

Advanced Pharmaceutical Manufacturing as an Enabler of QbD and Science-based Regulation Solid Dose Case Study

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Presented by
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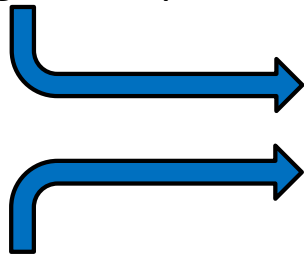
Advanced Pharmaceutical Development

The goal is to model pharmaceutical processes *in silico* and use these tools for optimization

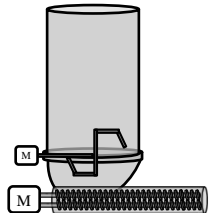
Material Properties



e.g., Flow, Bulk Density,
Angle of Repose



Unit Ops Models

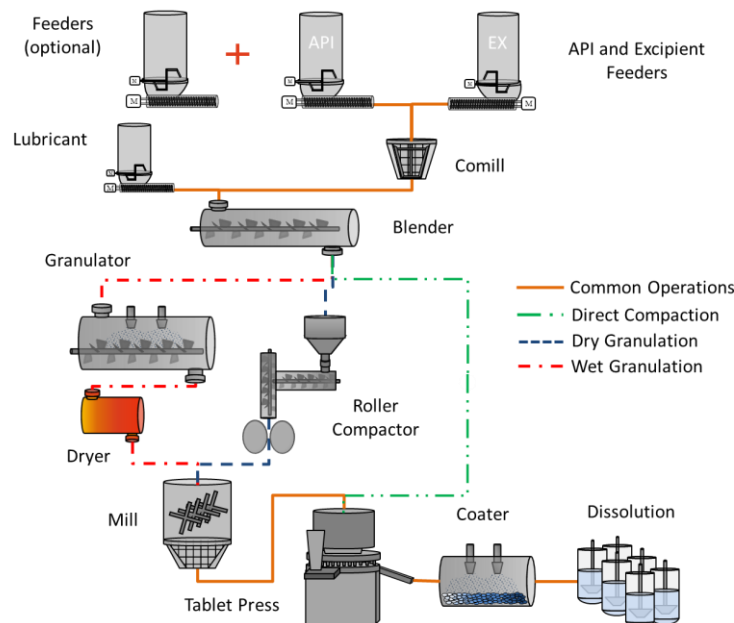


e.g., Feeders

$$y = f(x, a, t, m, n)$$

$$\frac{dy}{dt} = g(x, a, t, m, n)$$

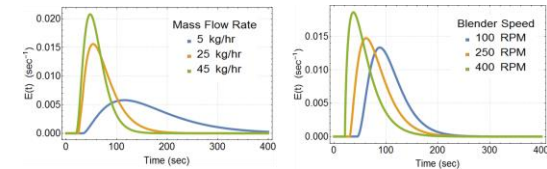
Integrated Process Model "Flowsheets"



Operating Parameters & Design

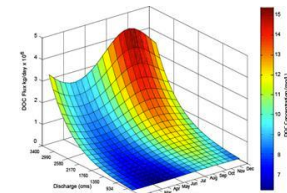


Predictive Modeling



Reduced Order Model

$$y = \beta_0 + \sum_{i=1}^k \beta_i x_i + \sum_{i=1}^k \beta_{ii} x_i^2 + \sum_{i < j} \beta_{ij} x_i x_j + \varepsilon$$



Optimization

$$\min f(x)$$

$$\text{st. } h(x) = 0$$

$$g(x) \leq 0$$

2

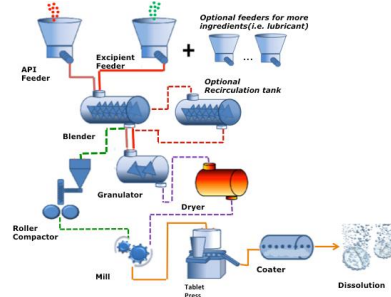
The Design Chain

How does the process create a structure?

How do material properties affect the structure?

How does the structure determine performance?

Bulk Ingredient



Process

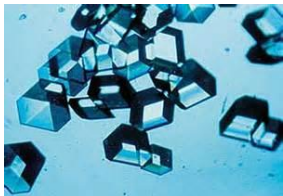


Product

In vitro
performance



In vivo
performance



Crystal

A Strategy for Minimizing time and materials Maximizing process understanding

(as defined as part of the collaboration with Janssen)

- Identify system failure modes
- Define measurements and metrics to predict impact of failure modes for a given formulation
- Build material property data base and predictive models for new materials and surrogates in unit ops
- Use relevant failure mode knowledge to define DOEs and select PAT and control
- Perform integrated formulation and process optimization

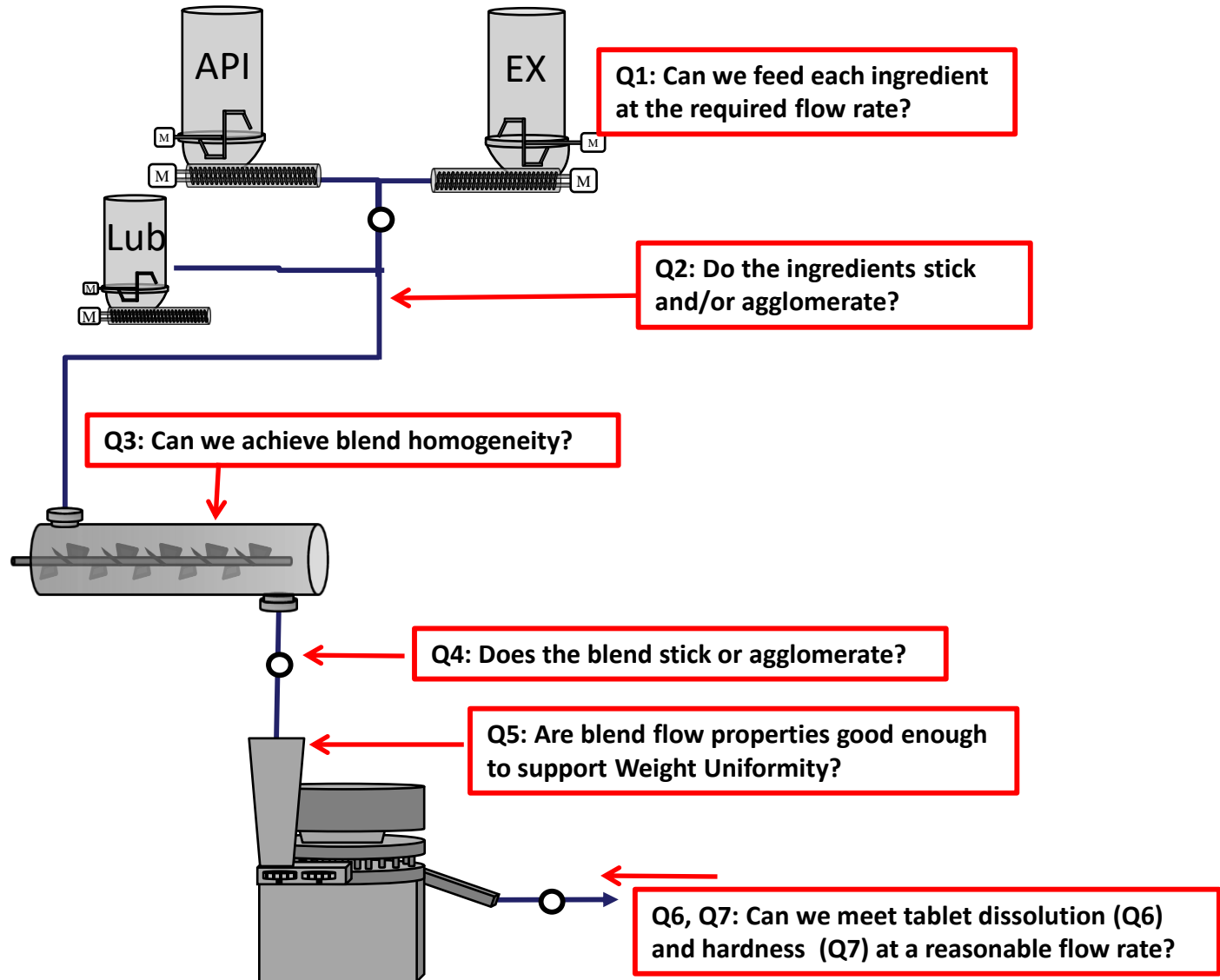


Critical Questions in DCCM

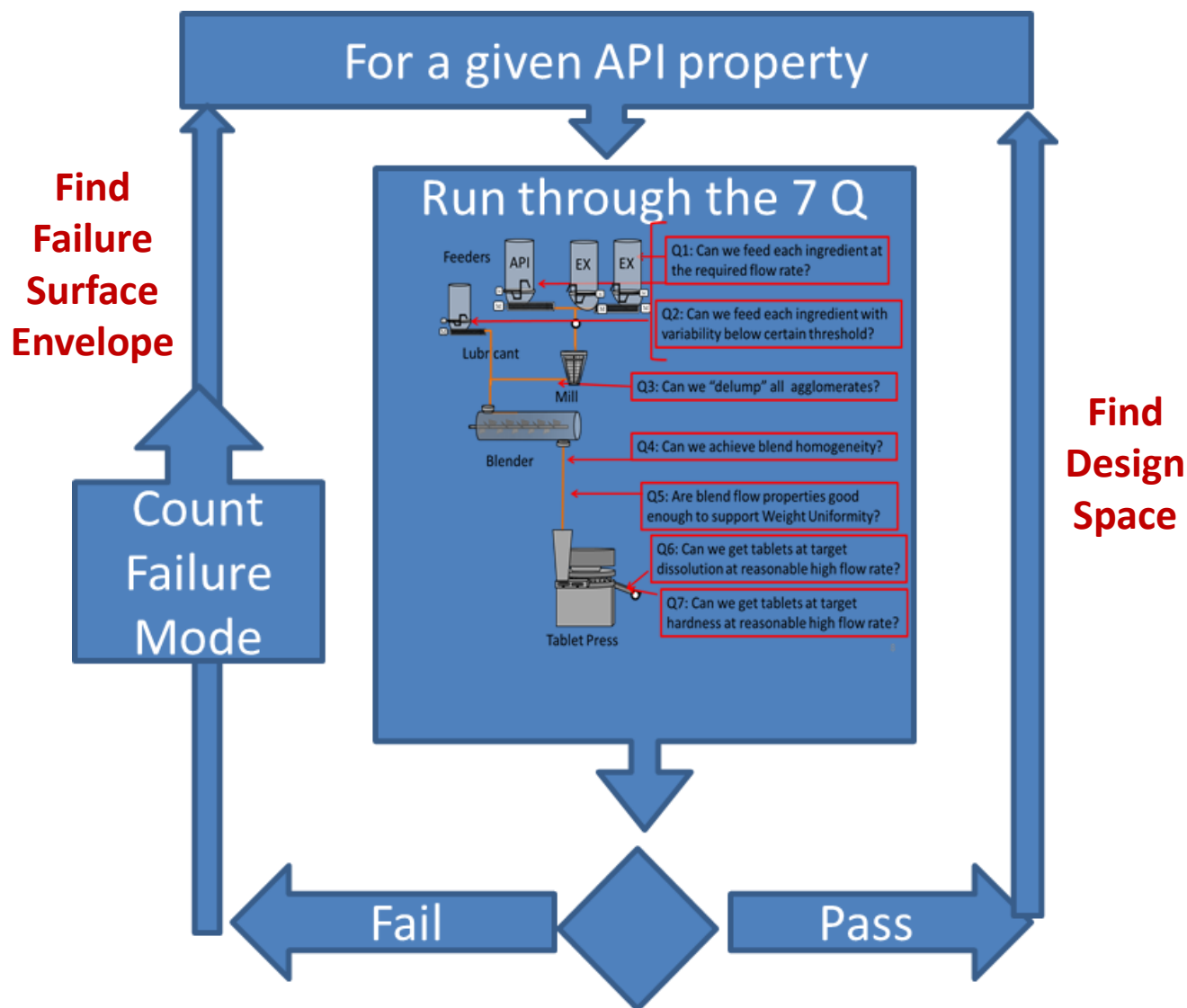
(as defined as part of the Collaboration with Janssen)

Improving API
processability

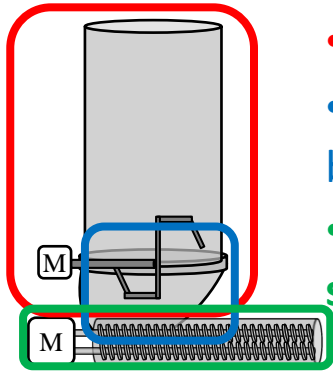
Minimizing
amounts of API
needed in
development



Strategy



What can go wrong in a Feeder?



- **Hopper**
- Flow aid system – bridge breaker
- **Conveying system – screws**



- Clogging – Obstructions:
 - **Cohesion, Electrostatic** (Surface Energy?, PSD?)
- Fluctuations
 - **Compressibility.**
- Refill
- Low Flow Rate is more challenging

Manufacturability (Next steps)

Feeder
Characterization

- Q1: Can we feed each ingredient at the required flow rate?
- Q2: Can we feed each ingredient with variability below certain threshold?

Blender
Characterization

- Q3: Does the blend stick/or agglomerate?
- Q4: Can we achieve blend homogeneity?
- Q5: Are blend flow properties good enough to support weight uniformity?

Tablet
Characterization

- Q6: Can we get tablets at target dissolution at reasonable high flow rate?
- Q7: Can we get tablets at target hardness at reasonable high flow rate?

Characterization Techniques

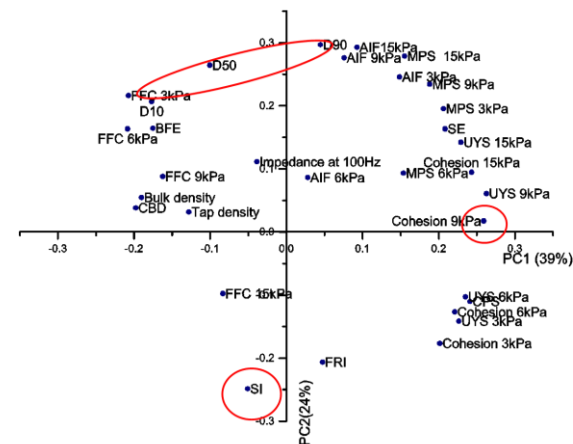
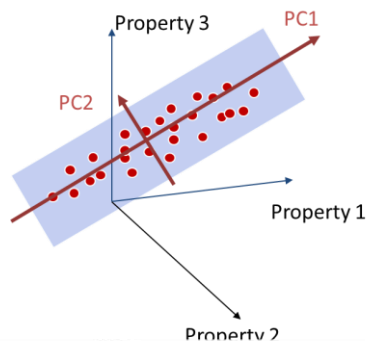
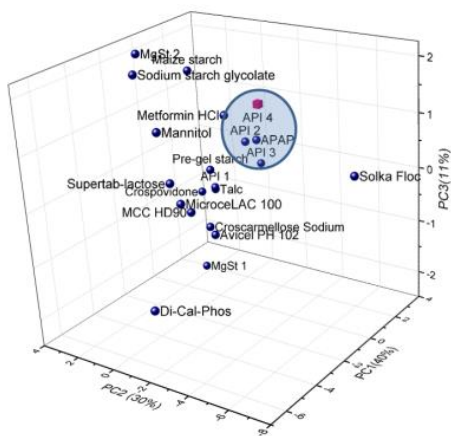
- Particle size distribution
 - *d10, d50, d90*
- Shear cell test
 - *Cohesion, Unconfined Yield Strength, Major Principal Stress, Flow Function Coefficient, and Angle of Internal Friction at initial consolidation stresses of 3kPa, 6kPa, 9kPa, and 15kPa*
- Compressibility test
 - *Conditioned bulk density, Compressibility index*
- Permeability test
 - *Pressure drop*
- Stability/ Variable Flow Rate test
 - *Basic Flow Energy, Stability Index, Specific Energy, Flow Rate Index*
- Electrostatics
 - *Impedance, dry impedance*

Define the design space

- 10-15 measurement techniques with 35-50 measured parameters
- Only 3-5 can explain more than 85% of variability

Full model.

Characterization time: 11hs



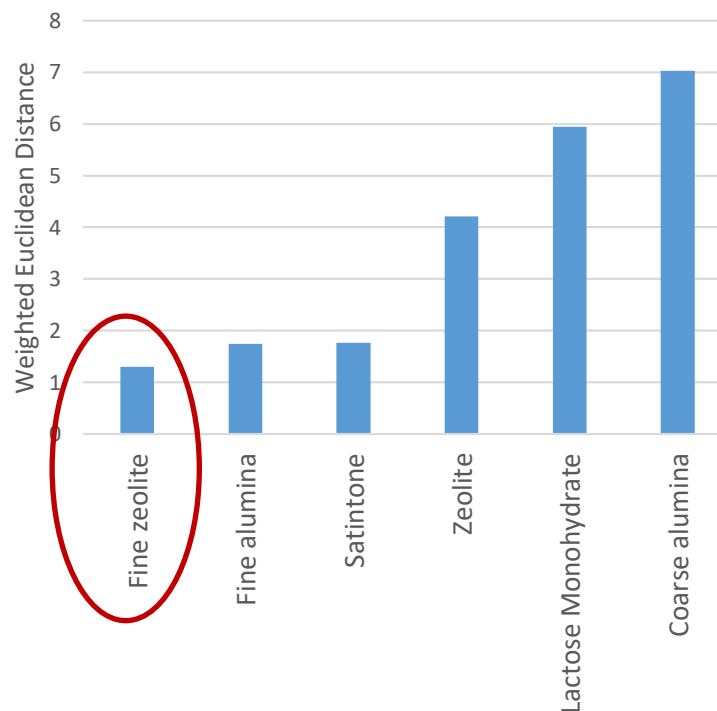
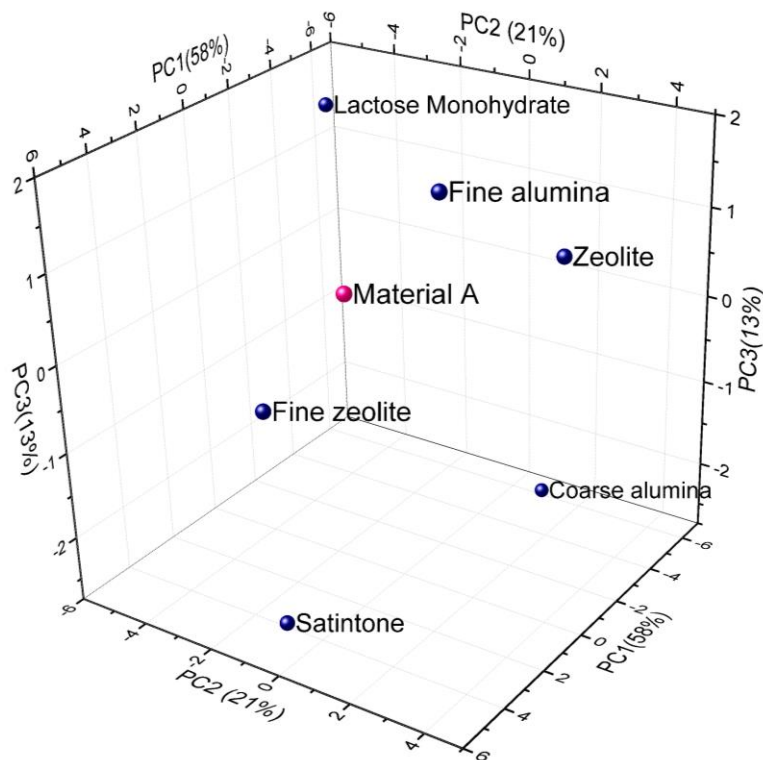
Reduced model.

Characterization time: 3hs

Predicting feeding performance from material flow properties

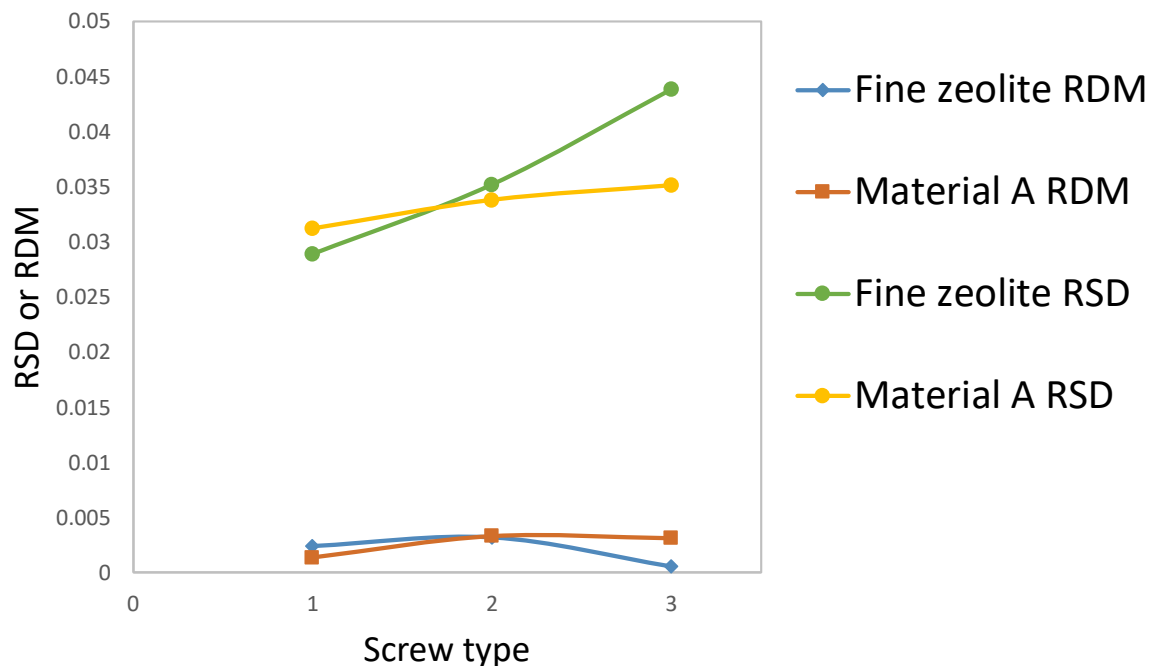
- For a given new material, can we compare it to existing materials in the library?
- Once a new material is included in the material library, can we predict its feeder performance?
- Can we predict the optimal screw choice for a given new material?

Similarity scores of the new material



Material similarity can be quantified by calculating weighted Euclidean distance. Smaller distance corresponds to higher similarity.

Prediction using similarity scores



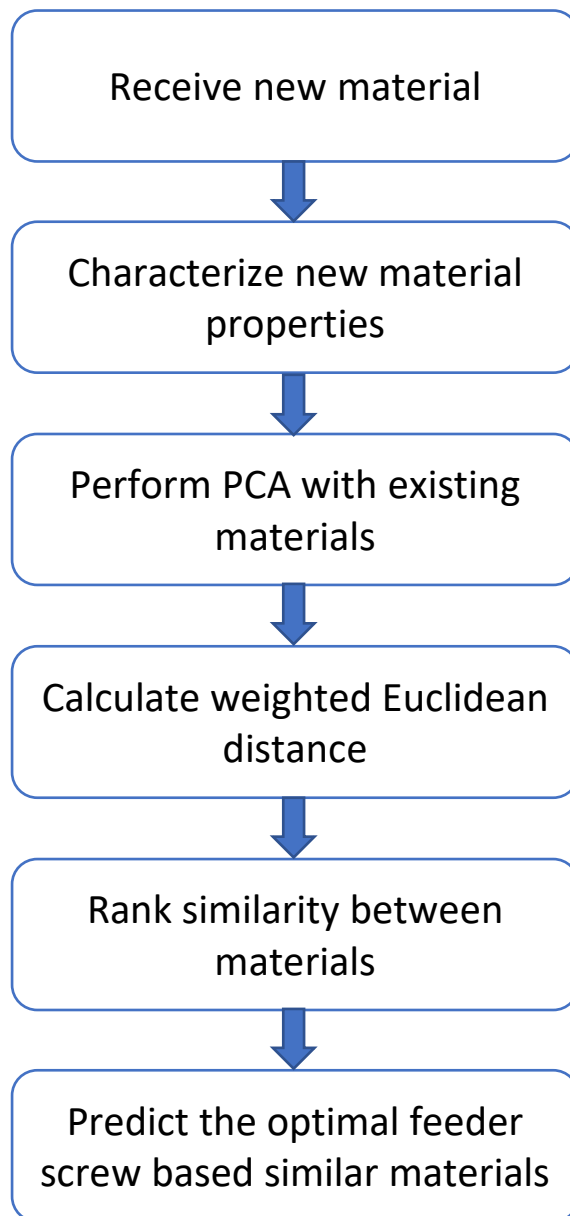
screw type 1
fine concave screw



screw type 2
fine auger screw

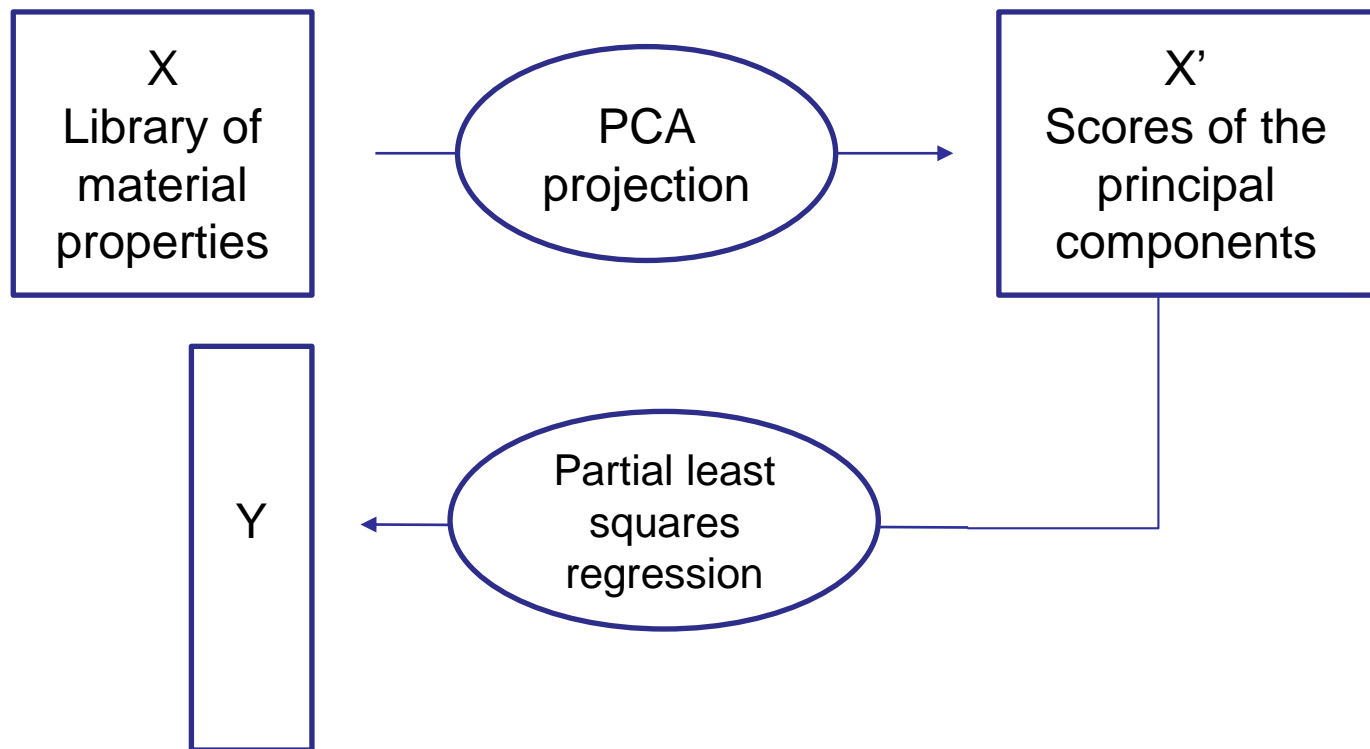


screw type 3
coarse concave screw



Prediction using PLS regression

Alternatively, when material with matching flow properties is difficult to find, a partial least squares (PLS) regression can be used. A PLS regression model relates material flow properties directly to feeder performance, quantified by RSD and RDM.

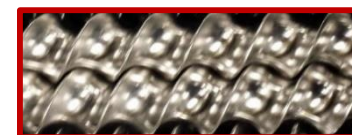
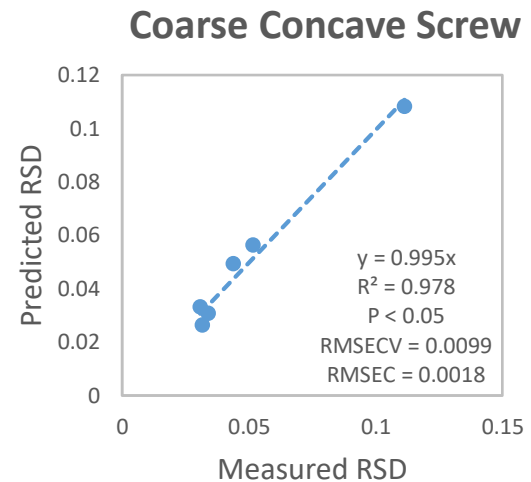
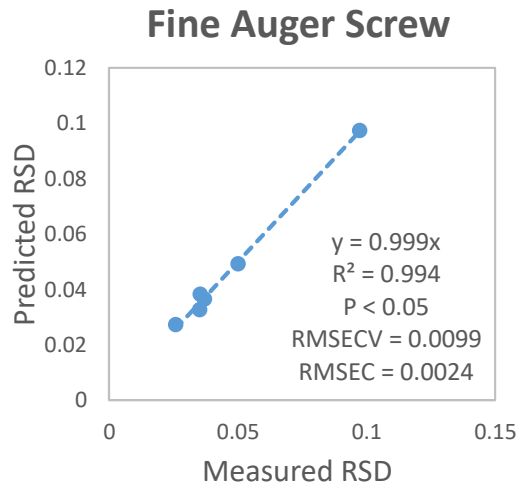
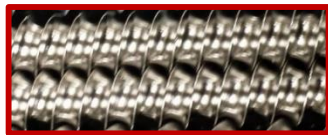
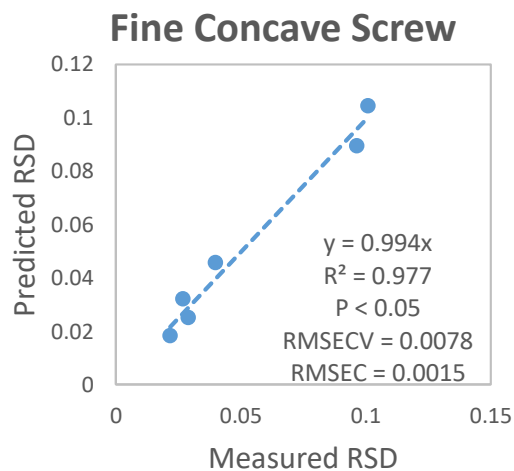


Predicting feeding performance

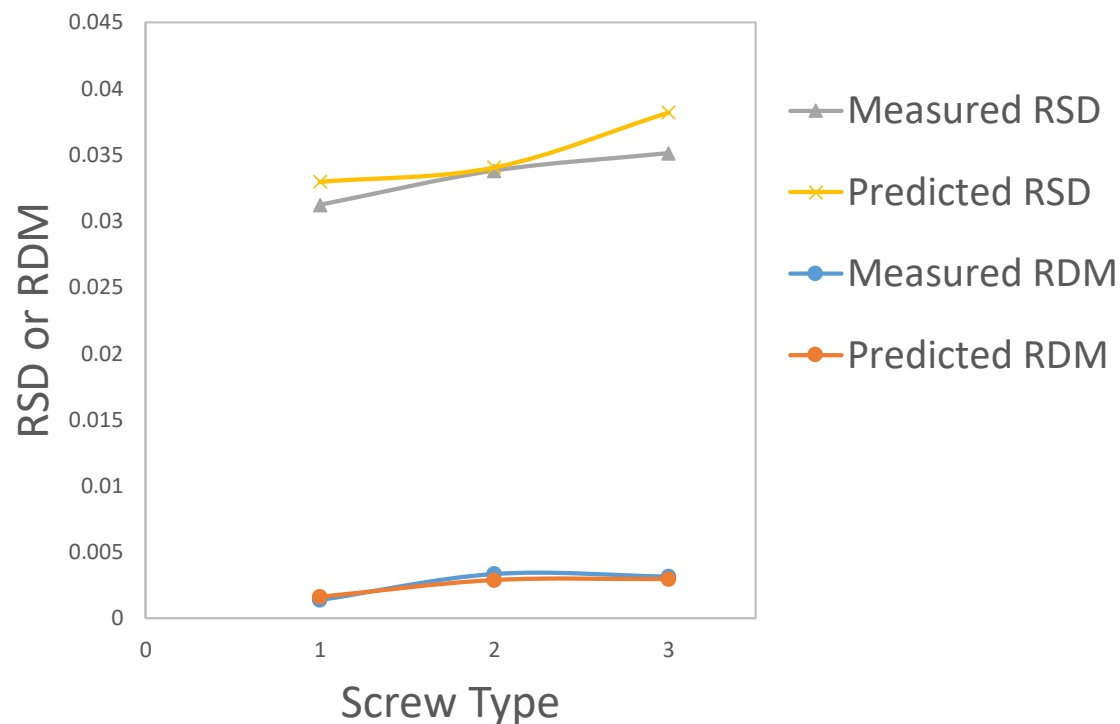
- PLS regression helps to answer:

1. For a new material with given properties, can we predict RSD or RDM for a certain screw?

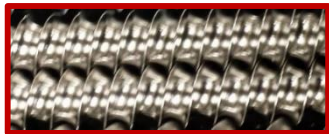
2. For a new material, what is the optimal screw selection?



Prediction using PLSR models



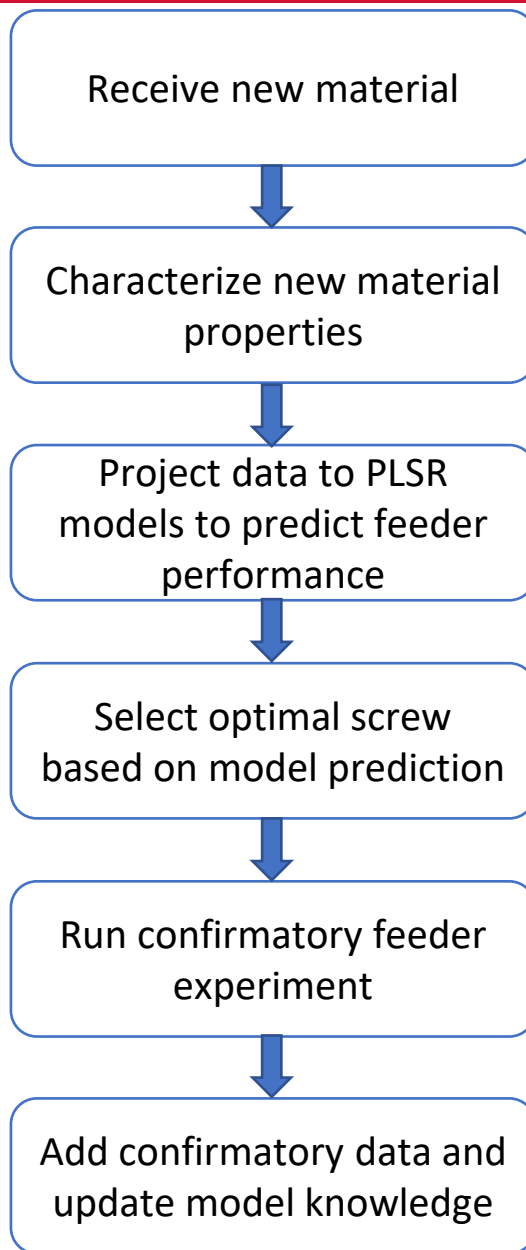
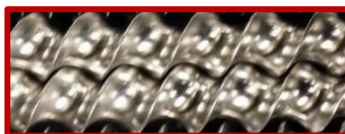
screw type 1
fine concave screw



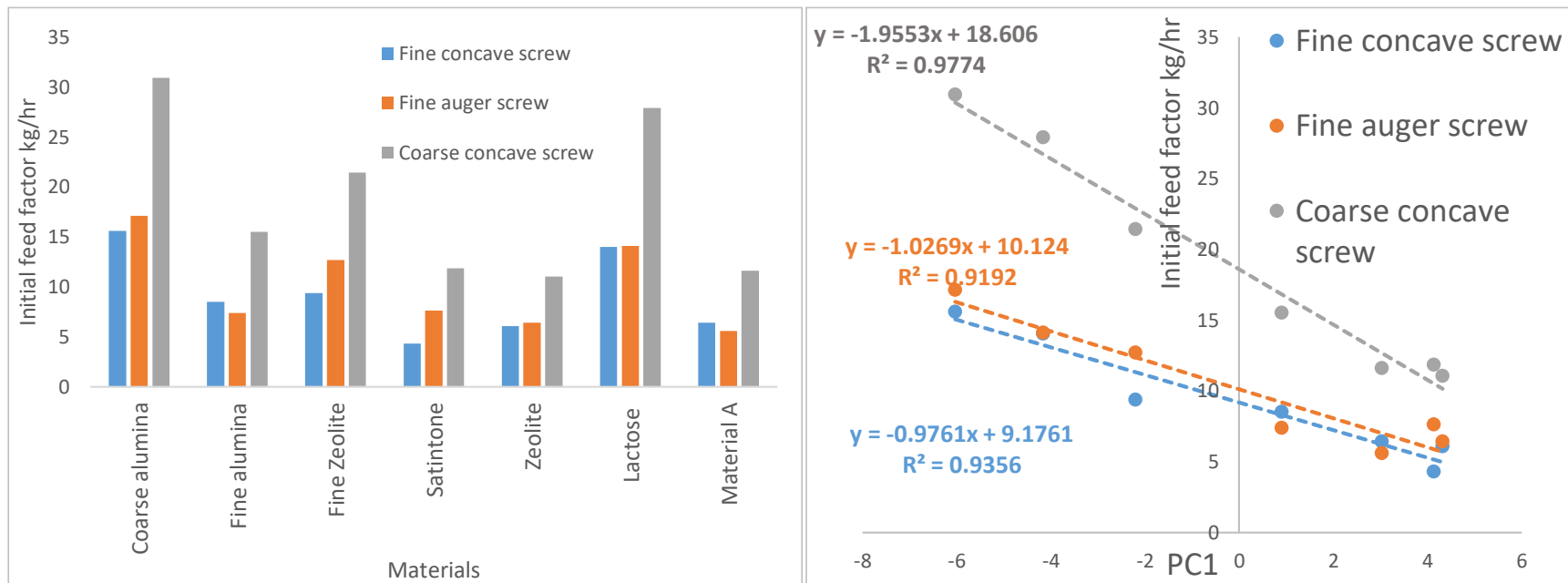
screw type 2
fine auger screw



screw type 3
coarse concave screw

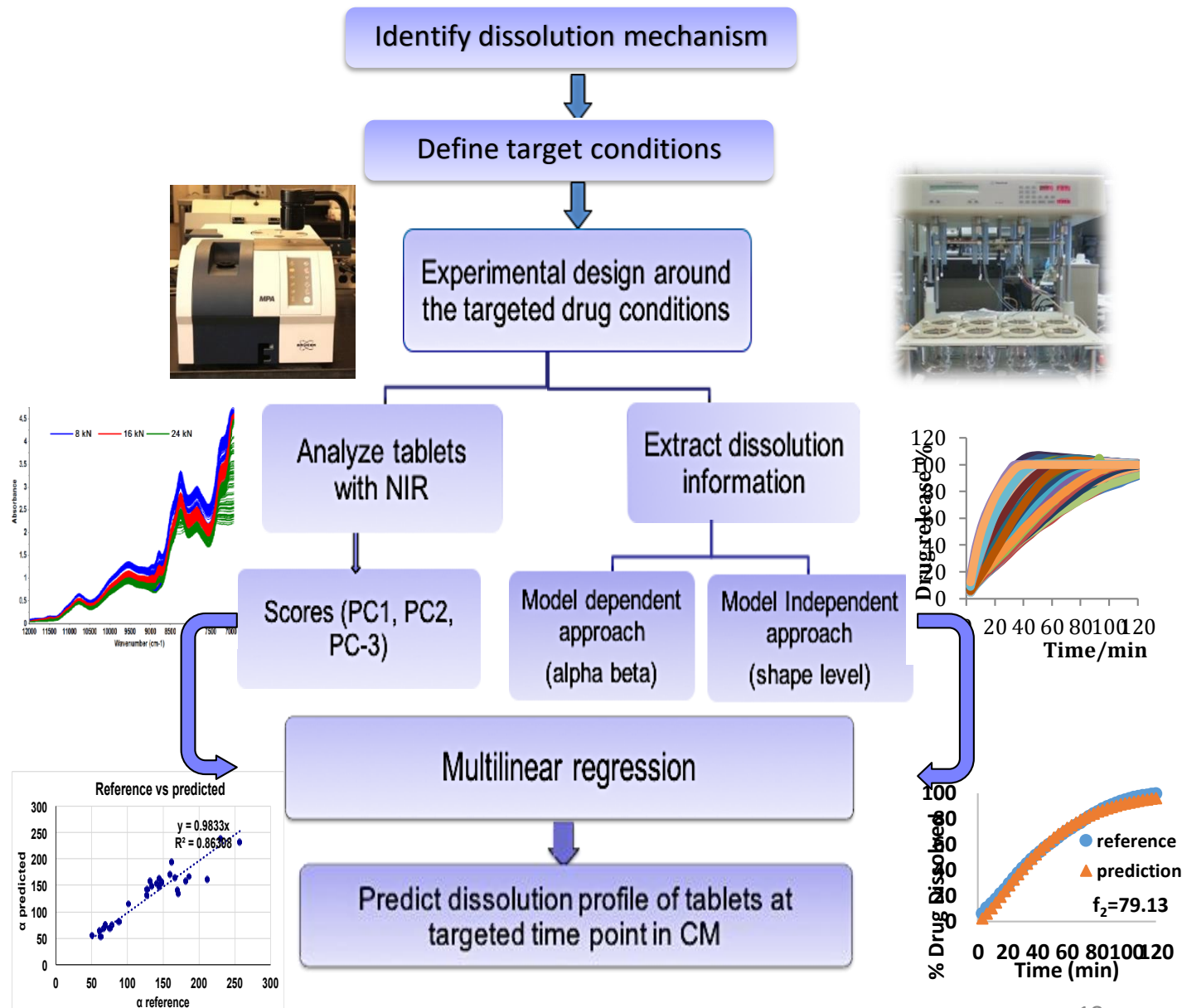


Predicting feed factor from material properties

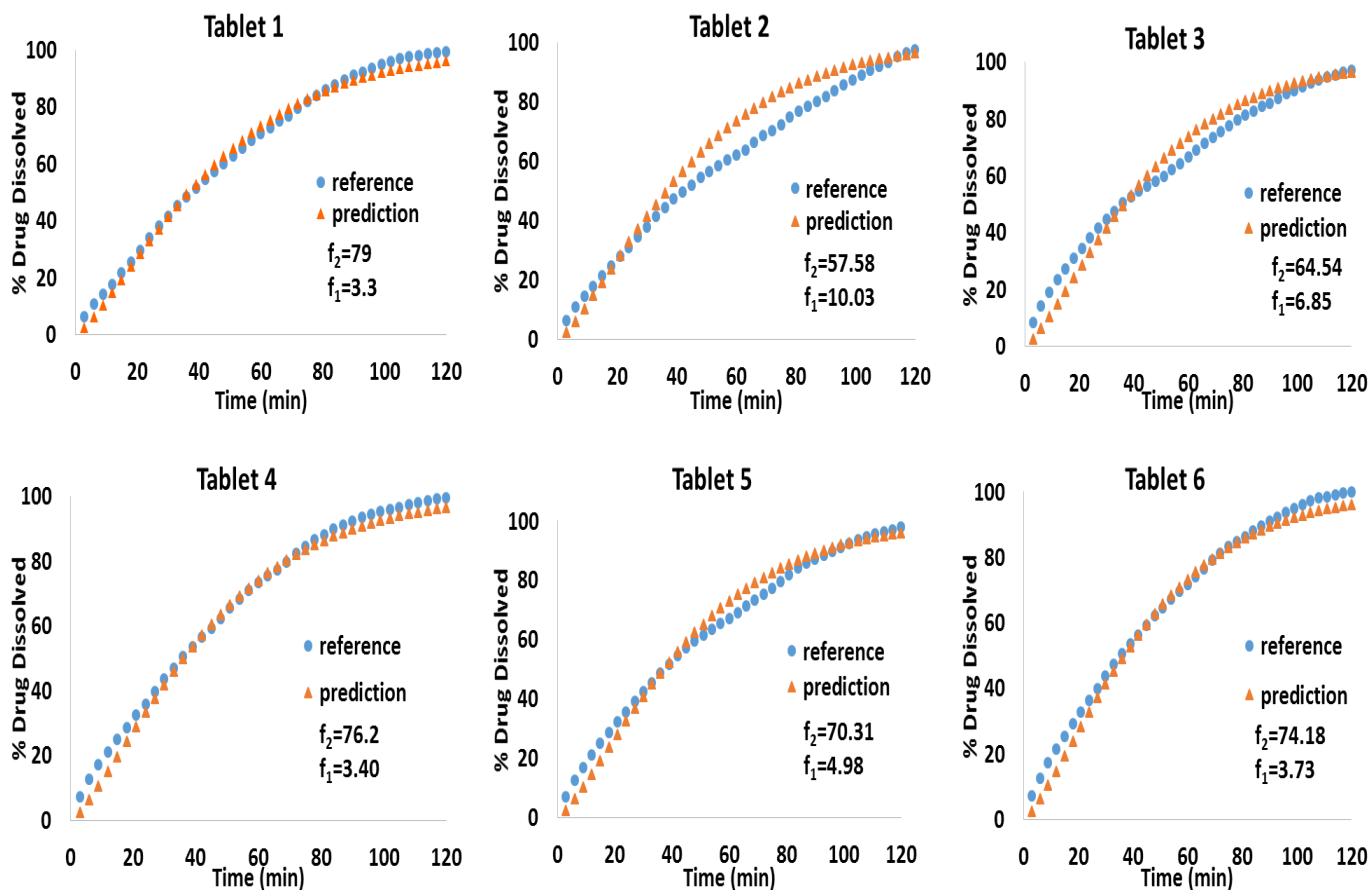


- Initial feed factor reflects maximal feeding capacity for a material.
- Results show that using scores of the first principal component, the initial feed factor can be predicted based on the linear correlation.
- The feed factor using different screws can also be predicted.

General dissolution prediction methodology



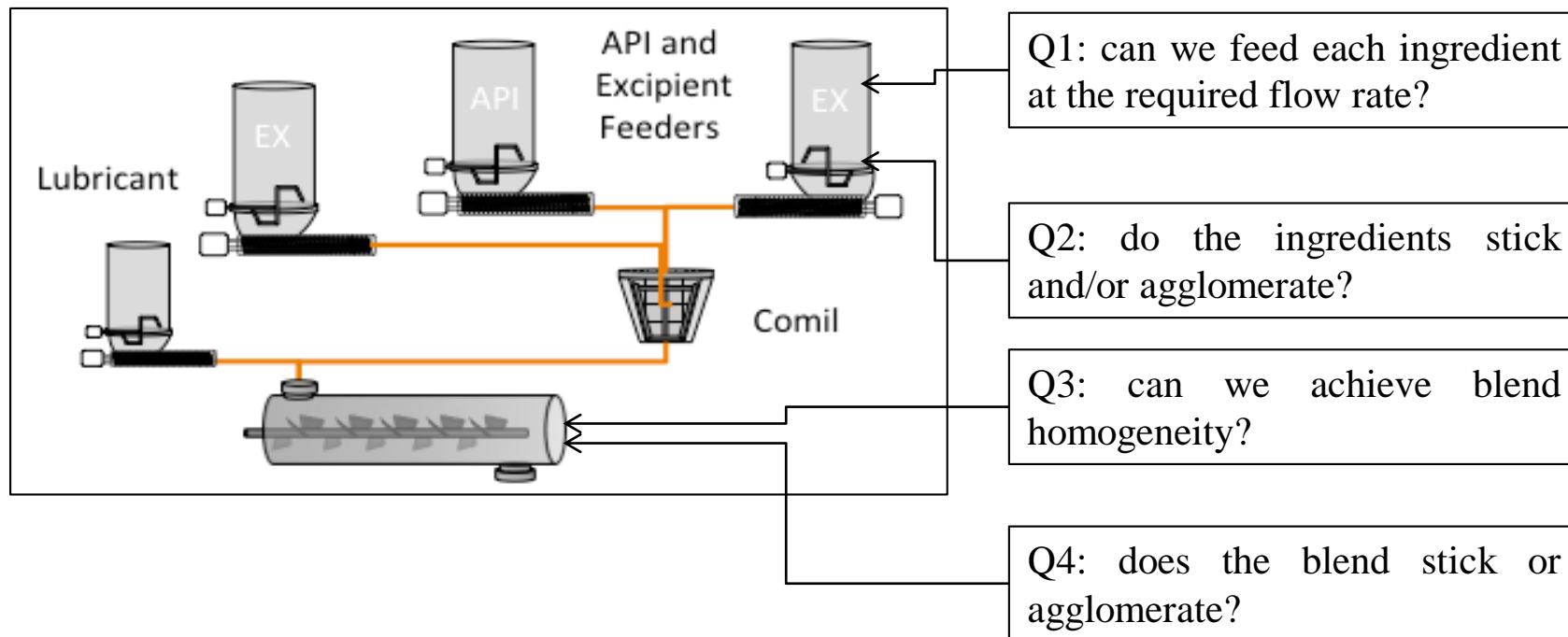
Capability of predict individual tablet dissolution profile: Model-dependent approach



Reference: dissolution profiles

Predicted: NIR PCs

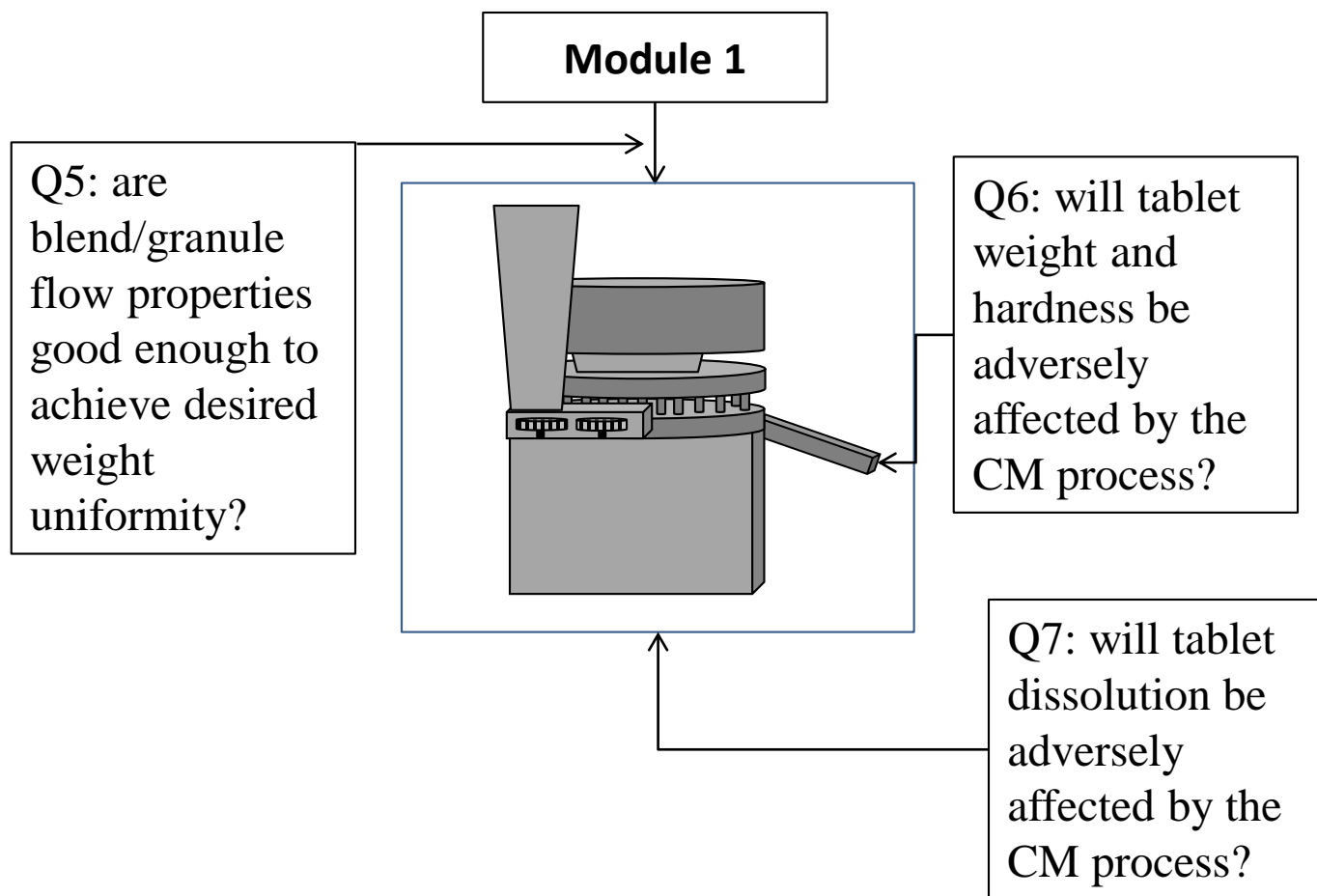
Module 1 – feeders and blenders



RUTGERS Feeder, Mill, Blender: Inputs and Outputs

Unit Op	Inputs	Processing Parameters	Responses	Output Material Properties
Feeder ⁽ⁱ⁾	RM Cohesion ⁽ⁱ⁾ [Coh1 ⁱ]	RPM Impeller (RPM1)	Feeder Flow Rate (FFR) = f [Coh1, Cps1, SE1, E1, RPM1, RPM2,FR, HSG, ST]	Cohesion 2 (Coh2) = f[Coh1, Cps1, SE1, E1, RPM1, RPM2,FR, HSG, ST]
	RM Compressibility ⁽ⁱ⁾ [Cps1 ⁱ]			
	RM Surface Energy ⁽ⁱ⁾ [SE1 ⁱ]	RPM Screw (RPM2)	Feeder Flow Rate Variability (σ_{FFR}) = f[Coh1, Cps1, SE1, E1, RPM1, RPM2,FR, HSG, ST]	Powder Bulk Density2 (DB2) = f [Coh1, Cps1, SE1, E1, RPM1, RPM2,FR, HSG, ST]
	RM Electrostatic ⁽ⁱ⁾ [E1 ⁱ]			
	RM PSD ⁽ⁱ⁾ [PSD1 ⁱ]	Refill Rate (RR)		
	RM Bulk Density ⁽ⁱ⁾ [BD1 ⁱ]	Hopper Size/geometry (HSG)		
	Screw type (ST)			
Mill	Coh2 ⁽ⁱ⁾	RPM Blade (RPM3)	Mill Holdup	Blend Homogeneity 3 (BH3) = f[Coh2, σ_{FFR2} , RPM3, FR5, C%, MSSG, ST]
	σ_{FFR2} ⁽ⁱ⁾	Mill Screen (MS)		Agglomeration 3 (Ag3) = f[Coh2, σ_{FFR2} , RPM3, FR5, HSG, ST, C%]
	Composition (PSD, ⁽ⁱ⁾ [C%]			Cohesion 3 (Coh3) = f[Coh2, σ_{FFR2} , RPM3, FR5, HSG, ST, C%]
	Bulk Density2 ⁽ⁱ⁾ [BD2 ⁱ] Hip: Density has no effect beyond what's captured by cohesion	Screw type (ST) Spacers Geometry (SG)		Density 3 (D3) = f [Coh2, σ_{FFR2} , RPM3, FR5, HSG, ST, C%]
Blender	Blend Homogeneity 3 [BH3]	RPM Blade (RPM4)	Holdup (investigate composition in blender)	Lubricity4 (L4) =f[FR5, Ag3, RPM4, BG, STBP, C%]
	Agglomeration 3 [Ag3]	Blender Geometry (BG)	Blender Residence Time (BRT)	Compatibility (Cpt4) = f[L4, FR5, Ag3, RPM4, BG, STBP, C%, PSD3 (i)]
	Composition [C%]		Dispersion Coefficient (BDC)	Cohesion 4 (Coh4) = f[Coh3, L4, RPM4, FR5, Ag3, HSG, ST, C%]
	Cohesion 3 [Coh3]	Screw type/ Blade pattern (STBP)	Blade Passes (BBP)	Agglomeration 4 (Ag4) = f [RPM4, FR5, Ag3, HSG, ST, C%]
	Bulk Density 3 [BD3]			Blend Homogeneity 4 (BH4) =f[BH3, RPM4, FR5, Ag3, HSG, ST, C%]
	Mill Holdup			Bulk Density 4 (BD4) =f [BD3, L4, RPM4, FR5, Coh3, HSG, ST, C%]

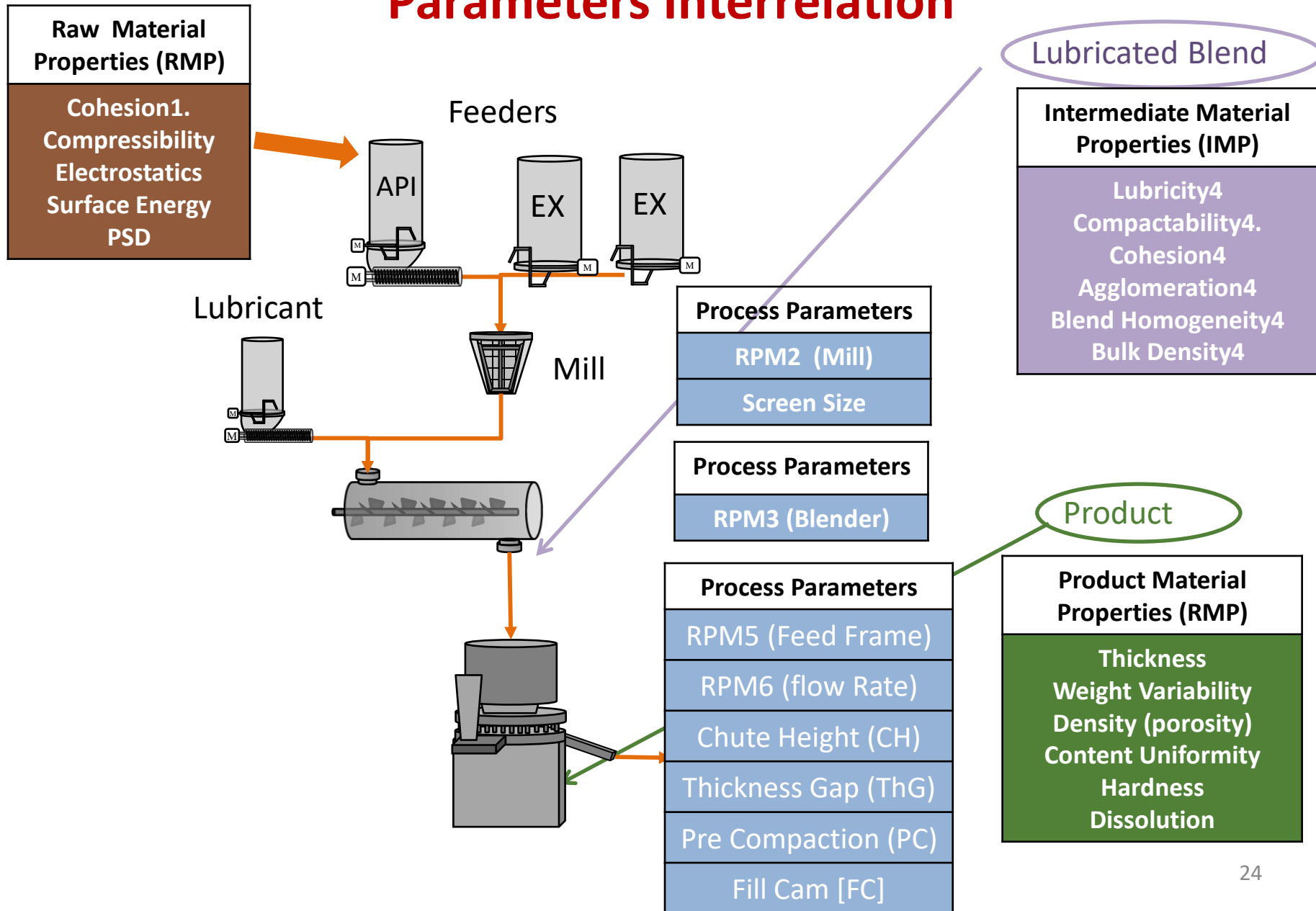
Feed Frame and Tablet Press



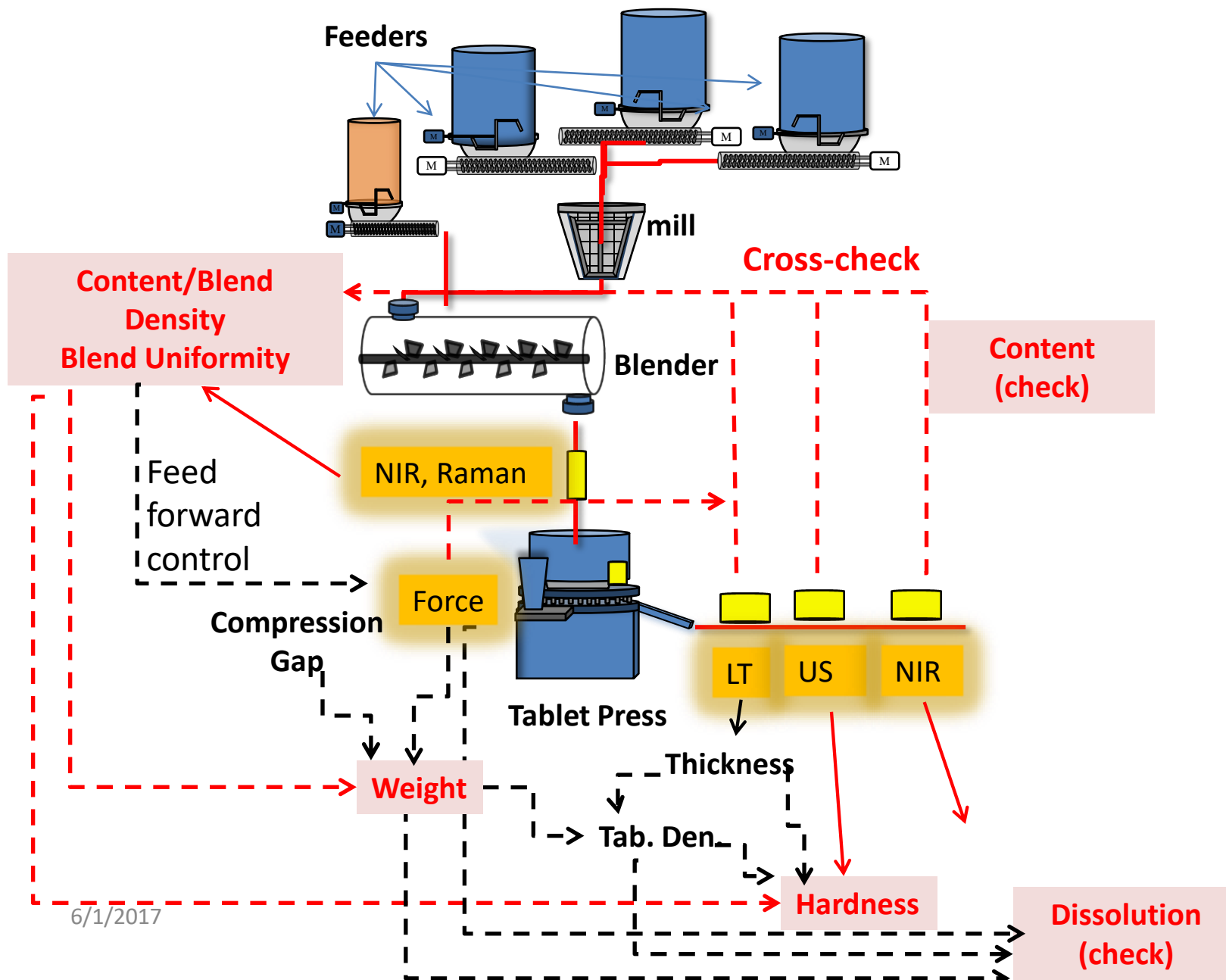
Feed Frame and Tablet Press: Inputs and Outputs

Unit Op	Inputs	Processing Parameters	Responses	Product Properties
Tablet Press and Feed Frame	Lubricity [L4]	RPM Feed Frame (RPM5)	Compaction Force (CF)	Tablet Thickness (TH5) = f[FR, L4, RPM5, CH, ThG, FC, C%, FFG, TT, #S, PC]
	Compactibility [Cpt4]		Ejection Force (EF)	
		RPM Turret (RPM6 = Flow Rate (FR))	Dwell Time (DT)	Weight Variability (WV5) = f[L4, FR, Ag4, RPM5, Coh4, BH4, BD4, CH, C%, FFG, TT, #S, PC]
	Composition [C%]	Chute Height (CH)		Tablet Density (porosity) 5 (TD5) = f [Coh4, L4, RPM4, FR, Ag3, PSD(i), C%]
	Cohesion 4 [Coh4]	Thickness Gap (ThG)		Content Uniformity 5 (CU5) = f[BH4, RPM5, Ag4, WV5, C%, FFG, TT, #S, PC]
		Fill Cam [FC]		Hardness 5 (H5) = f[Cpt4, RPM5, FR, L4, WV5, C%, FFG, TT, #S, PC]
		Feed Frame Geometry (FFG)		Dissolution 5 (Diss5) = [Cpt4, RPM5, FR, L4, WV5, C%, FFG, TT, #S, PC]
	Agglomeration 4 [Ag4]	Tablet Tooling (TT)		
	Blend Homogeneity 4 [BH4]	# stations (#S)		
	Bulk Density 4 [BD4]	Pre Compression (PC)		

Material Properties-Process Parameters Interrelation



General RTR Sensing Approach



Conclusions

- Process Engineering toolbox quickly reaching maturity
- Real Time Quality Assurance, Closed Loop Control, RTR are all feasible
- Solid dose CM is just the beginning – same toolbox applies, with moderate effort, to
 - API CM
 - Biologicals CM
 - Precision Manufacturing
- Non-destructive testing (dissolution predictions) potentially leads to new methods for understanding in vivo behavior
- Open Issue: What do we do with all this data?