

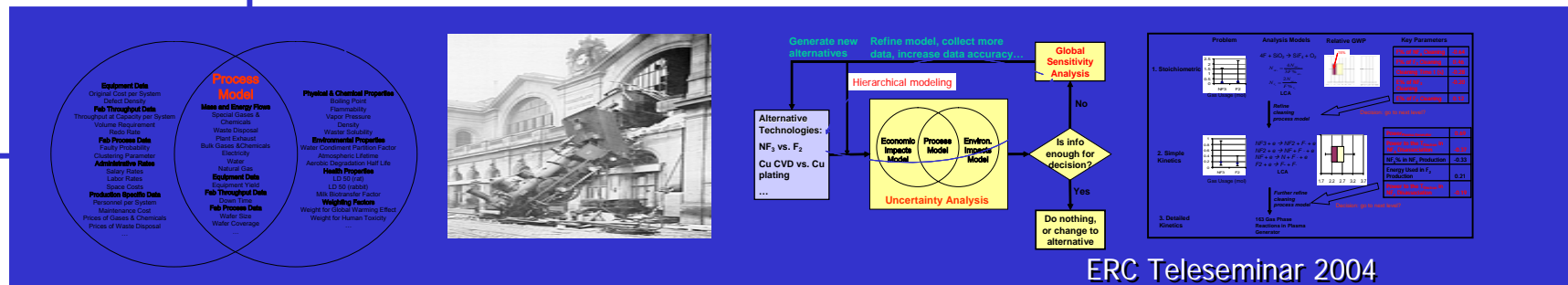
Integrating Environmental Considerations into Technology Selections Under Uncertainty

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ERC Teleseminar 2004

Why are Technology Choices Complex?

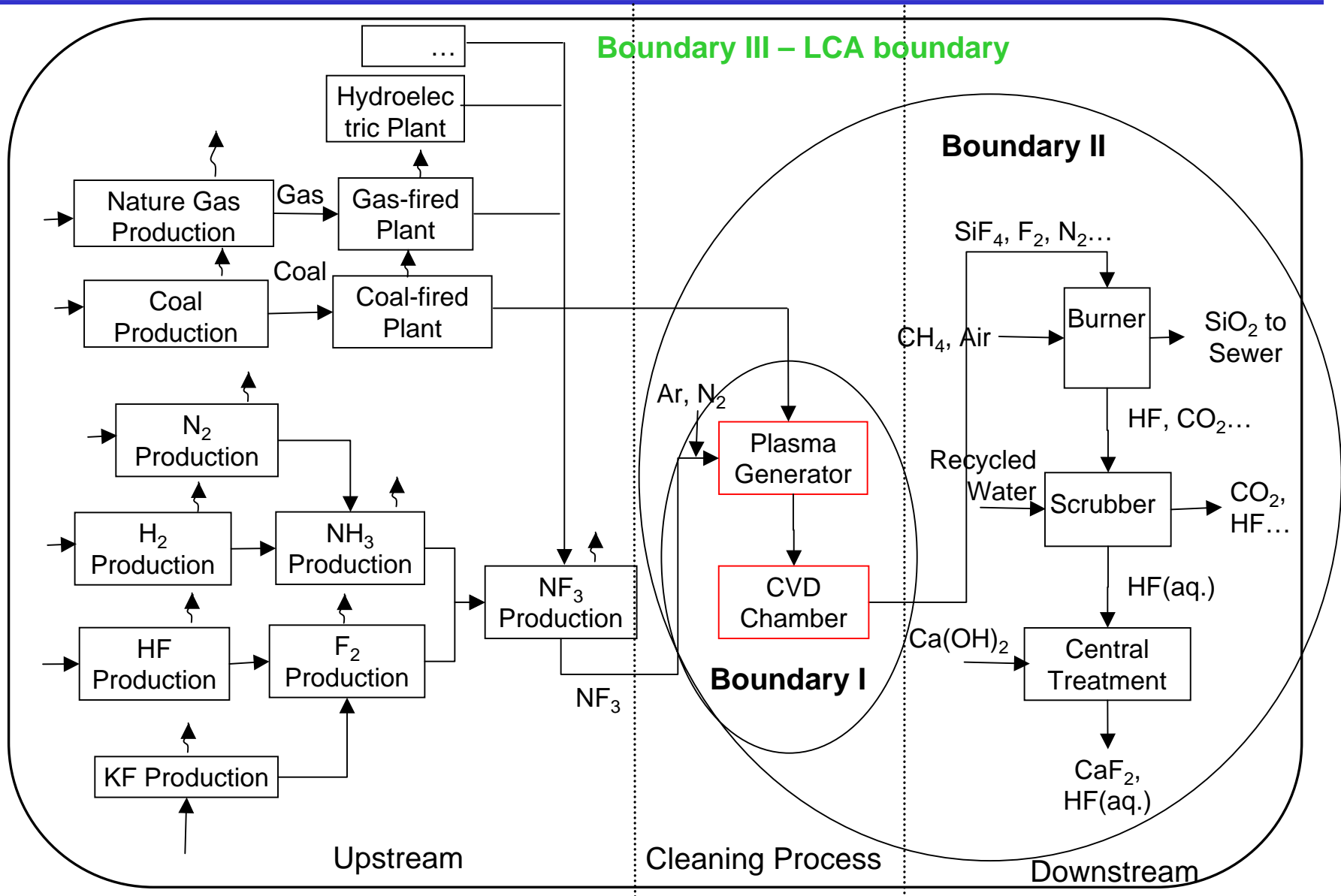
Example: Choosing a chamber cleaning gas (NF₃ vs. F₂?)

Decision Criteria	NF ₃	F ₂	Reference
Fluorine usage rate at the same etch rate (mole/min)	0.15	0.11	This work
Cost/mole of Fluorine	\$2	\$0.8	[1, 2]
LCA Global Warming Effect (kg CO ₂ equivalent/kg)	3.3	2.4	This work
Toxicity LC ₅₀ (ppm)	6700	180	[3,4]
Safety	Inert gas	Very reactive	

The Problem: How to choose between technologies

- When there are conflicting decision criteria
- Many uncertainties

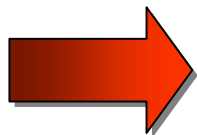
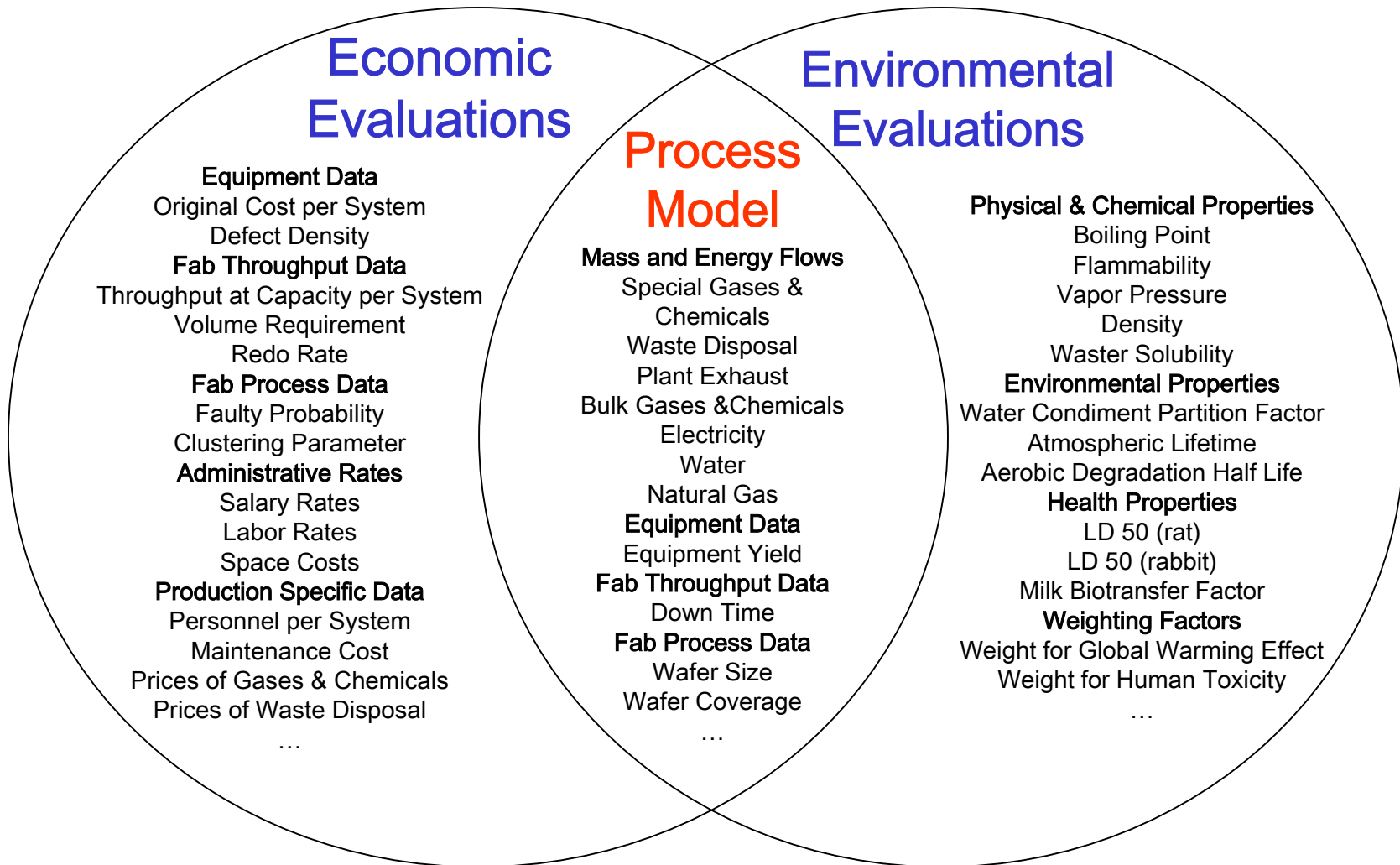
Boundary of Life Cycle Analysis (LCA)



Challenges Facing Integration of Life Cycle Analysis to Process Design

- Large amount of data are required
- Large uncertainties are imbedded in environmental evaluation
 - Example: ~1 order of magnitude in air pollutant emission factors
 - 2 ~ 3 orders of magnitude in cancer toxicity indicators
 - 3 ~ 6 orders of magnitude in non-cancer toxicity indicators
- Limited time allowed for evaluations while regular LCA methods require large amount of time.
 - Typical innovation cycle of semiconductor industry: 2 years.
- Large disconnection in the tools used for ESH analysis and process / equipment design despite significant overlapping of information needed for both.

Overlapping Data Requirements



**There are many areas of overlap in data.
We need tools that can connect them.**

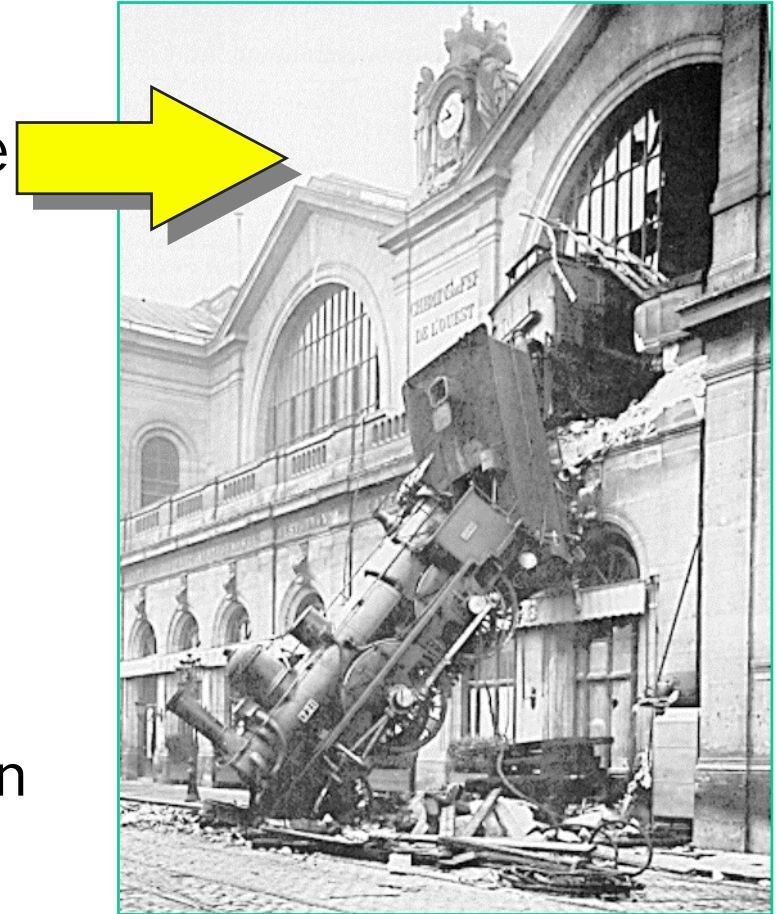
Key Message – *Outcomes are Important*

There are always uncertainties in technology evaluations, the real issue is to identify and **act** on those activities that **influence outcomes**.

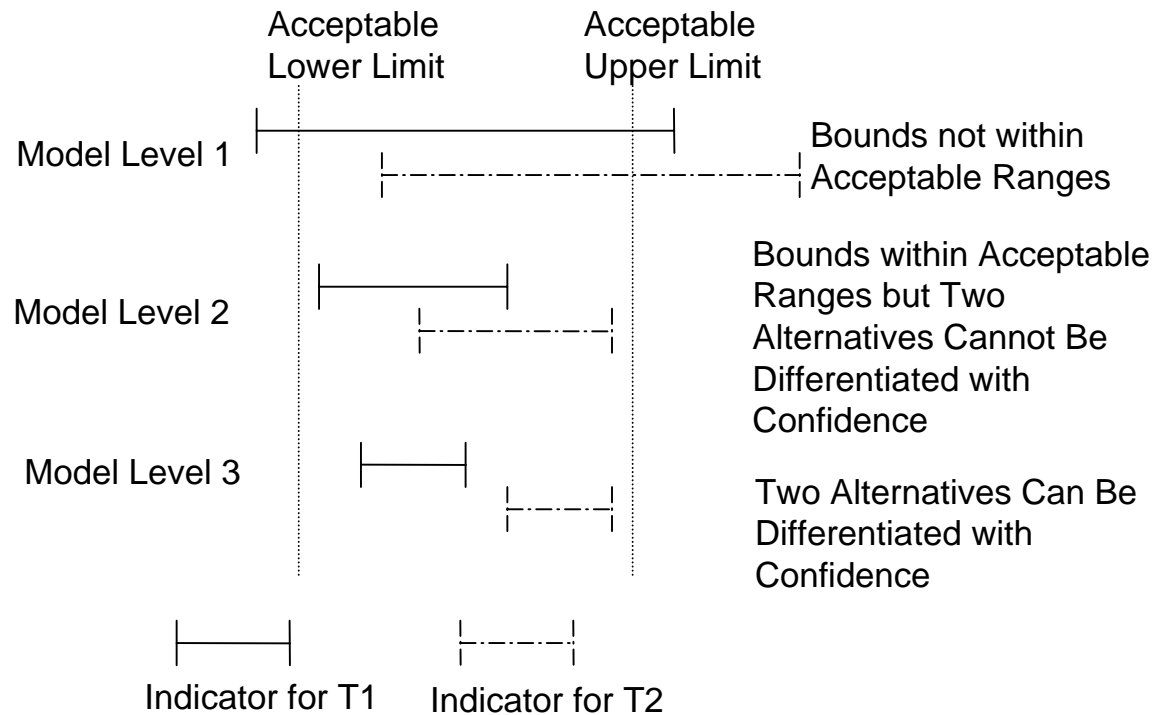


Essence of “Decision Problem”

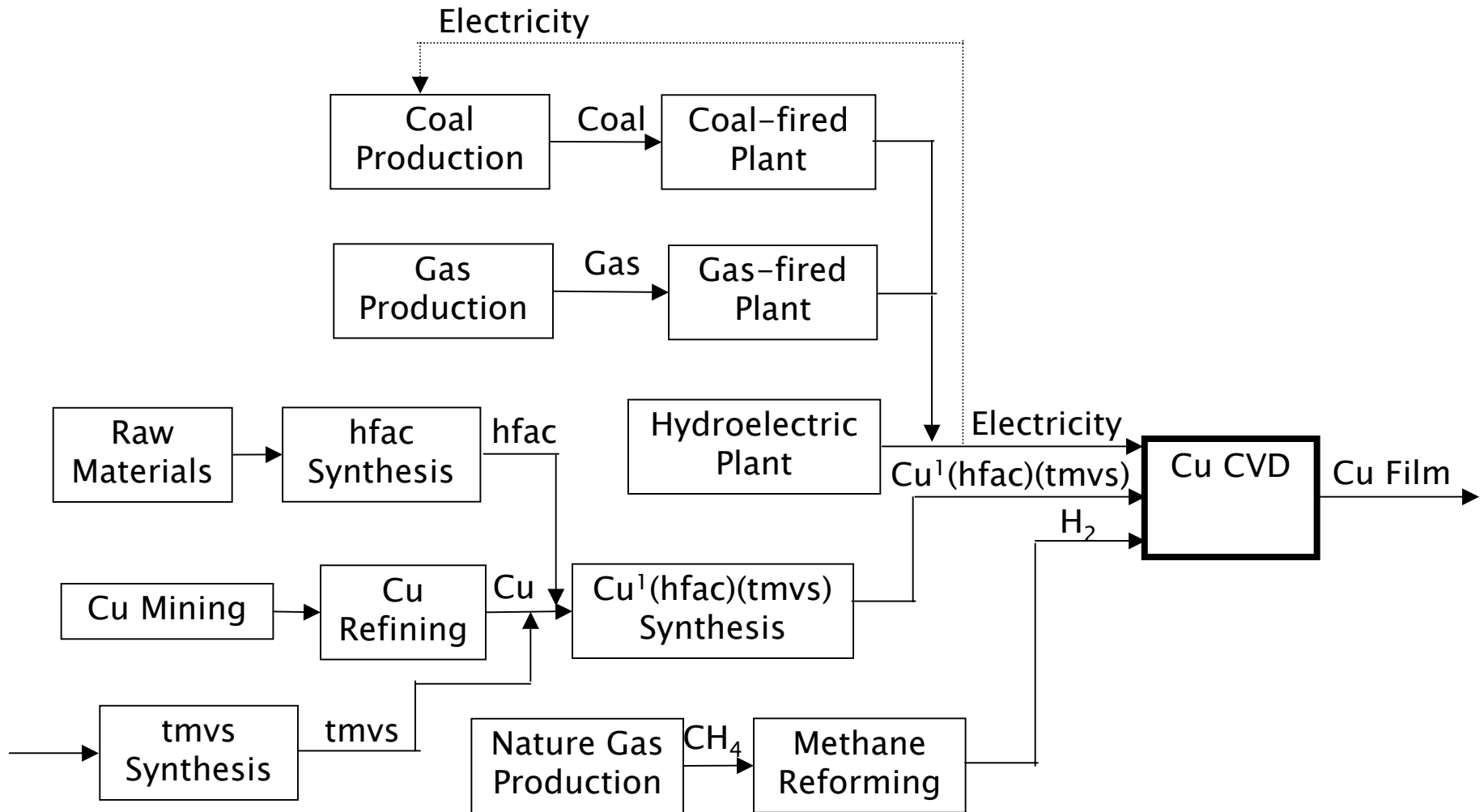
- How can we capture (efficiently) the uncertainties in outcomes given uncertainties in inputs?
- How much information do we need in order to make a decision?
- Where should we allocate resources (modeling, experiments,...) to reduce **risk** in **decision outcomes**?



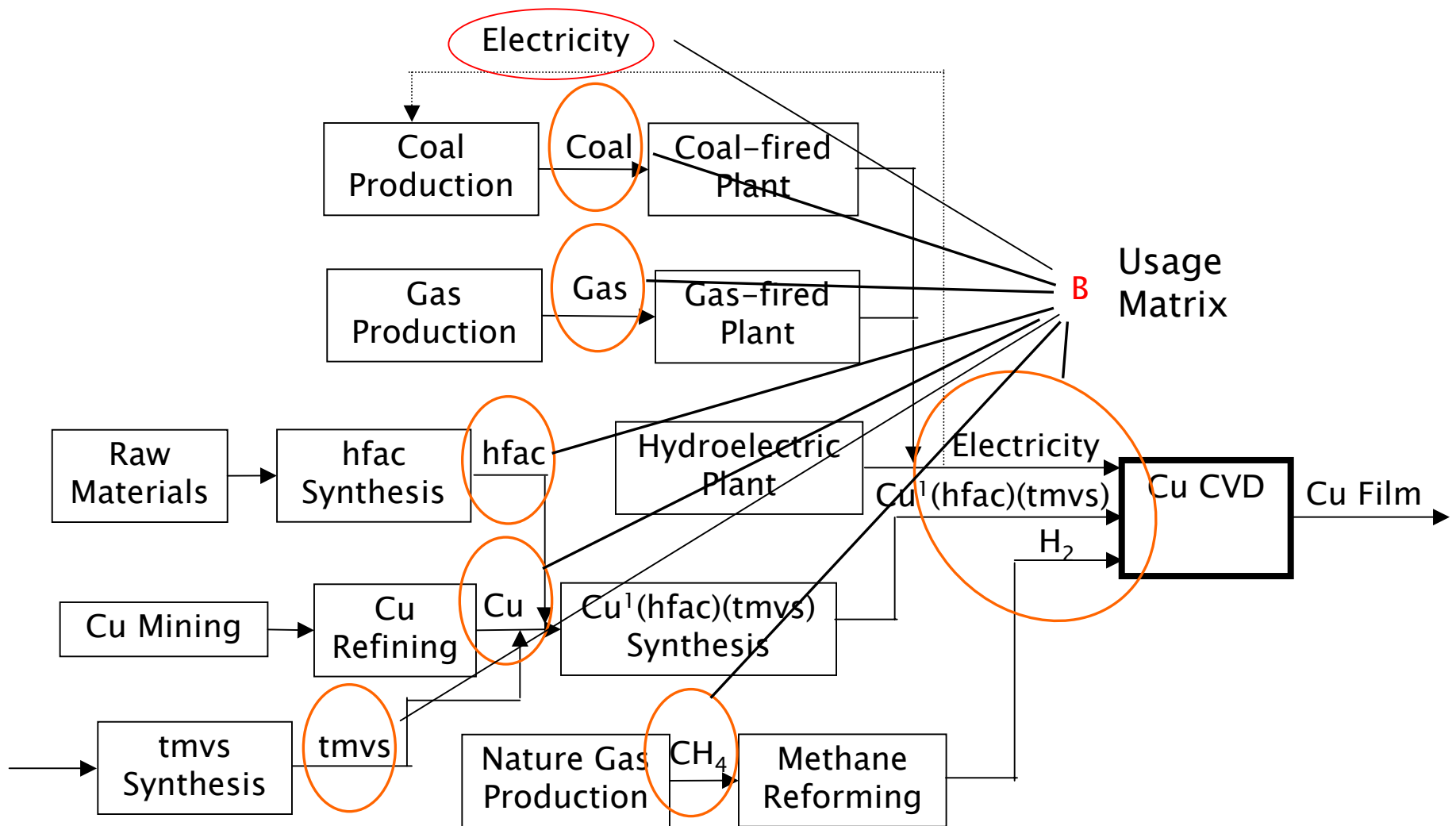
Hierarchical Modeling of Alternatives



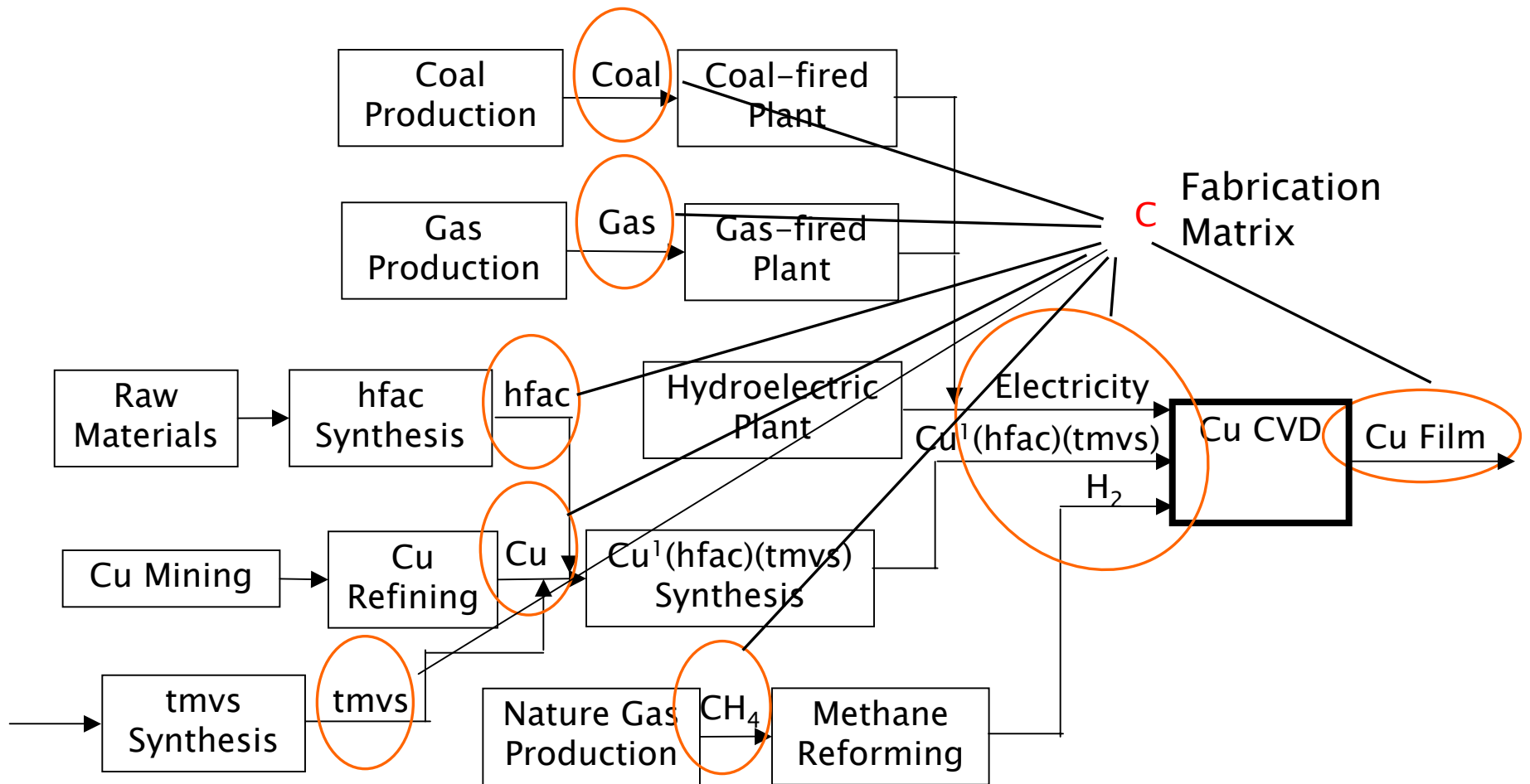
Process-Product Input Output LCA – an example



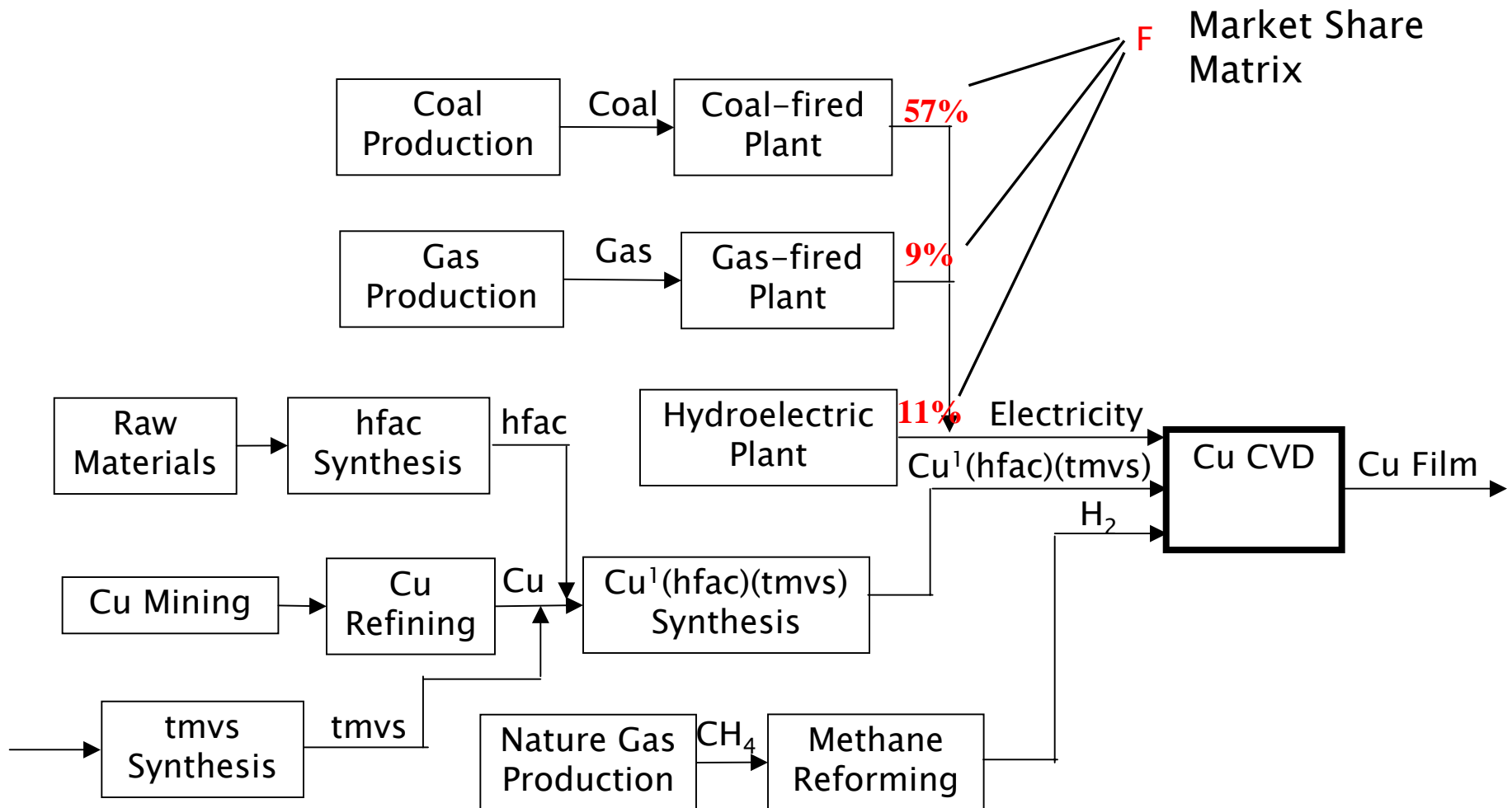
Model Input One: Usage Matrix (B)



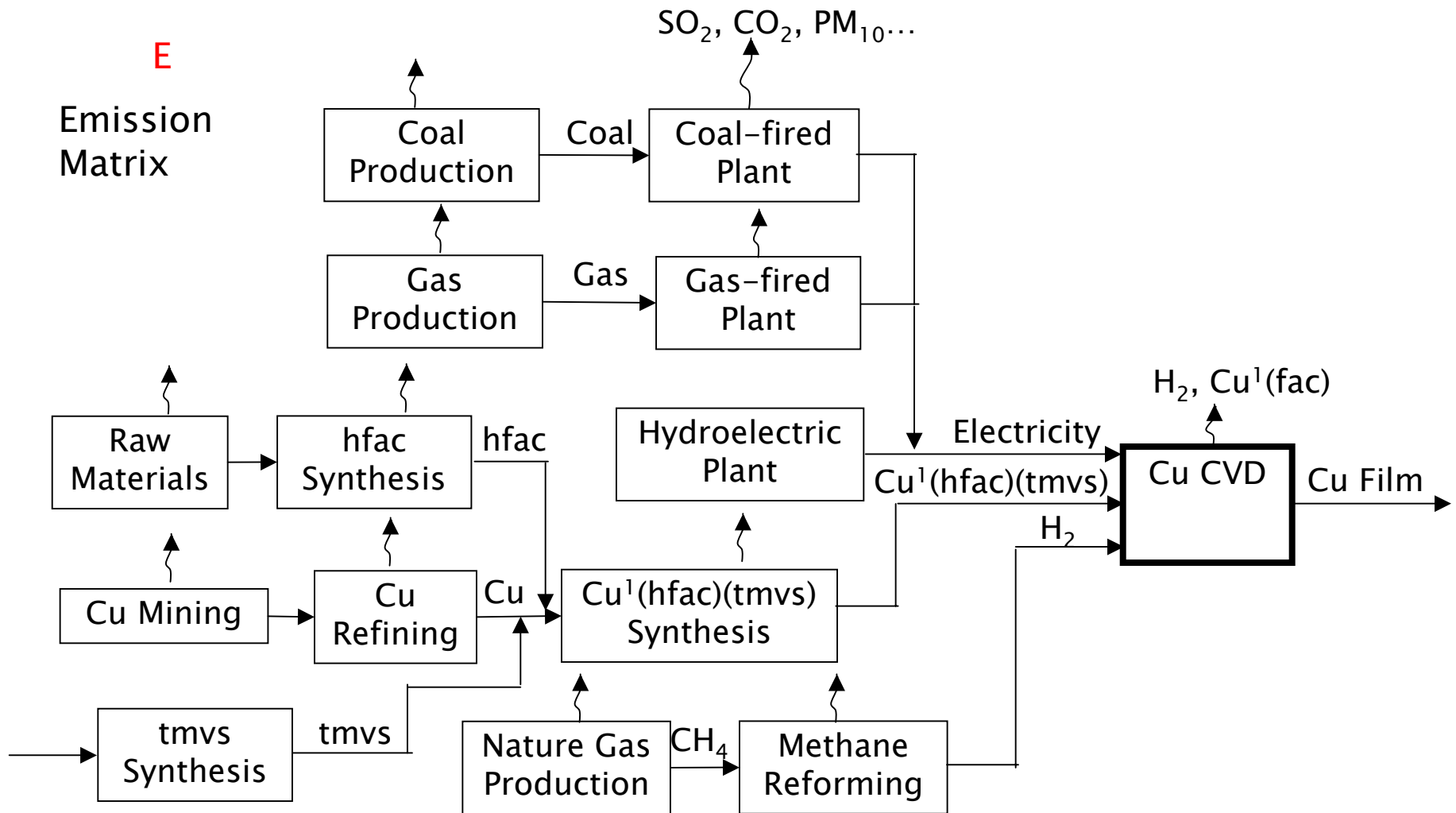
Model Input Two: Fabrication Matrix (C)



Model Input Three: Market Share Matrix (F)



Model Input Four: Emission Matrix (E)



Model Input Five: Characterization Matrix (H)

- Characterization matrix (H)

	Unit	GWP100 <i>kg CO2 equivalent/kg</i>	Respiratory Effect <i>kg PM10 equivalent/kg</i>	Human Toxicity Potential (non-cancer) <i>DALYs/kg</i>	...
CO ₂	<i>kg</i>	1]
SO ₂	<i>kg</i>	-23.3	0.15	4.21E-9	
PM ₁₀	<i>kg</i>	-8.3	1		
⋮					
Based on willingness to pay	Valuation Factor	<i>w</i>	<i>\$</i>		
]

Mathematical Model

- Model Input Six: Price vector (p)
- Allocation matrix (G): for multiple product processes

$$G_{ji} = \begin{cases} \frac{p_i}{\sum_k C_{kj} p_k} & \forall C_{ij} \neq 0 \\ 0 & \forall C_{ij} = 0 \end{cases}$$

G_{ji} : the amount of throughput of process j that is attributed to one unit of product i made in process j

- Throughput matrix (D)

$$D_{ji} = F_{ji} G_{ji}$$

D_{ji} : the amount of throughput of process j that is attributed to the demand of one unit of product i at current price and market share

- Direct product requirement (q_{direct})

$$q_{\text{direct}} = (I + BD)d$$

- Total product requirements

$$q = (I + A_{\text{prod}} + A_{\text{prod}}A_{\text{prod}} + A_{\text{prod}}A_{\text{prod}}A_{\text{prod}} + \dots)d = (I - A_{\text{prod}})^{-1}d$$

where $A_{\text{prod}} \equiv BD$

Mathematical Model

- Total process throughput requirements (x)

$$x = Dq$$

- Life cycle environmental exchanges inventory (e)

$$e = Ex$$

- Impact valuation by process (Ω_{process})

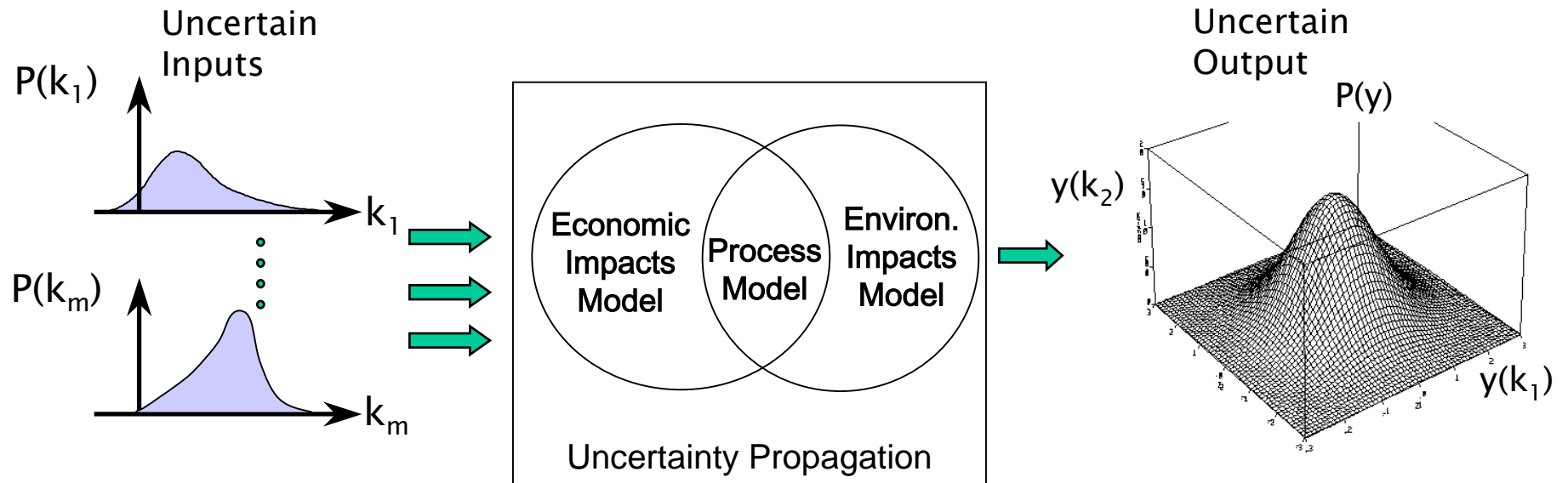
$$\Omega_{\text{process}} = \text{Diag}(x) E^T H w$$

- Impact valuation by emission (Ω_{emission})

$$\Omega_{\text{emission}} = \text{Diag}(e) H w$$

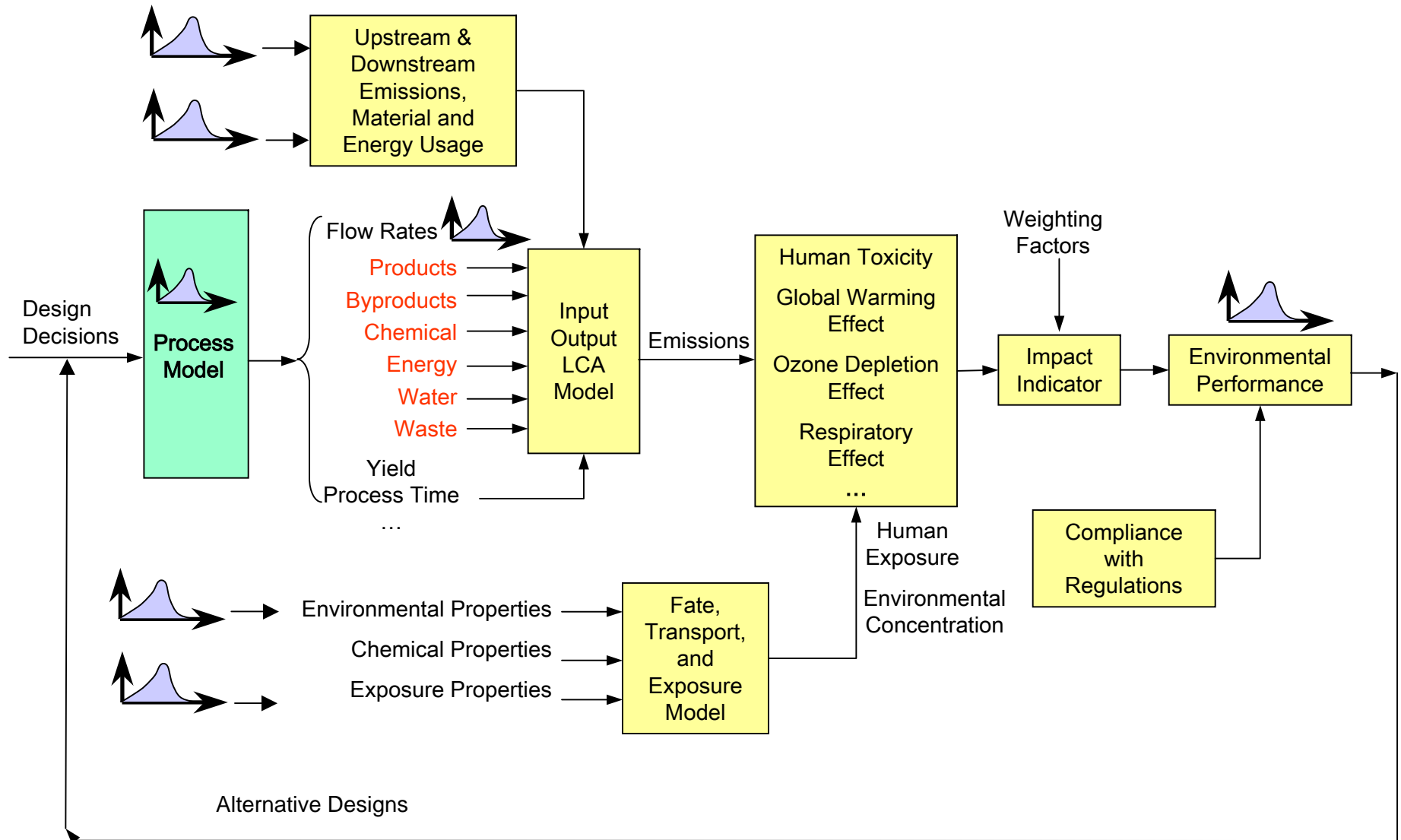
Large Uncertainties in Inputs?

Uncertainty Analysis!



Uncertainty Analysis: Propagating Uncertainty through System Model

Components of life cycle analysis



Which Parameters Drive Outcome?

- Goal: identify parameters that contribute most to **uncertainty** in outputs in highly **non-linear** systems with **large variations**.
 - Sensitivity Analysis Methods:
 - Local Sensitivity Analysis
 - Analysis of Variance (ANOVA)
 - Linear Correlation Coefficients
 - Rank Correlation Coefficients
 - Fourier Amplitude Sensitivity Test (FAST)
 - Deterministic Equivalent Modeling Method (DEMM)
 - Sobol's Method
- Assuming linearity*
- Assuming monotone*
- Variance based, global*

Linearity Based Methods

- Local sensitivity analysis

- Function $Y = g(\underline{x}, \underline{\theta})$ is sufficiently smooth near the point $(\eta_{\underline{\theta}})$.

$$\sigma_y^2 = \sum_{i=1}^p \left(\frac{\partial g}{\partial \theta_i} \Big|_{\eta_{\underline{\theta}}} \right)^2 \sigma_{\theta_i}^2 + \sum_{i=1}^p \sum_{j=1, j \neq i}^p \left(\frac{\partial g}{\partial \theta_i} \Big|_{\eta_{\underline{\theta}}} \right) \left(\frac{\partial g}{\partial \theta_j} \Big|_{\eta_{\underline{\theta}}} \right) r_{ij} \sigma_{\theta_i} \sigma_{\theta_j}$$

Contribution to variance if no correlation

- ANOVA

- Variance of the output is decomposed into partial variances of increasing dimensionality
- Based on linear regression: System satisfies the Gauss-Markov Conditions → Outputs are normally distributed

$$Y_{i_1 i_2 i_3} - Y_g = \sum_{k=1}^3 M_{i_k} + \sum_{k=1, 3 > j > k}^3 M_{i_k i_j} + M_{i_1 i_2 i_3}$$

Averaged over three factors Average of Y Decomposed contribution of one factor, two factors, and three factors

Correlation Methods

- Linear Correlation Coefficients

- Ratio of contribution to standard deviation to Y by θ_i alone and contribution of θ_i along with other θ_j s.

$$\rho_{\theta,Y} = E \left[\left(\frac{\theta - \mu_\theta}{\sigma_\theta} \right) \left(\frac{\theta - \mu_Y}{\sigma_Y} \right) \right] \quad \therefore \rho_{\theta,Y} = \frac{x_i \sigma_{\theta_i} + \sum_j x_j \frac{Cov(\theta_i, \theta_j)}{\sigma_{\theta_j}}}{\sigma_Y}$$

- Rank Correlation Coefficients

- Rank-based rather than value based.
- No assume of linearity, but monotone.

$$r_s = \frac{\sum_{i=1}^n \left(\text{rank}(x_i) - \frac{n+1}{2} \right) \left(\text{rank}(y_i) - \frac{n+1}{2} \right)}{\frac{n(n+1)(n-1)}{12}}$$

Variance Based Methods

- Similar to ANOVA, decompose variance into contributions by factors individually and collectively
 - No assumption of linearity or monotone
 - Model independent
 - Global
 - Example: One factor alone
- Fourier Amplitude Sensitivity Test (FAST)
 - Using a single variable search curve is used to cover the multidimensional space of the input factors

$$\eta^2 = \frac{\text{Var}_x \text{E}[Y | X]}{\text{Var}[Y]}$$

Transformation of inputs

$$\theta_l = F_l(\sin \omega_l s), \quad l = 1, 2, \dots, p$$

Transformation of output

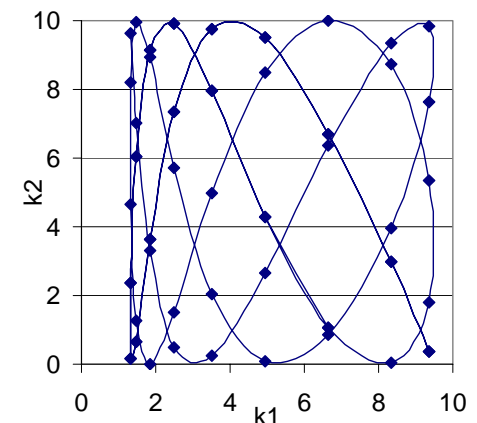
$$Y = \sum_{i=-\infty}^{\infty} \left[A_i(\underline{x}) \cos is + B_i(\underline{x}) \sin is \right].$$

Variance of Y

$$\sigma_Y^2 = 2 \sum_{i=1}^{\infty} \left\{ A_i^2(\underline{x}) + B_i^2(\underline{x}) \right\}$$

Contribution of factor ω_i

$$\sigma_{\omega_i}^2 = 2 \sum_{p=1}^{\infty} \left\{ A_{p\omega_i}^2(\underline{x}) + B_{p\omega_i}^2(\underline{x}) \right\}$$



Deterministic Equivalent Modeling Method

- Directly approximating distribution of Y by a polynomial expansion

Transformation of inputs $\underline{\theta} = \underline{\theta}(\{\xi_i(\omega)\})$

Transformation of output $\hat{g}(\underline{\theta}) = \sum_{j=1}^N a_j Z_j(\{\xi_i(\omega)\})$

Decomposition of Output

$$\begin{aligned}
 \hat{g}(\theta_1, \dots, \theta_p) = g(\theta_1(\xi), \dots, \theta_p(\xi)) &= g_0 + \underbrace{\sum_{i=1}^p g_{i1} L_1(\xi_i)}_{\text{linear}} + \underbrace{\sum_{i=0}^p g_{i2} L_2(\xi_i)}_{\text{2nd order}} + \underbrace{\sum_{i=0}^p \sum_{j < i} g_{i1j1} L_1(\xi_i) L_1(\xi_j)}_{\text{bilinear}} \\
 &+ \underbrace{\sum_{i=0}^p g_{i3} L_3(\xi_i)}_{\text{3rd order}} + \underbrace{\sum_{i=0}^p \sum_{j=1}^{i-1} g_{i2j1} L_2(\xi_i) L_1(\xi_j)}_{\text{2nd order in } \xi_i, \text{ 1st in } \xi_j} + \underbrace{\sum_{i=0}^p \sum_{j=1}^{i-1} g_{i1j2} L_1(\xi_i) L_2(\xi_j)}_{\text{1st in } \xi_i, \text{ 2nd in } \xi_j} \\
 &+ \underbrace{\sum_{i=0}^{p-2} \sum_{j=i+1}^{p-1} \sum_{k=j+1}^p g_{i1j1k1} L_1(\xi_i) L_1(\xi_j) L_1(\xi_k)}_{\text{trilinear}} + \text{higher order terms}
 \end{aligned}$$

- Calculating coefficients by forcing error of expansion at collocation points to zero or minimizing error over whole space of inputs

Sobol's Method

- Integrating over other factors to obtain contribution of each factor

$$D_{i_1 \dots i_s} = \int_0^1 \dots \int_0^1 g_{i_1 \dots i_s}^2(\theta_{i_1} \dots \theta_{i_s}) f_{\theta_{i_1} \dots \theta_{i_s}}(\theta_{i_1} \dots \theta_{i_s}) d\theta_{i_1} \dots d\theta_{i_s} \quad \text{Factor } \theta_{j \neq 1 \dots i_s} \text{ are fixed.}$$

$$S_{i_1 \dots i_s} = \frac{D_{i_1 \dots i_s}}{D}$$

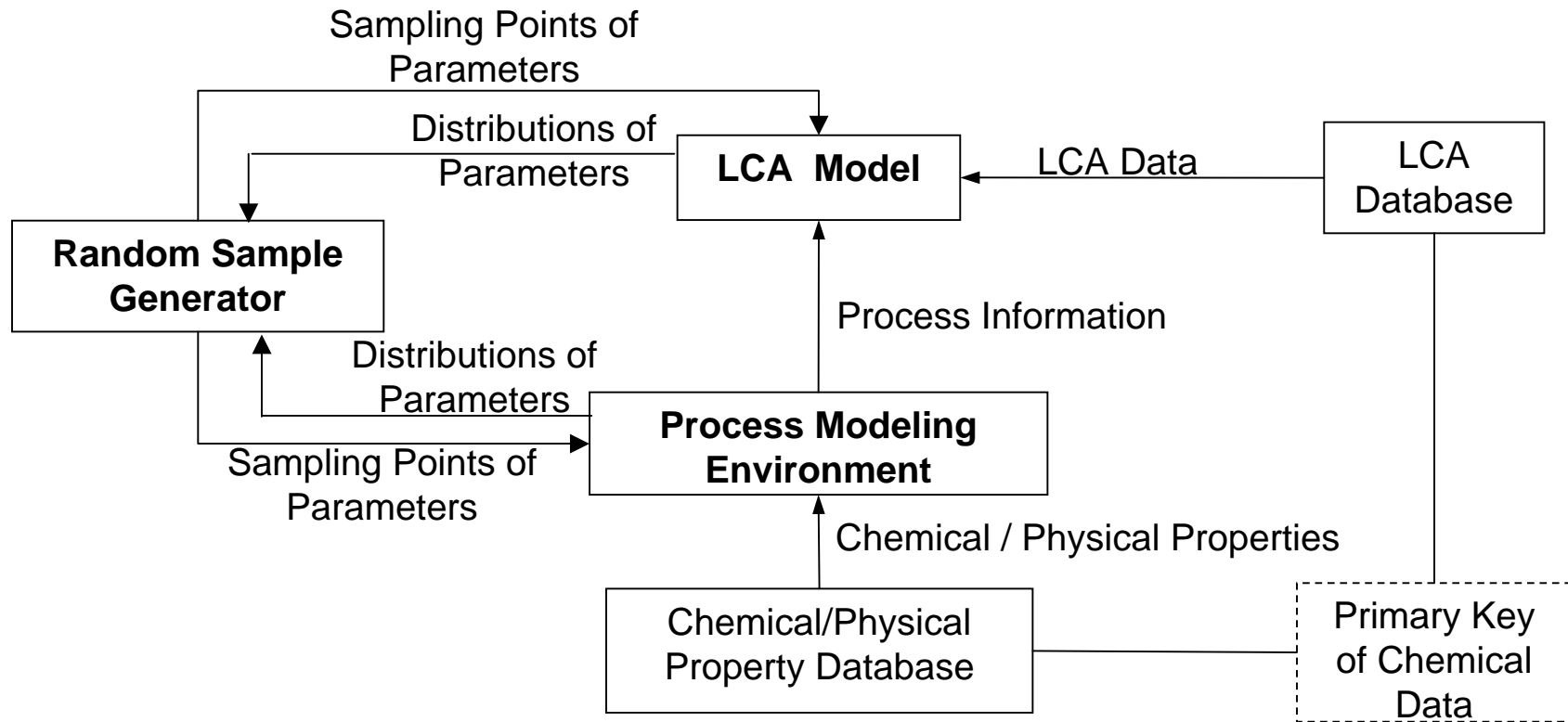
Global Sensitivity Indices (GSI) $S_{Ti} \equiv S_i + S_{i,ci} = 1 - S_{ci}$

- GSI – total effect of variable θ_j , including fraction of variance accounted for by θ_j alone and fraction accounted for by any combination of θ_j with remaining factors

Comparison of Methods

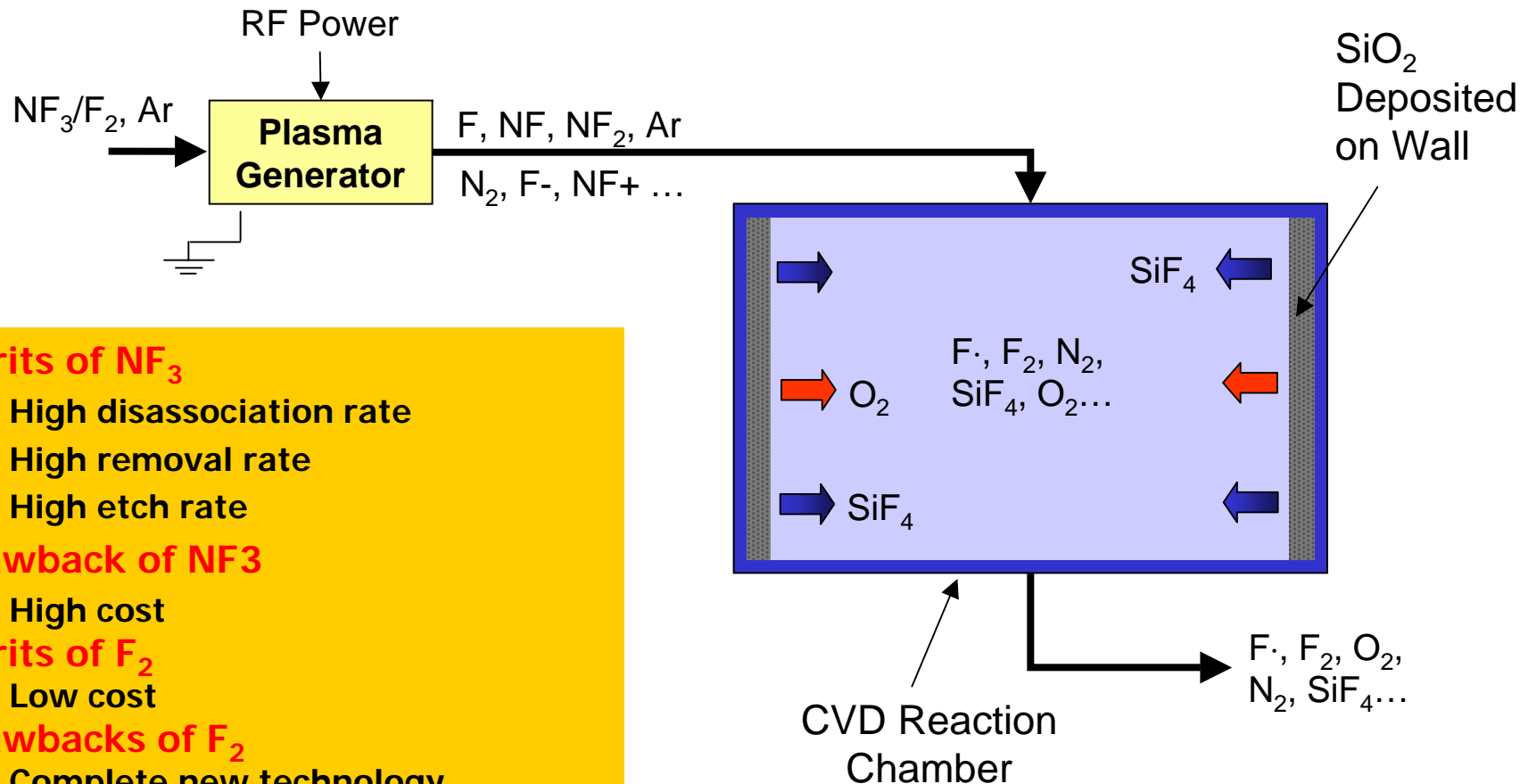
- Capturing global response with wide variation – variance based methods
- Easiness to implement -- correlation methods
- Suggestion: to use correlation methods as a starting point for many inputs, then to use variance based methods for detailed, quantitative analysis.

Integration of Software for LCA and Process Modelling

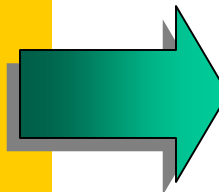


- Advantages of this integrated system:
 - Reduced cost and time for developing a process modelling environment that is compatible with LCA from scratch.
 - Allows uncertainty analysis on both the LCA models, economic models (not shown here), and process models.

Case Study: Clean Chamber with NF_3 or F_2 ?



- **Merits of NF_3**
 - High disassociation rate
 - High removal rate
 - High etch rate
- **Drawback of NF_3**
 - High cost
- **Merits of F_2**
 - Low cost
- **Drawbacks of F_2**
 - Complete new technology
 - High toxicity
 - High reactivity
 - On-site generation creates explosive H_2



Compare Life cycle impacts for the same cleaning performance

Modeling of Chamber Cleaning Processes

Driving forces of LCA impacts: Cleaning gas usages

Energy consumptions

Cleaning Gases

$$N_{NF_3} = \frac{4 N_{SiO_2}}{3 F \%_{NF_3}}, \quad N_{F_2} = \frac{2 N_{SiO_2}}{F \%_{F_2}}$$

Energy

$$E_{NF_3} = \frac{N_{SiO_2} E_{b-NF_3}}{F \%_{NF_3} \xi_{E-NF_3}} + tP_{plasma}, \quad E_{F_2} = \frac{N_{SiO_2} E_{b-F_2}}{F \%_{F_2} \xi_{E-NF_3}} + tP_{plasma}$$


where for NF_3 cleaning

$$F \%_{NF_3} = (4 \cdot N_{SiF_4} + N_{HF}) / (3 \cdot N_{NF_3}) \cdot 100 \%$$

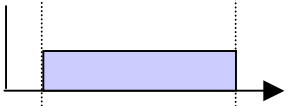
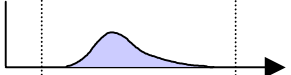
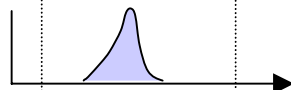
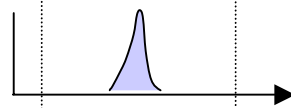
for F_2 cleaning

$$F \%_{F_2} = (4 \cdot N_{SiF_4} + N_{HF}) / (2 \cdot N_{F_2}) \cdot 100 \%$$

- Little process specific information is known for fluorine yield $F\%$, energy yield ξ_E , and cleaning time t .

What to do 

Process Modeling Hierarchy and Resource Needs

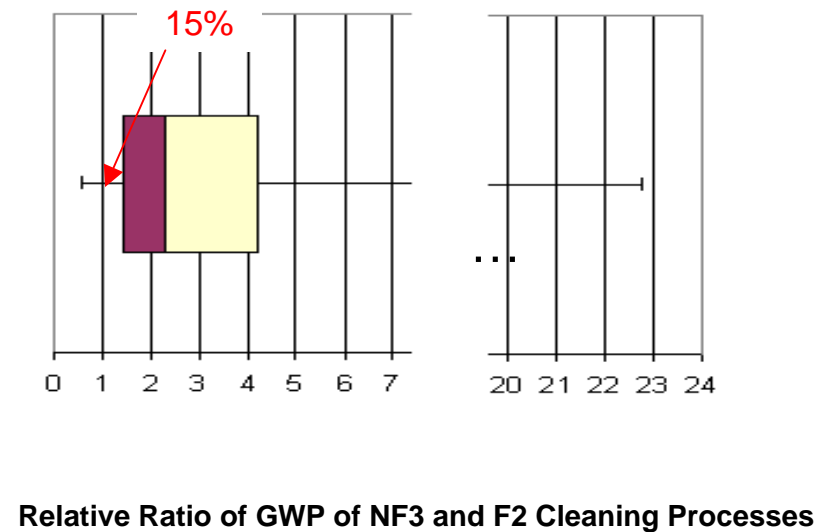
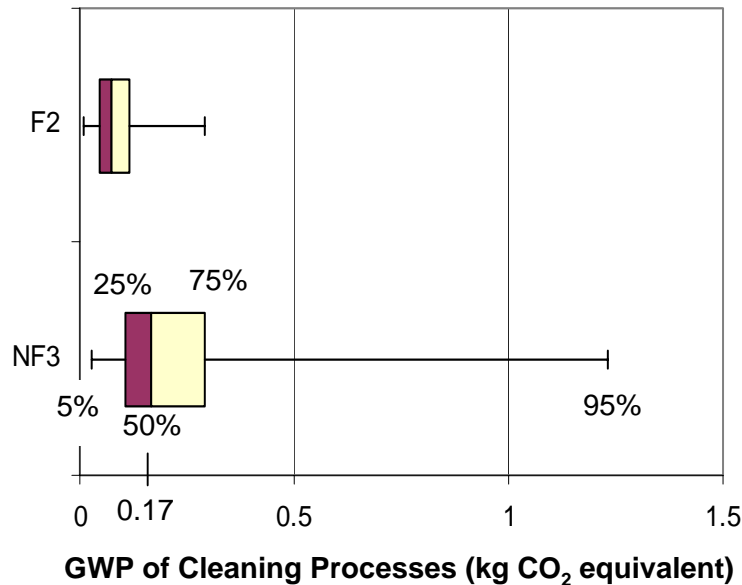
Process Model Hierarchy		Distributions of Yield	Resources Needed
1	Simple stoichiometric yield		1
2	Lumped kinetics (3 reactions)		10
3	Detailed kinetics (60 reactions)		100
4	Model based experiments		1000

Distributions Used in Process and LCA

- Fluorine Utilization Yield
 $F\% \sim \text{uniform}(10^{-5}, 0.6)$
- Energy Utilization Yield
 $\xi_E \sim \text{uniform}(10^{-10}, 0.6)$
- Cleaning Time
 $t(\text{s}) \sim \text{uniform}(6E^{-4}, 1200)$
- Examples of distributions of other variables
 - Environmental impact characterization factors:
 Lognormal, normal
 - Upstream resources consumption factors
 Lognormal, normal, triangular

Environmental Impacts from LCA

- Comparison of the global warming potentials (GWP) of the two processes



We can be 85% sure that the F₂ cleaning has lower a global warming impact than the NF₃ cleaning.

Do we still need a more detailed model?

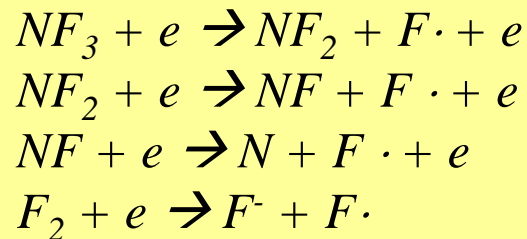
Important Parameters of Affecting Relative GWP

Parameter	Spearman Rank Correlation Coefficient
Fluorine Yield of NF_3 Cleaning	-0.64
Fluorine Yield of F_2 Cleaning	0.46
Cleaning Time t (s)	-0.28
Energy Yield of NF_3 Cleaning	-0.20
Energy Yield of F_2 Cleaning	0.12
NF_3 Yield in NF_3 Production from NH_3 and HF	-0.11
H_2S Emission from Oil-Fired Power Plant (kg/ kW-h Energy)	-0.083
Electricity Used in Diesel Fuel Production (MJ/kg)	0.078
GWP of $\text{C}_2\text{H}_3\text{Cl}_3$ (kg CO_2 equivalent/kg)	0.067
GWP of CH_2Cl_2 (kg CO_2 equivalent/kg)	0.061

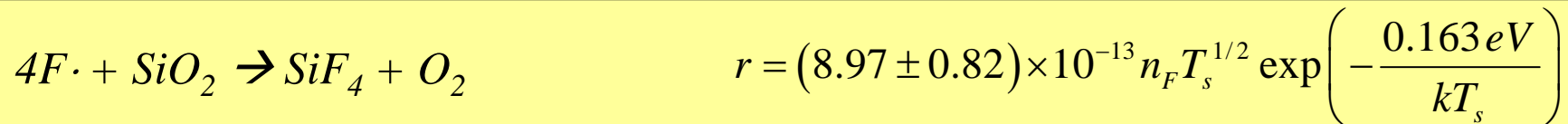
If we need more precise results,
process model need to be refined!

Hierarchical Modeling – 2nd Process Modeling Level

- Lumped kinetics and Perfectly Stirred Tank Reactor model
- Key assumptions
 - Free electrons are generated mainly by ionization $\text{Ar} + e \rightarrow \text{Ar}^+ + 2e$
 - Electron loss and production are linear to electron concentration
 - Diffusion of electrons dominates the transport of electrons.



$$\begin{aligned} k_3 &= 2.06E^{-17} T_e^{1.7} \exp(-37274/T_e) \\ k_2 &= 1.57E^{-17} T_e^{1.8} \exp(-27565/T_e) \\ k_1 &= 1.57E^{-17} T_e^{1.8} \exp(-27565/T_e) \\ k &= 1.02E^{-5} T_e^{-0.9} \exp(1081.8/T_e) \end{aligned}$$

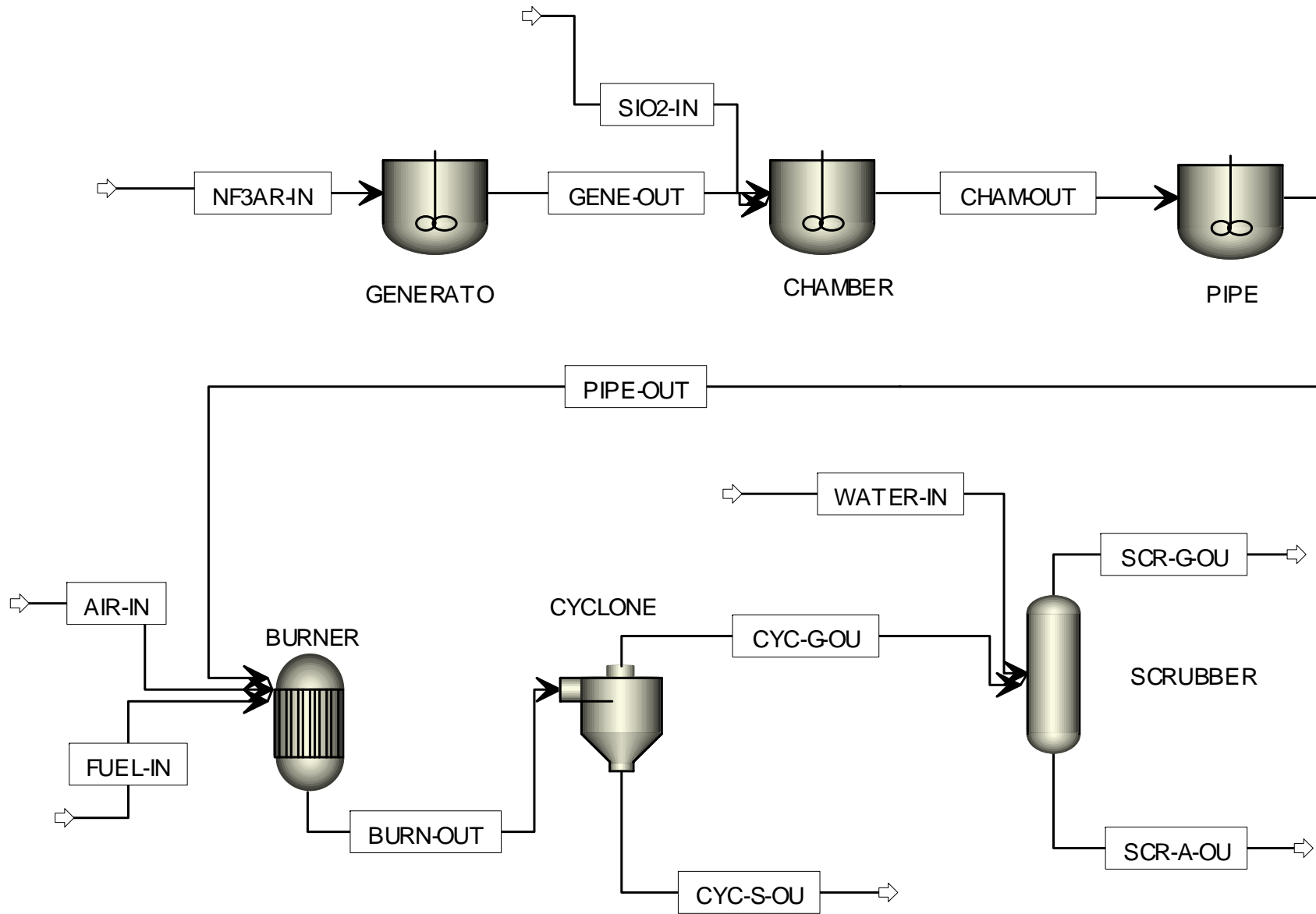


$$n_{F, \text{NF}_3} = \frac{\beta_3 \tau n_{\text{NF}_3, \text{in}}}{1 + \beta_3 \tau} + \frac{\beta_2 \beta_3 \tau^2 n_{\text{NF}_3, \text{in}}}{(1 + \beta_2 \tau)(1 + \beta_3 \tau)} + \frac{\beta_1 \beta_2 \beta_3 \tau^3 n_{\text{NF}_3, \text{in}}}{(1 + \beta_1 \tau)(1 + \beta_2 \tau)(1 + \beta_3 \tau)}$$

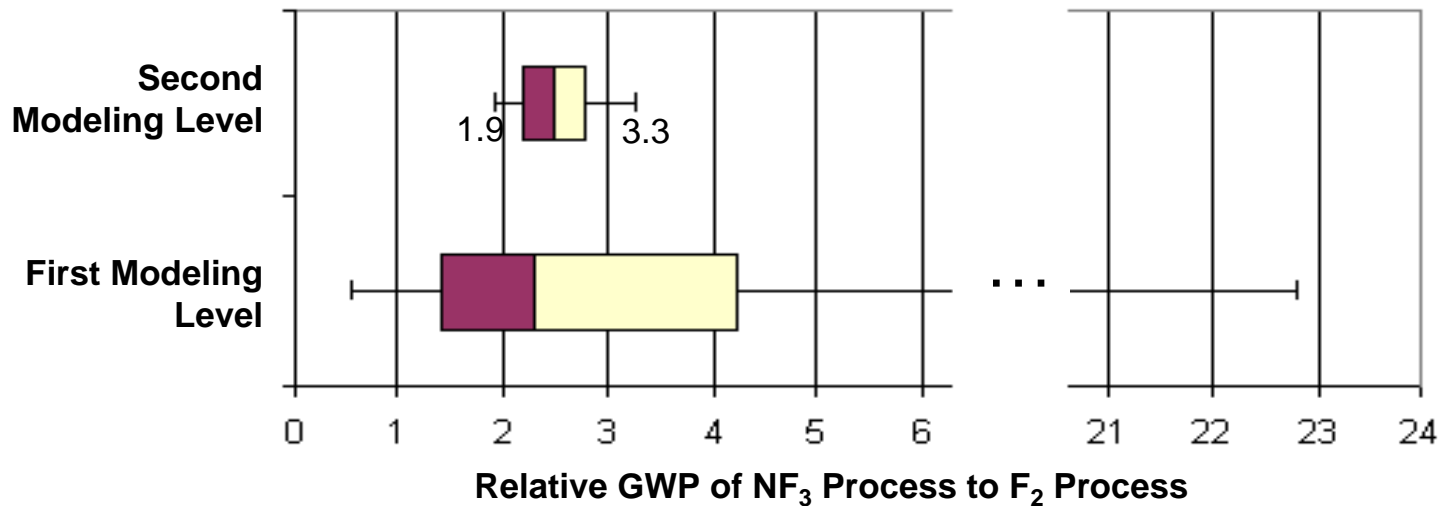
$$n_{F, \text{F}_2} = \frac{\beta_{\text{F}_2} \tau n_{\text{F}_2, \text{in}}}{1 + \beta_{\text{F}_2} \tau}$$

$$\beta_i \equiv k_i n_e$$

Aspen Plus Flow Sheet with Downstream Treatment

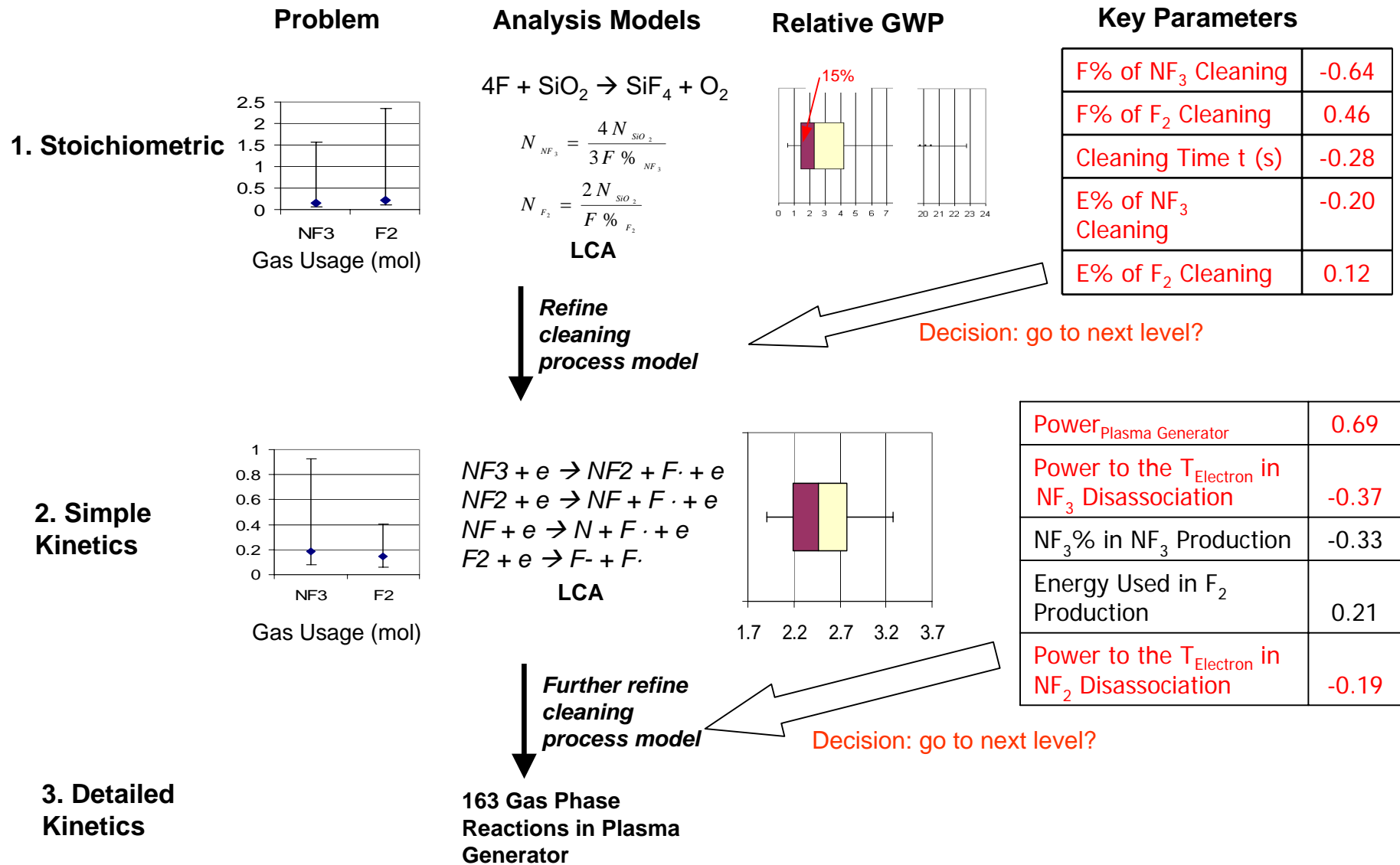


Relative Impact of GWP at 2nd Process Modeling Level

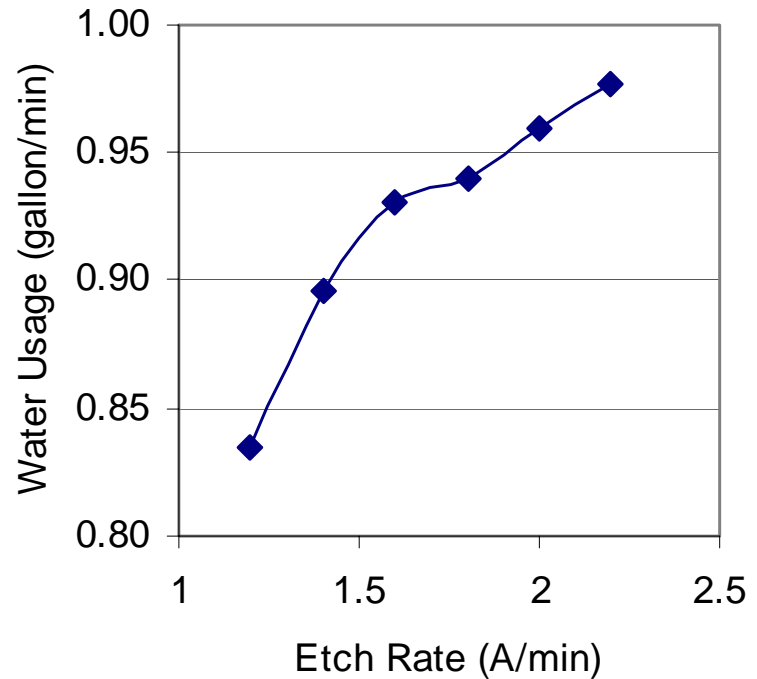
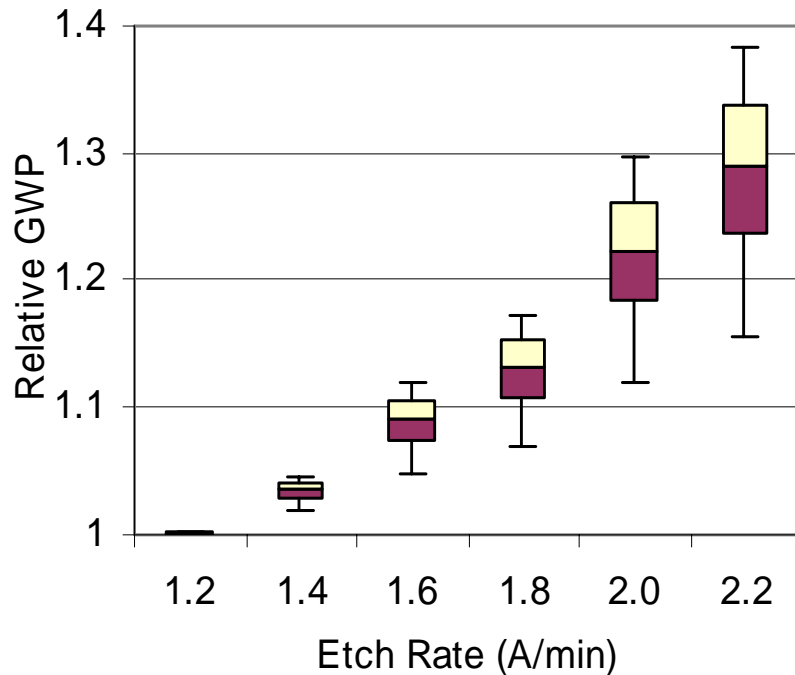


- 2~3 orders of magnitude of uncertainties in inputs does not necessarily lead to low confidence in decision
- Increase of modeling detail decreases the uncertainty of the outputs
- **But the decision is still the same – F₂ is better!**
- **Required confidence level should determine depth of analysis**

Hierarchical Modeling Can Save Time and Money



Integrated System Support Process Design



- Integrated system can also be used for studying how process design influences environmental impacts, downstream treatment design, and etc.

Conclusions

- Large uncertainty in the inputs does not necessarily lead to low confidence in decisions.
- Hierarchical modeling in combination with uncertainty analysis are efficient ways to support the decision making and resource allocation process.
- Integrated evaluation system facilitates the integration of environmental, economical, and technical evaluations.

UNCERTAINTY \neq IGNORANCE

Acknowledgement

- Laura Losey, David Bouldin, Mike Kasner, Tim Yeakley, and Tina Gilliland – **Texas Instruments**
- Larry Novak – **Novak Consulting, LLC**
- Alejandro Cano-Ruiz and Pauline Ho – **Reaction Design**
- Daren Dance – **WWK**
- Joe Van Gompel – **BOC Edwards**
- Holly Ho – **TSMC, Taiwan**
- ERC – **Funding**