Impact of Information Sharing on Statistical Quality Control

Fugee Tsung

***Abstract*—With recent advances in information technology (IT), the research on and practice of information sharing is now having a significant impact on many aspects of supply chains. Nevertheless, few investigations focus on the impact of information sharing on product and process quality. Furthermore, it is still not clear how and what information should be shared or used, and how to quantify the benefits of information sharing in terms of quality improvement. In this research, a "matching problem" is used to demonstrate the impact of information sharing on quality. We quantify and compare the impact of different information-sharing strategies on process and product quality, and suggest that real-time information sharing may lead to dramatic quality improvement for an assembly process, the example here being a two-stage supply chain. The proposed approach to evaluate information sharing in terms of quality improvement can be extended to a more complex supply chain.**

***Index Terms*—Automatic process control, engineering process control, statistical process control, supply chain management.**

I. Introduction

In past annual benchmarking meetings of some U.S. automotive companies, it has been observed that the quality of the individual parts they produce usually equals the quality of Japanese parts, but that assembled American automobiles often undermine rather than showcase the quality of their parts. One accepted reason for the high quality of assembled Japanese automobiles is the well-established cooperative relationship that exists between Japanese manufactures and their suppliers, who they generally regard as extended factories. The Japanese case suggests that supply-chain cooperation may be a critical factor for quality improvement and greater competitiveness in the global marketplace.

Supply chain management (SCM) has received an enormous amount of attention in both industry and academic circles. (e.g., [14] and the references therein). One recent interest in SCM is in incorporating information flow among various members of a supply chain. Due to the recent advances in information technology (IT) such as the development of Internet tools, many research projects on and practical applications of supply-chain information sharing have made a positive contribution to inventory control, production scheduling, and delivery planning (e.g., [3], [5], [15]), but little work has been done that is relevant to the area of product and process quality. The critical questions of what information should be used or shared and how to use or share it, as well as how to quantify the benefits of information sharing in terms of quality improvement, have been largely ignored.

A. Matching Problem

In this paper, a "matching problem" is used to illustrate the impact of supply-chain information sharing on quality. We specifically focus on the process capability and quality improvement of two components that are used in fuel injectors, in an actual automotive assembly facility: bodies from a tier-1 supplier and needles from a tier-2 supplier. The tier-1 supplier sorts components such that a needle from the upstream manufacturer can be matched with the body that they have produced in order to satisfy the tolerance requirements. If a needle is slightly too large for the body, the assembly may be sticky or have reliability problems. If a needle is too small, fuel leakage or other failures may occur. The potential quality loss due to imperfect matching will be estimated by a quality loss function. Gutierrez *et al.*[8] have studied the production control of this process. Here we will demonstrate how information sharing has an impact on process capability and quality.

B. Quality Measure

Process capability indices such as C_p and C_{pk} have been widely used as a measure of quality, with C_p measuring potential process performance and C_{pk} measuring actual process performance [12], [17]. There are many manufacturers in the U.S. and Japan who require suppliers to produce items with C_p and C_{pk} of more than 1.0. However, we will show that greater process capability for a single process may in fact lead to worse overall assembly quality.

Therefore, an alternative measure is needed to quantify the process and product quality. A quality loss function can provide this alternative, by relating process and product loss to the "loss to society" [11], [19]

$$QL = k((\mu - T)^2 + \sigma^2) \tag{1}$$

where

- μ estimate of the process mean;
- σ estimate of the process standard deviation;
- T target or nominal dimension;
- k constant used to convert the function into monetary units.

For situations with no fixed target T, such as the smaller-the-better and larger-the-better problems, some modifications are needed (see [19]). We assume that without loss of generality, $T = 0$ and $k = 1$. The quality loss function will be used to quantify the quality of matching. Also, the value of information sharing (VI) is defined as the percentage of improvement in quality loss

$$VI = 100(QL_0 - QL)/QL_0\% \tag{2}$$

where QL_0 is the quality loss without information sharing, and QL is the quality loss of the process to be evaluated with information sharing.

C. Key Results and Contributions

In this paper, we quantify the impact of various information sharing strategies on process and product quality in a two-stage supply chain framework. Our key results can be summarized as follows:

- Without information sharing, although an individual process may be controlled to have greater process capability and dimensional quality, that enhancement may in fact lead to poor assembly matching.
- Controlling the process based on information sharing will lead to better assembly matching, even though the capability and dimensional quality of an individual process may be adversely affected.
- As the process data are not fully utilized by merely sharing simple descriptive statistics, real-time information sharing may have a greater impact in quality improvement than non real-time information sharing.
- For the purpose of benchmarking, the lower bounds of quality loss for both real-time and nonreal-time information sharing processes are derived.

The remainder of this paper is organized as follows: Section II discusses the processes without and with information sharing. Section III investigates the processes with real-time information sharing.

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Section IV quantifies the value of information sharing in terms of quality improvement. Concluding remarks and implications for future research issues are provided in Section V.

II. Process Without and with Information Sharing

A. Without Information Sharing

Needle and body manufacturers, like many conventional tier-1 and tier-2 suppliers, have little communication with each other, and therefore represent a situation of no information sharing.

To match two sets of components to form assemblies without information sharing, Glover [6] developed an algorithm involving measuring and sorting all components to maximize the matching number. Lee, Hausman, and Gutierrez [13] suggested grouping the components into different classes for operational convenience. As it is not our intention to develop an optimal matching method, Glover's basic sorting and matching approach is used throughout this paper.

Consider the needle diameter D_t^n with mean μ_n and a standard deviation σ_n, and the body diameter D_t^b with mean μ_b and a standard deviation σ_b. μ_n and μ_b can be controlled by resetting the production equipment, but σ_n^2 and σ_b^2 cannot be reduced without implementing other quality control techniques.

Without information sharing, the needle manufacturer—the tier-2 supplier—is only responsible for producing needles within the specification limits. Thus, within the limits the needle distribution is not carefully controlled. On the other hand, the body manufacturer—the tier-1 supplier—is responsible for producing bodies within the specification limits as well as making acceptable assemblies. Without information from upstream, the tier-1 supplier will determine their machine setting based only on internal quality requirements. We can see from Fig. 1(a) that although the body distribution is controlled so that it has a greater process capability and dimensional quality ($\mu_b = T$), this may lead to poor assembly matching.

B. With One-Way Information Sharing

For a process with information sharing, we will match the components to form an assembly in the same sorting and matching approach. However, an advantage is derived from the proper control of the component distribution based on feed-forward information before matching. If one-way information sharing is possible, which means that the downstream manufacturers can obtain information from the upstream manufacturers, but not the other way around, there is still a chance to improve the quality of assembly matching.

There have been some studies to determine the optimal machine setting, i.e., the optimal process mean of a single process, based on upstream information. These studies usually consider the cost/loss of exceeding some specification limits [7], [10], [16]. We can see from Fig. 1(b) that bringing the body distribution closer to the needle distribution ($\mu_b = \mu_n$) based on feed-forward information may lead to better assembly matching, i.e., larger VI, although the process capability and dimensional quality of the body is adversely affected. This will be demonstrated by a numerical example later.

C. With Two-Way Information Sharing

If two-way information sharing is possible, which means that the upstream and downstream manufacturers can obtain information from each other, there will be a greater chance to improve the quality of assembly matching.

Lee *et al.* [13] and Gutierrez *et al.* [8] deal with the cooperation of settings for multiple processes for assembly operations, which is only achievable with two-way information sharing. Different criteria may lead to different suggestions for both machine settings. Our study is based on the criterion of maximizing long-run expected matchings,

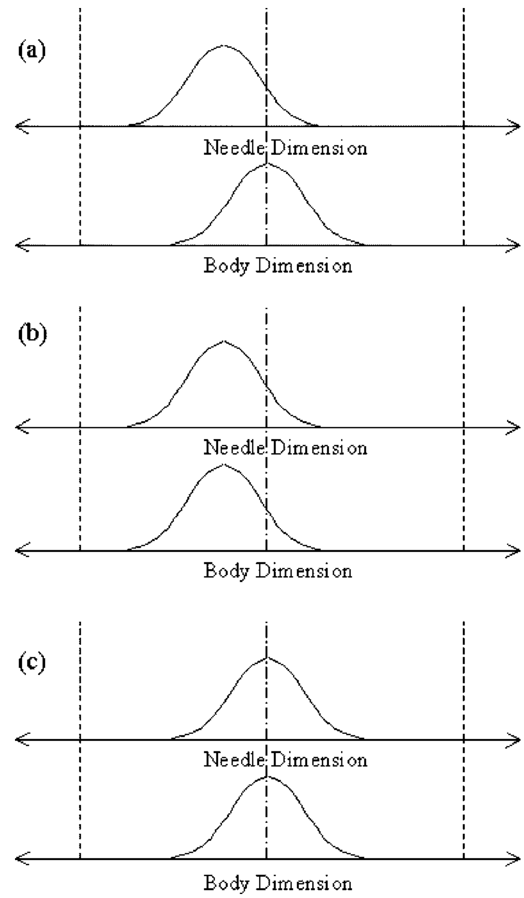

Fig. 1. Impact of information sharing: (a) processes without information sharing; (b) processes with one-way information sharing; and (c) processes with two-way information sharing.

where the optimal solution is to set both process means equally and on their targets (for proofs, see [13]). However, if an alternative criterion, the probability of next matching, is used, the optimal settings of the needle and body machines may not be the same and the processes may not be on their targets, especially when they have different process variations [13].

Here, we can see from Fig. 1(c) that controlling both the needle and body distributions so that they are close to each other and also close to their targets ($\mu_b = \mu_n = T$) based on information sharing will lead to better assembly matching, as well as to greater individual process capability and dimensional quality. This will be studied using a numerical example later.

Note that, in the two-way information sharing case with $\mu_b = \mu_n$, the quality loss of the assembly, i.e., the mean squared error of the clearance, is

$$\sigma_b^2 + \sigma_n^2 - 2\rho\sigma_b\sigma_n \quad -1 < \rho < 1 \tag{3}$$

where ρ is the correlation between body and needle in the matching sequence. Thus, theoretically, the best QL we can have is

$$QL_{NR} = (\sigma_b - \sigma_n)^2 \tag{4}$$

with $\rho = 1$, which assumes that the bodies and needles are perfectly correlated. The QL_{NR} value approaches to zero when σ_b is close to σ_n, but in many cases a significant loss may occur when σ_b is different from σ_n. This theoretical best quality loss value with two-way information sharing can be used as a lower bound for a non real-time information sharing situation. The difference for the real-time information sharing case will be discussed in the next section.

III. Process with Real-Time Information Sharing

Process data are not fully utilized by merely sharing simple descriptive statistics, e.g., the mean and standard deviation values. With recent advances in IT, real-time process data sharing has become common, and this has great potential for further quality improvement. Both statistical process control (SPC) and automatic process control (APC) [also called engineering process control (EPC)] are popular quality control techniques that utilize real-time process data [20]–[22]. Here, an SPC/APC method—the Box–Jenkins bounded adjustment approach—is used to adjust the body machine setting based on real-time needle process data (see [2], [9], and the references therein).

As a process with large volumes of routinely collected data (e.g., > 10 000 injectors/day) is often correlated, we consider both D_t^n and D_t^b as stationary autoregressive-moving average processes [ARMA(1, 1)]

$$D_t^n = \phi D_{t-1}^n + \epsilon_t - \theta\epsilon_{t-1} \tag{5}$$

and

$$D_t^b = \varphi D_{t-1}^b + \varepsilon_t - \vartheta\varepsilon_{t-1} \tag{6}$$

where $|\phi| < 1$, $|\theta| < 1$, $|\varphi| < 1$, $|\vartheta| < 1$, ϵ_t represents white noise with mean μ_ϵ and standard deviation σ_ϵ, and ε_t with mean μ_ε and standard deviation σ_ε.

The approach is first to calculate the exponentially weighted moving average (EWMA) statistic from the real-time D_t^n data

$$z_t = \lambda D_{t-1}^n + (1-\lambda)z_{t-1}. \tag{7}$$

At each point in time, the estimated EWMA is used as a forecast, which gives $100\ \lambda\%$ weight to the present D_t^n and $100(1-\lambda)\%$ weight to the previous history, which is gradually discounted. The EWMA scheme is not necessarily the theoretically best one, but has been proven to be robust and useful for correlated processes. Note that in industrial practice, a three-term adjustment scheme, i.e., proportional-integral-derivative (PID) scheme, is also a commonly used method [1], [23], [24]. In many situations, only one or two of these three terms are used [25]. In particular, if the proportional and derivative terms are set to zero, we have the integral (I) scheme, which is equivalent to the EWMA. We focus on the EWMA scheme throughout this paper.

Although the Box–Jenkins approach can be employed to adjust the body machine setting by the amount of EWMA forecast after every observation, the more practical bounded approach will be described.

Here, the control rule is to adjust the body machine setting, i.e., the target of D_t^b, to z_t as soon as

$$|z_t - z_r| \geq L \tag{8}$$

where r is time zero or the time you last made an adjustment, and $\pm L$ are the bounds. The bounds are commonly established on the basis of engineering judgment, taking into consideration the cost of adjustment and the cost of a mismatch. A systematic way to determine L can be found in [2]. As long as the EWMA falls within the bounded $\pm L$ it will serve as a basis for the next forecast. When the EWMA falls beyond the bounds, adjustment in D_t^b will force the clearance close to zero.

Here, the proposed approach will avoid the excessive cost and inconvenience of making an adjustment after every observation, and largely reduce the quality loss of the matching process by using real-time information. This will be demonstrated by examples in the following section.

For the purpose of benchmarking, we study the situation with $L = 0$. A closed-form solution of the assembly quality loss with the Box–Jenkins approach without bounds is derived. Consider the needle dimension D_t^n in (5), and apply its EWMA forecast z_t in (7) to adjust the body dimension D_t^b in (6), we then have the assembly clearance

$$\begin{aligned} e_t &= D_t^b + z_t - D_t^n \\ &= \varepsilon_t(1-\vartheta B)/(1-\varphi B) \\ &\quad + \epsilon_t\lambda(1-\theta B)/\{(1-B+\lambda B)(1-\phi B)\} \\ &\quad - \epsilon_t(1-\theta B)/(1-\phi B) \end{aligned} \tag{9}$$

where B is the usual backward shift operator, i.e., $B\varepsilon_t = \varepsilon_{t-1}$. Here, e_t can also be presented as

$$e_t \equiv \sum_{k=0}^{\infty} \psi_k \varepsilon_{t-k} + \sum_{k=0}^{\infty} \zeta_k \epsilon_{t-k} - \sum_{k=0}^{\infty} \eta_k \epsilon_{t-k} = I + II - III. \tag{10}$$

Note that the summation of items I and II is the body dimension after EWMA adjustment, and item III presents the needle dimension. The values of ψ_k, ζ_k, η_k obtained by equating (10) with (9) are

$$\psi_0 = 1, \qquad \psi_k = \varphi^{k-1}(\varphi - \vartheta) \ \ k > 0 \tag{11}$$

$$\begin{aligned} \zeta_0 &= 0, \\ \zeta_k &= \frac{\lambda}{1-\lambda-\phi}\Big((1-\lambda)^{k-1}(1-\lambda-\theta) \\ &\qquad + \phi^{k-1}(\theta-\phi)\Big)\ k > 0 \end{aligned} \tag{12}$$

and

$$\eta_0 = 1, \qquad \eta_k = \phi^{k-1}(\phi - \theta) \ \ k > 0. \tag{13}$$

Hence, the quality loss of the clearance is

$$QL = \mathrm{var}(I + II) + \mathrm{var}(III) - 2\mathrm{cov}(I + II,\ III) \tag{14}$$

where

$$\begin{aligned} \mathrm{var}(I+II) &= \sigma_\varepsilon^2 \sum_{k=0}^{\infty} \psi_k^2 + \sigma_\epsilon^2 \sum_{k=0}^{\infty} \zeta_k^2 + 2\sigma_\varepsilon\sigma_\epsilon \sum_{k=0}^{\infty} \psi_k\zeta_k \\ &= \sigma_\varepsilon^2(1 - 2\varphi\vartheta + \vartheta^2)/(1-\varphi^2) \\ &\quad + \sigma_\epsilon^2 \frac{\lambda^2}{(1-\lambda-\phi)^2}\big((1-\lambda-\theta)^2/\lambda(2-\lambda) \\ &\qquad + (\theta-\phi)^2/(1-\phi^2) \\ &\qquad + 2(1-\lambda-\theta)(\theta-\phi)/(1-\phi+\lambda\phi)\big) \\ &\quad + 2\sigma_\varepsilon\sigma_\epsilon \frac{\lambda}{1-\lambda-\phi}(\varphi-\vartheta) \\ &\quad \cdot ((1-\lambda-\theta)/(1-\varphi+\lambda\varphi) \\ &\qquad + (\theta-\phi)/(1-\phi\varphi)) \end{aligned} \tag{15}$$

and

$$\mathrm{var}(III) = \sigma_\epsilon^2 \sum_{k=0}^{\infty} \eta_k^2 = \sigma_\epsilon^2(1 - 2\phi\theta + \theta^2)/(1-\phi^2). \tag{16}$$

Note that the $\mathrm{cov}(I+II,\, III)$ value, i.e., the covariance between body and needle cannot be calculated by

$$\mathrm{cov}(I+II,\, III) = \sigma_\varepsilon \sigma_\epsilon \sum_{k=0}^{\infty} \psi_k \eta_k + \sigma_\epsilon^2 \sum_{k=0}^{\infty} \zeta_k \eta_k \tag{17}$$

as in practice the injector matching does not happen in the original production sequence on a real-time basis, but by a sorted sequence on a batch basis. To consider the correlation between body and needle after sorting and matching, the theoretically best QL we may have is to let the body and needle be perfectly correlated. Thus, by applying

$$\mathrm{cov}(I+II,\, III) = \sqrt{\mathrm{var}(I+II)}\sqrt{\mathrm{var}(III)} \tag{18}$$

to (14), we obtain a lower bound for a real-time information sharing situation

$$QL_{RT} = \left(\sqrt{\mathrm{var}(I+II)} - \sqrt{\mathrm{var}(III)}\right)^2 \tag{19}$$

where $\mathrm{var}(I+II)$and $\mathrm{var}(III)$ are given by (15) and (16).

IV. Information Quantification with Examples

In this section, we investigate the impact and quantify the value of information sharing in terms of improvement in quality loss. We consider the processes of needle dimension D_t^n and body dimension D_t^b as

$$\begin{aligned} D_t^n &= 0.95 D_{t-1}^n + \epsilon_t - 0.8\epsilon_{t-1} \\ D_t^b &= 0.5 D_{t-1}^b + \varepsilon_t - 0.4\varepsilon_{t-1} \end{aligned}$$

where ϵ_t values have standard deviation $\sigma_\epsilon = 1.2$, and ε_t values have standard deviation $\sigma_\varepsilon = 0.6$, the parameters being based on the field estimations cited in [8]. μ_ϵ and μ_ε will depend on the current machine setting.

By applying (4) and (19) to these processes, we obtain their lower bound for a nonreal-time information sharing situation: $QL_{NR} = 0.529$, and the lower bound for a real-time information sharing situation: $QL_{RT} = 0.106$. The difference between these two bounds indicates the possible quality improvement we may make by real-time information sharing. Here, we simulate 30 days of operation with component production of 10 000 units/day, and treat daily production as a batch. The specification limits of both the needle and body are scaled to be ±5, with nominal values equal to zero. Four types of processes are studied.

1) Process without information sharing: assume that the daily setting of the needle machine varies between −1 and 1, since this is good enough to be within the specification limits, while the daily setting of the body machine is fixed at zero, since no information from upstream is obtained. The simulation results in Table I show that although the process capability of body manufacturing C_{pk}^b is as great as 2.75, the quality loss QL of matched assembly is as high as 6.11, and its VI is zero as defined. We will see to what degree the quality loss can be improved by information sharing.
2) Process with one-way information sharing: the body manufacturer determines their daily setting according to the setting of the needle machine. Table I indicates that the process capability of body manufacturing C_{pk}^b is less than process a) due to its deviation from the target, but its quality loss QL is much improved with $VI = 37.9\%$.
3) Process with two-way information sharing: by optimizing expected matchings from both distributional information, both needle and body machine settings are at zero. In this case, process capacities of needle and body, C_{pk}^n and C_{pk}^b, are both improved to acceptable values (> 1.0). Also, quality loss is 0.53, which is quite close to the theoretical lower bound: $QL_{NR} = 0.529$, and the improvement is quantified by $VI = 74.5\%$.
4) Process with real-time information sharing: to implement the modified Box–Jenkins adjustment approach, the EWMA statistic is calculated from the real-time D_t^n data with $\lambda = 0.2$

$$z_t = 0.2 D_{t-1}^n + 0.8 z_{t-1}.$$

Note that a least squares estimate of λ can be obtained using the work of Montgomery and Mastrangelo (1991). Based on the control rule with $L = 0.8$ (see [2] on how to determine L), we adjust the body machine setting to z_t as soon as

$$|z_t - z_r| \geq 0.8.$$

This approach is graphically presented in Fig. 2. Fig. 2(a) shows the dimensional readings of needles, along with the EWMA statistics. In Fig. 2(b), the line based on the crosses shows the adjustments applied to the body process, and the dashed lines are the corresponding bounds L which indicate how the EWMA statistics trigger the adjustment. The body processes without and with adjustment are compared in Fig. 2(c). Fig. 2(d) compares the assembly dimensions without and with adjustment. We can see from Table I that the process capability of body manufacturing C_{pk}^b has deteriorated to 1.68 due to the active adjustment, but it is still within the acceptable range (>1.0). More importantly, the quality loss of the matched assembly is reduced to 0.12, which is fairly close to the theoretical bound: $QL_{RT} = 0.106$. Its $VI = 94.0\%$ indicates a dramatic improvement of this process.

TABLE I
Comparison of Four Processes Without/with Information Sharing

Process	C_{pk}^n	C_{pk}^b	QL	$VI(\%)$
(a) No sharing	0.73 (0.30)	2.75 (0.01)	6.11 (5.02)	0 (0)
(b) One-way	0.73 (0.30)	2.41 (0.20)	3.26 (2.45)	37.9 (14.8)
(c) Two-way	1.23 (0.01)	2.75 (0.01)	0.53 (0.02)	74.5 (29.3)
(d) Real-time	1.23 (0.01)	1.68 (0.03)	0.12 (0.01)	94.0 (6.8)

Note: numbers in ( ) are the corresponding standard deviations.

V. Conclusion

In this research, we quantify and compare the impact of different information-sharing strategies on process and product quality. We indicate that real-time information sharing may lead to dramatic quality improvement for an assembly process, an example being the two-stage supply chain.

In reality, some practical issues need to be addressed. First, to motivate the information-sharing strategy, it is critical to suggest a mechanism that spreads the benefits of information sharing between the supplier and manufacturer. Also, it is important to quantify the investment required to effect a real-time information sharing process before proposing this strategy.

The proposed approach to evaluate the impact of information sharing on quality can be directly extended to a more complex supply chain.

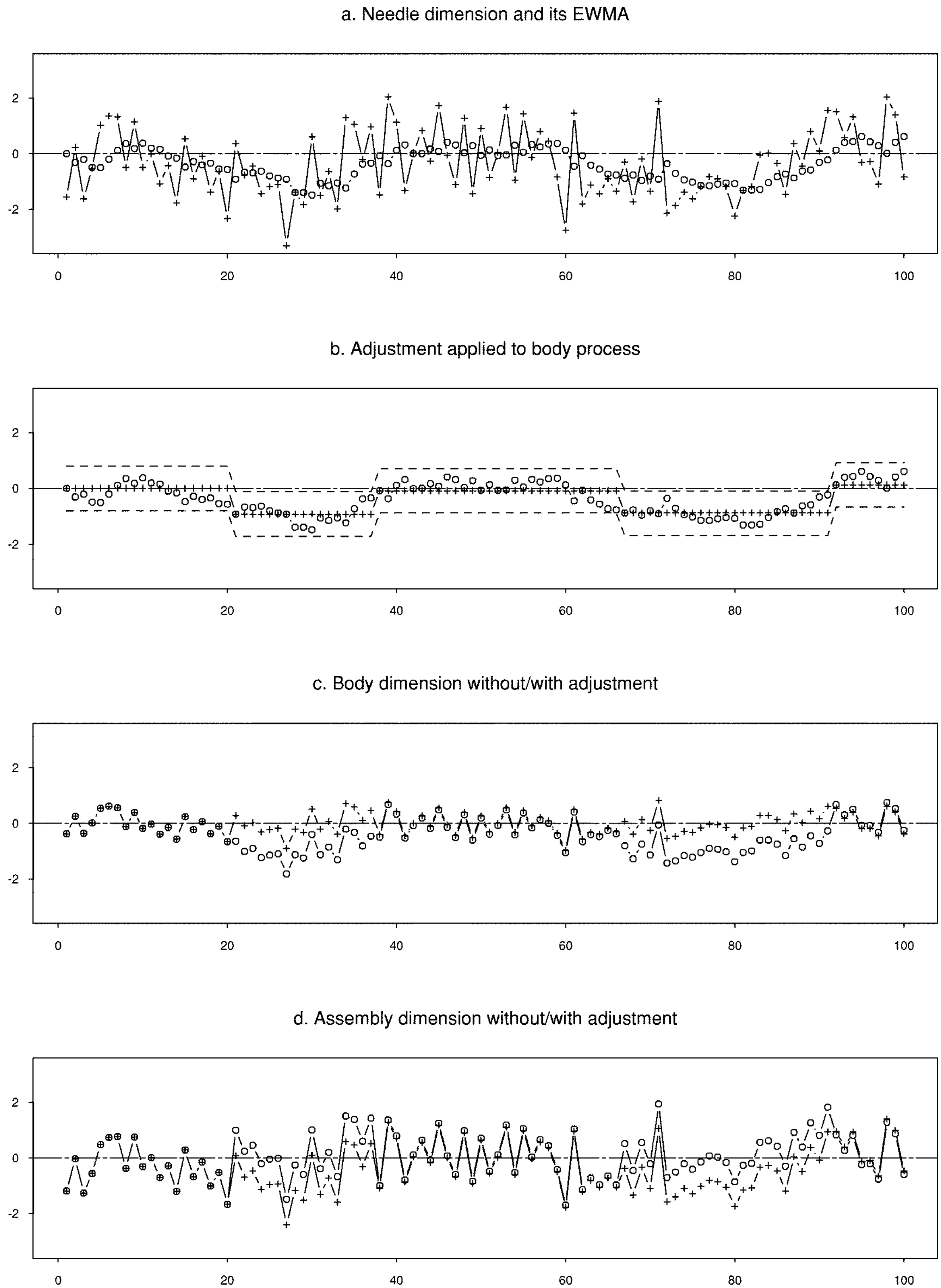

Fig. 2. The Box–Jenkins bounded adjustment approach: (a) cross: needle dimension, circle: EWMA statistic; (b) cross: body adjustment, dash: L bounds, circle: EWMA statistic; (c) cross: body dimension without adjustment, circle: with adjustment; and (d) cross: assembly dimension without adjustment, circle: with adjustment.

What information to use or share and how to use or share it for quality improvement in a complex supply chain still warrant further research.

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REFERENCES

[1] K. J. Astrom, *Automatic Tuning of PID Controllers*. Research Triangle Park, NC: Instrum. Soc. Amer., 1988.
[2] G. E. P. Box and A. Luceno, *Statistical Control by Monitoring and Feedback Adjustment*. New York: Wiley, 1997.
[3] G. Cachon and M. Fisher, "Supply chain inventory management and the value of shared information,", working paper, 1997.

[4] I. S. Chang and J. J. Visser, "A framework of distributed quality control," *Comput. Indust. Eng.*, vol. 35, pp. 181–184, 1998.

[5] S. Gavirneni, R. Kapuscinski, and S. Tayur, "Value of information in capacitated supply chains," *Manage. Sci.*, vol. 45, pp. 16–24, 1999.

[6] F. Glover, "Maximum matching in a convex bipartite graph," *Nav. Res. Logist.*, vol. 14, pp. 313–316, 1967.

[7] D. Y. Golhar, "Determination of the best mean contents for a canning problem," *J. Qual. Technol.*, vol. 19, pp. 82–84, 1987.

[8] G. J. Gutierrez, W. H. Hausman, and H. L. Lee, "Dynamic control of imperfect component production for assembly operations," *IEE Trans.*, vol. 27, pp. 669–678, 1995.

[9] J. S. Hunter, "The Box–Jenkins bounded manual adjustment chart," *Qual. Prog.*, vol. 31, pp. 129–137, 1998.

[10] W. G. Hunter and C. P. Kartha, "Determining the most profitable target value for a production process," *J. Qual. Technol.*, vol. 9, pp. 176–181, 1977.

[11] P. Jessup, "The value of continuing improvement," in *IEEE Conf. Commun.*, vol. 1, 1985, pp. 89–94.

[12] V. E. Kane, "Process capability indices," *J. Qual. Technol.*, vol. 18, pp. 41–52, 1986.

[13] H. L. Lee, W. H. Hausman, and G. J. Gutierrez, "Optimal machine settings of imperfect component production processes for assembly operations," *IEEE Trans. Robot. Automat.*, vol. 6, pp. 652–658, 1990.

[14] H. L. Lee, V. Padmanabhan, and S. Whang, "Information distortion in a supply chain: The bullwhip effect," *Manage. Sci.*, vol. 43, pp. 546–558, 1997.

[15] H. L. Lee, K. C. So, and C. S. Tang, "The value of information sharing in a two-level supply chain,", working paper, 1998.

[16] L. S. Nelson, "Best target value for a production process," *J. Qual. Technol.*, vol. 10, pp. 88–89, 1978.

[17] L. P. Sullivan, "Reducing variability: A new approach to quality," *Qual. Prog.*, vol. 17, pp. 15–21, 1984.

[18] K. Suzaki, *The New Manufacturing Challenge*. New York, NY: Free Press, 1987.

[19] G. Taguchi, E. A. Elsayed, and T. C. Hsiang, *Quality Engineering in Production Systems*. New York: McGraw-Hill, 1989.

[20] F. Tsung, "Improving automatic-controlled process quality using adaptive principal component monitoring," *Qual. Reliab. Eng. Int.*, vol. 15, pp. 135–144, 1999.

[21] ——, "Statistical monitoring and diagnosis of automatic controlled processes using dynamic PCA," Int. J. Prod. Res., vol. 38, pp. 625–637, 2000, to be published.

[22] ——, "On three-term adjustment schemes for statistical process control," Int. J. Indust. Eng., vol. 6, pp. 161–170, 1999, to be published.

[23] F. Tsung and J. Shi, "Integrated design of run-to-run PID controller and SPC monitoring for process disturbance rejection," *IIE Trans.*, vol. 31, pp. 517–527, 1999.

[24] F. Tsung, J. Shi, and C. F. J. Wu, "Joint monitoring of PID controlled processes," *J. Qual. Technol.*, vol. 31, pp. 275–285, 1999.

[25] F. Tsung, H. Wu, and V. N. Nair, "On the efficiency and robustness of discrete proportional-integral control schemes," *Technometrics*, vol. 40, pp. 214–222, 1998.

Robot Action Planning via Explanation-Based Learning

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***Abstract*—Domain-specific searching heuristics is greatly influential upon the searching efficiency of robot action planning (RAP), but its computer-realized recognition and acquisition, i.e., learning, is difficult. This paper makes an exploration into this challenge. First, a problem formulation of RAP is made. Then, by applying explanation-based learning, which is currently the only approach to acquiring domain-specific searching heuristics, a new learning based method is developed for RAP, named robot action planning via explanation-based learning (RAPEL). Finally, an example study demonstrates the effectiveness of RAPEL.**

***Index Terms*—Action sequence synthesis, autonomous robot, explanation-based learning, robot action planning (RAP), robotics, searching heuristics.**

I. Introduction

Research of robot action planning (RAP) started in early 1970's. As the earliest work on RAP, STRIPS [1] not only opened the area, but also established classics in the area, e.g., means-ends analysis searching mechanism, and precondition-effect expression of actions. Reference [3] presented a survey upon RAP.

A problem solving system can be modeled as a triangle pulled on its three angles by searching mechanism, knowledge base and data base, respectively. A problem solving is a process of utilizing knowledge upon data under the guide of searching mechanism. Along such a triangle, approaches to RAP can be classified into two streams, one weights knowledge and another weights searching.

Realized by knowledge-based/expert-system approaches, knowledge-weighted RAP [3], [4] can work fairly well within specific domains, but not in varied domains. This poses the motivation to computer-realized recognition and acquisition, i.e., learning, of domain-specific knowledge. The earliest learning based method for RAP was by [5]. Action sequences which were successful in the past are parametrically generalized to form macro actions. Another learning based method for RAP is by analogy learning [6]. Reference [7] proposed a supervised analogy learning, between rote and generalization, for RAP.

As another stream, searching-weighted RAP, in principle, has two types, i.e., by universal and by domain-specific searching mechanisms. However, existing searching-weighted RAP is all by universal searching mechanisms, and the type by domain-specific searching mechanisms is still a blank, neither manual nor computer-realized.

Random approximation is a universal searching mechanism without heuristics. References [8]–[10] proposed an off-line blind enumerating searching for RAP. Reference [11] formulated this idea of RAP as a Boltzmann machine. Means-ends analysis searching mechanism is a primary universal searching heuristics. It is first to compute the difference between the current and the desired world state and then to find a related action to reduce the existing difference. In fact, this is an on-line error compensation, as in feedback based control ([12] gave a system-and-control perspective to RAP). Other exploited universal searching heuristics are such as hierarchical (i.e., abstracting) expression of actions and world states, and opportunistic mechanism of human

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