Intelligent Product Manufacture Through Synergistic Interactions Among Modeling, Sensing and Learning

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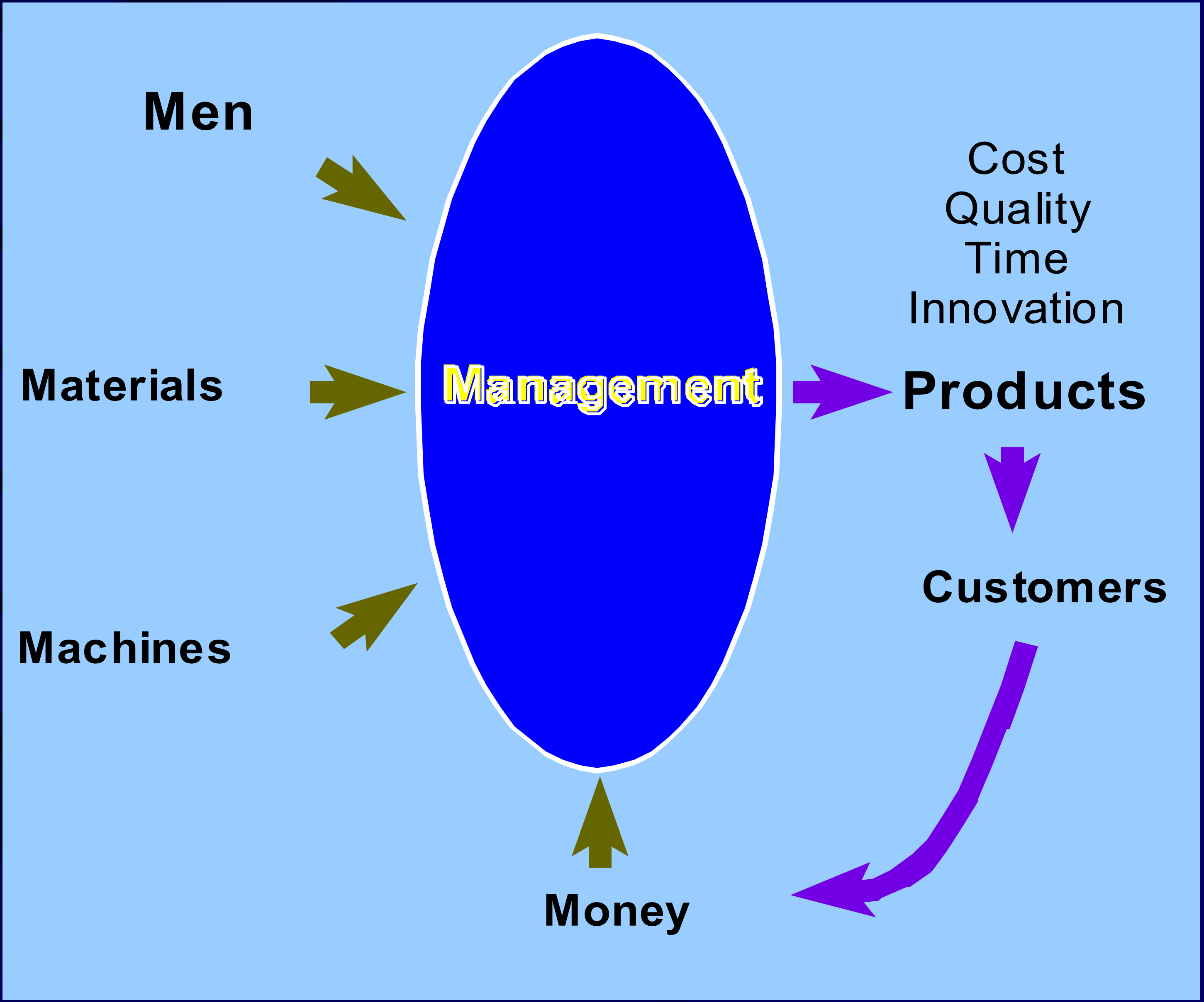
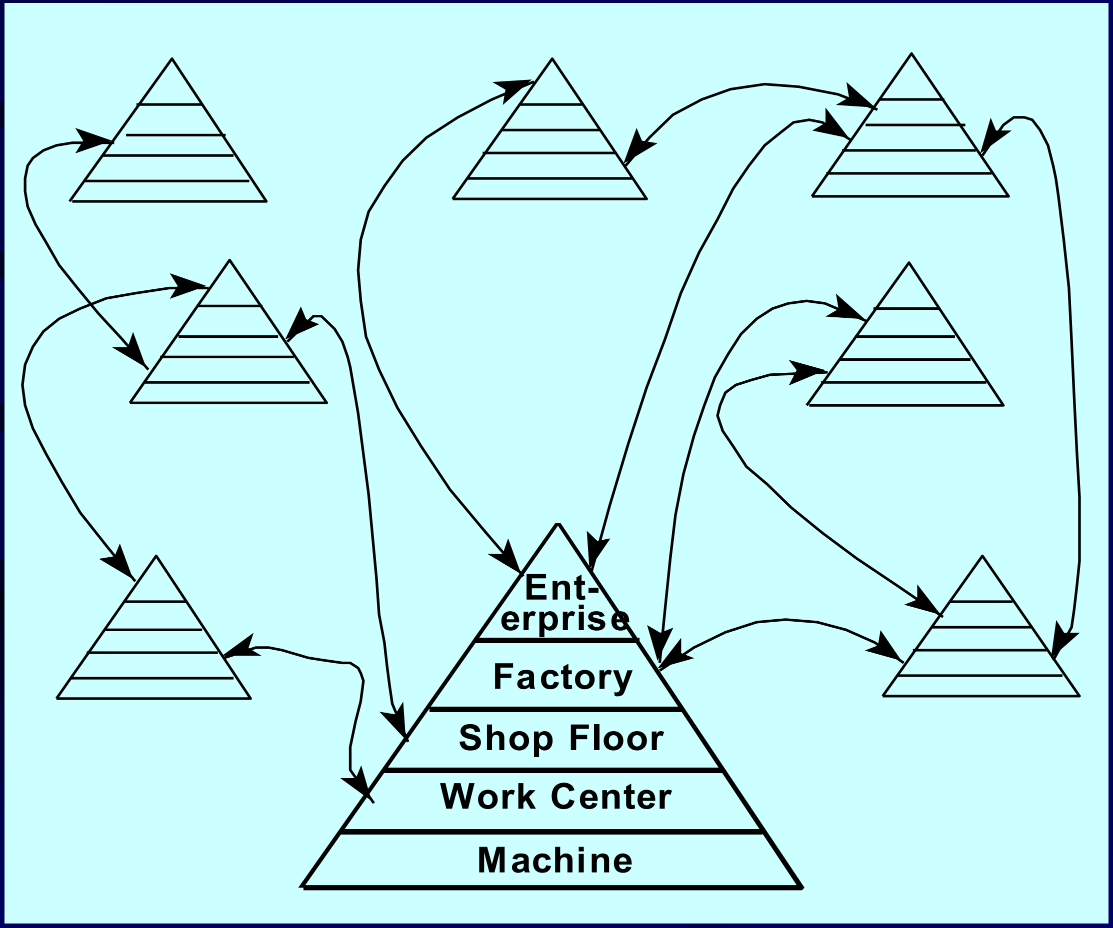
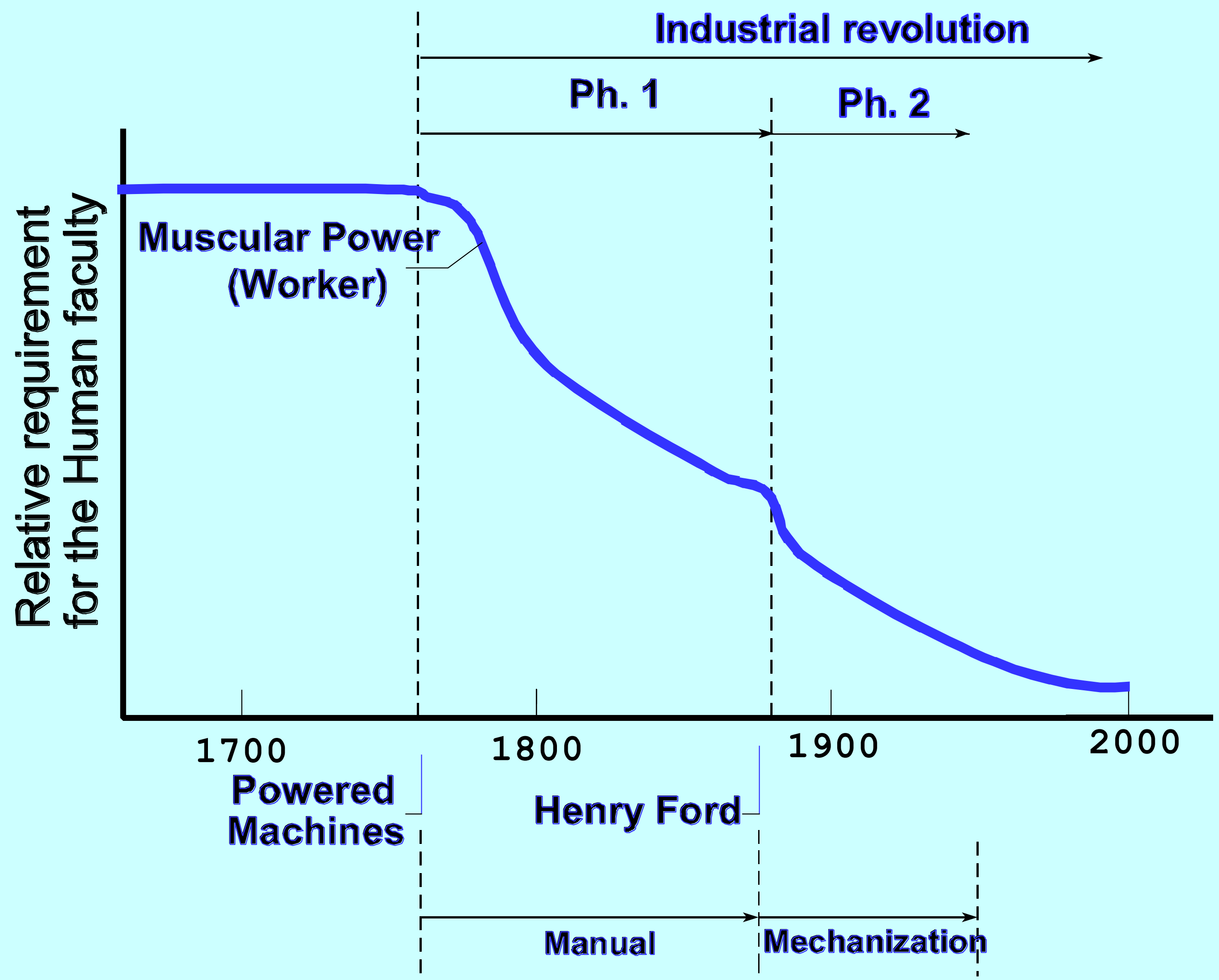

Men
Materials
Machines
Management
Money
Cost
Quality
Time
Innovation
Products
Customers

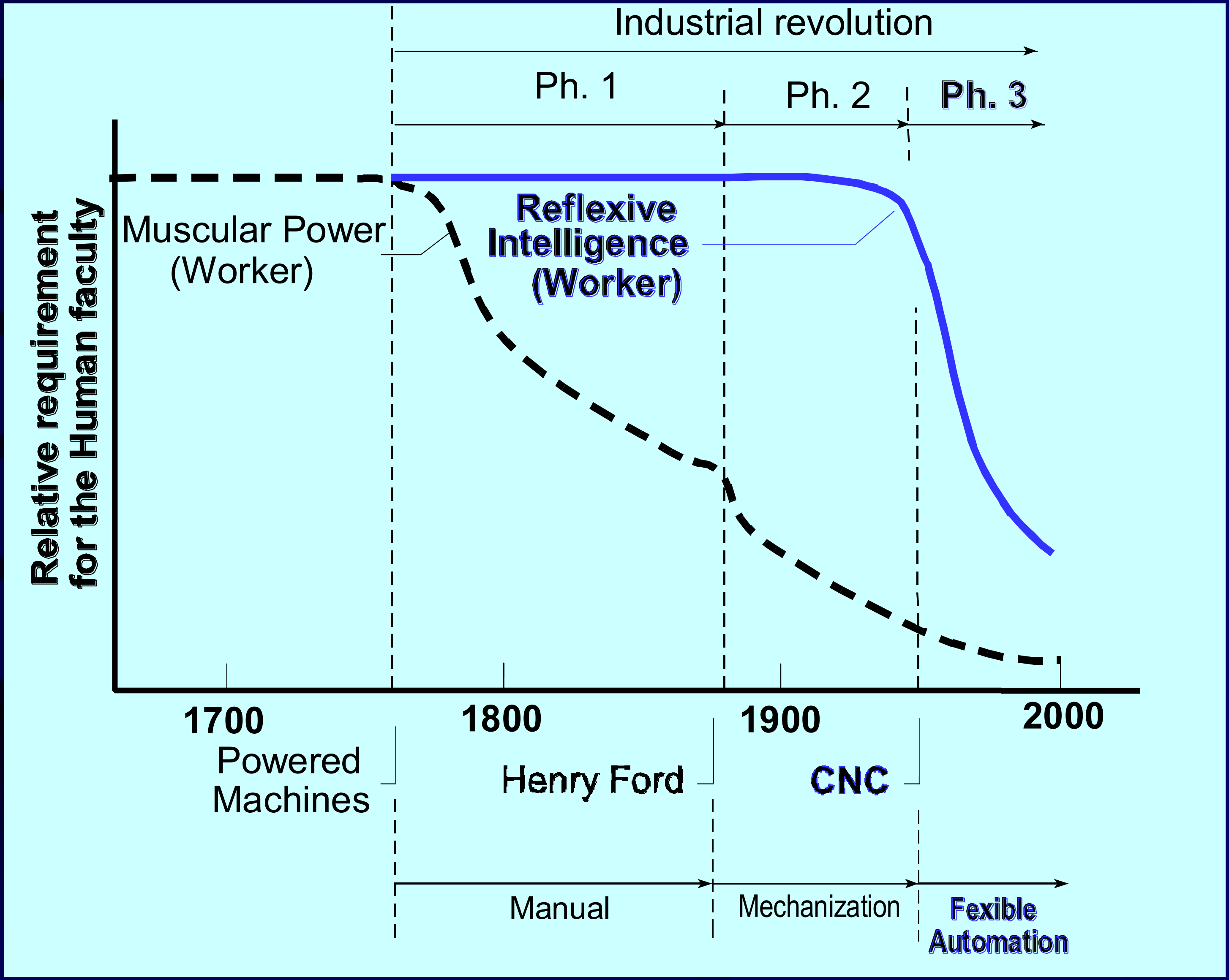
Organization of Modern Manufacture




Industrial revolution
Ph. 1
Ph. 2
Relative requirement for the Human faculty
Muscular Power (Worker)
1700
1800
1900
2000
Powered Machines
Henry Ford
Manual
Mechanization

Reflexive Intelligence

- Human workers need to possess the dexterity to perform manual operations and control machines.
- Human dexterity involves the application of human sensorimotor skills that, in turn, requires the application of human reasoning (intelligence) that is sub-conscious, non-deliberate, or reflexive.



Industrial revolution
Ph. 1
Ph. 2
Ph. 3
Relative requirement for the Human faculty
Muscular Power (Worker)
Reflexive Intelligence (Worker)
1700
1800
1900
2000
Powered Machines
Henry Ford
CNC
Manual
Mechanization
Fexible Automation

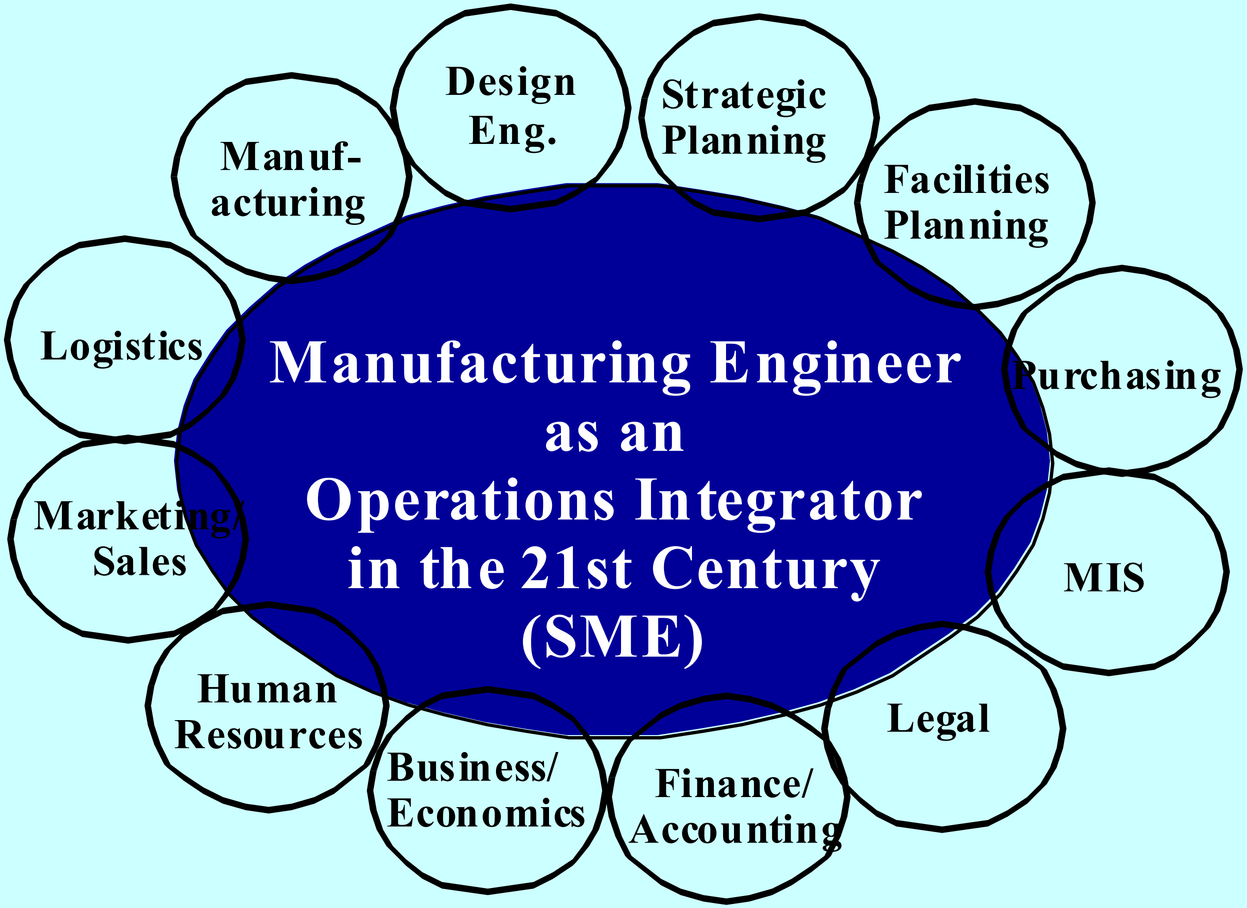
Reflective Intelligence

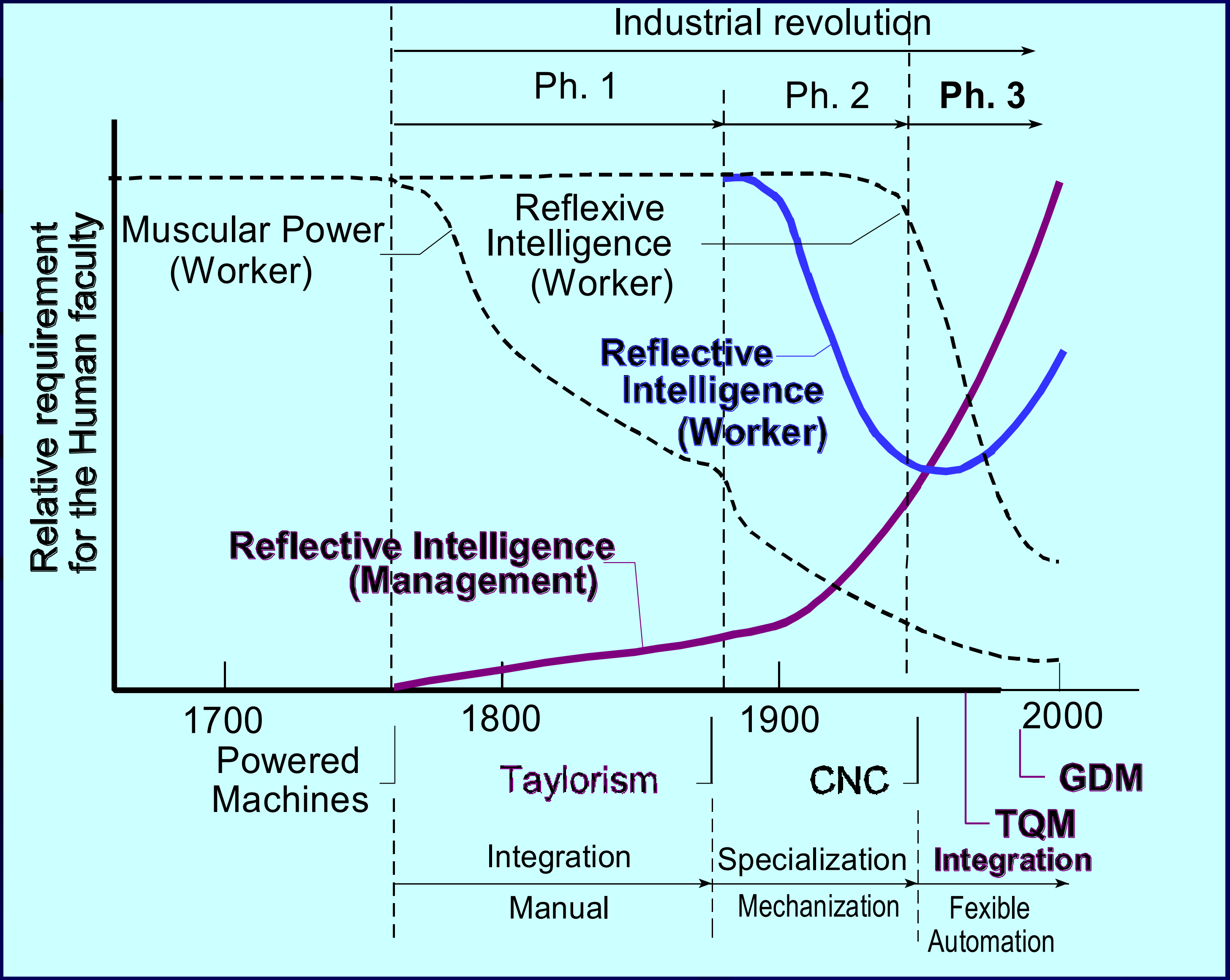
- Application of higher levels of reasoning in a conscious, deliberate, and reflective manner.
- Qualitative models (cause-effect models, explanation-based reasoning, case-based reasoning, etc.) and quantitative models.
- Use of standards, handbooks.
- Brain storming, consultation, etc.

Events leading to greater demand for reflective intelligence

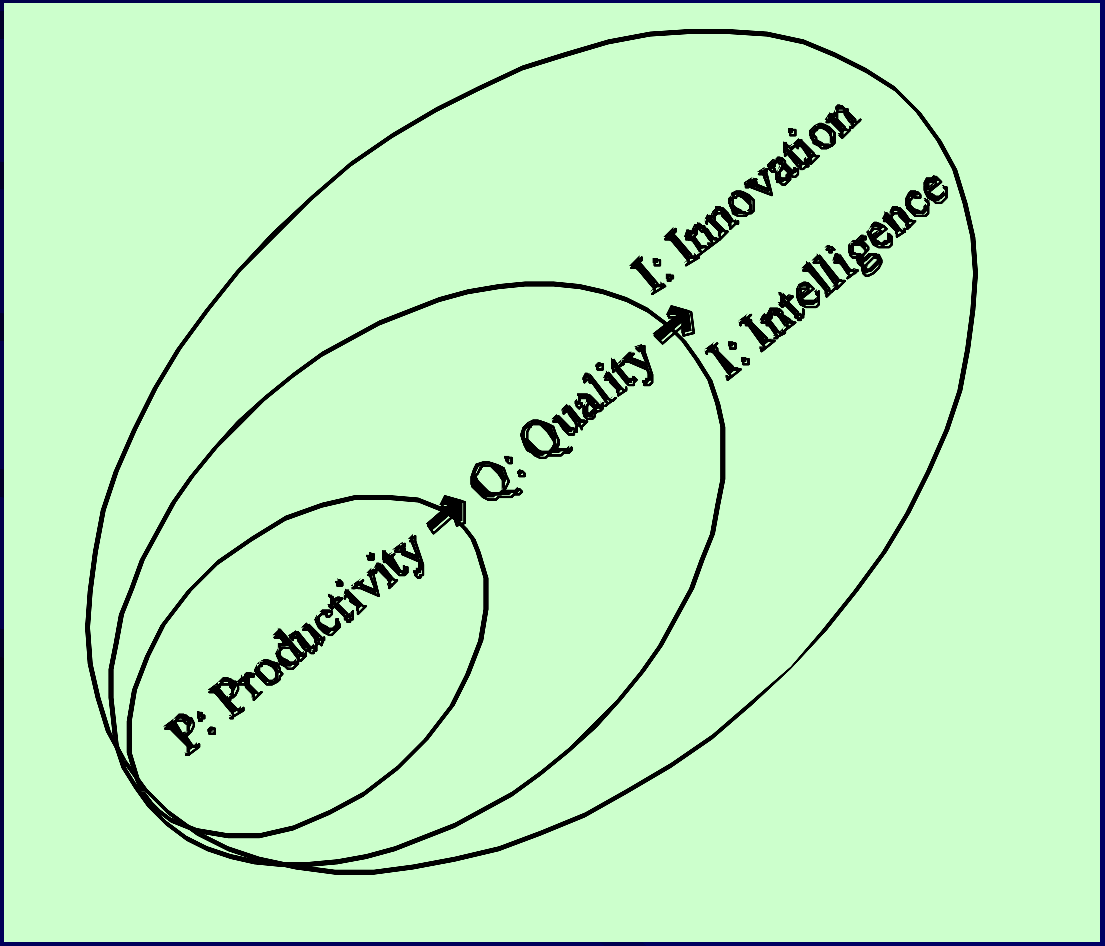
- F.W. Taylor, the acknowledged ‘Father of Scientific Management’ realized this need and suggested that "[T]he management take over all work for which they are better fitted than the workmen, while in the past all of the work and the greater part of the responsibility were thrown upon the men."

- FMS, Agile manufacture, unmanned manufacture
- Total Quality Management, QCC, ISO 9000
- Globally distributed manufacture, Internet
- Increased global competition
- Customer is the hub of the manufacturing wheel (SME wheel)


Manufacturing Engineer
as an
Operations Integrator
in the 21st Century
(SME)
Design
Eng.
Strategic
Planning
Facilities
Planning
Purchasing
MIS
Legal
Finance/
Accounting
Business/
Economics
Human
Resources
Marketing/
Sales
Logistics
Manuf-
acturing


Industrial revolution
Ph. 1
Ph. 2
Ph. 3
Relative requirement for the Human faculty
Muscular Power (Worker)
Reflexive Intelligence (Worker)
Reflective Intelligence (Worker)
Reflective Intelligence (Management)
1700
1800
1900
2000
Powered Machines
Taylorism
CNC
GDM
TQM
Integration
Specialization
Integration
Manual
Mechanization
Fexible Automation

The Maturing of an Industrial Region



In 1963, Turing anticipated that an intelligent computer must be

"kind, resourceful, beautiful, friendly, have initiative, have a sense of humour, tell right from wrong, make mistakes, fall in love, enjoy strawberries and cream, make someone fall in love with it, learn from experience, use words properly, be the subject of its own thought, have as much diversity of behaviour as man, [and] do something really new."

Alternative Views on AI within the AI Community

- Mind is logic [McCarthy et al].
- Mind is a connectionistic network [Rumelhart and McClelland].
- Mind is conceptualization [Schank].
- Mind is rule-chunking [Newell et al].
- Mind is connectionism and conceptual dependency [Minsky].

Manufacturing Engineer’s View of AI

- “The study of ways in which computers can be made to perform tasks which require intelligence if performed by humans.” [Flach ’91]
- Use AI to either automatically perform or significantly assist human workmen and engineers in performing the myriad manufacturing tasks that typically require human intelligence.
- The subject matter of AI is the computer rather than the human mind.

AI Bag of Tools

Genetic Algorithms

Knowledge Based Systems (KBS)

Agent Theory

Case Based Reasoning (CBR)

Semantic Networks

Emergent Behavior

Frames

Explanation Based Reasoning

Artificial Neural Nets (ANN)

Expert Systems

Object Oriented Modeling

MEs prefer to identify AI with the functionality it provides

- AI is learning
- AI is memory organization and access.
- AI is functional constraints plus knowledge analysis.
- AI is scale-up.

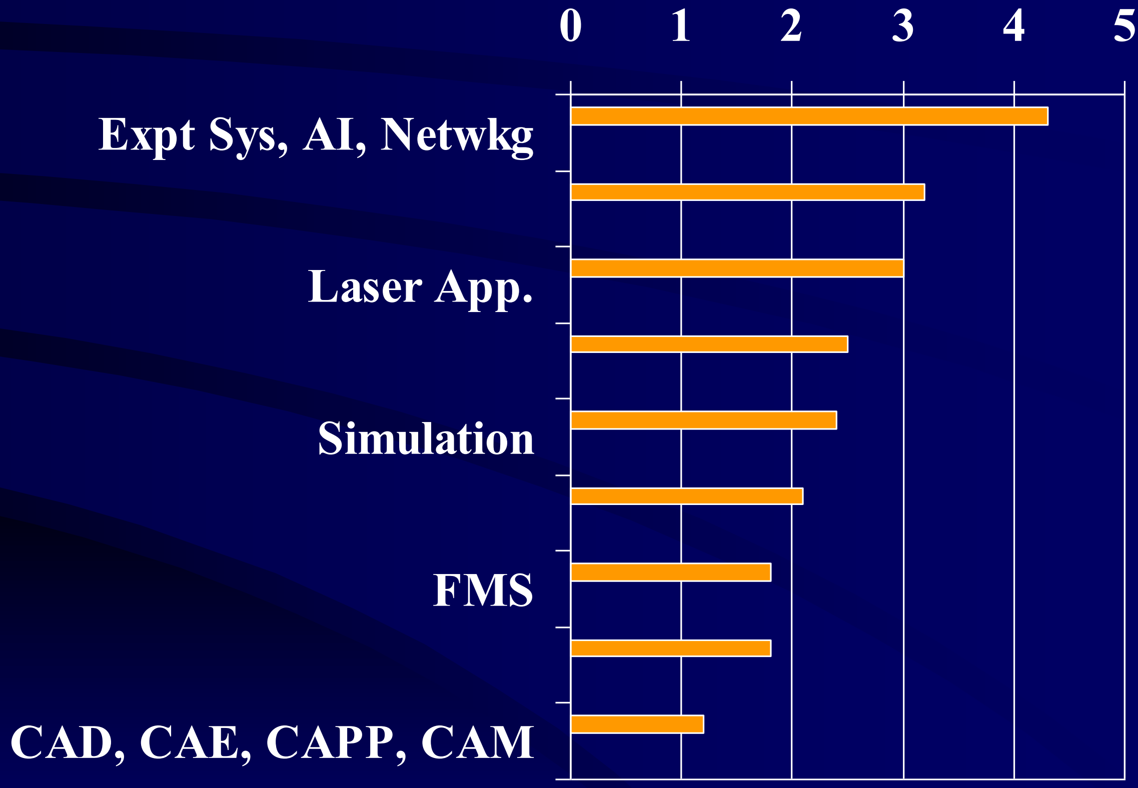
[Schank and Jona, ’94]

Manufacturing Engineers have been interested in AI

- Hatvany (‘83) had noted the non-deterministic nature of manufacturing systems and stated that AI had the potential to transform such a system into an intelligent system that is “capable of solving, within certain limits, unprecedented, unforeseen problems on the basis even of incomplete and imprecise information.”

- 1985, 87, 89: CIRP seminars on AI in manufacturing in Dubrovnik.
- 1992: Yoshikawa observed that intelligent techniques had became one of the most important fields of manufacturing automation.
- 1993: Merchant identified expert systems, neural networks and smart sensors as the most promising.
- 1996: Monostori's keynote paper at CIRP cited 251 papers on machine learning approaches in manufacturing.

Growth Factor of Mfg Tech. (1988-2000) [A.T. Kearney, Inc., 1988]



AI Penetration into Manufacturing

- Very few manufacturing applications have stood up to the ‘scale up’ criterion.
- Considerable interest in learning through the use of artificial neural nets (ANN) and fuzzy logic for applications in control and robotics, AGV navigation, machine diagnostics etc. that mainly require a combination of reflexive intelligence and low level reflective intelligence when performed by human operators.

- Expert systems have been used extensively in the context of higher level manufacturing tasks that require reflective intelligence. However, in most cases the production rules have been derived from the intuition of the system writer rather than on the basis of a rigorous application of knowledge engineering approaches developed by the AI community.
- There is a significant gap with regard to the use of AI in the context of planning tasks at higher levels of manufacturing.

- Solving a problem using sub-symbolic approaches (such as by using a neural net) cannot be called ‘reasoning’. A neural net helps make a decision but it does not explain why, i.e. *it does not give the reason*.
- “It is so patently obvious when you work with experts, namely that they have so much difficulty laying out consistent networks and describing relations among concepts in a principled way” [Winograd ‘94].
- Expert systems can only “replicate mechanical, highly regular actions” [Clancey ‘94].

- Penetration of AI into deep tasks such as planning at higher levels of manufacture has only been ‘skin deep’ so far.
- Manufacturing engineers need to explore more vigorously the application of symbolic approaches such as explanation-based reasoning (EBR) and case-based reasoning (CBR).

Holonic Manufacturing Systems (HMS): The Society of Manufacture

- Koestler (1989) had argued that real life complex systems (e.g. biological systems) are able to function as they do only because they are built from sub-systems that are *autonomous* and *co-operative*.
- In a HMS, these sub-systems are called *holons*.

- Holons can be physical entities or software entities.
- All holons have information processing capabilities. Physical holons have, in addition, a physical processing part.
- A holon by itself need not be complex or intelligent. Complexity and intelligence *emerge* at higher levels through interactions amongst holons at lower levels.
- ”Information which is absent at lower levels can exist at the level of collective activities" [Hofstadter - an AI scientist].

Minsky's "Society of Mind" (1985)

- "[M]ind is made up of many smaller processes.
- These we'll call *agents*.
- Each mental agent by itself can only do simple things that needs no mind or thought at all.
- Yet when we join these agents in societies—in certain special ways—this leads to true intelligence."

What is an Agent?

It is “a self contained problem solver entity (implemented in hardware, software or a mixture of the two) which exhibits a collection of possible properties ranging from autonomy, social ability, responsiveness, proactiveness, adaptability, mobility, veracity, and rationality.”

[Wooldridge and Jennings] (1985)

CASE 1

HOLONIC GEOMETRIC FEATURE RECOGNITION

S.Y. Wong, C.F. Yuen,
and
P. K. VENUVINOD

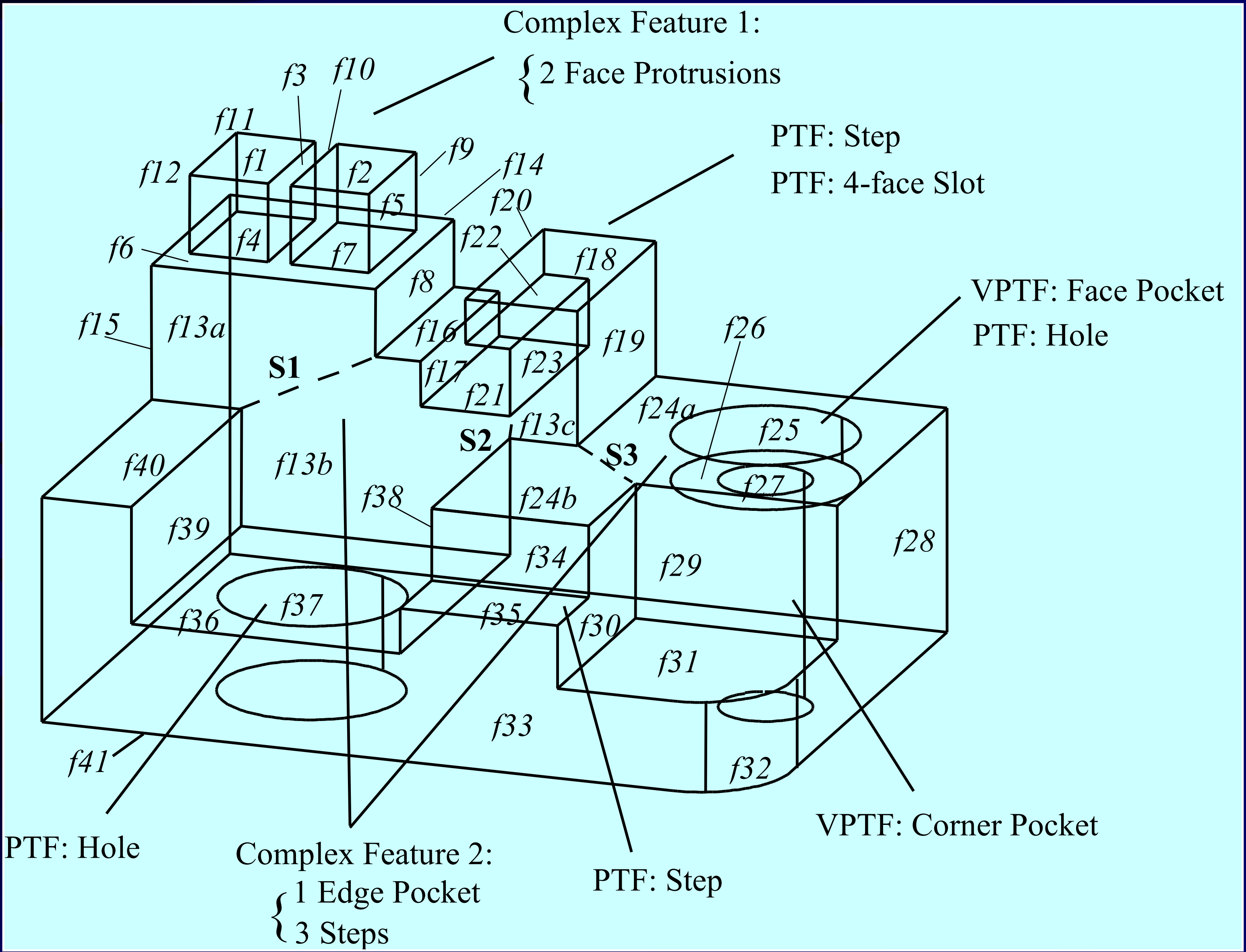
- GFR is regularly required in CAPP, DFM, DFA, Inspection planning, GT, fixture design, etc. : multiple users with varying needs.
- Widely invstigated since the eightees.
- Henderson ’85 devloped rule based expert system for GFR.
- Writing the rules themselves became an expert task.
- A new rule had to be written for each new feature.
- Coping with the infinite variety and complexity of geometric features remained the major problem.

- We entered the field in 1990-91.
- S.Y. Wong developed a method of unambiguously writing the rules from the face-adjacency graph of the feature.
- The problem of a new rule to be written for each new feature remained.
- We tried neural nets and were not satisfied.
- Then we came across Biederman’s work on human cognition of objects through it’s features.

Biederman’s Theory (1985)

- Three ‘geons’—the container, spout, and handle.
- Concave adjacency between each pair of contiguous geons triggers human cognition of the object.

- We then developed a taxonomy of features:
  - Primitive Template Features (PTFs)—atomic features)
  - Variations on PTF (VPTFs)
  - Complex features formed by interactions amongst PTFs and VPTs.
- Algorithms based on concave and (complementary convex) triggering to extract and identify any geometric feature in the polyhedral plus cylindrical domain.


Complex Feature 1:
2 Face Protrusions
f3
f10
f11
f12
f1
f2
f9
f14
f5
f20
f6
f4
f7
f22
f18
f8
f15
f13a
f16
f19
f26
S1
f17
f23
f21
f24a
f25
f13c
S2
S3
f40
f13b
f27
f38
f24b
f39
f28
f34
f29
f37
f35
f36
f30
f31
f33
f41
f32
PTF: Step
PTF: 4-face Slot
VPTF: Face Pocket
PTF: Hole
PTF: Hole
Complex Feature 2:
1 Edge Pocket
3 Steps
PTF: Step
VPTF: Corner Pocket

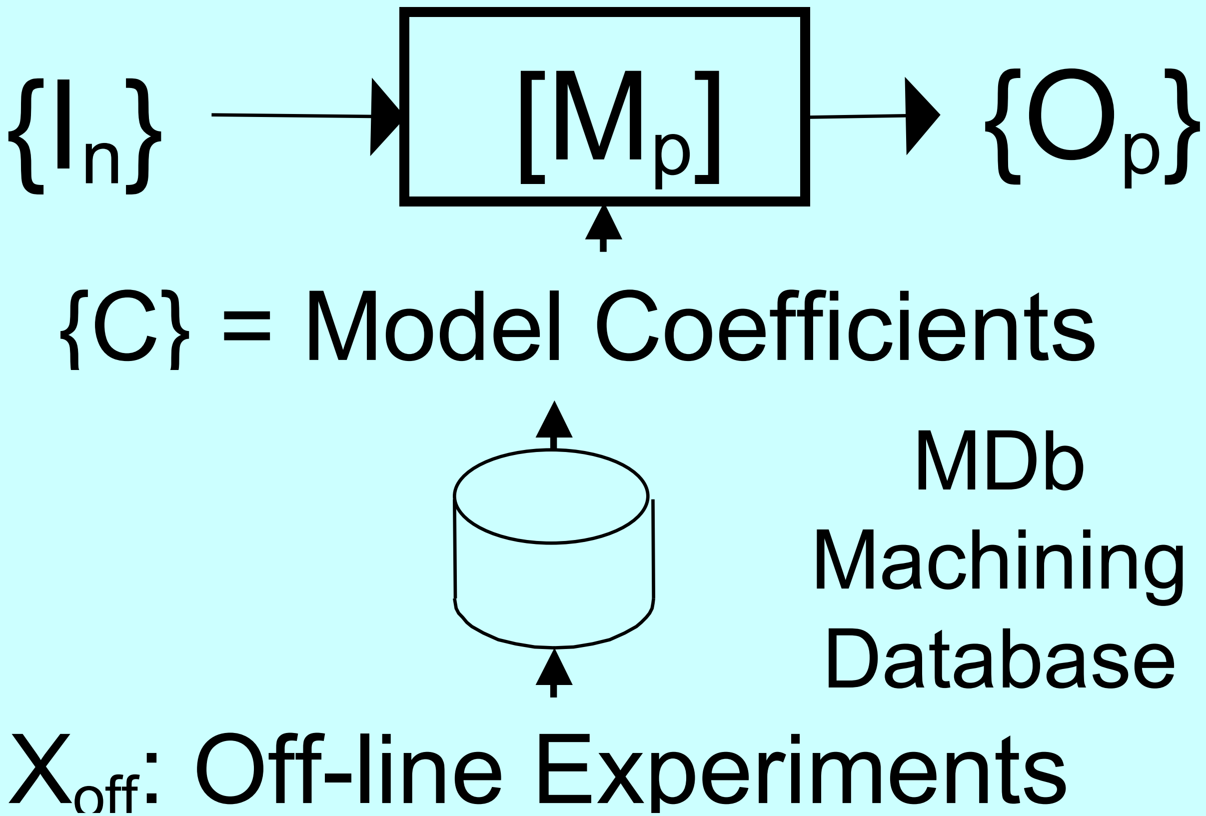
Is this an AI-based approach?

- We have not explicitly used any AI tool.
- But, we have explicitly used heuristics that seem to emulate human cognition of features.
- We then started to develop a holonic GFR system using Object-Oriented programing.

Goal: To satisfy GFR specific Turing Test

- Turing (1963): Shouldn’t be able to distinguish between the intelligent computer and a human consulatant when a answers to a series of questions are received.
- A variety of generic GFR questions posed on the fly in the context of variety of objects.
- A holonic system provides the necessary versatality.
- Each procedure or alogorithm is a holon.

The Current Ethos of Modeling

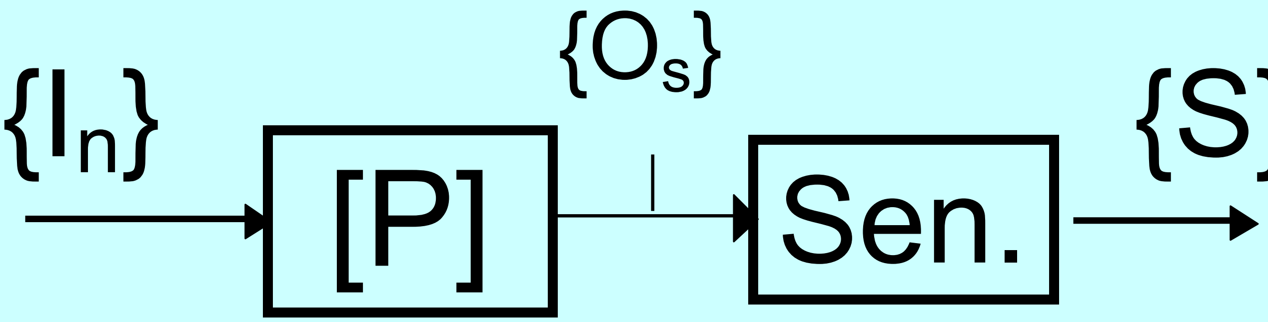


Persisting Problems

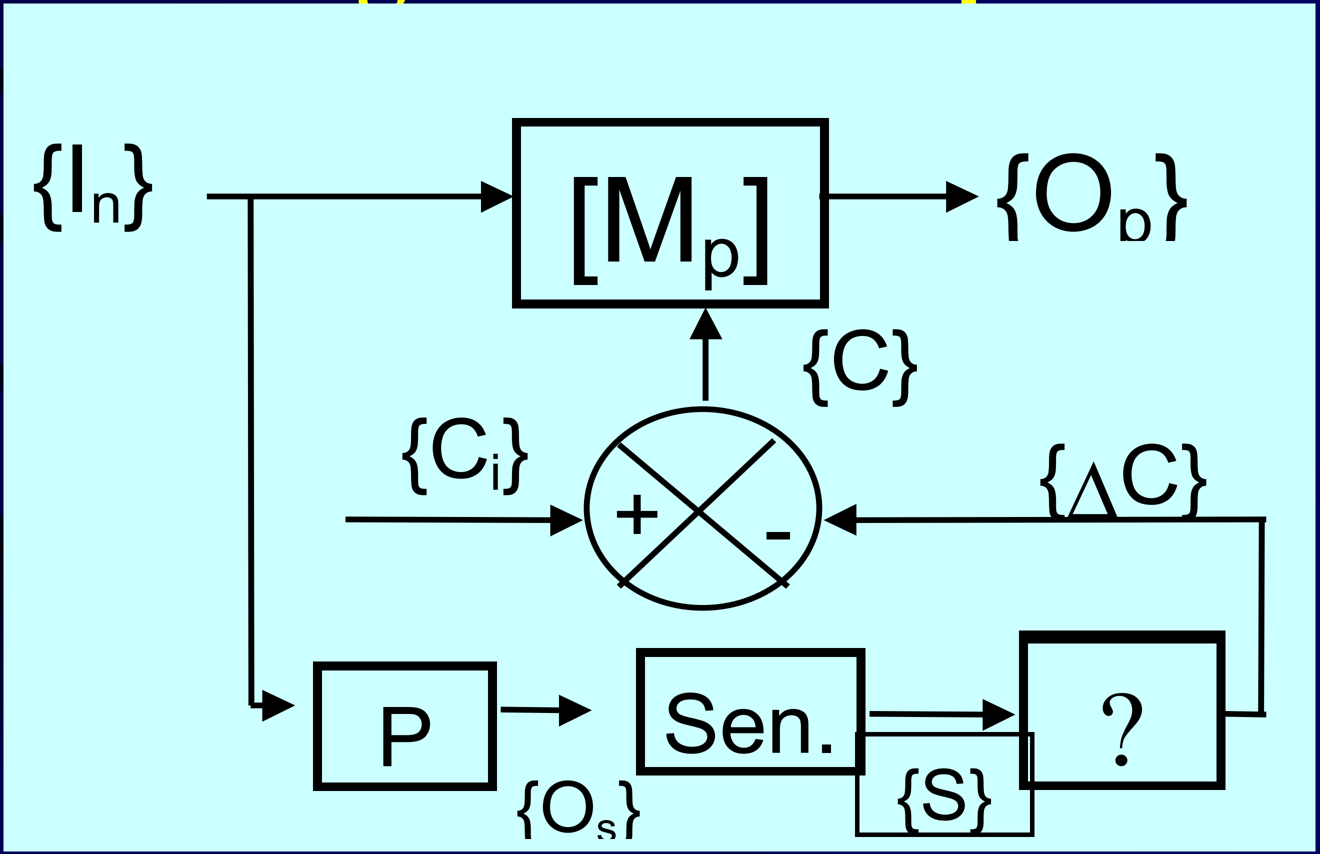
Very few practical operations adequately modeled
Limited success with quantitative prediction
Models must change when chip forms change. Need to anticipate chip form change.
Expensive and static Machining Data Base

Can we find an alternative to MDb?

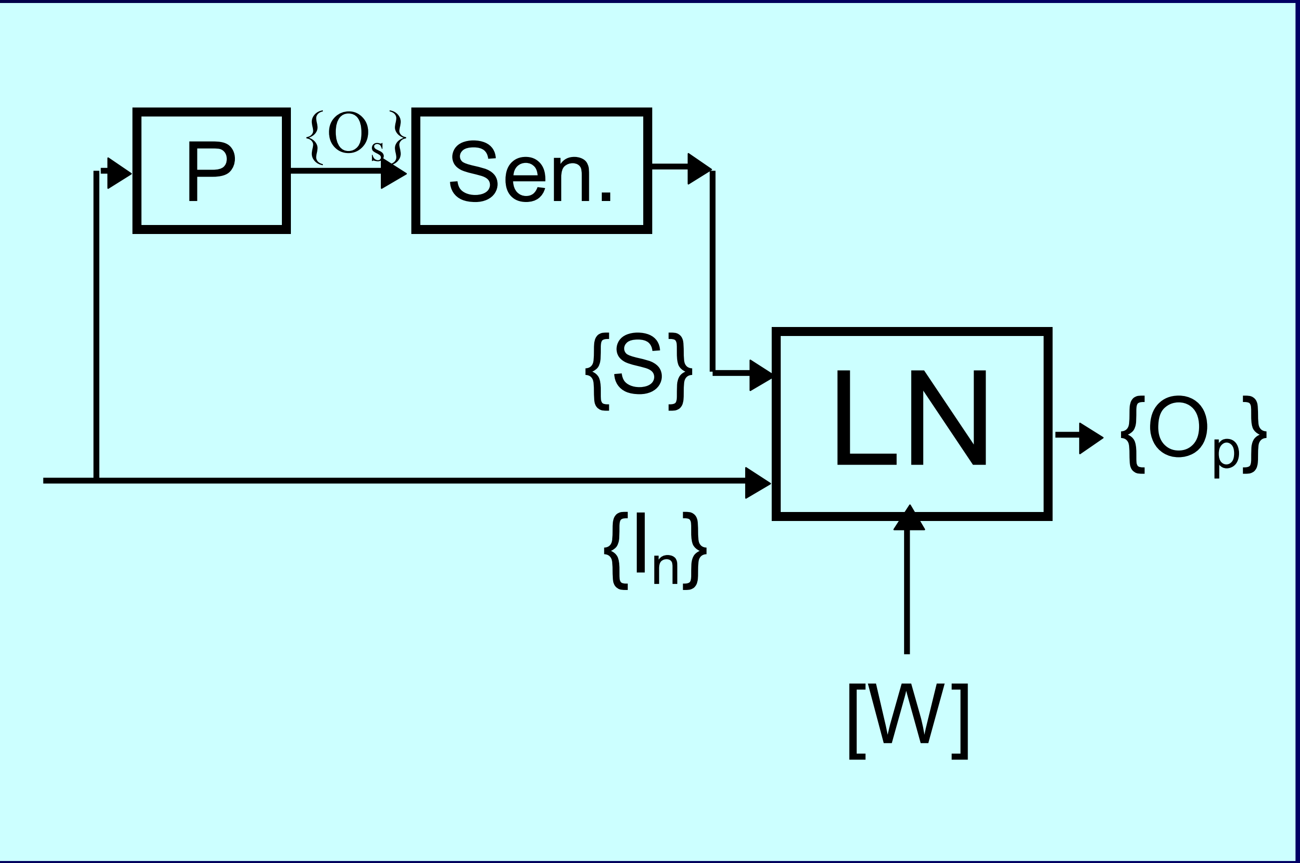
Sensing



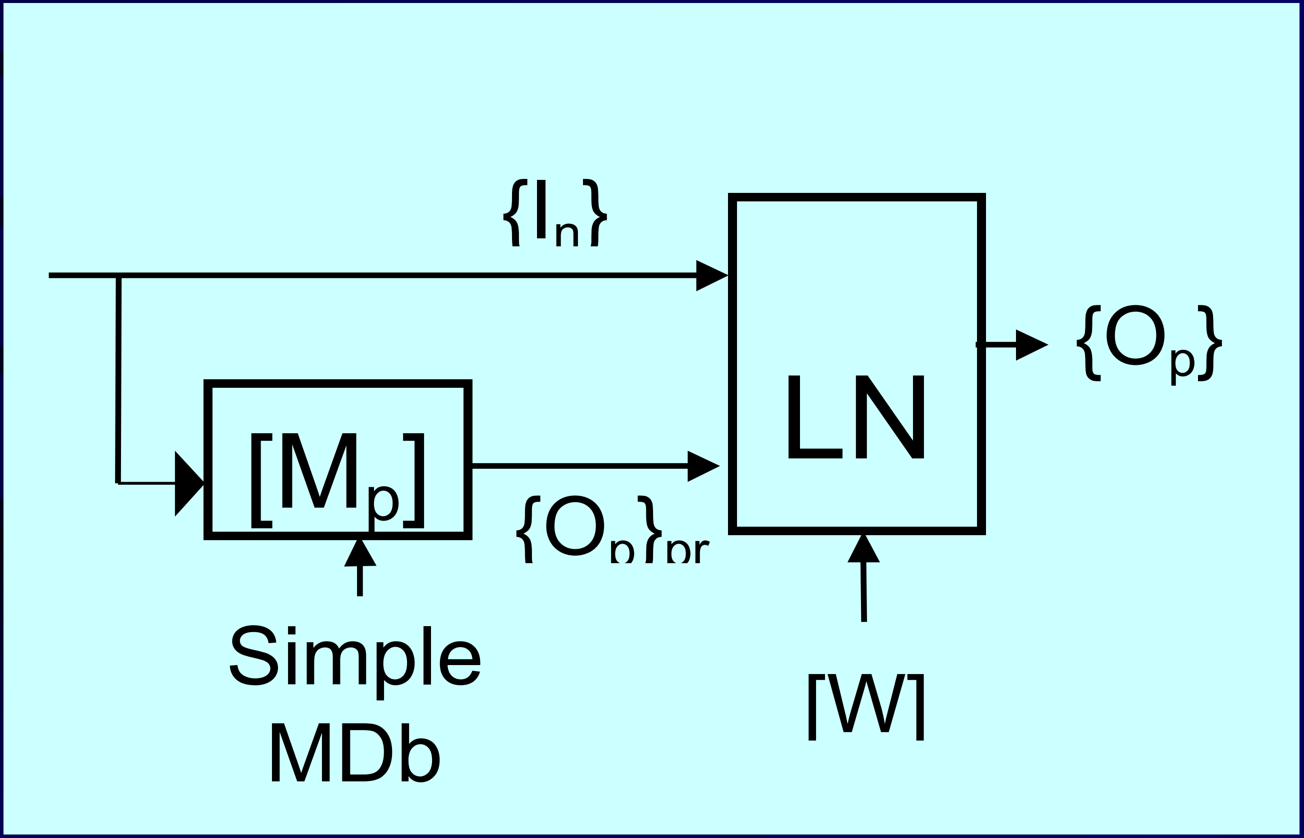
Calibrating A Predictive Model Using Sensed Output



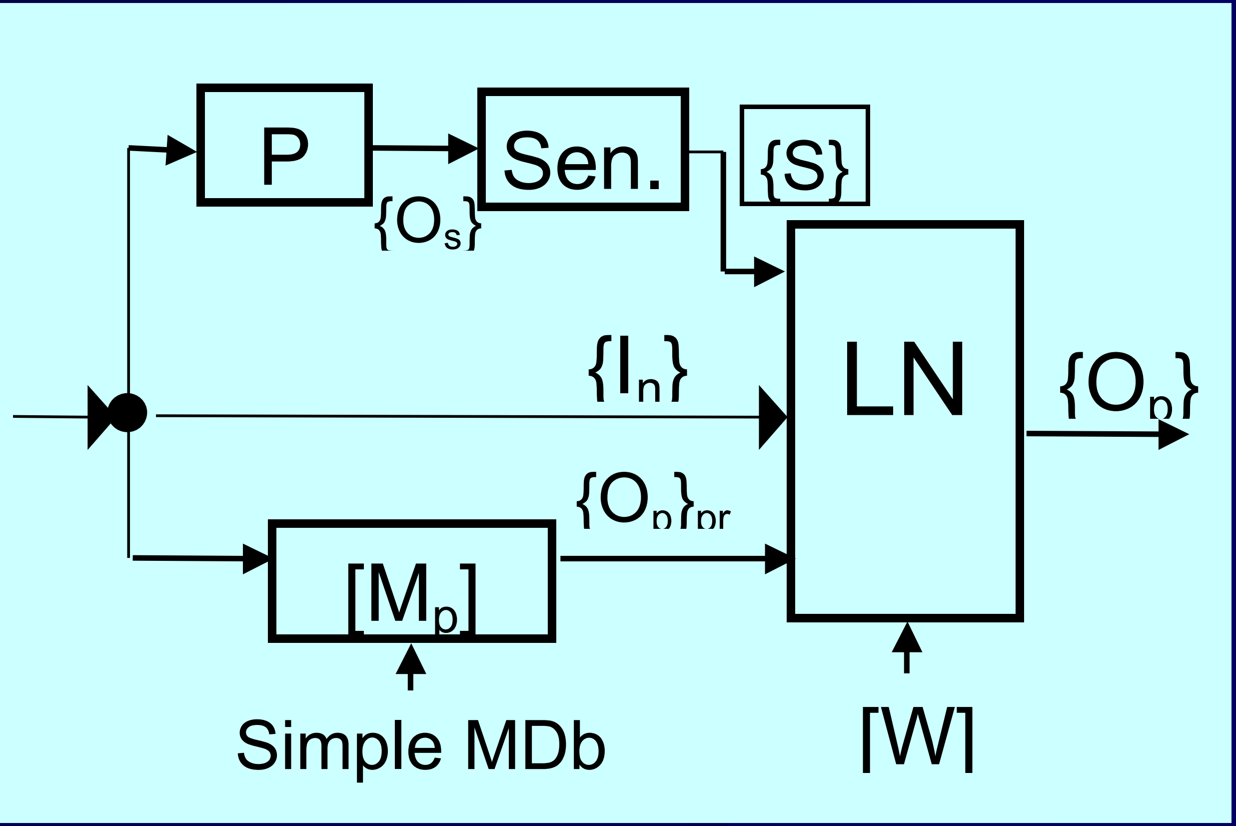
Augmenting a Learning System Through $\{O_s\}$



Augmenting Learning with Modeling



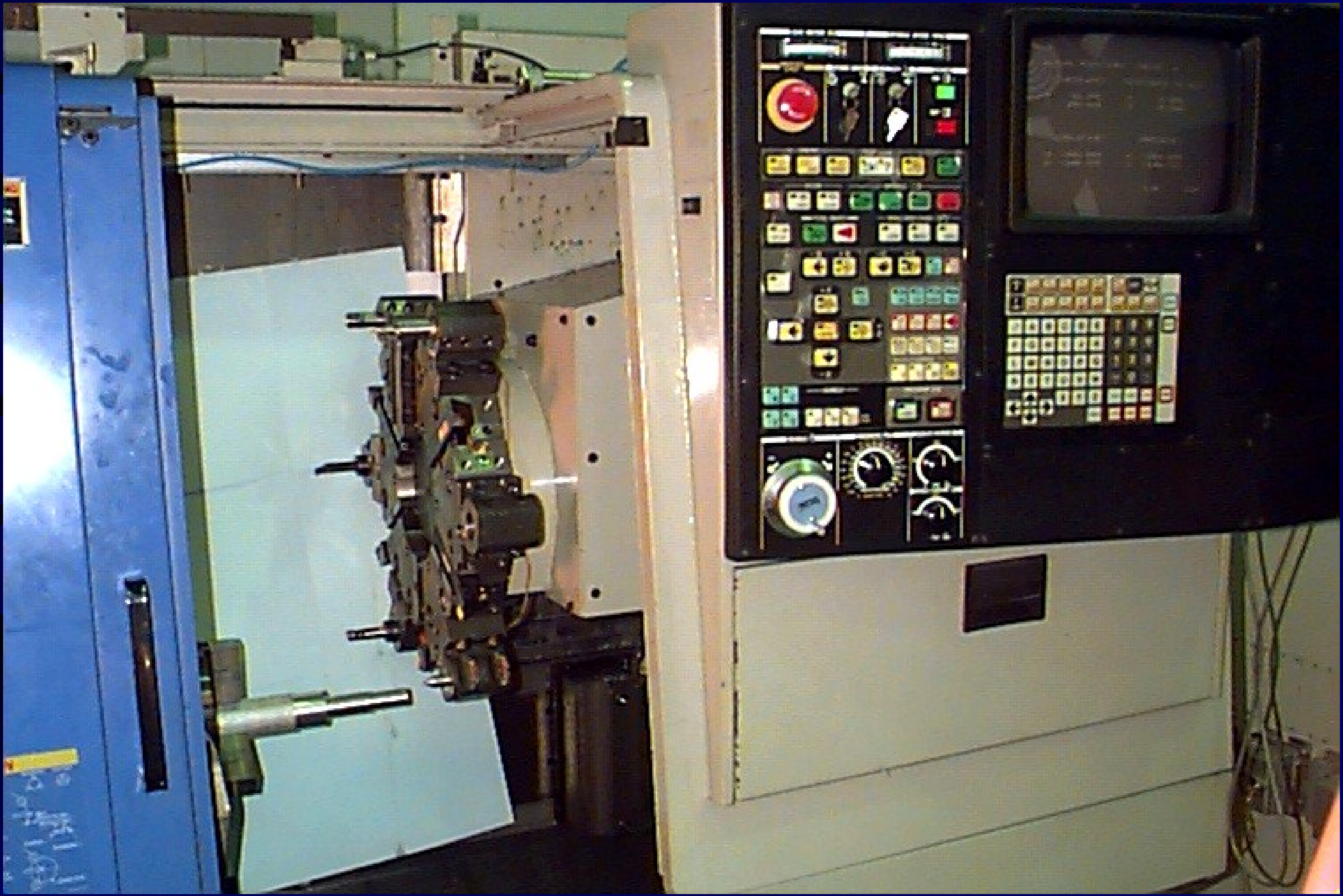
Augmenting Learning Through Modeling as well as Sensing

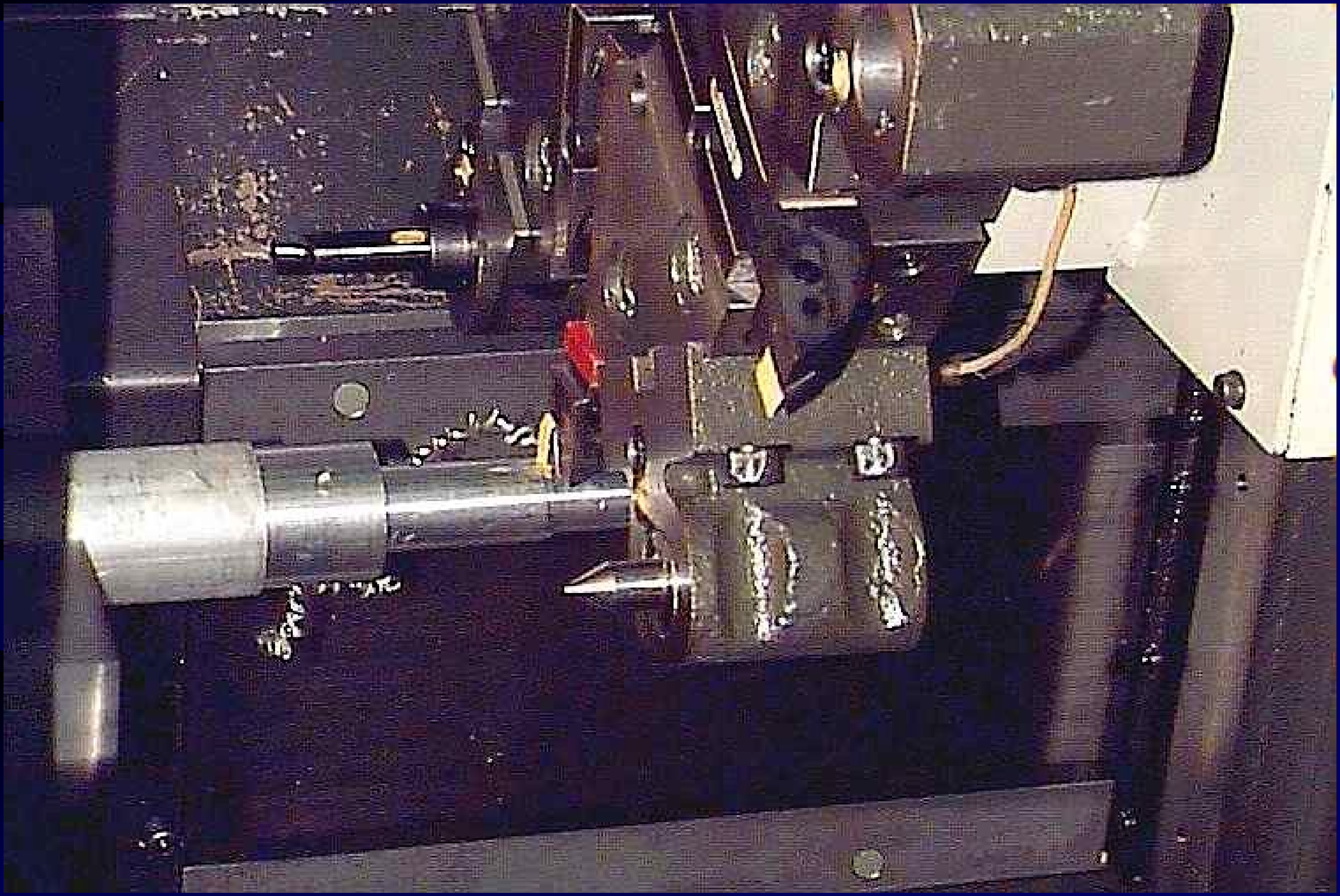


CASE 2

ERROR COMPENSATION IN CNC TURNING SOLELY FROM DIMENSIONAL MEASUREMENTS OF PREVIOUSLY MACHINED PARTS

Z. Q. LIU and P. K. VENUVINOD





ERROR SOURCES:

geometric errors of machine tool (δ_g),

thermally induced distortions of machine tool elements (δ_{th}),

errors arising from the static deflections of the machine-fixture-workpiece-tool (MFWT) system under cutting force (δ_f), and

other errors such as those arising from clamping force, tool wear, etc. (δ_{other}).

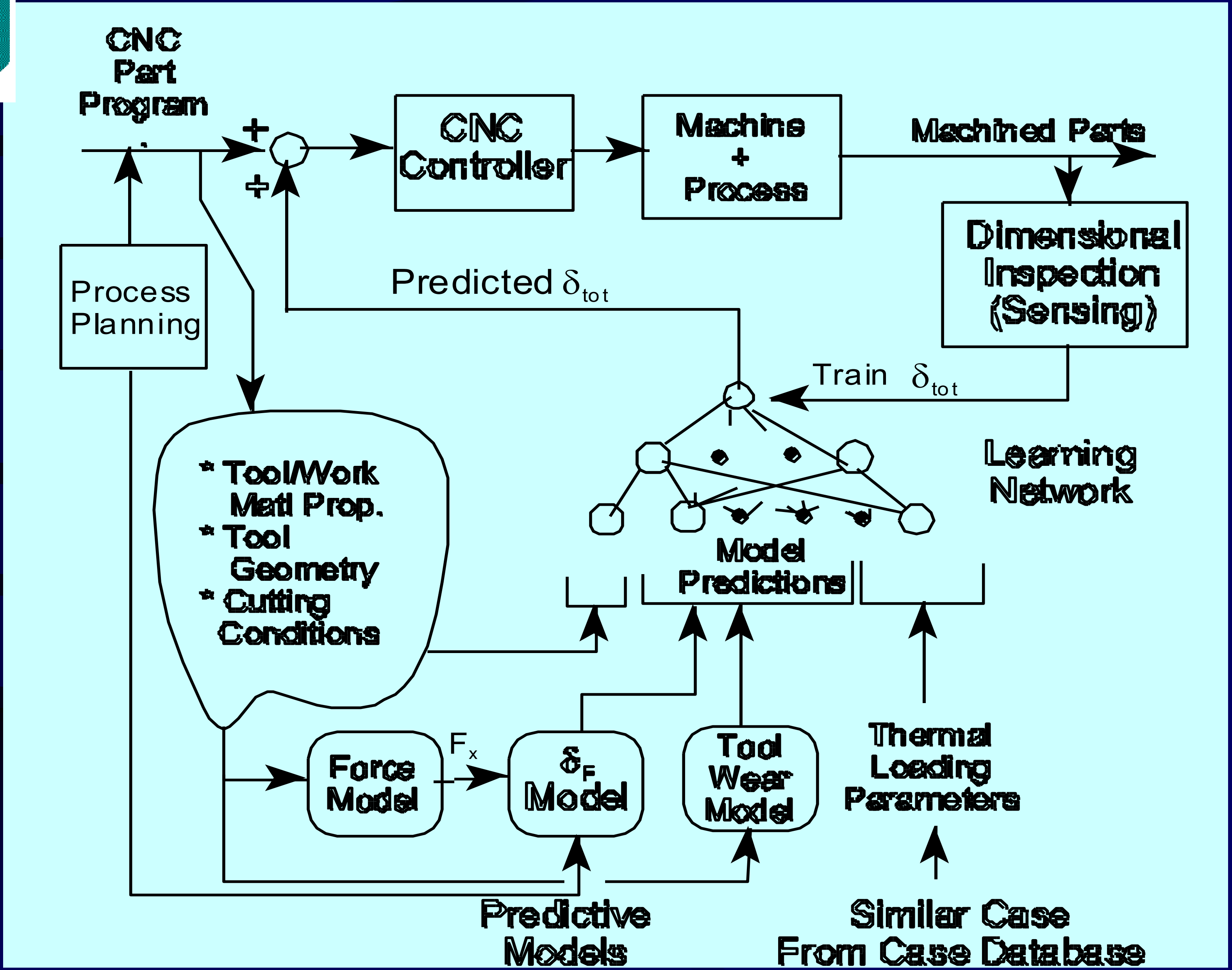
Traditional error compensation strategies have not been shop floor friendly because

➔ laser interferometer etc. for measuring δ_g and δ_{th},

➔ FEM and multiple sensors, arrays of thermocouple for δ_{th},

➔ in-process measurement using laser-based photo-detector, etc.

have been too expensive, sophisticated and tedious for routine shop floor use.


CNC
Part
Program
+
+
CNC
Controller
Machine
+
Process
Machined Parts
Dimensional
Inspection
(Sensing)
Process
Planning
Predicted δ_{tot}
Train δ_{tot}
Learning
Network
* Tool/Work
Matl Prop.
* Tool
Geometry
* Cutting
Conditions
Model
Predictions
Force
Model
F_x
δ_F
Model
Tool
Wear
Model
Thermal
Loading
Parameters
Predictive
Models
Similar Case
From Case Database

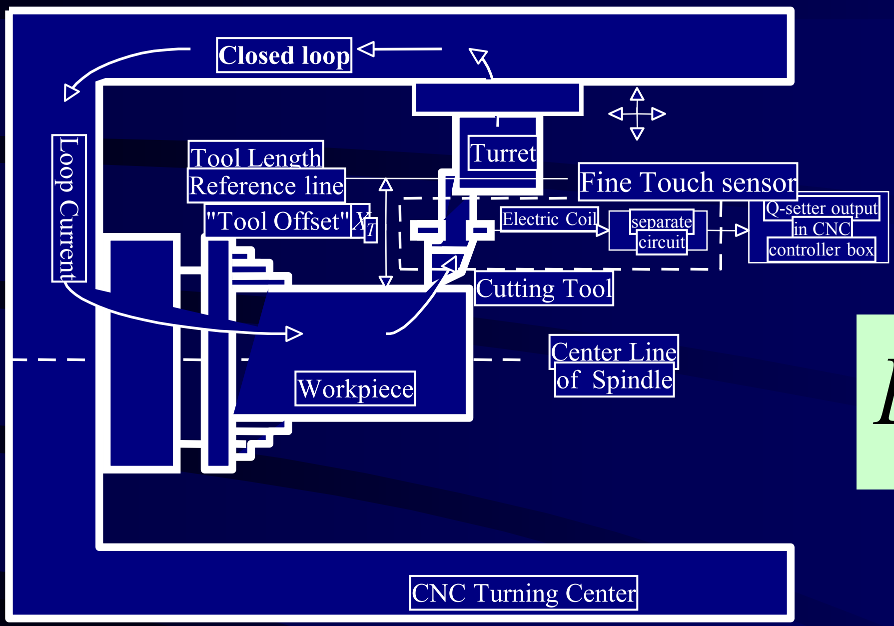
THE PROPOSED INSPECTION PROTOCOL

Only
one post-process measurement (PPM) using a coordinate Measuring Machine, and
two on-machine measurements (OMM)

- one immediately after machining, and
- the other after the machine has cooled down

using a recently developed **Fine-Touch (FT)** contact probe in combination with a **Q-setter**.

ON-MACHINE MEASUREMENT (OMM) METHOD:



$$D_{om} = 2 \times H + |X| - |X_T|$$

FT probing enables the cutting tool itself to be used as the contact probe.

TOTAL ERROR:

$$\delta_{tot} = D_{pp} - D_{des}$$

$$\delta_{tot} = \delta_g + \delta_{th} + \delta_f + \delta_{other}$$

GEOMETRIC ERROR:

$$\delta_g = D_{pp} - D_{omc}$$

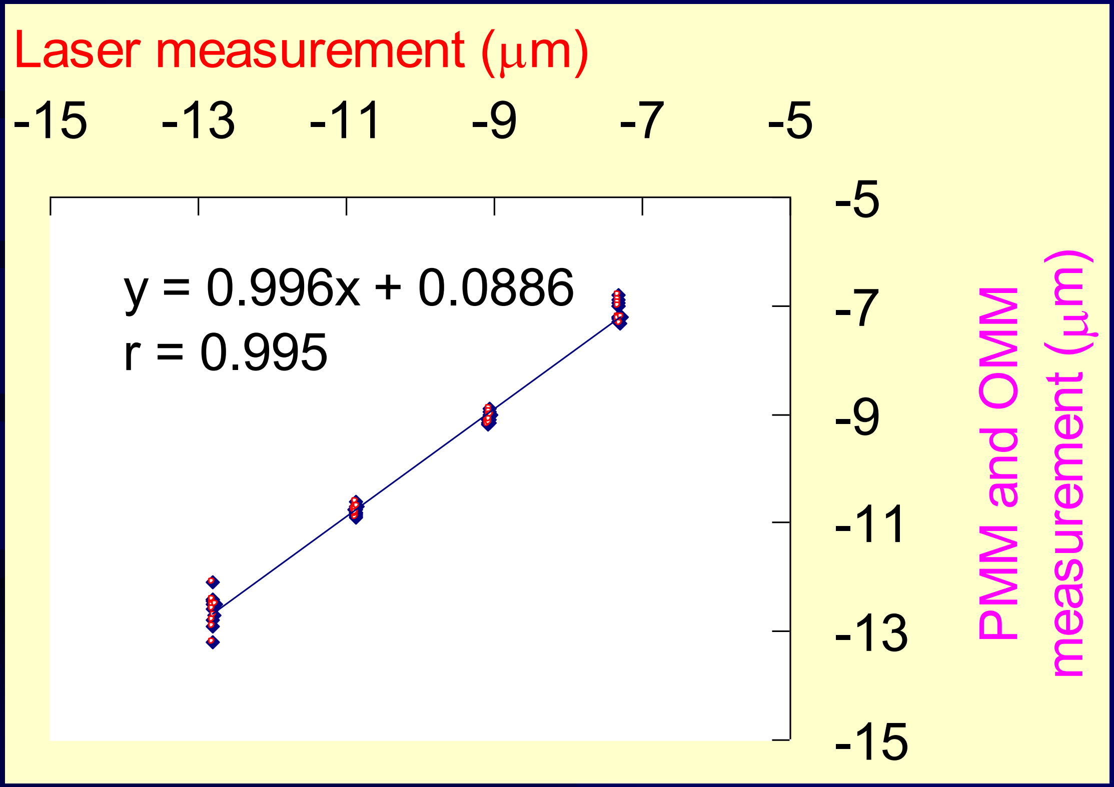
ERROR DECOMPOSITION:

$$\delta_f -> Domw - Ddes$$

$$\delta_{th} = Domc - Domw$$

$$\delta_g = D_{pp} - Domc$$

Comparison of δ_g estimates from PPM/OMM and laser interferometer:

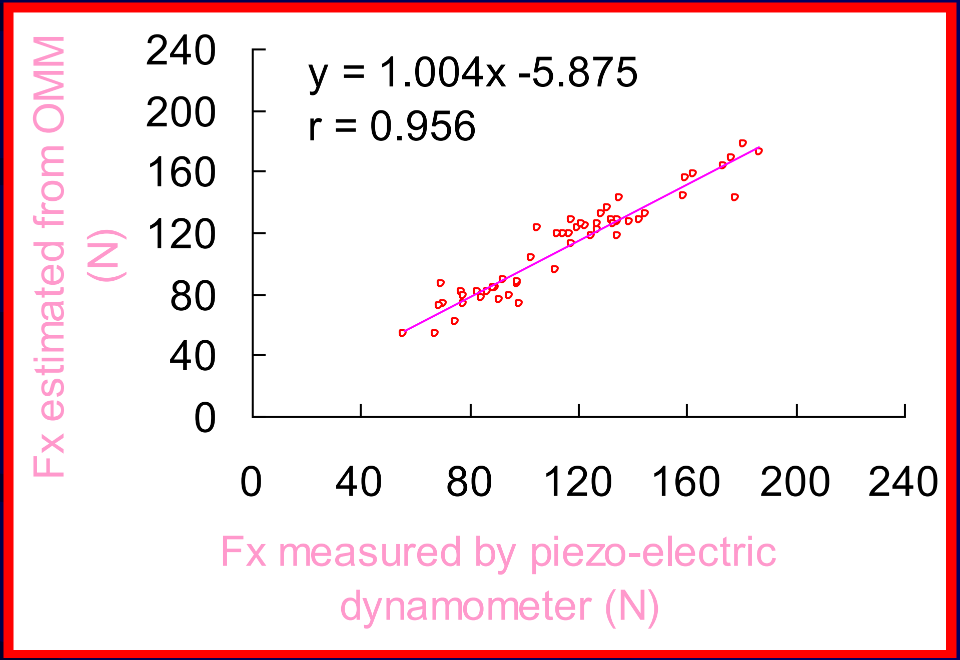


Comparision between the estimations of k_t, K_{csh} and R from OMM and load cell measurements:

	Estimates from PMM/OMM		Estimates from Load Cell		Confidence (t-test)
	Mean	Std. Dev.	Mean	Std. Dev.	
$k_t \times 10^4$ (N/mm)	1.771	0.056	1.799	0.031	91.2%
$K_{csh} \times 10^8$ (N·mm/rad)	5.878	0.039	5.867	0.030	97.6%
R (mm)	191.1	9.8	202.5	11.7	97.3%

(Note that the agreement of t-test is very good.)

Comparision between the estimations of F_x from OMM and piezo-electric dynamometer measurements:



It can be seen that, notwithstanding the assumption that $\delta_{other} \approx 0$, the correlation is acceptably high (r-value is 0.956). It indictaes that the machine tool can be made to act as its dynamometer from workpiece on-machine measurements performed on the same cutting machine!

CASE BASED REASONING IN ERROR COMPENSATION

For the method of error compensation based on PPM/OMM, it is straight forward to apply Case Based Reasoning (CBR) to predict the dimensional error on the next part. One can retrieve a case similar to the next part from a progressively compiled case base and adapt the data to the new situation.

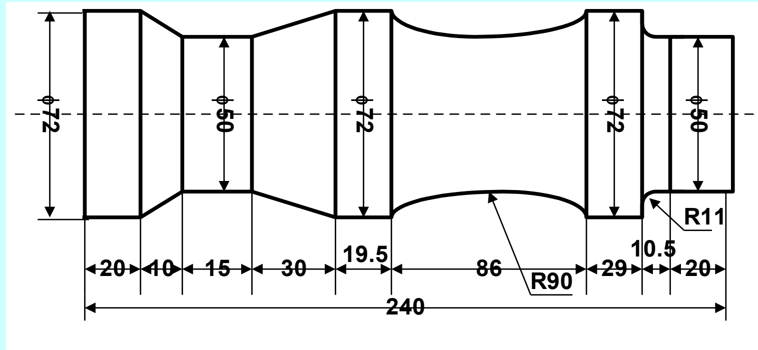
Note that:

little adaptation is needed with regard to the prediction of δ_g, k_t, K_{csh} and R for the new MFWT system;

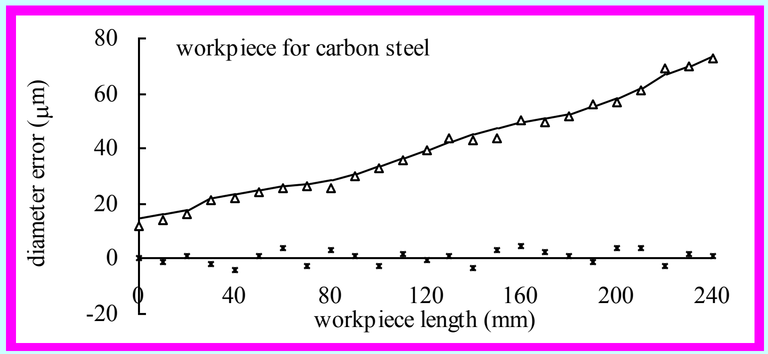
k_{wp} is easily determined for the new part by the FD program;

adaptation of F_x can be done by suitable interpolation or extrapolation of previous force data by an analytical model of turning forces.

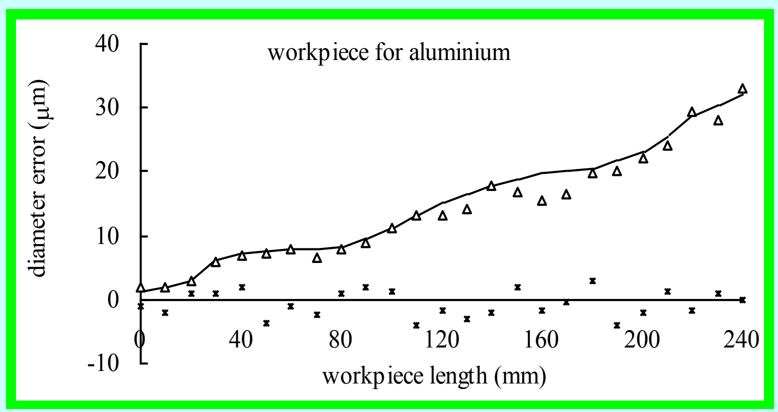
However, with regard to δ_{th} further research is needed to resolve some difficulties concerning the characterization of thermal loading to facilitate case retrieval.



φ72
φ50
φ72
φ72
φ50
R11
10.5
20
10
15
30
19.5
86
R90
29
20
240



workpiece for carbon steel
diameter error (μm)
80
60
40
20
0
-20
0
40
80
120
160
200
240
workpiece length (mm)



workpiece for aluminium
diameter error (μm)
40
30
20
10
0
-10
0
40
80
120
160
200
240
workpiece length (mm)

What is CBR?

“Most people prefer not to have to think hard if they can help it. They will try to get by with whatever worked before, even if it is less than optimal. We believe that, roughly speaking, people's everyday cognition consists of abut 90% retrieving of past solutions and only about 10% or less of actual novel problem solving.”

"Because of our belief about the relative importance of retrieval, it follows that if one wants to understand what it makes to model human intelligence one should focus on the type of processing that contributes the most to people's everyday behavior, namely retrieval and adaptations of old solutions."

[Schank '94]

Imagine that you are walking through a production facility. Your guide points to one work center and says "He is a baby. He still has a lot to learn." He then walks to another and says "Ah! This guy is the smartest. He knows what he is doing. He is correct 80% of the time."

Thank You

THERMAL ERROR:

$$\delta_{th} = (\delta_g + \delta_{th}) - \delta_g$$
$$= (Dpp - Domw) - (Dpp - Domc)$$
$$= Domc - Domw$$

ERRORS DUE TO CUTTING FORCE:

$$\delta_f = Domw - Ddes - \delta_{other}$$

$$\delta_f -> Domw - Ddes (when \delta other -> 0)$$

The errors arising from deflections of MFWT system under cutting force:

$$\delta_f = 2F_x(1/k_t + 1/k_{wp} + 1/k_{sp})$$

where,

F_x is the radial cutting force,

k_t is the overall stiffness of the tool and its supporting structure,

k_{wp} is the stiffness of the workpiece on its own,

k_{sp} is the overall stiffness of the chuck-spindle-headstock sub-assembly.