


Strategies for Variation Reduction → quality improvement

1. Sampling inspection: passive, sometimes last resort.

↑ 抽樣調查 target 

However, SPC might not identify what is the cause

2. Control charting and process monitoring: can remove special causes. If the process is stable, it can be followed by using a designed experiment.

SPC → for system changing over time (in control, out of control)

→ detect the appearance of unstable conditions

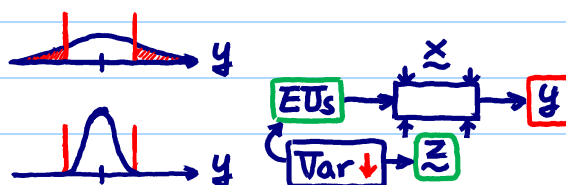
3. Blocking, covariate adjustment: passive measures but useful in reducing variability, not for removing root causes.

not a method that can reduce total variation in normal usage. But, when possible, block factors → noise factors

variation affecting treatment comparison in data analysis

4. Reducing variation in noise factors: effective as it may reduce variation in the response but can be expensive. Better approach is to change control factor settings (cheaper and easier to do) by exploiting control-by-noise interactions, i.e., use robust parameter design!

have a better control on the variation of EUs & Z



$$Y = X_1 \beta_1 + \epsilon$$

$$Y = X_1 \beta_1 + X_2 \beta_2 + \epsilon'$$

treatment effects

block effects

$$\text{Var}(\epsilon) \geq \text{Var}(\epsilon')$$

❖ Reading: textbook, 11.2

Types of Noise Factors

- ① Variation in process parameters.

check LNp.10-9~10 \underline{Z} → \underline{X} cannot be well controlled

- ② Variation in product parameters.

EUs

- ③ Environmental variation.

- ④ Load Factors.

- ⑤ Upstream variation.

- ⑥ Downstream or user conditions.

- ⑦ Unit-to-unit and spatial variation.

- ⑧ Variation over time.

- ⑨ Degradation.

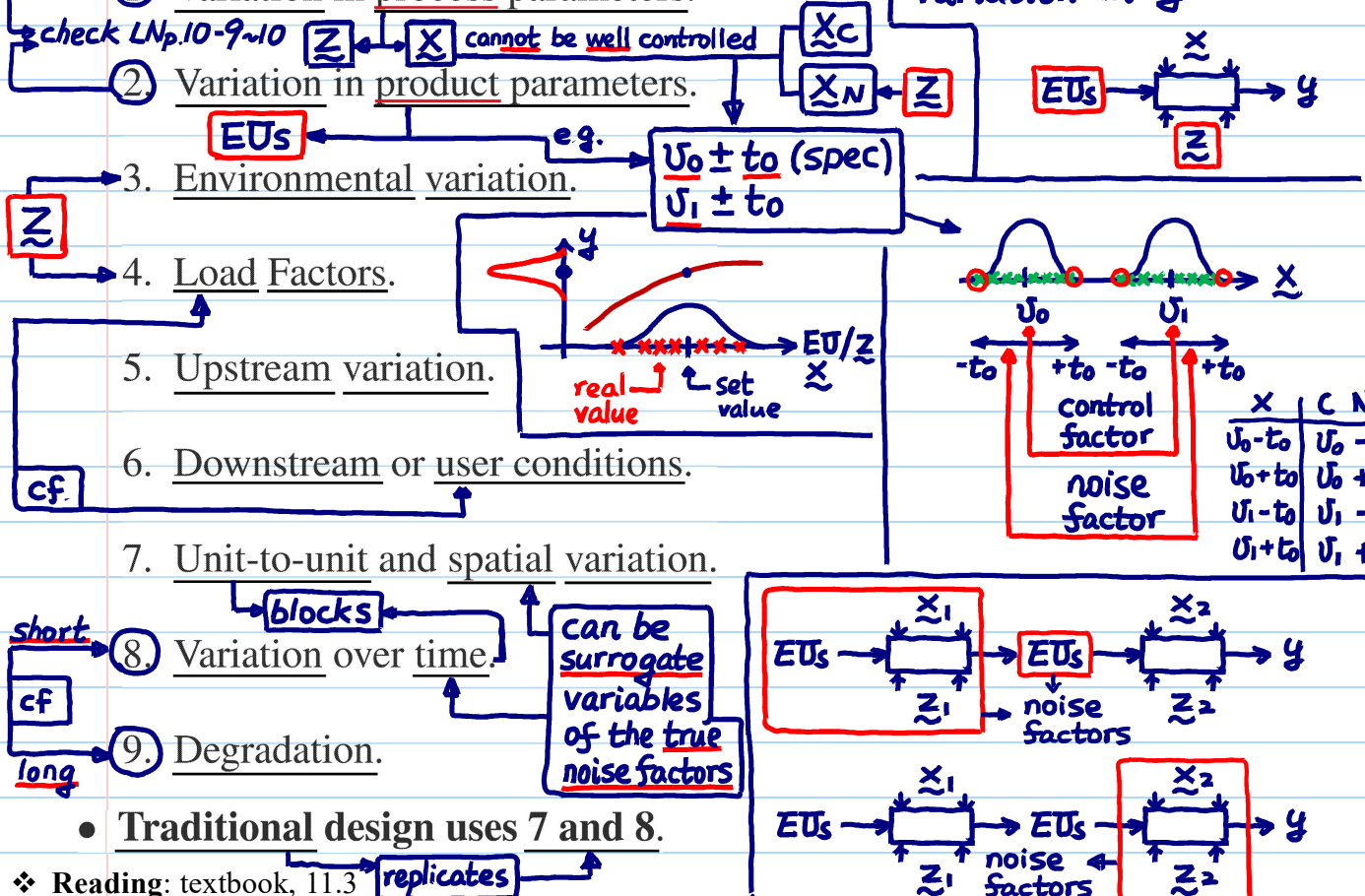
• Traditional design uses 7 and 8.

❖ Reading: textbook, 11.3

replicates

① they are EUs or Z

② they are sources of "large" variation in y



Variation Reduction Through RPD

- Suppose $y = f(\underline{x}, \underline{z})$, \underline{x} control factors and \underline{z} noise factors. If \underline{x} and \underline{z} interact in their effects on y , then the $\text{var}_{\underline{z}}(y)$ can be reduced either by reducing $\text{var}(\underline{z})$ (i.e., method 4 in LNp.10-6) or by changing the \underline{x} values (i.e., RPD).

In normal usage

- An example:

treat \underline{z} as r.v. with $E(\underline{z})=0$

$$\text{Var}_{\underline{z}}(y|\underline{x}) = (\beta + \gamma x_2)^2 \cdot \text{Var}(\underline{z}) + \sigma^2$$

$$E_{\underline{z}}(y|\underline{x}) = \mu + \alpha x_1$$

$$\begin{aligned} y &= \mu + \alpha x_1 + \beta \underline{z} + \gamma x_2 \underline{z} + \varepsilon, \\ &= \mu + \alpha x_1 + (\beta + \gamma x_2) \underline{z} + \varepsilon. \end{aligned}$$

NME \rightarrow CxN interaction \rightarrow r.v.

In exp't

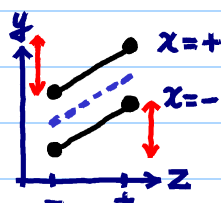
$$\begin{aligned} E(y) &= \mu + \alpha x_1 + \beta z \\ &\quad + \gamma x_2 z \\ \text{Var}(y) &= \sigma^2 \end{aligned}$$

By choosing an appropriate value of x_2 to reduce the coefficient $\beta + \gamma x_2$, the impact of \underline{z} on y can be reduced. Since β and γ are unknown, this can be achieved by using the control-by-noise interaction plots or other methods to be presented later.

$\text{Var}_{\underline{z}}(y|\underline{x})$

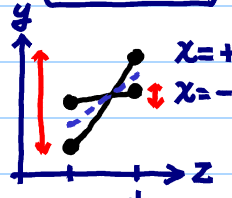
- \underline{Z} : sig.
- $\underline{X} \times \underline{Z}$: not sig.

① works



① works

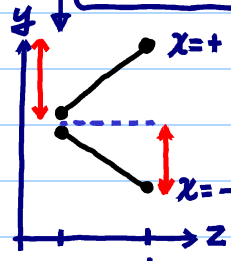
- \underline{Z} : sig.
- $\underline{X} \times \underline{Z}$: sig.



② works... perhaps

- \underline{Z} : not sig.
- $\underline{X} \times \underline{Z}$: sig.

① works



\underline{X} : qualitative
 \underline{X} : quantitative

