Quality control of geometric features: monitoring roundness profiles obtained by turning

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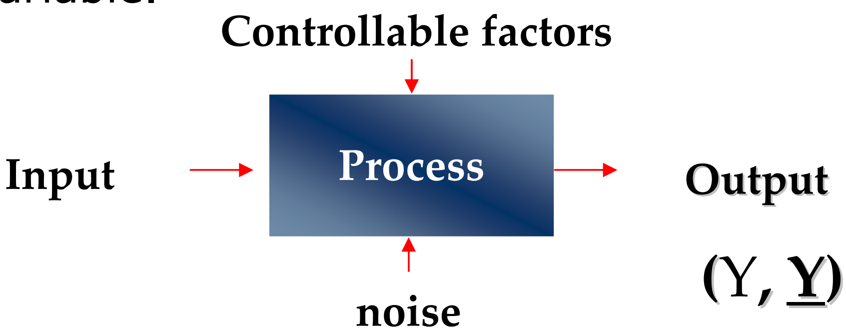
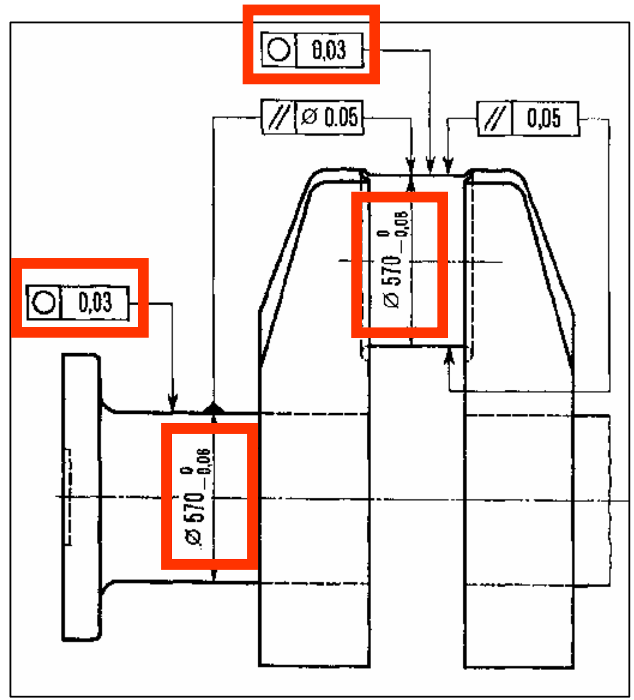
Dimensional and geometric specifications

Quality of mechanical components is critically related to both dimensional and geometric specifications (straightness, roundness or circularity, cilindricity, flatness).

Most of the literature on SPC focuses on the first type of characteristics since product (or process) quality is modeled as a univariate or a multivariate random variable.



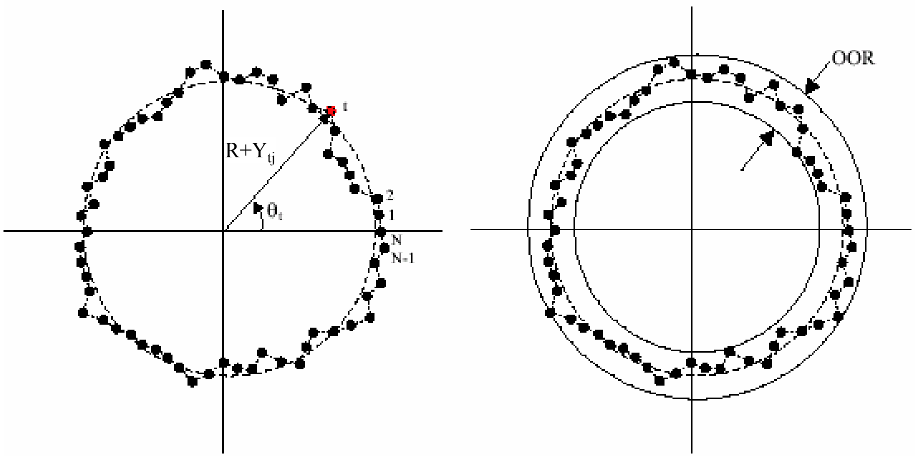


A process is judged in-control when the main moments of the random variable distribution (i.e., mean and variance) are stable with time.

SPC for geometric specifications (profile) ?

Industrial practice for monitoring geometric specifications : the roundness example

j-th profile

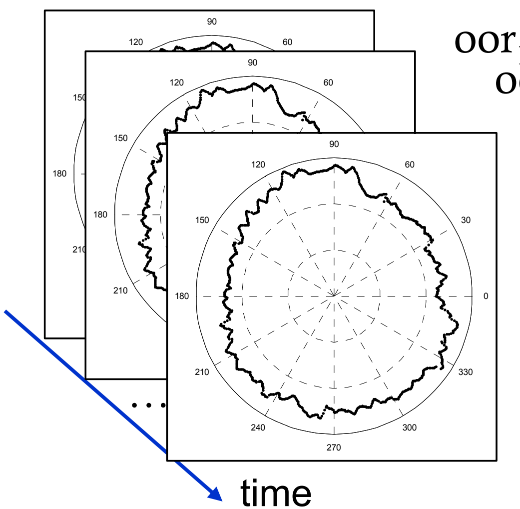


"Out-of-roundness":

MZ) distance between two concentric circles enclosing the roundness profile and having least radial separation

LS) peak-to-valley deviation of the actual profile from a least squares reference circle

ISO/TS 12181-1 and 2:2003 Geometrical Product Specifications (GPS) Roundness

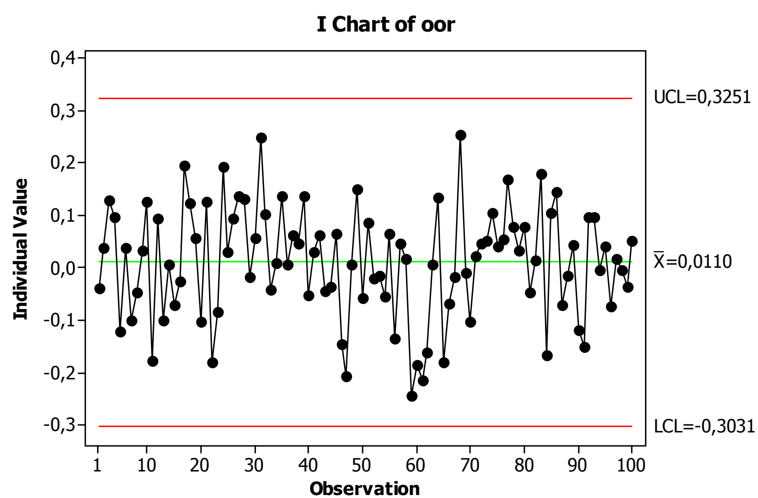


oor_1

oor_2

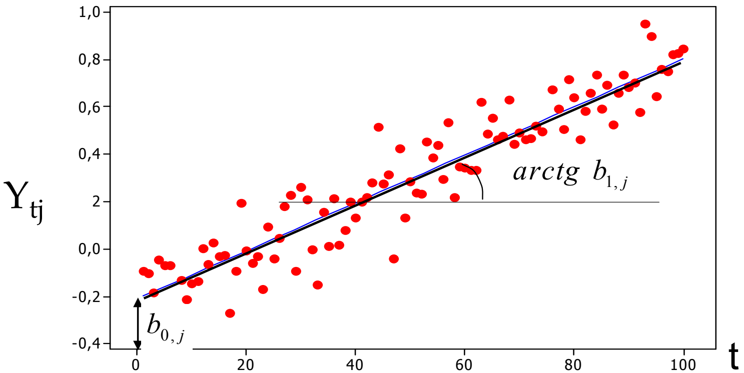
...

oor_j



Monitoring profiles: the main idea

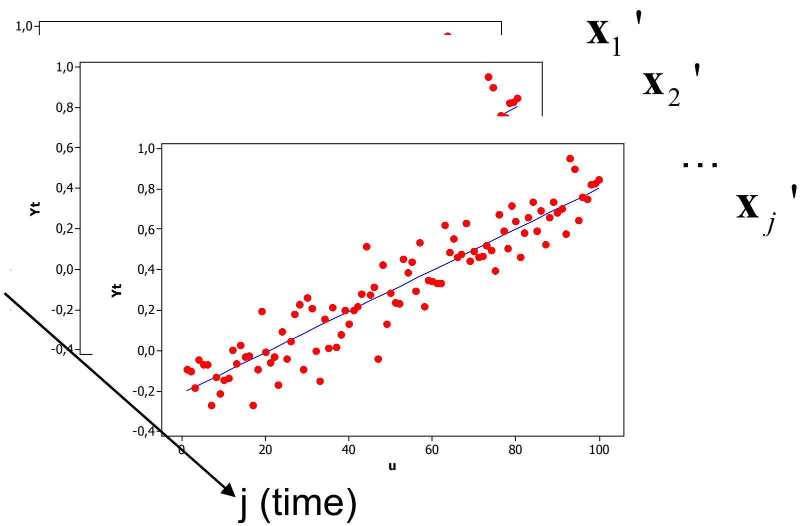
Recent literature: Woodall et al. (2004) ; Kim and Woodall (2003); Walker, and Wright (2002); Jin and Shi (2001); Kang and Albin (2000)…



At time j:

Assuming white noise – When a proper parametric model is identified, the profile is related to the (estimated) parameters:

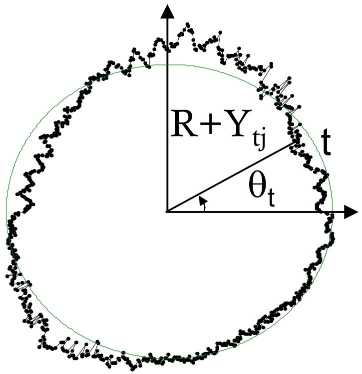
$$\mathbf{x_j}' = (b_{0,j}, b_{1,j}) \quad \text{where} \quad \begin{aligned} b_{0,j} &= \hat{\beta}_{0,j} \\ b_{1,j} &= \hat{\beta}_{1,j} \end{aligned}$$

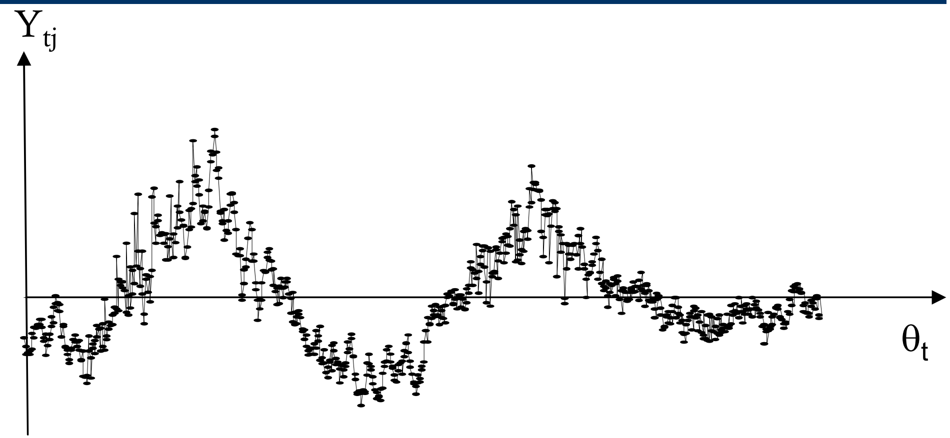


Monitoring profile ⇒monitoring with time (j=1,..,) the vector of parameter estimates $\mathbf{x}_j'$ by using a multivariate control chart

A profile monitoring approach

j-th profile





Controllable factors

Input → **Process** → **Output**

noise

$(Y, \underline{\mathbf{Y}}, Y_t=f(t)+e\ )$

Quality & geometric specifications:

- the process should be judged in-control if the relationship (e.g., the function) used to represent that profile or surface in the space, is stable with time;
- When the process moves out of control, the geometric feature will probably bring the “signature” of this shift: the SPC tool should quickly detect deviation of the form obtained by the one characterizing the in-control state.

The main objective of the research

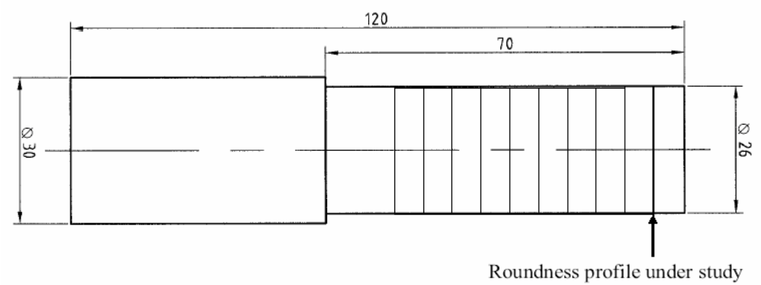
- Approaches presented in the literature on profile monitoring can be simply applied to profiles related with geometric specifications?

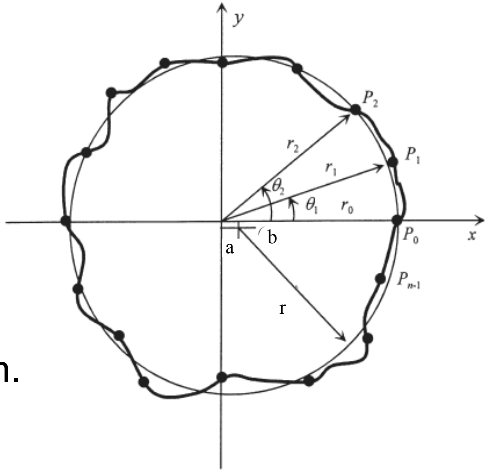
  The main problem is the spatial correlation characterizing adjacent measured points (possible causes: similar machining conditions, local mechanical properties of the material machined)

- Is there any advantage in using profile monitoring instead of using traditional SPC on synthetic tolerance indicators (as OOR) ?

  Performance (Average Run Length in Phase II) of competing methods will be compared

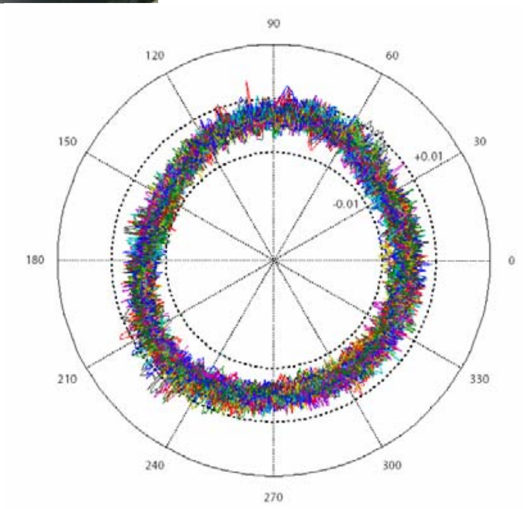
Roundness profiles obtained by turning

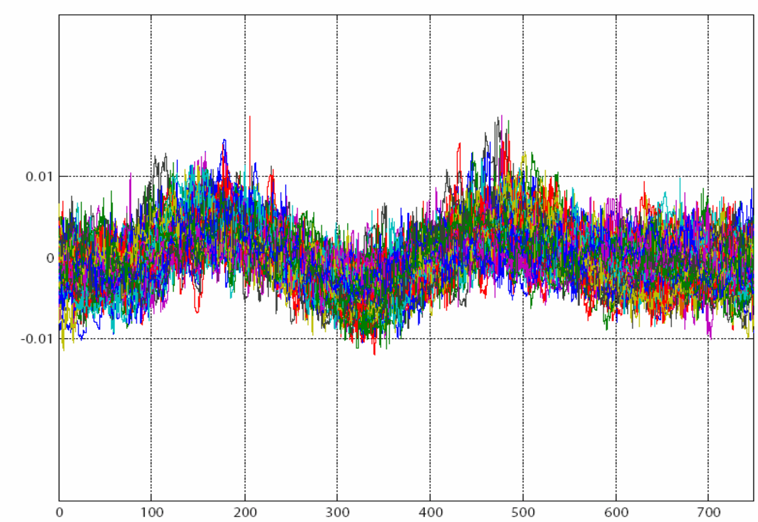




J=100 cast C20 carbon steel cylinders (supplied in Ø30 mm rolled bars) machined to nominal Ø26 mm.

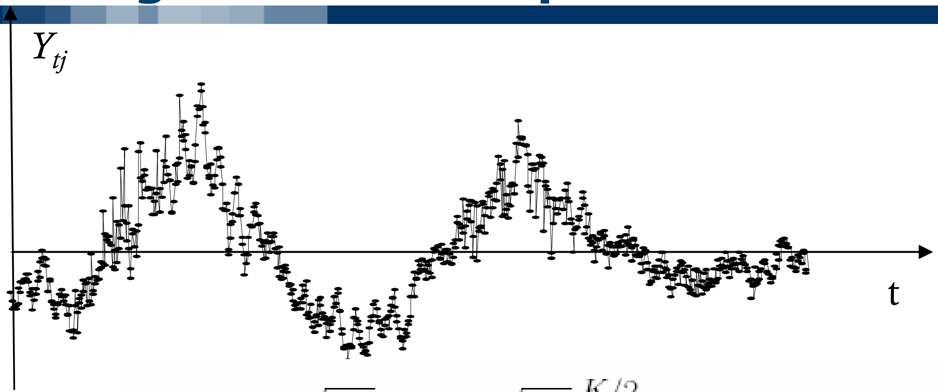
Each profile was sampled (t=1,…,748) by a CMM.





Manufacturing "signature": the systematic behavior characterizing all the profiles

Profile related with geometric specifications: The signature of the process



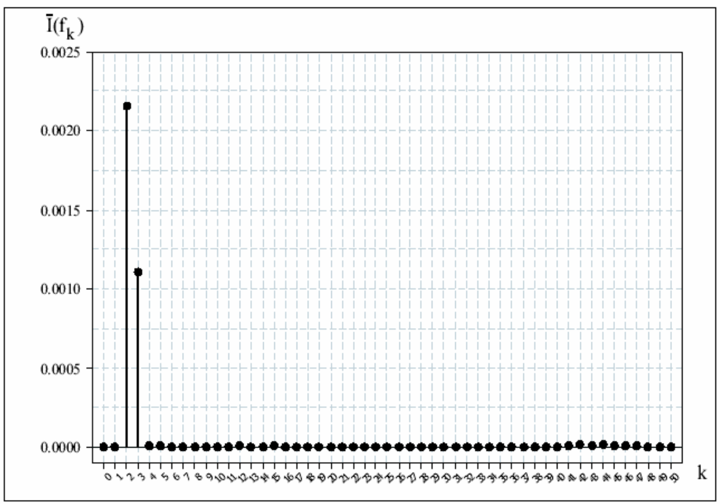
$$Y_{tj} = \boldsymbol{b_j}'\boldsymbol{u_t} + \nu_{tj}$$

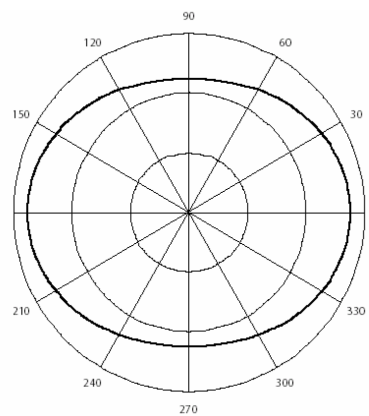
$$t = 1, 2, ..., N \;\; \text{and} \;\; j = 1, 2, ..., J$$

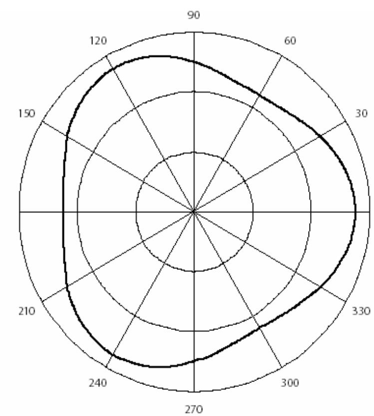
where $$\boldsymbol{b_j}'\boldsymbol{u_t} = \sqrt{\frac{1}{N}} b_{0j} + \sqrt{\frac{2}{N}} \sum_{k=1}^{K/2} \left[b_{2k-1\ j}\ cos(f_k(t-1)) + b_{2k\ j}\ sin(f_k(t-1)) \right]$$

$$t = 1, 2, ..., N \;\; \text{and} \;\; j = 1, 2, ..., J$$

$$f_k = k(2\pi/N) \text{ rad/sample}$$





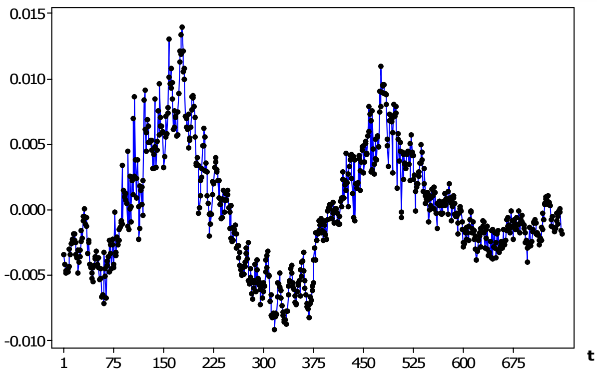


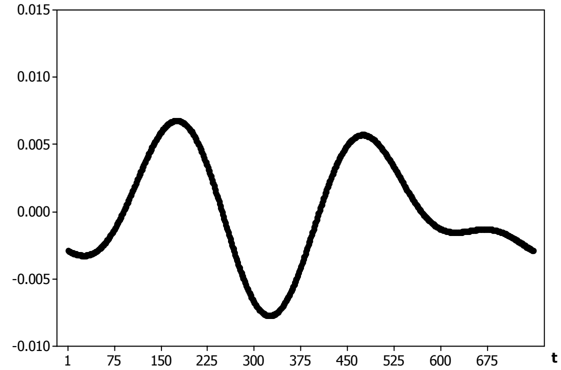
Cho and Tu, 2001; Hii et al. 2004: for roundness obtained by turning, Fourier-based predictors are able to model the radial error motion of the spindle and clamping effects

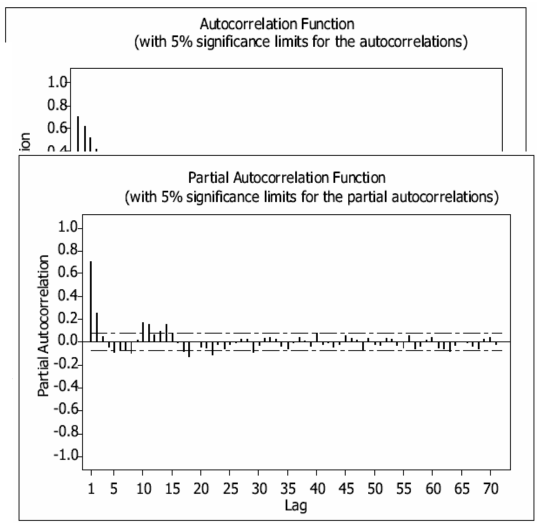
Roundness profiles: Fourier-based regressors + ARMA noise

Example: j=1 (first profile)

$$Y_{tj} = \boldsymbol{b_j}'\boldsymbol{u_t} + \nu_{tj}$$







(Box et al., 1994; Montgomery et al. 2001; Ljung, 2005)

AR(2)

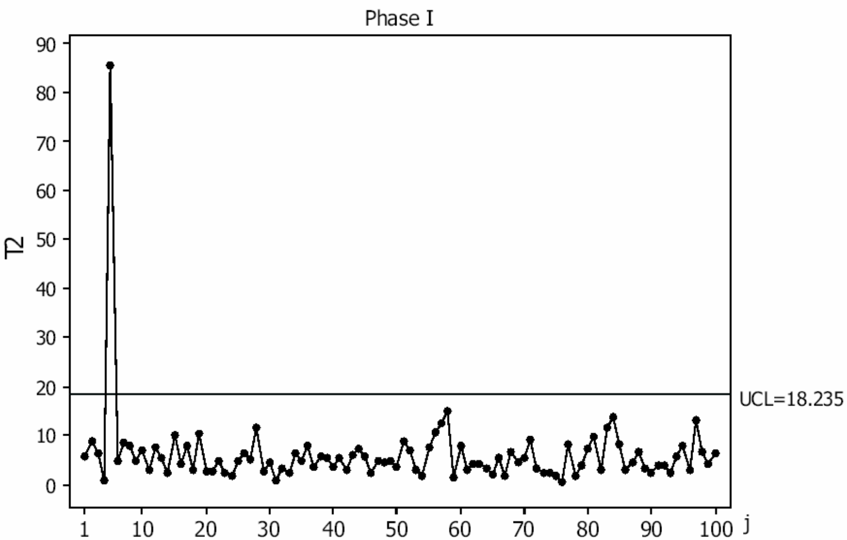
$$Y_{tj} = \sqrt{\frac{2}{N}}\left[b_{3j}cos(f_2(t-1)) + b_{4j}sin(f_2(t-1)) + b_{5j}cos(f_3(t-1)) + b_{6j}sin(f_3(t-1))\right] + + \frac{1}{1 - a_{1j}\mathcal{B} - a_{2j}\mathcal{B}^2}\varepsilon_{tj}$$

$t = 1, \dots, N; \; j = 1, \dots, J$ $\quad N = 748 \quad J = 100$ $\qquad f_k = k(2\pi/N)$ rad/sample

For each profile (j=1,..,100) this model structure is adopted (LBQ statistics to test randomness of new residuals $\hat{\varepsilon}_{tj}$'s): multivariate control chart based on

$$\boldsymbol{x_j}' = [\; x_{1j} \;\; x_{2j} \;\; \dots \;\; x_{6j} \;] = [\; \hat{b}_{3j} \;\; \hat{b}_{4j} \;\; \hat{b}_{5j} \;\; \hat{b}_{6j} \;\; \hat{a}_{1j} \;\; \hat{a}_{2j} \;]$$

Phase I control chart: T^2 control chart of individual observations (Sullivan and Woodall, 1996; Vargas, 2003)



$$v_j = x_{j+1} - x_j \quad j = 1, \ldots, J-1$$

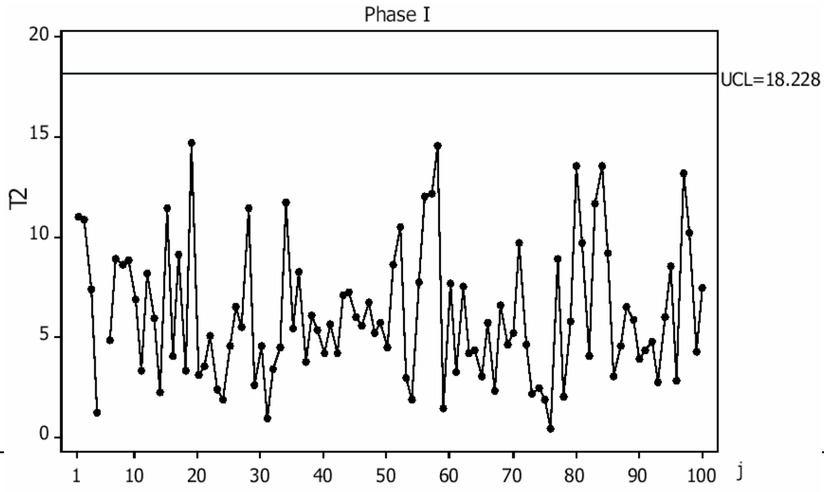
$$S_2 = \frac{1}{2}\frac{V'V}{J-1}$$

$$T_j^2 = (x_j - \bar{x})' S_2^{-1} (x_j - \bar{x})$$

$$UCL = \frac{(J-1)^2}{J} B_{d/2,(f-d-1)/2,\alpha}$$

$$f = 2(J-1)^2/(3J-4)$$

Fifth sample ⇒assignable cause (improper probe in CMM): sample removed

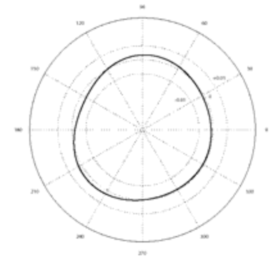


Final control chart:

Control limit in Phase II

$$UCL = \frac{d(J+1)(J-1)}{J^2 - Jd} F_{d,J-d,\alpha}$$

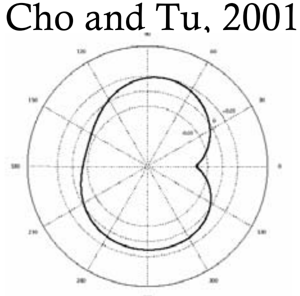
Run length comparison in Phase II



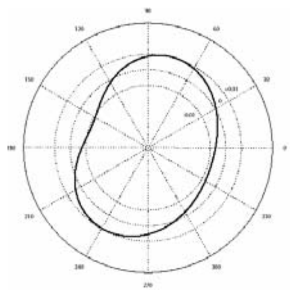
Starting from the baseline model identified,

different conditions characterizing roundness profile (obtained by turning) in Phase II were simulated

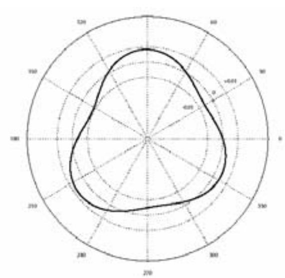
(conditions related to spindle-motion errors due for instance to wear on one ball bearing or whirling in hydrodynamic bearing – Cho and Tu, 2001)



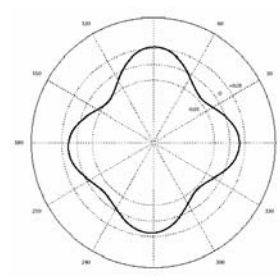
Half-frequency out-of-control



Bi-lobe out-of-control



Tri-lobe out-of-control



Four-lobe out-of-control (fixed and random phase)

$$U_{tj} = Y_{tj} + \sqrt{\frac{2}{N}}\delta_1 sin((t-1)\pi/N)$$

$$U_{tj} = Y_{tj} + \sqrt{\frac{2}{N}}\delta_2[b_3 cos(f_2(t-1)) + b_4 sin(f_2(t-1))]$$

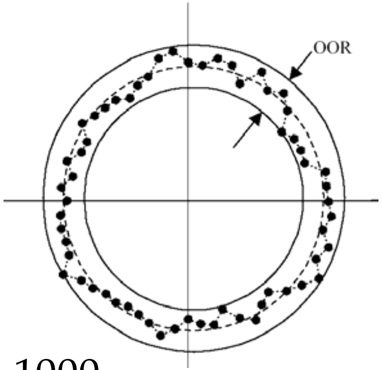
$$U_{tj} = Y_{tj} + \sqrt{\frac{2}{N}}\delta_3[b_5 cos(f_3(t-1)) + b_6 sin(f_3(t-1))]$$

$$U_{tj} = Y_{tj} + \sqrt{\frac{2}{N}}\delta_4 cos(f_4(t-1) - \phi)$$

$1 + 5 \times 4 = 21$ roundness models

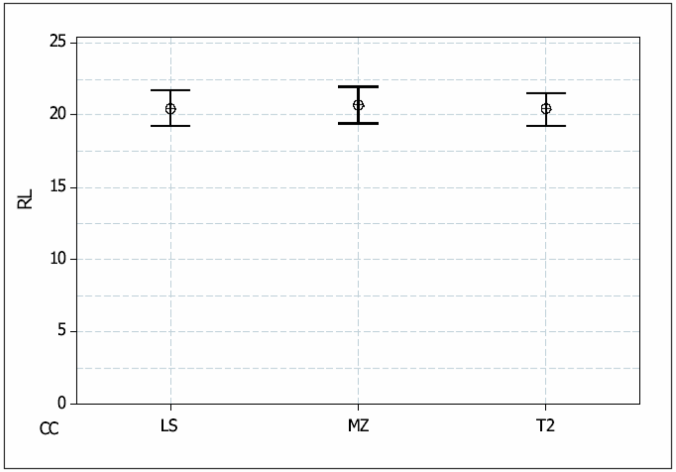
Competing methods

- T2: The multivariate approach proposed (monitoring coefficients of the Fourier-based regression + AR(2) noise)
- LS: The individuals control chart based on the OORs-LS (λ=0.33)
- MZ: The individuals control chart based on the OORs-MZ (λ=0.33)



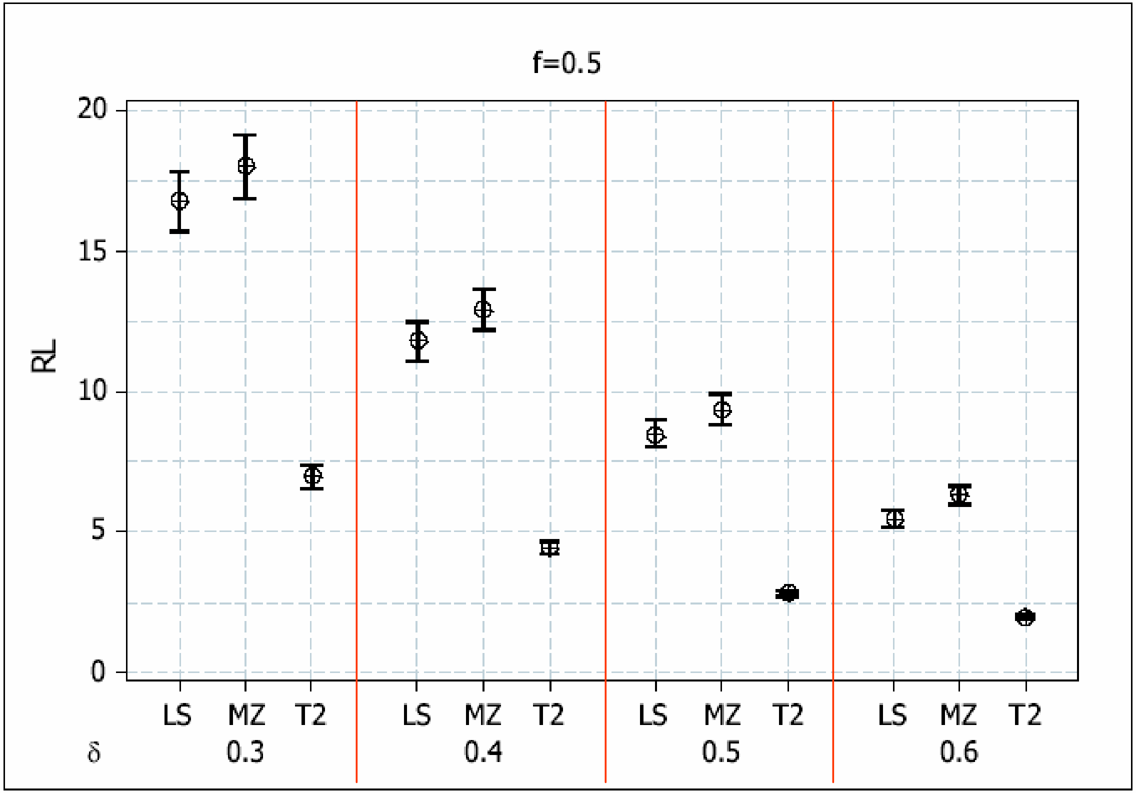
Simulation in phase II:

For each type of condition, profiles were simulated in order to obtain 1000 realizations of run lengths for each of the monitoring approaches (LS, MZ, T2)

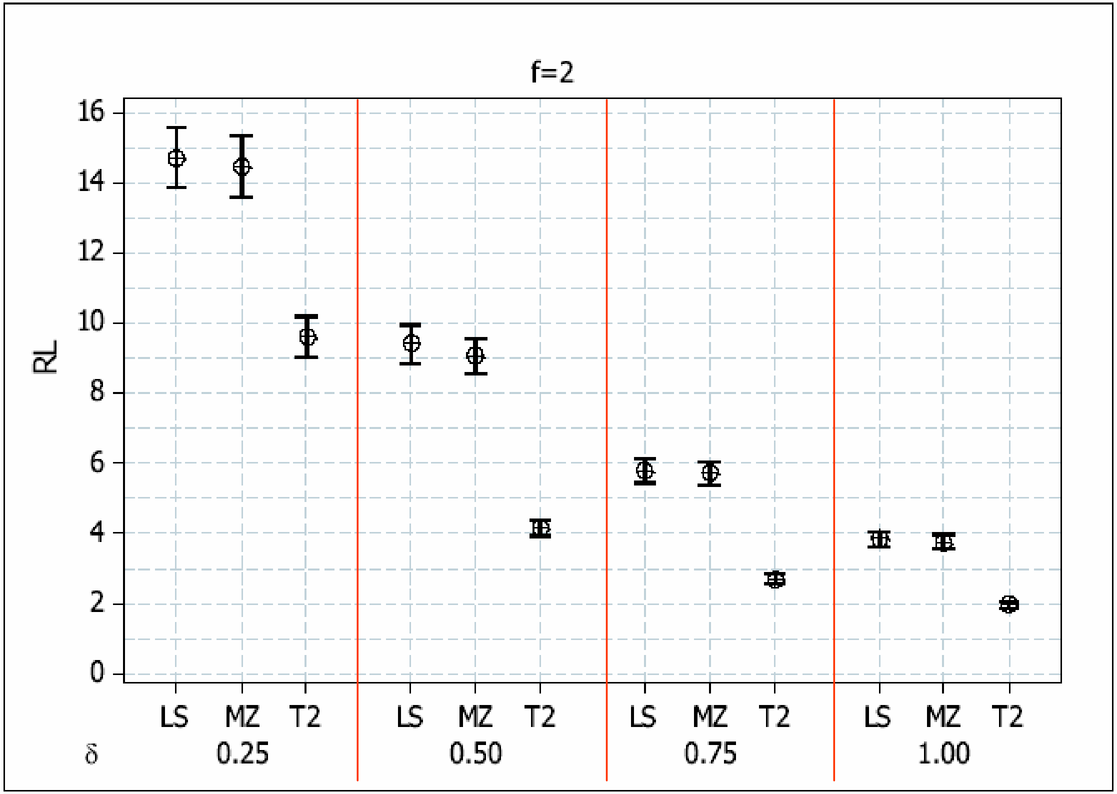


Basic model (ARL_0=20, α=5%)

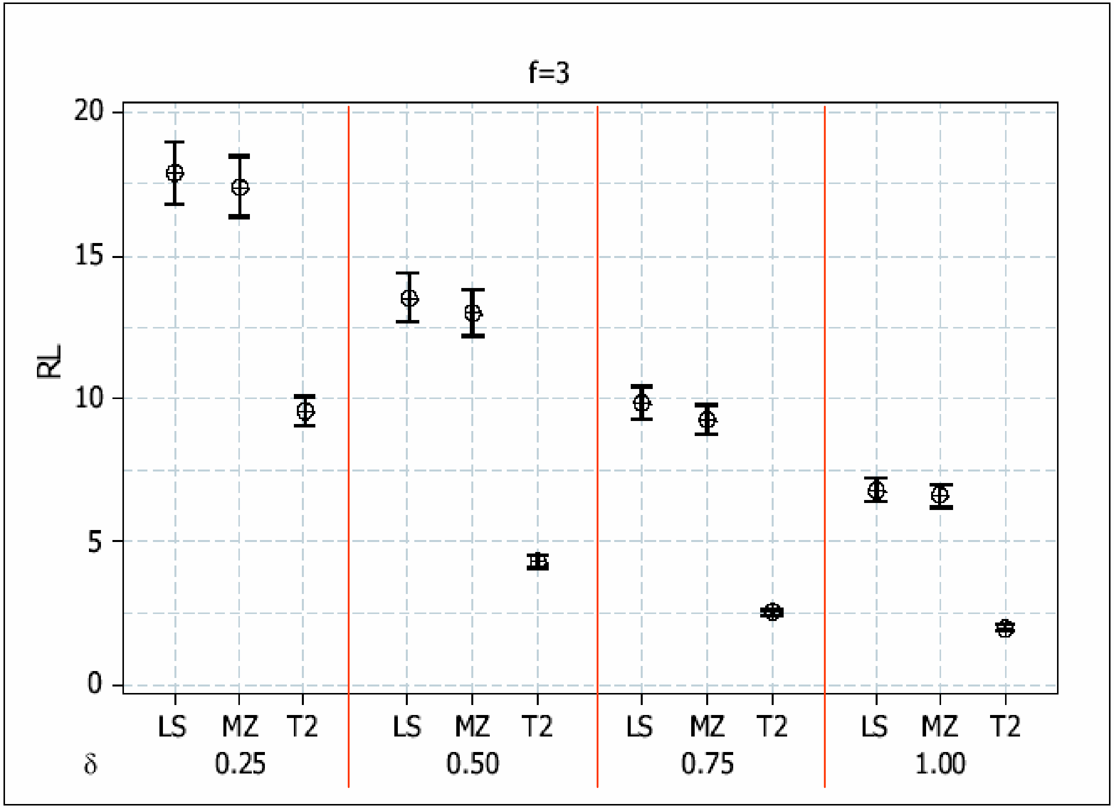
Run length performance in Phase II



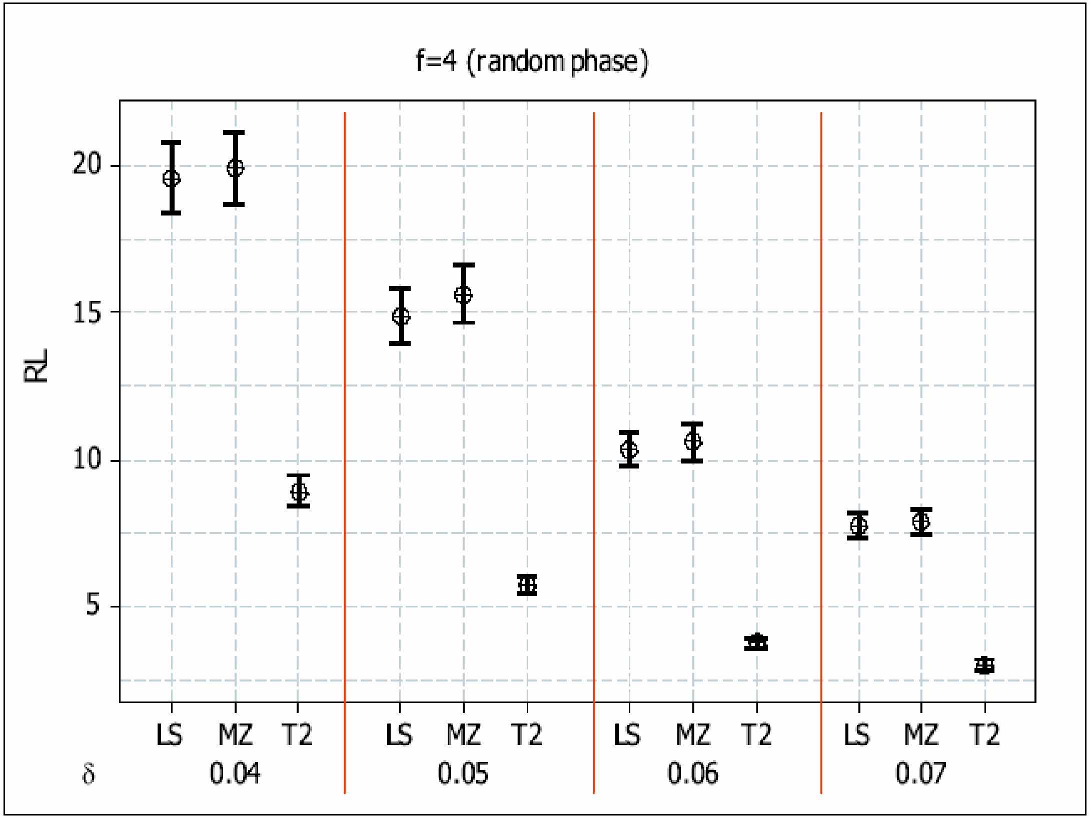
Run length performance in Phase II



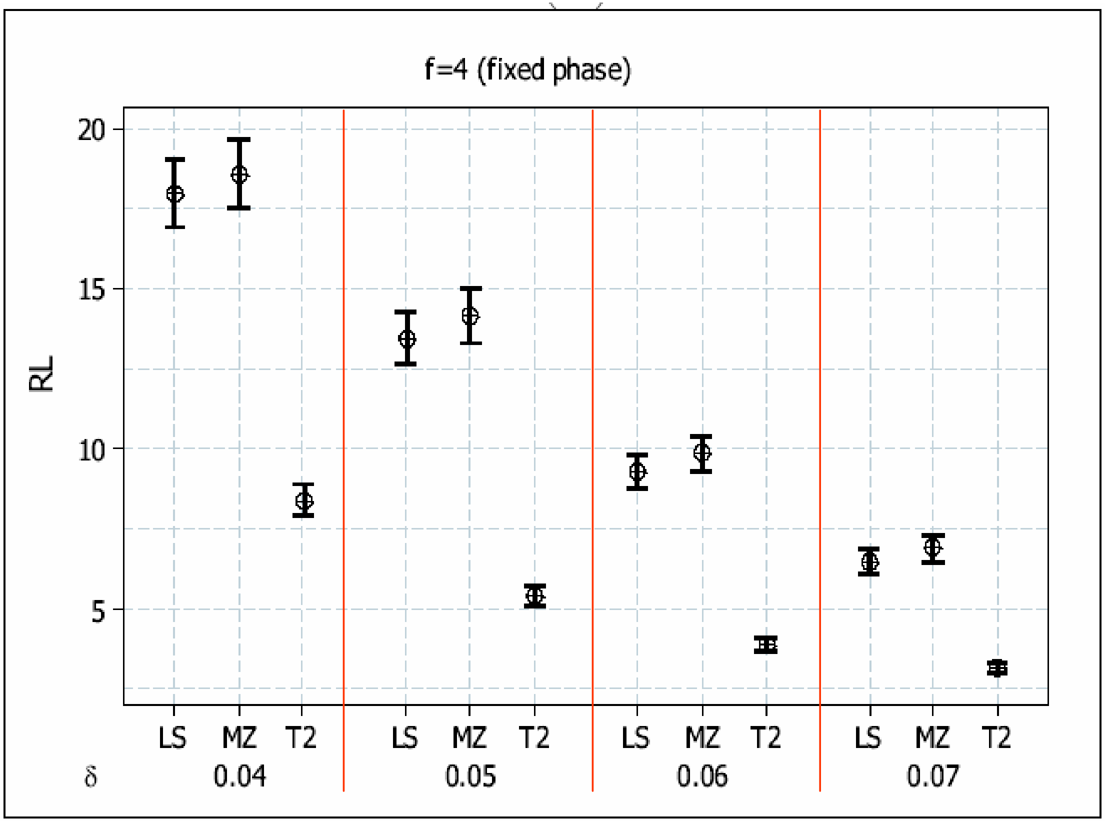
Run length performance in Phase II



Run length performance in Phase II



Run length performance in Phase II



		ARL savings	
Phase II model	delta	(LS-T2)/LS%	(MZ-T2)/MZ%
half frequency	0.30	58%	61%
	0.40	62%	66%
	0.50	67%	70%
	0.60	64%	69%
bi-lobe	0.25	35%	34%
	0.50	56%	54%
	0.75	54%	53%
	1.00	49%	48%
tri-lobe	0.25	47%	45%
	0.50	69%	67%
	0.75	75%	73%
	1.00	71%	70%
four-lobe fixed	0.04	53%	55%
	0.05	60%	62%
	0.06	58%	61%
	0.07	51%	54%
four-lobe random	0.04	55%	55%
	0.05	62%	63%
	0.06	64%	65%
	0.07	61%	62%

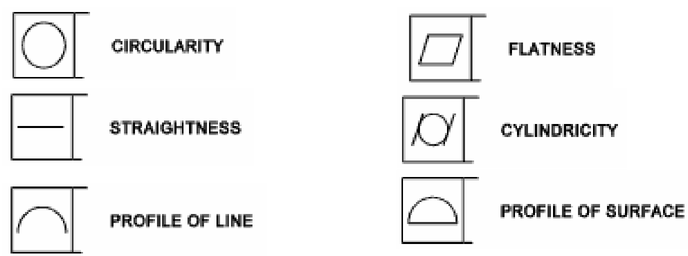
Similar results were obtained with α=1%

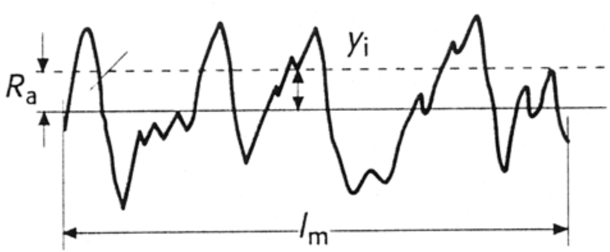
Main conclusions

When product quality is related to geometric specifications, profile-monitoring approaches outperform simpler methods aimed at detecting out-of-control conditions

The approach does not affect the inspection costs (the number of inspected points was constant) but just the complexity of the model used to deal with the measured data. In particular, regression with autocorrelated noise could be the viable model to capture the manufacturing signature and its natural spatial correlation

The approach presented can be extended to different geometric specifications
and texture specifications (e.g. roughness)





$$R_a = \frac{1}{l_m}\int_0^{l_m} |y(x)|dx \cong \frac{1}{N}\sum_{i=1}^{N}|y_i|$$