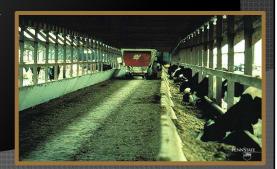
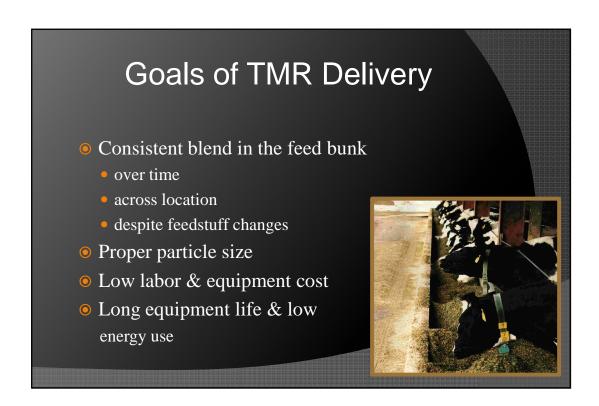
# OPTIMIZING PERFORMANCE OF TMR MIXERS

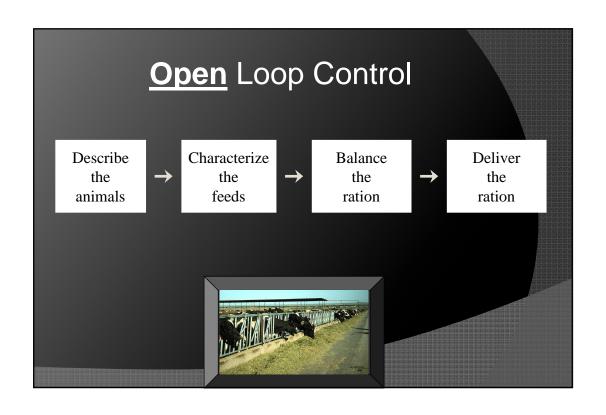
Dennis R. Buckmaster
Purdue University
Agricultural & Biological Engineering

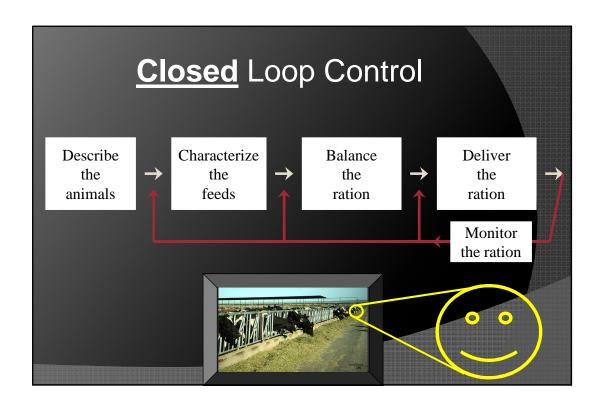
### Outline

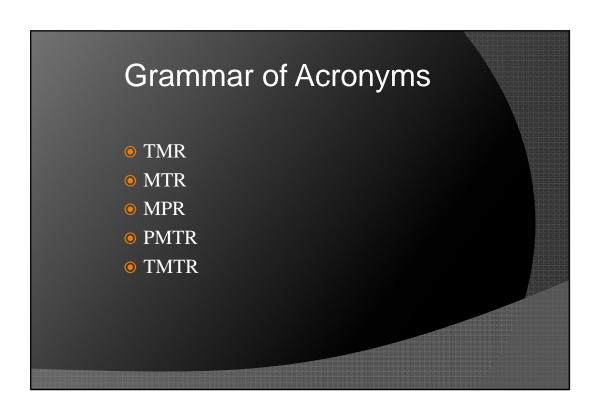
- Introduction
- Variation **Among** Batches
- Variation Within Batches
- Experimenting on the farm
  - How
  - Example analysis
- Summary





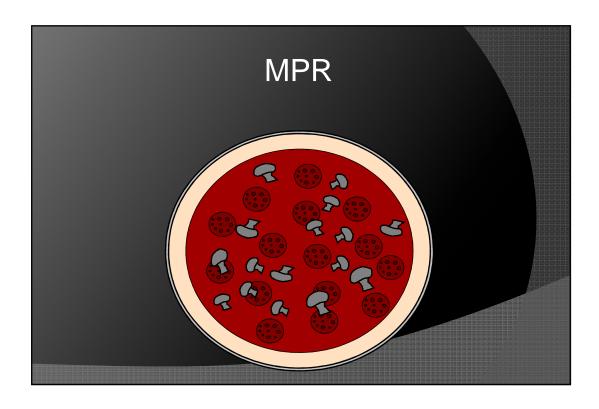


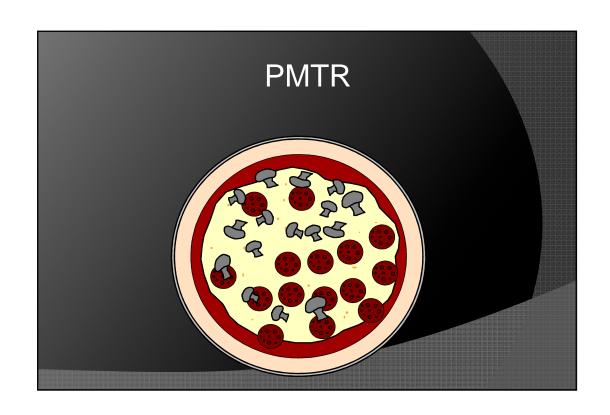


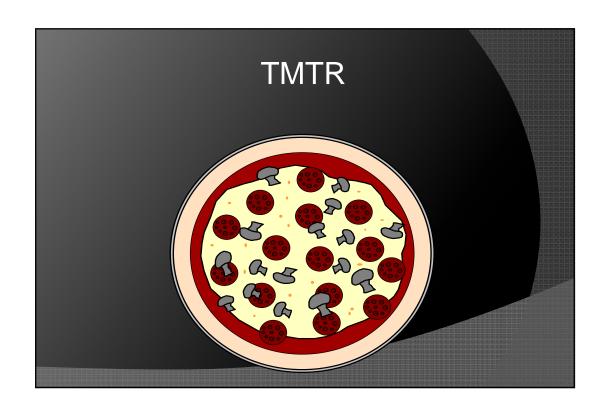


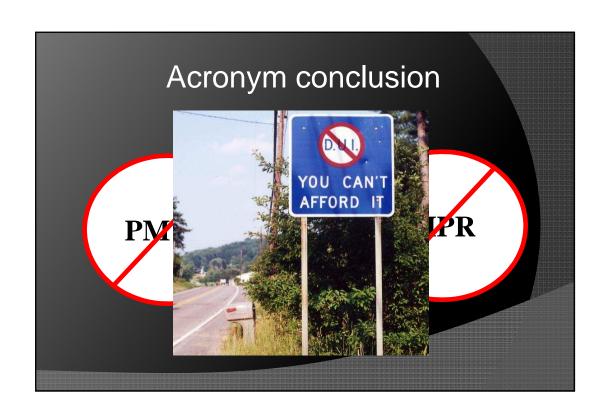
# **Grammar of Acronyms**

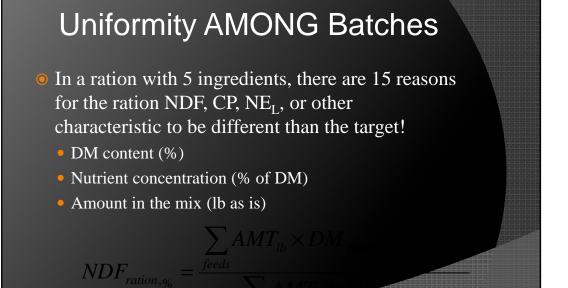
- TMR Total Mixed Ration
- MTR Mixed Total Ration
- MPR Mixed Partial Ration
- PMTR Partially Mixed Total Ration
- TMTR Totally Mixed Total Ration











fraction

# **Uniformity AMONG Batches**

- Monitor
  - ingredient nutrient concentrations
  - ingredient DM concentrations
  - particle size reduction

#### Control

- amounts in the ration
- mixing protocol (fill order & mixing time)



#### **Variation AMONG Batches**

- EXAMPLE 1
  - Ration with:
    - haycrop silage
    - corn silage
    - grain premix



• Haycrop silage moisture goes up (a 5 to 10 percentage point swing over a week time span is certainly possible)

#### **Variation AMONG Batches**

- EXAMPLE 1 (haycrop moisture increases)
  - Consequences if no corrective action is taken
    - less haycrop DM in ration
    - lower protein in the ration
    - higher energy concentration in the ration
    - likely reduced effective fiber in the ration
    - more grain consumption than planned
  - Corrective action: adjust amounts in the ration

### Variation AMONG Batches

- EXAMPLE 2
  - Ration with:
    - haycrop silage
    - corn silage
    - grain premix





#### **Variation AMONG Batches**

- EXAMPLE 2 (corn silage amount varies)
  - Consequences if no corrective action is taken
    - inconsistent energy concentration in the ration
    - inconsistent protein concentration in the ration
    - inconsistent effective fiber in the ration
    - intake is inconsistent and likely decreases
  - <u>Corrective action:</u> meter in more consistently or vary other ingredients proportionally

#### **Variation AMONG Batches**

• EXAMPLE 3

Fill order #1

haycrop silage

corn silage

grain premix

Fill order #2

grain premix

corn silage

haycrop silage

Mixer (which is designed to do some particle size reduction) is run during filling

#### **Variation AMONG Batches**

- EXAMPLE 3 (varied fill order)
  - Consequences if no corrective action is taken
     inconsistent particle size distribution in the ration
     inconsistent effective fiber in the ration
  - Corrective action: Implement a consistent mixing protocol

# **Uniformity WITHIN Batches**

- Mixer capacity
  - select for minimum batch size
  - select for maximum batch size
- Mixer management
  - fill order
  - mixing time
  - particle size reduction

### Mixer Sizing

Don't overlook the obvious

- Size for maximum batch size
- Size for minimum batch size
- Maybe not all groups get the same number of batches per day
- Most mixers don't work well when "full" (likely 70% full
   -- the fine print is always most important!)

# Mixer Management

#### **General principles**

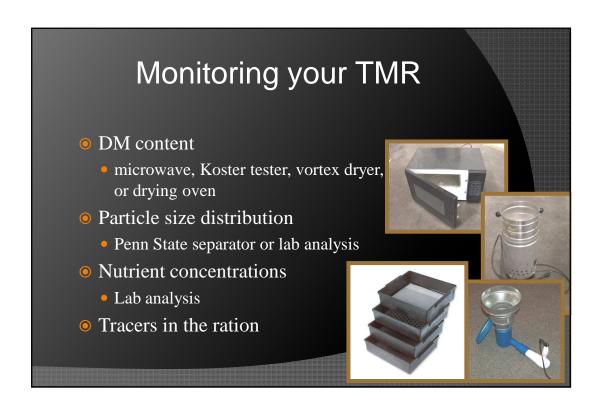
- Mix long enough (assure uniformity)
- Don't mix too long (avoid excessive wear, particle size reduction, energy & labor)
- Control particle size reduction
- Understand the material flow in the mixer



# Mixer Management

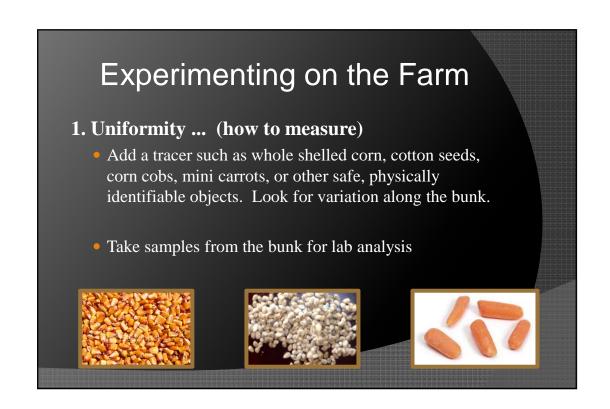
#### **Sample Mixing Protocol**

- Mixer off during loading
- Small quantity and liquid ingredients loaded in first
- Haycrop silage loaded last
- Mix 3-5 minutes after filling is complete
- Unload quickly, mixer off except when unloading









# Experimenting on the Farm

#### 2. Exploring particle size reduction

- "mix" a single forage (vary time and monitor particle size reduction)
- hand mix a mini-ration as a comparison
- compute weighted average particle size distribution from ingredients used

# Experimenting on the Farm

#### 2. Particle size ... (how to measure)

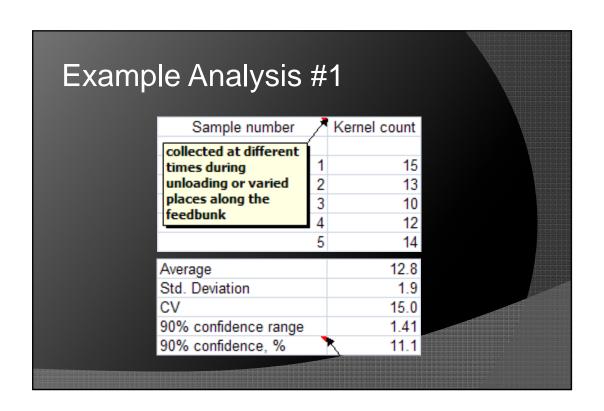
- Penn State separator
- Laboratory analysis



Note: To a degree, particle size analysis of samples within a batch (along the feed bunk) can be useful for identifying within batch variation.

# Example Analysis #1

- 15 lb of whole shelled corn was added for each ton of TMR which otherwise did not contain whole kernels
- 2 lb samples were pulled along the feed bunk
- Kernel counts per 2 lb sample is reported.



# Example Analysis #2

- Five similar replicate batches
  - Same mixer
  - Same ingredients from the same structures
  - Same fill order
  - Same mixer operation and procedure
- 2 lb samples pulled from bunk
- Hay was a significant part of the ration
- % long particles (top sieve of PSU separator) reported

#### What should be evaluated?

- % long material
- OV of % long material
- Confidence interval of CV of % long material

It's time to think about the CV of CVs

					<b>**</b>	
Example	F	Analy	sis#	2 <u>\</u>	<u>Withi</u>	<u>n</u>
		Batch #1	Batch #2	Batch #3	Batch #4	Batch #5
Sample number	Ζ	% long mass	% long mass	% long mass	% long mass	% long mass
collected at different times during	1	8.2	10.0	9.4	12.0	5.5
unloading or varied	2	7.0	9.5	7.8	7.0	7.2
places along the	3	5.5	6.0	7.6	8.1	3.4
feedbunk	4	9.2	7.4	10.7	10.3	3.8
	5	8.0	8.0	8.5	8.0	8.0
Within batch analysis						
Ave	9122230930930	7.6	8.2	8.8	9.1	5.6
Std. Devia	tion	1.4	1.6	1.3	2.0	2.0
	CV	18.5	19.8	14.5	22.3	36.3
90% confidence ra	nge	1.0	1.2	0.9	1.5	1.5
90% confidence	, %	13.6	14.5	10.7	16.4	26.7
90% lower	end	6.5	7.0	7.9	7.6	4.1
90% higher	90% higher end		9.4	9.7	10.6	7.1

Example A	naly	sis#	2 <u>.</u>	<u>Amor</u>	10
Mishin basah anahusia					
Within batch analysis Average	7.6	8.2	8.8	9 1	5.6
Std. Deviation	1.4	1.6	1.3	2.0	2.0
CV	18.5	19.8	14.5	22.3	36.3
Among batcl	n analysis				
Among batch	n analysis				
		Average b		22.3	
	Std. de	viation of b	atch CV	8.3	
		CV of ba	tch CVs	37.4	
90% co	nfidence r	ange of ba	tch CVs	6.1	
90%	confidenc	e of batch	CVs, %	27.5	

Example  Previous ex			s#3	<u>Co</u>	<u>mpari</u>	ison
		Batch #1	Batch #2	Batch #3	Batch #4	Batch #5
Sample number		% long mass	% long mass	% long mass	% long mass	% long mass
collected at different	ſ					
times during	- 1	8.2	10.0	9.4	12.0	5.5
unloading or varied	2	7.0	9.5	7.8	7.0	7.2
places along the	3	5.5	6.0	7.6	8.1	3.4
feedbunk	4	9.2	7.4	10.7	10.3	3.8
	5	8.0	8.0	8.5	8.0	8.0
<ul><li>Same mixe</li><li>Sample number</li></ul>	er, i	new proc		% long mass	% long mass	% long mass
collected at different	Ĺ					
times during	- 1	8.9	10.3	7.0	10.2	6.5
unloading or varied	2	7.1	9.0	8.6	6.3	6.9
places along the feedbunk	3	8.8	6.6	7.0	7.4	5.1
ICCUDUIK	4	10.1	7.8	7.2	9.0	5.0
	5	8.0	9.2	8.2	8.3	7.4

LABITIPIC AT	nalysi	is#3.	Cor	npari:	son
<ul><li>Previous exam</li></ul>	nple				
Within batch analysis					\\
Average	7.6	8.2	8.8	9.1	5.6
Std. Deviation	1.4	1.6	1.3	2.0	2.0
CV	18.5	19.8	14.5	22.3	36.3
CV	18.5	19.8	14.5	22.3	36.3
			14.5	22.3	36.3
			14.5	22.3	36.3
<ul><li>Same mixer, n</li></ul>			14.5	22.3	36.3
<ul><li>Same mixer, n</li></ul>			14.5	22.3	36.3
			7.6	22.3	36.3
<ul><li>Same mixer, n</li><li>Within batch analysis</li></ul>	ew pro	cedure		22.0	
<ul> <li>Same mixer, n</li> <li>Within batch analysis</li> <li>Average</li> </ul>	ew proc	cedure 8.6	7.6	8.2	6.2
<ul> <li>Same mixer, n</li> <li>Within batch analysis</li> <li>Average</li> <li>Std. Deviation</li> </ul>	8.6 1.1	8.6 1.4	7.6 0.7	8.2 1.5	6.2

Example Analysis #	3 <b>C</b>	ompar	ison
Analysis of 25 sampled meal portions			<b>\</b>
Average of meal portions	7.8		7.8
Std. Deviation of meal portions	1.4		2.0
CV of meal portions	18.3		25.6
90% confidence range of meal portions	0.5		0.7
90% confidence of meal portions, %	6.0	Errors	8.4
90% low of meal portions	7.4	in print	7.2
90% high of meal portions	8.3		8.5
T test results of c	omparing m p=	neal portion 0.494	

Example Analysis #	3 <b>C</b>	omp	arison
al	ternative mixir	ıg	baseline procedu
Among batch analysis of the CVs	procedure		from example 2
Average batch CV	15.0		22.3
Std. deviation of batch CV	3.5		8.3
CV of batch CVs	23.2		37.4
90% confidence range of batch CVs	2.6		6.1
90% confidence of batch CVs, %	17.1		27.5
The state of			
T test results of con			
	p= 0	.055	

## About this example

- 25 samples, 5 each from 5 batches
- With this limited data, a very slight change in any one sample largely influences the analysis
- Batch CV averages 23.2 vs. 37.4 (p=0.055)
   With 5 samples from each of 10 batches (2x the work), p=.007
- Average of meals 7.8 in both casesCV of meals 18.3 vs. 25.6
- Even so, if procedure 2 "didn't cost anything"....





