{n}}\big\{\beta_0 + \boldsymbol{\beta}_1^T\mathbf{x} + \boldsymbol{\beta}_2^T\hat{\mathbf{e}} + \boldsymbol{\beta}_3^T\mathbf{n} \\ &\qquad + \mathbf{x}^T\mathbf{B}_1\hat{\mathbf{e}} + \mathbf{x}^T\mathbf{B}_2\mathbf{n} + \mathbf{x}^T\mathbf{B}_3\mathbf{x} + \mathbf{n}^T\mathbf{B}_4\hat{\mathbf{e}}\big\}, \\ &\quad = (\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x})^T\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}(\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x}) + \text{tr}(\mathbf{B}_4\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}\mathbf{B}_4^T\boldsymbol{\Sigma}_{\mathbf{n}}) \\ &\qquad + (\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x} + \mathbf{B}_4\hat{\mathbf{e}})^T\boldsymbol{\Sigma}_{\mathbf{n}}(\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x} + \mathbf{B}_4\hat{\mathbf{e}}) + \sigma_\varepsilon^2, \end{aligned} \quad (8)$$

where $\text{tr}(\cdot)$ is the trace of a matrix and we use the result $\text{cov}[\mathbf{e} \mid \hat{\mathbf{e}}] = \text{cov}[\mathbf{e} - \hat{\mathbf{e}} \mid \hat{\mathbf{e}}] + \text{cov}[\hat{\mathbf{e}} \mid \hat{\mathbf{e}}] = \boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$. Therefore, the objective function is:

$$\begin{aligned} J(\mathbf{x}) = &\ (\beta_0 - t + \boldsymbol{\beta}_1^T\mathbf{x} + \boldsymbol{\beta}_2^T\hat{\mathbf{e}} + \mathbf{x}^T\mathbf{B}_1\hat{\mathbf{e}} + \mathbf{x}^T\mathbf{B}_3\mathbf{x})^2 \\ &+ (\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x})^T\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}(\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x}) + \text{tr}(\mathbf{B}_4\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}\mathbf{B}_4^T\boldsymbol{\Sigma}_{\mathbf{n}}) \\ &+ (\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x} + \mathbf{B}_4\hat{\mathbf{e}})^T\boldsymbol{\Sigma}_{\mathbf{n}}(\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x} + \mathbf{B}_4\hat{\mathbf{e}}) + \sigma_\varepsilon^2, \end{aligned} \quad (9)$$

The constrained optimization as described in Equation (4) has to be solved by numerical search. Searching algorithms can be found in the optimization literature (Pierre, 1986). There are two approaches to conduct the search. One way is to conduct a search over the constrained region and find the optimal solution according to the objective function. An alternative way is to solve an unconstrained problem first, by setting the first-order partial derivative of $J(\mathbf{x})$ to zero, i.e., $\partial J(\mathbf{x})/\partial\mathbf{x} = 0$. In this case, the solution $\mathbf{x}_\text{p}^*$ may not be the final optimal solution because the constraint $\|\mathbf{x}_\text{p}^*\|_\infty \le 1$ might be violated. However, if the solution is outside the unit hypercube $\{\mathbf{x}: \|\mathbf{x}\|_\infty \le 1\}$, the optimal solution will be achieved on the boundary $\mathcal{D} \equiv \{\mathbf{x}: \|\mathbf{x}\|_\infty = 1\}$. Denote the optimal points on the boundary:

$$\mathbf{x}_\text{b}^* = \min_{\mathbf{x}\in\text{D}}\{J(\mathbf{x})\}. \quad (10)$$

Thus, the eventual optimal solution is:

$$\mathbf{x}^* = \begin{cases} \mathbf{x}_\text{p}^* & \text{if} \quad \|\mathbf{x}_\text{p}^*\|_\infty \le 1, \\ \mathbf{x}_\text{b}^* & \text{if} \quad \|\mathbf{x}_\text{p}^*\|_\infty > 1. \end{cases} \quad (11)$$

The second approach could be more efficient in finding the optimal solution since searching is only conducted on the boundary. The computation complexity is much less than the first approach which searches the entire constrained region.

The resulting control law described by Equation (11) (or a control law derived from Equation (9) by a direct search) is a CC because the control action $\mathbf{x}$ (the control setting here) is a function of not only the instantaneous noise observation, $\hat{\mathbf{e}}$, but also the variance of observations, $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$. The description of *cautious* comes from the fact that control actions tend to be smaller if the estimation error of states in a dynamic system is large (Stengel, 1986; Shi and Apley, 1998). For the settings of controllable factors in this static control, the key property of CC is that it automatically adjusts the settings according to the observation uncertainty of noise factors. The objective function in Equation (9) is accordingly labeled as $J_{\mathrm{CC}}(\mathbf{x})$.

Another principle widely used in controller design is called CE control (Stengel, 1986; Astrom and Wittenmark, 1995). In this paper, the CE control law is obtained through the separate design of a controller and an observer by assuming that the observation $\hat{\mathbf{e}}$ is the true $\mathbf{e}$. Thus, the CE control law can be generated by using the objective function of Equation (9) with $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}} = \mathbf{0}$.

$$J_{\mathrm{CE}}(\mathbf{x}) = \left(\beta_0 - t + \boldsymbol{\beta}_1^T\mathbf{x} + \boldsymbol{\beta}_2^T\hat{\mathbf{e}} + \mathbf{x}^T\mathbf{B}_1\hat{\mathbf{e}} + \mathbf{x}^T\mathbf{B}_3\mathbf{x}\right)^2 + \left(\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x} + \mathbf{B}_4\hat{\mathbf{e}}\right)^T \times \boldsymbol{\Sigma}_{\mathbf{n}} \times \left(\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x} + \mathbf{B}_4\hat{\mathbf{e}}\right) + \sigma_\varepsilon^2. \tag{12}$$

This equation is almost the same as the objective function used in Pledger (1996) except that we include the control-by-control interaction $\mathbf{x}^T\mathbf{B}_3\mathbf{x}$. The procedure of control law generation is the same as that for the CC.

It is worth noting that the existence of the control-by-(observable noise) interaction $\mathbf{x}^T\mathbf{B}_1\mathbf{e}$ results in the essential difference between CC and CE control. If $\mathbf{B}_1 = \mathbf{0}$, the difference between $J_{\mathrm{CC}}(\mathbf{x})$ (Equation (9)) and $J_{\mathrm{CE}}(\mathbf{x})$ (Equation (12)) is $\boldsymbol{\beta}_2^T\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}\boldsymbol{\beta}_2 + \mathrm{tr}(\mathbf{B}_4\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}\mathbf{B}_4^T\boldsymbol{\Sigma}_{\mathbf{n}})$, which is not related to any controllable variable $\mathbf{x}$. After taking the first partial derivative of $\mathbf{x}$ in the objective function, the difference between $J_{\mathrm{CC}}(\mathbf{x})$ and $J_{\mathrm{CE}}(\mathbf{x})$ vanishes. Thus, the resulting control law is always CE control if there is no interaction between controllable factors and observable noise factors in the regression model.

If the noise factor $\mathbf{e}$ is not observable, the controller design becomes equivalent to choosing an offline RPD setting instead of an online adjustment mechanism. In RPD, it is generally assumed that $\mathbf{e}$ has a zero mean and a known covariance $\boldsymbol{\Sigma}_{\mathbf{e}}$. Then, finding the control law becomes a matter of determining a constant setting for controllable factors in RPD. The quality loss is:

$$J_{\mathrm{RD}}(\mathbf{x}) = (E_{\mathbf{e},\mathbf{n},\varepsilon}[y \mid \mathbf{x}] - t)^2 + \mathrm{var}_{\mathbf{e},\mathbf{n},\varepsilon}[y \mid \mathbf{x}]. \tag{13}$$

where $E_{\mathbf{e},\mathbf{n},\varepsilon}[y \mid \mathbf{x}] = \beta_0 + \boldsymbol{\beta}_1^T\mathbf{x} + \mathbf{x}^T\mathbf{B}_3\mathbf{x}$, and

$$\begin{aligned}\mathrm{var}_{\mathbf{e},\mathbf{n},\varepsilon}[y \mid \mathbf{x}] &= E_{\mathbf{e}}\{\mathrm{var}_{\mathbf{n},\varepsilon}[y \mid \mathbf{x},\mathbf{e}]\} + \mathrm{var}_{\mathbf{e}}\{E_{\mathbf{n},\varepsilon}[y \mid \mathbf{x},\mathbf{e}]\},\\ &= \sigma_\varepsilon^2 + \left(\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x}\right)^T\boldsymbol{\Sigma}_{\mathbf{n}}\left(\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x}\right)\\ &\quad + \mathrm{tr}\left(\mathbf{B}_4^T\boldsymbol{\Sigma}_{\mathbf{n}}\mathbf{B}_4\boldsymbol{\Sigma}_{\mathbf{e}}\right)\\ &\quad + \left(\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x}\right)^T\boldsymbol{\Sigma}_{\mathbf{e}}\left(\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x}\right).\end{aligned} \tag{14}$$

Then, $J_{\mathrm{RD}}(\mathbf{x})$ becomes:

$$\begin{aligned}J_{\mathrm{RD}}(\mathbf{x}) &= \left(\beta_0 - t + \boldsymbol{\beta}_1^T\mathbf{x} + \mathbf{x}^T\mathbf{B}_3\mathbf{x}\right)^2\\ &\quad + \left(\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x}\right)^T\boldsymbol{\Sigma}_{\mathbf{n}}\left(\boldsymbol{\beta}_3 + \mathbf{B}_2^T\mathbf{x}\right) + \mathrm{tr}\left(\mathbf{B}_4^T\boldsymbol{\Sigma}_{\mathbf{n}}\mathbf{B}_4\boldsymbol{\Sigma}_{\mathbf{e}}\right)\\ &\quad + \left(\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x}\right)^T\boldsymbol{\Sigma}_{\mathbf{e}}\left(\boldsymbol{\beta}_2 + \mathbf{B}_1^T\mathbf{x}\right) + \sigma_\varepsilon^2.\end{aligned} \tag{15}$$

In this sense, the setting of the controllable factors in RPD can be considered a constant control law without including any feedback/feedforward information.

2.2. *Noise factor observer and uncertainty analysis*

Observer design significantly depends on specific applications. Determination of the observation uncertainty $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$ will, in turn, depend on how the observations $\hat{\mathbf{e}}$ are obtained. The following subsections briefly discuss three typical noise observers, as well as how to assess the associated observation uncertainty. More details of observer design techniques can be found in Stengel (1986) and McGarty (1974).

2.2.1. *Direct sensor measurement of observable noise factors*

With the advanced development of sensor techniques, different types of in-process sensors are now available for directly measuring the change of noise factors. When this direct measurement can be done, $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$ is actually the measurement uncertainty. The covariance, $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$, induced by sensors or devices can be calibrated offline through a gage repeatability and reproducibility (known as *gage R&R*) study. The value $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$ is often indicated by the manufacturer's specifications of particular sensor devices. In this case, if each noise factor is measured independently, the diagonal elements of $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$ will correspond to the variance of measurement errors of each sensor device, and the covariance terms in $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$ will be zero.

2.2.2. *Indirect estimation of noise factors from other measurable variables*

When the noise factors of interest cannot be directly measured, we may be able to estimate them through the measurements of other variables correlated with these noise factors. In this case, the observation uncertainty, $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}$, needs to be estimated based on an observer model. In general, the process noise factors can be classified into two classes in terms of state characteristics of noise factors: (i) noise factors with time-dependent states, i.e., the state of a noise factor depends on its previous states; and (ii) noise factors with independent states, i.e., the occurrence probability of each state is independent of all others. In the second case, usually a noise factor will have finite states that are known to the observer designer. The following discussion will show how to analyze the observation uncertainty for these two classes of noise factors.

2.2.2.1. *Kalman filter observer for noise factors having time-dependent states.* When the states of noise factors are time dependent, a state space model is generally used to model the dynamics of the noise factors as:

$$\mathbf{e}(t+1) = \mathbf{G}\,\mathbf{e}(t) + \boldsymbol{\xi}(t), \tag{16}$$

$$\mathbf{Z}(t) = \mathbf{F}\,\mathbf{e}(t) + \boldsymbol{\zeta}(t), \tag{17}$$

where $\mathbf{Z}(t)$ is the observation or measurement vector at time $t(t = 1, 2, \ldots)$ and will be used for inference about the states of noise factors $\mathbf{e}(t)$, $\mathbf{G}$ is the state transition matrix, $\mathbf{F}$ is the observer model parameters, $\boldsymbol{\xi}(t) \sim \mathrm{N}(\mathbf{0}, \mathbf{W})$ and $\boldsymbol{\zeta}(t) \sim \mathrm{N}(\mathbf{0}, \mathbf{V})$ are the state equation error and the observation error, respectively, and are assumed independent of each other.

The state space representation describes the state dependency of the noise factor $\mathbf{e}(t)$ by the state Equation (16) and the relationship between observations and noise factor states by the observation Equation (17). When the variances of $\mathbf{V}$ and $\mathbf{W}$ are known through system identification and measurement error calibration, the well-known Kalman recursive algorithm can be used to obtain the state estimate $\hat{\mathbf{e}}(t \mid \mathbf{Z}(1), \ldots, \mathbf{Z}(t))$ and its estimation uncertainty $\boldsymbol{\Sigma}_{\hat{\mathbf{e}}} = E\{[\mathbf{e}(t) - \hat{\mathbf{e}}(t)][\mathbf{e}(t) - \hat{\mathbf{e}}(t)]^T \mid \mathbf{Z}(1), \ldots, \mathbf{Z}(t)\}$ as (McGarty (1974) and Astrom and Wittenmark (1995) give detailed derivations):

$$\hat{\mathbf{e}}(t) = \hat{\mathbf{e}}(t-1) + \mathbf{K}(t)(\mathbf{Z}(t) - \mathbf{F}\hat{\mathbf{e}}(t-1)) \tag{18}$$

$$\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}(t) = \mathbf{G}\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}(t-1)\mathbf{G}^T + \mathbf{W} - \mathbf{K}(t)\mathbf{F}\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}(t-1)\mathbf{G}^T, \tag{19}$$

where $\mathbf{K}(t)$ is the Kalman gain matrix, defined as $\mathbf{K}(t) = \mathbf{G}\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}(t-1)\mathbf{F}[\mathbf{V} + \mathbf{F}\boldsymbol{\Sigma}_{\hat{\mathbf{e}}}(t-1)\mathbf{F}^T]^{-1}$.

If a time series model is used for noise factor modeling, the Kalman filtering algorithm can also be applied, provided that the time-series model is translated into an equivalent state space model (McGarty, 1974).

2.2.2.2. *Classification observer for noise factors having independent states.* When the states of a noise factor are finite, or we can discretize a continuous state by a finite set of discrete states, the state of the noise factors can be estimated by performing a classification (Johnson and Wichern, 2002) of online observations of other correlated variables. For example, vibration signals of a machine tool can be used for classifying its degradation states (normal versus worn-out), and stamping force signals can be used for classifying the in-coming material thickness state (normal versus thinner/thicker material). Given k states of a noise factor, each of which is characterized by a mean vector $\boldsymbol{\mu}_k$ and a common covariance matrix $\boldsymbol{\Sigma}$, a linear discriminant function for state k can be defined as:

$$\delta_{k*} = \max_k \left[\mathbf{f}^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_k - \frac{1}{2} \boldsymbol{\mu}_k^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_k + \log \pi_k \right], \tag{20}$$

where π_k is the prior probability of state k and $\mathbf{f}$ is the measurement vector or a transformation of the measurement vector. Using this linear discriminant function, the noise factor is considered in state k^* if δ_{k^*} is the largest among all δ_k of all states (Johnson and Wichern, 2002).

In practice, those easily measured physical quantities (i.e., the correlated variables) such as vibration or force signals are often waveform signals, which have a high data dimension. In this situation, data transformation and feature extraction becomes unavoidable for data dimension reduction in the classifier design. The methods for data transformation and feature extraction are rather diverse and also application specific. Jin and Shi (2000) have demonstrated that Principle Component Analysis (PCA) is one effective multivariate statistical tool for feature extraction. In their paper, PCA is employed as an integral component of a hierarchical classifier, which determines the states of significant process variables identified by Design Of Experiments (DOE). This hierarchical classifier will be used as the observer for in-coming material thickness in the latter case study in Section 3. For the reader's convenience, a brief review of the hierarchical classification method is given in Appendix A. Overall, Fig. 2 illustrates how the classification-based observer works.

The performance of a classification method is benchmarked by its misclassification rate. This misclassification rate will be used to determine the uncertainty of the noise factor estimation. Appendix B derives a formula for observation uncertainty using the misclassification rate when the noise factor e has a binary state, i.e., it can only take two values $+1$ and -1. For a general case where e has k discrete states, the observation uncertainty can be computed similarly.

2.3. *Simulation study*

The direct analytical comparison of the system performances under given control laws (including RPD) is very difficult, if not impossible. We therefore employ a simulation study to provide a general understanding of the performance of APC strategies and their applicability. The performance of the automatic controller is compared to the RPD solution through a leaf spring experiment adopted from Wu and Hamada (2000).

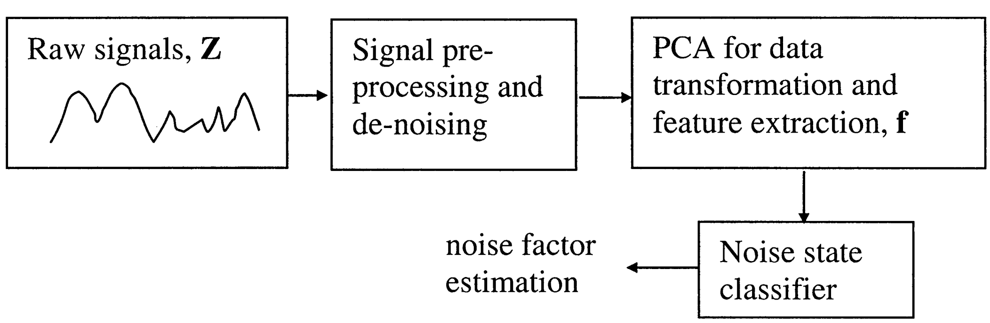


Fig. 2. Classification-based noise factor observer.

A forming process followed by a heat treatment process creates the curvature in leaf springs and should theoretically generate an unloaded spring with a height of 8.0 inches. The objective of process control is to make the free spring height as close to the target 8.0 inches as possible. Five factors were chosen across various stages of the process: high heat temperature (B), heating time (C), transfer time (D), hold down time (E), and quench oil temperature (Q). The labels B through Q are chosen to be the same as those used in Wu and Hamada (2000). The quench oil temperature (Q) is the hard-to-control factor, namely the noise factor. The detailed physical meanings of these factors may be found in Wu and Hamada (2000) or the original report (Pignatiello and Ramberg, 1985).

Among these factors, the quench oil temperature can be measured during the heat treatment process so that Q is an observable noise factor and $e = [Q]$. The other four factors are controllable factors. According to the analysis in Wu and Hamada (2000), we have a reduced response model with the significant factors being:

$$y = 7.6360 + 0.1106B + 0.0881C - 0.1298Q + 0.0519E - 0.0827CQ + 0.0423BQ + \varepsilon. \quad (21)$$

Equation (21) is used to generate various control laws, including the CC law, the CE control law, and the RPD setting, following the approaches outlined in Section 2.1.

Note that the response in this experiment is much less than the target of 8.0 inches. The intercept is only 7.636 inches, suggesting that the deviation from the nominal dominates the quality loss. If 8.0 inches is used as the target value, all efforts will be made to move the mean value closer to the target. Under that circumstance, the control factors B, C and E are always set to (+) for both automatic control laws and RPD setting. In order to demonstrate the APC strategy, we change the target value to 7.6 inches to balance the effects from both location deviation and dispersion.

Suppose that the quench oil is varied within the range 170°F (high level) to 130°F (low level) in an uncontrolled environment during the processing. We can see that Q is almost uniformly distributed in the coded range of [–1, 1], thus $\sigma_Q = 0.5774$ and $E(Q) = 0$.

The APC control law is a function of online observations $\hat{Q}$ and is generated by conducting the search within the unit hypercube $\{\mathbf{x}: \|\mathbf{x}\|_\infty \leq 1\}$, where $\mathbf{x} = [B, C, E]$ in this example. The control law will be different under different levels of observation uncertainty. In this simulation, we assume that the observation uncertainty is uniform over the experimental region. That is, $\sigma^2_{\hat{Q}} = \mathrm{var}(\hat{Q} - Q \mid \hat{Q})$ is constant regardless of the value of $\hat{Q}$. This is similar to a practical case where the temperature is measured using a thermometer and its $\sigma_{\hat{Q}}$ is the precision of this thermometer indicated by the instrument specification.

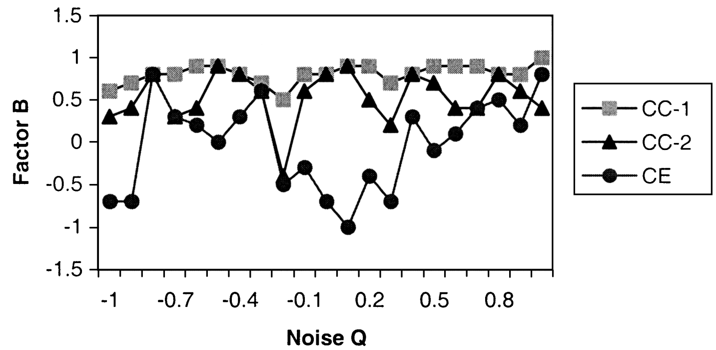


Fig. 3. Factor B against noise Q under different estimation uncertainty levels.

The discussion about the impact of uncertainty is classified into three levels: (i) no observation uncertainty $\sigma_{\hat{Q}} = 0$; (ii) low observation uncertainty $\sigma_{\hat{Q}} = 0.01\sigma_Q$; and (iii) fair observation uncertainty $\sigma_{\hat{Q}} = 0.1\sigma_Q$. The optimal setting of factor B in terms of $\hat{Q}$ under the different levels of observation uncertainty is shown in Fig. 3, where CC-1 represents the control setting with $\sigma_{\hat{Q}} = 0.1\sigma_Q$, CC-2 is the control setting with $\sigma_{\hat{Q}} = 0.01\sigma_Q$, and CE means that there is no uncertainty in the observation. It can be seen that the magnitude of changes in control setting is larger when the observation is more accurate. On the other hand, the controller takes a smaller magnitude adjustment (in changing the setting) when the observation of the noise factor is less accurate. The same conclusion holds true for other control factors, but only factor B against Q is plotted in Fig. 3 for illustration. This conclusion is consistent with the meaning of CC in control theory (Stengel, 1986; Astrom and Wittenmark, 1995). In fact, the control law determined under $\sigma_{\hat{Q}} = 0$ is the CE control. The other two cases are CCs. When the noise observation is so uncertain that it is close to the anticipated noise variability, the setting of factor B becomes constant and with the value close to the RPD setting.

These control laws, together with the RPD setting, are used to control the simulated leaf spring forming process. We would like to use a different system model than Equation (21) to simulate the process. A full response model containing various factors and interactions is (also obtained by Wu and Hamada (2000)):

$$y = 7.6360 + 0.1106B + 0.0881C - 0.1298Q + 0.0519E - 0.0827CQ + 0.0423BQ + 0.0269DQ - 0.0235BEQ - 0.0202CEQ - 0.0177BE + 0.0144D + 0.0135EQ + 0.0098CE + 0.0085BC + 0.0052BCQ + \varepsilon. \quad (22)$$

The comparison of the process performances under different control laws is given in Fig. 4(a and b). Discussions in regard to each control setting are given as follows.

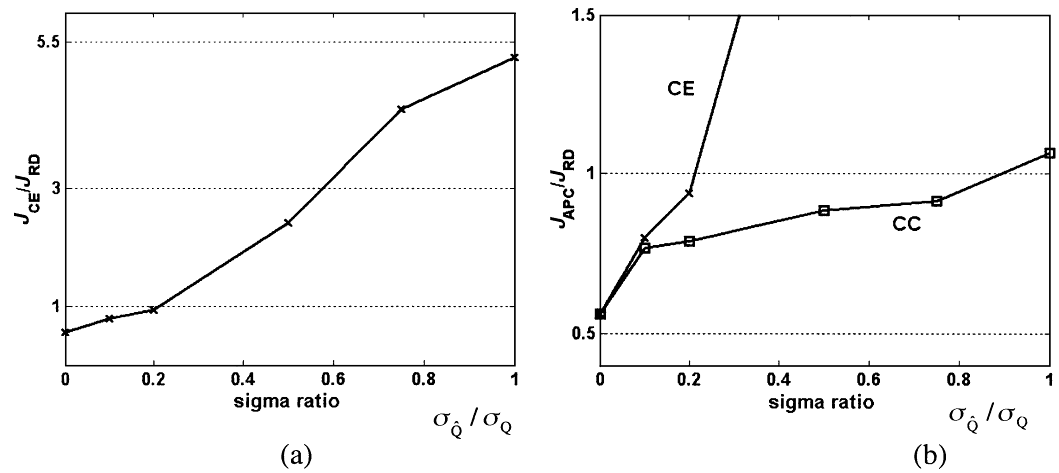


Fig. 4. (a) Quality loss obtained using the CE control law compared to the RPD setting; and (b) the performance of the CC law.

1. RPD setting: the RPD setting is [B C E] = [1 −1 −1]. This is different from that given in Wu and Hamada (2000, ch. 10) because the target value has been changed to 7.6 inches. If this new target value is used, Equations (10.8) and (10.9) in Wu and Hamada (2000) yield the same values for [B C E]. Factor D is not significant: it is always set to a low level (i.e., the transfer time is 2 seconds) so that throughput can be increased. The quality loss using this RPD setting is $J_{\mathrm{RD}} = 8.84 \times 10^{-3}$.
2. CE control law: there is considered to be no observation error when the CE controller is designed. Its performance compared with the designer performance under RPD setting is shown in Fig. 4(a), where the abscissa is the sigma ratio of $\sigma_{\hat{Q}}/\sigma_{Q}$ and the ordinate is the ratio of quality loss under the CE control and RPD. The CE controller performs well when the observation is accurate. It can reduce the quality loss approximately 43.9% as compared with the RPD design solution when the observation is perfect. However, the performance of this CE controller deteriorates quickly when there exists observation uncertainty. The CE controller causes a larger quality loss than RPD controller when $\sigma_{\hat{Q}}/\sigma_{Q} > 0.2$.
3. CC law: a cautious controller considers observation uncertainty explicitly. Its performance compared with the RPD performance is shown in Fig. 4(b), where J_{APC} is the quality loss under a given control law: APC could be CE or CC. The cautious controller, which does not change the control factor settings as aggressively as the CE controller does, yields a better performance than a CE controller. Meanwhile, the performance of the CC controller is better than that of RPD even when $\sigma_{\hat{Q}}/\sigma_{Q}$ is as large as 0.9. When the observation uncertainty is too large, the RPD yields a better performance. On average the CC law reduces the quality loss about 15% as compared to RPD and is 11% better than the CE controller with a fair observation uncertainty (e.g., $\sigma_{\hat{Q}}/\sigma_{Q} = 0.2$).

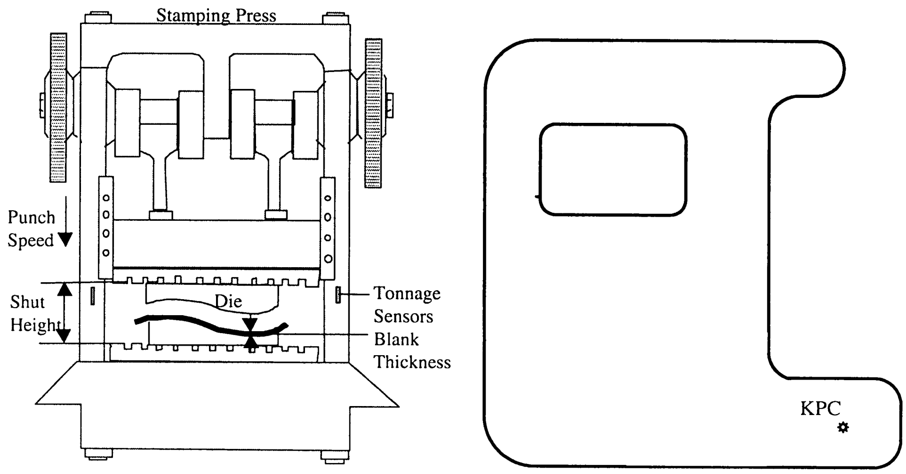
3. Implementation: stamping process

3.1. *Sheet-metal stamping process*

Sheet-metal stamping is a complex manufacturing process used to produce products by deforming the sheet metal in accordance with the prefabricated geometry of a die. An example of a stamping press, with some of the important process variables, is shown in Fig. 5(a). In this case study, the product is a quarter panel of a truck body, shown in Fig. 5(b). The quality concern is the dimensional accuracy at the defined Key Product Characteristics (KPC) points on the stamped part. The position of each KPC point is measured in the normal direction of the sheet metal surface by using a coordinate measuring machine. In this article, one KPC point, as shown in Fig. 5(b), is selected for illustration. The deviation from its nominal value, denoted as y, is used as the system response. Our objective is to make y as close to zero as possible.

Stamping tonnage signals contain rich process information and have been widely used for monitoring the changes of process variables (Jin and Shi, 2000). In order to measure the stamping tonnage force, four tonnage sensors (shown in Fig. 5(a)) are mounted on the four press uprights. The total stamping force is obtained by summing the tonnage forces on the four uprights.

Figure 6 shows tonnage signals of one stroke. It is clear from the graph that if the thickness of incoming metal blanks changes, the tonnage signal will change accordingly, providing the possibility of detecting a change of blank thickness during production. Therefore, in this case study, material thickness is treated as an observable noise factor, and the adjustable process setup variables, such as shut



(a) (b)

Fig. 5. (a) A stamping press; and (b) a stamped part.

height and punch speed, can be used as controllable factors, and the lubrication on the blank surface is consider an unobservable noise factor.

The general analysis procedure for implementing the APC strategy is shown in Fig. 7. In the following sections, we will discuss the regression modeling of the stamping process and the determination and evaluation of the control strategy.

3.2. *Process regression model*

Six important process variables are selected based on the engineering understanding of the characteristics of forming operations and the performance of the tooling and a press machine. The selected process variables are: (i) lubrication; (ii) material thickness; (iii) inner shut height; (iv) outer shut height; (v) punch speed; and (vi) blank wash pressure. These variable are denoted A, B, C, D, E and F, respectively.

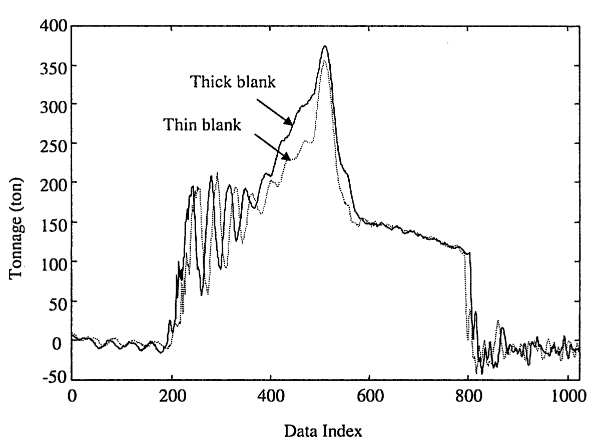


Fig. 6. A one-stroke tonnage signal.

Using a fractional factorial design, the regression model with significant factors is obtained by Jin and Shi (2000) as:

$$y = 0.018\,97\text{B} - 0.113\,59\text{C} - 0.013\,03\text{BC} - 0.021\,93\text{D} + \varepsilon. \tag{23}$$

According to the regression model in Equation (23), only factors B, C and D are identified as significant factors, where factor B (material thickness) is considered an online observable noise factor, and factor C (inner shut height) and factor D (outer shut height) are considered controllable factors. Lubrication factor A, an unobservable noise factor, is identified as being insignificant by the DOE. Using the notation defined in Equation (5), we have that $\mathbf{x} = [x_1 x_2] = [\text{C D}]$, and $\mathbf{e} = e_1$, $\beta_0 = 0$, $\boldsymbol{\beta}_1^T = [\beta_{11}\beta_{12}]^T = [-0.11359\ -0.02193]^T$, $\boldsymbol{\beta}_2 = [\beta_{21}] = 0.018\,97$, and $\mathbf{B}_1 = [B_{11}] = -0.013\,03$.

3.3. *Uncertainty of thickness observer and constraints on controller implementation*

If there is an online thickness measurement sensor installed in the stamping process, the variance of the thickness observer measurement can be easily obtained from the device

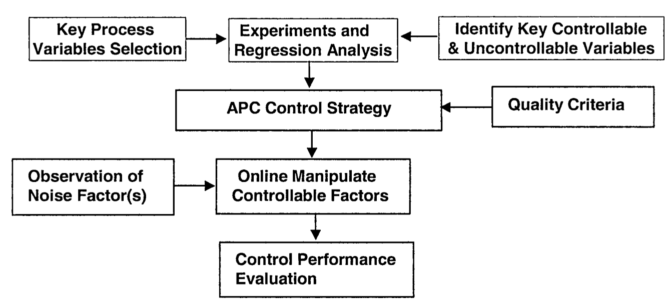


Fig. 7. Analysis procedure of APC of a stamping process.

specification or using an offline gage R&R study. In practice, however, most stamping plants do not have a direct online sensor measurement of blank thickness. Instead, they usually have a tonnage monitoring system on the stamping press machine. Figure 6 illustrates the feasibility of using online tonnage sensing signals as an alternative way to monitor material thickness change. A hierarchical classifier has been developed (Jin and Shi, 2000), which can classify the material thickness into a binary state (normal status = −1 and thicker status = +1) at an acceptable correct rate. A brief review of the hierarchical classifier is included in Appendix A for the reader's information. More details of its design and analysis can be found in Jin and Shi (2000).

In our stamping process, the shut height adjustment (both the inner shut height x_1 and the outer shut height x_2) is manually performed by operators, setting them either at a high level (+1) or low level (−1). It is thus prohibitive to make adjustments too often during the production since frequent adjustments could cause too much production downtime or even press damage due to a wrong adjustment from a fatigued operator. For this reason, classifying the in-coming material thickness to a binary state (normal or thicker) actually better fits this control constraint because the resulting control strategy will take no action under a frequent yet small fluctuation in material thickness but will adjust the shut height when the state of the material thickness is flipped, that is, when the material thickness undergoes a significant yet infrequent change, such a change would probably occur only between different batches. Box and Luceno (2002) discussed a feedforward controller to compensate an expected step change of the material thickness occurring at different batches. In their research, a dynamic first-order IMA time series model was used for the controller development, which is different from our cautious controller development based on a static regression model with consideration of the interaction among the controller variables and the observable noise variables.

The constraints on controller implementation in the stamping process make it reasonable to adopt the hierarchical classifier as the noise factor observer. When a classification-based observer is used, its observation uncertainty will be computed using the misclassification error rate, which is determined through a cross-validation assessment of an offline training data set. The obtained misclassification rates for the hierarchical classifier are $p = \Pr(\hat{e}_1 = -1 \mid e_1 = 1) = 2.78\%$ and $q = \Pr(\hat{e}_1 = 1 \mid e_1 = -1) = 1.39\%$. Thus, the observer variance is calculated as $\sigma^2_{\hat{e}_1=1} = 0.056$ and $\sigma^2_{\hat{e}_1=-1} = 0.107$. The detailed computations are given in Appendix B.

3.4. *Control strategy*

According to Equation (9), the $J_{CC}(\mathbf{x})$ of Equation (23) is:

$$J_{CC}(x) = (\beta_{11}x_1 + \beta_{12}x_2 + \beta_{21}\hat{e}_1 + B_{11}\hat{e}_1 x_1)^2 + (\beta_{21} + B_{11}x_1)^2\sigma^2_{\hat{e}_1} + \sigma^2_{\varepsilon}. \quad (24)$$

Since in our stamping process, the shut height adjustment (inner shut height x_1 and the outer shut height x_2) are set either at a high level (+1) or low level (−1), and thickness observation $\hat{e}_1$ is also classified as binary states (−1) and (+1). A simple search conducted on the corner points of the constrained border $\mathfrak{D} \equiv \{\mathbf{x} : \|\mathbf{x}\|_\infty = 1\}$ will yield the optimal value of $J_{CC}(\mathbf{x})$, given different settings of x_1 and x_2 as well as different values of $\hat{e}_1$. The values of $J_{CC}(\mathbf{x})$ for each of the total of eight combinations are calculated and listed in Table 1.

The control law is determined by selecting the setting of x_1 and x_2 that yields the minimal $J_{CC}(\mathbf{x})$ for an observed $\hat{e}_1$. In this particular example, the CC law is the same as the CE control law. It is:

$$[x_1^*, x_2^*] = \begin{cases} [-1, 1] & \text{if } \hat{e}_1 = -1, \\ [1, -1] & \text{if } \hat{e} = 1. \end{cases} \quad (25)$$

The RPD setting can also be computed using Equation (23). First, we consider using the factor x_1 to reduce the variability since x_1 has interaction with noise factor $\hat{e}_1$. Given that:

$$\sigma^2_{\hat{y}} = \text{positive constant } + 2(-0.013\,03)(0.018\,97)x_1\sigma^2_{e_1}, \quad (26)$$

then x_1 is set to the high level (+1) to minimize $\sigma^2_{\hat{y}}$. On the other hand, the mean of y is:

$$E(y|_{x_1=1}) = 0.018\,97E(e_1) - 0.113\,59 - 0.013\,03E(e_1) - 0.021\,93x_2, \quad (27)$$

which suggests that x_2 should be set at the low level (−1) to minimize the mean deviation. Thus, the RPD setting of this process is $[x_1, x_2] = [1, -1]$.

Factors E (punch speed) and F (blank wash pressure), since they are not significant in the response model, are free to be set to either the high level or low level. Because of the desire to achieve a higher throughput, they are set at the high level for both the APC and RPD cases.

Table 1. $J_{CC}(\mathbf{x})$ for the eight combinations of control settings $[x_1\ x_2]$ and observations $\hat{e}_1$

	$[x_1\ x_2] = [-1,-1]$	$[x_1 x_2] = [-1,1]$	$[x_1\ x_2] = [1,-1]$	$[x_1\ x_2] = [1,1]$
$\hat{e}_1 = 1$	0.0282	0.0154	0.0074	0.0168
$\hat{e}_1 = -1$	0.0108	0.0037	0.0095	0.0200

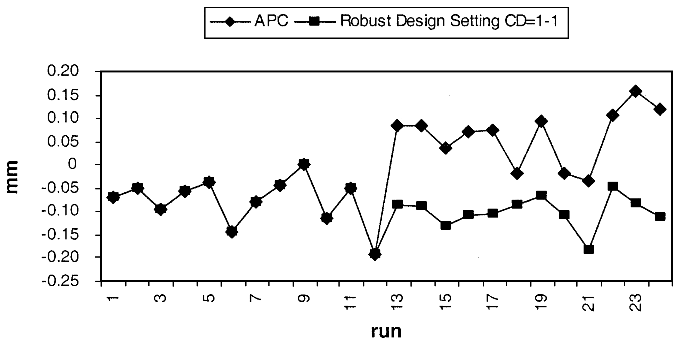


Fig. 8. Controlled output and deviation of y.

3.5. *Control performance evaluation*

The cautious APC strategy was successfully demonstrated in a stamping plant of a major automobile manufacturer. Data were collected for the cases corresponding to a constant RPD setting and an online APC adjustment strategy. The two data curves correspondence to RPD and APC are shown in Fig. 8. The quality losses as defined in Equation (3) are also calculated for each case, and the results are listed in Table 2.

In Fig. 8, the first 12 points correspond to the case of $\hat{e}_1 = 1$, and the next 12 points correspond to $\hat{e}_1 = -1$. We note that the data shifts accordingly under the APC strategy. The APC strategy, in fact, automatically adjusted the control setting to yield the minimum quality loss in each case, that is, $[x_1, x_2] = [-1, 1]$ when $\hat{e}_1 = -1$; and $[x_1, x_2] = [1, -1]$ when $\hat{e}_1 = 1$. After comparing the values of quality loss in Table 2, the APC strategy produces gains in quality by taking the best setting whenever the noise factor changes. In comparison to the RPD, the new APC methodology renders a 31.9% improvement in quality when the noise factor is at the low level ($\hat{e}_1 = -1$). Since the APC setting and the RPD setting are the same when $\hat{e}_1 = 1$, the overall quality improvement that APC gains is 17.9%.

In this example, the facility limitation in adjusting the control settings mandates that the APC setting must be the same as the RPD setting for half of the production runs, where no quality improvement is achieved as compared to the RPD. In a general situation when control settings could have been adjusted continuously given different observations of noise variable, the APC strategy can minimize quality loss over all the settings and thus gain more in quality improvements than RPD.

This case study shows that the methodology is effective when it is applied to a stamping process under actual industrial circumstances. It also demonstrates how to implement the proposed APC strategy when there are special facility constraints during the development of a real-world controller. Although the stamping process model is a special simple model of the general regression model, the developed methodology in Section 2.1 can also be applied to other manufacturing processes. These processes may have a different model from the stamping process but can still be covered by the general regression model of Equation (5).

Table 2. Comparison of CC and constant RPD settings for the stamping process

Approach	*CC*	*RPD setting* $[x_1, x_2] = [1, -1]$
Quality loss J		
$\hat{e}_1 = -1$	0.0077	0.0113
$\hat{e}_1 = 1$	0.0088	0.0088
Overall	0.0165	0.0201

4. Summary and conclusions

Process control to achieve on-target production with minimized variation significantly impacts manufacturing quality, productivity, and cost. This paper proposed an APC methodology based on the regression models of complex manufacturing processes. Both the analysis framework and implementation procedures were presented.

The central idea of the proposed method is to develop a general APC strategy, which is capable of better solving RPD-like problems with a feedforward controller. The paper further classifies the noise factors in the traditional offline RPD into observable noise factors and unobservable noise factors, and utilizes the in-process observations of observable noise factors to automatically adjust the settings of controllable factors.

Generally, when there exists an observable noise factor and $\sigma_{\hat{\mathbf{e}}}^2 < \sigma_{\mathbf{e}}^2$, an APC approach should be employed. When $\sigma_{\hat{\mathbf{e}}}^2 \approx \sigma_{\mathbf{e}}^2$ or there exists no observable noise factors, a RPD approach should be employed. If the observation uncertainty is explicitly considered in the control laws, a CC approach is used to achieve better control performance over a wide range of observation uncertainty, as evidenced in the simulation study. When the observation is perfect $\sigma_{\hat{\mathbf{e}}}^2 = 0$ or there is no interaction between controllable factors and observable noise factors $\mathbf{B}_1 = \mathbf{0}$, the CC becomes a CE control, and the observer and controller can be designed and implemented separately. When the observation has a large uncertainty, the CC is close to the RPD.

According to the simulation study, the quality loss is reduced by 15 to 44% (depending on the ratio of $\sigma_{\hat{\mathrm{Q}}}/\sigma_{\mathrm{Q}}$) by employing the resulting APC strategy, compared to the use of RPD. The method was successfully implemented in a sheet-metal stamping process, where product quality is improved about 20% in comparison to the RPD.

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References

Astrom, K.J. and Wittenmark, B. (1995) *Adaptive Control*, 2nd edn., Addison-Wesley, Reading, MA.

Box, G.E.P. and Draper, N.R. (1987) *Empirical Model-Building and Response Surfaces*, Wiley, New York, NY.

Box, G. and Luceno, A. (2002) Feedforward as a supplement to feedback adjustment in allowing for feedstock change. *Journal of Applied Statistics*, **29**, 1241–1254.

Jin, J. and Shi, J. (2000) Diagnostic feature extraction from stamping tonnage signals based on design of experiments. *ASME Journal of Manufacturing Science and Engineering*, **122**, 360–369.

Johnson, R.A. and Wichern, D.W. (2002) *Applied Multivariate Statistical Analysis*, 5th edn., Prentice Hall, Upper Saddle River, NJ.

McGarty, T.P. (1974) *Stochastic Systems and State Estimation*, Wiley, New York, NY.

Nair, V. (ed.) (1992) Taguchi's parameter design: a panel discussion. *Technometrics*, **34**, 127–161.

Pierre, D.A. (1986) *Optimization Theory with Applications*, Dover, New York, NY.

Pignatiello, J. J., Jr. and Ramberg, J. S. (1985) Discussion of "Off-line quality control, parameter design, and the Taguchi method" by Kackar, R.N. *Journal of Quality Technology*, **17**, 198–206.

Pledger, M. (1996) Observable uncontrollable factor in parameter design. *Journal of Quality Technology*, **28**, 153–162.

Shi, J. and Apley, D.W. (1998) A suboptimal N-step-ahead cautious controller for adaptive control applications. *ASME Journal of Dynamic Systems, Measurement, and Control*, **120**, 419–423.

Stengel, R.F. (1986) *Stochastic Optimal Control: Theory and Application*, Wiley, New York, NY.

Taguchi, G. (1986) *Introduction to Quality Engineering*, Asian Productivity Organization, Tokyo, Japan.

Wu, C.F.J. and Hamada, M. (2000) *Experiments: Planning, Analysis, and Parameter Design Optimization*, Wiley, New York, NY.

Appendix A

In Jin and Shi (2000), a hierarchical classifier is developed to classify the states of the significant process variables identified by the DOE regression model in a stamping process. The development procedures for a hierarchical classifier are shown in Fig. A1. The measured waveform signals of the stamping tonnage force as shown in Fig. 6 are represented by a high dimensional data vector. The training data were collected under the DOE tests with different settings of six tested variables: (i) lubrication; (ii) material thickness; (iii) inner shut height; (iv) outer shut height; (v) punch speed; and (vi) blank wash pressure which are denoted as A, B, . . . , F, respectively. Each variable has two levels namely either −1 or +1.

As shown in Fig. A1, the PCA transform is first used to identify the significant variation patterns of the stamping tonnage forces, which are associated with the larger eigenvalues. Starting from the first loading score vector of the variation patterns, a DOE regression analysis is used to determine the significant variables, called diagnostic variables, of the corresponding variation pattern, which are the major contributors to the variability of this principal component. This iteration analysis is repeated until all significant variation patterns have been analyzed. The identified diagnostic variables are used to cluster the DOE observations to obtain the training data set. Then, a piecewise linear classifier is trained for the identified diagnostic variables and the cross-validation method is used to assess the classifier performance.

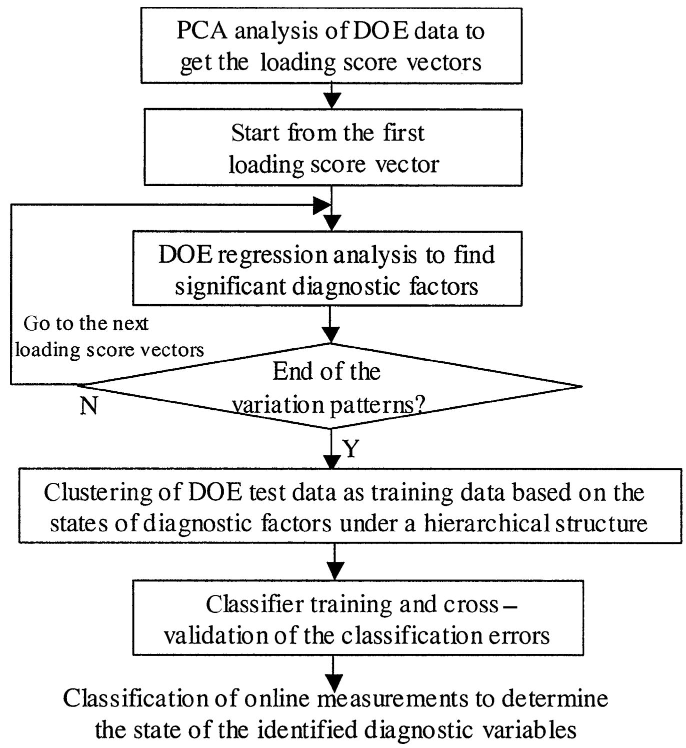

Fig. A1. Development procedures for a hierarchical classifier.

In the design of classifiers, a hierarchical classification structure is used to remove the effect of the factor interactions. Figure A2 shows a hierarchical classifier with three layers which is used to determine the binary states of four diagnostic variables (B C D E) in the stamping process. The states of those four diagnostic process variables are identified layer by layer, in which the state of factor B (thickness) is determined at layer 2 and used as the online thickness observer in our case study in Section 3 of this paper.

At layer 2, two classifiers will be designed corresponding to the binary states of factor D at the first layer. Since two factors B and E are identified as the diagnostic factors at layer 2, there will be four possible states (BE = −1−1, −11, 1−1, 11) to be classified at layer 2 under the given state of factor D. A piecewise linear classifier is designed in Jin and

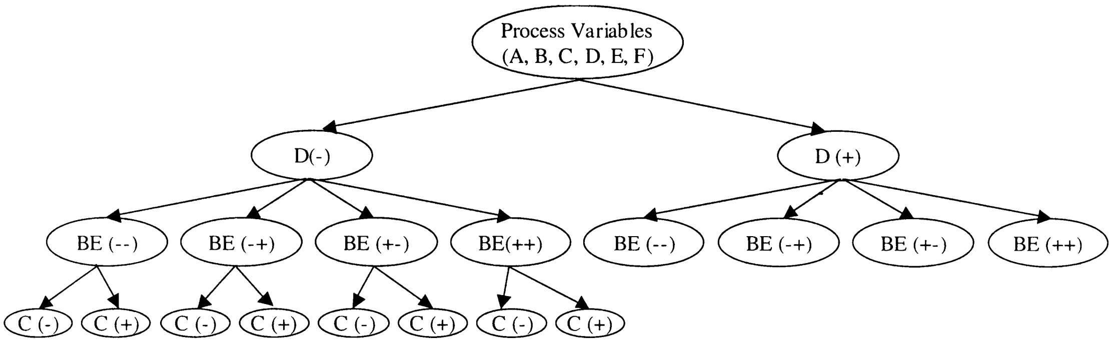

Fig. A2. Hierarchical classification structure for variable state classification.

Shi (2002) as:

$$\text{Cluster } k^* = \max_k \left\{ \boldsymbol{\mu}(k)^T \boldsymbol{\Sigma}^{-1} \mathbf{x}_i - \frac{1}{2} \boldsymbol{\mu}(k)^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}(k) + \log P_0(k) \right\}, \tag{A1}$$

where $\boldsymbol{\mu}(k)$ is the mean vector of the principle components at layer 2 corresponding to state k ($k = 1, 2, 3, 4$) of the two diagnostic factors (BE = −1−1, −11, 1−1, 11) for a given state of factor D. $P_0(k)$ is the occurrence probability of state k, and Σ is the pooled variance of those states (we are more interested in the difference of states induced by the mean difference, and assume the same variance for all states).

After the classifier is designed using the DOE training data set, the cross-validation method is used to obtain the average misclassification error rate to evaluate the performance of the designed classifier (Jin and Shi, 2002). The misclassification error rate is represented by the ratio of the number of misclassified samples to the total number of the samples clustered by the given states in the DOE training data set. In layer 2, the misclassification error rates of factor B are obtained as: $p = \text{prob}(\hat{B} = -1 \mid B = 1) = 2.78\%$, and $q = \text{prob}(\hat{B} = 1 \mid B = -1) = 1.39\%$.

In our DOE, two-level tests are conducted for each factor leading to a binary state of each factor in the classifier. In fact, the developed hierarchical classification method can be generally applied to multiple state classifier design if training data with multiple states are available.

Appendix B

As discussed in Appendix A, a hierarchical classifier is used to classify factor B at two levels based on online tonnage signal measurements. Let p and q be the misclassification rate when B equals 1 and −1, respectively, i.e., p, q are defined as $p = \Pr(\hat{B} = -1 \mid B = 1)$ and $q = \Pr(\hat{B} = 1 \mid B = -1)$.

In the test, the raw material is assumed equally likely to have a high level (+1) or low level (−1) thickness; using the Bayesian formula, we have:

$$\Pr(B = -1 \mid \hat{B} = 1) = \frac{q}{(1-p)+q} \quad \text{and} \quad \Pr(B = 1 \mid \hat{B} = -1) = \frac{p}{(1-q)+p}. \tag{A2}$$

The observation is slightly biased, as indicated by the following equation:

$$E(B \mid \hat{B} = 1) = 1 - 2\Pr(B = -1 \mid \hat{B} = 1) \quad \text{and} \quad E(B \mid \hat{B} = -1) = -1 + 2\Pr(B = 1 \mid \hat{B} = -1). \tag{A3}$$

The conditional observation uncertainty is:

$$\text{var}(B \mid \hat{B} = 1) = (-1 - E(B \mid \hat{B} = 1))^2 \Pr(B = -1 \mid \hat{B} = 1) + (1 - E(B \mid \hat{B} = 1))^2 \Pr(B = 1 \mid \hat{B} = 1),$$

and

$$\text{var}(B \mid \hat{B} = -1) = (-1 - E(B \mid \hat{B} = -1))^2 \Pr(B = -1 \mid \hat{B} = -1) + (1 - E(B \mid \hat{B} = -1))^2 \Pr(B = 1 \mid \hat{B} = -1). \tag{A4}$$

The classifier developed in Jin and Shi (2000) has $p = 2.78\%$ and $q = 1.39\%$. Then, substituting those values, we have $\text{var}(B \mid \hat{B} = 1) = 0.056$ and $\text{var}(B \,||\, \hat{B} = -1) = 0.107$.

Biographies

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