Intelligent Extruder for Polymer Compounding

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US Department of Energy / OIT
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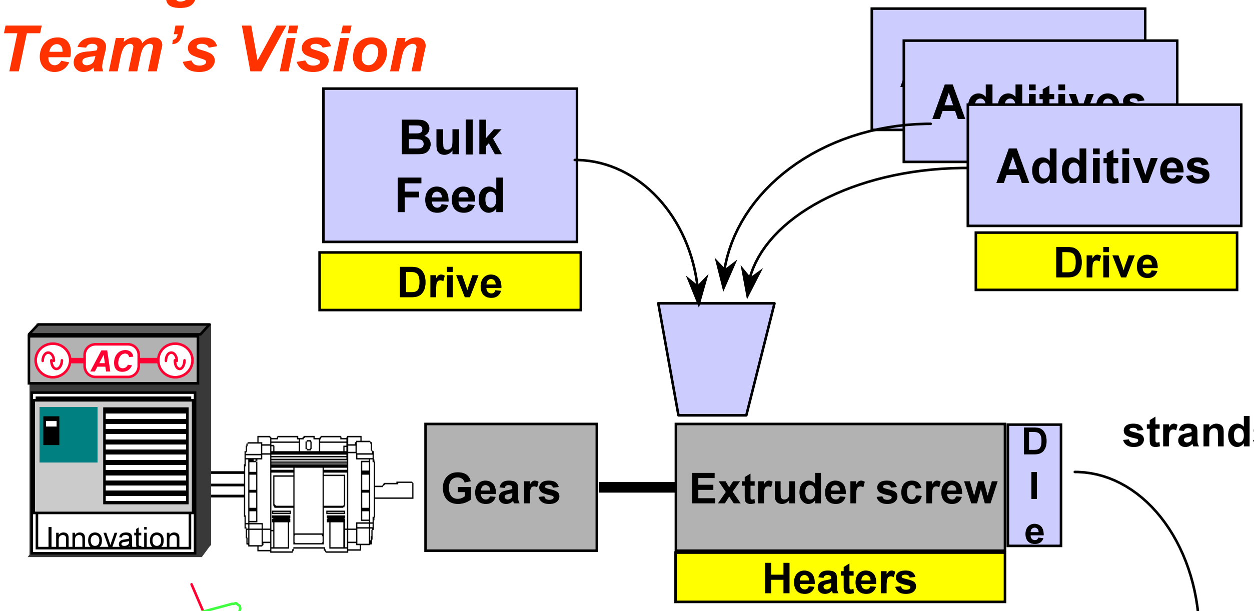
Presentation Outline

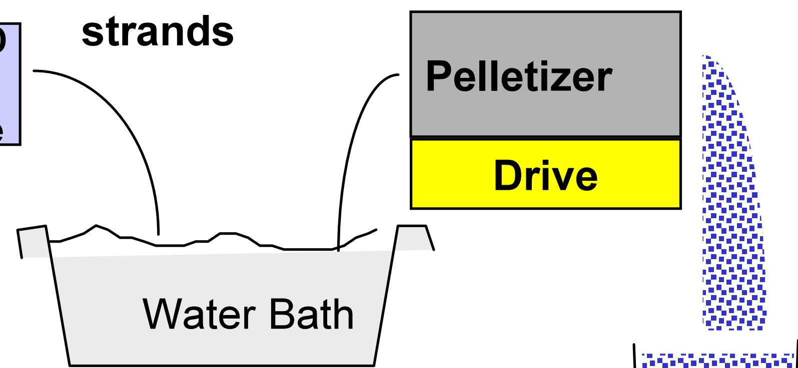
- Overview of program
- Highlights of Technical Progress
  - Inferential sensing (viscosity)
  - Sensor & Process fault detection (multivariate)
  - Bad lot detection (single sensor)
- Program status, plans and financials

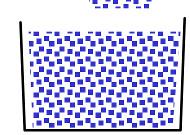
Intelligent Extruder Services: Team's Vision

Detect process upsets

- *feeder mat'l flow*
- *feed property shifts*
- *out of spec production*
- *use existing sensors & drive signals*







Detect incipient faults

- *drive motor / gear box/ screw*
- *feeder / pelletizer drives*
- *cutter (wear)*

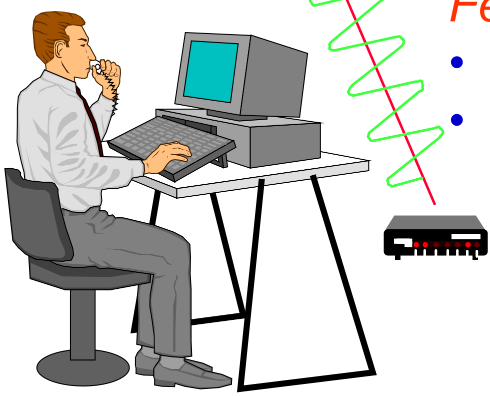
Estimate key variables

- *material properties (viscosity)*
- *intra batch quality*

ONSITE Center

Feedback Control

- *auto fine corrections (MV, Color, comp)*
- *fast changeover (grade, color)*



Remote on-line support

- *calibration, setup, maintenance*
- *data interpretation, problem solving*
- *24X7 process expertise availability*

Customer Payoff

- ***First Pass Yield***
- ***'free' capacity***
- ***Reduce QA lab testing***
- ***less customer returns***
- ***reduced landfill waste***
- ***lower energy use***

Why Polymer Compounding Advanced Automation?

Where the market was...

- Occasional QA testing
- Large batch runs
- Make to inventory
- Long lead times (30 days)
- Non critical specification limits
- Good price…fewer competitors

…has been recently

- Once per batch QA checks
- More pounds, smaller Lots
- More make to order (--> 100 %)
- Shorter lead times (72 hrs)
- Tighter specification limits
- Lower prices
- Costly waste disposal

And what's needed tomorrow

Continuous compounding (zero changeover time)

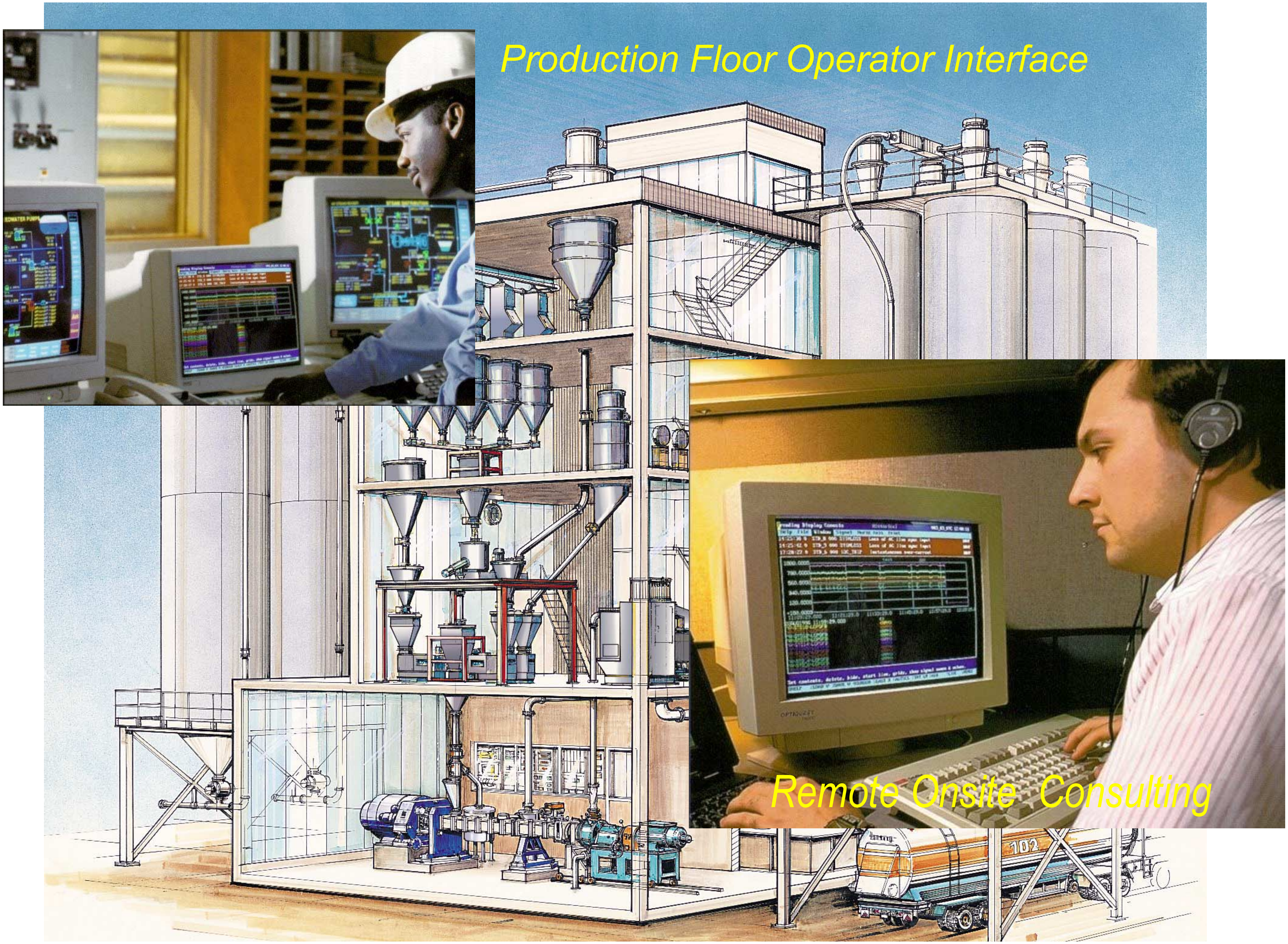
Guaranteed first time quality (100% FPY)

Intra batch quality audit trail…less QA, happy customers

Quality measurements without costly sensors / waste streams

Feeback control to hold spec limits

Diagnostics to predict problems…no unscheduled repairs



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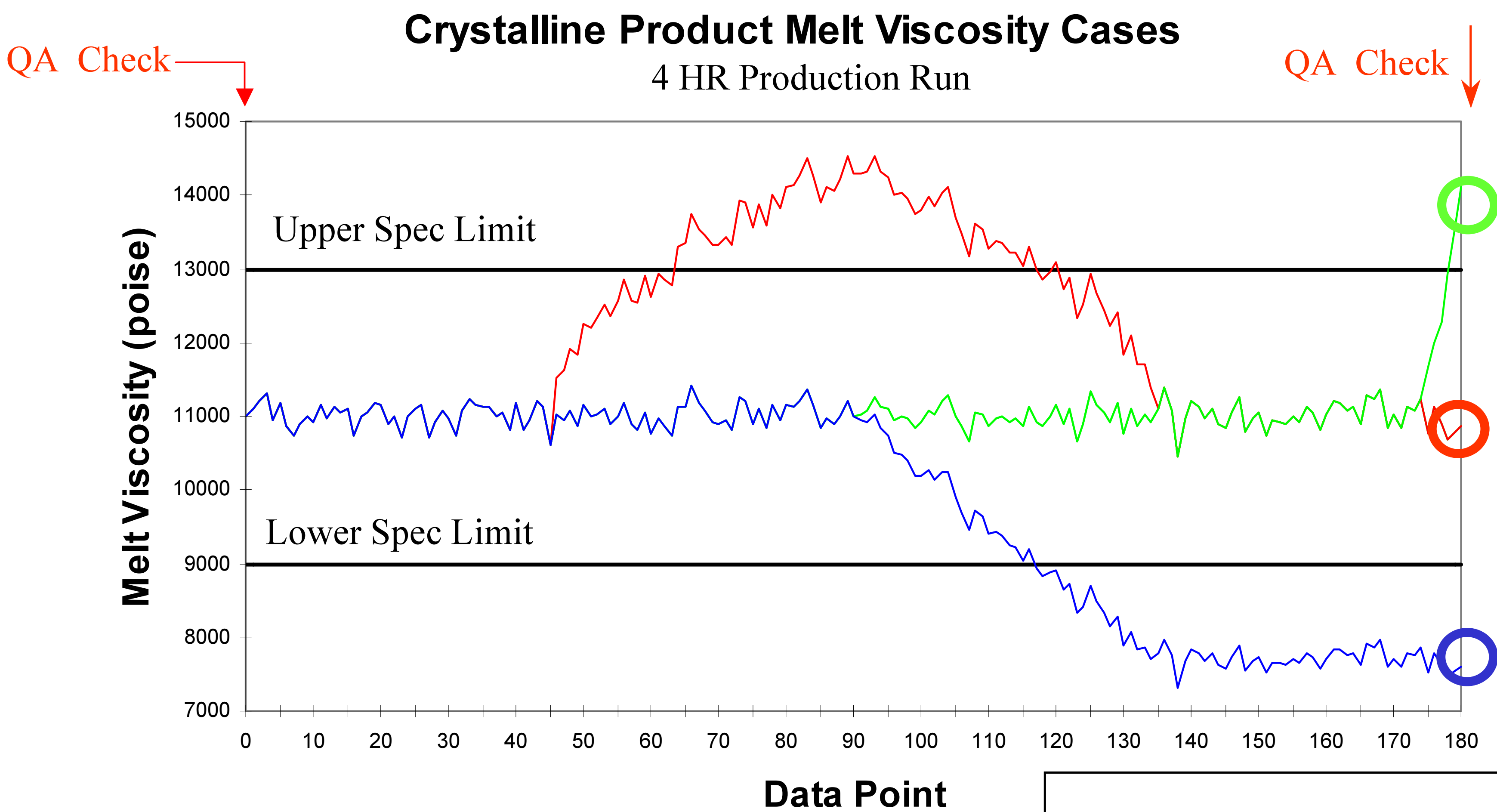


Good material failed (lower FPYield)

Bad material passed (cust. disatisfaction)

Good material contaminated (lower FPYield)

Key program goal: to detect process upsets <u>early and reliably</u> via continuous monitoring and signal analysis

SOURCES OF FINISHING VARIABILITY

Process Faults

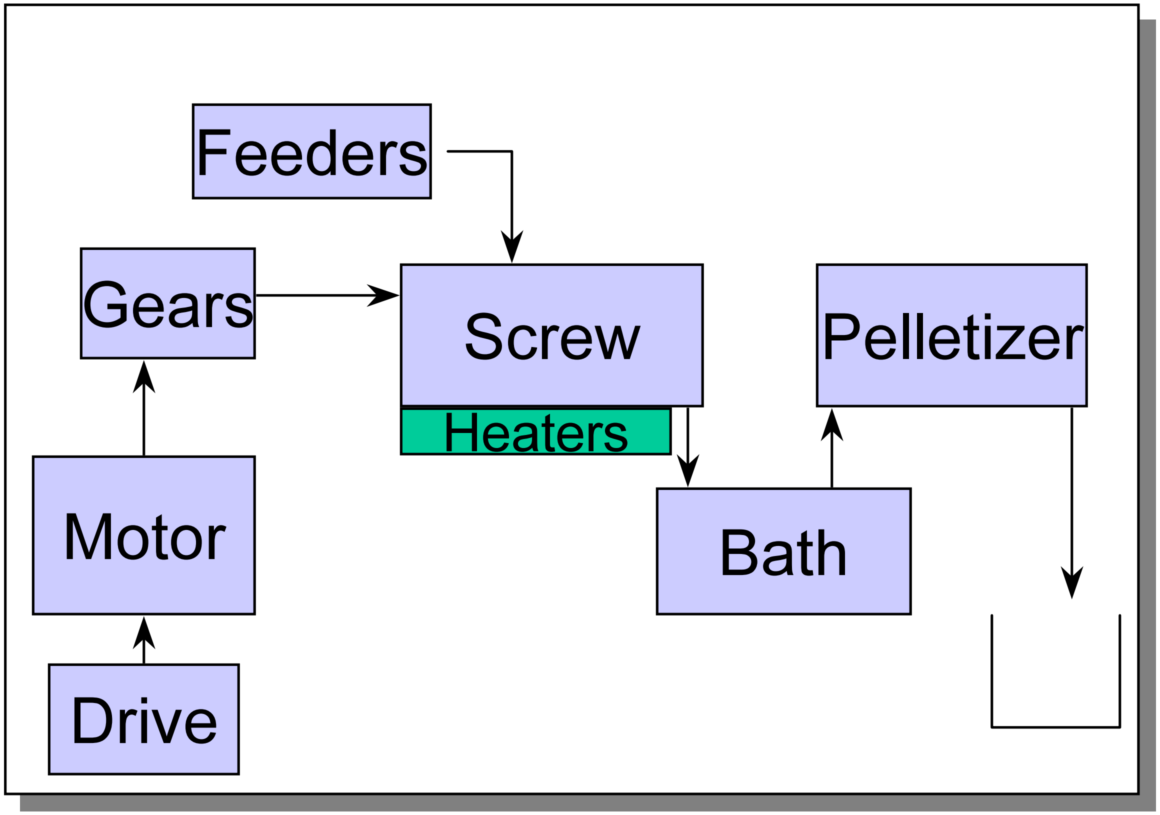
- clogged feeders, die screen
- poor barrel temp regulation
- vent, die screen blockage
- strand drop, fuse
- pellets hot

Operator Errors

- formulation
- setup
- QC errors

Incoming Material Variation

- Resin MW
- Resin color
- Resin morphology
- SPD pellet
- Additive feed rates



Product Variability

- MV
- Composition
- Color
- FPY
- COST / #

Equipment Faults

- feeder drive, motor , control
- dull pellet cutter
- screw shaft breakage
- screw wear
- gear box (bearing, gears)

Common Extruder Process / Sensor Faults

Category	Upset / Fault	Impact
Raw Material Variability	Resin IV variation	viscosity shift ==> customer mold flow problems
	Resin Flowability variation	feeder mass flow rate error and composition error
Process Variability	Feeder variation	improper screw filling and composition ratio error
	Screw speed variation	change in residence time and specific energy input to material (usually small)
	Zone Temperature variation	shift in solid-melt transition point, excess or not enough mixing, unmelt passage
	Sceen Pack variation	variation in screen pack clogging from run to run - leads to unknown die pressure bias
Sensor Drift/Bias	Feeder bias/drift	composition and viscosity drift, confounds process diagnostics
	Screw speed bias	screw speed drive not at set point, confounds process diagnostics
	Torque bias	machine runs below capacity, confounds inferential sensing / process diagnostics
	Die Pressure bias	false over-pressure alarms, confounds inferential sension/process diagnostics
	Temperature sensor bias	wrong correction for temperature effects in viscosity estimation (die zone)

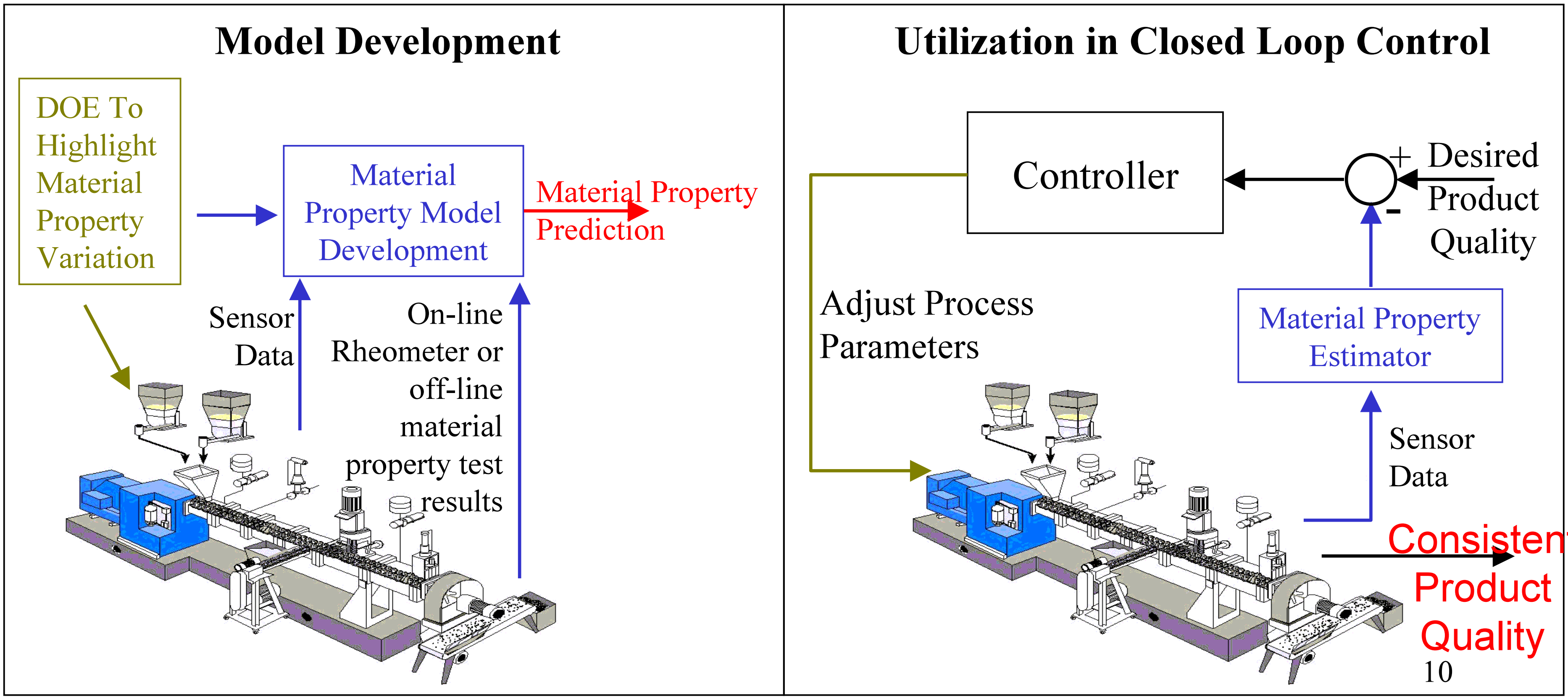
Sensor and process anomalies have confounding interactions to be unraveled for proper diagnosis

Inferential Sensing

Objective

Utilize extruder sensor information in combination with process model and estimation techniques to predict product quality information (e.g., viscosity) on-line.

Benefits (a) Rapid upset detection, (b) Continuous QA audit, (c) Basis for closed loop correction

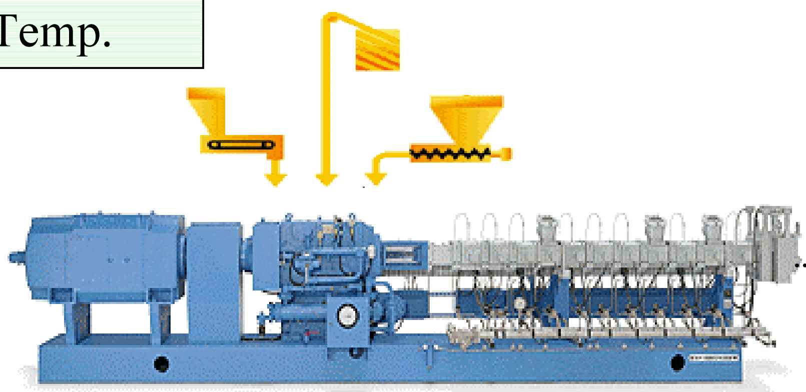


On-line Inferential Viscosity Estimation

Why viscosity?

- key quality parameter for broad range of customers
- directly correlated to composition in most materials
- proportional impact strength in engineering polymer blends

Measured Inputs
- Feedrates
- Screw Speed
- Barrel Temp.



Pellets

Off-Line Measurement of Viscosity in QA Lab
- initial calibration
- periodic update
- for each material grade
- machine configuration

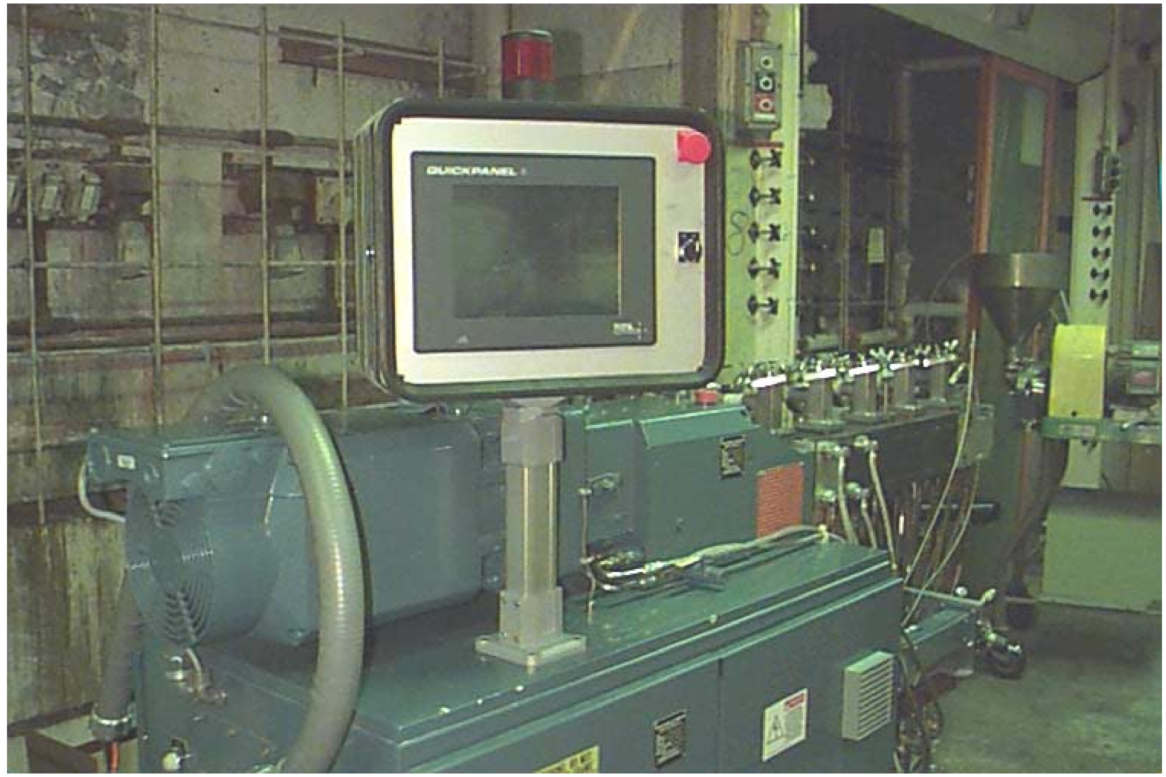
Measured Outputs
- Torque
- Die pressure

Calibration

Viscosity Estimation from Machine Variables
- continuous, on-line

GE CR&D ZSK-25MM Twin Screw Extruder Facility

- Capable of 1200 rpm, 164 Nm of torque, resulting in throughputs of 100 lb/hr
- Computer controlled side feeders
- Utilize K-Tron loss of weight feeders
- 30HP GE Innovation Drive



Data Acquisition Capabilities

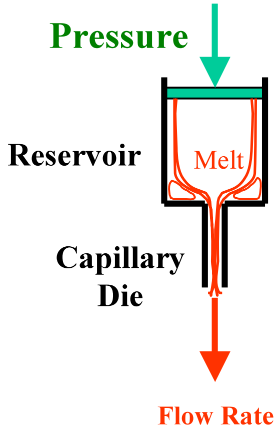
- Monitor 24 data channels simultaneously
- Monitor barrel temperatures, barrel heater reactions, feed rates, torque, speed, die pressure, melt temperature
- Motor shaft encoder

Other ZSK twin screw facilities used

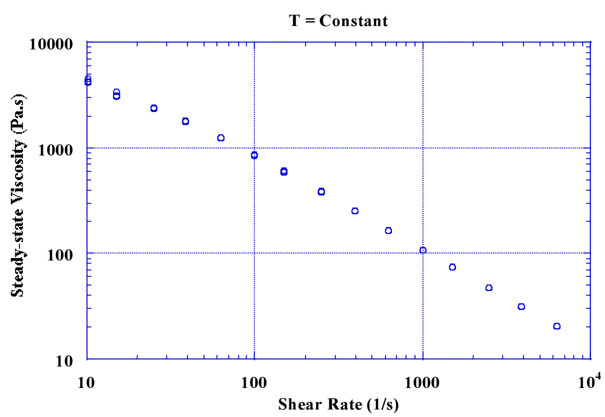
- 120 mm ~2000 lb/hr (GEP Selkirk)
- 133 mm (GEP Selkirk)
- 58 mm ~ 500 lb/hr (W-P Ramsey)

Viscosity Measurement

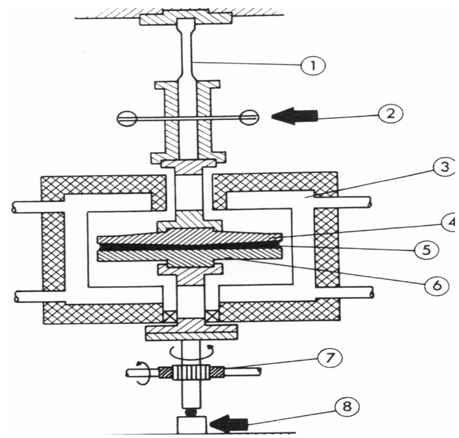
Capillary Rheometer



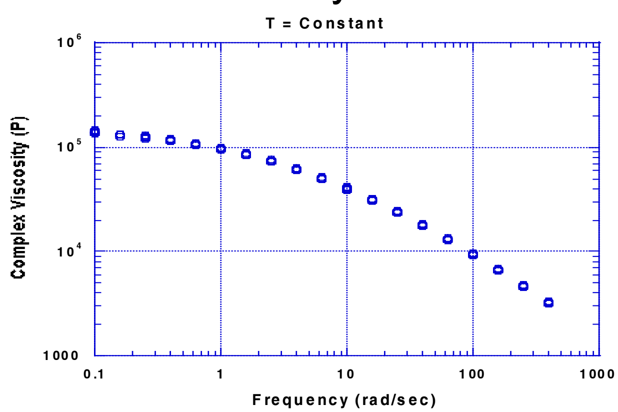
- Melt is subjected to constant shear through a capillary
- Measure steady state viscosity at medium-high shear rates
- Measurement accuracy: σ ~ 0.08 mean



RDS Rheometer



- Melt is subjected to oscillatory shear between parallel disks
- Measure dynamic viscosity at low-medium shear rates
- Measurement accuracy: σ ~ 0.02 mean



Viscosity Estimation

- **Viscosity of extruded polymer product depends on**
  - composition
  - shear rate
  - temperature
- **Use extruder as on-line rheometer**
  - estimate viscosity from on-line measurements of machine variables
  - necessary to account for variations in composition, shear rate and temperature in extruder
- **General form of transfer function fit between measured viscosity and machine variables**

$$\mu = \alpha_0 + \sum (\alpha_i * \text{Feedrate}_i) + \beta_1 (\text{Die Pr.} * \text{ScrewSpeed}) + \beta_2 (\text{Barrel Temp.})$$

OR

$$\mu = \alpha_0 + \sum (\alpha_i \quad + \quad + \beta_2 (\text{Barrel Temp.})$$

account for composition, throughput (shear rate)

account for temperature variation

Viscosity Estimation - Summary

- **Viscosity estimation robust different conditions**
  - different raw materials
  - small / large extruder
  - varying operating conditions (feedrates, screwspeed, barrel temp.)
  - capillary / RDS rheometer calibration

- **Typical Results**

Material	Extruder	Rheometer	R^2	% Error
Polycarbonate	ZSK 25 *	RDS	n/a	5
Noryl PX5511	ZSK 25 *	RDS	0.894	5-7
Noryl PX0844	ZSK 25 *	RDS	0.7	6
Noryl PX5511	ZSK 120 **	RDS	0.64	5
Noryl PX0844	ZSK 120 **	capillary	0.856	6.5
Noryl PX5511	ZSK 25 *	capillary	0.964	8

(*) - 100 lb/hr (**) - 2000 lb/hr

Good correlation between measured viscosity and machine variables using same general form of TF, with prediction error between 5-8%

Viscosity Estimation 25mm Research Extruder - Noryl PX5511

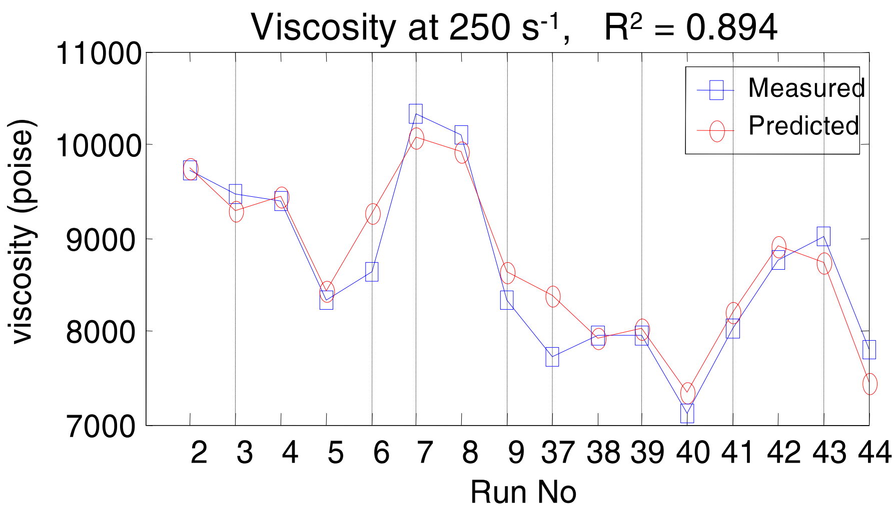
Viscosity TF:

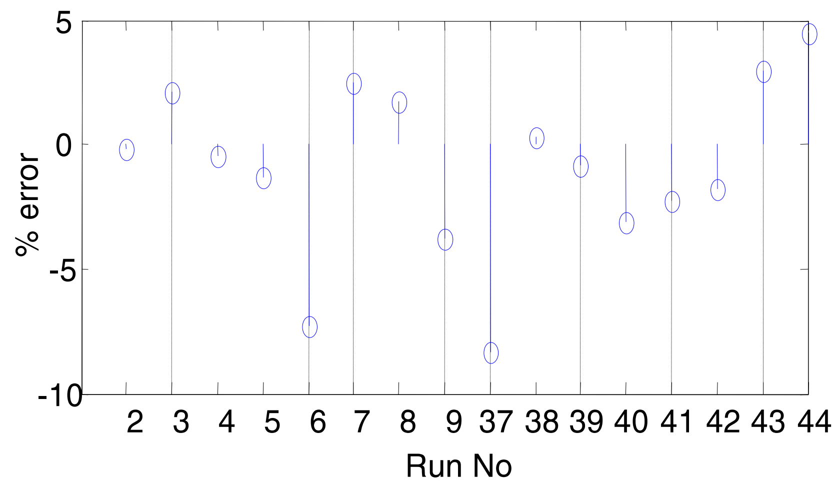
$\mu = \alpha_0 + \alpha_1 * \text{Blend\_FR} + \alpha_2 * \text{(PS+XPS)\_FR} + \alpha_3 * \text{(DieP*ScrewSpeed)} + \alpha_4 * \text{BarrelT}$

ZSK25 extruder

- 2 feeders for Blend, (PS+XPS)
- varied barrel temperature

Viscosity of samples measured with RDS
at 4 shear rates (100, 150, **250**, 400 s^{-1})





Good correlation obtained
- prediction error ~ 5-7%

Stability of Viscosity Estimation over time - Noryl PX5511

Viscosity TF:

$$\mu = \alpha_0 + \alpha_1 *\text{Blend\_FR} + \alpha_2 *(\text{PS+XPS})\_\text{FR} + \alpha_3 *(\text{DieP*ScrewSpeed}) + \alpha_4 *\text{BarrelT}$$

<ins>**ZSK25 extruder**</ins>

- 2 feeders for Blend, (PS+XPS)
- experiments done over different days with very different operating conditions

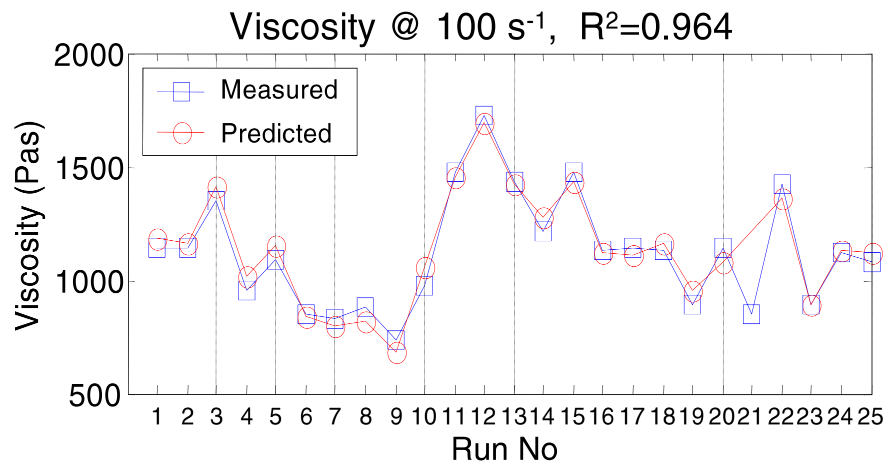
4/2/2001 - Runs 1-15
Blend_FR=23(lb/hr), (PS+XPS)_FR=21(lb/hr),
ScrewSpeed = 480rpm, BarrelT = 285 C

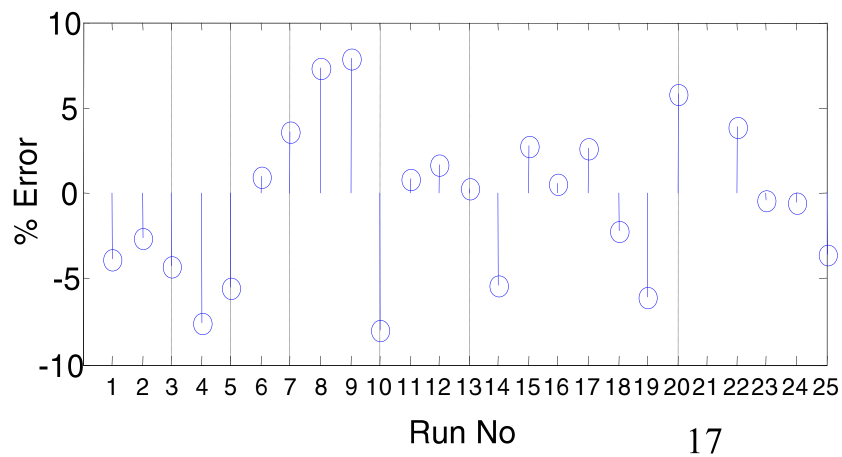
5/8/2001 - Runs 16-25
Blend_FR=16(lb/hr), (PS+XPS)_FR=15(lb/hr),
ScrewSpeed= 250rpm, BarrelT = 275 C

Viscosity of samples measured with <ins>capillary rheometer</ins> at shear rates 100-1000 s^{-1}

Good prediction with same model over ~ month

- prediction error ~ 8%





Production scale (2000 lb/hr) - Noryl PX5511

Viscosity TF:

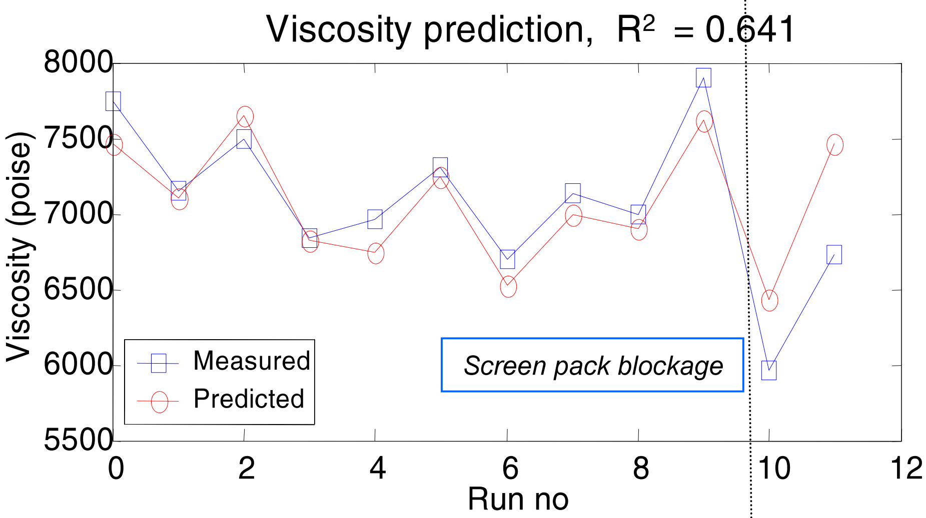
$$\mu = \alpha_0 + \alpha_1 * (\text{Torque}*\text{ScrewSpeed}) + \alpha_2 * \text{Blend\_FR} + \alpha_3 * \text{PS\_FR} + \alpha_4 * \text{XPS\_FR}$$

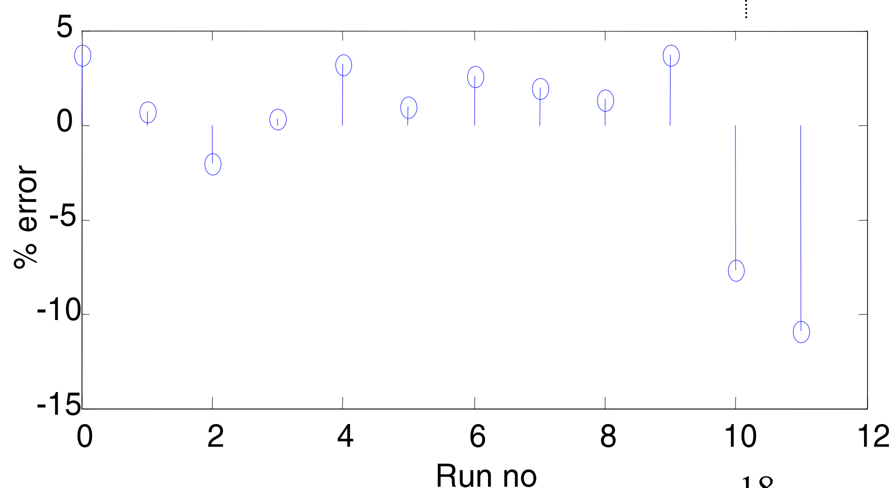
Experiment done at GEP Selkirk on production scale ZSK120 extruder
- 3 feeders for Blend, PS, XPS

Viscosity of samples measured with RDS

Die pressure measurements are unreliable due to screenpack clogging
- used Torque instead of Die Pr in model

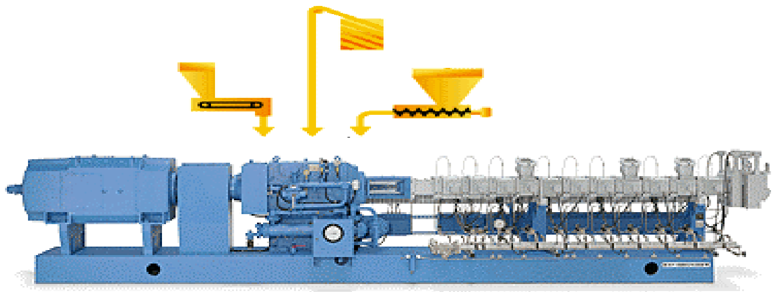
Fairly good correlation with prediction error ~ 5% (except for runs 10,11)
- shows impact of partially clogged die screen
- torque works in place of die pressure





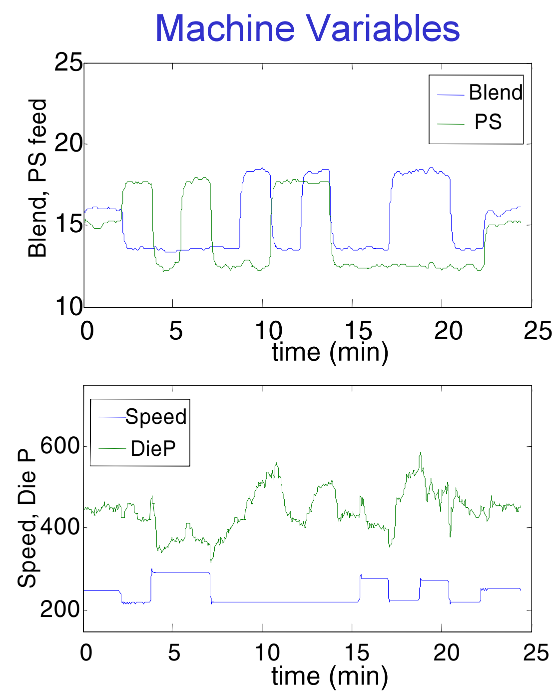
Using inferential sensing for 'bad material' detection

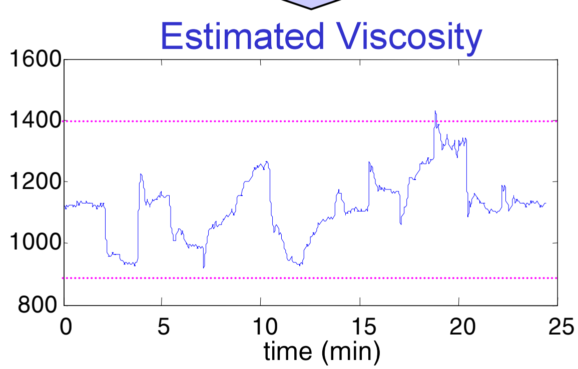
- **Viscosity Estimation from Machine Variables**



Measurement of Machine Variables

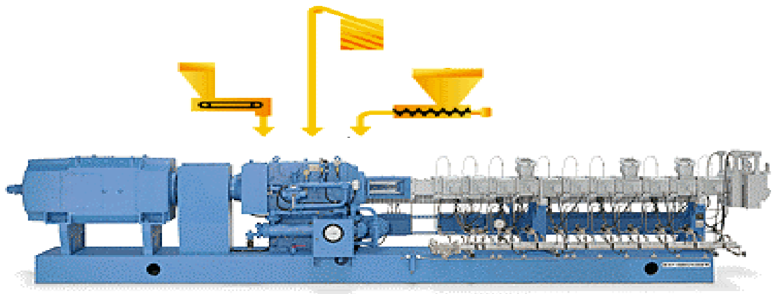
Viscosity TF





Monitor viscosity on-line to distinguish between good/bad product
- develop and maintain viscosity TF for multiple extruder lines and product grades

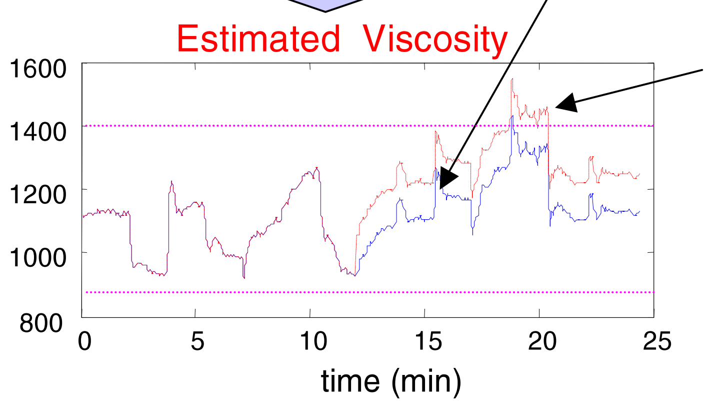
Key Challenge: Detecting and correcting sensor errors



Measurement of Machine Variables ← **Unknown Sensor Bias/Drift**

Viscosity TF

Actual viscosity

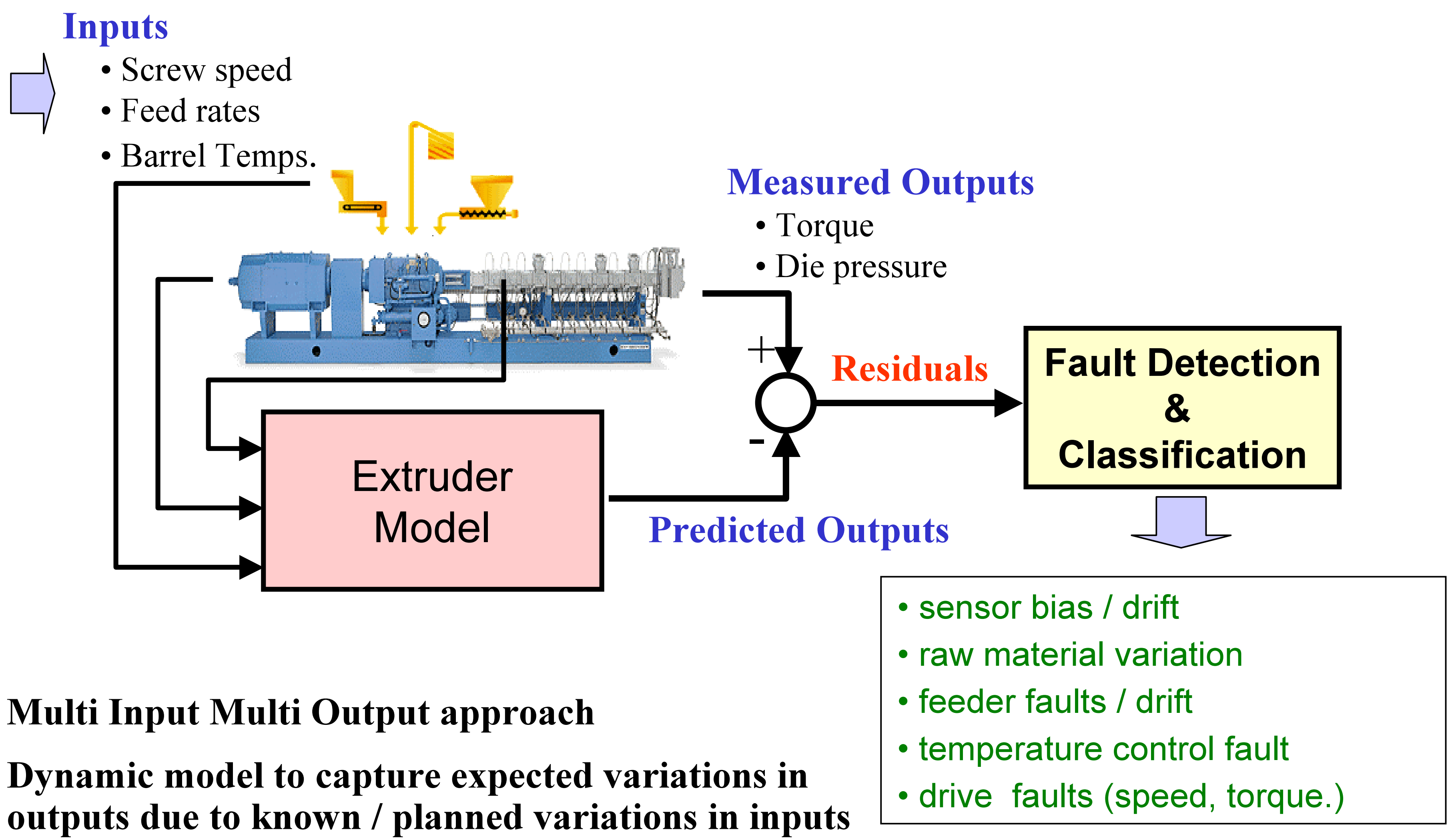


Error in estimated viscosity due to sensor bias

- false alarm on off-spec product

Use model based methods
to detect and classify sensor errors

Model Based Diagnostics



- **Multi Input Multi Output approach**
- **Dynamic model to capture expected variations in outputs due to known / planned variations in inputs**
- **Use residuals generated by the model to identify abnormal variations**

Dynamic Model

Develop Dynamic Input/Output Models for Extruder Variables

Inputs (u)

- Master (total) Feedrate (u_1)
- Blend % (u_2)
- ScrewSpeed (u_3)
- Die Zone Temperature (u_4)

Outputs (y)

- Torque (y_1)
- Die Pressure (y_2)

Dynamic model for each output y_i of the form

$$y_i = \sum_j G_{ij} u_j$$

where the transfer function G_{ij} is of the form

$$G_{ij} = K \frac{(s - z_1)\ldots(s - z_m)e^{-T_d s}}{(s - p_1)\ldots(s - p_n)}$$

K : gain

Z_i : zeros

p_i : poles

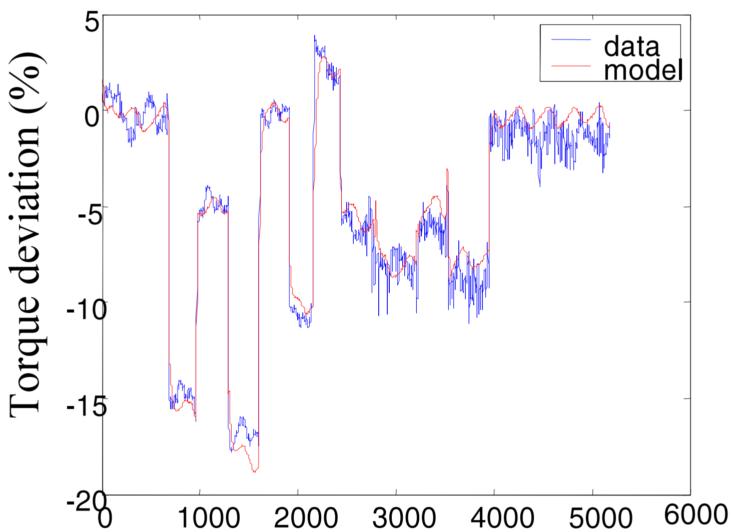
T_d : delay

Model parameters are identified using input/output data from experiments

Model for Torque

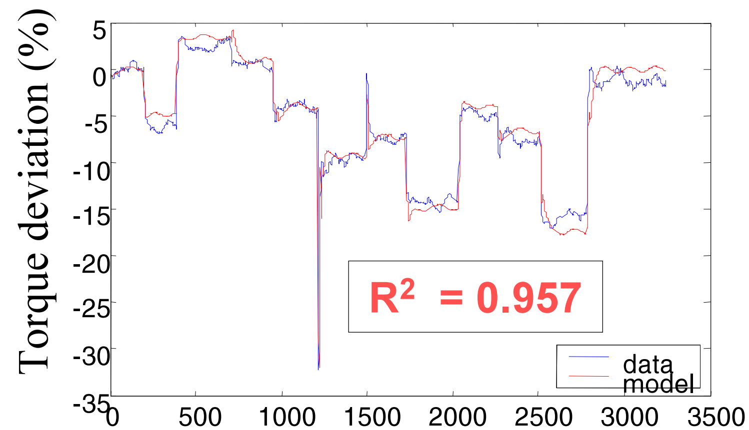
- **Input/Output data collected from large extruder at GEP Selkirk** (2000 lb/hr)
- **Dynamic model: fit from one data set and validate against two other data sets**

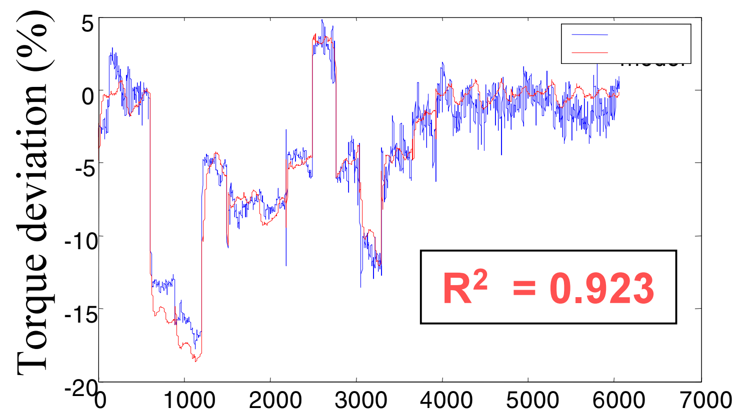
Model Fit



R^2 = 0.955

Model Validation



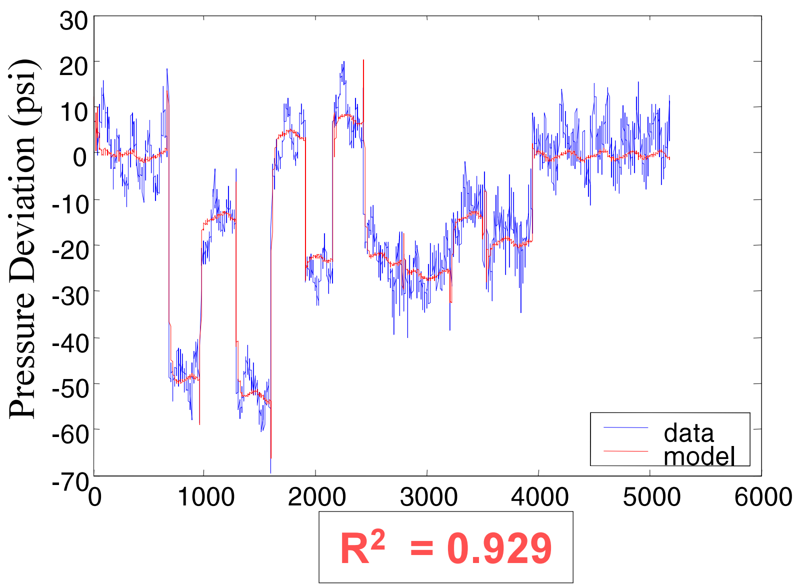


Dynamic model for Torque fits well against measured data

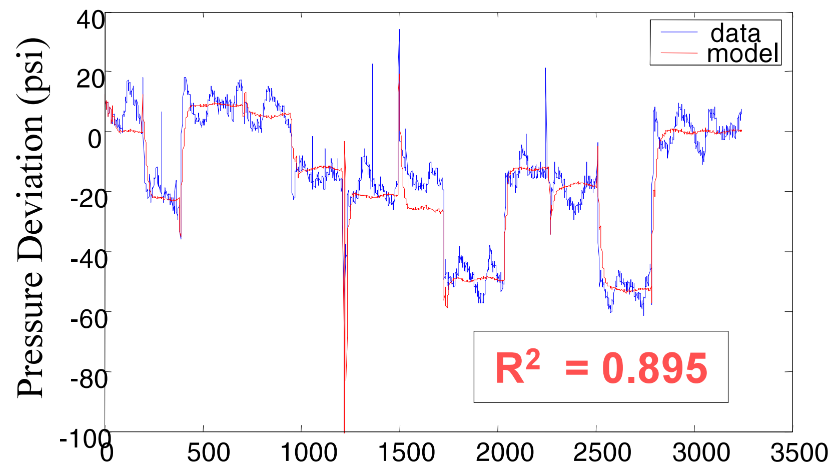
Model for Die Pressure

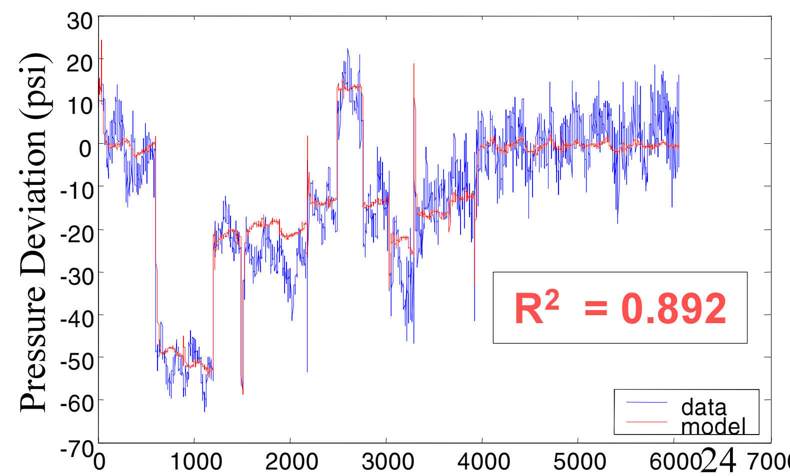
- **Input/Output data collected from large extruder at GEP Selkirk** (2000 lb/hr)
- **Dynamic model: fit from one data set and validate against two other data sets**

Model Fit



Model Validation





Dynamic model for Die Pressure fits well against measured data

Use Input/Output Models for Residual Generation and Fault Detection

Residuals for Sensor Fault Detection

- **Residuals between Measurement & Model Prediction**

$$y_1 - \{G_{11}u_1 + G_{12}u_2 + G_{13}u_3 + G_{14}u_4\}$$
$$y_2 - \{G_{21}u_1 + G_{22}u_2 + G_{23}u_3 + G_{24}u_4\}$$

Residuals	independent of fault in
r_1	y_2
r_2	y_1

Generate 4 more residuals with unique signature of a fault (bias) in an input sensor (u_i), e.g

$$(G_{21}y_1 - G_{11}y_2) - \{G_{21}(\Sigma G_{1j}u_j) - G_{11}(\Sigma G_{2j}u_j)\}$$

Residuals	independent of fault in
r_3	u_1

Residual - Fault Signature Table

Faults	Residuals 1	2	3	4	5	6
No Fault	F	F	F	F	F	F
Bias in Torque	T	F	T	T	T	T
Bias in Die Pressure	F	T	T	T	T	T
Bias in Master Rate	T	T	F	T	T	T
Bias in Blend %	T	T	T	F	T	T
Bias in Screw Speed	T	T	T	T	F	T
Bias in Die Zone Temp.	T	T	T	T	T	F

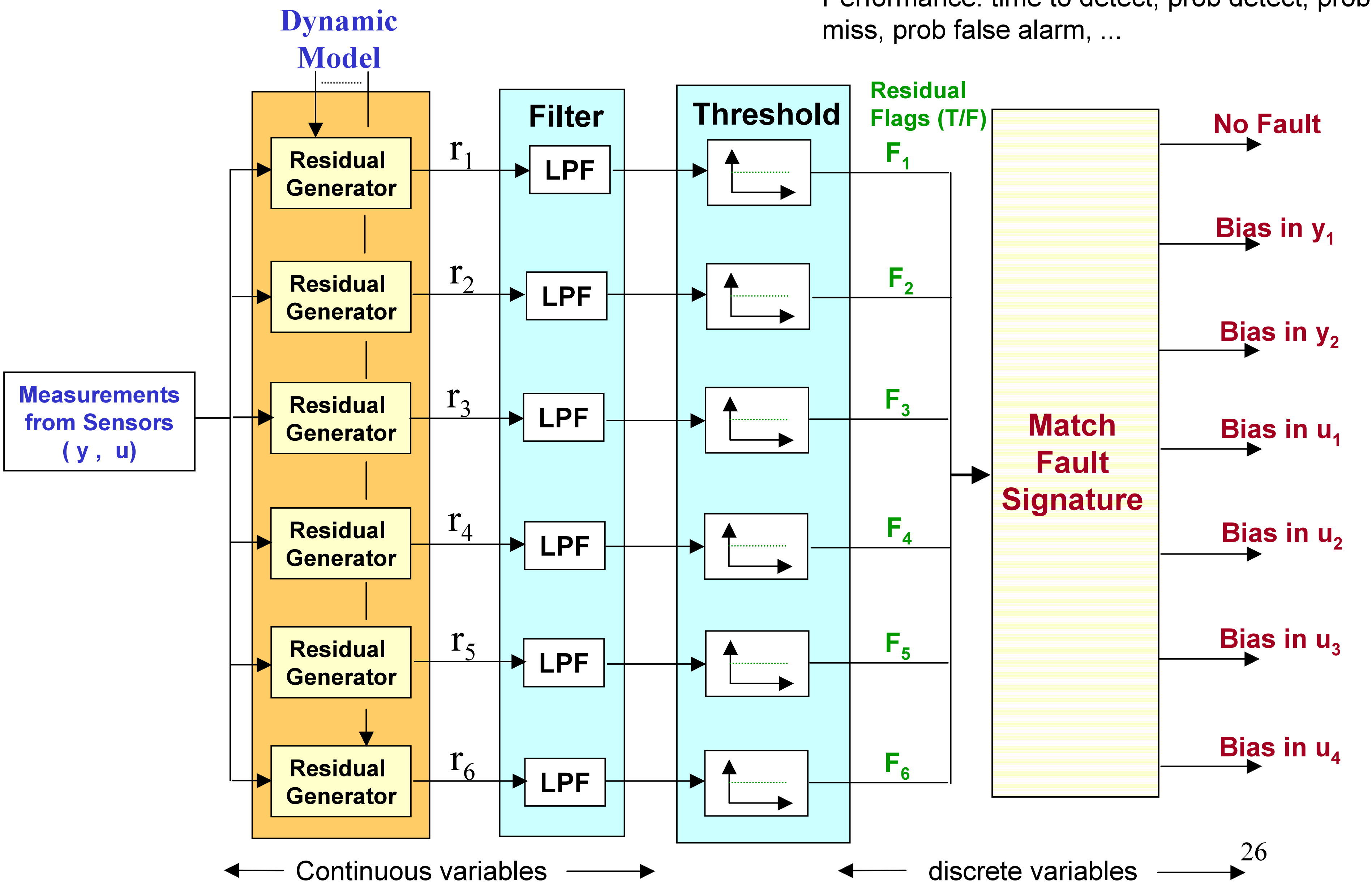
F : Zero Residual T : Non-Zero Residual

Unique Fault Signature for Each Sensor Bias Fault

- Issue : Measured signals and thus residuals have noise
- Simple approach: Filter and data optimized threshold tuning for “zero”/ “non zero”
- Rigorous approach: Multiple model or generalized likelihood ratio based on models

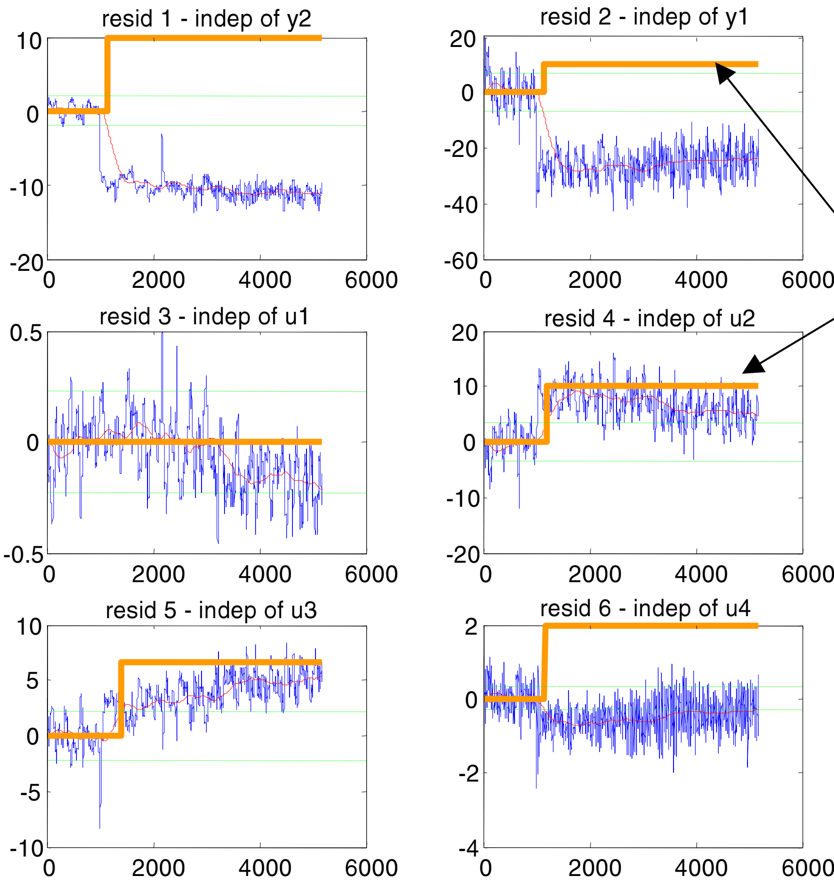
Model Based Fault Detection Block Diagram

Performance: time to detect, prob detect, prob miss, prob false alarm, ...



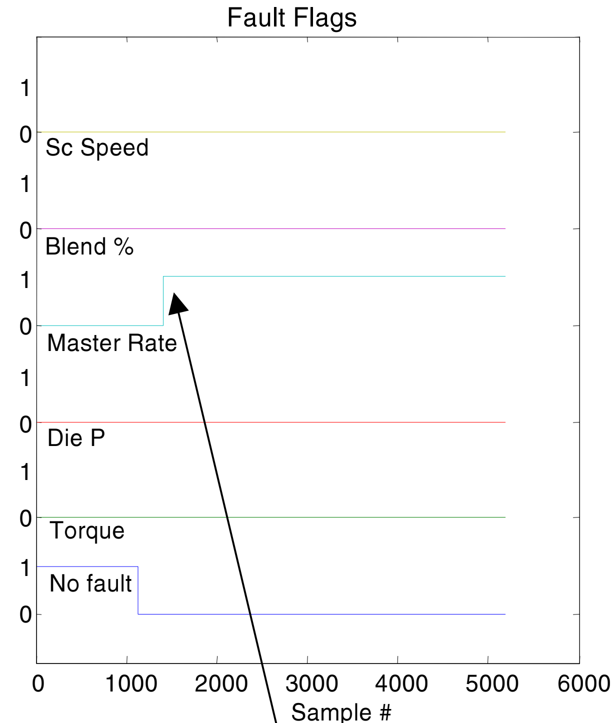
Detection of Sensor Bias or Drift

Residuals



Analyzing sensor data from DOE run with **300 lb/hr bias** introduced in **master feedrate (u1)** at sample# 1000 (simulation run)

Residual Flags



Residual Flags for ALL residuals except r_3 become TRUE - matches fault signature of a bias in Master Rate (u_1)

- **Bias detected in master feedrate** after ~250 samples

Sensor Bias Detection will Improve Reliability of Viscosity Estimation and Detection of Good/Bad Product

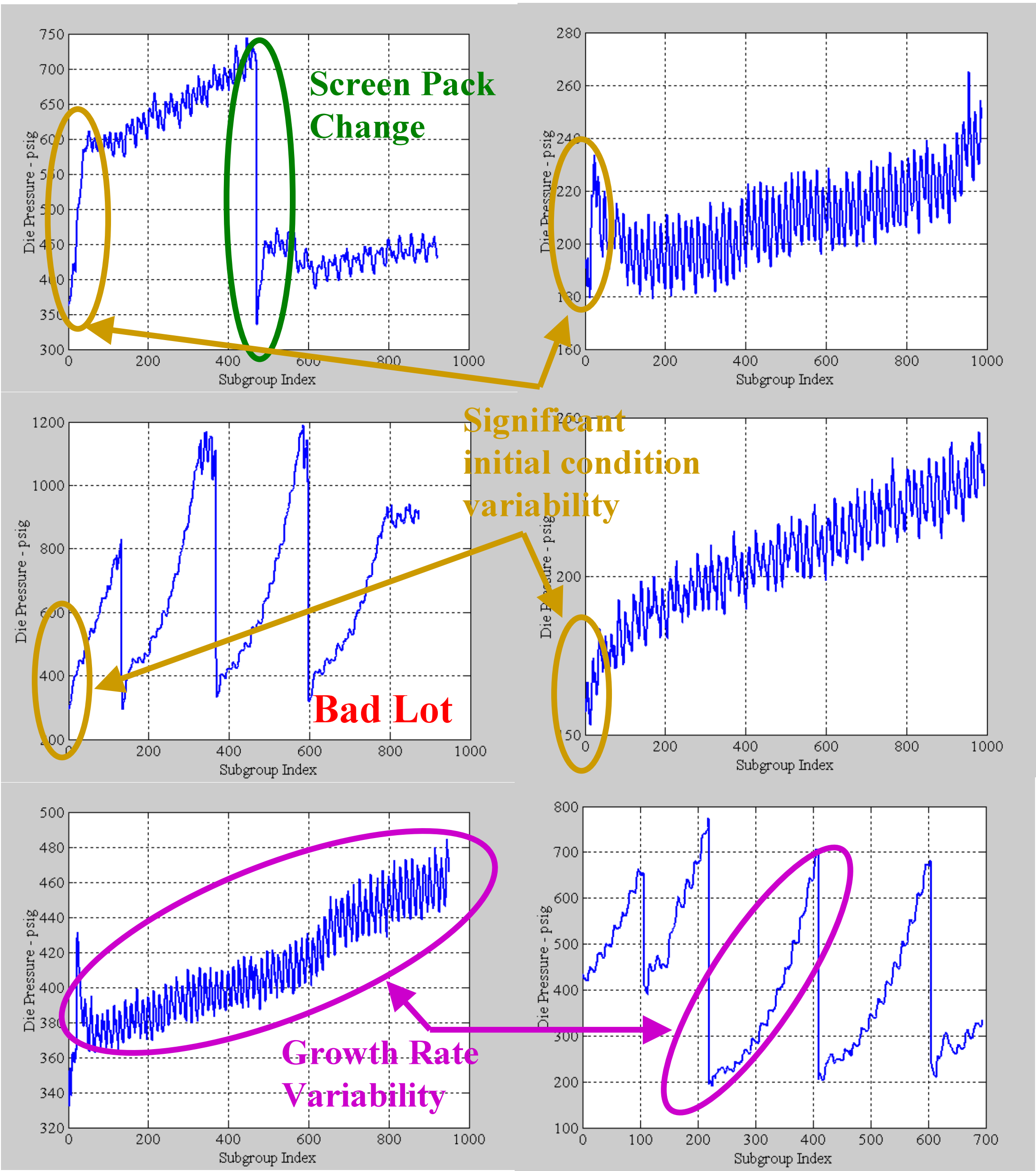
Die Pressure/ Screen Pack ProblemCase study

When can a single machine variable and its statistics or spectral features be used to detect out spec production?

- Problem: Screen packs commonly used upstream of die to filter un-melted junk
- Impact: Variable % blockage corrupts die pressure measurement
  - Large lot-to-lot variability in the initial die pressure
  - Large within lot variability due to process variability and maintenance practices (e.g. when screen pack changed)
  - Inconsistency in die pressure change rate
- Result: SPC on die pressure alone unreliable
- Approach: Could adopt model based methods above, but are there simpler ways?.

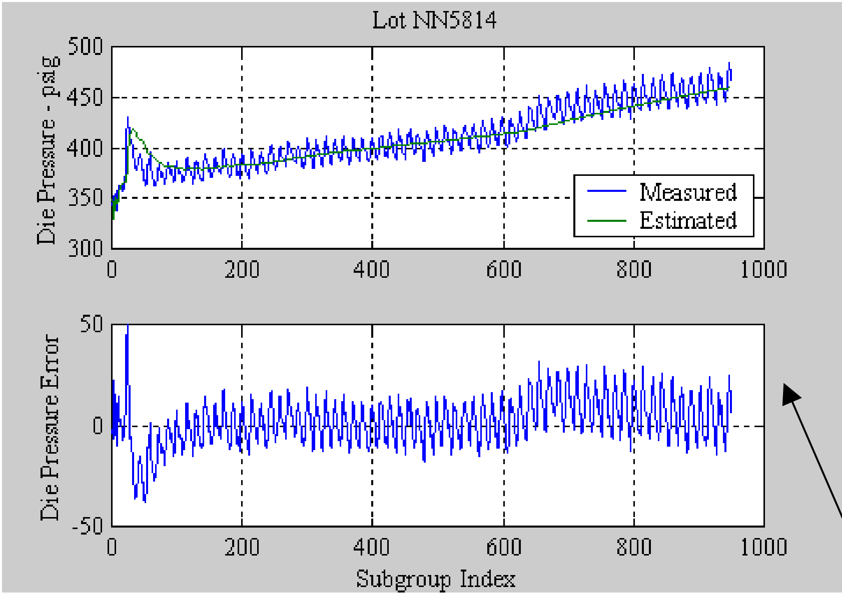
Here Illustrate diagnostic methodology developed using data from a 120mm production scale extruder producing Noryl™ (PX0844).

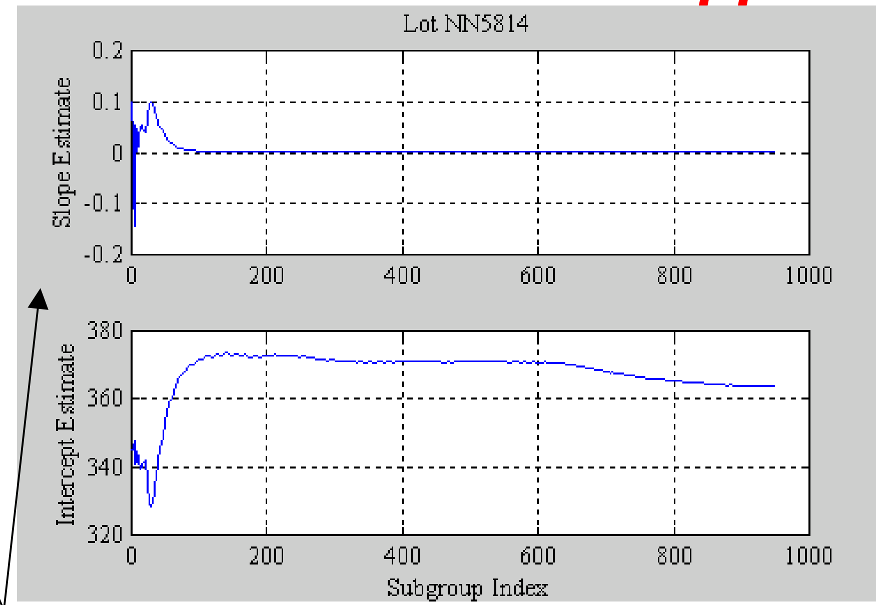
Kalman filter based bad lot detection

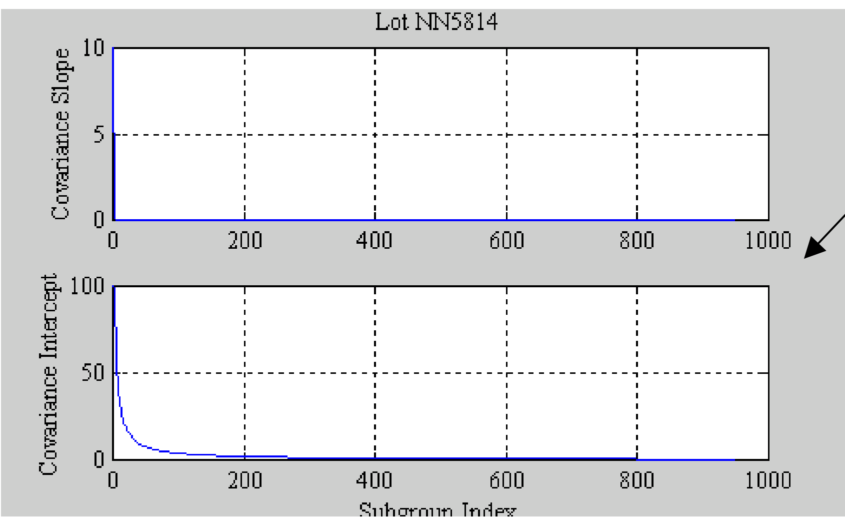


- Data from different production runs shows significant variability in die pressure signal even though only one lot is considered out of product viscosity spec
- Diagnostic technique must be robust to uncertain initial condition and maintenance impacts such as screen pack changes.
- Chosen diagnostic approach is to optimally estimate the slope and the intercepts using a Kalman Filter. The estimates and the confidence of these estimates is compared with a threshold to differentiate between good and bad lots.

Example of Diagnostic Approach



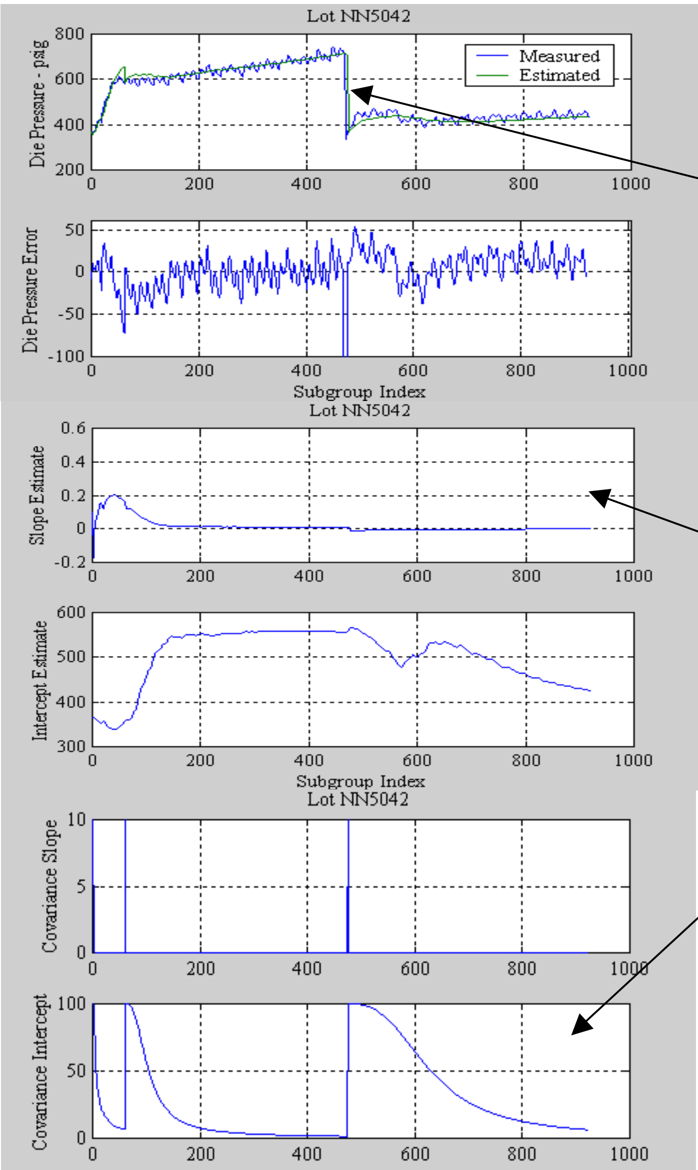




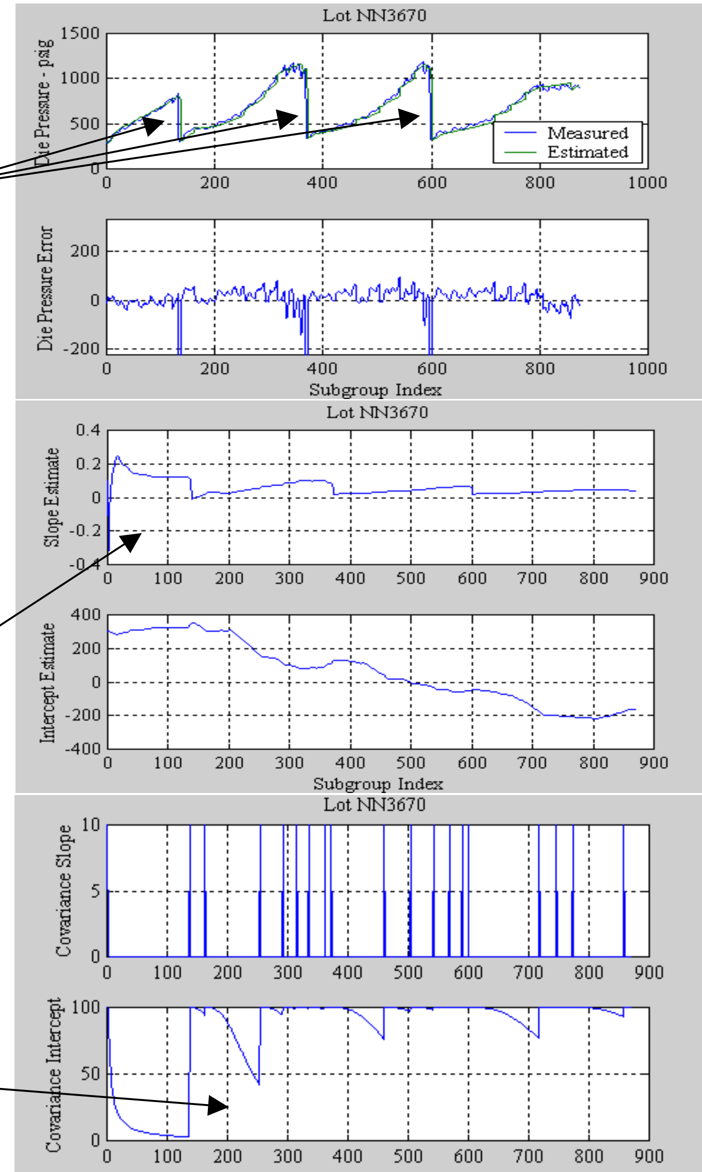
- Comparison of measured and estimated die pressure signal
- Optimal estimates of slope and intercepts
- Uncertainty (I.e., covariance) in the estimates of slope and intercept.
- Diagnostic approach is based on information fusion of:
  - Monitor slope estimate and compare with threshold
  - Monitor covariance of intercept estimate and if intercept uncertainty remains large for a prolonged period of time, then high probability that the lot is bad.

Kalman filter bad lot detection

Approach Applied to A Good Lot



Approach Applied to A Bad Lot



Handle screen pack changes via reset of algorithm. Screen pack change is a known event and is easily incorporated into approach.

Slope estimate below threshold.

Slope estimate above threshold.

Covariance of intercept decreases over time.

Covariance of intercept remains high.

Bad lot detection summary

- Die pressure may be used to differentiate between good and bad lots.
- Table below provides summary of various predictors that help to differentiate good and bad lots based on die pressure data for PX0844:

Property	Good Lots	Bad Lots
Die Pressure	<650	>650
Slope estimate	<0.006	>0.01
% Time with high covariance	<30 (Estimates not reset often – process stable)	>70 (Estimates reset often – process unstable)

- Performance: 28 correct bad lot detections, one false alarm and one possible miss with non optimized threshold settings.
- To improve robustness, the basic approach is extended by incorporating a process model and identifying a more optimal threshold for resetting of estimates due to screen pack changes.
- Thresholds can be determined easily by using historical data.

Program Summary: Key 2000-2001 Results

Inferential sensing from machine variables

- multivariate viscosity estimation with no waste calibration works for multiple polymer materials on research extruder
- repeatable 5-7% viscosity accuracy suitable for continuous quality audit

On-Line Process diagnostics

- new model based strategies for detecting feeder and extruder “drift” and “bias” type system faults
- demonstration on lab extruder and production scale (Selkirk Line 8)
- new “bad lot” detection algorithm

Commercialization

- Working closely with GEIS in Salem and GE Fanuc sales team to develop Services strategy based on algorithm developments
- First cut at computer architecture to support computational needs

Demonstrations

- Invited to particpate in “x_based” controls team at GEP (Selkirk)
- Validate viscosity estimator on commercial scale Noryl production line in Selkirk
- Validated on-line bad-lot detection on Noryl
- 7/01 visit to GEP BOZ (Netherlands) planned for additional demonstrations

Building software tools for machine sensor data fusion for fault diagnostics, inferential sensing and control

Ongoing and Future Work

- Continue viscosity estimation/diagnostics demonstration on production scale machines from new or available data (including Mt. Vernon, BOZ)
- Implement and test closed loop control based on inferential sensor in 25mm research extruder
- Evaluate new high bandwith ‘clamp-on-shaft’ torque sensors (“FACTS”) for use as alternative to drive based torque estimation for screw torque distribution estimation
- Downselect and software algorithms and data handling/interface and storage requirements for use in initial service offerings
- Implement selected algorithms on industrial grade platform as prototype for commercial system
- Develop and transition commercialization plan and integrate with GEIS tollgate and multigenerational product planning cycle
- Final project reporting
- Continue dialog with third party sensor suppliers (e.g., ultrasound, dielectric, transient infrared spectrometry) for possible integration into Intelligent Extruder platform (with resources outside scope of DOE funding)

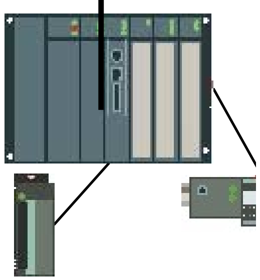
Intelligent Extruder Implementation Platform

Supervisory Control
- Plant wide control (DCS)
- Data Acq./Historian
- Product Tracking

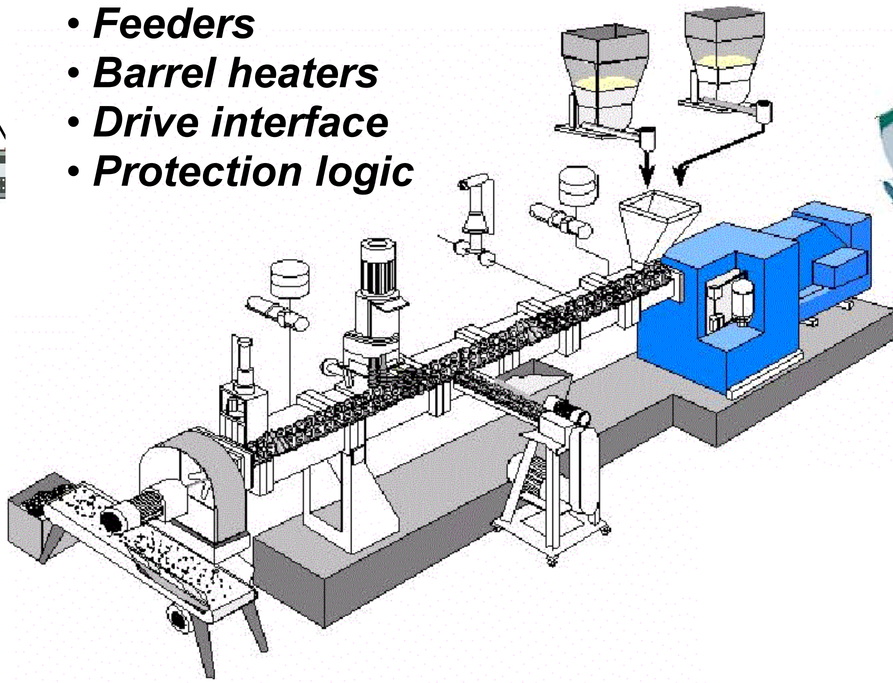
300 Mhz NT Board
- Diagnostics
- Estimation
- Control
- R/T MATLAB C-shell (dev't only)

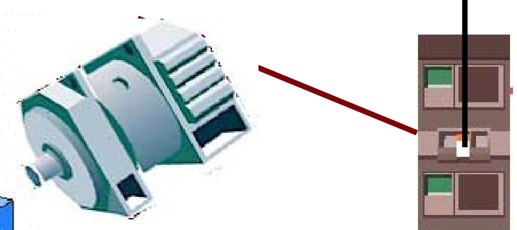
CIMPLICITY HMI
- Custom Screen Apps
- Integrated Diagnostics
- Internet Gateway to OnSite

Internet



PLC Control
- Feeders
- Barrel heaters
- Drive interface
- Protection logic

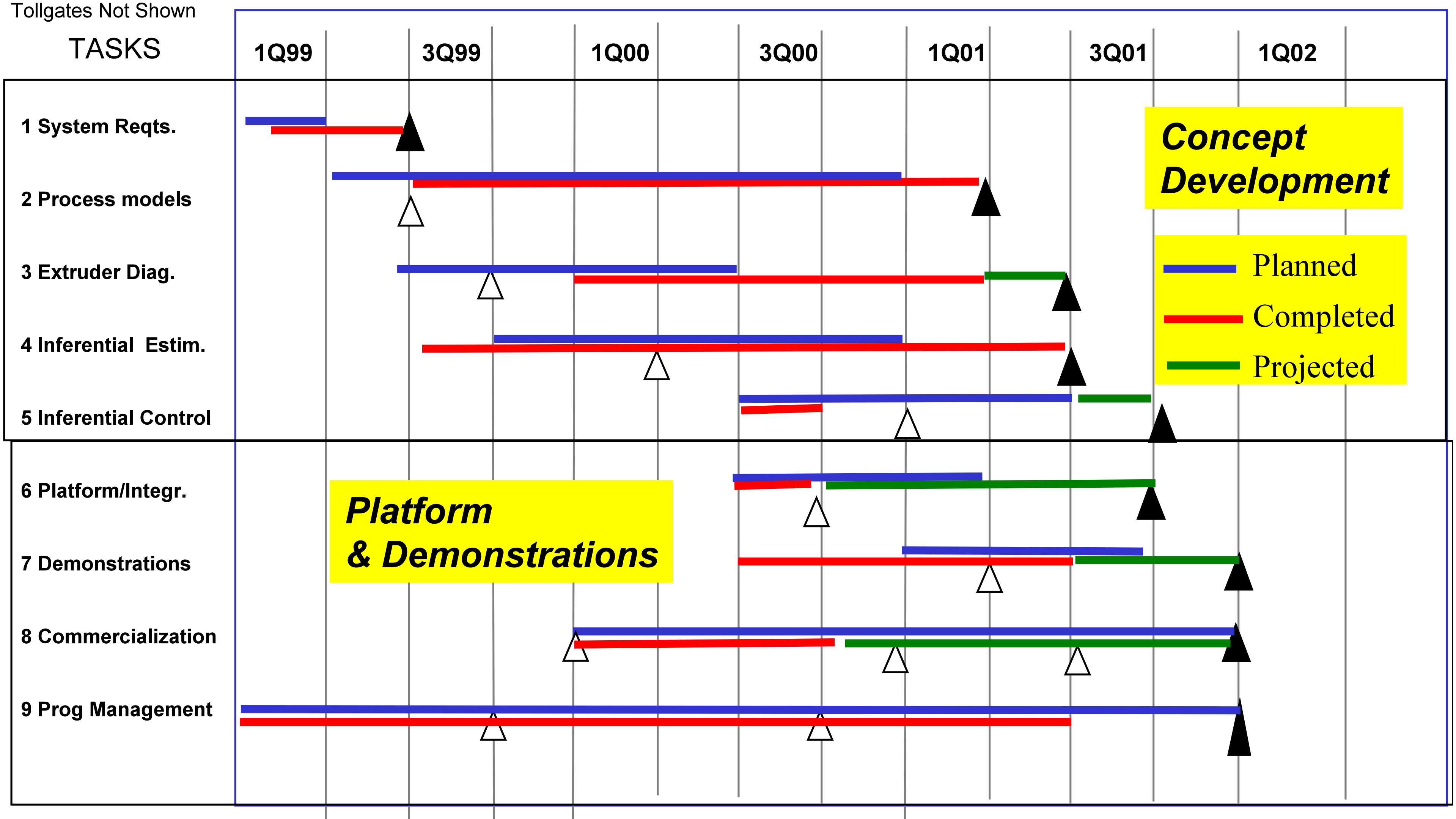




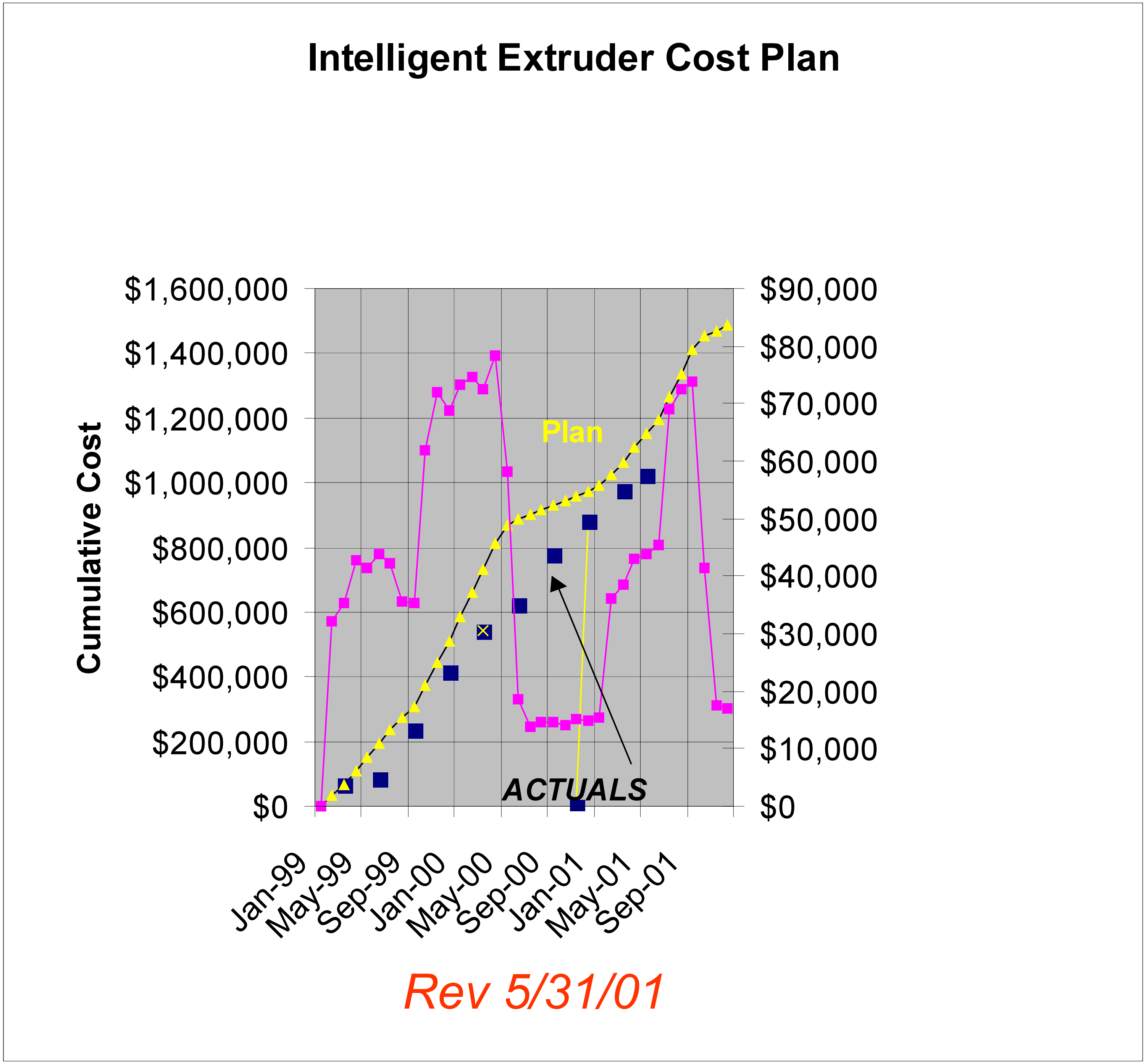
Innovation AC Drive
- Energy -saving AC Drive
- Speed and Torque Control
- Torque resonance elimination
- Auto-tune & Drive diagnostics

Intelligent Extruder Project Plan

GE Industrial Systems Dev't Tollgates Not Shown



△ = interim release/ completion milestone ▲ = task completion


Intelligent Extruder Cost Plan
Cumulative Cost
$1,600,000
$1,400,000
$1,200,000
$1,000,000
$800,000
$600,000
$400,000
$200,000
$0
$90,000
$80,000
$70,000
$60,000
$50,000
$40,000
$30,000
$20,000
$10,000
$0
Plan
ACTUALS
Jan-99
May-99
Sep-99
Jan-00
May-00
Sep-00
Jan-01
May-01
Sep-01
Rev 5/31/01

More Information
(see handout)
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