Emerging Methods for the Intelligent Processing of Materials

P.H. Garrett, J.G. Jones, D.C. Moore, and J.C. Malas

Emerging methods, procedures, and performance measures are presented for the design of intelligent materials processing systems that combine both comprehensive new process representations and correspondingly advanced process control systems. The description of these developments is presented in five parts. The first provides the partitioning of global processes into decoupled finite subprocesses for improved accommodation of process nonlinearities with accompanying simplification of control system complexity. The second is sensor/controller/actuator accountability to establish an on-line process variability baseline whose greatest sensitivity is attributable to process measurement limitations. Development three combines multiloop control with decoupled subprocesses for enhanced process disorder reduction and improved likelihood of achieving material parameters of interest. The fourth, closely associated with development three, provides accurate multiloop control compensation by identification of decoupled trapezoidal subprocess models. The fifth presents a process description language of qualitative subprocess influences for augmenting incompletely modeled processes and unmeasurable control elements by supervising the control space to minimize control conflicts and process variability.

Keywords

Decoupled subprocesses, *in situ* measurement, multiloop control, qualitative subprocess influences, sensor/controller/actuator error, trapezoidal controller tuning

1. Introduction

INTERNATIONAL competitiveness has prompted a renewed emphasis on advanced materials and their manufacture, which requires process and control systems capable of operation far from process equilibrium conditions with nonlinearities and additive disturbances. Such performance is necessary because material specifications have migrated from requirements defined at process boundaries to microstructures of molecular interactions described by distributed parameters. Presented here are a new understanding, emerging methods, and performance measures for the intelligent processing of materials that combine comprehensive process representations matched by correspondingly capable control systems.

Contemporary materials processes involve the transport of mass, momentum, and energy and are fundamentally distributed parameter control problems both spatially and in time.[1] Because many process elements possess no known analytical models, incomplete or nontraditional models are often substituted. Accordingly, effective new control algorithms are required for interfacing between execution level numerical controllers and higher level qualitative controllers that reason by hypothesis testing.[2] Methods presented in this article include partitioning of global processes into decoupled subprocesses for simplification of control complexity, defined error control loops that establish a known process variability quality baseline, multiloop subprocess control for enhanced reduction of process disorder, trapezoidal subprocess identification for accurate controller compensation, and qualitative description of subprocess influences that augments numerical control by supervising the control space to minimize conflicts and error in achieving material parameters of interest.

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2. Design of Decoupled Material Subprocesses

Suh's[3] independence and information design axioms govern good design practice and provide needed formalism in a previously undefined area. The independence axiom refers to the ability of a design to achieve functional requirements of interest in a straightforward manner. Decoupled designs (i.e., those satisfying the independence axiom) eliminate trial-and-

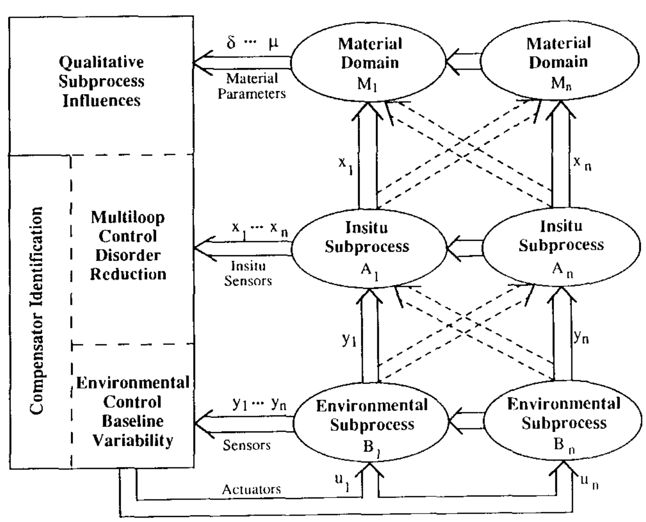


Fig. 1 Self-directed materials subprocess control.

error searching for combinations of control variables that yield required product attributes. Figure 1 illustrates the independence axiom for a materials process. Note that with partitioning into subprocess domains ($A_1 - A_n$) dominant influences can be linked to the material parameters (δ—μ). The crossed arrows are weaker cross-couplings between the subprocesses levels. Weaker cross-couplings indicate more effective decoupling between the subprocesses, which will render material parameters of interest easier to achieve.

For complex processes partitioned into subprocesses, decoupled linkages are essential to effectiveness and may be represented either by diagonal or triangular mapping matrices in Eq 1 as a function of available choices in the process design. Decoupling permits the control of subprocesses with the simpler single input/single output control structures illustrated by Fig. 1. Coupled subprocesses accordingly require more complicated control structures and compensator identification in terms of multiple input/multiple output systems described by Ljung.[4]

$$\begin{bmatrix} \delta \\ | \\ \mu \end{bmatrix} = \begin{bmatrix} M_{11} & — & \\ & \diagdown & \\ & & M_{nn} \end{bmatrix} \begin{bmatrix} A_{11} & — & \\ & \diagdown & \\ & & A_{nn} \end{bmatrix} \begin{bmatrix} B_{11} & — & \\ & \diagdown & \\ & & B_{nn} \end{bmatrix} \begin{bmatrix} u_1 \\ | \\ u_n \end{bmatrix} \qquad [1]$$

The essence of decoupling is to design the process such that interaction between the subprocesses is minimized. It would seem that a simple way to decouple a coupled process would be to simply model the interconnections between the subprocesses and cancel them by applying the inverse of this coupling in cascade with the coupled process. However, this requires high-fidelity modeling because any modeling errors will make this method of decoupling unreliable. In practice, the inverse is not physically realizable, because it requires time advances to compensate for dead times in the process. A practical method of subprocess decoupling is the addition of series process elements that increase the order of a mapping matrix while constraining it to a triangular form. For example, considering a 2 × 2 mapping matrix defining the coupling between environmental and *in situ* subprocesses, decoupling requires that at least one of the following conditions is met:

$$A_{12} = B_{12} = 0$$

Table 1 Controlled variable defined error

$\varepsilon_{steady\text{-}state}$		0.05%
$\varepsilon_{measurement\ average}$		0.106
$\varepsilon_{interpolation}$		0.015
$\varepsilon_{A/D}$		0.008
ε_{sinc}		0.009
$\varepsilon_{D/A}$		0.005
ε_y	root sum square total	0.118% FS

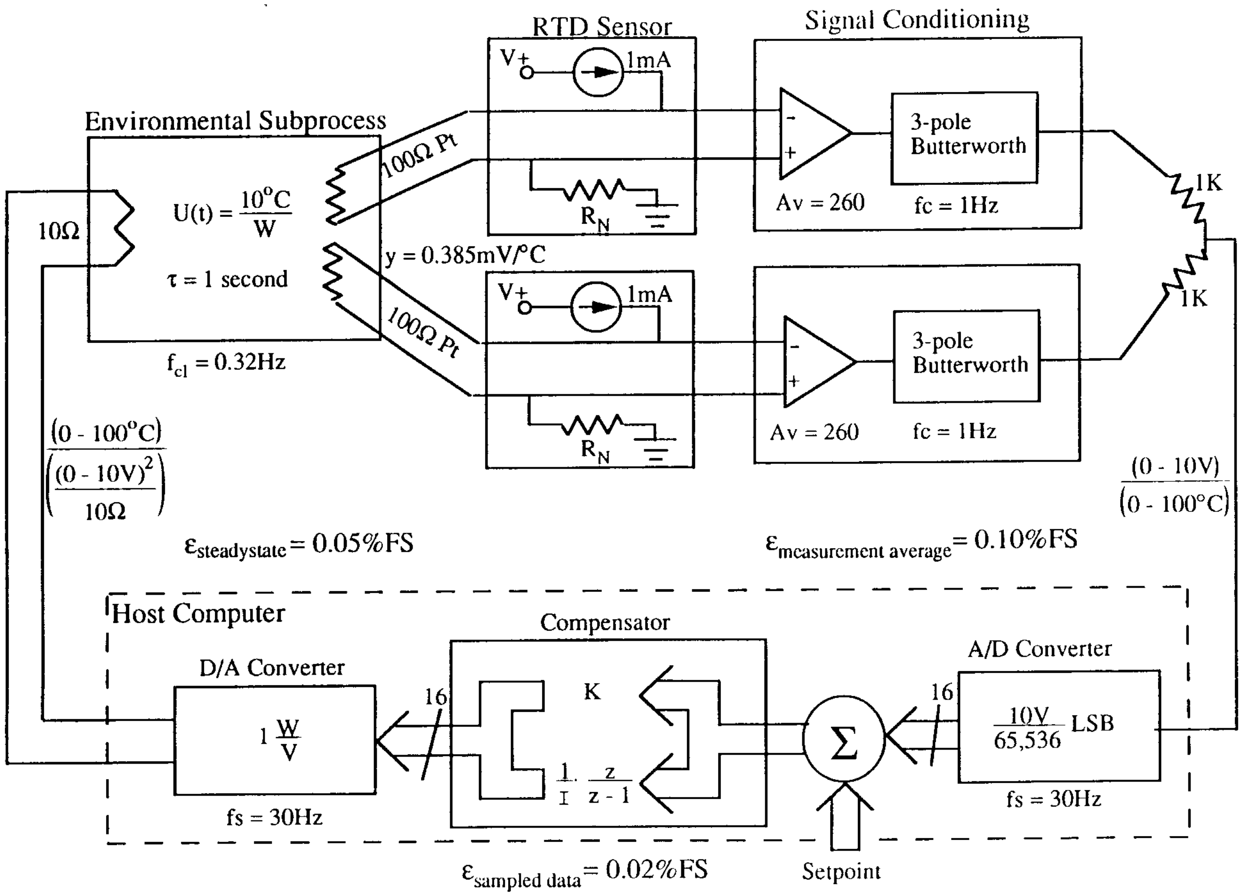


Fig. 2 Defined error environmental control loop.

$A_{21} = B_{21} = 0$

$A_{11}B_{12} = -A_{12}B_{22}$

$A_{21}B_{11} = -A_{22}B_{21}$

3. Minimum Process Variability Design

The information axiom defines a good design as one in which the information content is minimized. An interpretation of this requirement for process control applications is the variability minimization of subprocess variables from choices available in the system design. This follows from Goldman's[5] measure of information defined by Eq 2, which suggests that increased uncertainty (H) in a system requires increased information (I) to describe it. Uncertainty in a process control system may be reduced to a nominal level through minimization of implementation error. To illustrate this, an analytical solution is presented in terms of a defined error accountability of sensing and actuation elements.

$$I = \sum^{H} \frac{1}{H} \log \frac{1}{H} \rightarrow \infty \text{ as } H \rightarrow \infty \qquad [2]$$

The following discussion focuses on the implementation errors of control loops that determine the baseline process variability. Because disturbances are encountered frequently in the measurement of process variables, an issue of concern is acquiring sensor values while minimizing process variable errors (ε) characterized by Eq 3. A generic sensor channel introduced by Fig. 2 provides the capability for upgrading measurements in the presence of random and/or coherent disturbances. Measurements (A) corrupted by disturbances (ΔA) are accordingly enhanced by signal conditioning to obtain a typical measurement error of 0.15% FS (full scale). This constitutes the input uncertainty of a control loop.

The performance of sensor channels can be extended with the fusion of multiple sensor sources to achieve a more accurate perception of an environment through signal averaging shown in Fig. 2. Equation 4 defines a one third reduction in $\varepsilon_{\text{measurement}}$ to 0.1% FS from the value of Eq 3 for the averaged value of two channels. Digital control loops provide the execution backbone in process control systems irrespective of higher level quantitative or qualitative algorithms that may augment them. The basic control loop is divisible into a measurement function and a sampled data conversion/compensation/interpolation function. A sampling rate of 30 Hz ensures unconditionally stable control for nominal proportional gain values (K), yielding a closed loop bandwidth (f_{cl}) in the 0.32 Hz range, considering for example, a 1-s process time constant for a first-order process with no pure delay. An integral compensator (I) that furnishes substantial gain relative to K at a lowpass corner frequency significantly below f_{cl} also beneficially results in a negligible steady-state error. Furthermore, the interpolated error of the controlled variable (y) is determined by Eq 5 to be 0.015% FS by Garrett[6] for a typical first-order subprocess. The complete control loop implementation error (ε_y) is tabulated in Table 1 as 0.118% FS.

$$\begin{aligned}\varepsilon_{\text{measurement}} &= \left[\varepsilon^2_{\text{sensor}} + \varepsilon^2_{\text{amplifier}} + \varepsilon^2_{\text{filter}} + \varepsilon^2_{\text{random}} + \varepsilon^2_{\text{coherent}}\right]^{1/2} \\ &= \left[0.1\%^2 + 0.05\%^2 + 0.1\%^2 + 0.05\%^2 + 0.05\%^2\right]^{1/2} \\ &= 0.15\% \text{ FS}\end{aligned} \qquad [3]$$

Sensor fusion enhancement:

$$\begin{aligned}\varepsilon_{\text{measurement average}} &= \frac{1}{\sqrt{n}} \sum_{j=1}^{n} \varepsilon_{\text{measurement}} \\ &= \frac{1}{\sqrt{2}} \sum^{2} 0.15\% = 0.106\% \text{ FS}\end{aligned} \qquad [4]$$

$$\varepsilon_{\text{interpolation}} = \left[\frac{V^2_{\text{FS}}}{V^2_s \operatorname{sinc}^2\left(1 - \frac{f_{cl}}{f_s}\right) \times \left[1 + \left(\frac{f_s - f_{cl}}{f_{cl}}\right)^2\right]^{-1} + V^2_s \operatorname{sinc}^2\left(1 + \frac{f_{cl}}{f_s}\right) \times \left[1 + \left(\frac{f_s + f_{cl}}{f_{cl}}\right)^2\right]^{-1}}\right]^{-1/2} \times 100\%$$

$$= \left[\frac{1}{\operatorname{sinc}^2\left(1 - \frac{0.32 \text{ Hz}}{30 \text{ Hz}}\right) \times \left[1 + \left(\frac{30 \text{ Hz} - 0.32 \text{ Hz}}{0.32 \text{ Hz}}\right)^{2}\right]^{-1} + \operatorname{sinc}^2\left(1 + \frac{0.32 \text{ Hz}}{30 \text{ Hz}}\right) \times \left[1 + \left(\frac{30 \text{ Hz} + 0.32 \text{ Hz}}{0.32 \text{ Hz}}\right)^{2}\right]^{-1}}\right]^{-1/2} \times 100\% = 0.015\% \text{ FS} \qquad [5]$$

$$\begin{aligned}\varepsilon_{\text{sinc}} &= \frac{1}{2} \times \left(1 - \frac{\sin \pi f_{cl}/f_s}{\pi f_{cl}/f_s}\right) \times 100\% \\ &= \frac{1}{2} \times \left(1 - \frac{\sin \pi\, 0.32 \text{ Hz}/30 \text{ Hz}}{\pi\, 0.32 \text{ Hz}/30\text{Hz}}\right) \times 100\% \\ &= 0.009\% \text{ FS}\end{aligned} \qquad [6]$$

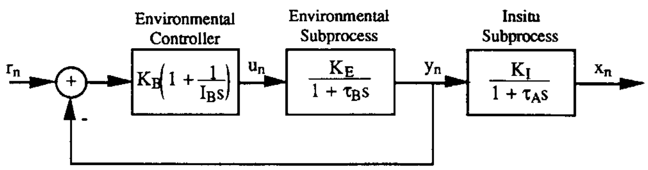


Fig. 3 Environmental subprocess control.

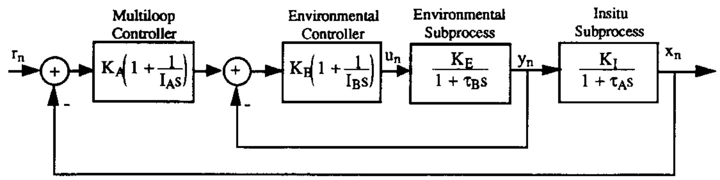


Fig. 4 Multiloop subprocess control.

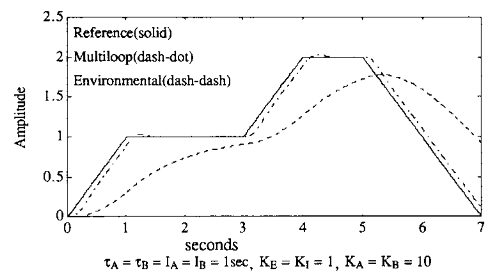


Fig. 5 Comparison of environmental and multiloop control.

4. Multiloop Subprocess Control

Materials frequently are manufactured by processes that are constrained to sensing and actuation at the process environmental boundary. Although measurement and actuation at a process environmental boundary often can provide unconditional stability and minimum variability of controlled variables, such structures usually are deficient in the visibility and manipulation of subprocess gain and time constraints to accurately achieve material parameter values of interest. Figure 3 describes a traditional process control system whereby only environmental variables are within the control loop, with an extended subprocess model included as a cascaded lag element in Eq 7. From this context, multiloop control of partitioned subprocesses is conceived for improved disorder reduction.

A principal advantage of multiloop subprocess control, described by Fig. 4, is a reduction in the effective time constant of the environmental subprocess by the value of the multiloop controller gain, or $\tau_B/(1 + K_A)$. The resulting control response improvement provides corresponding process disorder reduction. The system in Fig. 4 is defined by the fourth-order transfer function of Eq 8 consisting of single time constant subprocesses and standard proportional plus integral controllers. Identification of the compensator values for these controllers is described in the following section, and their implementation for minimum variability is guided by the error accountability methods of the preceding section.

Figure 5 presents a simulation exercise comparing the transfer functions of Eq 7 and 8 for an arbitrary reference setpoint, r_n, with the normalized controller and process parameter values shown to preclude the possibility of parameter choices that are more advantageous to one control system than the other. Under these conditions, neither control system is optimized, but a significant improvement in control is evident when the *in situ* subprocess is included within the feedback path of the multiloop system. The principle of subprocess partitioning and decoupling within a multiloop control structure clearly offers improved performance and the increased likelihood of successfully achieving material parameters of interest when complemented by optimum compensator identification.

Environmental process control transfer function:

$$\frac{x_n}{r_n} = \frac{K_B K_E(1 + I_B s)/I_B \tau_B}{s^2 + [(1 + K_B K_E)/\tau_B]s + K_B K_E/I_B \tau_B} \times \frac{K_I}{1 + \tau_I s} \qquad [7]$$

Multiloop subprocess control transfer function:

$$\frac{x_n}{r_n} = \frac{a_0(1 + I_A s)(1 + I_B s)}{s^4 + a_3 s^3 + a_2 s^2 + a_1 s + a_0} \qquad [8]$$

where

$$a_0 = \frac{K_A K_B K_I K_E}{I_A I_B \tau_A \tau_B}$$

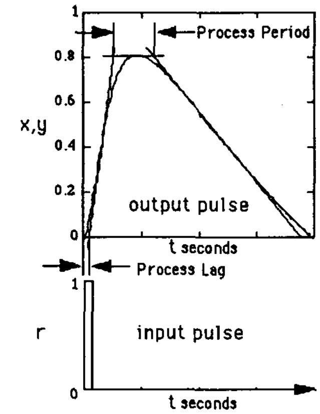
$$a_1 = \frac{K_B K_E}{I_B \tau_B \tau_A} + \frac{K_A K_I K_B K_E (I_B + I_A)}{I_B I_A \tau_B \tau_A}$$

$$a_2 = \frac{1 + K_B K_E}{\tau_B \tau_A} + \frac{K_B K_E}{I_B \tau_B} + \frac{K_B K_E K_A K_I}{\tau_A \tau_B}$$

$$a_3 = \frac{1}{\tau_A} + \frac{1 + K_B K_E}{\tau_B}$$

5. Decoupled Control Compensator Identification

Controller compensator identification is described historically by the work of Ziegler and Nichols.[7] However, there exist no standards against which PID selection may be evaluated.[8] Most controller tuning methods ensure loop stability and robustness against disturbances because both the process and controller dynamics are simultaneously analyzed experimentally. However, obtaining high-performance PID values by these approximations are difficult because of their cross-coupling and the iteration required in their identification.



$$\text{Process Gain}_{\text{(trapezoidal tuning)}} = \sqrt{\frac{\int_{\text{area}} \text{output pulse power} \cdot dt}{\int_{\text{area}} \text{input pulse power} \cdot dt}}$$

Trapezoidal PID Parameters
P = 100% · Process Gain $_{\text{trapezoidal tuning}}$
I = Process Period sec
D = 0.44 (Process Lag + Process Period) sec

Fig. 6 Trapezoidal compensator identification.

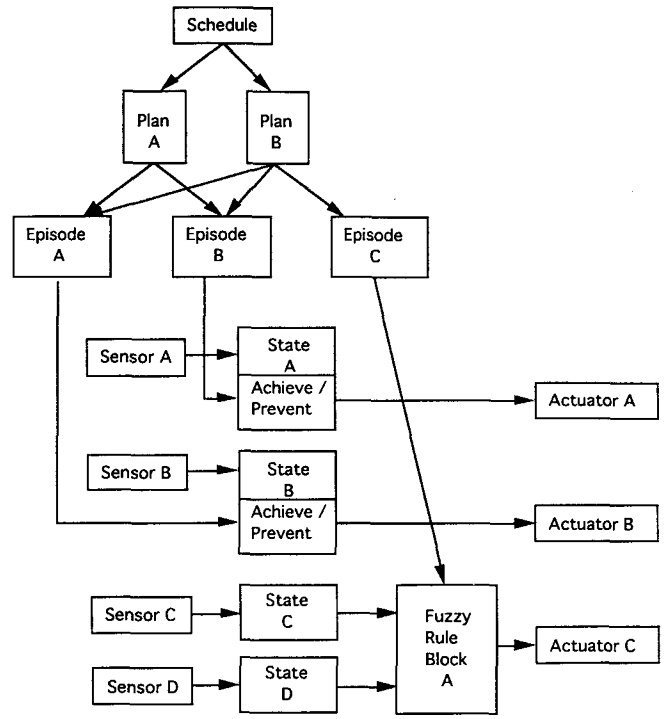


Fig. 7 Qualitative process automation structure.

Automated trapezoidal PID compensator identification was subsequently developed by Heyob[9] as a decoupled tuning method to augment the utility of applications requiring highly accurate controlled variables in addition to unconditional stability and robustness.

Referring to Fig. 6, process pulse excitation generally provides a trapezoidal process response. If the product of process and controller gains equals unity or less around a control loop, then unconditional stability is assured, and the controller proportional band (P) may be defined as the process gain times 100%. The process gain is accordingly acquired as the ratio of process measured output to power input over the time interval defining the process response baseline area. The controller integral time (I) is independently derived from the process period measurement to define the bandwidth $1/2\pi I$ Hz for the controller error signal, such as $r_n - y_n$, necessary to minimize the steady-state error. Derivative time (D) is determined from a piecewise-linear fit to the trapezoidal process response for increasing control loop bandwidth.

6. Qualitative Process Automation

To effect the realization of material parameter values of interest, reference inputs (r_n) must be generated for each multiloop controller that influences the achievement of parameter goals. These requirements can be met by an object-oriented process description language providing a qualitative control strategy such as QPAL (Qualitative Process Automation Language).[10] In QPAL, modeled subprocess states are encoded as domain knowledge for comparison with the *in situ* measurement of actual subprocess states to enable nonprescriptive material parameter optimization for each processing cycle. The merit of this is to augment accompanying quantitative control algorithms by supervising the control space to minimize control error and manage conflicts. This process control language evolved from research conducted at the Air Force Wright Laboratory for the manufacture of advanced aerospace composite components.

Qualitative process automation[11] (QPA) is the basis of QPAL and embodies a philosophy of self-directed process control. The central premise of QPA is the control of a process based on a track of its arbitrary behavior instead of a predefined schedule of setpoints that is unvarying for every processing cycle. This approach provides the capability for control adaptation to accommodate unique process behavior that may be different for each processing cycle. This allows improved product quality through the reduction of process disorder and parameter variability.

The conditional logic of QPA is structured in five levels, as shown in Fig. 7 describing the schedule, plan, episode, state, and sensors for a process. The *in situ* sensors detect process states mapped *a priori* as discrete events in the knowledge base, and the knowledge base also defines which environmental actuators affect mapped process state values both positively and negatively for control coordination. Episodes define single goals that typically change over different segments of a processing cycle, and the plans define the interrelationship of goals for process episodes in the processing cycle. The schedule provides executive service functions including process plan management and alarm handling.

7. Conclusions

The advancement of materials processes has migrated from requirements described at physical boundaries to microstructures of molecular interactions described by distributed parameters. This, in turn, has necessitated comprehensive new process representations matched by correspondingly complex process control structures capable of operation far from process equilibrium conditions to achieve material parameters of interest. Methods, procedures, and performance methods have accordingly been developed drawn from diverse fields and presented in five parts.

The first provides the partitioning of global processes into decoupled finite subprocesses for improved accommodation of process nonlinearities with accompanying simplification of control system complexity. The second is defined error sensor/controller/actuator accountability to establish an on-line process variability quality baseline whose greatest sensitivity is shown generally to be attributable to process measurement limitations. Development three combines multiloop control with decoupled subprocesses for enhanced process disorder reduction and the improved likelihood of achieving material parameters of interest. The fourth is closely associated with development three and provides accurate multiloop control compensation by means of decoupled trapezoidal subprocess model identification. The fifth presents a process description language of qualitative subprocess influences for augmenting incompletely modeled process and unmeasurable control elements by supervising the control space to minimize control conflicts and process variability.

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