Effective Normalized Response Function in controlled systems - Naotoshi Taniguchi

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Introduction:
Data driven Fault Detection and Fault Prediction (FD/FP) system has been developed as IoT expands in recent years. IoT creates so-called Big Data and tends to create heavy load in communication and in data analysis when stored directly to the clouds remain unstructured [1]. Moreover, only a single temperature control is done by various different targeted temperatures that makes more complicated to watch the controlled system continuously. We propose the local computing [2] that can provide useful health indexes for FD/FP with novel but simple sensors and controllers. In this study, the benefit of the health index, normalized response function on the PID temperature controller is demonstrated in comparison with a *fuzzy quantification theory type 2* [4] that can handle the data of vague qualities.

Algorithm of Normalized Response R = Kp/Tp:
Figure 1 shows a block diagram of the adaptive Internal Model Control (IMC) logic we developed [3]. The internal model Pm gives characteristics of the controlled system P approximated into 1st order lag with dead time given in equation (1).

$$Pm = Km \exp(-Lm\,s) / (1 + Tm\,s) \qquad (1)$$

Where in equation (1), Km is a model gain, Tm is a model time constant and Lm is a model dead time.
In the design rule of the adaptive IMC, the internal model Pm is automatically tuned into the dynamics that is equivalent to the controlled system P as equation (2).

$$Pm \neq P \rightarrow Km / Tm = Kp / Tp, \quad Lm = Lp \qquad (2)$$

In equation (2), Kp is its process gain, Tp is its process time constant and Lp is its process dead time.
For detecting the dynamics of P and tuning Pm, the ratio ΔPV and the ratio ΔPVm are measured in the process step that the controlled system is being heated up. And Pm is automatically tuned by the rule of equations (3) and (4). Therefore this function can tell the dynamics detector of the controlled system.

$$Km / Tm = Kp / Tp \rightarrow \Delta PVm = \Delta PV \qquad (3)$$

$$Km\_new = (\Delta PV / \Delta PVm)\, Km\_old \qquad (4)$$

Figure 2 shows a block diagram of the normalized response R = Kp/Tp that is equivalent to the adaptive function. Figure 3 shows ΔPV_max and ΔPVm_max in the step response. The PID controller plays as the platform to detect ΔPV_max and ΔPVm_max.
Figure 4 shows control simulations and detected results of the normalized response R = Kp/Tp.

Experiments:
We compared the precision of the function between the normalized response and a simplified machine learning method [4]. Proposed method is described in Figure 2 and can be said as structured approach. The compared method is a *fuzzy quantification theory type 2* that can be said as unstructured approach (example data Table 1).
Variables X1 to X7 in Table 1 are shown as below.

- X1 : Initial Temperature
- X2 : Control Target Temperature (Set Point)
- X3 : Initial Manipulated Value
- X4 : Upper Limit of Manipulated Value
- X5 : Rise Time
- X6 : Maximum Rise Rate
- X7 : Time of Upper Limit Maintained

R = Kp / Tp can be estimated by equation (5) and (6) derived by the simplified machine learning method.

$$S = -0.017727 + 0.000591{*}X1 - 0.00068{*}X2 - 0.001428{*}X3 + 0.002439{*}X4 - 0.00001{*}X5 - 0.002019{*}X6 + 0.000871{*}X7 \qquad (5)$$

$$R = 0.0504 - 0.284{*}S + 0.660{*}S^2 - 0.449{*}S^3 \qquad (6)$$

Results and Discussions:
Figure 5 shows the calculated results by unstructured approach. Figure 6 shows calculated results by the normalized response algorithm.
Table 2 shows comparison between Figure 5 and Figure 6. Standard deviation by the proposed method is 3 times smaller than that of by unstructured method. That means the sensitivity of detecting the faults of controlled system by proposed method is 3 times higher than that of compared method.

Conclusions:
We developed the normalized response function on the PID temperature controller and demonstrated its benefit in comparison with unstructured approach. We believe it can play the important role in the age of IoT for effective FD/FP with light computing load.

References:
[1] Y. Orii：“Perspective on required packaging technologies for cognitive computing devices”,
[2] E. Toyoda：“The new direction for providing effective data for EES from sensors and digital controllers”, [1, 2]AEC/APC Symposium Asia (2015)
[3] M. Tanaka：Patent JPB-2913135 (1998)
[4] M. Tanaka：Patent JPB-2643699 (1996)

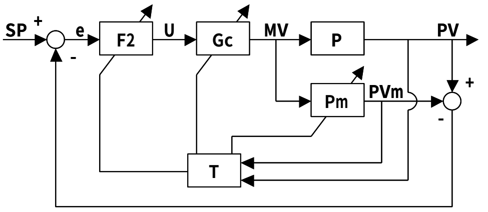

Figure 1. Adaptive Internal Model Control

Table 1. Example of simulation condition

X1	X2	X3	X4	X5	X6	X7	Kp/Tp
50	300	5.00	100	171.0	2.182	100.0	0.0250
50	350	5.00	100	212.0	2.182	127.0	0.0250
50	400	5.00	100	257.0	2.182	157.0	0.0250
50	450	5.00	100	317.0	2.182	188.0	0.0250
50	300	5.00	90	193.0	1.953	116.0	0.0250
50	350	5.00	90	242.0	1.953	148.0	0.0250
50	400	5.00	90	304.0	1.953	183.0	0.0250
50	450	5.00	90	388.0	1.953	221.0	0.0250
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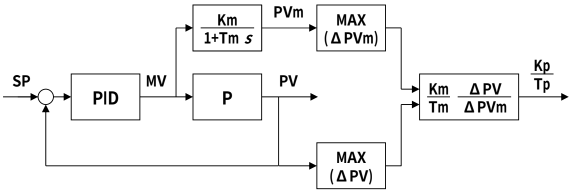

Figure 2. Block diagram of normalized response

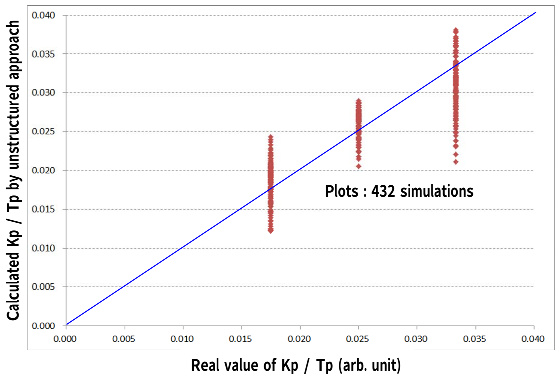

Figure 5. Results by unstructured approach

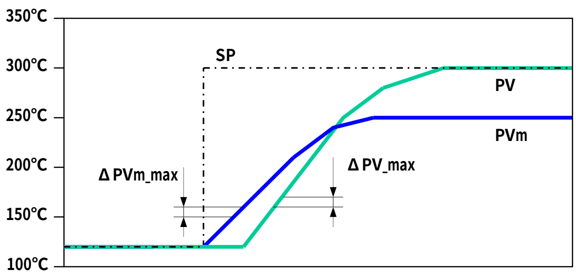

Figure 3. PV and PVm of normalized response

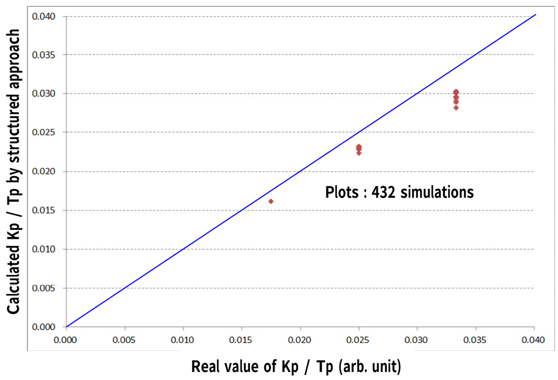

Figure 6. Results by structured approach

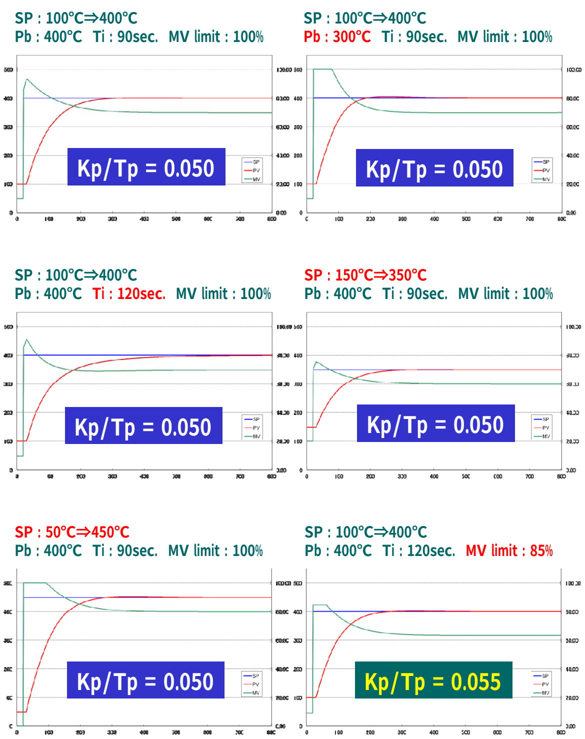

Figure 4. Control simulations

Table 2. Comparison between Figure 5 and Figure 6

	Figure 5	Figure 6
Mean Error	0.0026	0.0021
Standard Deviation	0.0020	0.0008