Design of Serial Assembly Lines Under Labor Turnover

Rene Villalobos, Adrian Montaño, Luis Mar, Luis Muñoz
Department of Industrial Engineering
Arizona State University

Labor Turnover/Problem Definition

- One estimate calculates the cost of turnover to American industry at about $11 billion a year.
- Turnover is an important factor in declining productivity and competitiveness.
- High labor turnover is often cited as a factor for low productivity.
- Turnover is caused by internal or externals factors. Solutions are limited or non existent.

Labor Turnover/Problem Definition

- Input costs:
  - Replacement costs
  - Training costs
- Output costs:
  - Reduction of production per employee
  - Production loss due to differential in assembly speed between an experienced and a new employee
- Whatever the causes, the negative effects of turnover translate into high monetary costs.

Arizona State University

Statement of the Problem/Research Objectives

- Focus on the design of the assembly line to diminish the effect of labor turnover.
- Investigate whether hybrid methods that combine the characteristics of current dynamic work allocation methods (such as Work Sharing and Bucket Brigades) and Traditional assembly lines, mitigate better the effects of labor turnover than the original methods.

Statement of the Problem/Research Objectives

- In particular we explored the performance of three serial assembly line designs
  - Traditional (Balanced)
  - Bucket Brigades (BB)
  - Hybrid (MWS)

→

- Dynamic Work Allocation Methods (DWAM)
- Active replacement policies

ARIZONA STATE UNIVERSITY

Assembly Methods

- Methods make use of different work allocation strategies and worker replacement policies in order to reduce the effects of variability.
- The *traditional method* will serve as a reference point since is by far the most widely used design.
- The *Bucket Brigades* uses a flexible allocation method shown to perform well under labor turnover (Munoz, 2000).
- Our *Hybrid method* uses flexible allocation based on the Worksharing method in order to reduce the effects of variability.

Bucket Brigade Method

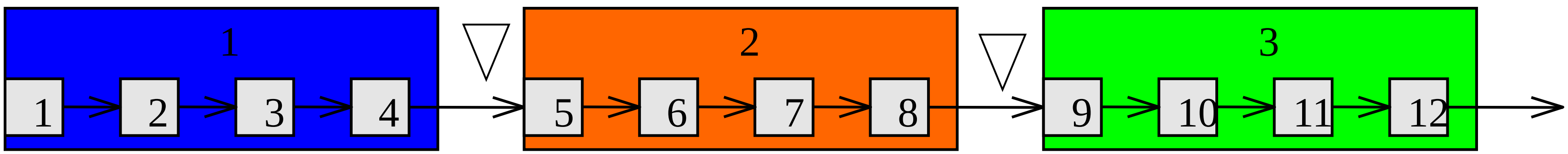
- Method developed by Bartholdi and Eisenstein that proposes a flexible allocation of work.
- Each worker processes an item from station to station until it is taken over (preempted) by a downstream worker.
- When preempted, the worker walks back and takes over the item of the upstream worker and starts to work downstream again.
- The operators are sequenced from slowest to fastest.
- Work content spontaneously allocates, creating an equilibrium.
- Workers are not explicitly limited to a set of stations.

Hybrid Method

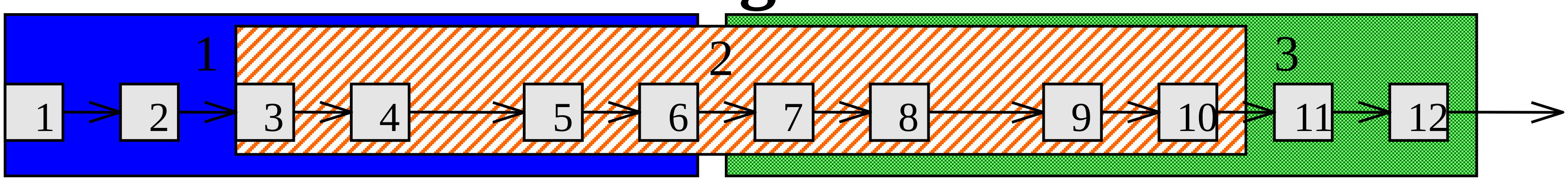
- Method based on Worksharing (McClain, 2000) systems that use flexible allocation of work and the use of variable control buffers.
- The method defines work zones and each operator has primary responsibility over a workstation but shares responsibility on the work elements in the neighboring workstations.
- Buffers are placed between workstations and along with the work zones, define the amount of work each operator must perform.
- Workers perform the elements of their assigned workstation and if the buffer is full, they start with the neighboring elements until finished or preempted and start the backward phase. Go back to the start of the assigned station and take a part form the buffer, if empty, preempt the upstream operator.

Methods/Operator Replacement

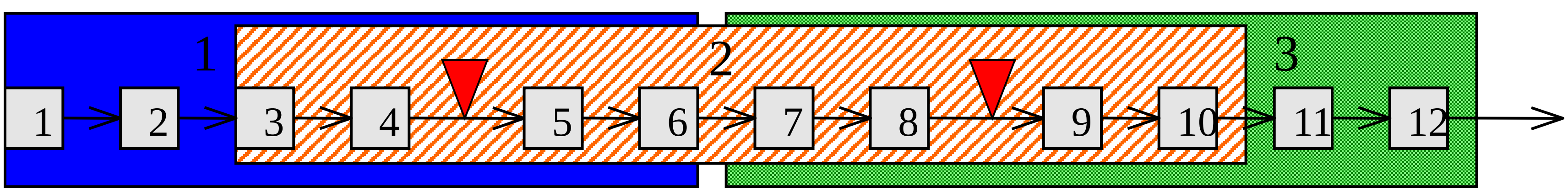
Traditional Line Balancing Method



Bucket Brigade Method



Modified Work Sharing Method

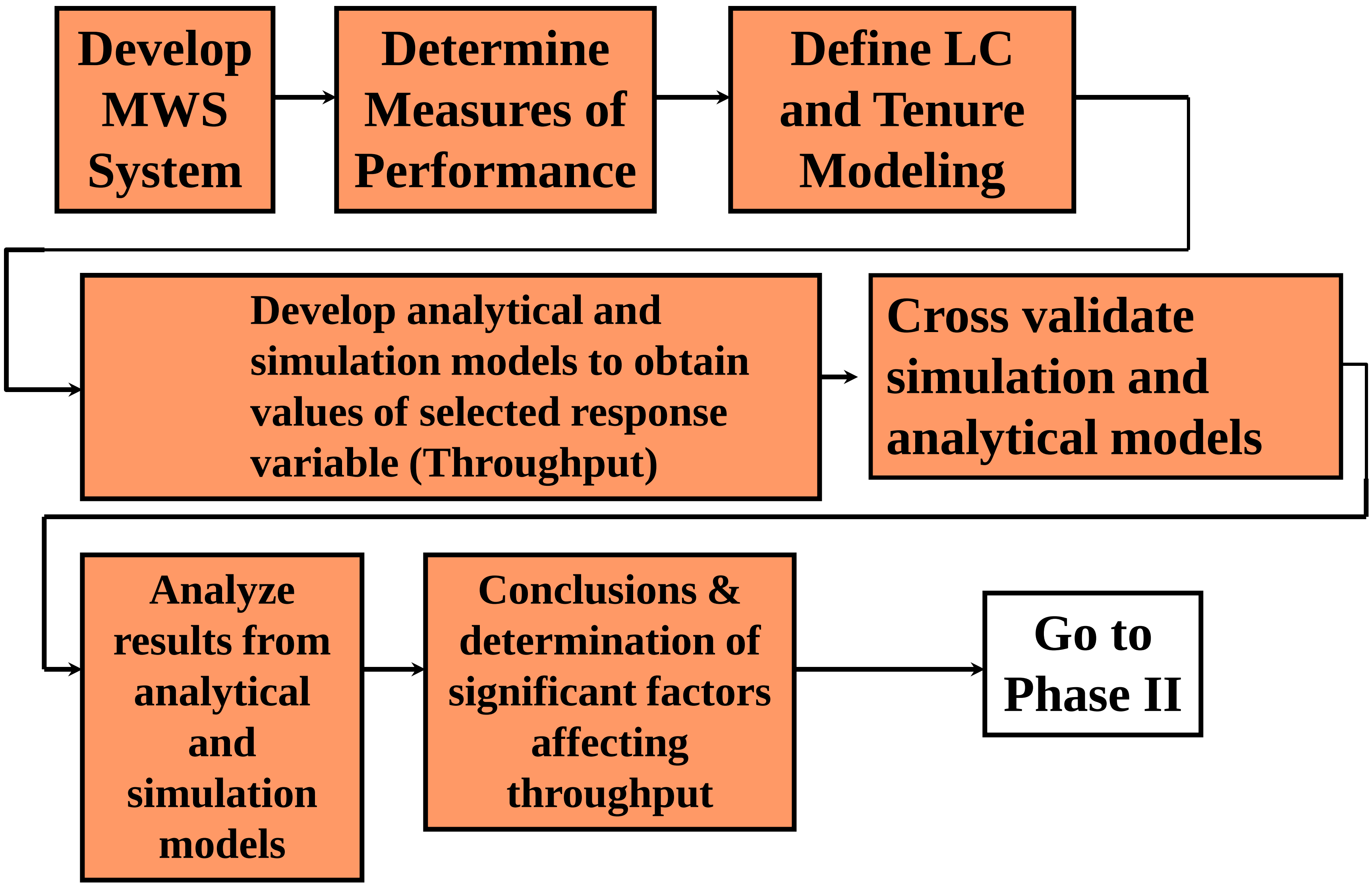


Objectives and Characteristics of MWS

- Avoid blockage observed in BB when assembly speeds of operators is similar.
- Operational Rules:
  - Complete as many operations as possible
  - If there is space available in buffer leave part
  - If not, continue working in the operations of the next station
  - Take next part first from the buffer and if no parts in the buffer from previous operator

Methodology

Phase I



Methodology

Phase II

Develop six Operators/ six station simulation models

↓

ANOVA

↓

Comparison of the behavior of the three production systems

↓

Draw general conclusions of the behavior of the methods

Objectives of Phase I and II

- Phase I (three-operator, three-stations)
  - Develop small instance analytical models of the line designs (Traditional, BB and MWS) that relate throughput to labor turnover and learning behavior, in order to gain insight into the nature of the problem and to provide insight on the behavior of longer lines.
  - Develop building blocks of logic to be used in the construction of simulation models for the longer lines of Phase II.
  - Cross-validate the simulation results (building blocks of logic) and the analytical models.

Objectives of Phase I and II

- Phase II (six-operator, six-station)
  - Compare the performance of the three production methods in more realistic scenarios.

Phase I (Analytical Models)

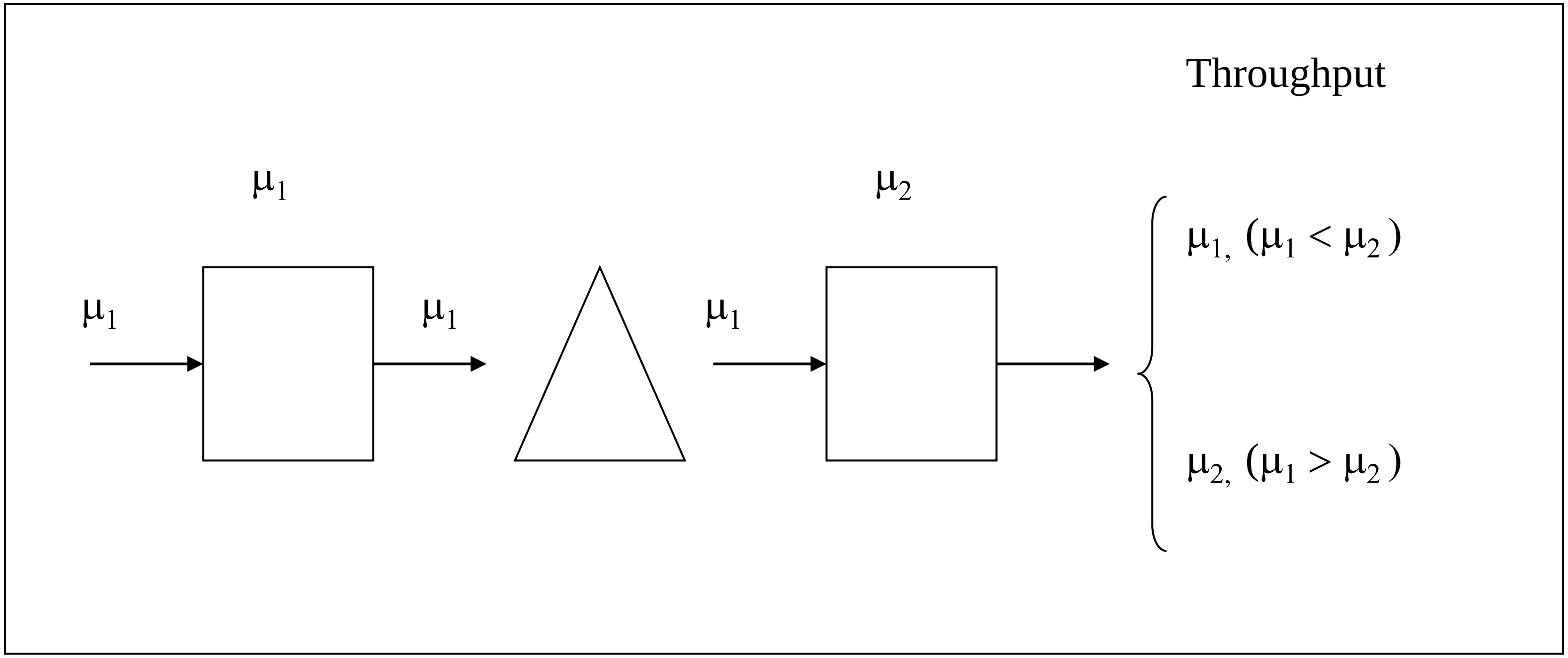
- Assumptions of the analytical models:
  - Exponential tenure distribution.
  - Exponential processing times.
  - After a departure, operators are re-sequenced to maintain slowest to fastest arrangement.
  - Operator speed is a function only of the experience acquired, i.e. parts produced.

Assembly Methods

Method	Balanced	Work Allocation	Replacement Policy	Buffers
Traditional	Yes	Fixed	Replace whoever leaves (passive)	Yes
BB	No	Dynamic	Slow to Fast (active)	No
MWS	No	Dynamic	Slow to Fast (active)	Yes

Traditional Method

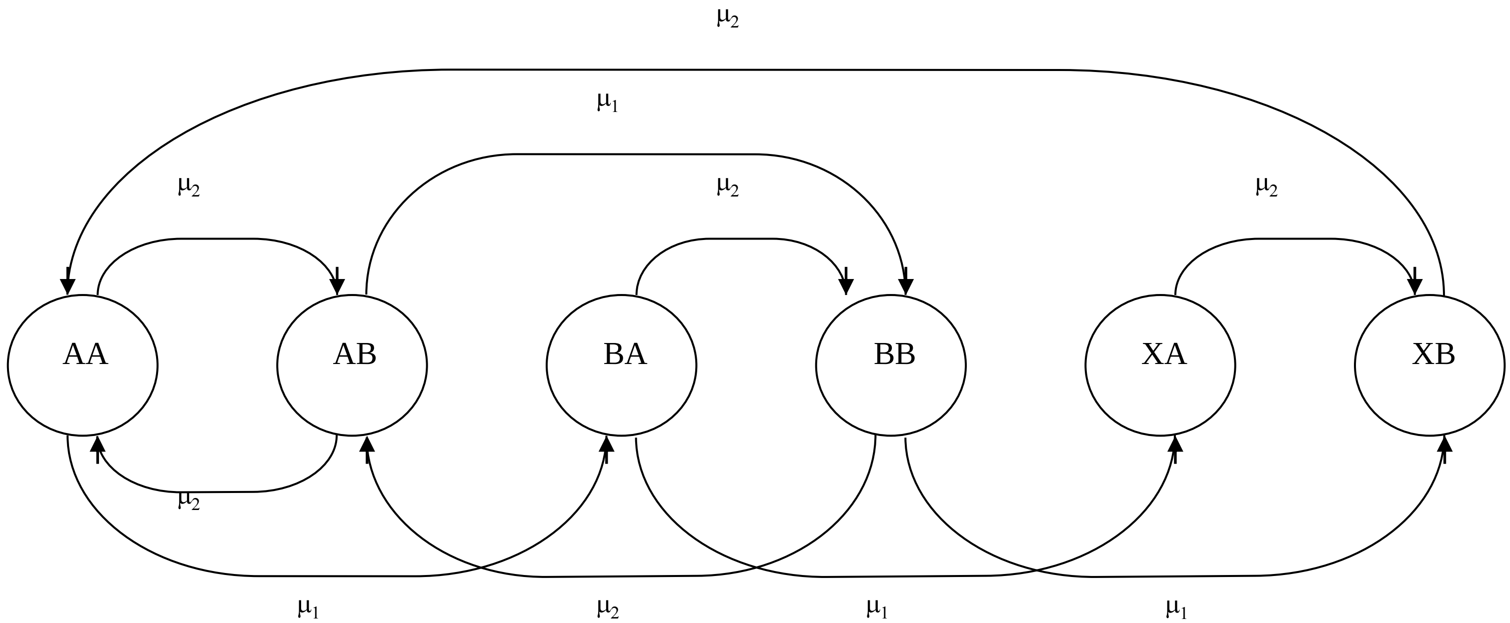
- Consider a 2-operator traditional line where μ_i is the speed of operator *i*.



Model of 2-Operator Traditional Balanced Line

Bucket Brigade Method

Where μ_i is the speed of operator *i*



Transition Diagram for the Two-operator Two-phase Bucket Brigades Model

Bucket Brigade Method

- In the previous model, throughput is defined by the following relationship:

$$TH = \mu_2 \left(\frac{1}{2} \frac{\left(\mu_2^2 + 3\mu_1\mu_2 + \mu_1^2\right)\mu_2^2}{\mu_2^4 + 4\mu_1\mu_2^3 + 5\mu_1^2\mu_2^2 + 3\mu_1^3\mu_2 + \mu_1^4} + \frac{\mu_1\mu_2^2}{\mu_2^3 + 3\mu_1\mu_2^2 + 2\mu_1^2\mu_2 + \mu_1^3} \right.$$

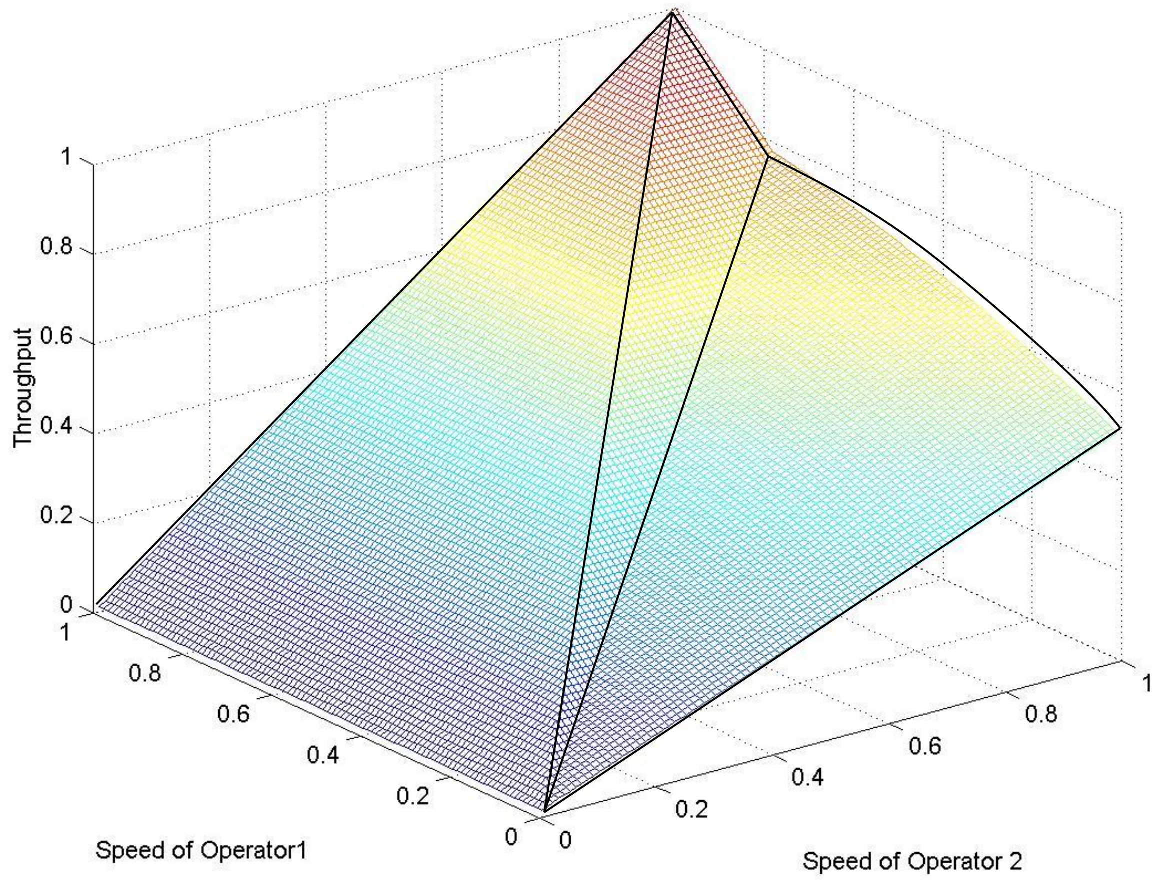
$$\left. + \frac{\left(\mu_1^2 + 3\mu_1\mu_2 + 3\mu_2^2\right)\mu_1^2}{\mu_2^4 + 4\mu_1\mu_2^3 + 5\mu_1^2\mu_2^2 + 3\mu_1^3\mu_2 + \mu_1^4} \right)$$

MWS Method

		A0B	A0A	A1B	A1A	A2B	A2A	A3B	A3A	B3B	B3A	B2B	X3B	X3A	B1B	X2B	B0B	X1B	X0B
1	A0B	$-\mu_1-\mu_2$	μ_2	μ_1															
2	A0A	μ_2	$-\mu_1-\mu_2$		μ_1														
3	A1B	μ_2		$-\mu_1-\mu_2$		μ_1													
4	A1A			μ_2	$-\mu_1-\mu_2$		μ_1												
5	A2B			μ_2		$-\mu_1-\mu_2$		μ_1											
6	A2A					μ_2	$-\mu_1-\mu_2$		μ_1										
7	A3B					μ_2		$-\mu_1-\mu_2$		μ_1									
8	A3A							μ_2	$-\mu_1-\mu_2$		μ_1								
9	B3B									$-\mu_1-\mu_2$		μ_2	μ_1						
10	B3A									μ_2	$-\mu_1-\mu_2$			μ_1					
11	B2B											$-\mu_1-\mu_2$			μ_2	μ_1			
12	X3B					μ_2							$-\mu_2$						
13	X3A												μ_2	$-\mu_2$					
14	B1B														$-\mu_1-\mu_2$		μ_2	μ_1	
15	X2B			μ_2												$-\mu_2$			
16	B0B	μ_2															$-\mu_1-\mu_2$		μ_1
17	X1B	μ_2																$-\mu_2$	
18	X0B		μ_2																$-\mu_2$

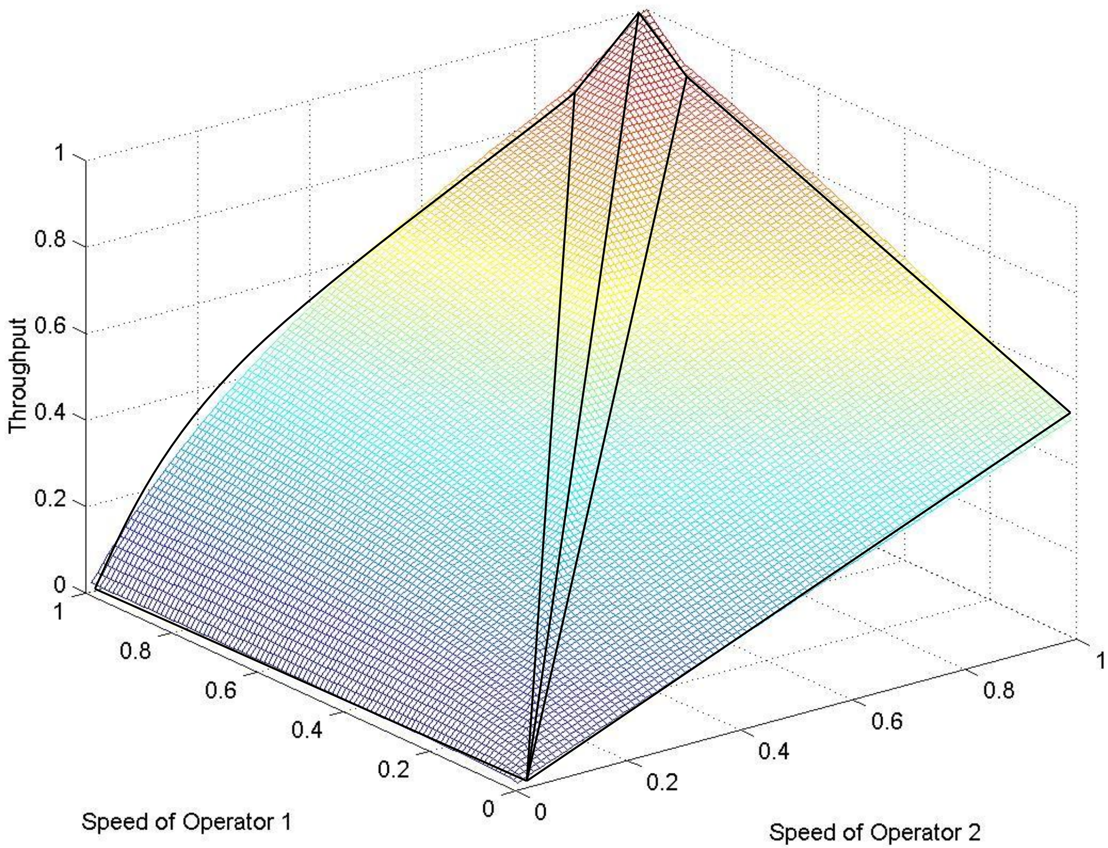
Transition Matrix for a Two-operator, Two-phase MWS Model

Optimal Policies

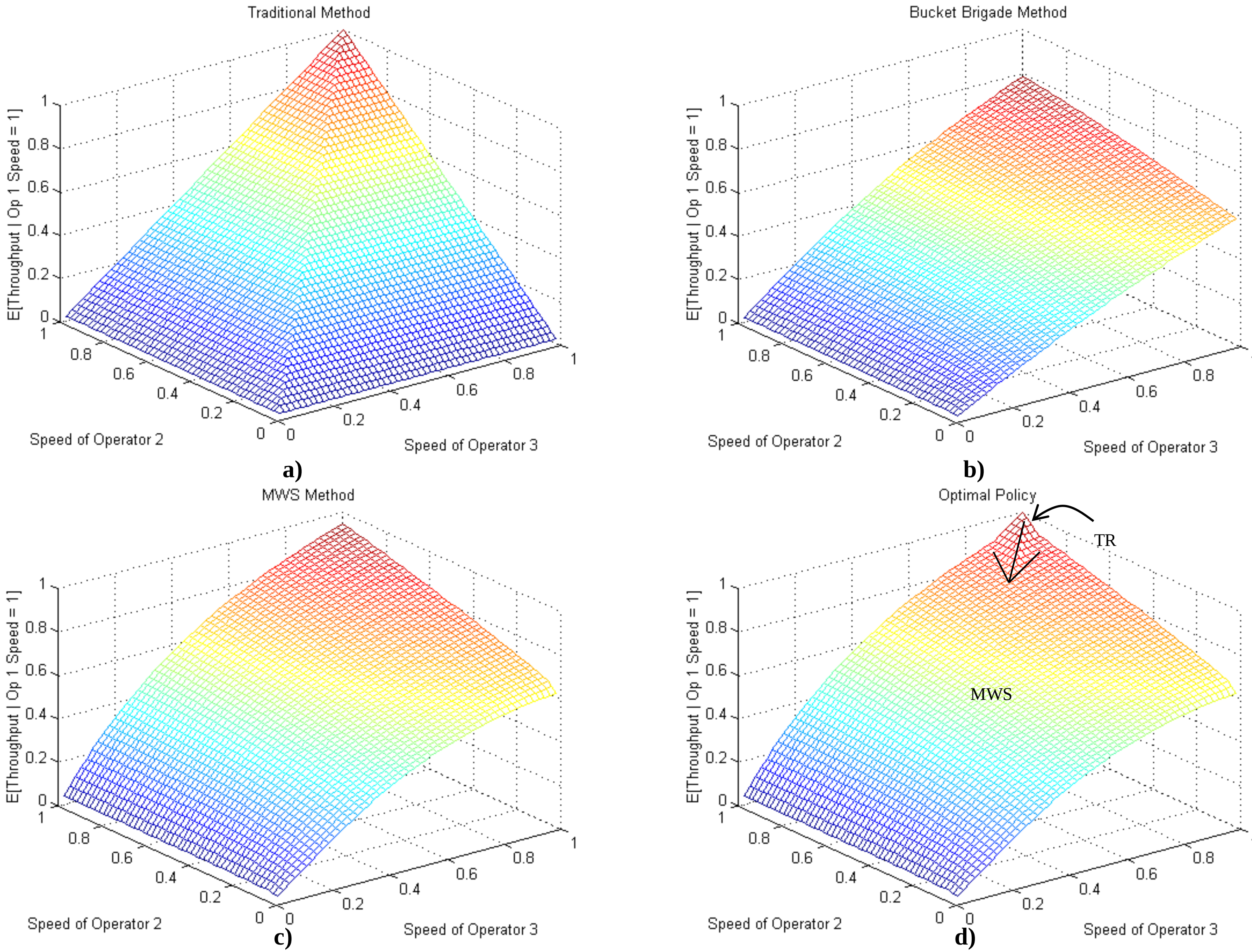


Bucket Brigades vs. Traditional

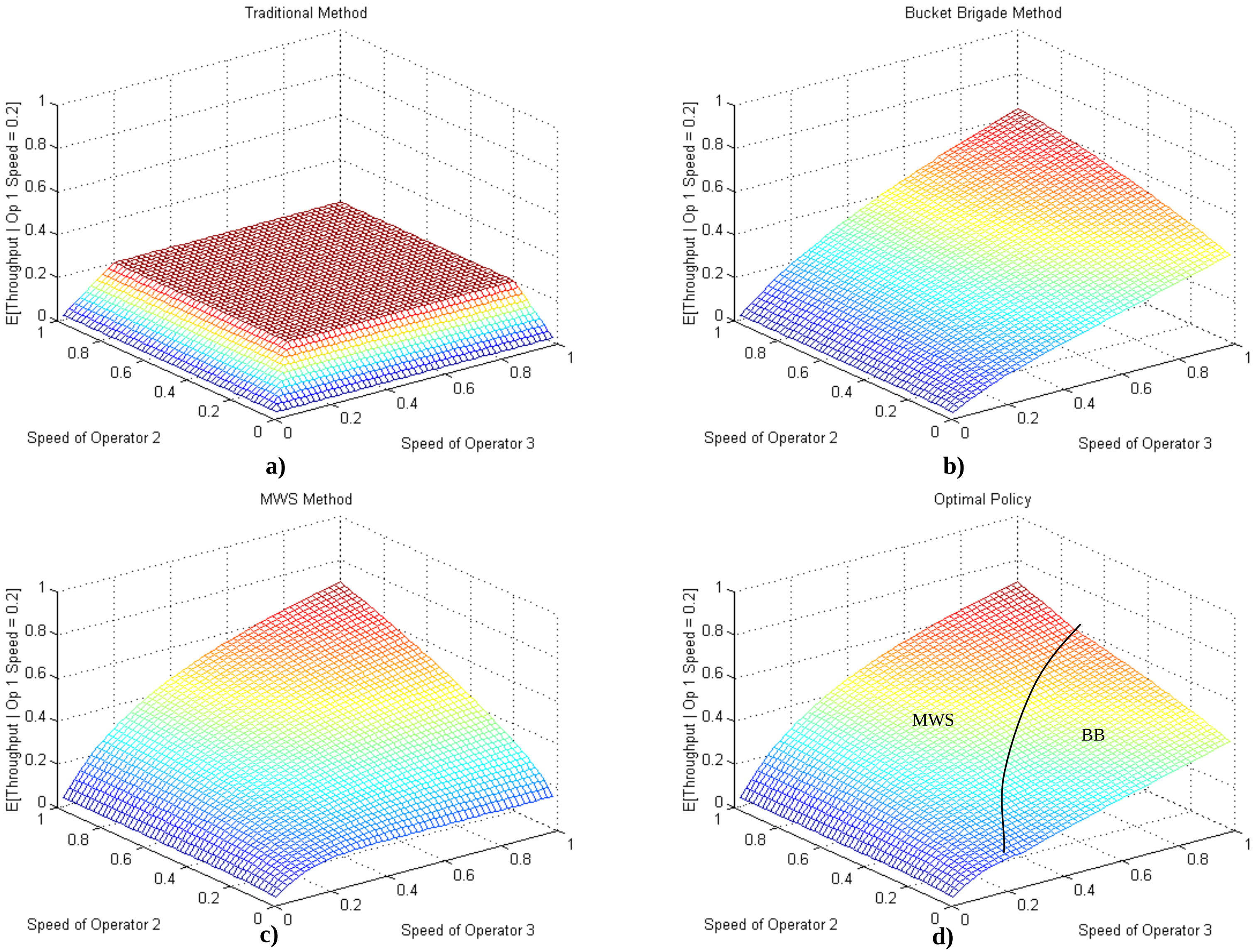
Optimal Policies



Hybrid vs. Traditional



Expected Throughput for 3-Operator Line (Operator 1 Speed = 1.0 parts/time unit)



Expected Throughput for 3-Operator Line (Operator 1 Speed = 0.2 parts/time unit)

Models with Operator Learning

Objective:

- Determine the effect that the learning curves of the operators have on a serial assembly line.

Assumptions:

- Operators learn according to a Log-linear model.
- Operators learn until they reach *full rate*, denoted by T_{∞}, after which the speed becomes constant.
- Operator speed is a function only of the acquired experience, i.e. parts produced.

The Learning Process

- New operators experience a learning process as their tasks are reinforced through repetition.
- The graphical representation of learning by doing is called a *learning curve model*.
- Log-linear model

$$T_n = \frac{T_1}{n^m}$$

T_n = Time to produce the n^{th} part

T_1 = Time to produce the first part of a batch

n = number of parts produced

m = learning coefficient

Throughput: A Function of Learning

- $\Uparrow$ Experience(n) $\Downarrow$ Process Time(T_n) $\Rightarrow$ $\Uparrow$ Line Throughput
- From production theory we know: $r_e = 1/t_e$
- In a similar way, and from the Log-linear definition:

$1/T_n$ = rate or speed at which the n^{th} part is produced, which we denoted as:

$$\gamma_i(n) = \frac{n^m}{T_1}$$

Consequently, the *TH* of the line as a function of the experience of the operators is obtained by substituting the static speeds μ_i with the dynamic definition of speed $\gamma_i(n)$

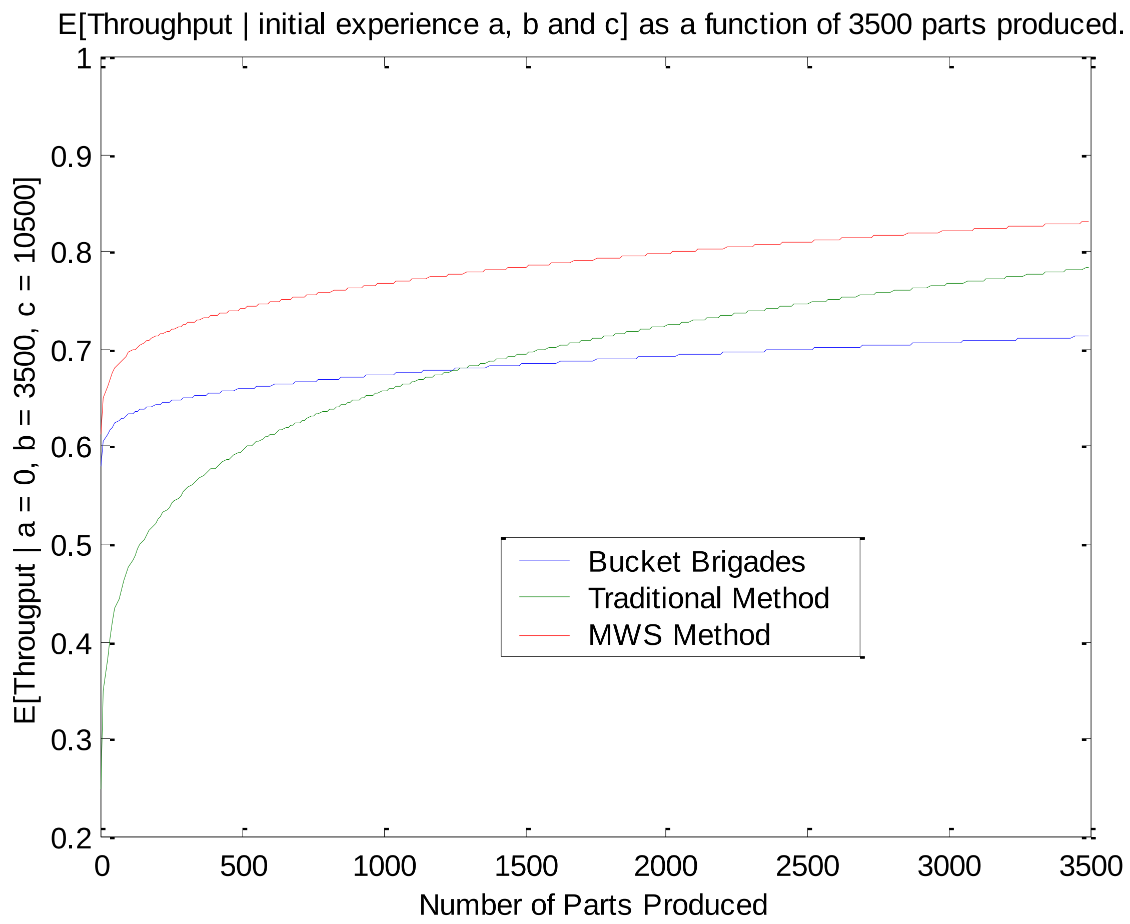
Throughput: A Function of Learning

- The substitution of this new expression for the rate or speed of the operator in previous expressions for throughput renders a new characterization of the output of the line as a function of the experience of the operators.

- As an example consider a 3-operator model, where the experience of operators 1, 2 and 3 is 0, 3500 and 10500 parts respectively. The task learning factor is $m = 0.14$ and the time to produce the first part is $T_1 = 40.0$ min.

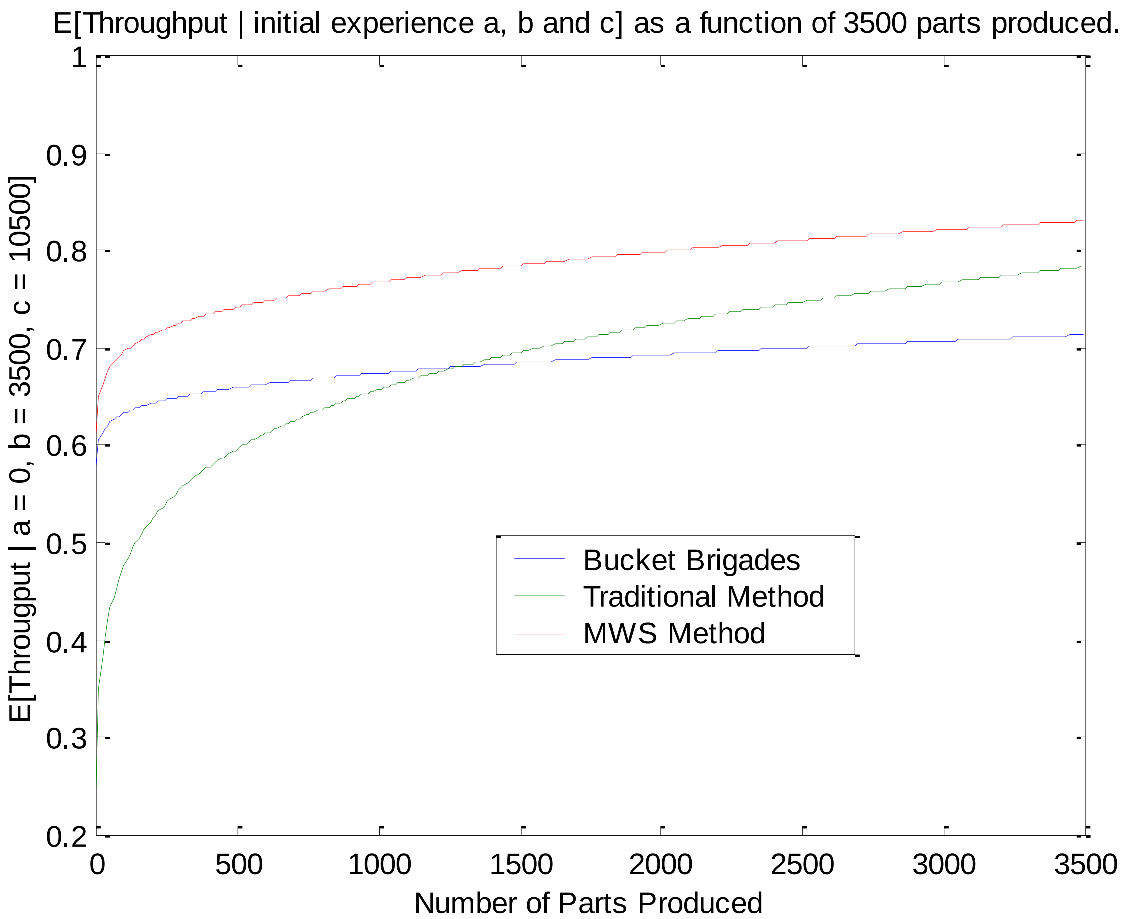
- The resulting throughput graph follows:

Throughput: A Function of Learning



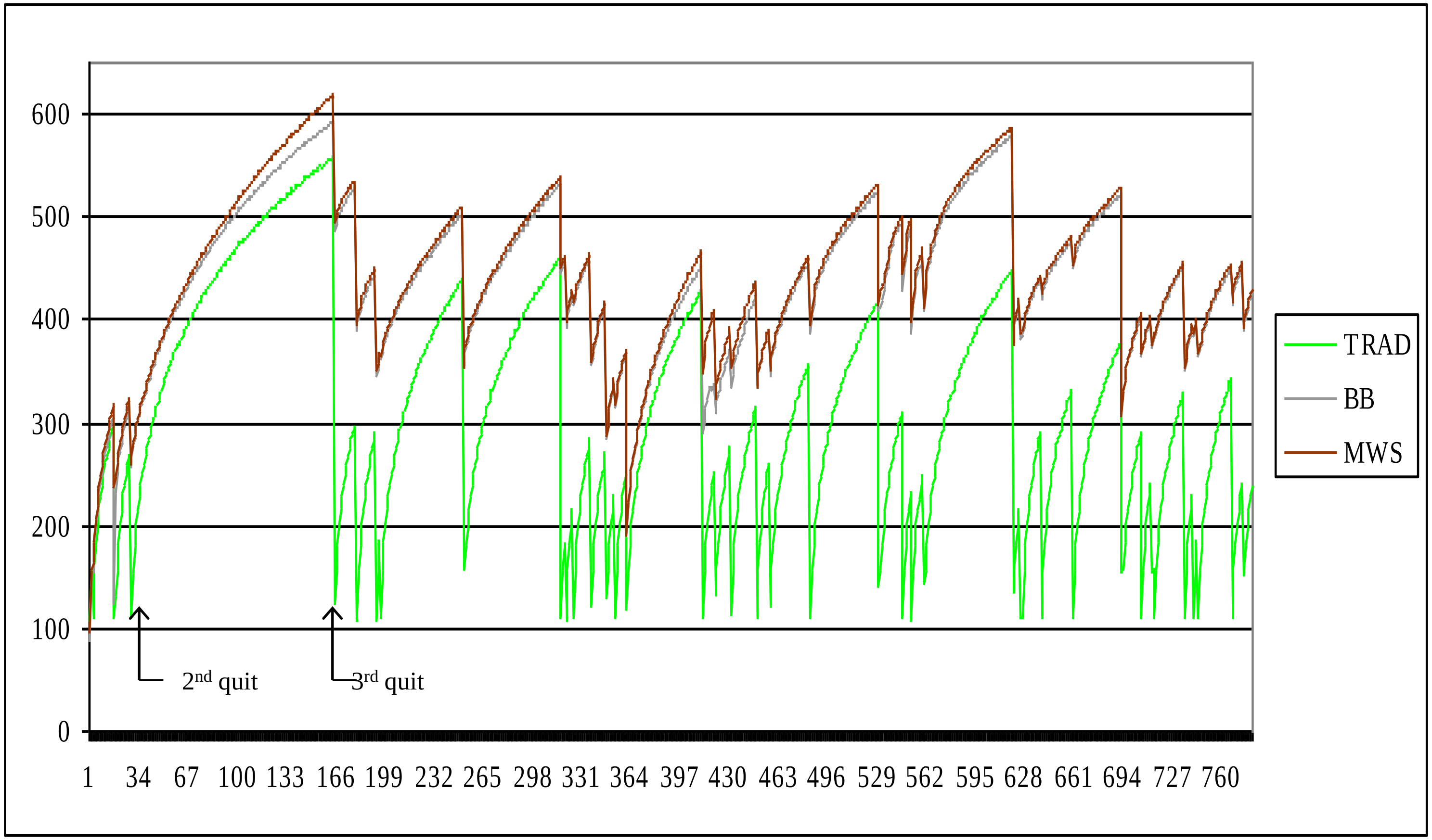
Expected Throughput as a Function of the Learning Process

Serial Line Learning Curve (Analytical Models)



Expected Throughput as a Function of the Learning Process

Results from Simulation (6 operators)



Arizona State University

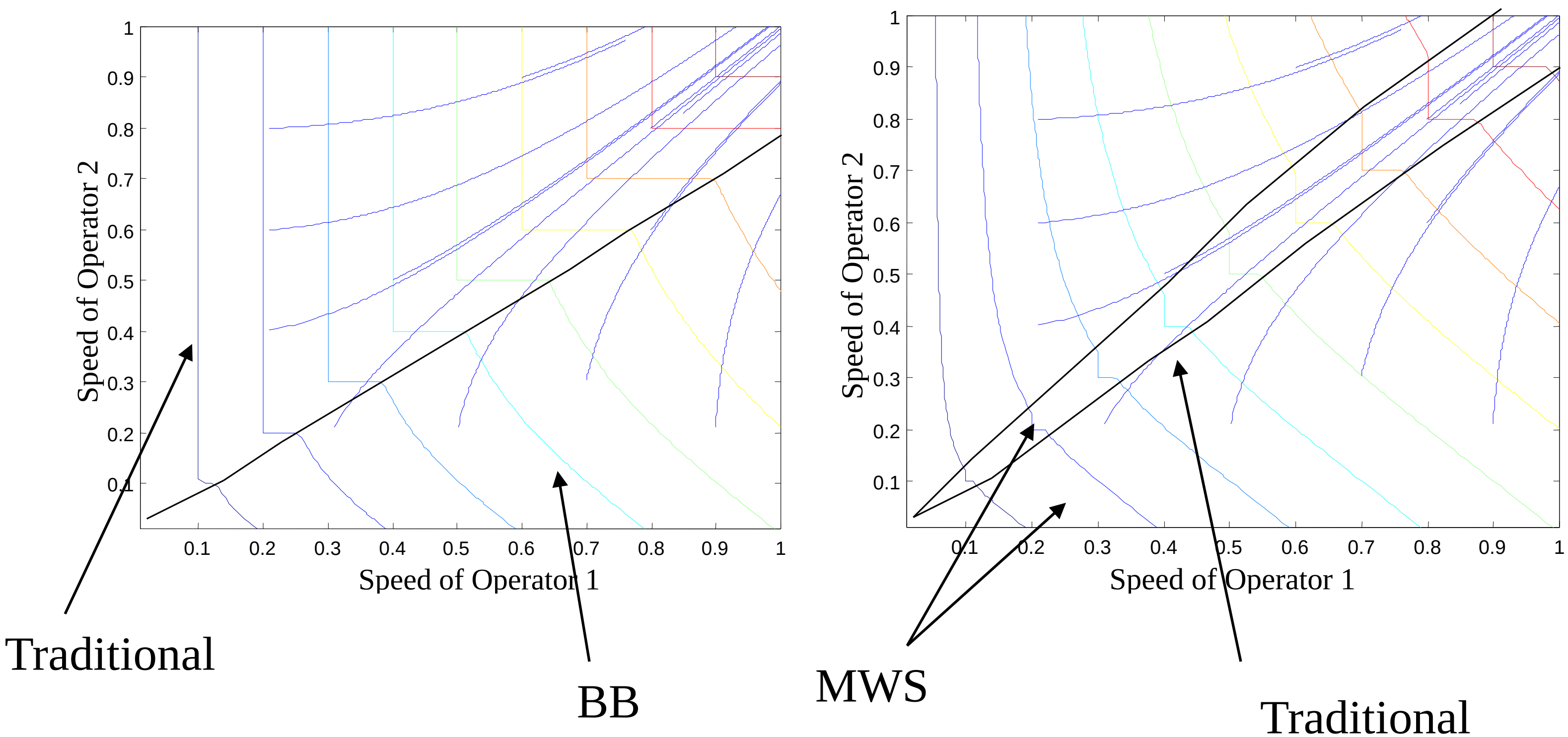
Serial Line Learning Curve (Analytical Models)

- Results
  - Representation of the TH of a serial line as a function of the experience (i.e. parts produced) of the operators.
- Implications
  - The Traditional method is the most affected by the introduction of new operators.
  - Dynamic allocation methods absorb better the variability introduced by new operators.

Learning and Optimal Policy

Traditional Vs. Bucket Brigade (m = .322)

Traditional Vs. Modified Work Sharing (m = .322)



ARIZONA STATE UNIVERSITY

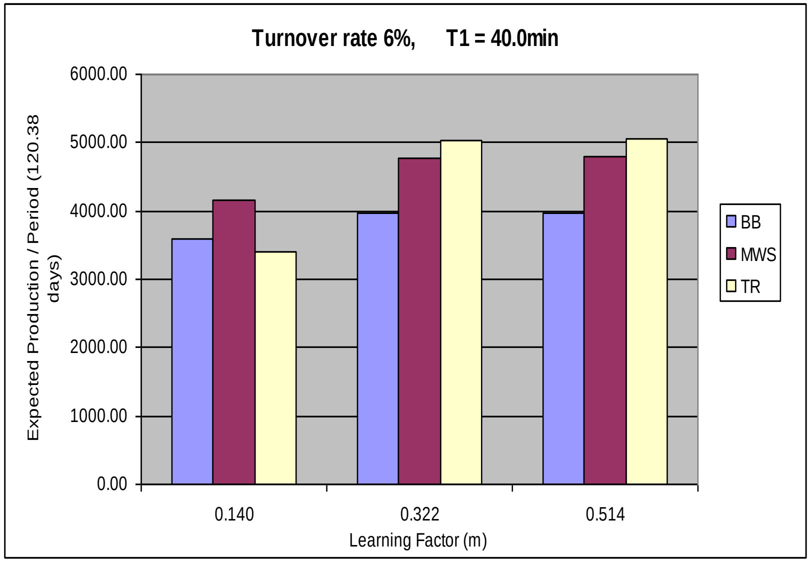
Cases Studied with Analytical Models

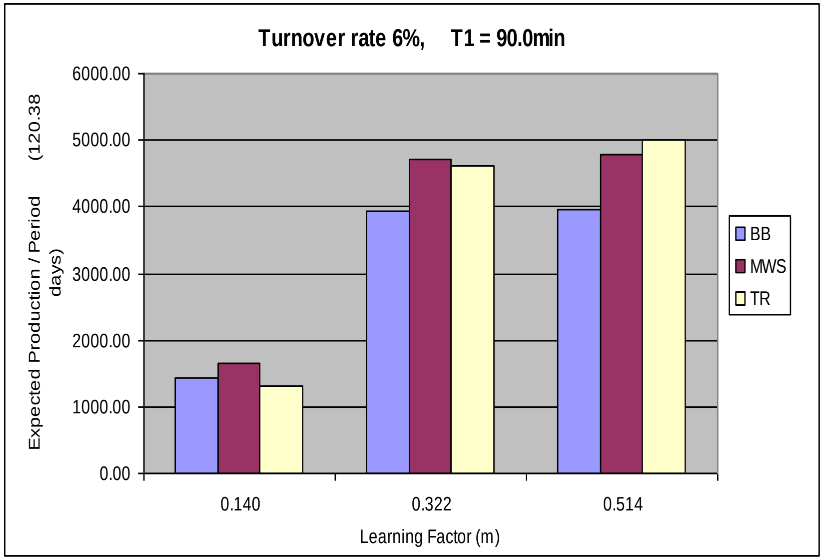
Turnover rate (month)	T_1 (min)	T_∞ (min)	Learning Factor (m)	MTBD (days)
6%	40.0	10.0	0.14 0.322 0.514	120.37
6%	90.0	10.0	0.14 0.322 0.514	120.37
12%	40.0	10.0	0.14 0.322 0.514	60.19
12%	90.0	10.0	0.14 0.322 0.514	60.19

MTBD → Mean Time Between Departures

Results/Insight from Analytical Models

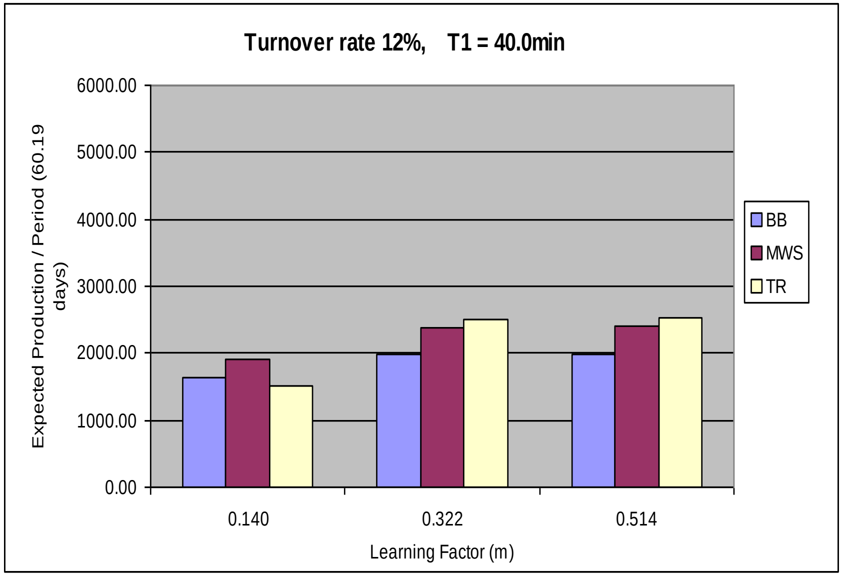
6% Turnover

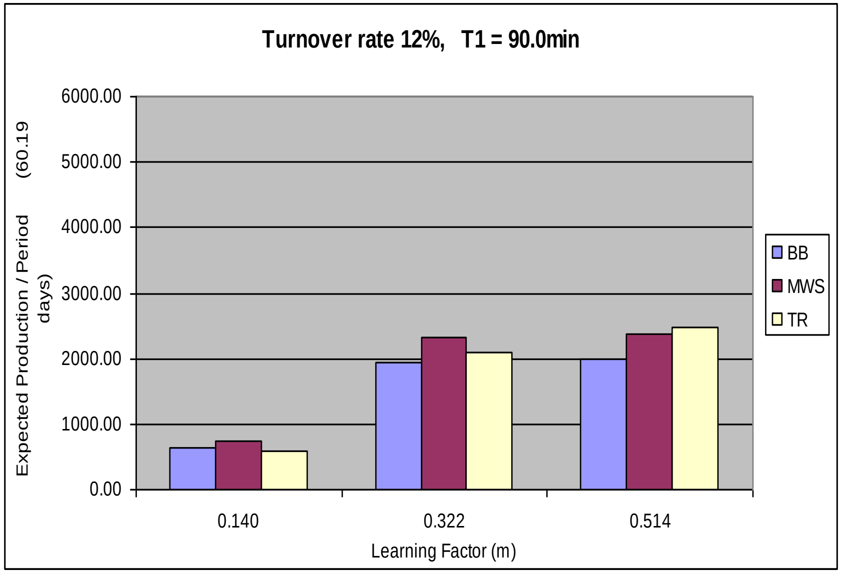




Results/Insight from Analytical Models

12% Turnover





Arizona State University

Conclusions from Analytical Models

- Lower learning factors (m = 0.14), the MWS method clearly performs the best.
- Moderate to high learning factors (m=0.322, 0.514) we recommend also the MWS method, although the traditional method generates higher yields in some instances.
- MWS method surpasses the Traditional method in all instances when buffer capacity is of 20 parts or less.
- Dynamic allocation methods (i.e. Bucket Brigades and MWS) are an attractive alternative to absorb the variability of turnover.
- Promote WIP control
- Promote discipline over the production line.

Phase I (Simulation Models)

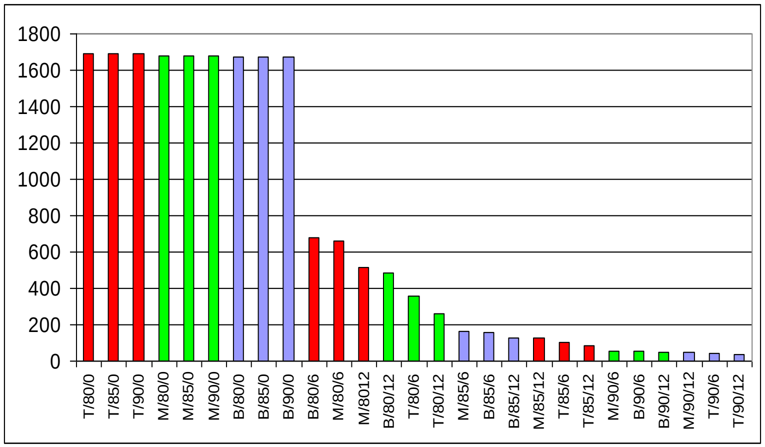
- Assumptions of the simulation models:
  - Weibull tenure distribution.
  - Gamma processing times
  - After a departure, operators are re-sequenced to maintain slowest to fastest arrangement.
  - Operator speed is a function only of the experience acquired, i.e. parts produced

ANOVA Results

Source	Sum of Squares	Df	Mean Square	F-Ratio	*P*-Value
Model	9455.418	26	363.6699	13802.59	< 0.0001
MAIN EFFECTS					
A: Method	153.8074	2	76.9037	2918.773	< 0.0001
B: Learning Curve	8384.673	2	4192.336	159114.3	< 0.0001
C: Turnover Rate	258.3055	2	129.1528	4901.813	< 0.0001
INTERACTIONS					
AB	426.7892	4	106.6973	4049.548	< 0.0001
AC	1.323152	4	0.330788	12.55459	< 0.0001
BC	334.9436	4	83.7359	3178.08	< 0.0001
ABC	3.762818	8	0.470352	17.85157	< 0.0001
PURE ERROR	13.01589	494	0.026348		
TOTAL (CORRECTED)	9468.434	520			

Arizona State University

Comparison Results



Case		T/80/0	T/85/0	T/90/0	M/80/0	M/85/0	M/90/0	B/80/0	B/85/0	B/90/0
	AVTH	1693.9	1693.9	1693.9	1677.18	1677.18	1677.18	1672.64	1672.64	1672.64
T/80/0	1693.9		NSD	NSD	S	S	S	S	S	S
T/85/0	1693.9	NSD		NSD	S	S	S	S	S	S
T/90/0	1693.9	NSD	NSD		S	S	S	S	S	S
M/80/0	1677.18	S	S	S		NSD	NSD	S	S	S
M/85/0	1677.18	S	S	S	NSD		NSD	S	S	S
M/90/0	1677.18	S	S	S	NSD	NSD		S	S	S
B/80/0	1672.64	S	S	S	S	S	S		NSD	NSD
B/85/0	1672.64	S	S	S	S	S	S	NSD		NSD
B/90/0	1672.64	S	S	S	S	S	S	NSD	NSD	

Case		T/80/6	T/85/6	T/90/6	B/80/6	B/85/6	B/90/6	M/80/6	M/85/6	M/90/6
	TH	354.9	104.9	42.8	694.2	159.8	52.4	661.6	160.7	53.7
T/80/6	354.9		S	S	S	S	S	S	S	S
T/85/6	104.9	S		S	S	S	S	S	S	S
T/90/6	42.8	S	S		S	S	S	S	S	S
B/80/6	694.2	S	S	S		S	S	NSD	S	S
B/85/6	159.8	S	S	S	S		S	S	NSD	S
B/90/6	52.4	S	S	S	S	S		S	S	NSD
M/80/6	661.6	S	S	S	NSD	S	S		S	S
M/85/6	160.7	S	S	S	S	NSD	S	S		S
M/90/6	53.7	S	S	S	S		NSD	S	S	

Case		T/80/12	T/85/12	T/90/12	B/80/12	B/85/12	B/90/12	M/80/12	M/85/12	M/90/12
	TH	258.1	85.7	37.8	487.4	126.4	47.4	517.9	125.9	47.4
T/80/12	258.1		S	S	S	S	S	S	S	S
T/85/12	85.7	S		S	S	S	S	S	S	S
T/90/12	37.8	S	S		S	S	S	S	S	S
B/80/12	487.4	S	S	S		S	S	NSD	S	S
B/85/12	126.4	S	S	S	S		S	S	NSD	S
B/90/12	47.4	S	S	S	S	S		S	S	NSD
M/80/12	517.9	S	S	S	NSD	S	S		S	S
M/85/12	125.9	S	S	S	S	NSD	S	S		S
M/90/12	47.4	S	S	S	S	S	NSD	S	S	

Results/Insight from Simulation Models

- Both MWS and BB are superior to the Traditional Assembly method (except under no turnover)
- No statistical significant difference between MWS and BB in small instance models

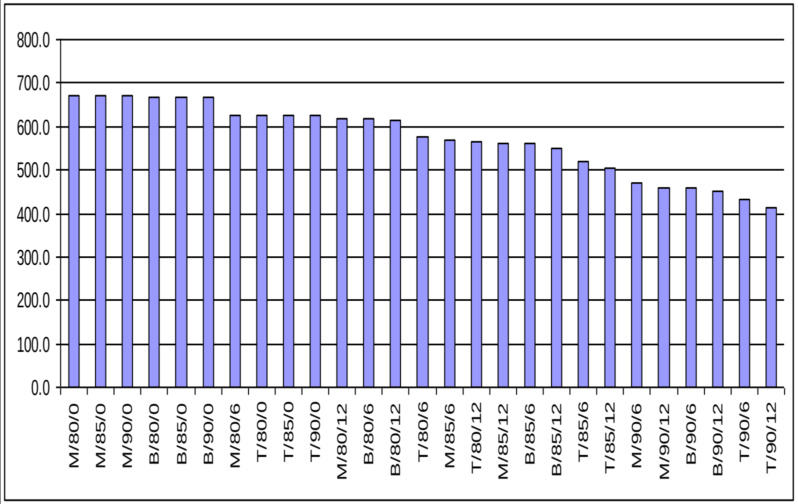
Phase II (six-station, six-operator models)

- Identical assumptions as in the 3-op., 3-station simulation models

ANOVA

Source	Sum of Squares	Df	Mean Square	F-Ratio	*P*-Value
MAIN EFFECTS					
A: Method	120338	2	60169	1308.09	< 0.0001
B: Learning Curve	498719	2	249360	5421.14	< 0.0001
C: Turnover Rate	924665	2	462332	1.0E+04	< 0.0001
INTERACTIONS					
AB	788	4	197	4.28	0.002
AC	596	4	149	3.24	0.013
BC	249460	4	62365	1355.83	< 0.0001
ABC	402	8	50	1.09	0.370
PURE ERROR	11177	243	46		
TOTAL (CORRECTED)	1806145	269			

Comparison Results



Case		T/80/0	T/85/0	T/90/0	B/80/0	B/85/0	B/90/0	M/80/0	M/85/0	M/90/0
	AVTH	625.9	625.9	625.9	668.0	668.0	668.0	672.6	672.6	672.6
T/80/0	625.9		NSD	NSD	S	S	S	S	S	S
T/85/0	625.9	NSD		NSD	S	S	S	S	S	S
T/90/0	625.9	NSD	NSD		S	S	S	S	S	S
B/80/0	668.0	S	S	S		NSD	NSD	S	S	S
B/85/0	668.0	S	S	S	NSD		NSD	S	S	S
B/90/0	668.0	S	S	S	NSD	NSD		S	S	S
M/80/0	672.6	S	S	S	S	S	S		NSD	NSD
M/85/0	672.6	S	S	S	S	S	S	NSD		NSD
M/90/0	672.6	S	S	S	S	S	S	NSD	NSD	

Case		T/80/6	T/85/6	T/90/6	B/80/6	B/85/6	B/90/6	M/80/6	M/85/6	M/90/6
	AVTH	576.9	521.3	430.7	619.3	560.0	459.1	626.9	570.0	468.9
T/80/6	576.9		S	S	S	S	S	S	NSD	S
T/85/6	521.3	S		S	S	S	S	S	S	S
T/90/6	430.7	S	S		S	S	S	S	S	S
B/80/6	619.3	S	S	S		S	S	S	S	S
B/85/6	560.0	S	S	S	S		S	S	S	S
B/90/6	459.1	S	S	S	S	S		S	S	S
M/80/6	626.9	S	S	S	S	S	S		S	S
M/85/6	570.0	NSD	S	S	S	S	S	S		S
M/90/6	468.9	S	S	S	S	S	S	S	S	

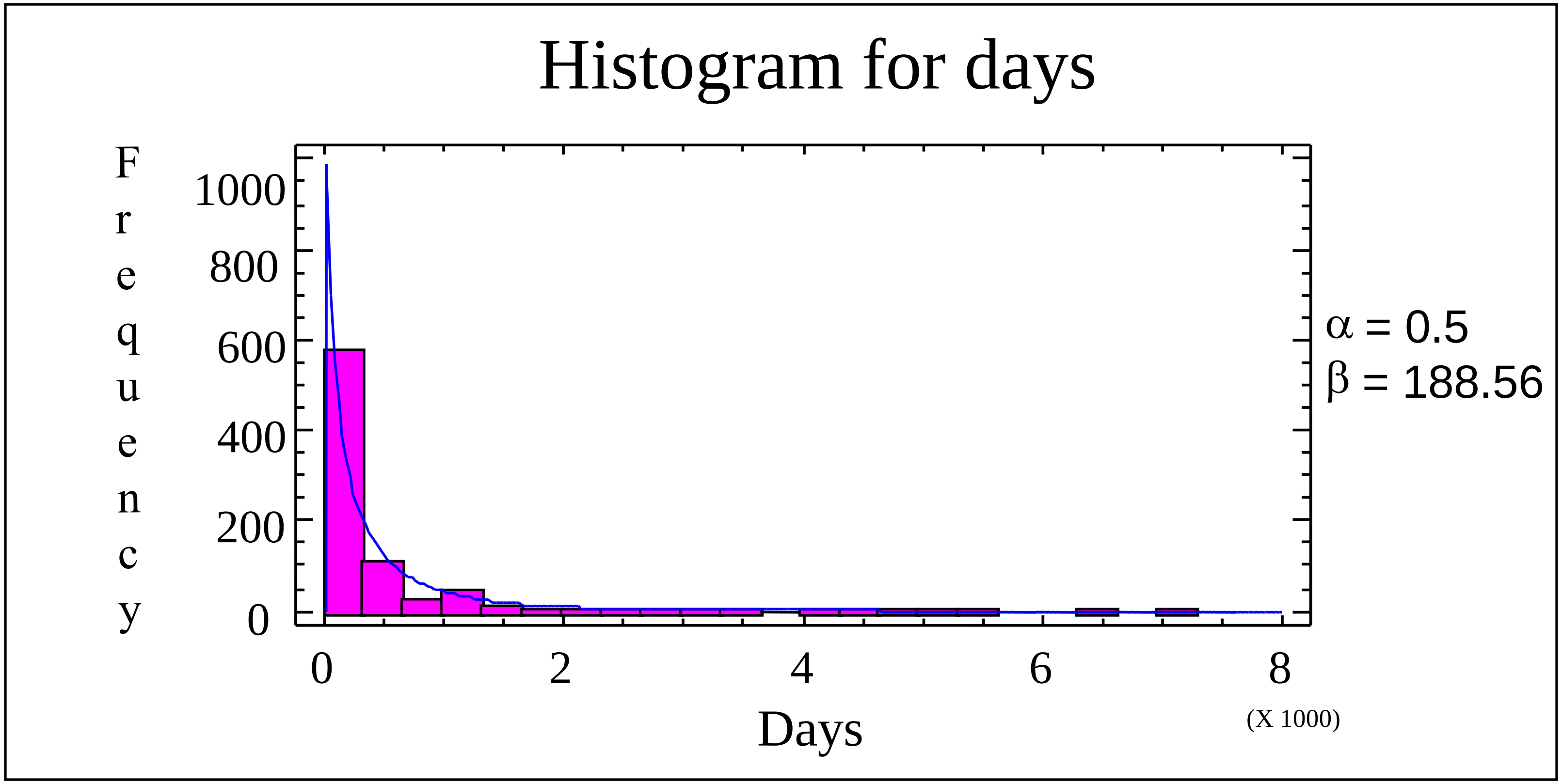
Case		T/80/12	T/85/12	T/90/12	B/80/12	B/85/12	B/90/12	M/80/12	M/85/12	M/90/12
	AVTH	564.9	504.8	414.4	612.9	551.1	450.3	619.8	560.3	459.2
T/80/12	564.9		S	S	S	S	S	S	NSD	S
T/85/12	504.8	S		S	S	S	S	S	S	S
T/90/12	414.4	S	S		S	S	S	S	S	S
B/80/12	612.9	S	S	S		S	S	S	S	S
B/85/12	551.1	S	S	S	S		S	S	S	S
B/90/12	450.3	S	S	S	S	S		S	S	S
M/80/1	619.8	S	S	S	S	S	S		S	S
M/85/1	560.3	NSD	S	S	S	S	S	S		S
M/90/1	459.2	S	S	S	S	S	S	S	S	

Conclusions

- Assembly line designs based on dynamic work allocation absorb better the variability introduced by new operators.
- The MWS method has the potential of self-adjusting to different levels of labor turnover.
- Generally the MWS method outperforms the BB method and the traditional balanced line under conditions of medium and high labor turnover in longer, more realistic assembly lines.
- In smaller assembly lines, under medium and high labor turnover conditions the BB and MWS tend to perform similarly. When additional sources of variation -other than processing times- are present, such as machine breakdowns, the MWS tends to outperform the BB.
- Further research in the following topics is needed: operational rules, development of detailed design rules, impact of hand-over times

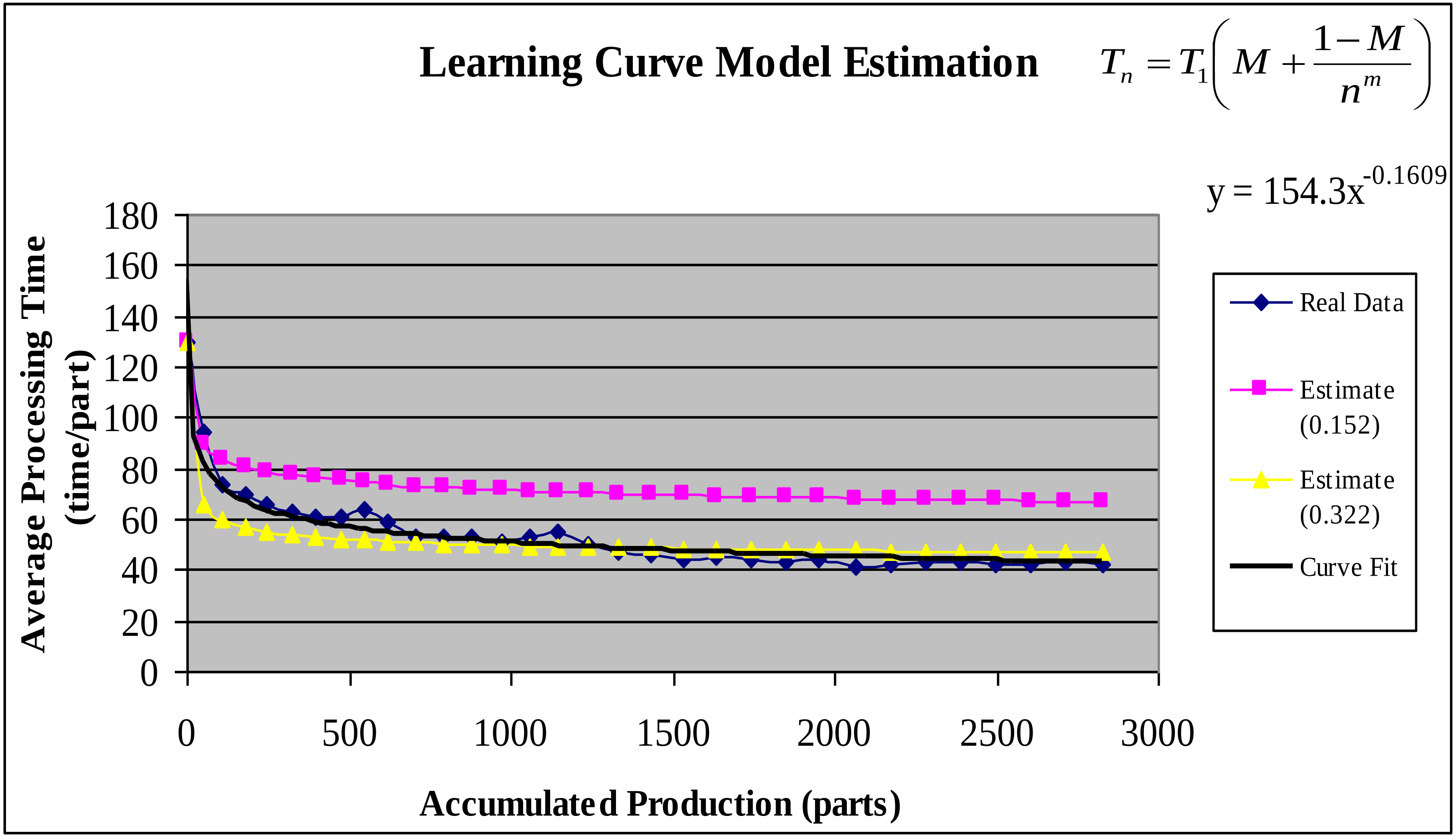
Weibull Distribution

- Real-world data from Lear Co.
- Provides non-negative numbers



Learning Curve Selection

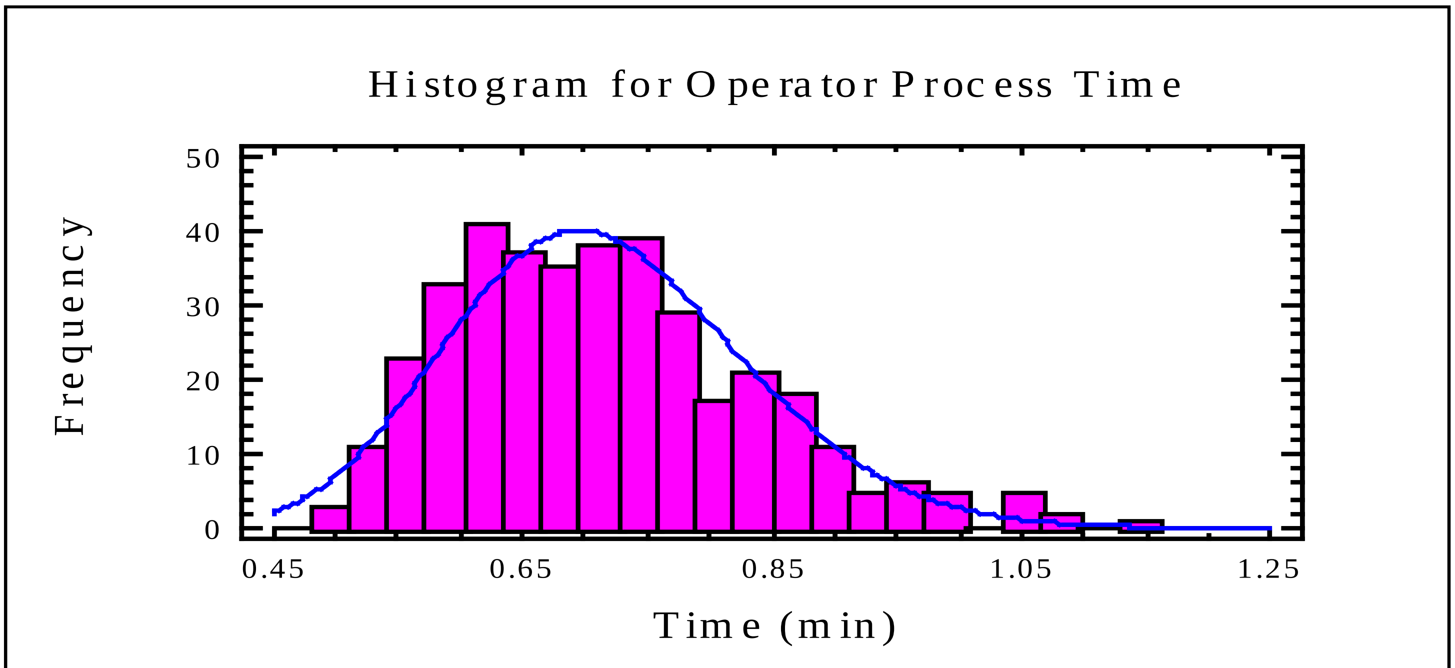
De Jong's Model



Gamma Distribution

- **Represents Processing Time**
- The variability can be modeled with the mean
- Set α and β for
- Mean = 130 sec. & Var = 30 sec. using:

α = 563.33
β = Mean/ α



Gamma Distribution