Methodology for Selecting Process Variables for Feedback Control with Application to Reactive Ion Etching

Oliver D. Patterson
Advisor: Prof. Pramod P. Khargonekar

17 September 1998

Outline

1. Introduction
2. Condition Under Which Feedback Control Reduces Process Variation
3. Description of Methodologies
4. Simulation Results
5. Experimental Results in Reactive Ion Etching
6. Contributions and Future Work

1. Introduction

- Motivation
- Research Goal
- Related Work

Motivation

- Reducing variation in manufacturing is desirable.

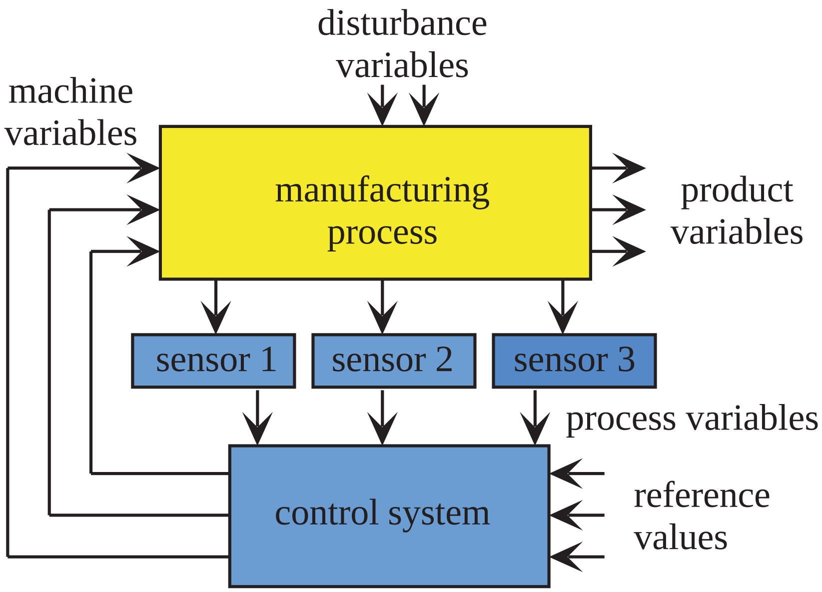
=> Reduces product cost.

=> Improves product performance and quality.

Standard Approaches

- Statistical Process Control (SPC)
- Robust Design
- SISO Feedback on Actuators
- Identification and repair of problem areas using analysis of production and DOE data

New Approach: Real-Time Feedback Control (RFC)


disturbance variables

machine variables

manufacturing process

product variables

sensor 1

sensor 2

sensor 3

process variables

control system

reference values

In semiconductor manufacturing

McLaughlin 91 RIE SISO
Rashap 93,95 RIE MIMO
Hershkowitz 93 ECS SISO
Mutsukura, 94 RIE SISO
Vincent 94 RIE nonlin MIMO
Yamada 96 ICP sim, SISO
Mak 96 ECS SISO
Chandhok 96 RIE
El-Awady 96 LPCVD MIMO
Patterson 96 RIE MIMO
Knight 97 PECVD MIMO

Process variable feedback is common in semiconductor manufacturing since the product variables often cannot be monitored.

Control System Assumptions

- The control system is an integrator-based tracking controller.
- There are N_I independent actuators. Therefore, at most N_I process variables can be regulated to independent setpoint values.

Selecting Feedback Variables

- Typically use qualitative knowledge of the process to select process variables for feedback. Examples:
  1. V_{bias}, [F] and flow (RIE, Rashap *et al*.)
  2. disilane and triaminosilane pressures, V_{bias} (PECVD, Knight *et al*.)
- Process knowledge is often limited.

Research Goal

Develop a methodology for selecting process variables for feedback control to minimize variation in the product variables.

Approach: We will use statistical analysis of data from designed experiments.

Assumptions

- The controller will be used for set-point regulation of the selected process variables.
- The dynamics of the closed loop system are fast compared to the processing time.
- The sensor noise consists of high frequency components well above the designed loop gain of the system and variable, unknown sensor bias.
- In general the dynamics of process disturbances are slow.

Methodology is also applicable to run-to-run control

- Typically, run-to-run control adjustments are made after *ex situ* characterization, which takes time and can be expensive.
- For single wafer processes, with process variable feedback, adjustments may be made for the next wafer rather than at the end of the lot.

Related Work

- Butler *et al*. ‘91 - Selected 3 of 4 process variables based on whether they could be controlled and the effect they have on product variables. Disturbances not considered.
- Hershkowitz *et al*. ‘93 - Recognized need to ID key process variables. Search by looking for correlation between single process variables and product variables.
- Lee and Spanos, ‘95 - Data reduction of real time tool data for generation of predictive models for real-time SPC.

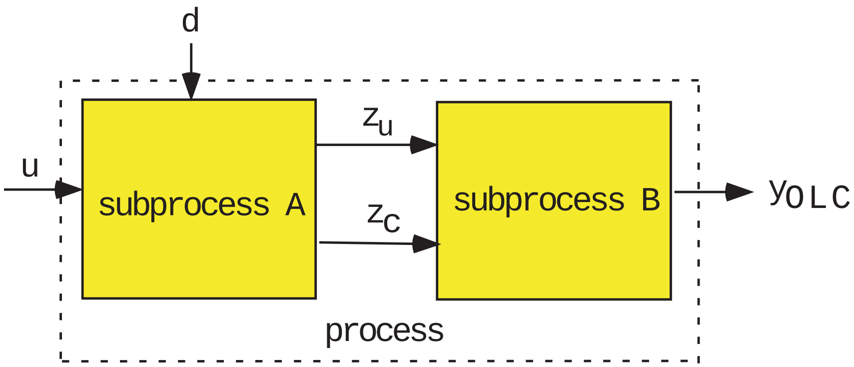
2. Condition Under Which Feedback Control Reduces Process Variation

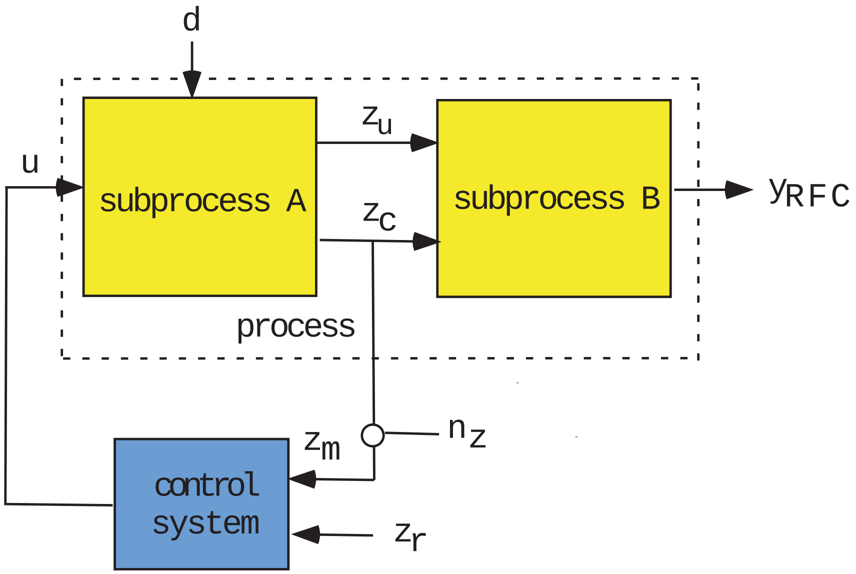
- Model
- Condition Statement
- Special Case: All important process variables are measurable.

Consider the following static, linear model:

$$\begin{bmatrix} z_u \\ z_c \end{bmatrix} = \begin{bmatrix} F & G \\ H & J \end{bmatrix} \begin{bmatrix} d \\ u \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} , \qquad y = \begin{bmatrix} S & T \end{bmatrix} \begin{bmatrix} z_u \\ z_c \end{bmatrix} + v_3 , \qquad z_m = z_c + n_z$$

$$\begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} = N\left(\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} R_1 & 0 & 0 \\ 0 & R_2 & 0 \\ 0 & 0 & R_3 \end{bmatrix} \right), \qquad d = N(d_0, R_d) , \qquad n = N(0, R_n)$$





d - disturbance variables,
u - machine variables or actuators,
v_1, v_2 and v_3 – noise variables,
n – sensor noise on z_c,

z_u - uncontrolled process variables,
z_c - controlled process variables,
y - product variables,
N(m,R) - normally distributed random vector with mean m and covariance R.

z_m - measurement of z_c

Condition Statement

RFC reduces process variance when:

$$
\begin{aligned}
&trace\left(SGJ^{-1}HR_dH'\left(J^{-1}\right)'G'S' + TR_nT' + SGJ^{-1}R_2\left(J^{-1}\right)'G'S'\right) < \\
&trace\left(THR_dF'S' + SFR_dH'T' + THR_dH'T' + TR_2T'\right)
\end{aligned}
$$

Case 1: If all important process variables are measurable, i.e. S=0

$$trace(R_n) < trace(HR_dH' + R_2)$$

Other special cases are discussed in the dissertation.

3. Description of Methodologies

- Factors contributing to product variable variation
- Methodology 1
- Methodology 2
- Subset Selection

Factors Contributing to Product Variable Variation

1. How well z_c is able to predict y.
2. The impact adjustments of u used to keep z_c constant have on y through z_u.
3. Sensor Noise

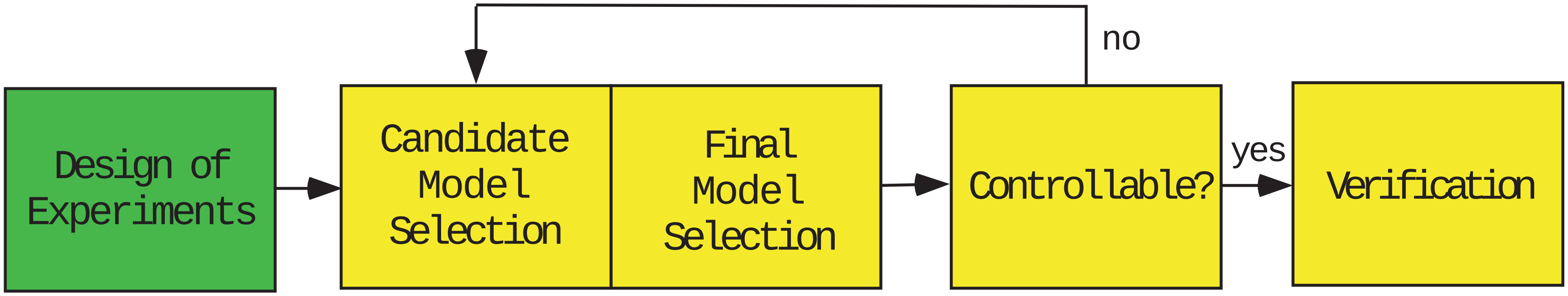
Methodology 1 considers factor 1.

Methodology 2 considers all three factors.

Scenario

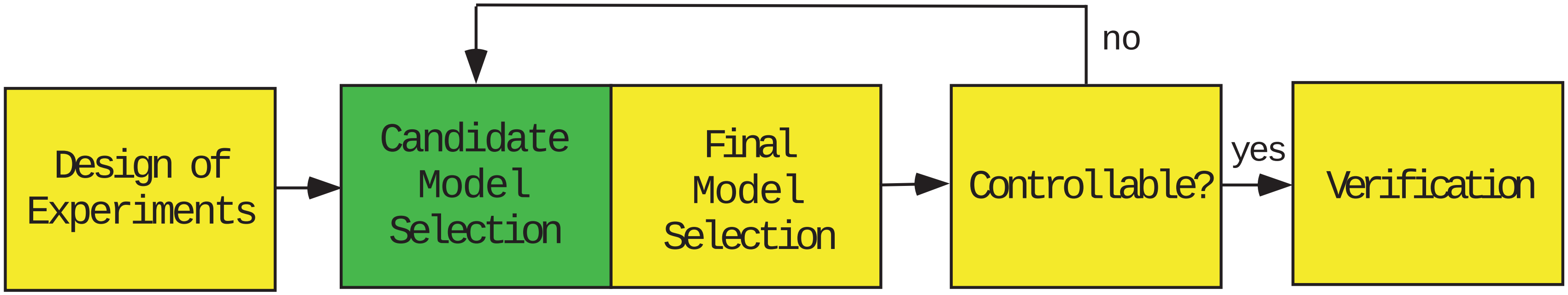
- Product variables have been identified.
- Sensors potentially useful for RFC are set up.

Methodology 1



Design of Experiments

- Include disturbance and machine variables as factors.
- Should be sufficient to capture anticipated nonlinearities.



Design of Experiments

Candidate Model Selection

Final Model Selection

Controllable?

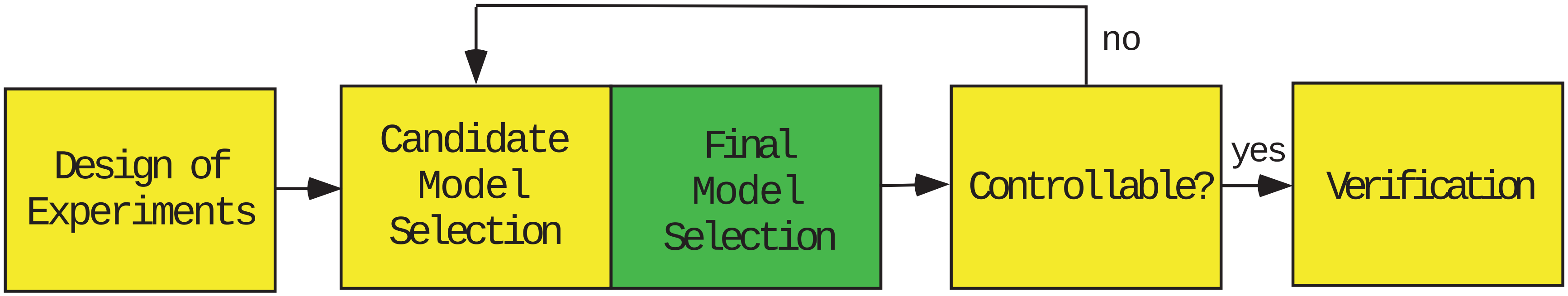
no

yes

Verification

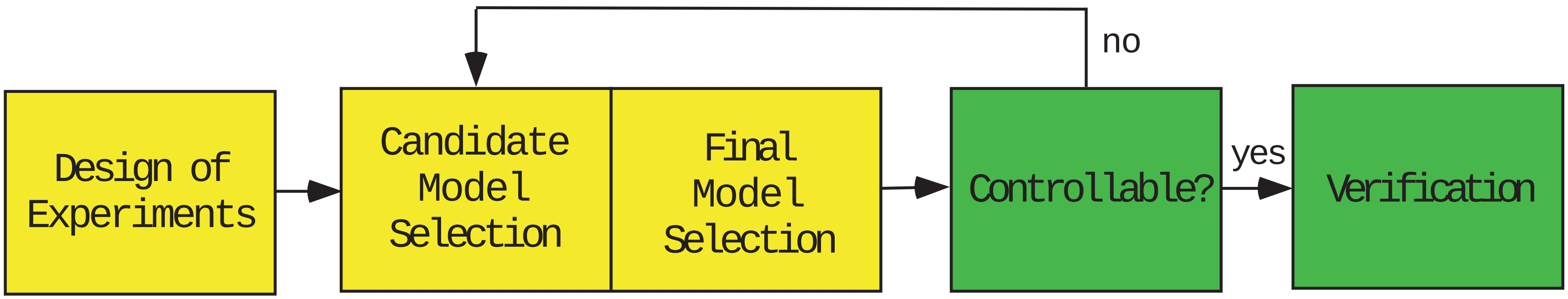
Candidate Model Selection

- The ability of all possible combinations of N_I product variables and postulated nonlinear terms to predict the product variables is compared. The top 10 models are gathered.
- Numerous subset selection techniques were evaluated for this purpose. A new approach, which works better than the existing techniques, was developed. More on this in four slides.



Final Model Selection Criteria

- Look for common terms.
- Use qualitative knowledge about process.
- Use testing data.
- For two otherwise equal models, choose least expensive model in terms of number of required sensors.



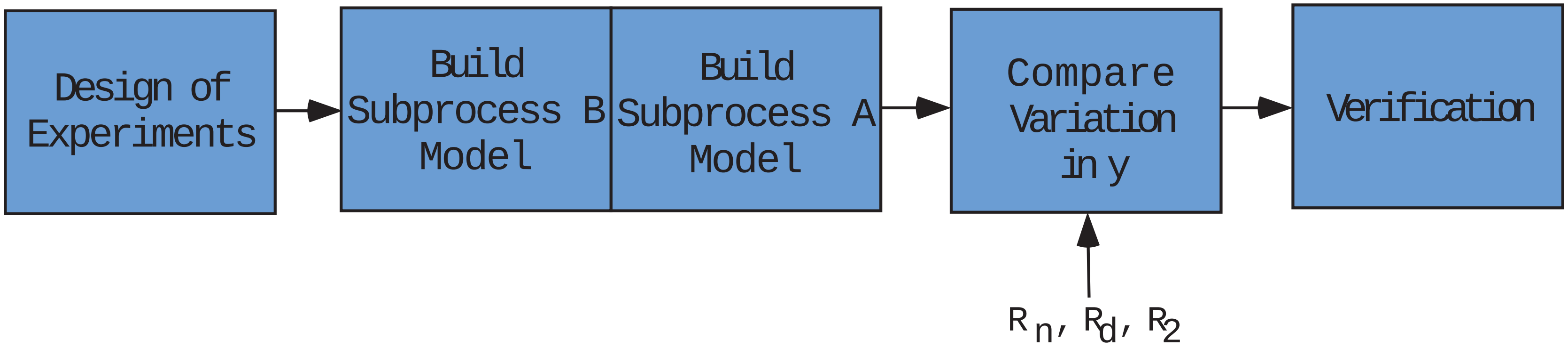
Controllability Check

- Use system ID to determine if the machine variables can independently control each of the selected process variables. If not, either decrement N_I or choose different set of process variables.

Verification

- Build controller and compare with conventional control.

Methodology 2



Design of Experiments

Build Subprocess B Model

Build Subprocess A Model

Compare Variation in y

Verification

R_n, R_d, R_2

- Build Subprocess B Model: Use candidate/final model selection procedure.
- Build Subprocess A model: Easy as machine variables are orthogonal.
- Compare variation in y for each combination of predictors using this model.

Subset Selection Challenges

- Large amount of multicollinearity between product variables, interaction and quadratic terms

=> Estimates of significance of terms is highly dependent upon other terms included in model.

- Large number of terms in quadratic model

=> If product variables = 15, terms = 135, possible models = 2^{135}. Splus will only consider 33 terms. Also observations ≥ terms to use the OLSR solution to regression function.

- Need to identify multiple candidate models.

Existing Subset Selection Approaches and their Limitations

- All-possible-regressions - Too many models.
- Leaps method - Too many models.
- Stepwise regression - Significance of terms distorted by multicollinearity.
- Ridge regression - Unwieldy for large numbers of variables.
- PCR and PLSR - Only one model and this model may not even be best in terms of metric.

Proposed Approach: Constraint-Limited Exhaustive Search (CLES)

- Constraint 1: Only N_I process or machine variables can be held constant.
- Constraint 2: All interaction and higher order terms will also be automatically held constant by the controller.

Approach: Compare all possible regression models given these constraints.

- If product variables = 15,

  all-possible-regressions: 2^{135} possible models

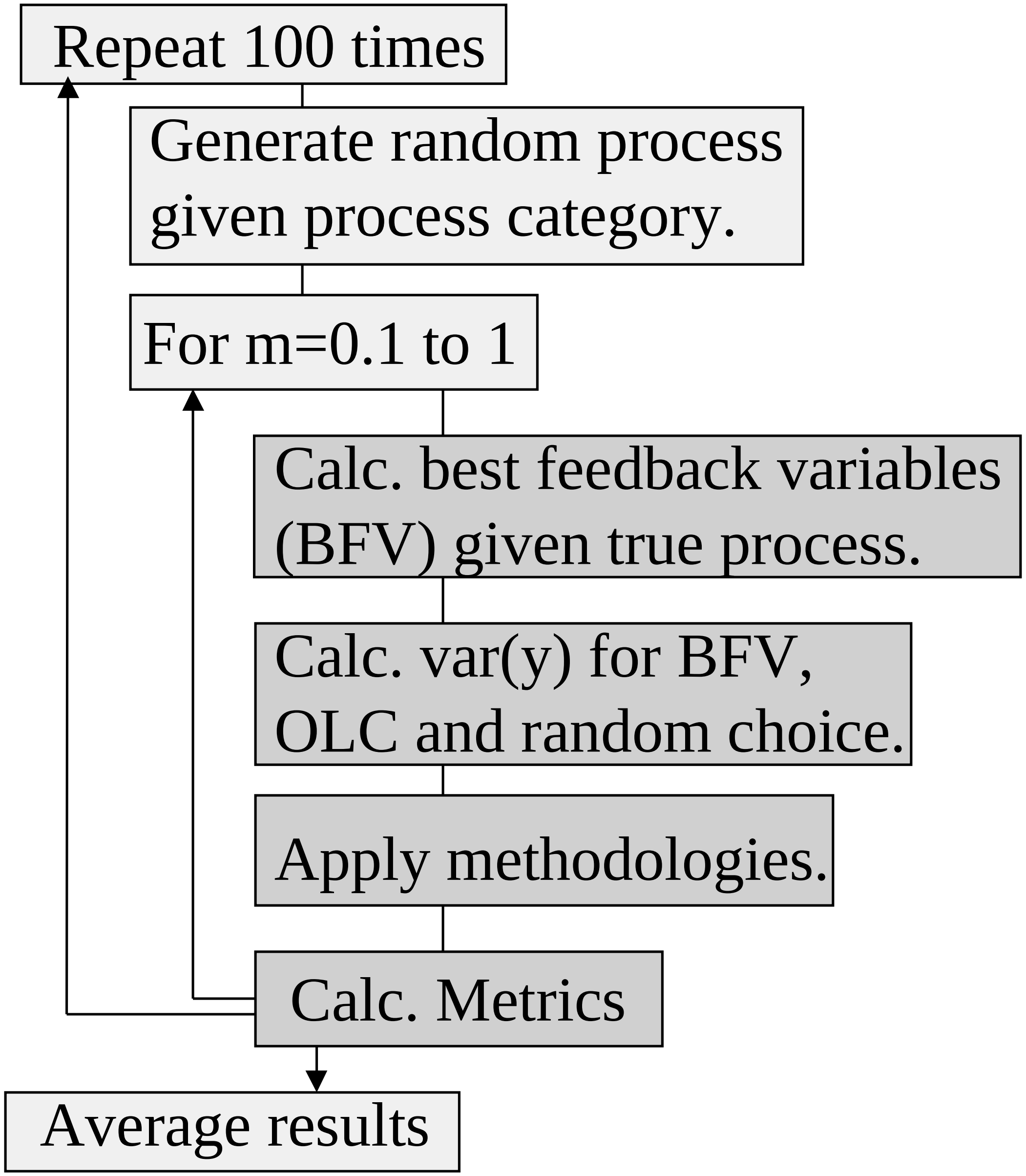
  CLES: 455 possible models

4. Simulation Results

- Implementation
- Metrics
- Process Categories
- Select Results
- Merits and Limitations of the Methodologies

Implementation

- Used extension of static, linear model used for theoretical work.
- One product, two disturbance, two machine, six measurable process and two unmeasurable process variables.
- Programmed in MATLAB.



Repeat 100 times

Generate random process given process category.

For m=0.1 to 1

Calc. best feedback variables (BFV) given true process.

Calc. var(y) for BFV, OLC and random choice.

Apply methodologies.

Calc. Metrics

Average results

Metrics

- P_S - the percentage of times all the best feedback variables are identified.
- P_{S1} - the percentage of times at least one of the best feedback variables is identified.
- var(y) - the variance of the product variables y calculated using the true process assuming the indicated process variables are regulated.

Process Categories

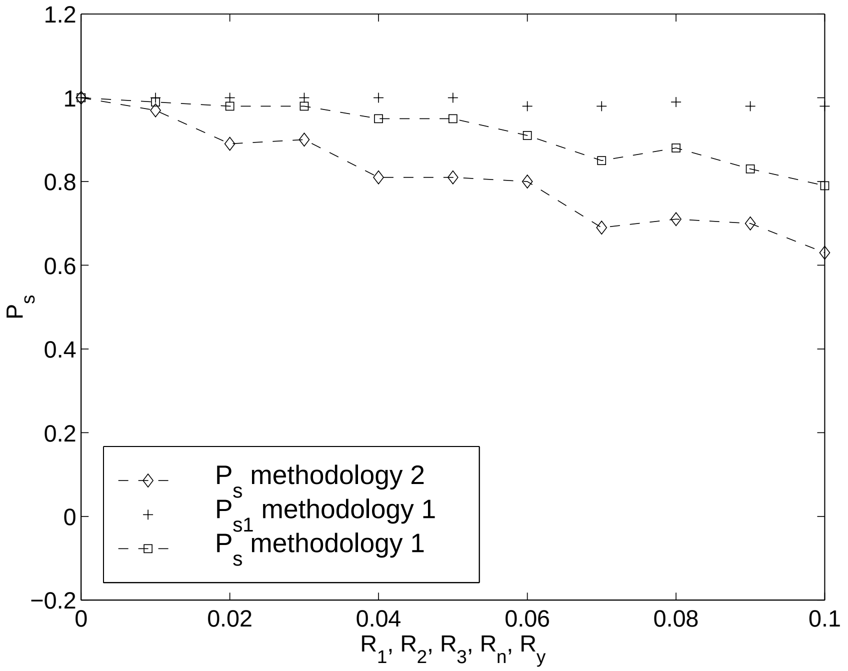
- Category A - all process variables which affect y are measurable and they are N_I or less in number.
- Category B - some unmeasurable process variables and N_I or less measurable process variables affect y.
- Category C - more than N_I measurable process variables affect y.

Select Results

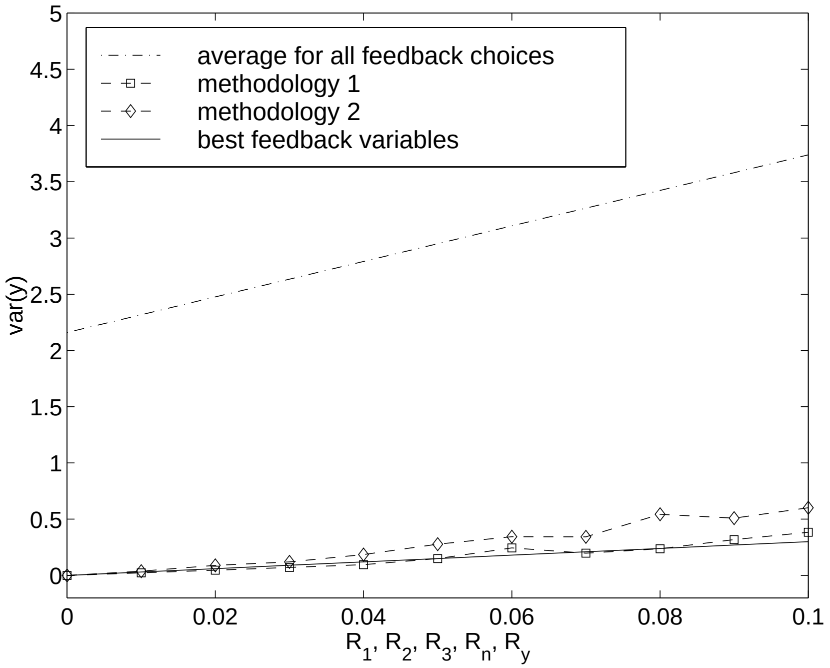
- Theorem 1 - Suppose the sensor and process noise covariance matrices are zero. For any Category A process, Methodology 1 will identify the variables which minimize trace(cov(y)).

- Similar theorem for Methodology 2.

Category A - noisy case



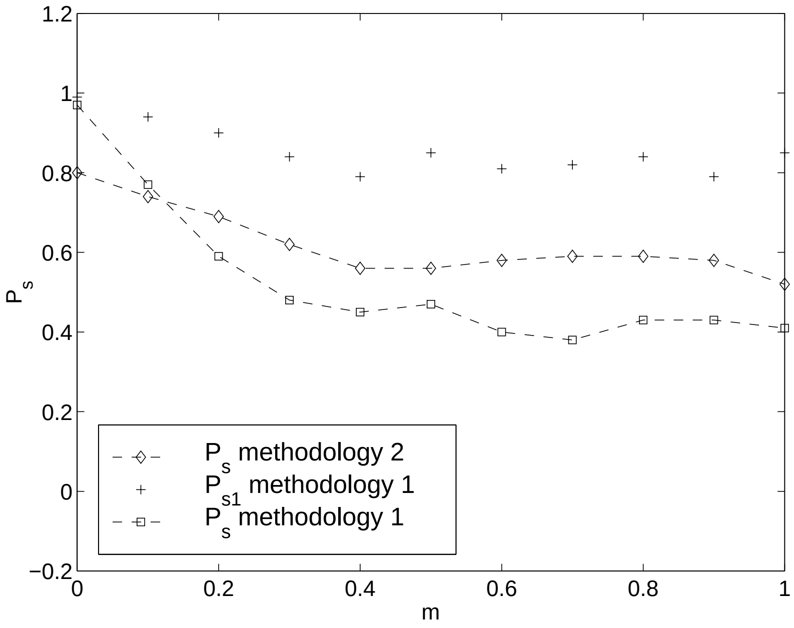
var(y) for OLC > 18



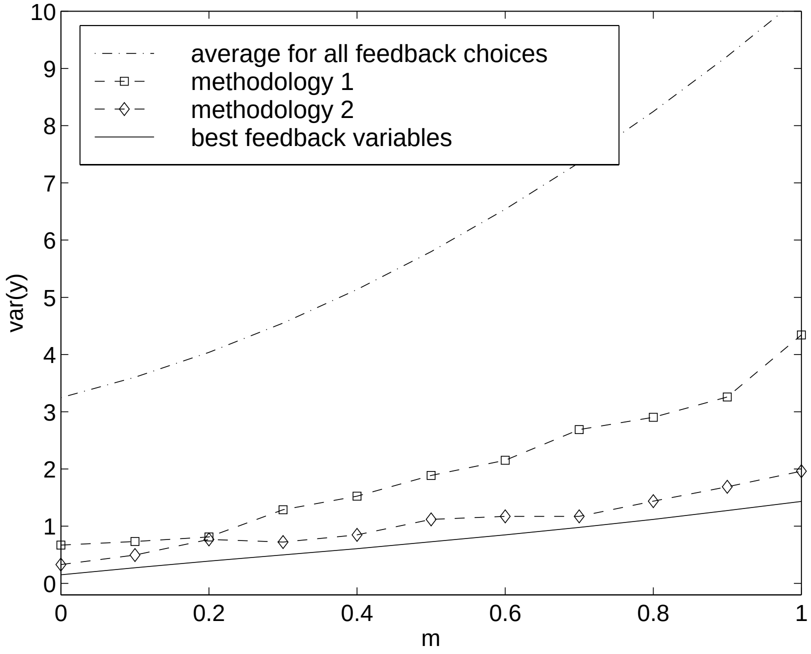
Both methodologies are much better than OLC and random selection of feedback variables. The best feedback variables are selected most of the time. Methodology 1 slightly better than Methodology 2.

Category B - noisy case

S=m*[1 1], T=[1 1 0 0 0 0]



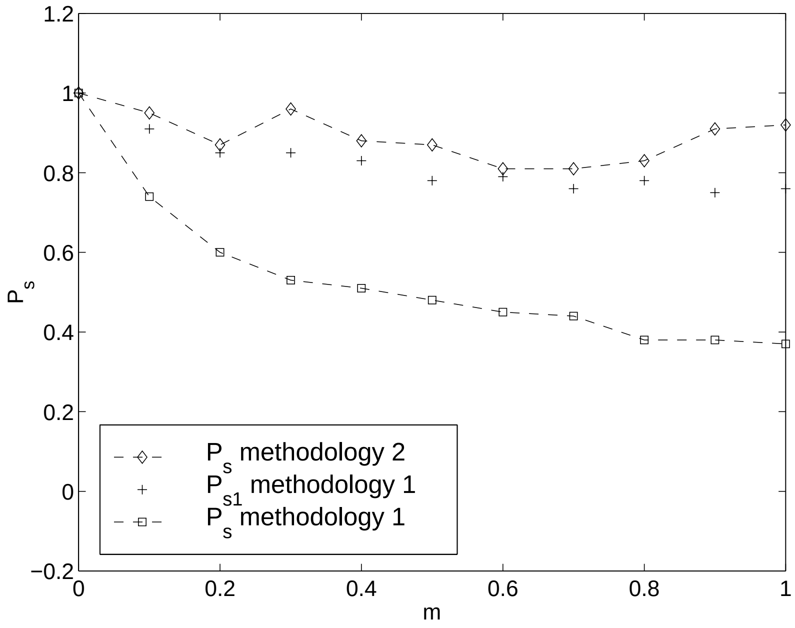
var(y) for OLC > 18



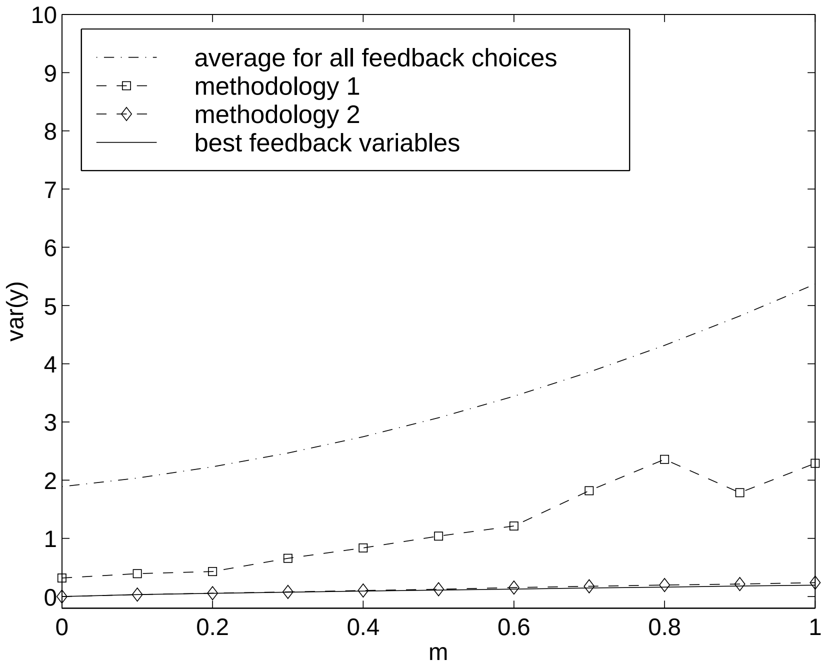
The best feedback variables are not always identified. Both methodologies are much better than OLC and random selection of feedback variables, particularly when m is small. Methodology 2 is also much better than Methodology 1.

Category C - noisy case

S=[0 0], T= [1 1 m m 0 0]



var(y) for OLC > 18



Methodology 1 is much better than OLC and better than random selection of feedback variables particularly for low levels of m. Methodology 2 is much better than Methodology 1.

Merits of Methodologies

- Alternative to selection of feedback variables using qualitative process knowledge
- Knowledge about process not required
- Focuses on disturbance rejection
- Large sets of multicollinear process and machine variables may be considered.
- Also applicable to run-to-run control.

Limitations of Methodologies

- Limited by the generic model postulated.
- Disturbance variables may be difficult to identify and control for DOE.
- Final model selection difficult if the most common variables for the different sets of best product variable models vary greatly.

Comparison of Methodologies

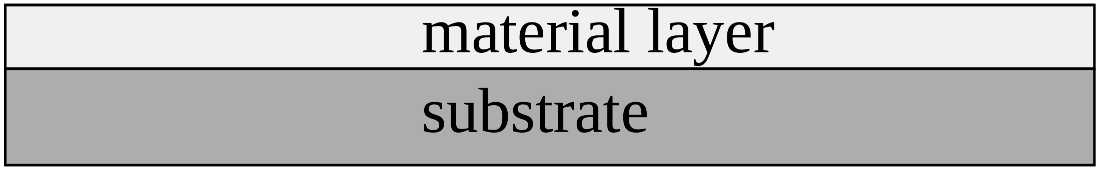
- Methodology 2 is generally more effective than Methodology 1.
- Methodology 1 is much easier to implement than Methodology 2 and is also effective.

5. Experimental Results

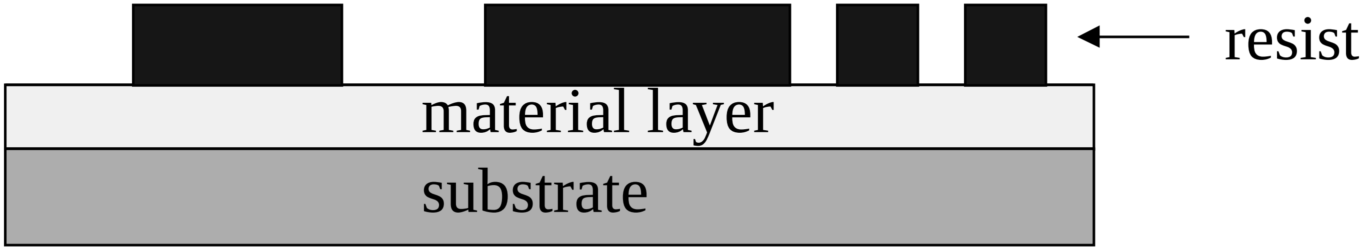
- Introduction to Semiconductor Manufacturing
- Experiment Description
- Results

Introduction to Semiconductor Manufacturing

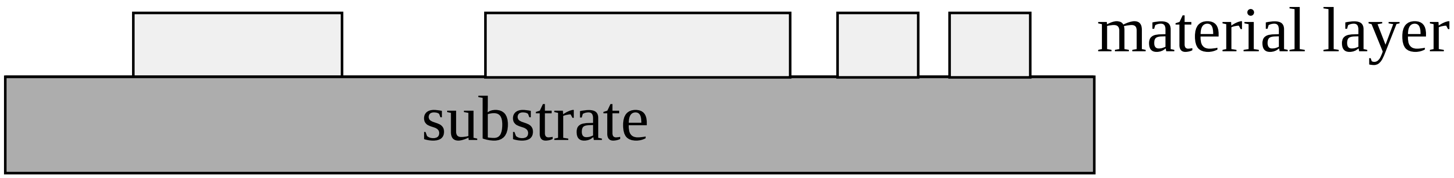
Deposition (e.g. chemical vapor deposition, evaporation, oxidation)



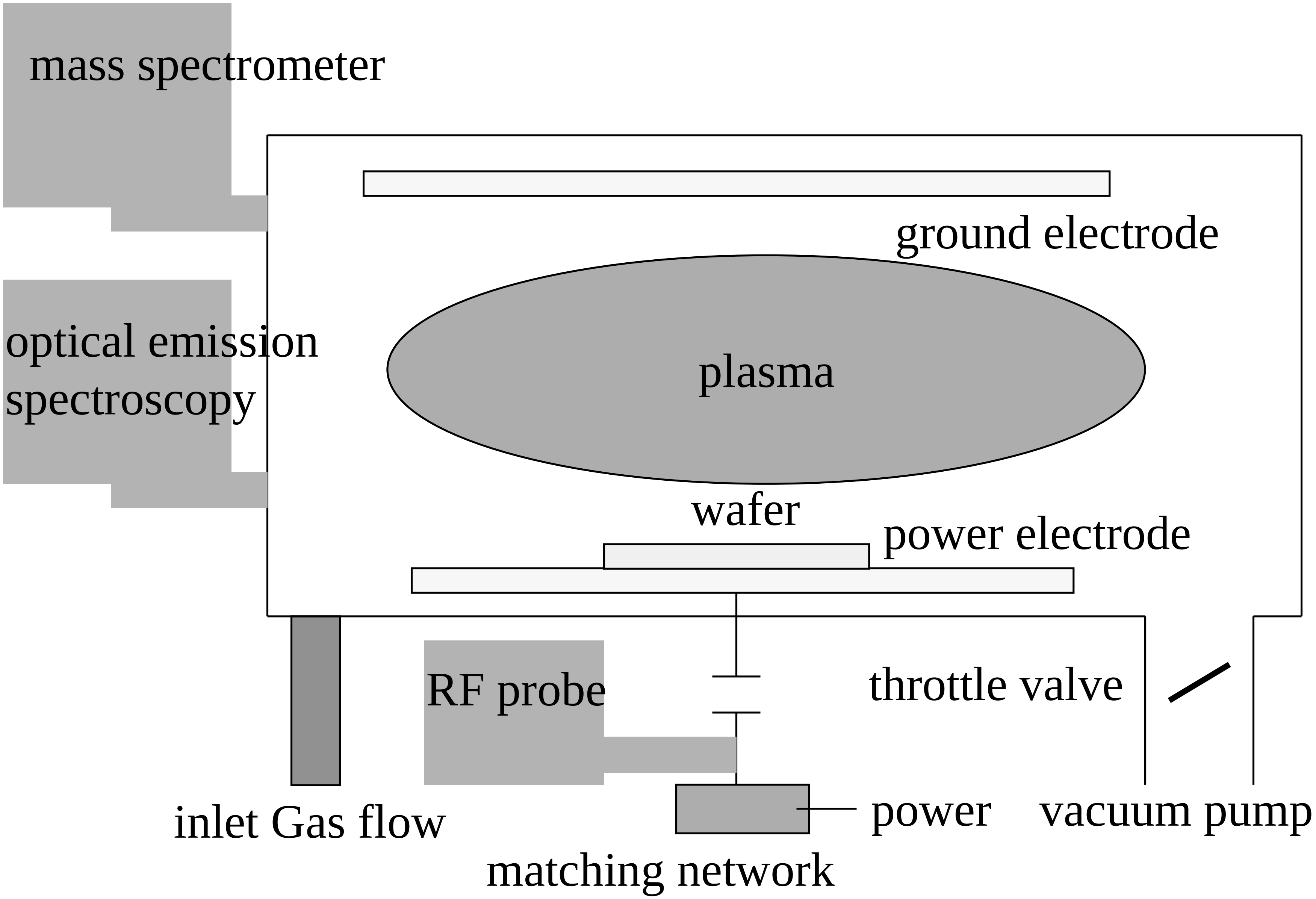
Patterning (e.g. lithography)



Etch (e.g. reactive ion etch, wet etch)



Generic Reactive Ion Etch System



mass spectrometer

ground electrode

optical emission
spectroscopy

plasma

wafer

power electrode

throttle valve

RF probe

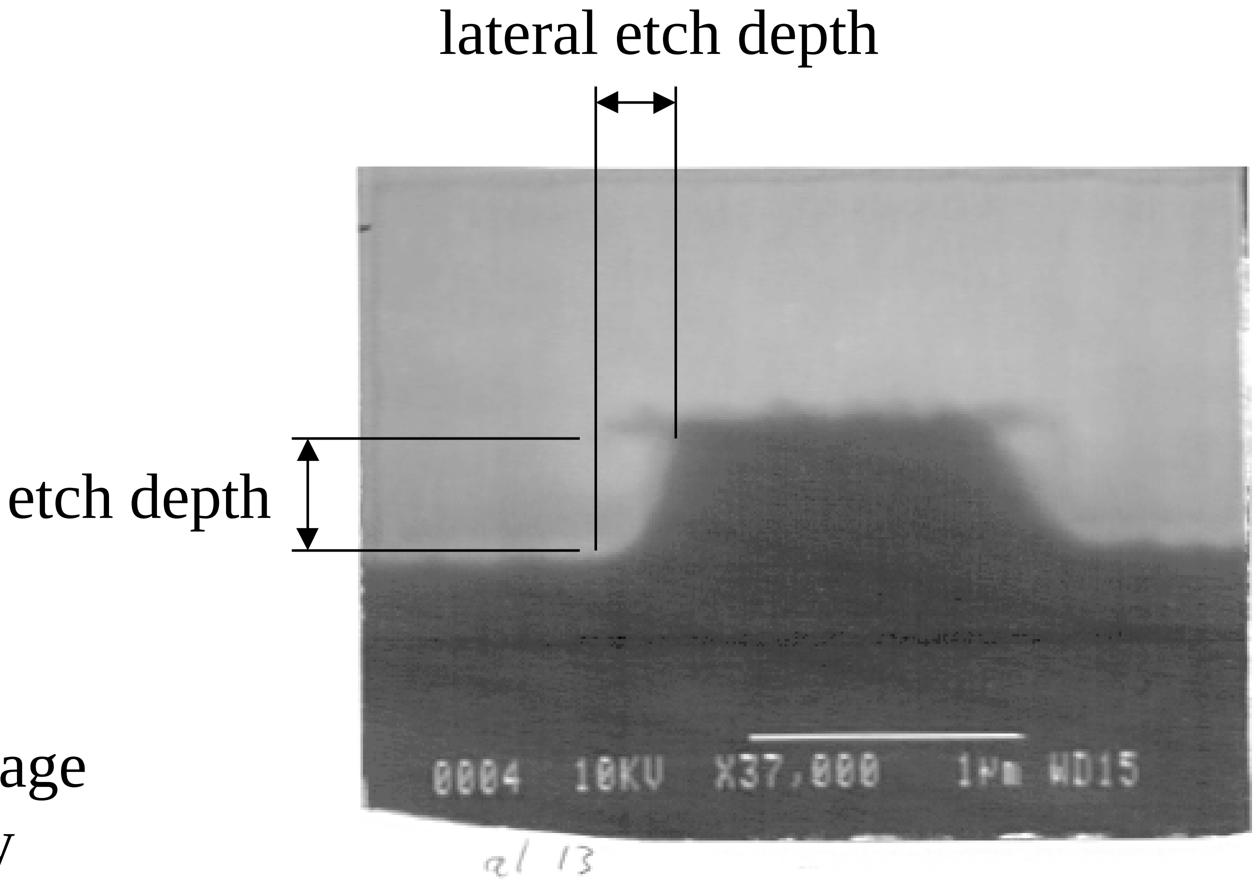
inlet Gas flow

power

vacuum pump

matching network

Etch Product Variables



others:

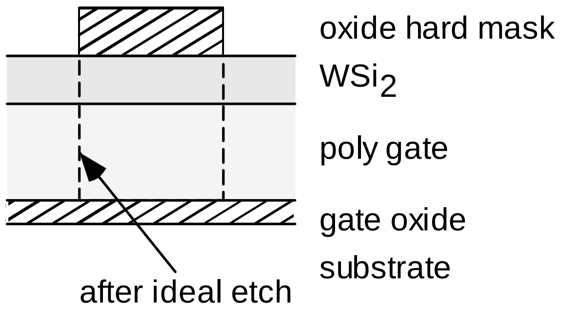
- substrate damage
- nonuniformity
- selectivity

Experiment Description

- Target Application: Etch of self-aligned gate
- Product Variables: etch rate across wafer (EAW), lateral etch rate (E_{lat})
- Applied 8300 batch reactor was used for experiments because our high density plasma, etch tool, the Lam 9400, not yet available.

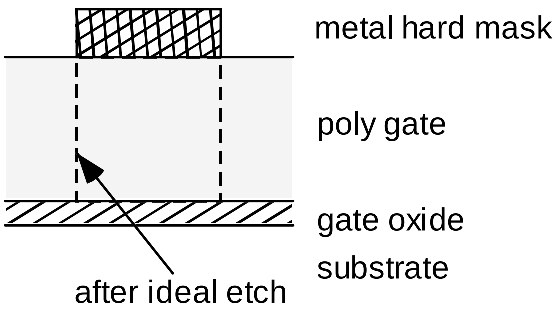
- Chemistry: $CF_4/CHF_3/Ar/O_2$
- Metal hardmask
- Test structure used rather than actual gates.

Actual System



Cl and HBr etchant chemistries

Used for Study



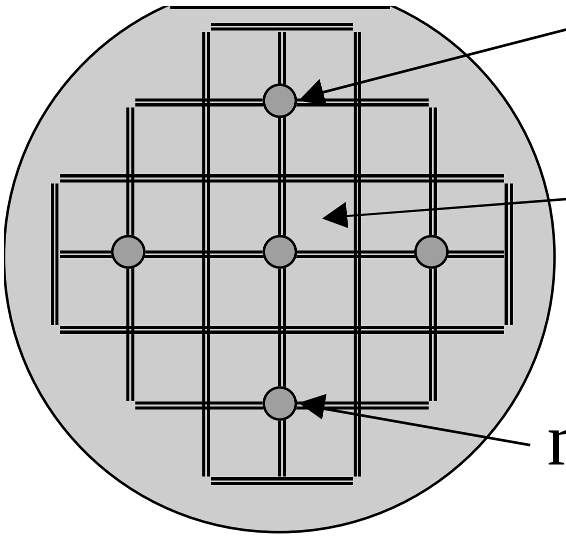
F etchant chemistry

Sensors

- OES - Selected promising wavelengths based on strength and isolation during scan of spectrum, and literature. These were sequentially scanned during etch.
- Mass Spectrometer - Extrel MS250, dominant masses for constituent molecules recorded.
- RF probe - Advanced Energy RFZ60.
- HeNe Reflectometry - to stop etch ~100nm early to allow measurement of N_E.

Characterization

- Cross-Sectional SEM - for undercut.
- SP - for EAW



maximum etch depth

cross section
this die

minimum etch depth

DOE

- Disturbance variable: load
- Central composite design x 2
- Used screening experiments to select levels.
- Randomized order.

Results: Final List of Process Variables

P_G	generator power
P	chamber pressure
CHF	CHF_3 flow
V_{bias}	bias voltage
V_{pp}	peak to peak voltage
θ	throttle valve position
OES_F	703.7 nm fluorine line intensity
OES_{CF2}	CF_2 intensity
rf_P	power measured at RF probe
rf_V	voltage measured at RF probe
rf_I	current measured at RF probe
||Z||	impedance measured at RF probe
<Z	phase angle measured at RF probe
IFE	ion flux energy
IFEP	ion flux energy power

Methodology 1: Candidate Models and Final Model

Best models for EAW			R^2	sum of R^2's
OES$_F$,	P$_G$,	IFEP	0.94	1.78
OES$_F$,	P,	V$_{bias}$	0.95	1.78
OES$_F$,	P,	RF$_I$	0.94	1.77
OES$_F$,	P,	||Z||	0.94	1.76
OES$_F$,	CHF,	V$_{pp}$	0.95	1.78
OES$_F$,	CHF,	rf$_I$	0.95	1.78
OES$_F$,	θ,	V$_{bias}$	0.96	1.80
OES$_F$,	θ,	rf$_I$	0.95	1.78
OES$_F$,	θ,	||Z||	0.96	1.79
OES$_F$,	θ,	IFEP	0.95	1.81
conventional control			0.85	

Best models for E$_{lat}$			R^2	sum of R^2's
CHF$_3$,	<Z,	P	0.87	1.54
OES$_F$,	<Z,	P	0.90	1.69
CHF$_3$,	<Z,	||Z||	0.86	1.50
OES$_F$,	<Z,	V$_{bias}$	0.86	1.74
OES$_F$,	V$_{bias}$,	IFEP	0.87	1.72
OES$_F$,	θ,	rf$_V$	0.87	1.68
OES$_F$,	<Z,	OES$_{CF2}$	0.86	1.67
OES$_F$,	rf$_I$,	IFEP	0.87	1.77
OES$_F$,	<Z,	||Z||	0.86	1.69
OES$_F$,	||Z||,	IFE	0.86	1.70
conventional control			0.85	

- Variation in y due to factor 1 is much better for all these models than for conventional control.
- Using Methodology 1, OES$_F$, θ, and V$_{bias}$ were selected.

Analyze performance of other subset selection techniques

- Stepwise Regression - Can’t postulate quadratic model.
- Ridge Regression - Does not even find best linear model.
- PCR and PLSR - (linear case) They find only one model for each product variable. Not even the best model.

Methodology 2

Appearances in top models for EAW

process var.	within 10%	within 20%	within 50%
P_G	10	11	13
P	1	2	4
CHF	0	1	3
V_{bias}	2	2	3
θ	0	0	3
OES_F	14	20	36
OES_{CF2}	1	2	3
rf_P	4	10	13
rf_V	0	0	2
rf_I	2	2	4
$\|Z\|$	2	2	3
<Z	1	2	3
IFE	1	2	3
IFEP	1	2	3

Appearances in top models for E_{lat}

process var.	within 10%	within 20%	within 50%
P_G	1	7	9
P	6	7	8
CHF	0	3	4
V_{bias}	2	9	12
θ	2	7	8
OES_F	13	42	61
OES_{CF2}	0	0	3
rf_P	1	6	9
rf_V	1	6	8
rf_I	3	6	11
$\|Z\|$	0	0	10
<Z	2	6	8
IFE	2	11	12
IFEP	5	9	12

Using Methodology 2, OES_F, P_G and P were selected.

Results correspond well with our previous experience

- Previously applied RFC to the Applied running a fluorine plasma.
- Fed back [F] and V_{bias}
- Studied the effect on steady state etch rate variation when load was varied.
- Observed an 80% reduction in variation.
- Rejection of oxygen leak and power variation disturbances also demonstrated.

6. Contributions and Future Work

- Contributions
- Future Work

Contributions

- A general condition under which real-time feedback control reduces process variation was derived.
- Two methodologies for selecting process variables for feedback control have been developed. Each has distinct advantages.
- The effectiveness of the methodologies has been demonstrated through simulated and real experiments.

Future Work

- Develop version of Methodology 2 which uses a quadratic model for subprocess B.
- Develop theory to optimize the DOE so that for a reasonable number of experiments, the variance of the regression coefficients is minimized.
- Evaluate the methodologies using simulations of nonlinear processes.
- Apply the methodologies to the Lam 9400, a state-of-the-art, high density plasma, etch tool.