

# **Analysis of Performance Approximations for Queueing Networks with Non-Homogeneous Arrival Processes**

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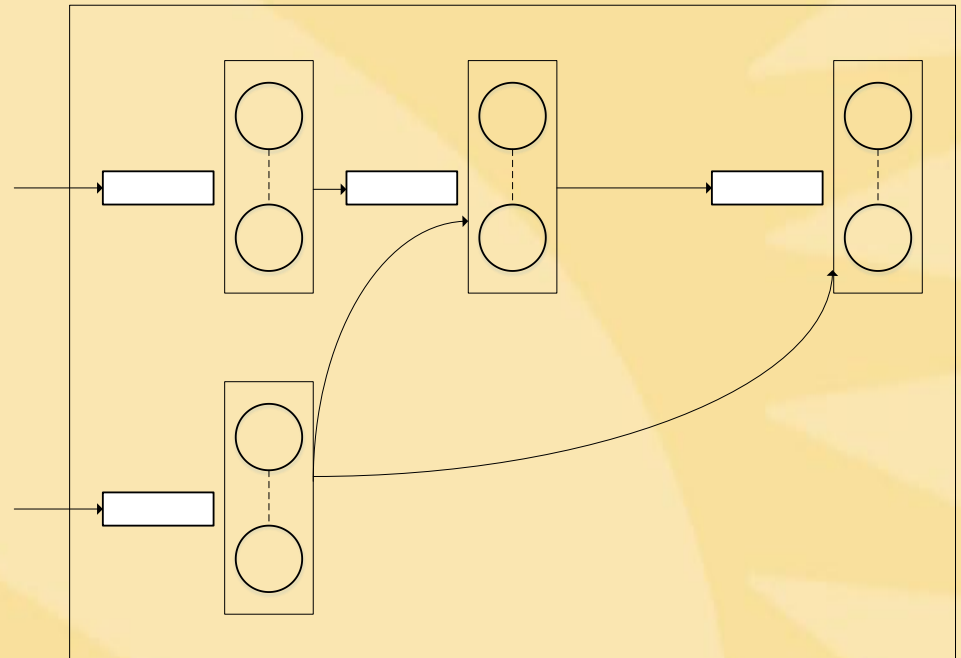
[gjampani@asu.edu](mailto:gjampani@asu.edu)

# Dynamic Queueing Network Analysis Outline

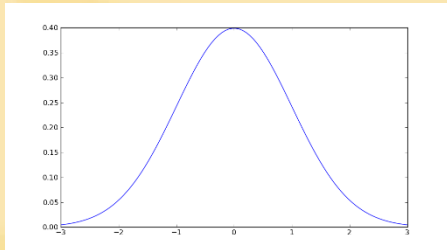
- Introduction
- Problem Definition
- Impact of Non-stationarity
- Literature Review
- Research Methodology
- Results
- Conclusions and Future Research

# Introduction

The manufacturing facility as a dynamic queueing network



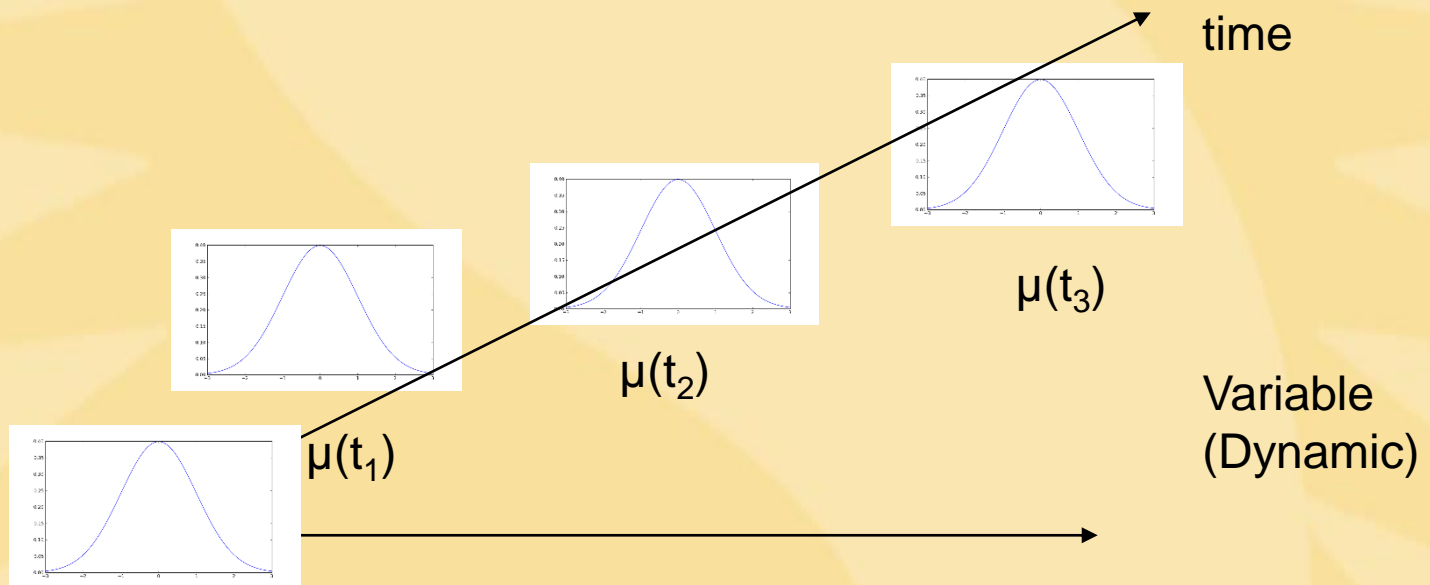
# Randomness, Certainty, Variability



$\mu$   
Random

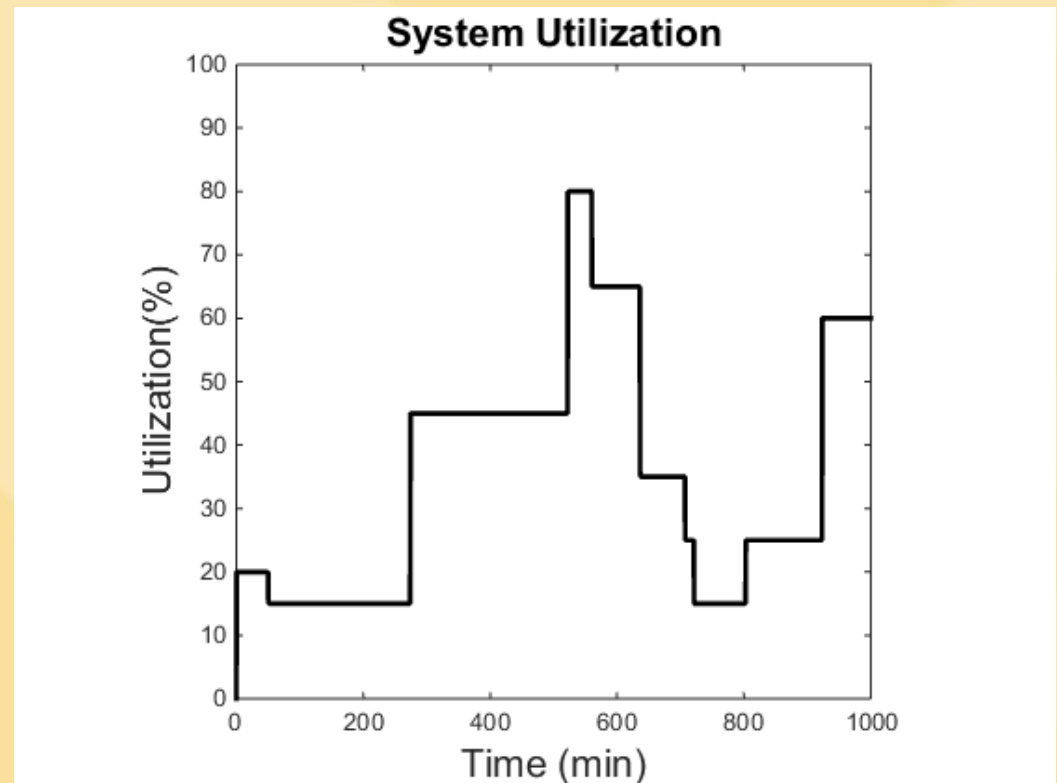
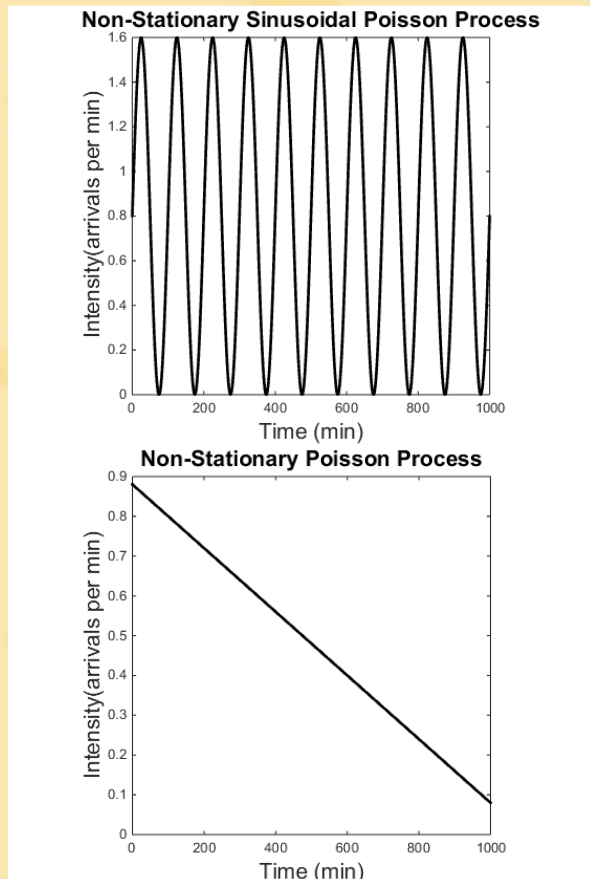


$f(\mu)$   
Uncertain (Bayesian)



# Introduction

- Often systems may not adhere to product form model assumptions



# Introduction

- Rough cut planning and scenario analysis under dynamic conditions call for efficient algorithms.
- Research question : How do we leverage available efficient algorithms for steady-state analysis to develop reliable approximations for first (and maybe higher) order estimates of performance measures under dynamic conditions?

# Problem Definition

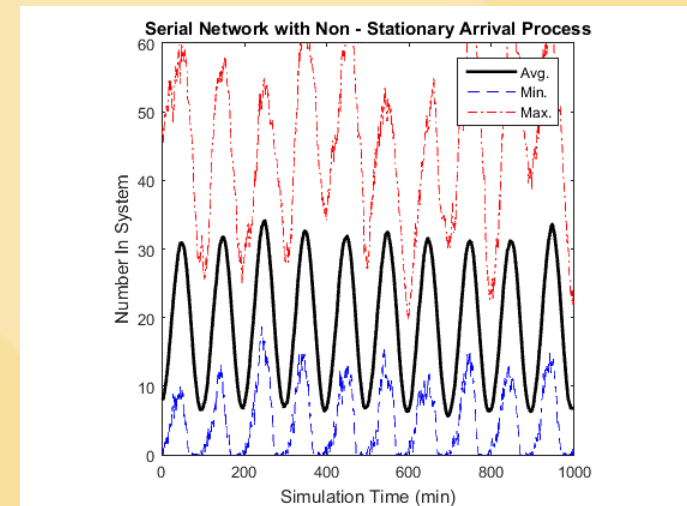
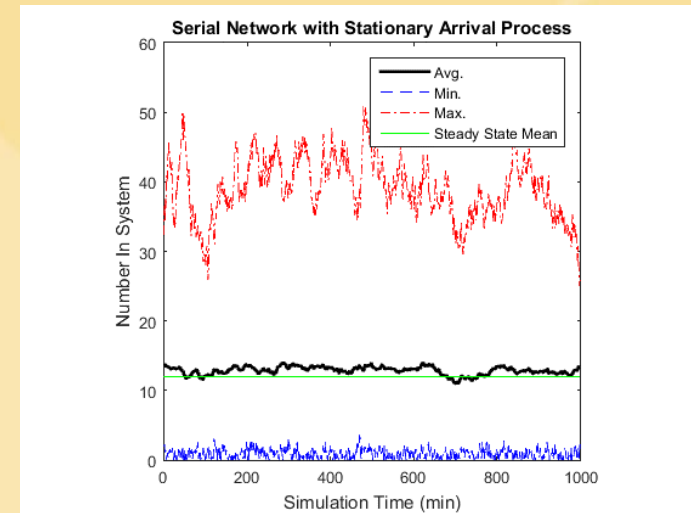
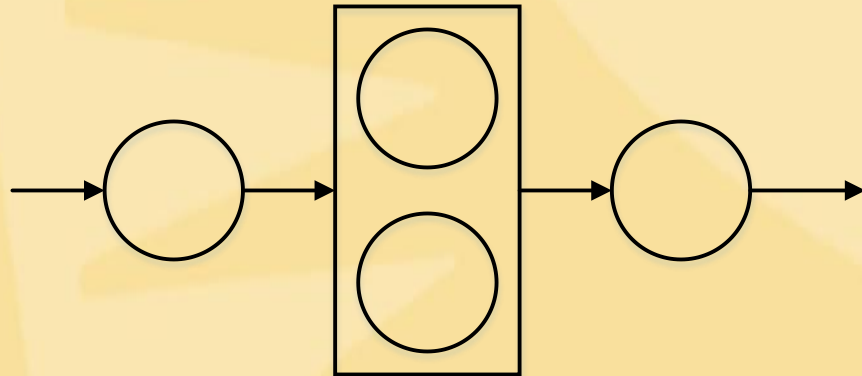
- Consider an interconnected system of servers
- Non-stationary arrivals, Markovian service processes (possibly intermittent or non-homogenous) and FCFS queueing discipline.
- $L$  workstations and  $R$  routing chains (customer classes/part types).
- Infinite queue capacity and no migration.
- External and internal arrivals governed by an irreducible stochastic routing matrix,  $P_r$  (i.e. process plans by part type)
- State of the system can be described by state vector

$$\mathbf{K} = (\mathbf{k}_1, \dots, \mathbf{k}_R) \text{ where } \mathbf{k}_r = (k_{r,1}, \dots, k_{r,L})$$

where  $k_{r,l}$ : number of class  $r$  jobs at workstation  $l$

# Impact of Non-stationarity

- Example 1: Three stage serial production line.

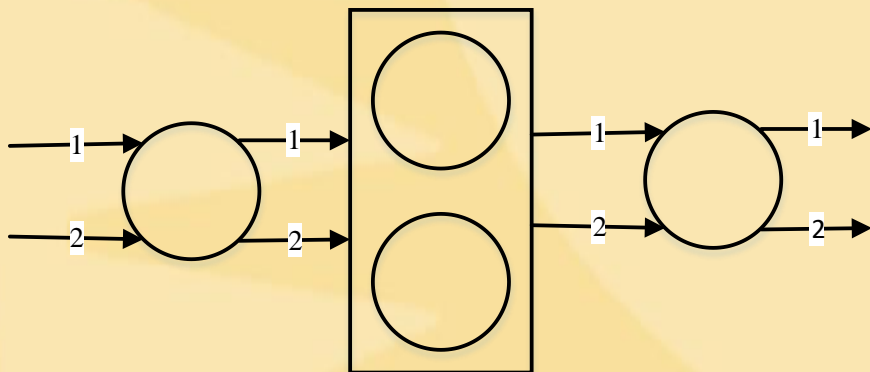


Sinusoidal  
Arrival  
Process



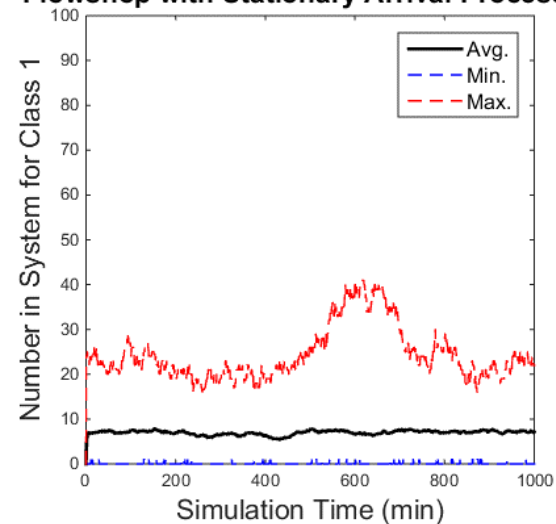
# Impact of Non-stationarity

- Example 2: Three stage flow shop.

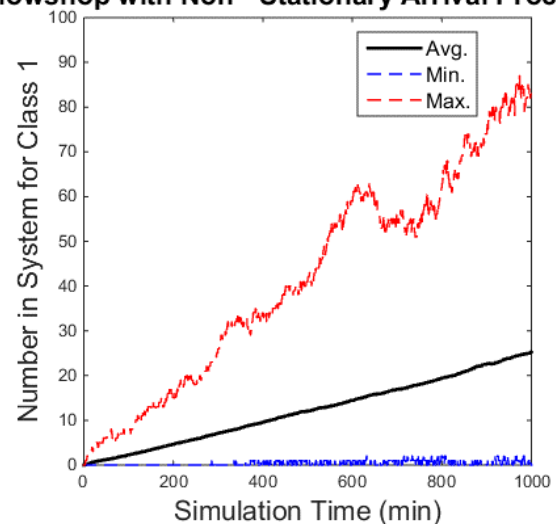


Arrival Process : Complementary Linear  
Non – Homogenous Poisson Processes

Flowshop with Stationary Arrival Processes



Flowshop with Non - Stationary Arrival Processes



# Literature Review : Nonstationary Queues

Some general results e. g. Heyman and Whitt (1984): dynamic steady state for  $M_t/G/c$

Three broad categories of approximations

- Systems Approximations (period by period stationary approximation)
  - Green and Kolesar (1991): Pointwise stationary approximation (PSA)
  - Green et al. (2001): Stationary independent period-by-period (SIPP) approximation
  - Stolletz (2008): Stationary backlog carryover (SBC) approximation
- Numerical Approximations (Simplification assumptions and numerically compute)
  - Rothkopf and Oren (1979): Closure approximation
  - Grassmann (1977): Randomization method
- Process Approximations (Limiting heavy traffic fluid/diffusion methods)
  - Mandelbaum and Massey (1995)

Wang et al. (1996): Pointwise stationary fluid flow approximation(PSFFA)

Ingolfsson et al. (2007): Experimental comparison of seven service-level approximations for nonstationary queues.

# Literature Review : Nonstationary Queueing Networks

Duda (1986): Parametric decomposition based on transient analysis of  $GI/GI/1$  queue

Massey and Whit (1993): Networks of infinite-servers queues with nonstationary Poisson input.

Malone (1995): Decomposition approximation for open networks with nonstationary input.

Mandelbaum and Massey (1995): Fluid and diffusion limits for large scale Markovian service networks

Whitt (1999): Generalized Jackson network based approximation framework for time-dependent Markovian networks-simplifying system of ODEs

Liu and Whitt (2013): Analysis of networks of time-varying many-server fluid queues.

# Motivation

- Research focus so far has been on
  - Nonstationary queues
  - Queuing networks under stationary arrival assumptions or special conditions
- Need efficient algorithms for QN's under dynamic conditions.
- Incorporating network structure enables
  - Understanding evolution of congestion at different points
  - Modelling class priorities
- Focus is on first-order estimates of system performance.

# System Approximation Research Methodology

- Total observation window  $T$  is broken down into a finite number of time epochs of equal length  $t_s$ ,  $s=1,\dots,T/t_s$ .
- System dynamics are studied through snapshots of system performance tracked for each time epoch.
- Snapshots are a weighted combination of steady state performance metrics for two closed queueing networks, with the floor and ceiling levels of WIP (Basic Closed Model).

# Research Methodology

- Steady state estimates are precomputed using an exact Mean Value Analysis (MVA) algorithm (see Reiser and Lavenberg (1980)).
- Characteristics of MVA
  - Provides steady state estimates for all intermediate levels of WIP (provides performance for all values of  $k = 1, \dots, K_r$ )
  - Complexity :  $O(\prod_{r=1}^R K_r)$ , where  $K_r$  is number of jobs of class 'r'.

# Research Methodology

- Step 1. Solve closed network,  $C(\mathbf{N}^*)$  using the MVA algorithm. The state vector  $\mathbf{N}^*$  is set to a sufficiently large value.
- Step 2. Initialize  $i=0$ ,  $t=0$  and the vector of total jobs in each routing chain for initial conditions,  $\mathbf{N}_0 = (n_1(0), n_2(0), \dots, n_R(0))$   
Set  $X_r(0) = X_r^c(\mathbf{N}_0)$

# Research Methodology

- Step 3. Set  $i = i + 1, t = t + t_s$ .

Update mean number in routing chain  $r = 1, \dots, R$  as

$$n_r(t) = \max\left(n_r(t - t_s) + t_s \sum_{j=1}^L \lambda_{rj}(t - t_s, t) - t_s \cdot X_r(t - t_s), 0\right)$$

(Starting + Arrivals – Completions; or 0)

If  $t < T$  go to step 4 else STOP.



# Research Methodology

- Step 4. For each  $r = 1, \dots, R$

a) Update throughput rate as

$$X_r(t) = (1 - \alpha_r) X_r^c(\mathbf{N}_l) + \alpha_r X_r^c(\mathbf{N}_u) , \text{ where}$$

$$\mathbf{N}_l = (\lfloor n_1(t) \rfloor, \lfloor n_2(t) \rfloor, \dots, \lfloor n_R(t) \rfloor) \quad ,$$
$$\mathbf{N}_u = (\lceil n_1(t) \rceil, \lceil n_2(t) \rceil, \dots, \lceil n_R(t) \rceil) \quad , \text{ and} \quad \alpha_r = n_r(t) - \lfloor n_r(t) \rfloor$$

b) Update mean total time in system as

$$W_r(t) = \frac{n_r(t)}{X_r(t)} \quad (\text{Little's law for each routing chain})$$

c) Update Cumulative production as

$$\chi_r(t) = \chi_r(t - t_s) + \min(X_r(t) \cdot t_s, (n_r(t - t_s) + t_s \sum_{j=1}^L \lambda_{rj}(t - t_s, t)))$$

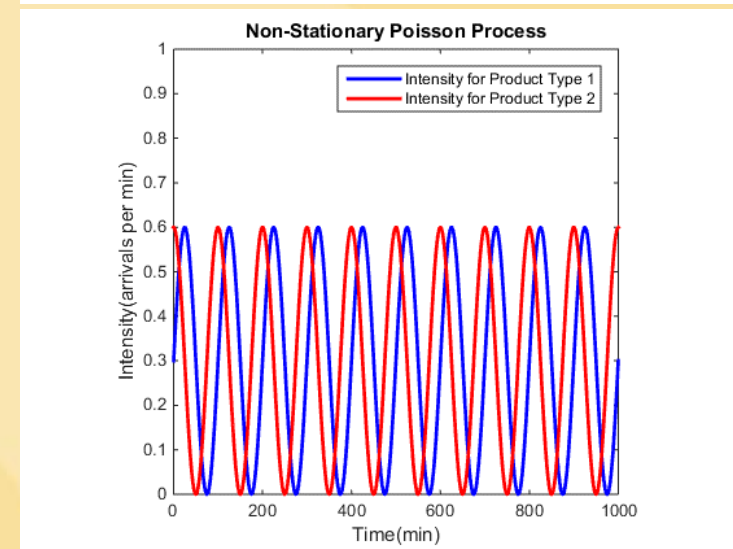
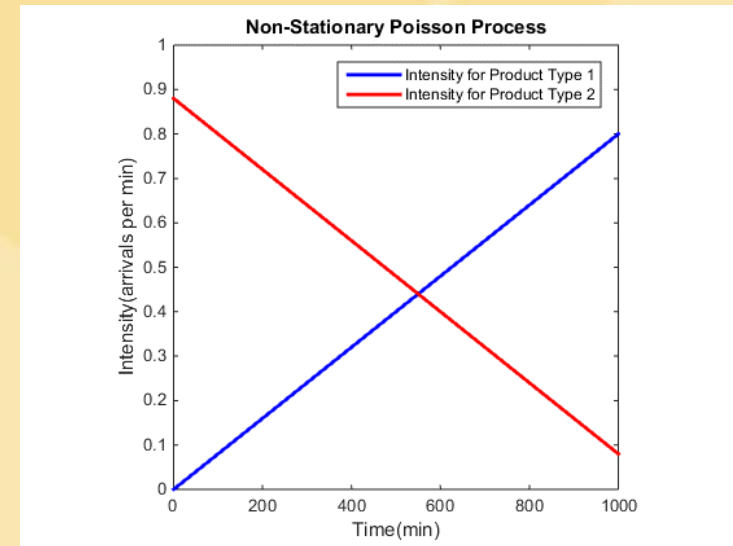
- Step 5. Go to step 3.

# Computational Analysis

- Method pieces together snapshots of how a stationary system would perform at each time step with the given WIP level.
- Approximation MVA assumes distribution of jobs across workstations not representative of actual distribution for non-homogenous process.
- Approximation was applied to a simple serial system and a jobshop with four classes and sixteen workstations.
- First order moments of interest were compared against simulation results.

# Experiments

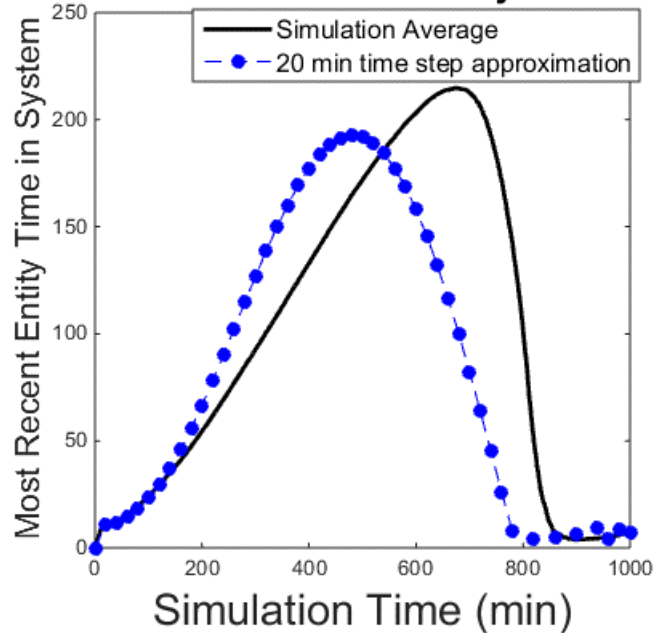
- Models
  - 1a.
    - Type: Three workstation serial line
    - Arrival Process: Non – homogenous Sinusoidal Poisson Process with  $2\pi = 1000$  min .
  - 1b.
    - Type: Three workstation serial line
    - Arrival Process: Non – homogenous Sinusoidal Poisson Process with  $2\pi = 100$  min .
  - 2.
    - Type: Two class three workstation flow shop
    - Arrival Processes: Complementary non-homogenous linear Poisson process
  - 3.
    - Type: Two class three workstation flow shop
    - Arrival Processes: Complementary non-Homogenous sinusoidal Poisson process.



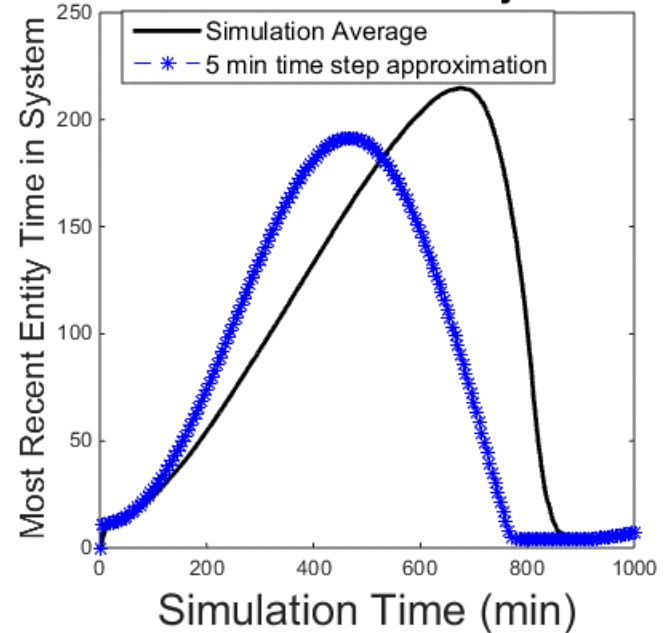
# Model 1a : Time in system

$$2\pi = 1000 \text{ min.}$$

Serial Network with Non-Stationary Arrival Process

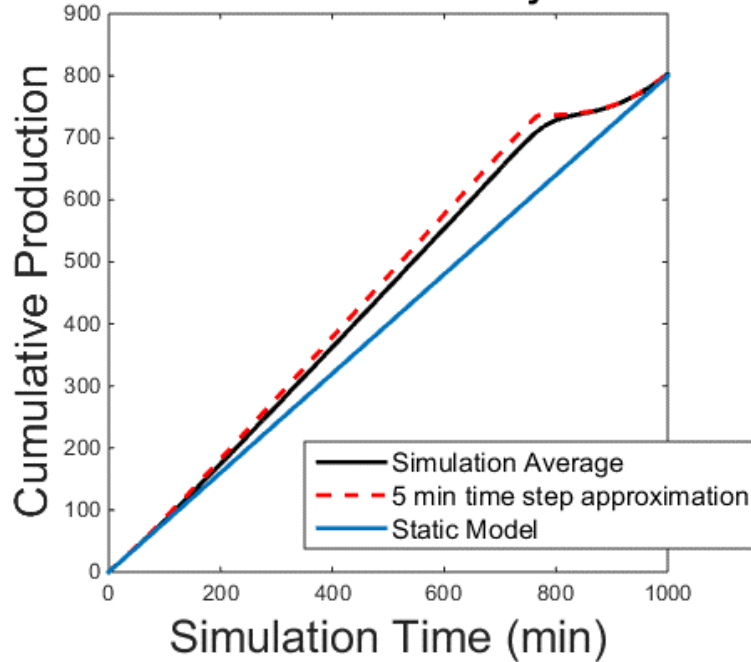


Serial Network with Non-Stationary Arrival Process



# Cumulative production results

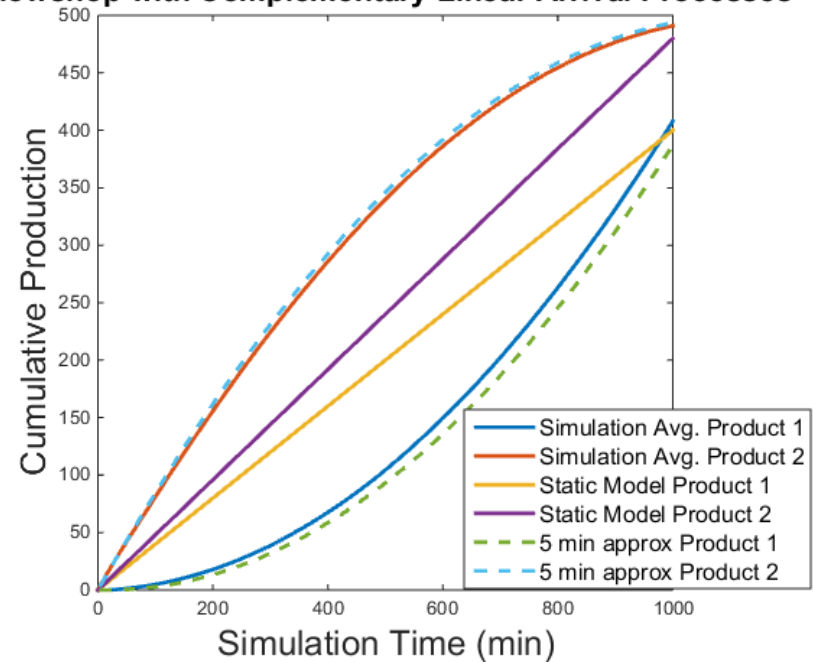
## Serial Network with Non-Stationary Arrival Process



$2\pi = 1000$  min.

Model 1a

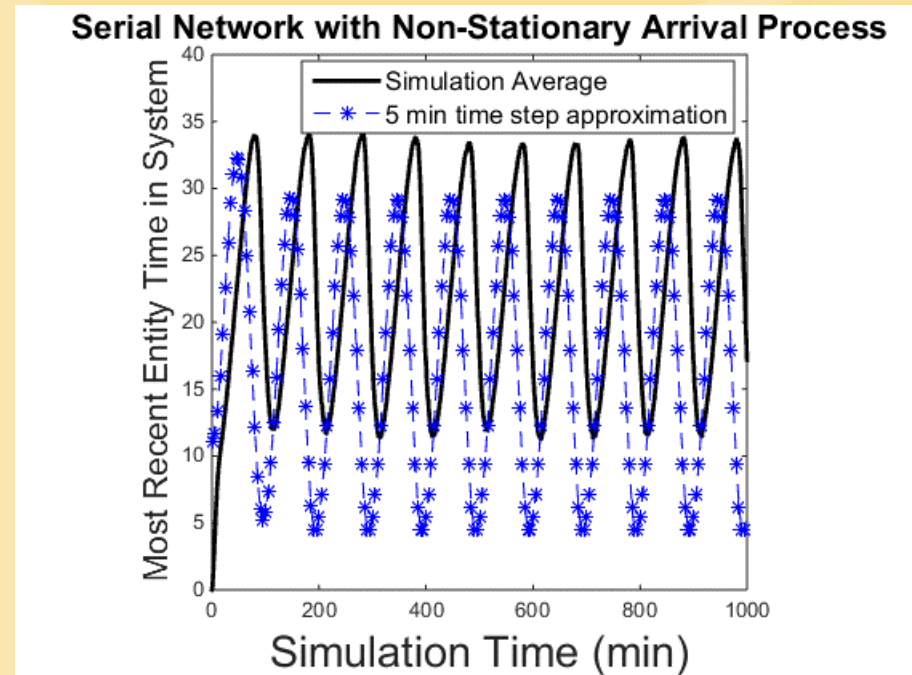
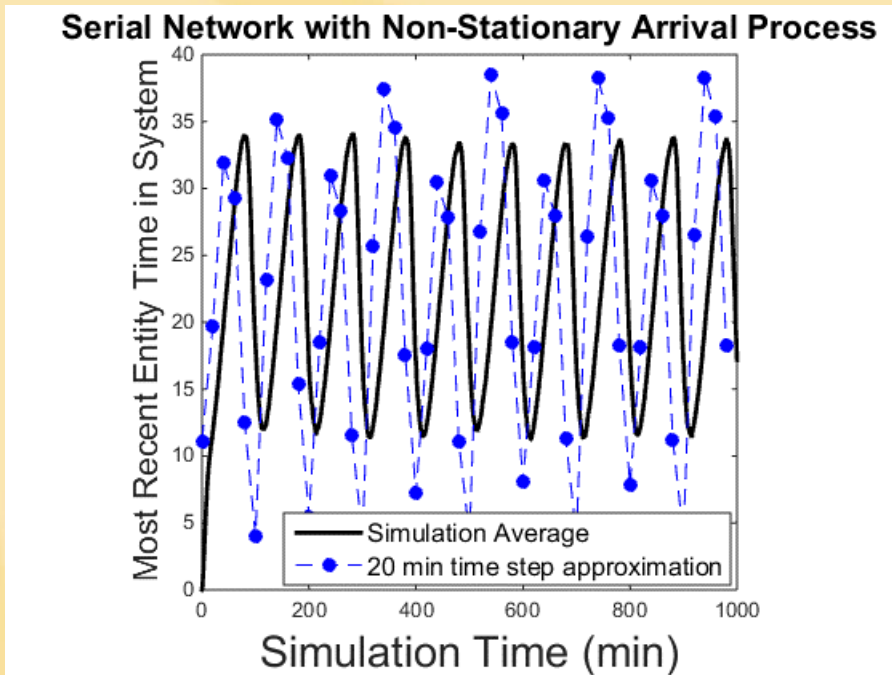
## Flowshop with Complementary Linear Arrival Processes



Model 2

# Model 1b: Time in system

$$2\pi = 100 \text{ min.}$$

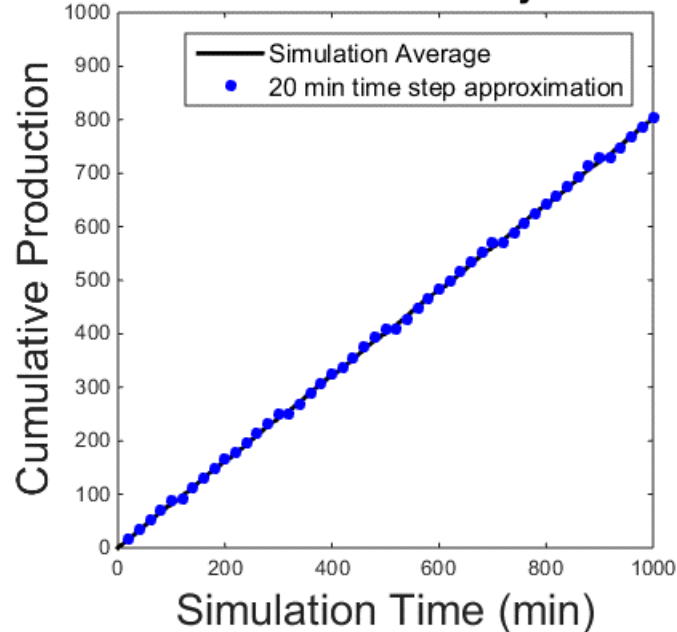


Note: Static model gives a constant time in system of 15.56 mins

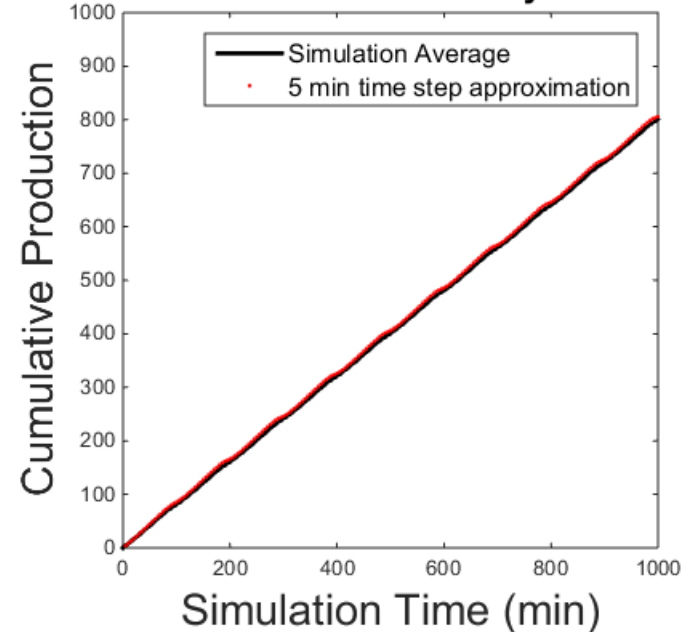
# Model 1b: Cumulative production

$$2\pi = 100 \text{ min.}$$

Serial Network with Non-Stationary Arrival Process



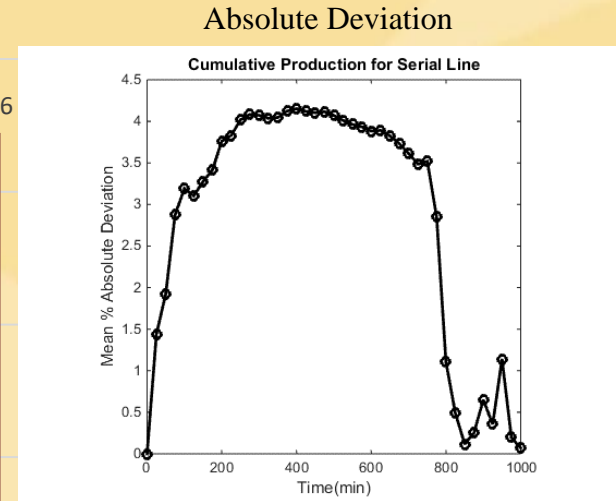
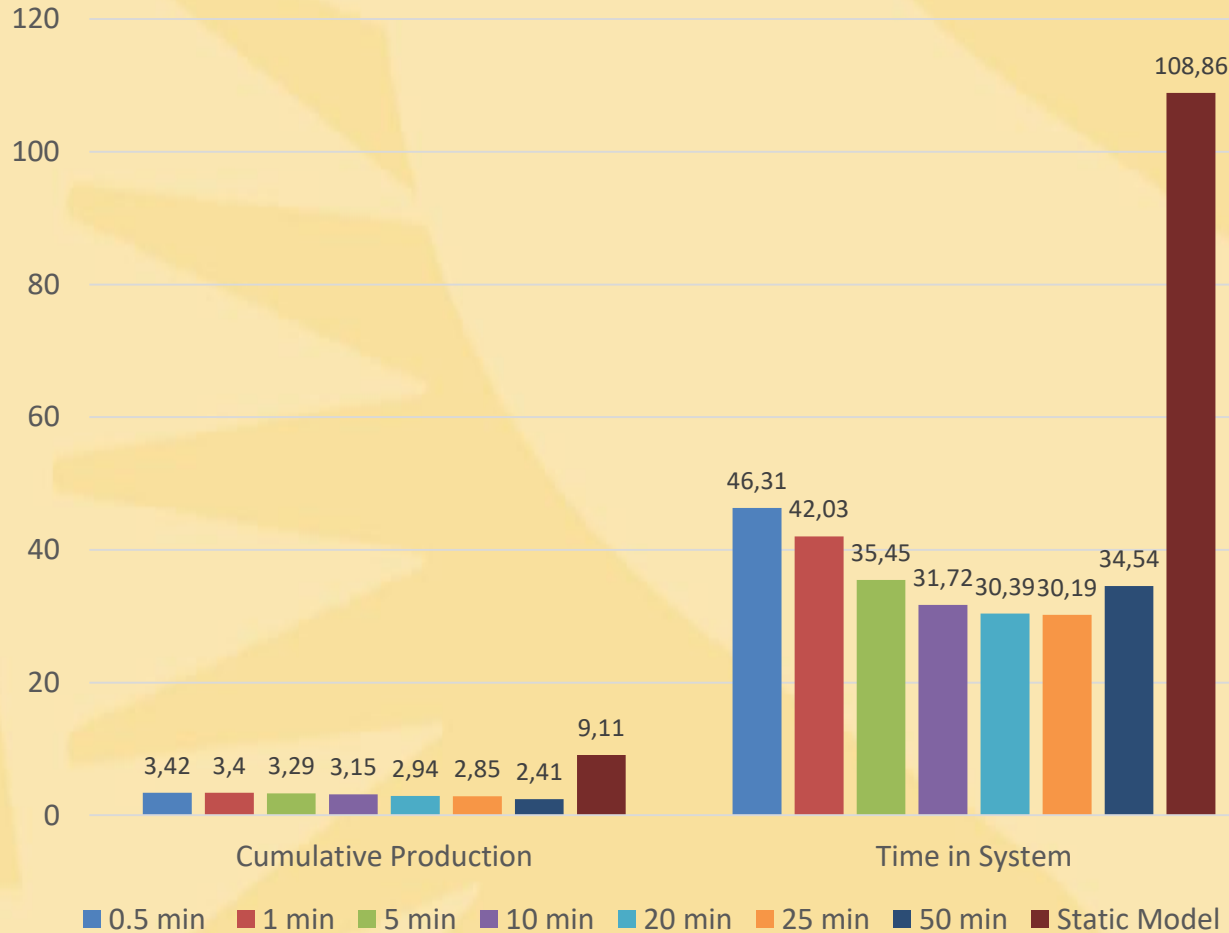
Serial Network with Non-Stationary Arrival Process



# Model 1b: Absolute Deviation

$$2\pi = 100 \text{ min.}$$

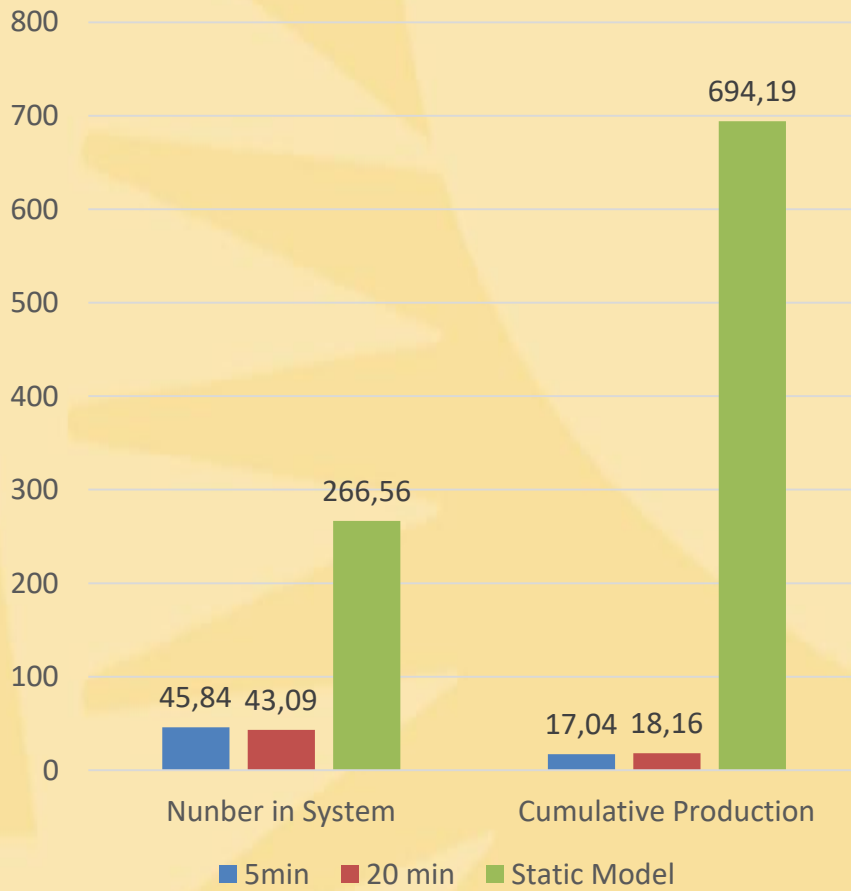
Mean % Absolute Deviation Approx. vs Simulation



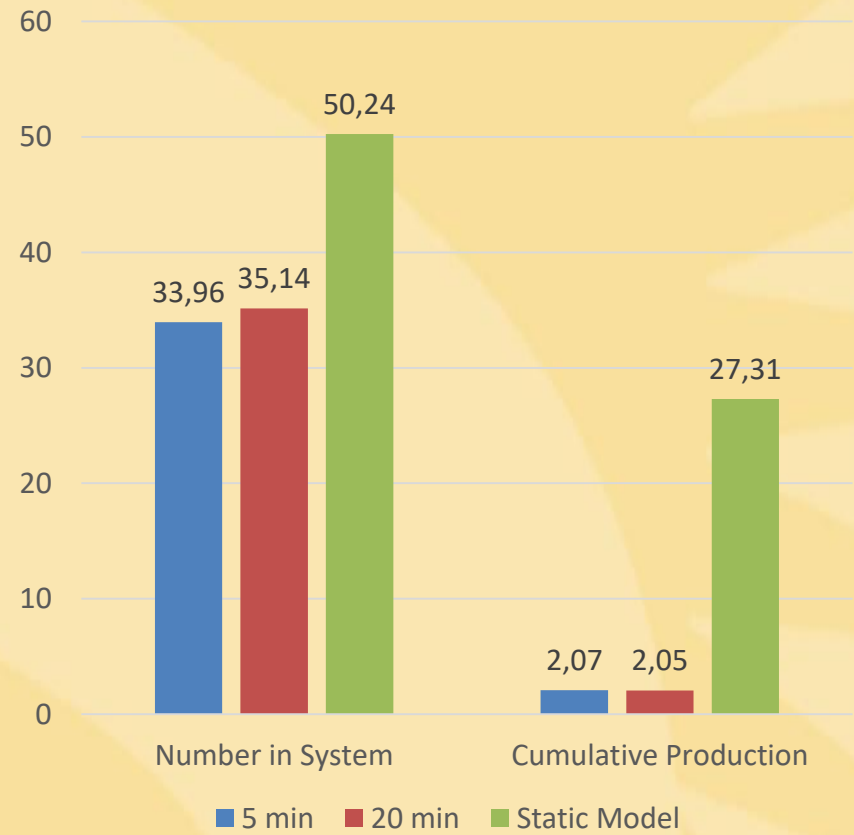


# Model 2: Absolute Deviation

## Mean % Absolute Deviation Approx. vs Simulation for Product1

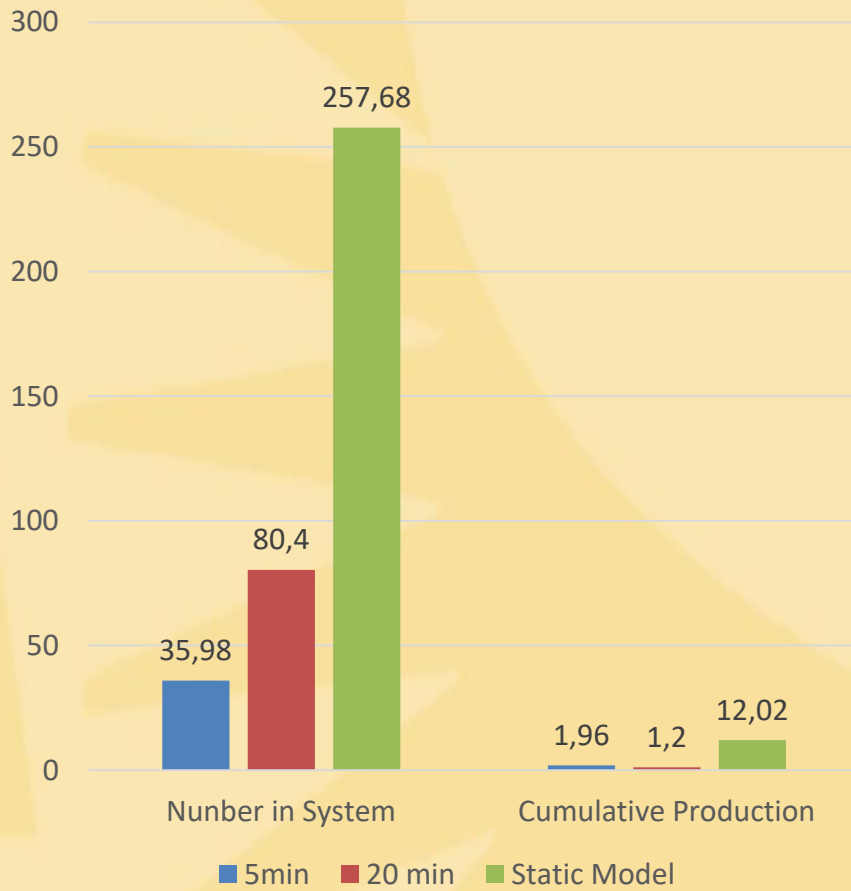


## Mean % Absolute Deviation Approx. vs Simulation for Product2

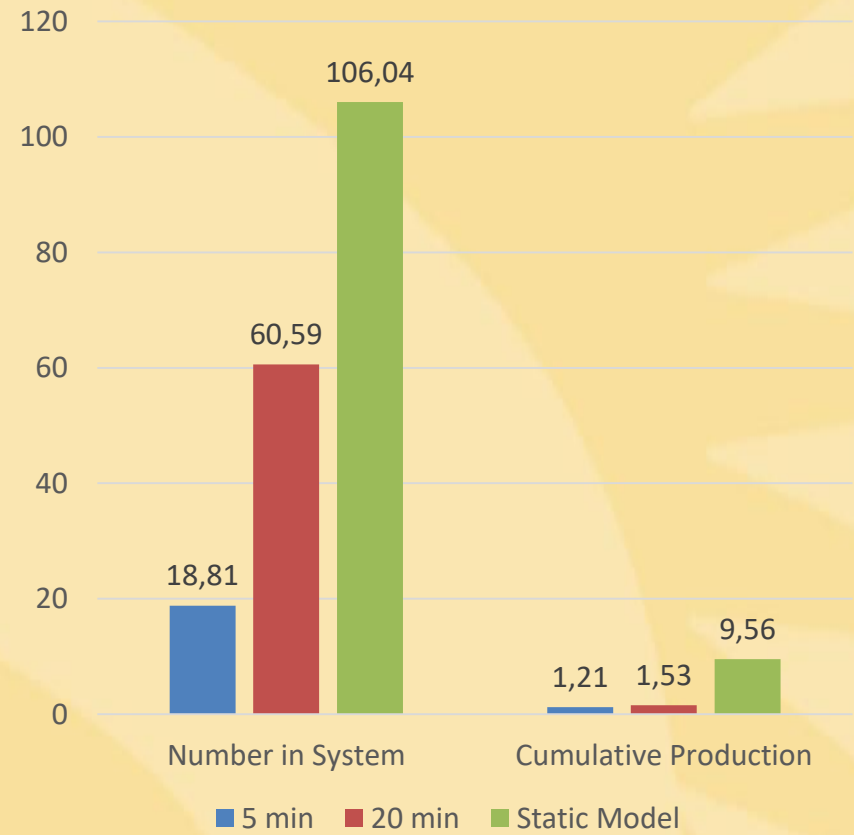


# Model 3: Absolute Deviation

## Mean % Absolute Deviation Approx. vs Simulation for Product1



## Mean % Absolute Deviation Approx. vs Simulation for Product2



# Enhancements to Base model :

## Motivation

- Implicit Dynamic distribution of jobs ignored in previous model.
- Steady state assumptions don't hold under transient conditions.
- Instantaneous throughput rates of individual workstations need not be identical.

# Route Workstation Based Throughput Model (RWBTM)

- Step 1

Use MVA to solve the closed queueing network  $C(\mathbf{N}^*)$  ( $\mathbf{N}^*$  sufficiently large).

- Step 2

Initialize  $i = 0, t = 0$ .

Set  $\mathbf{N}_0 = (n_1(0), \dots, n_R(0))$  to match an equivalent open queueing network.

Set  $X_r(0) = X_r^c(\mathbf{N}_0)$  for each  $r = 1, \dots, R$ .

Set  $n_{rl}(0) = n_{rl}^c(\mathbf{N}_0), \gamma_{rl}(0) = 0, \psi_{rl}(0) = 0, X_{rl}(0) = \nu_{rl} X_r^c(\mathbf{N}_0)$  for each  $r = 1, \dots, R$  and each  $l \in S(r)$ .

- Step 3

Set  $t = t + t_s$

# Route Workstation Based Throughput Model (RWBTM)

- Step 4

For each  $r = 1, \dots, R$  and each  $l \in S(r)$

1. Compute mean number of jobs of routing chain  $r$  leaving workstation  $l$  at time  $t$

$$\psi_{rl}(t) = \min(n_{rl}(t - t_s) + t_s \lambda_{rl}(t - t_s, t), t_s X_{rl}(t - t_s))$$

2. Compute total internal arrivals of routing chain  $r$  at workstation  $l$  at time  $t$

$$\gamma_{rl}(t) = \sum_{j=1}^L \psi_{rj}(t) p_{jl}^r$$

# Route Workstation Based Throughput Model (RWBTM)

- Step 5

Update cumulative production at time  $t$  for each  $r = 1, \dots, R$

$$\chi_r(t) = \chi_r(t - t_s) + \sum_{l=1}^L \left[ \left( 1 - \sum_{j=1}^L p_{lj}^r \right) \psi_{rl}(t) \right]$$

# Route Workstation Based Throughput Model (RWBTM)

- Step 6

For each  $r = 1, \dots, R$  and  $l \in S(r)$

1. Update mean number in routing chain  $r$  at workstation  $l$  as

$$n_{rl}(t) = n_{rl}(t - t_s) + t_s \lambda_{rl}(t - t_s, t) + \gamma_{rl}(t) - \psi_{rl}(t) \quad (1)$$

2. Obtain closest CQN,  $\mathbf{N}_l^*(t)$  for each workstation  $l$  as

$$\mathbf{N}_l^*(t) = \{ \mathbf{N} : \mathbf{n}_l^*(t) = \min_{\mathbf{N} \in \mathbf{N}^*} \|\mathbf{n}_l(t) - \mathbf{n}_l^c(\mathbf{N})\|_2 \} \quad (2)$$

3. Update throughput rate for routing chain  $r$  at workstation  $l$  as

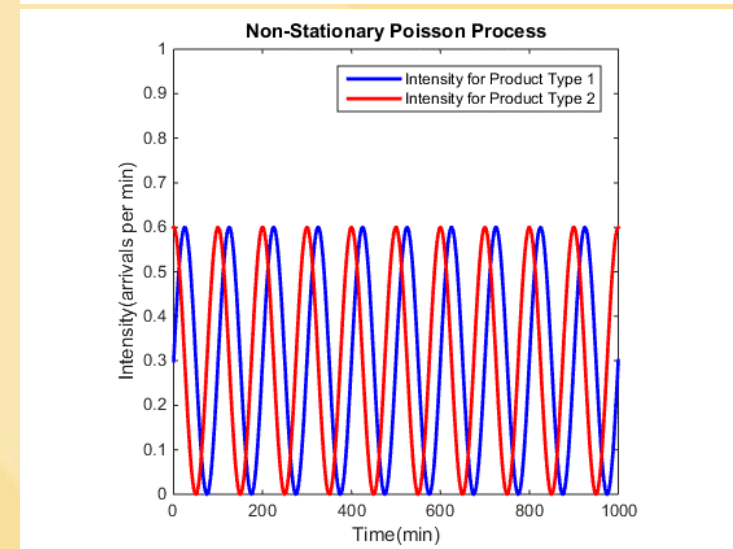
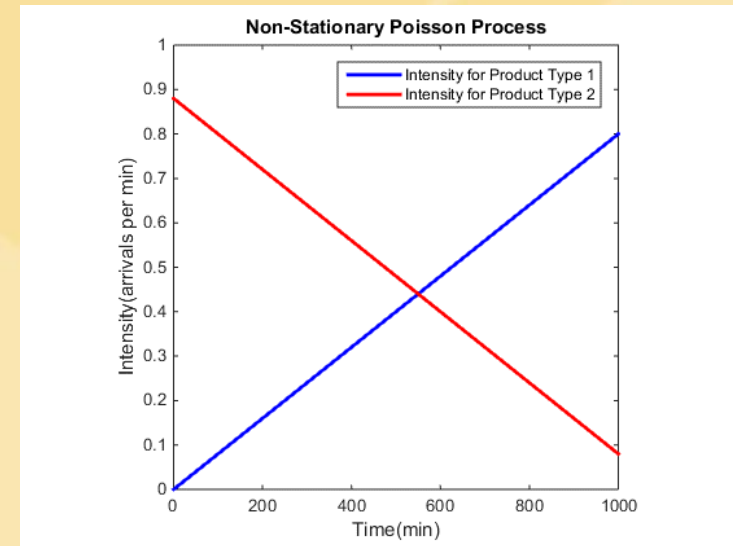
$$X_{rl}(t) = \nu_{rl} X_r^c(\mathbf{N}_l^*(t)) \quad (3)$$

- Step 7

If  $t < T$  GO TO 3. Else STOP.

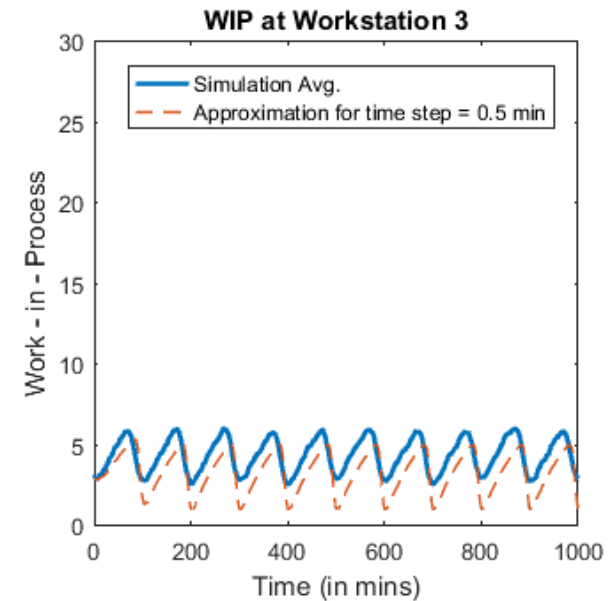
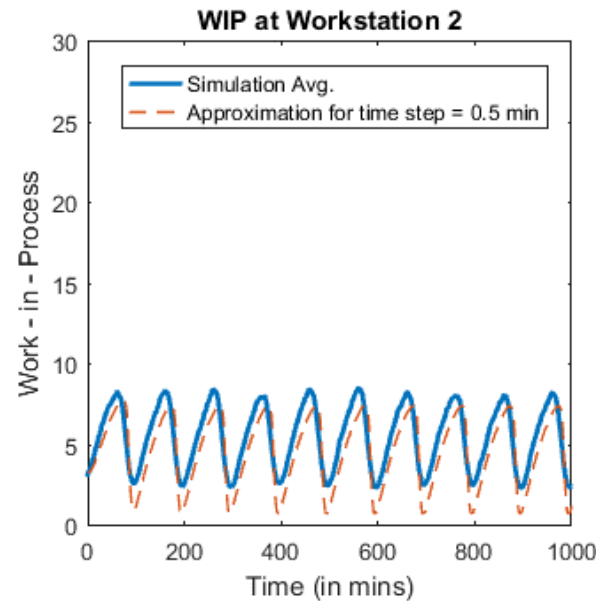
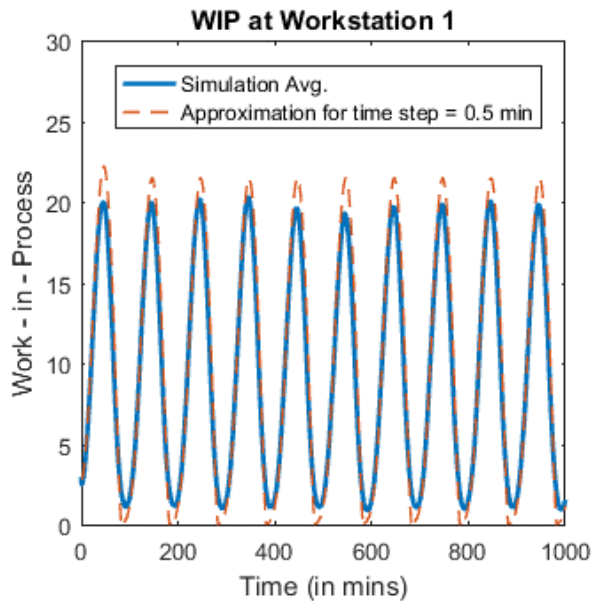
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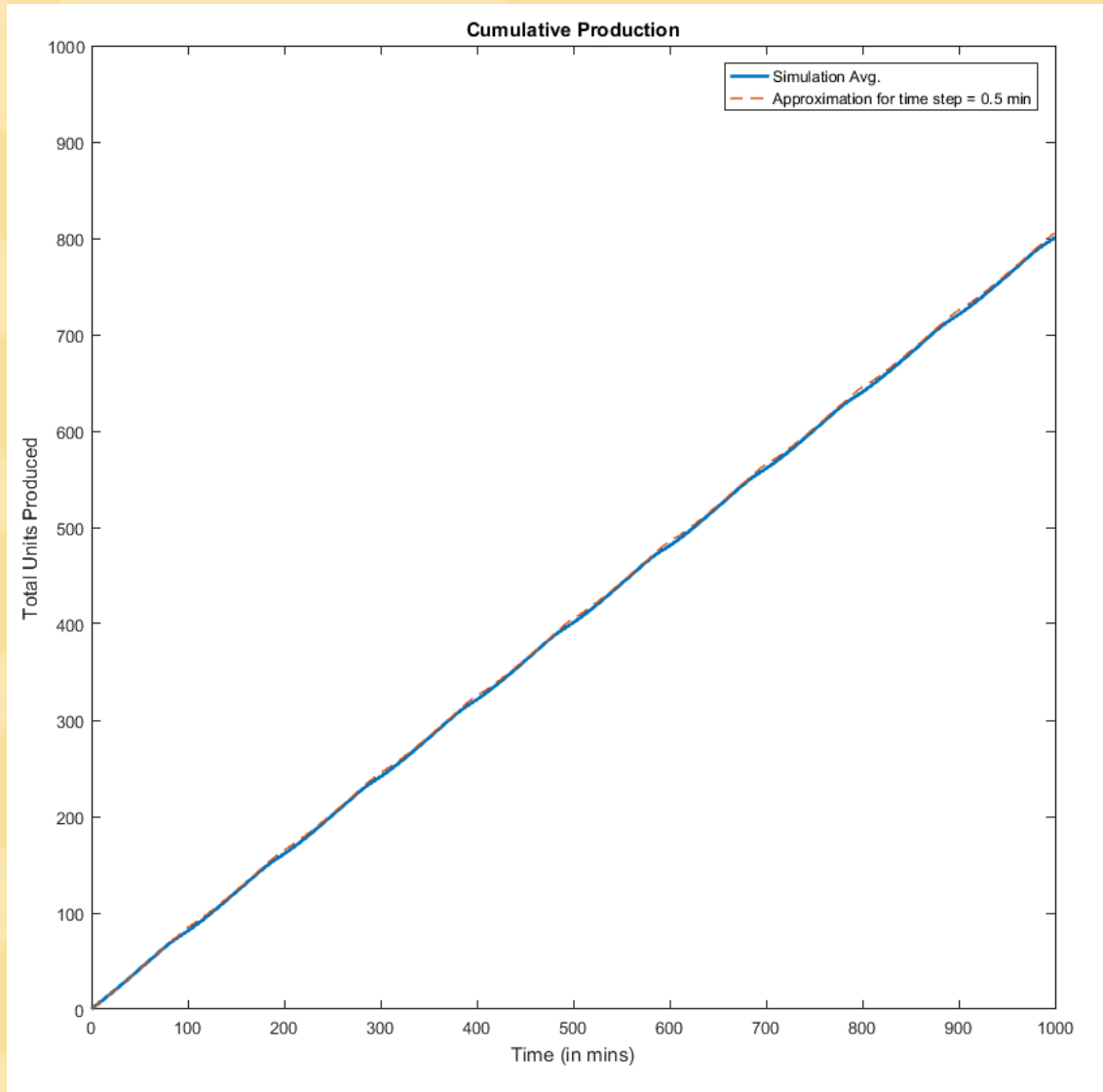




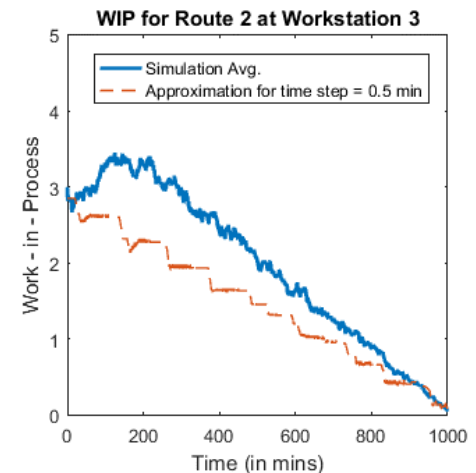
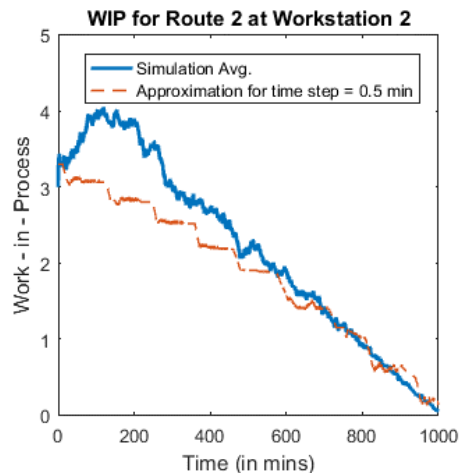
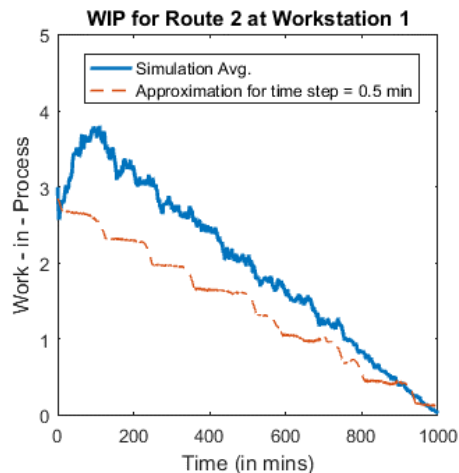
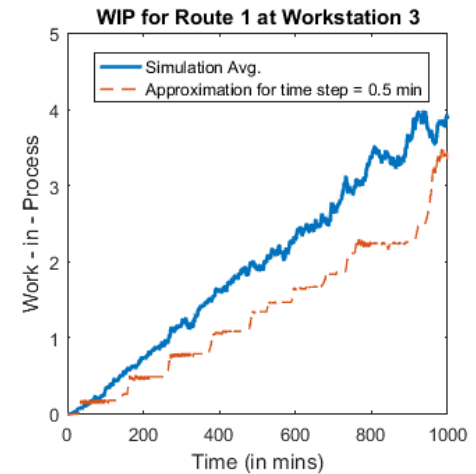
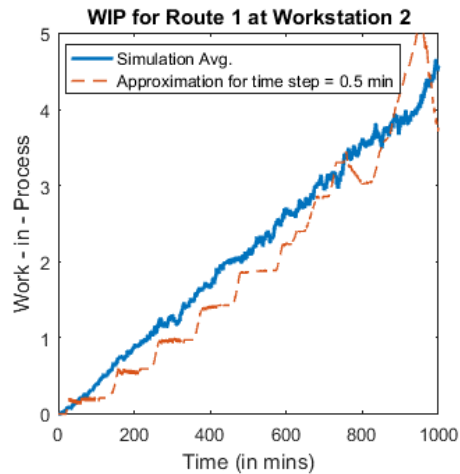
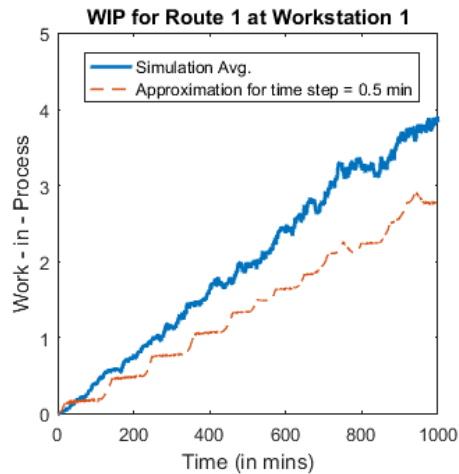
# RWBTM: Model 1b WIP



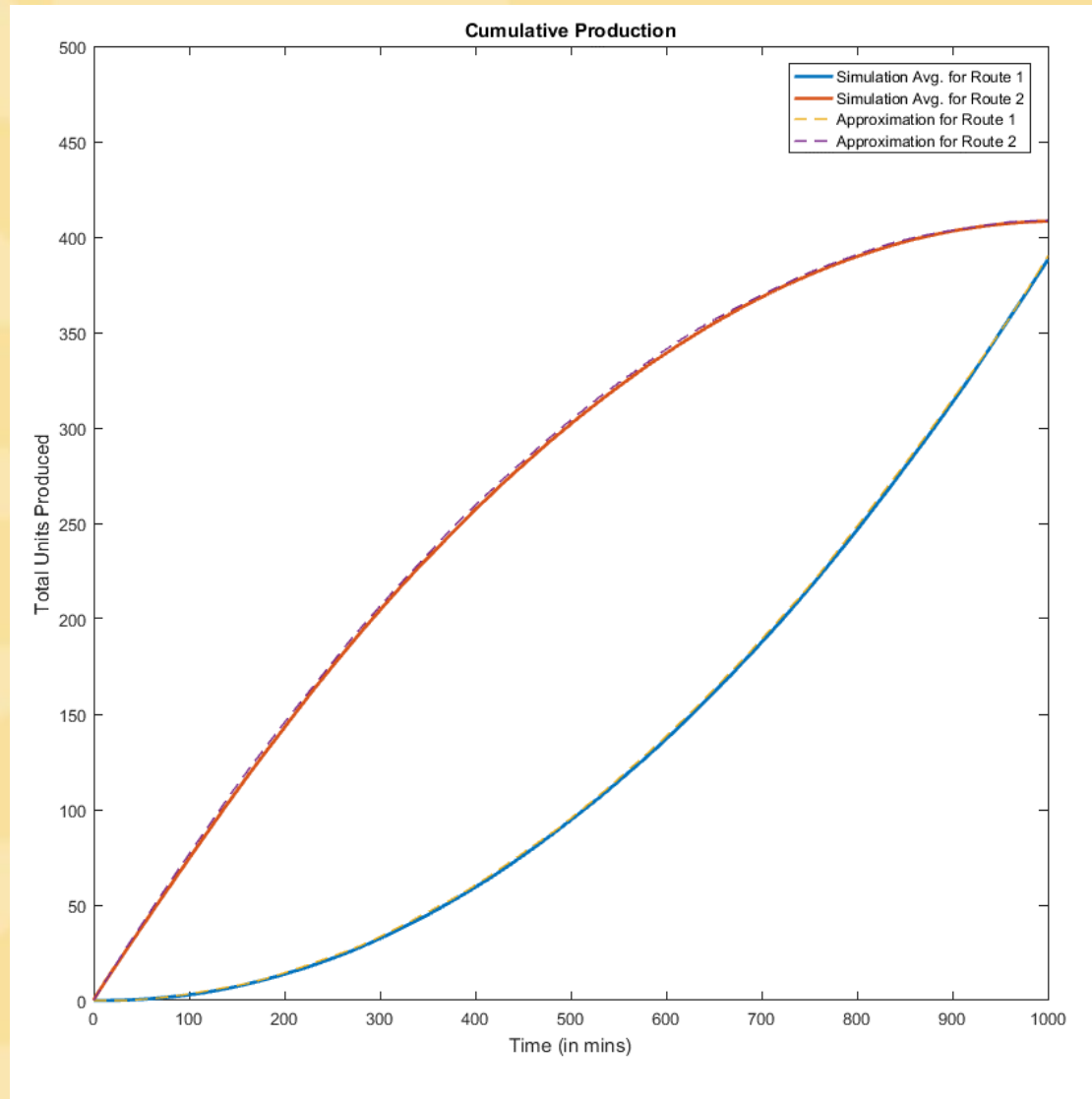
# Model 1b: Cumulative production



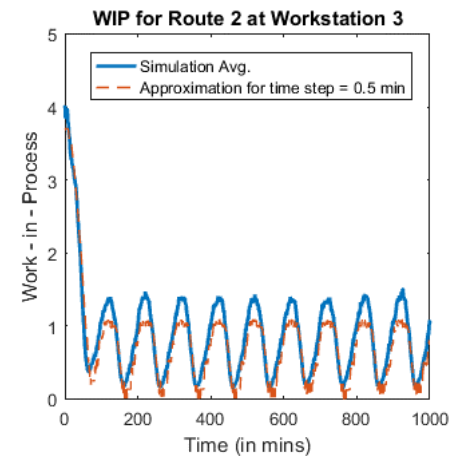
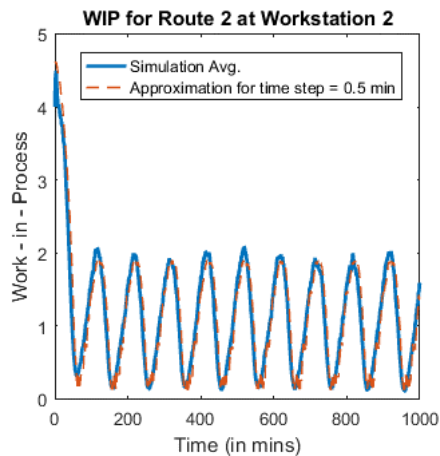
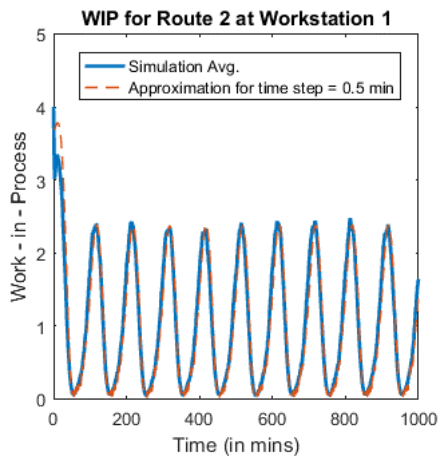
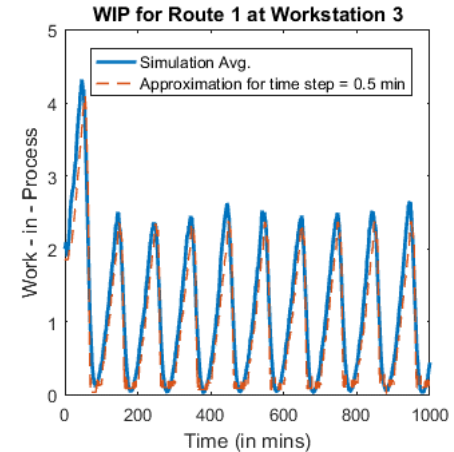
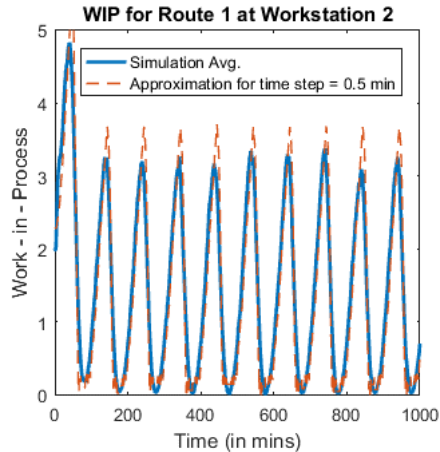
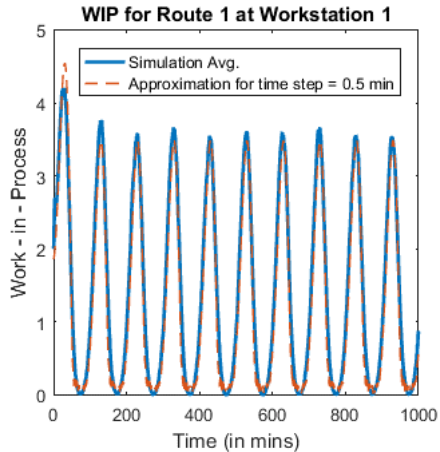
# Model 2: Work - in - Process



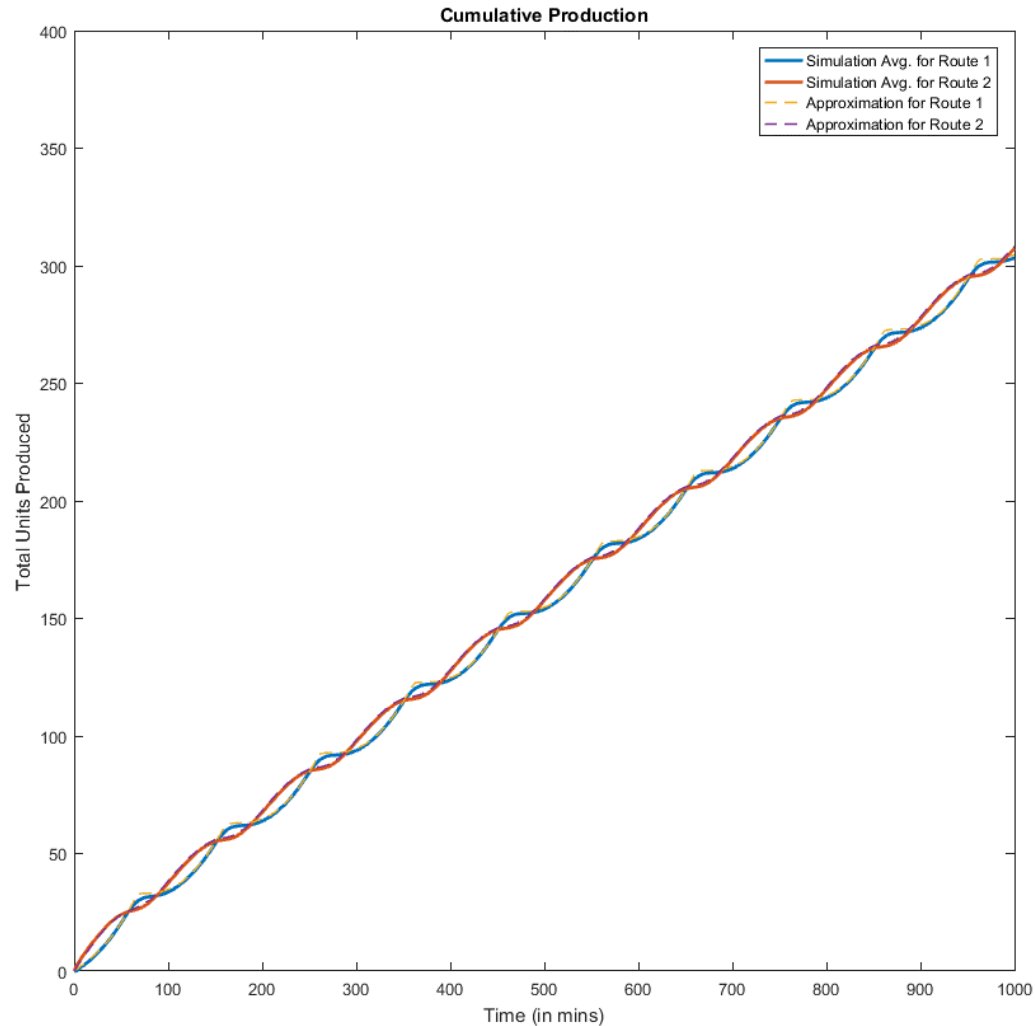
# Model 2: Cumulative production



# Model 3: Work - in - Process

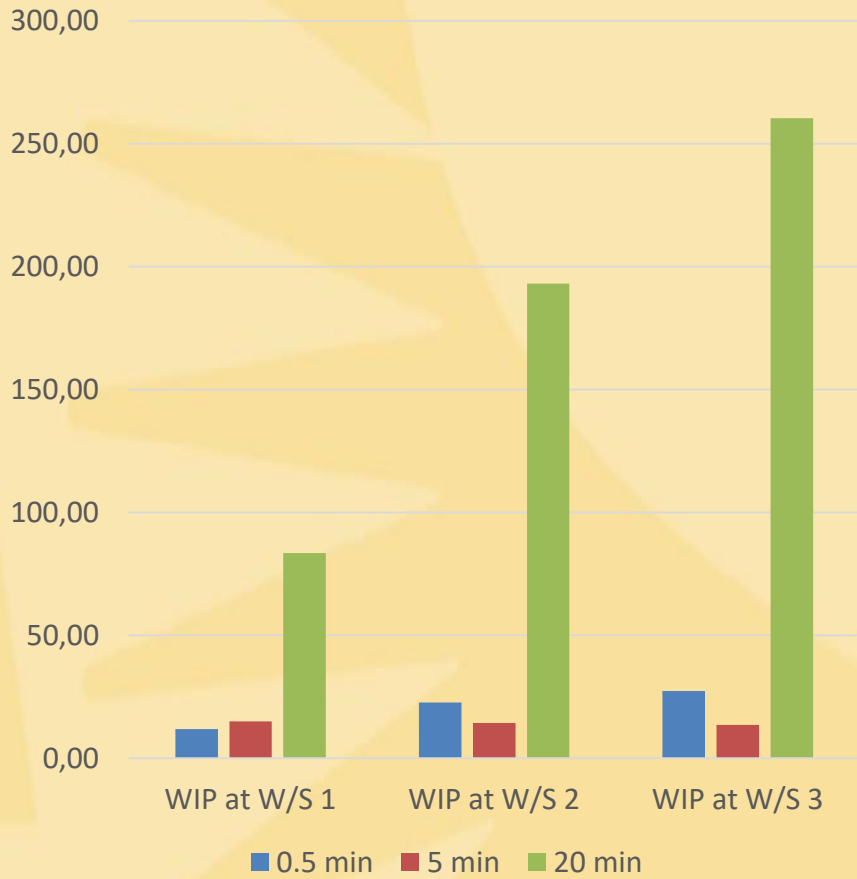


# Model 3: Cumulative production

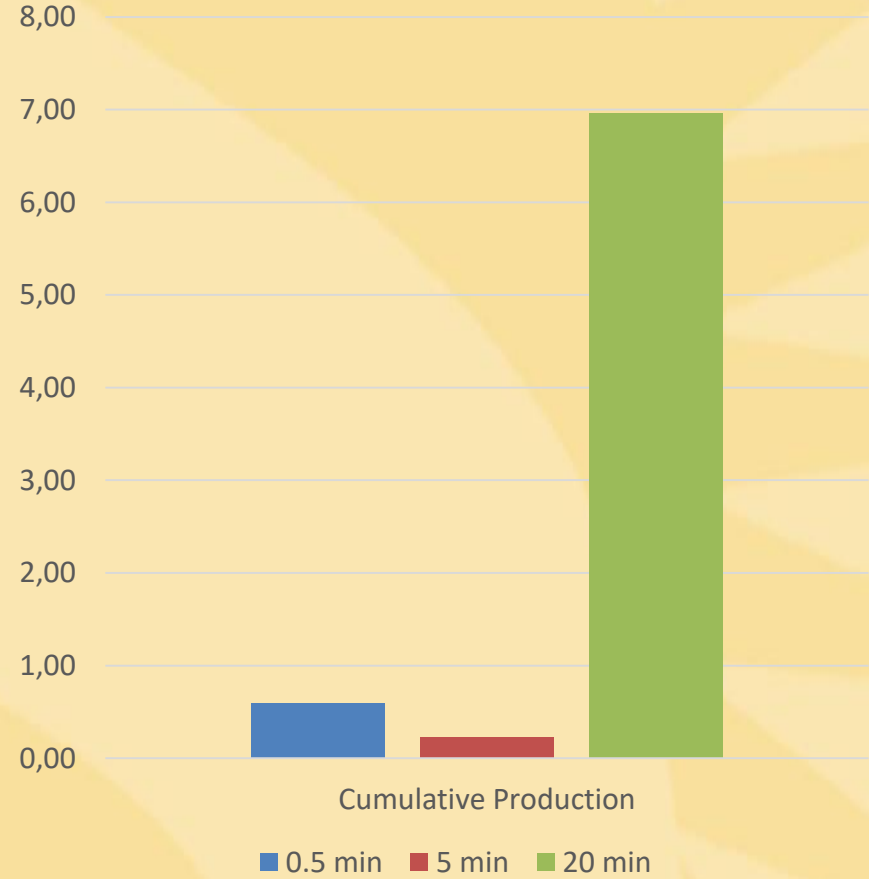


# Model 1a: Absolute Deviation

Mean % Absolute Deviation  
Approx. vs Simulation - WIP

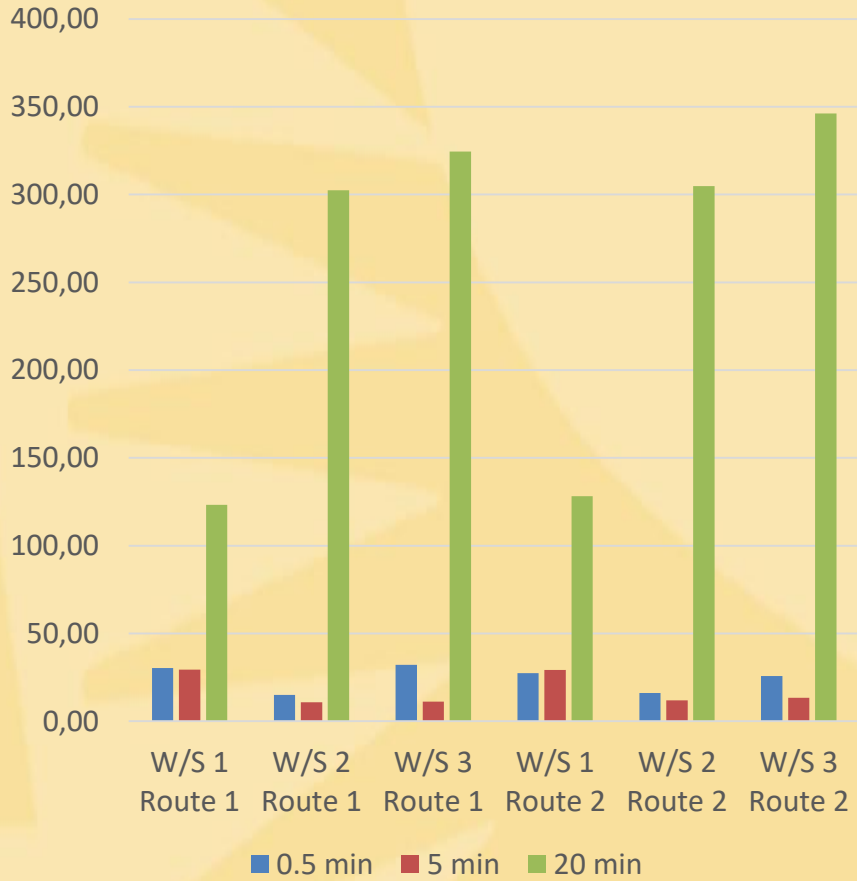


Mean % Absolute Deviation Approx.  
vs Simulation

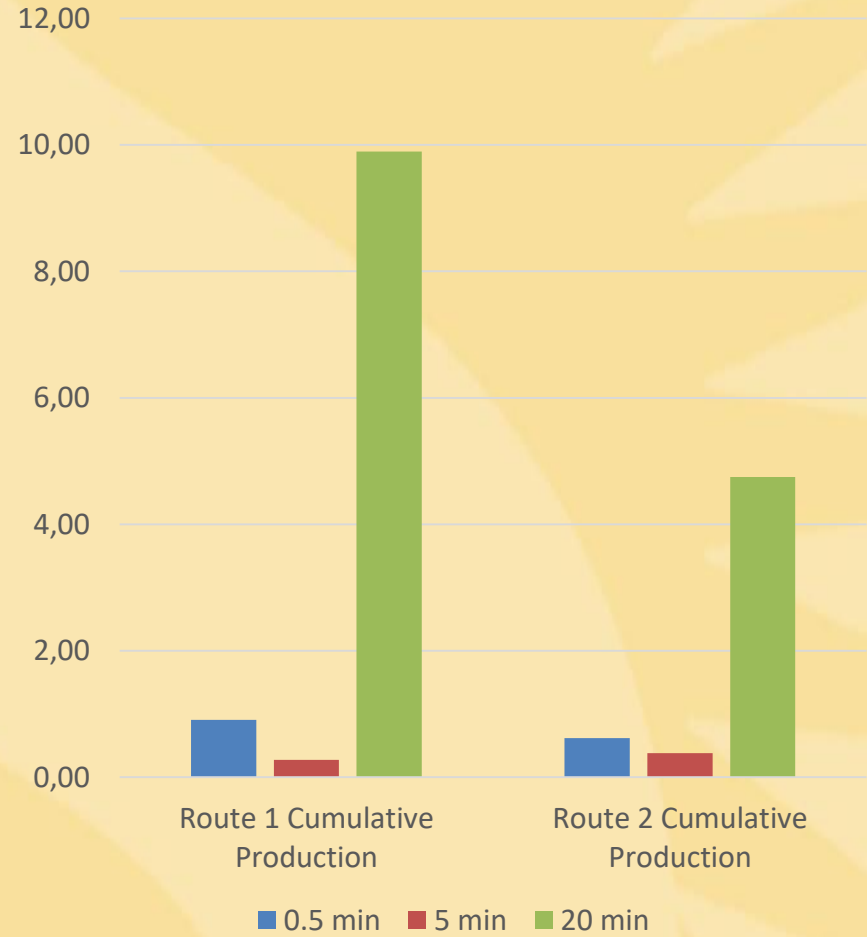


# Model 2: Absolute Deviation

Mean % Absolute Deviation Approx.  
vs Simulation - WIP



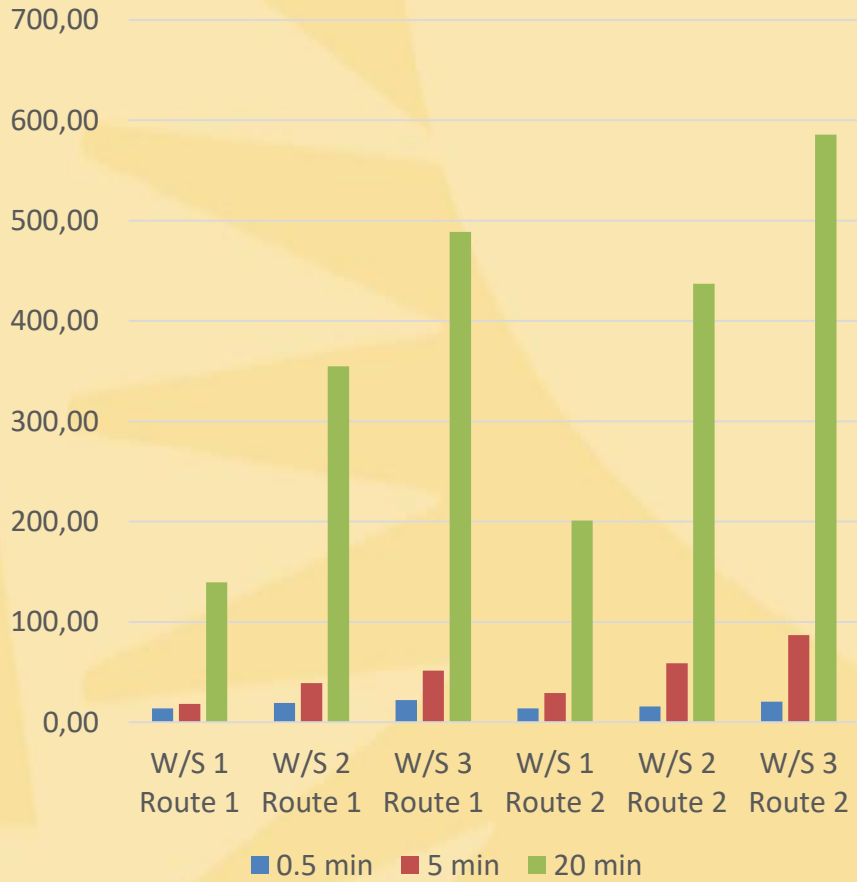
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# Model 3: Absolute Deviation

Mean % Absolute Deviation Approx.  
vs Simulation - WIP



Mean % Absolute Deviation Approx.  
vs Simulation



# Open Network Based Throughout Model(ONBTM)

$\lambda_{ij}^r(t)$ ,  $r \in \{0, \dots, R\}$ ,  $i \in \{0, \dots, L\}$ ,  $j \in \{1, \dots, L\}$ : rate of class  $r$  arrivals at station  $j$  from station  $i$  (station 0 for external arrivals).

- Step 1

Initialize  $n_{rl}$ .

- Step 2

Update throughput for class  $r$  at workstation  $l$  for each  $r = 1, \dots, R$  and  $l \in S(r) \setminus \{0\}$

$$X_{rl}(t) = \min \left[ \left( \frac{n_{rl}(t)}{\sum_{p=1}^R n_{pl}(t) + 1} \right) \mu_{rl}, \left( \frac{n_{rl}(t) + \frac{t_s \lambda_{0l}^r(t)}{2}}{t_s} \right) \right]$$

Min of (Effective allocated production resource; Available WIP)

# Open Network Based Throughout Model(ONBTM)

- Step 3

For each  $r = 1, \dots, R$  and  $l \in S(r) \setminus \{0\}$  (0 is external)

Update arrival rates of class  $r$  arriving at workstation  $l$  from workstation  $k$

$$\lambda_{kl}^r(t) = p_{kl}^r X_{rk}(t), \quad k \in S(r) \setminus \{0\}$$

- Step 4

Update WIP for each  $r = 1, \dots, R$  and  $l \in S(r) \setminus \{0\}$

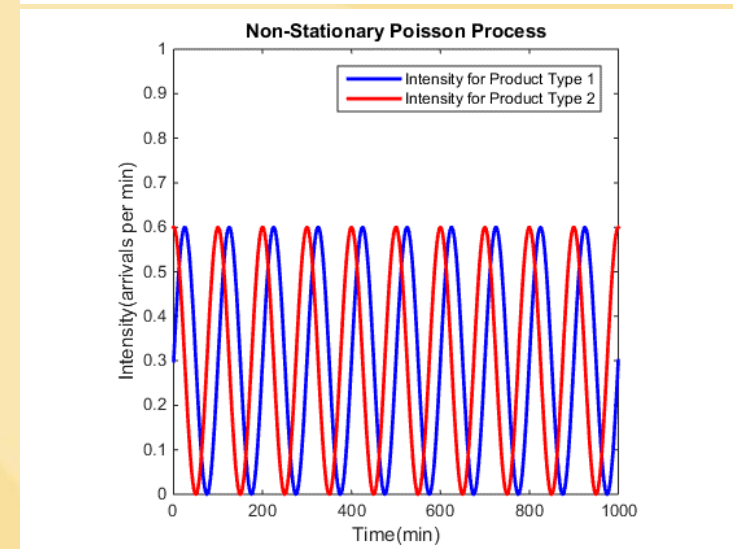
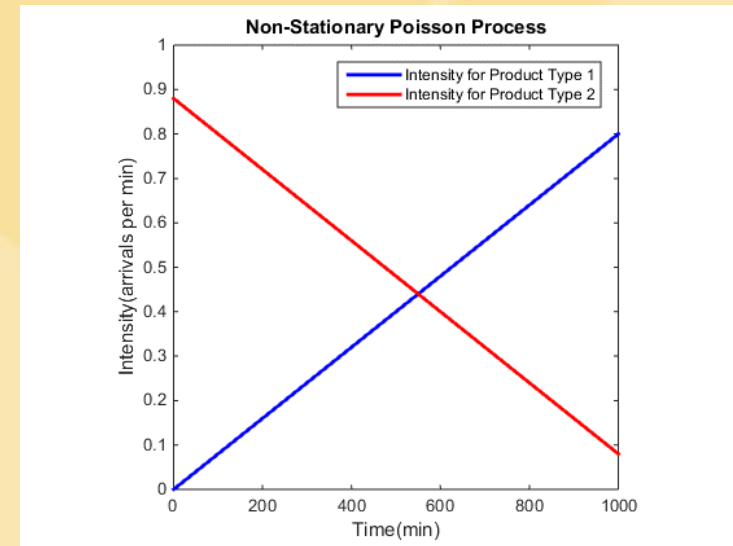
$$n_{rl}(t + t_s) = \max \left[ n_{rl}(t) + t_s \left( \sum_{j=0}^L \lambda_{jl}^r(t) - \sum_{j=0}^L \lambda_{lj}^r(t) \right), 0 \right]$$

- Step 5

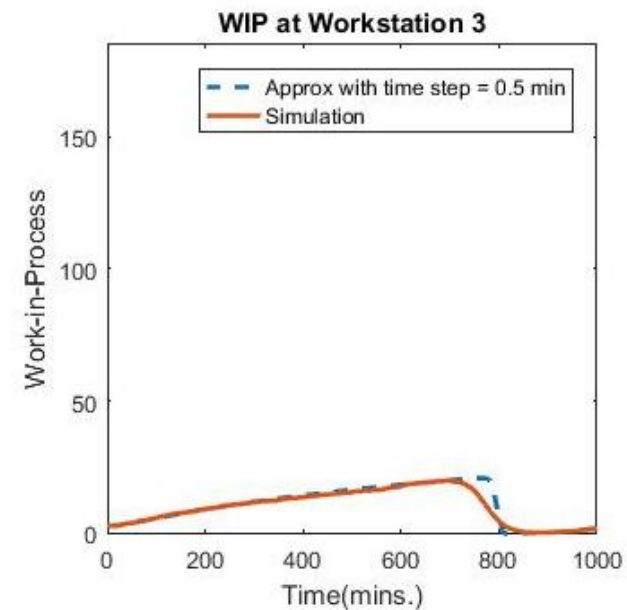
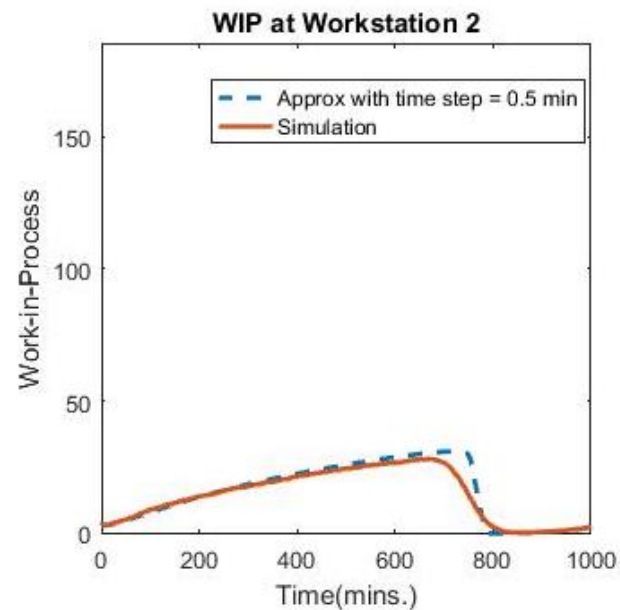
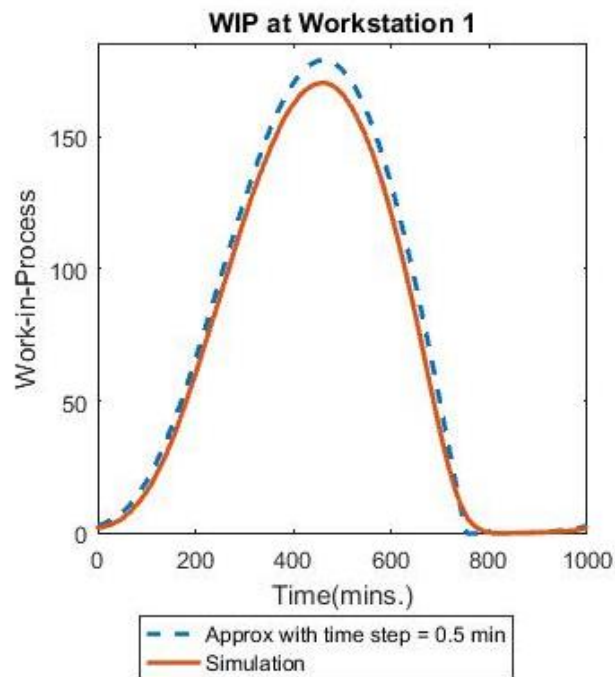
Set  $t = t + t_s$ . If  $t < T$  GO TO 2. Else STOP.

# Experiments

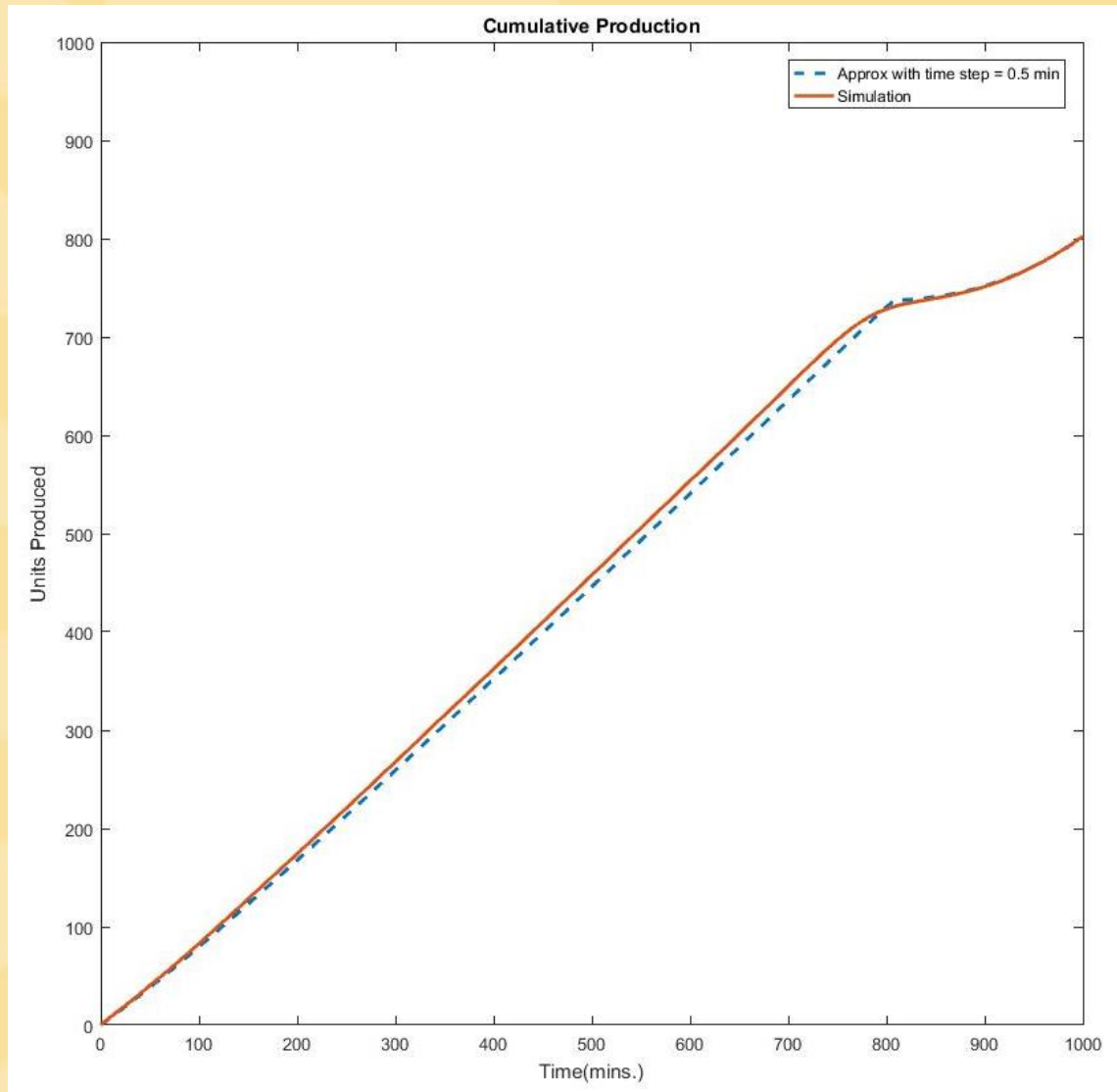
- Models
  - 1a.
    - Type: Three workstation serial line
    - Arrival Process: Non – homogenous Sinusoidal Poisson Process with  $2\pi = 1000$  min .
  - 1b.
    - Type: Three workstation serial line
    - Arrival Process: Non – homogenous Sinusoidal Poisson Process with  $2\pi = 100$  min .
  - 2.
    - Type: Two class three workstation flow shop
    - Arrival Processes: Complementary non-homogenous linear Poisson process
  - 3.
    - Type: Two class three workstation flow shop
    - Arrival Processes: Complementary non-Homogenous sinusoidal Poisson process.



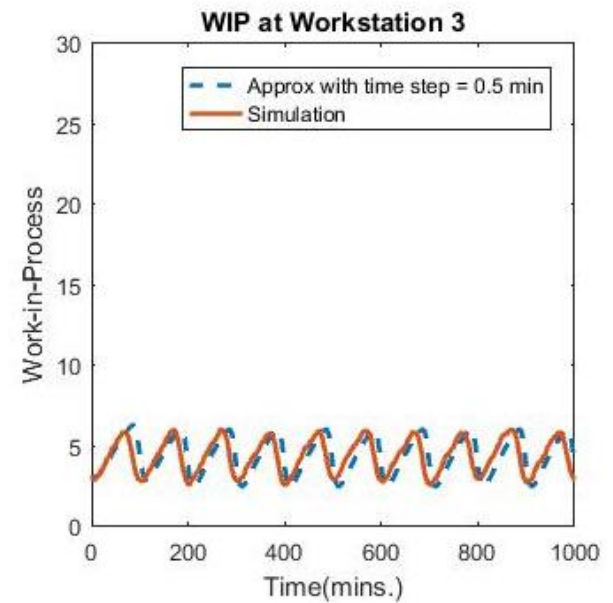
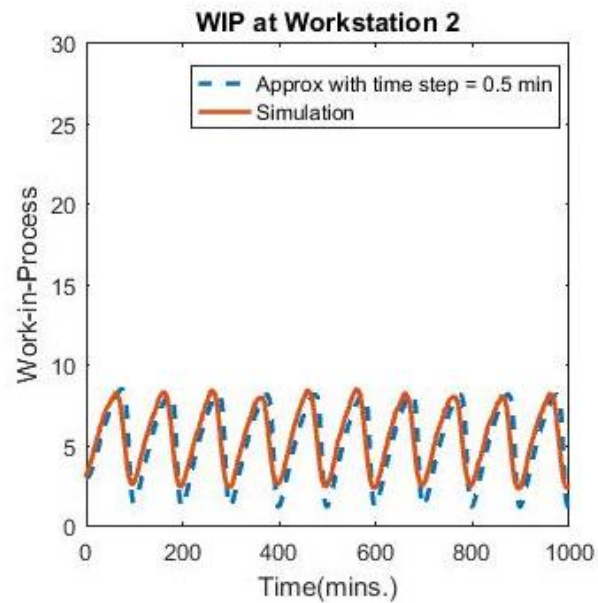
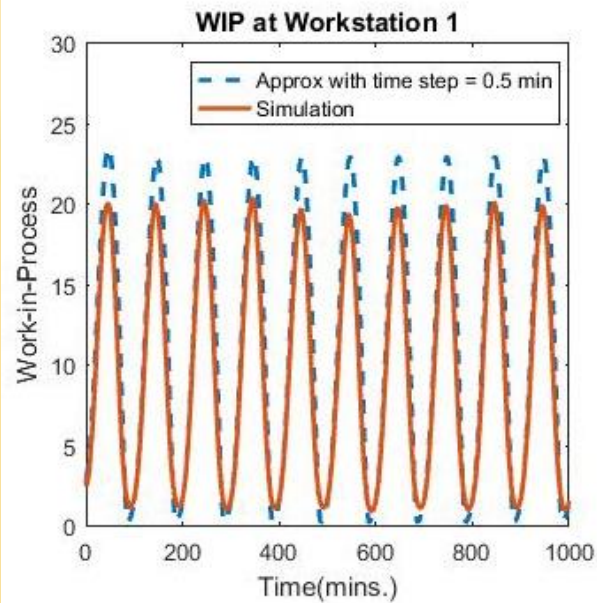
# ONBTM Results: Model 1a Work - in - Process



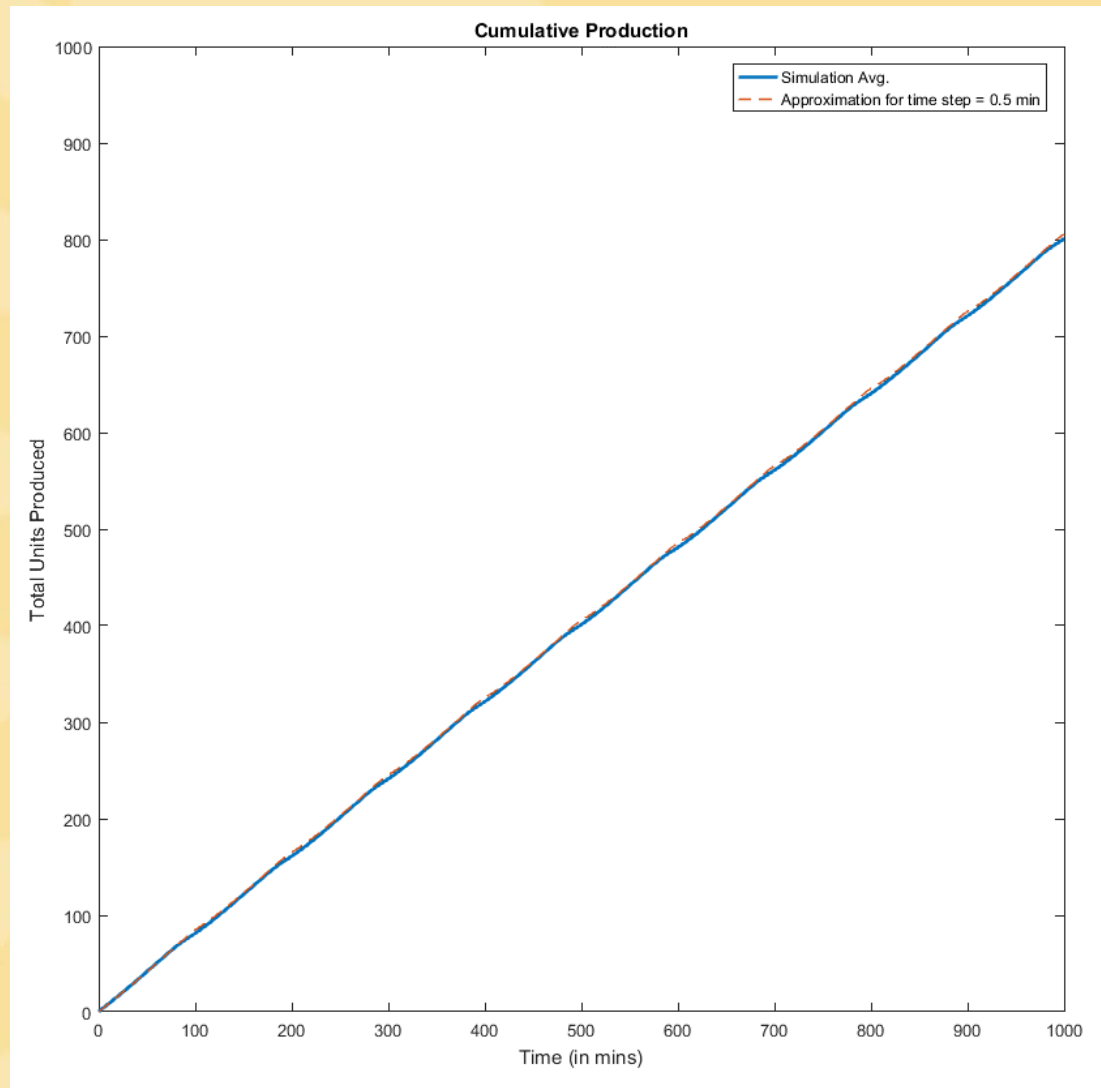
# Model 1a: Cumulative production



# Model 1b : Work - in - Process

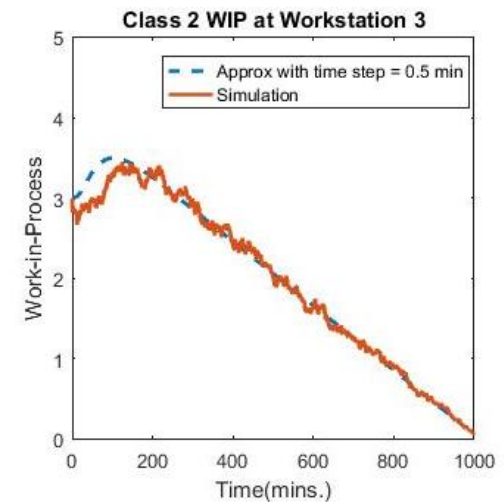
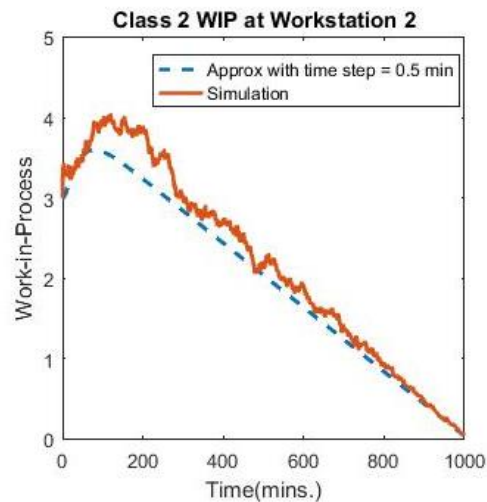
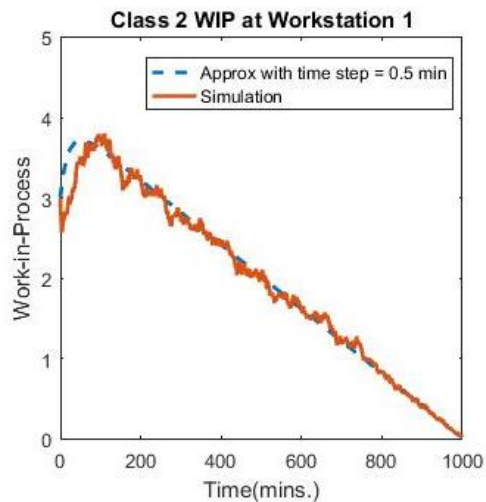
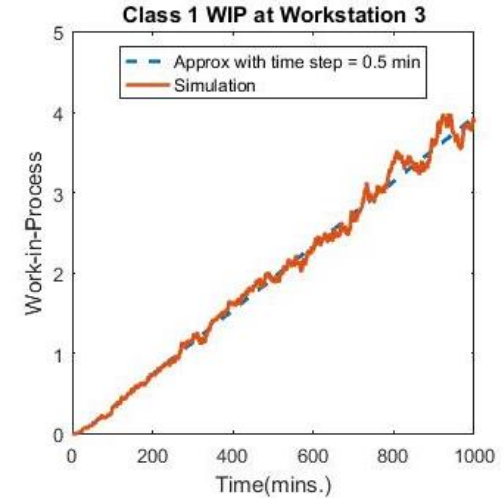
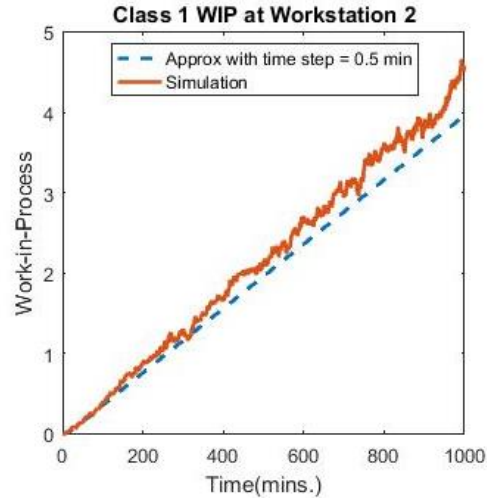
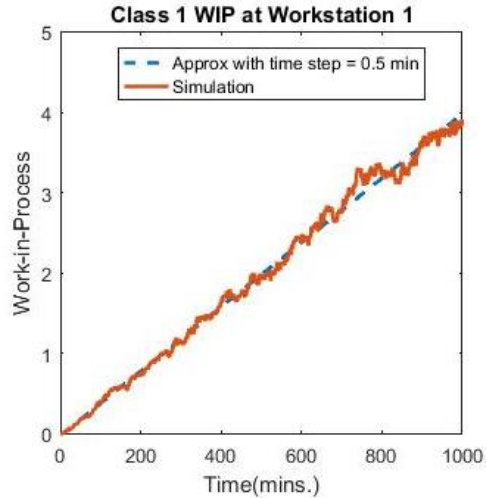


# Model 1b: Cumulative production

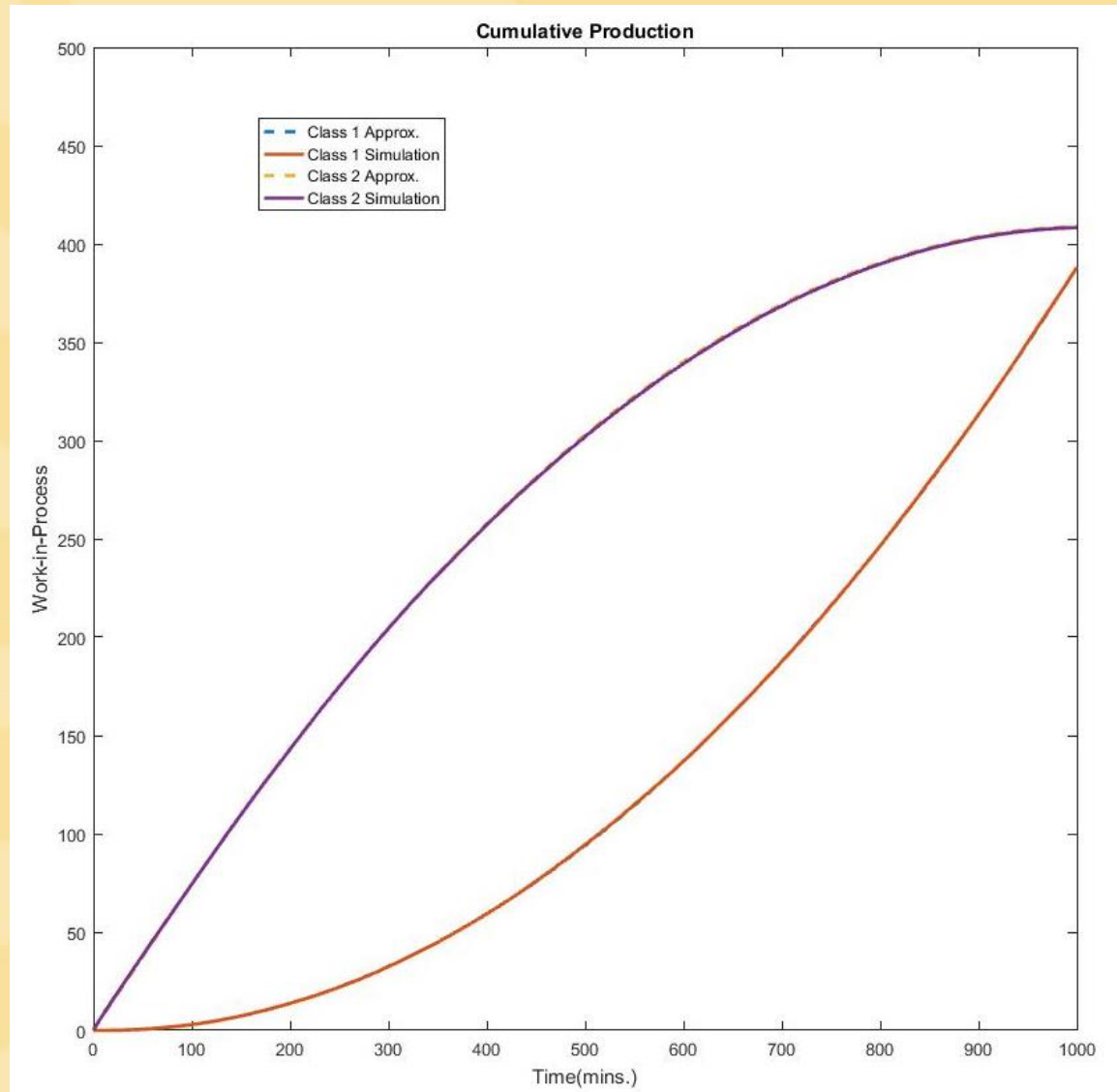




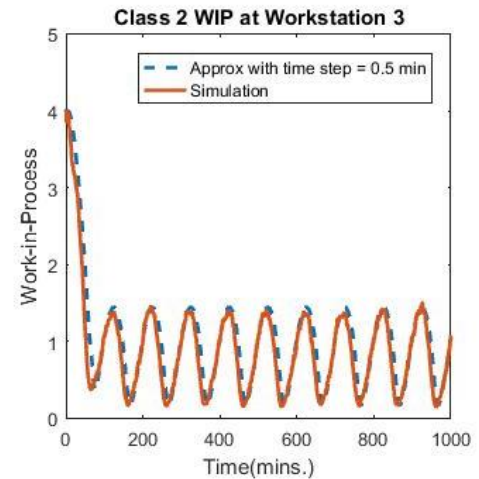
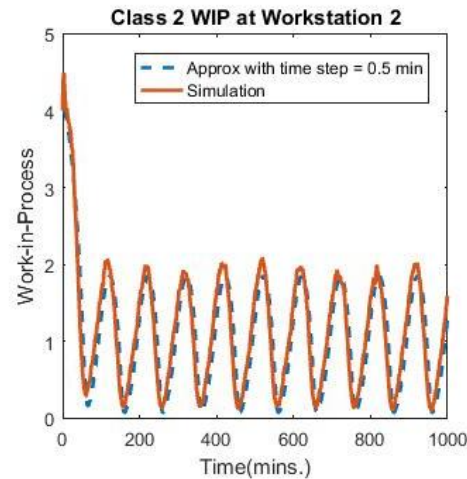
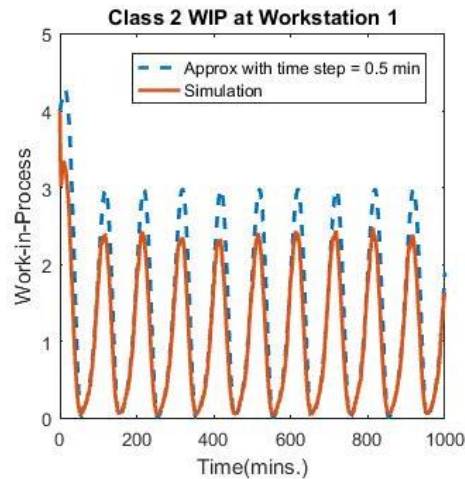
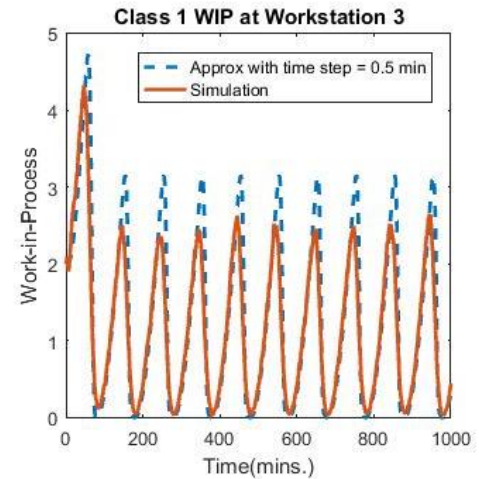
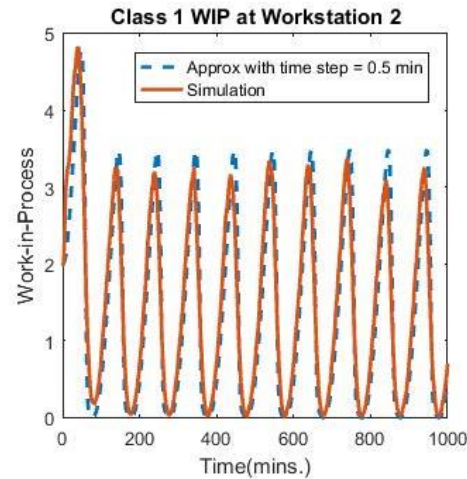
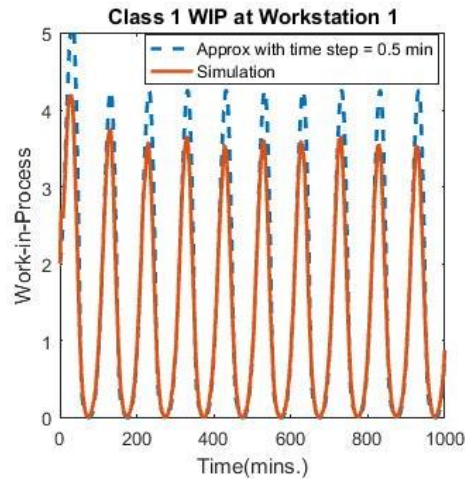
# Model 2: Work - in - Process



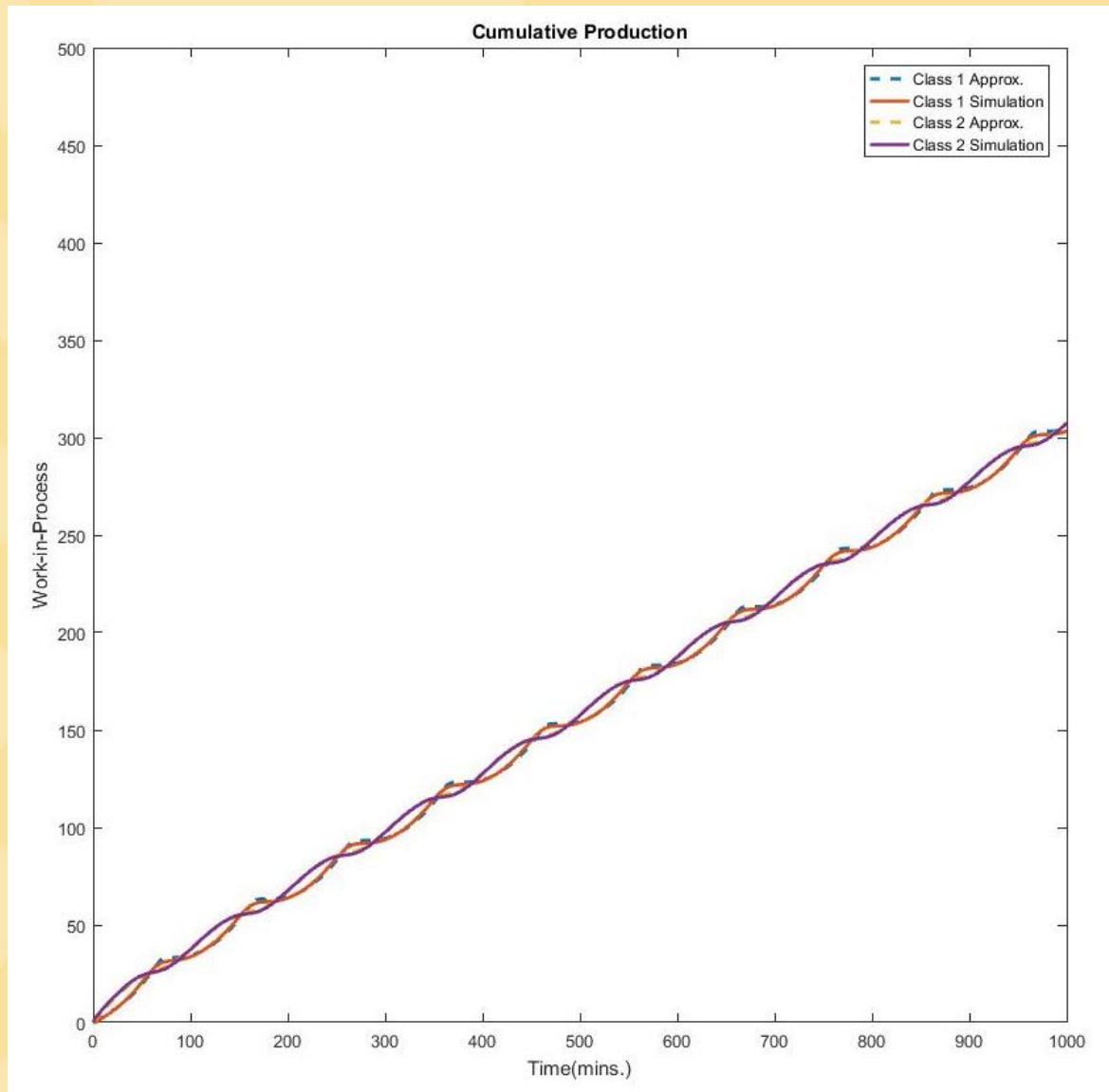
# Model 2: Cumulative production



# Model 3: Work - in - Process



# Model 3: Cumulative production



# Experiment: “Large” Jobshop Instance

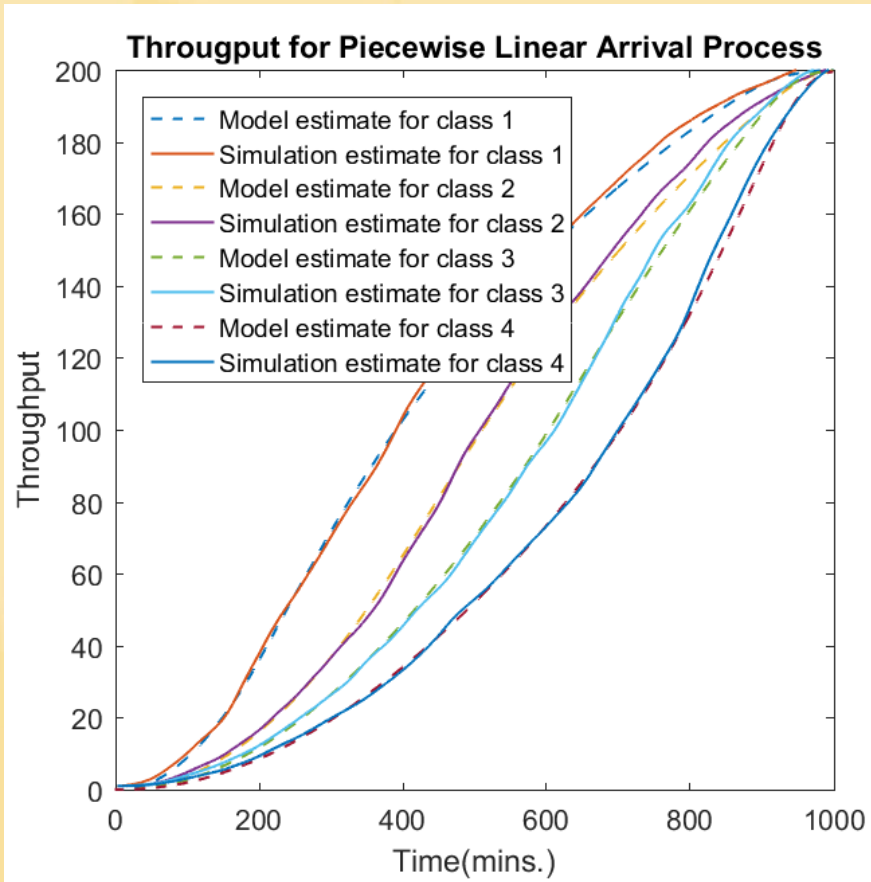
- Jobshop instance with four classes (1,..,4) and sixteen workstations (1,..16) (bottleneck: workstation 4)

Product	Routing
1	4 → 12 → 2 → 5 → 13 → 8
2	2 → 3 → 1 → 4 → 6 → 7 → 5 → 9 → 10 → 11 → 12 → 13 → 14 → 15 → 16
3	1 → 8 → 10 → 9 → 11 → 13 → 14 → 4 → 16
4	4 → 5 → 3 → 8 → 10 → 6 → 9 → 12 → 1 → 15 → 16

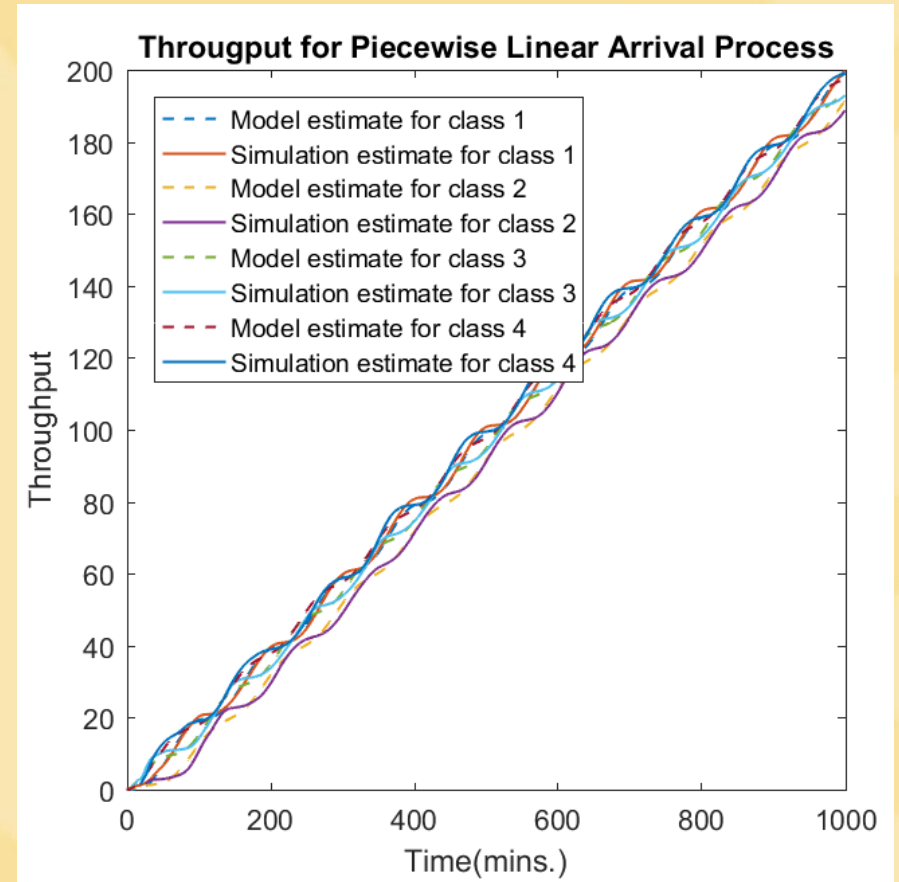
Table 1: Jobshop Routing

- Basic Model and ONBTM estimates compared against thousand simulation replications
- Two non-homogenous arrival patterns were investigated
  - Peak shifted triangular pattern with peak offset = 200 mins. (Pattern 2)
  - Phase shifted sinusoidal with  $2\pi = 100 \text{ mins.}$  (Pattern 1)

# Basic Model: Cumulative Production



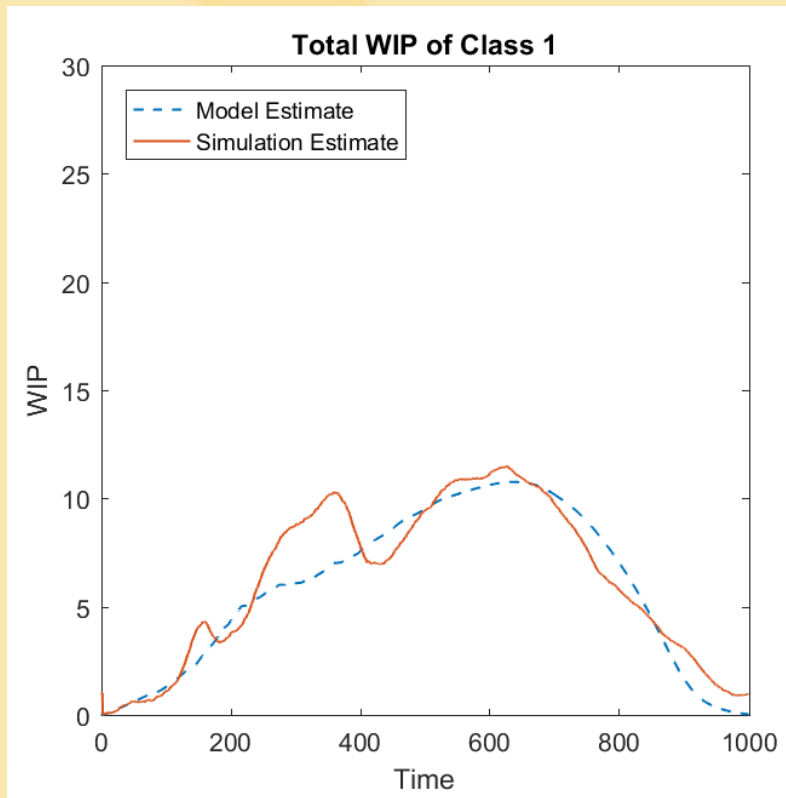
Pattern 1



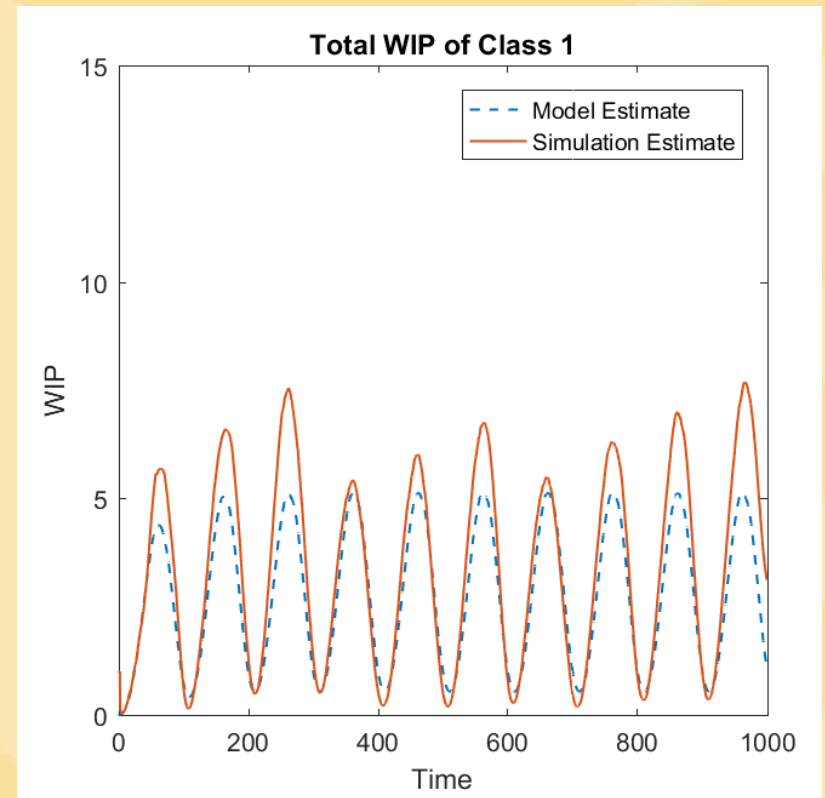
Pattern 2



# Basic Model: Class 1 WIP

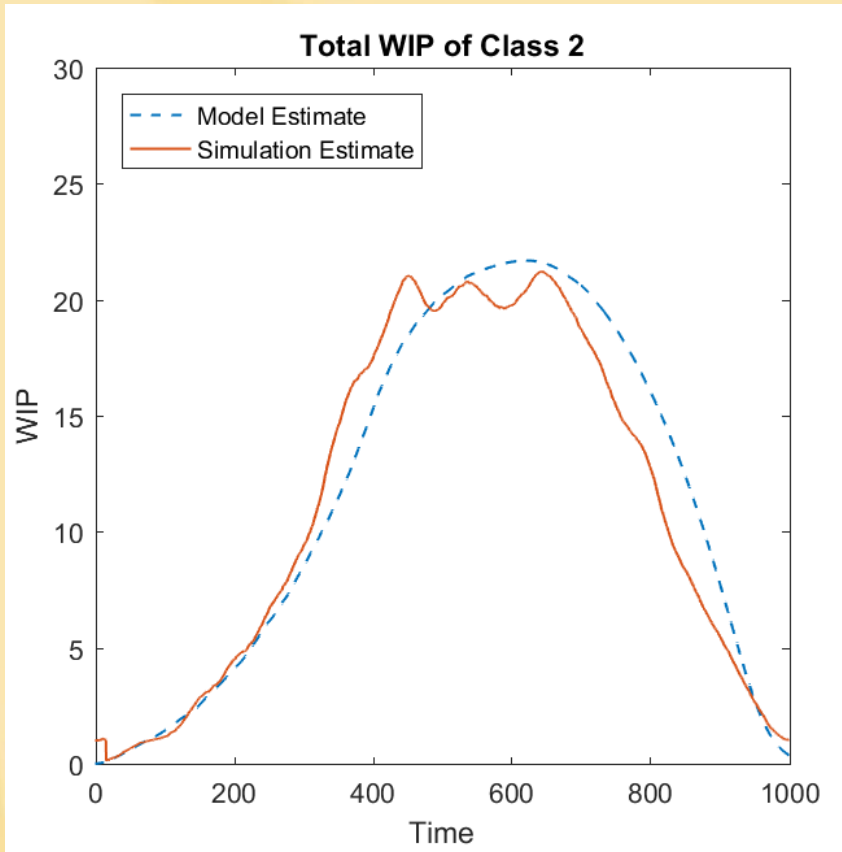


Pattern 1

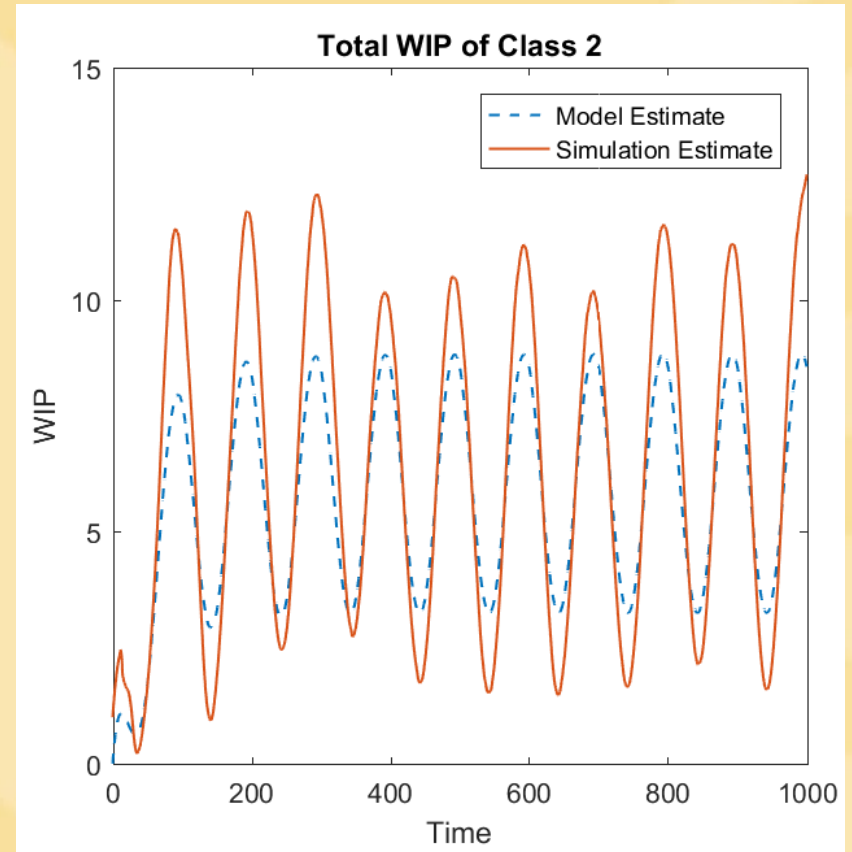


Pattern 2

# Basic Model: Class 2 WIP



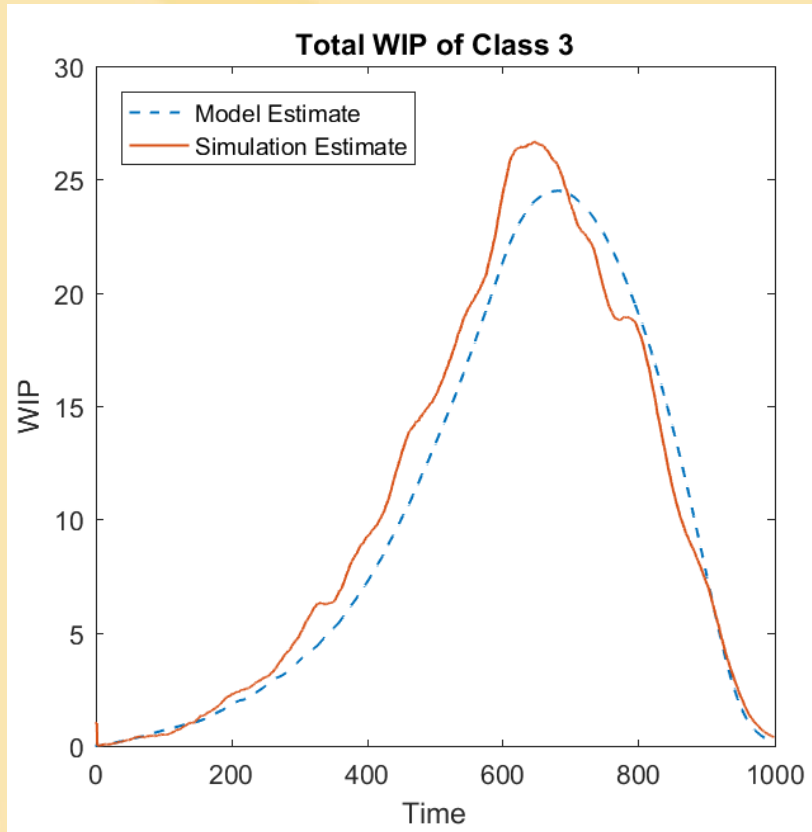
Pattern 1



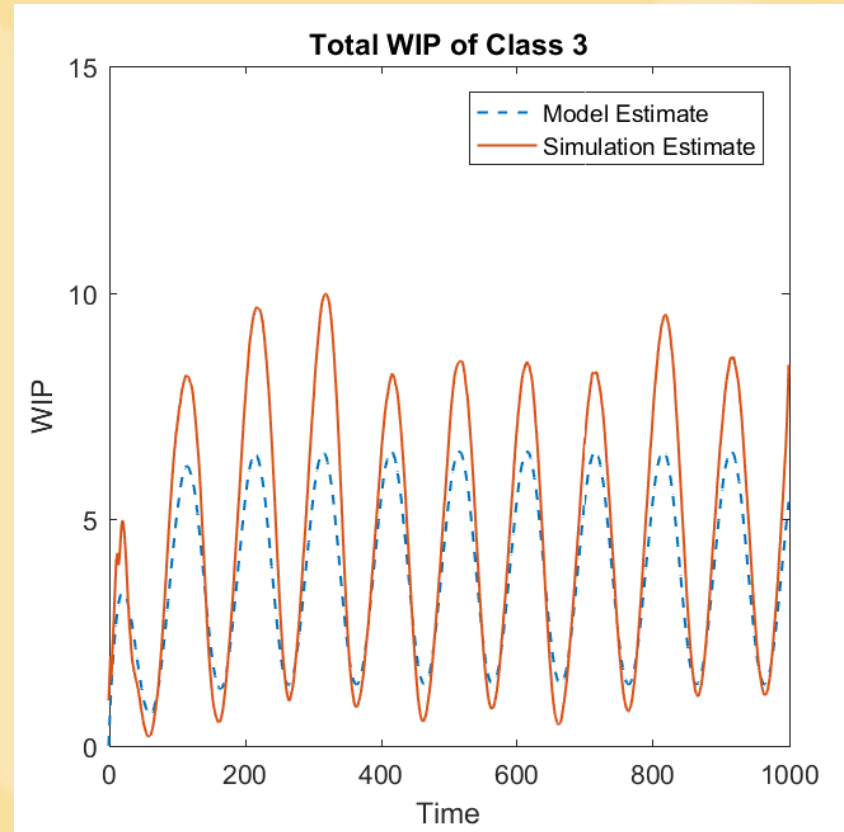
Pattern 2



# Basic Model: Class 3 WIP

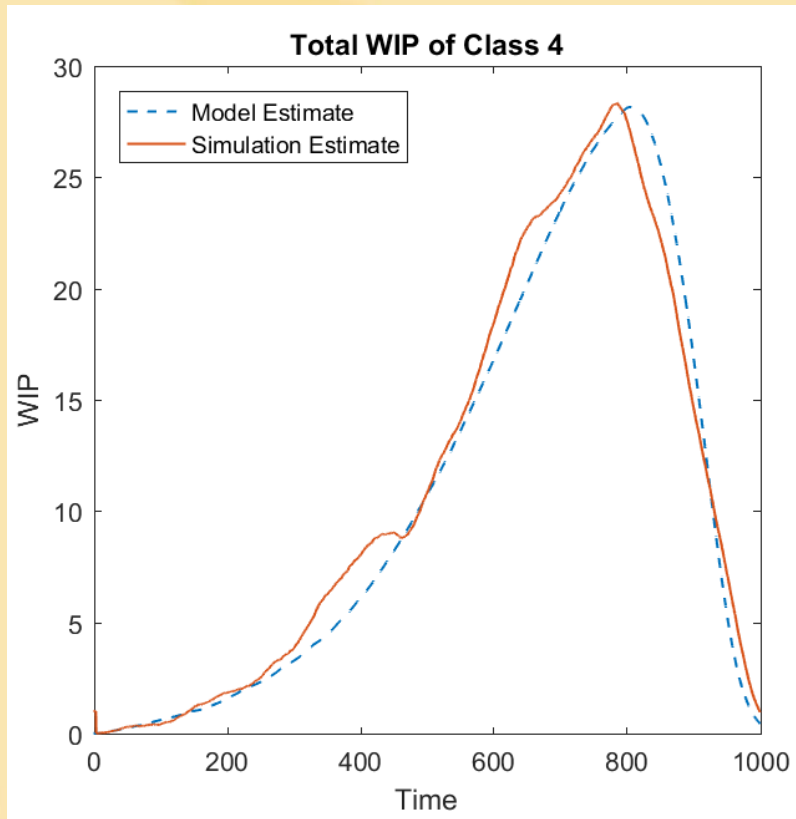


Pattern 1

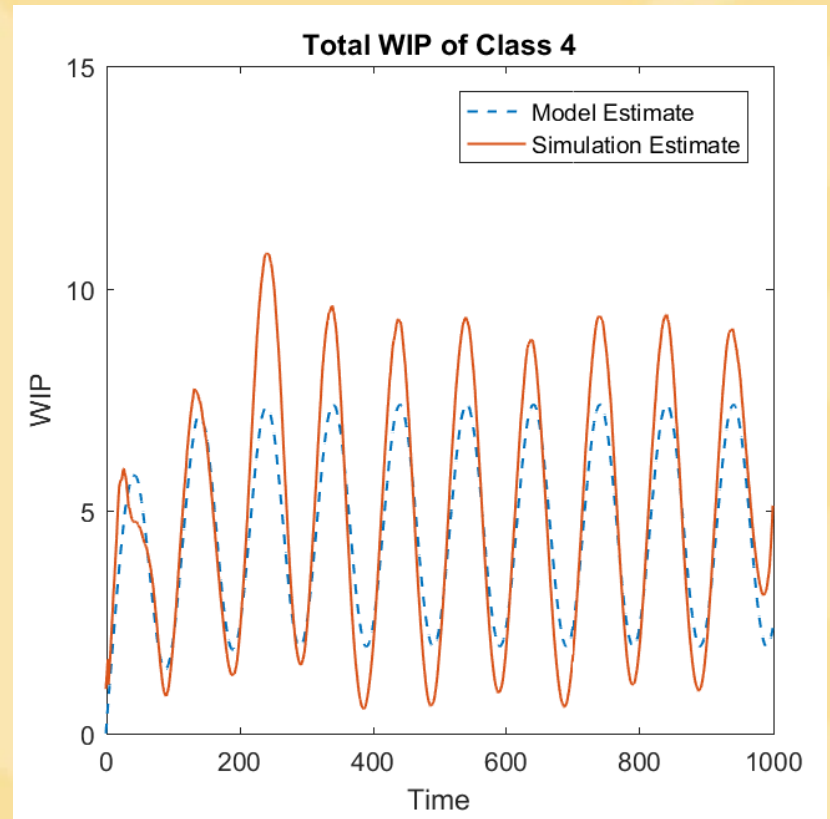


Pattern 2

# Basic Model: Class 4 WIP

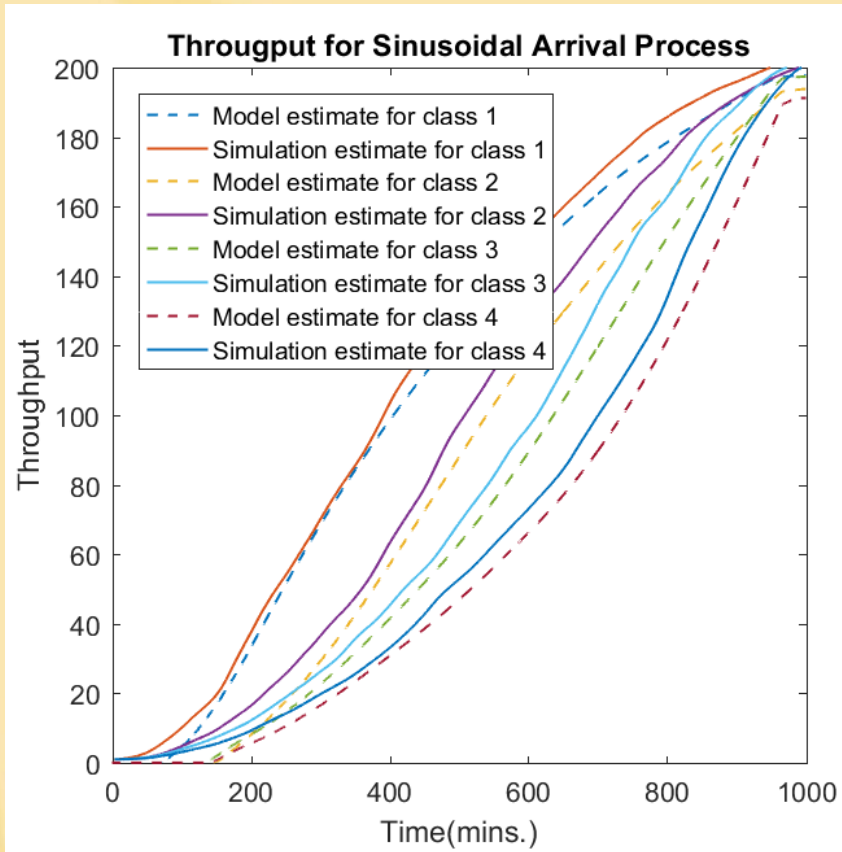


Pattern 1

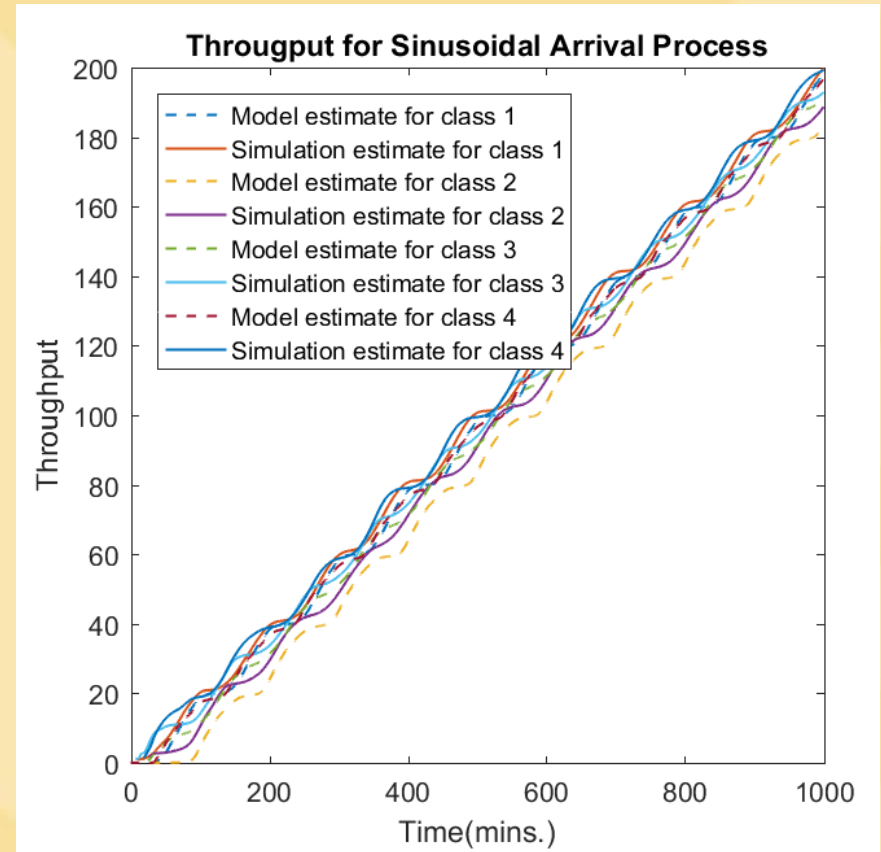


Pattern 2

# ONBTM: Cumulative Production

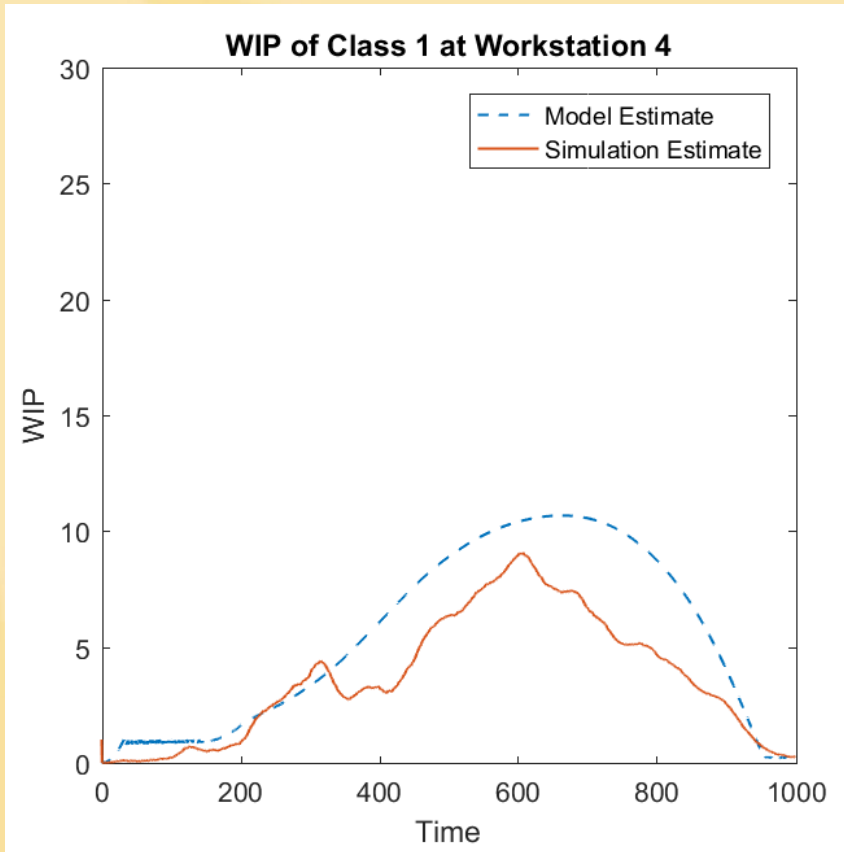


Pattern 1

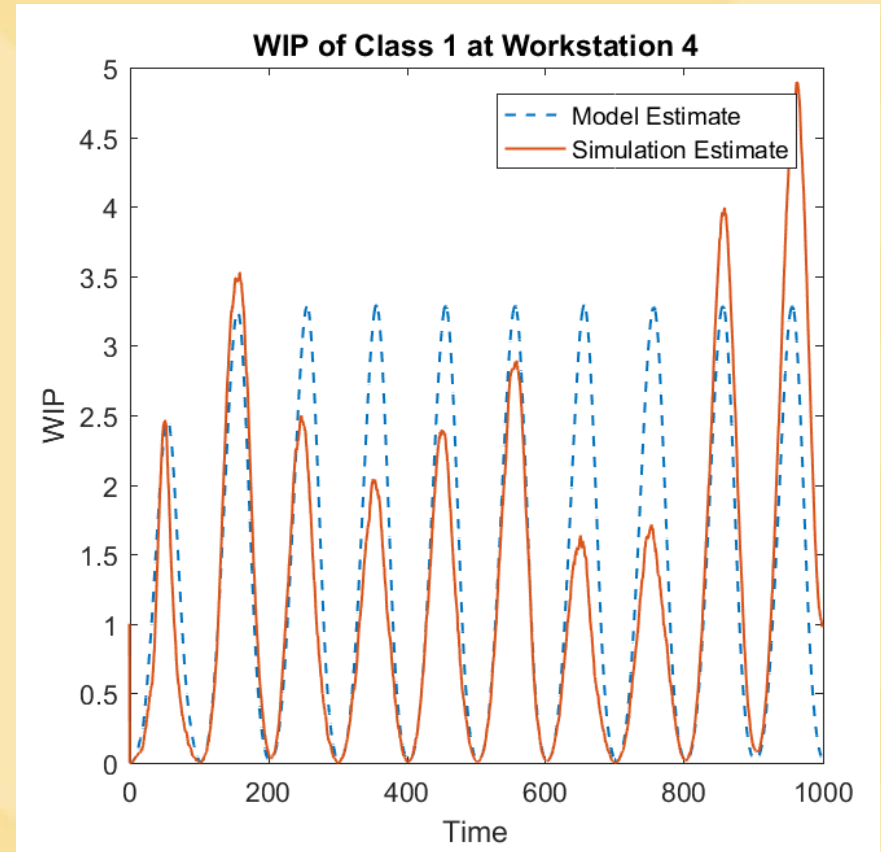


Pattern 2

# ONBTM: Class 1 WIP at Workstation 4

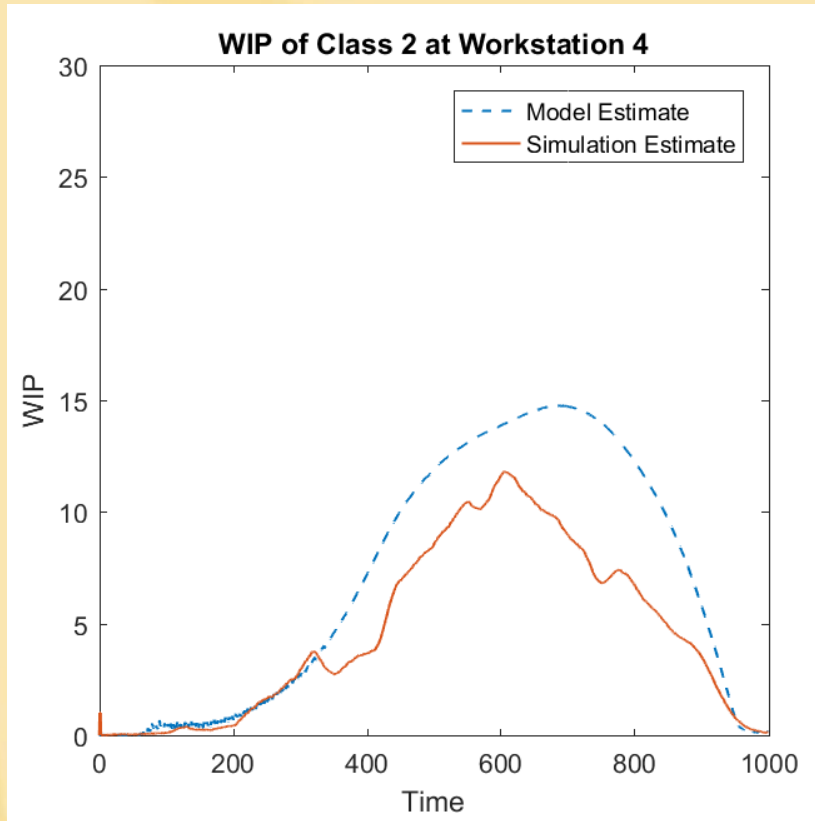


Pattern 1

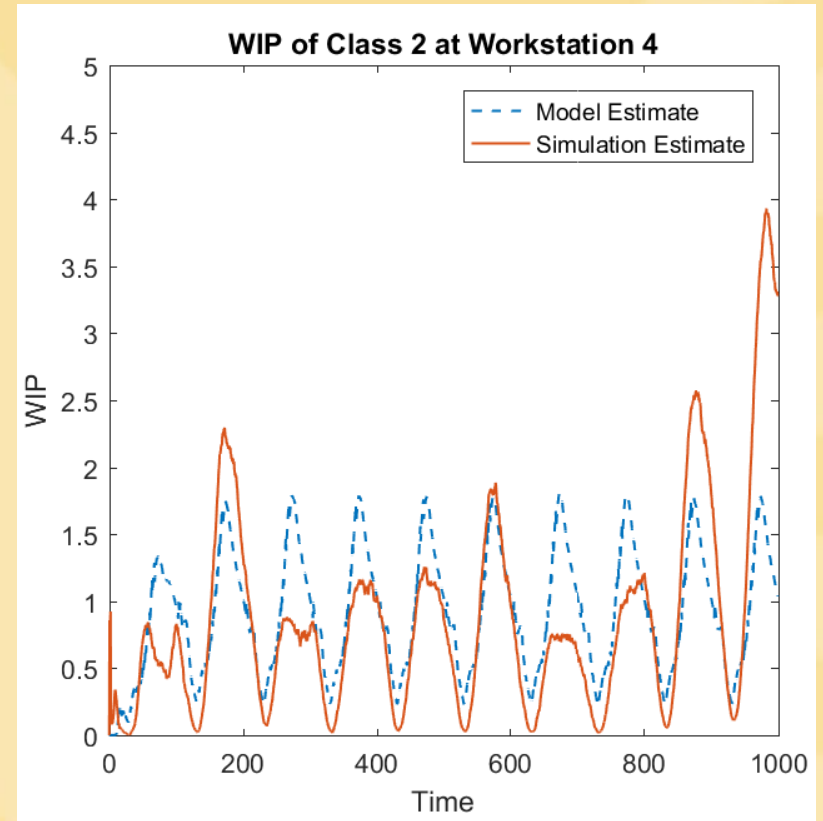


Pattern 2

# ONBTM: Class 2 WIP at Workstation 4

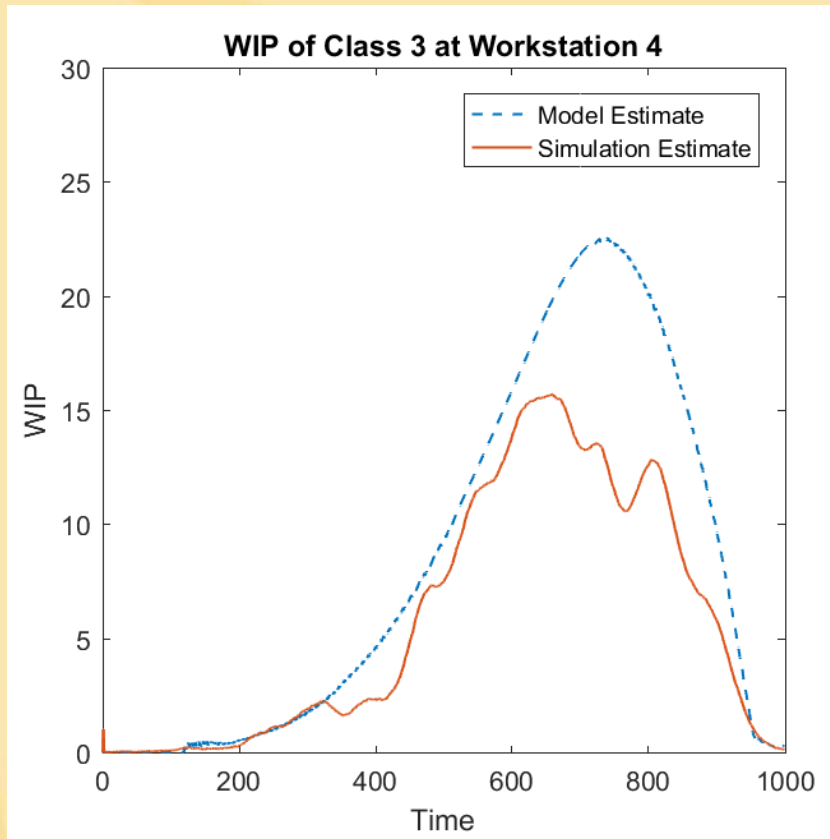


Pattern 1

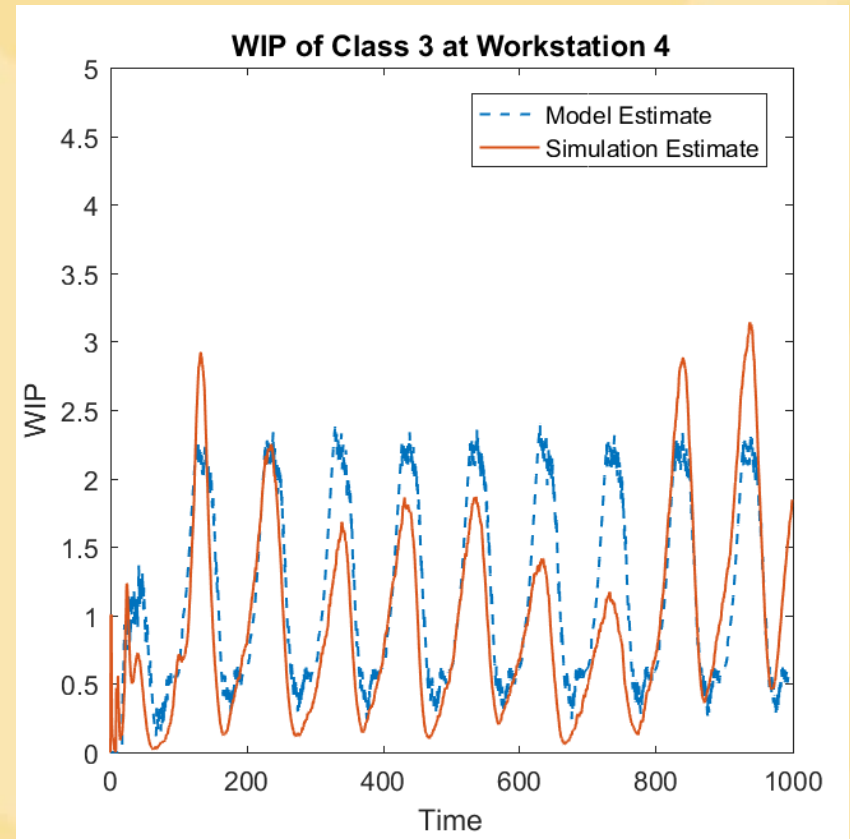


Pattern 2

# ONBTM: Class 3 WIP at Workstation 4

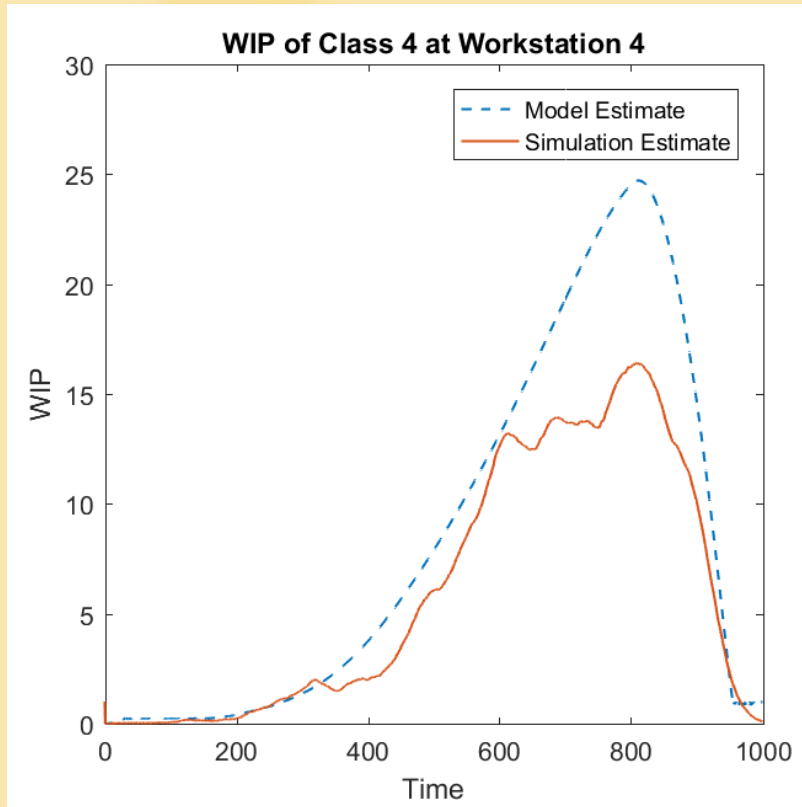


Pattern 1

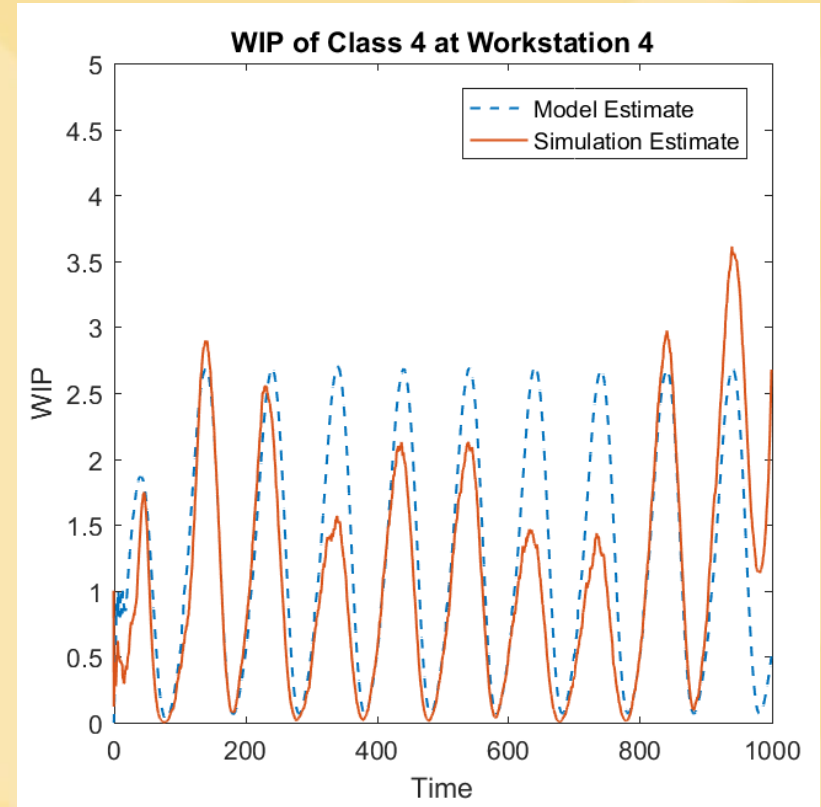


Pattern 2

# ONBTM: Class 4 WIP at Workstation 4



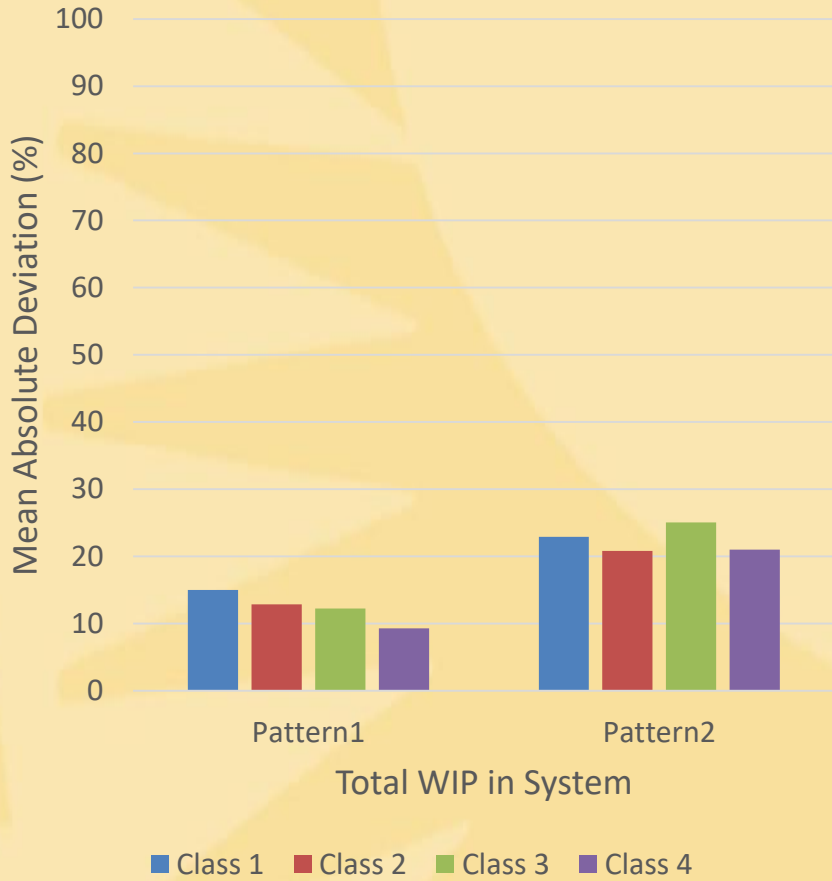
Pattern 1



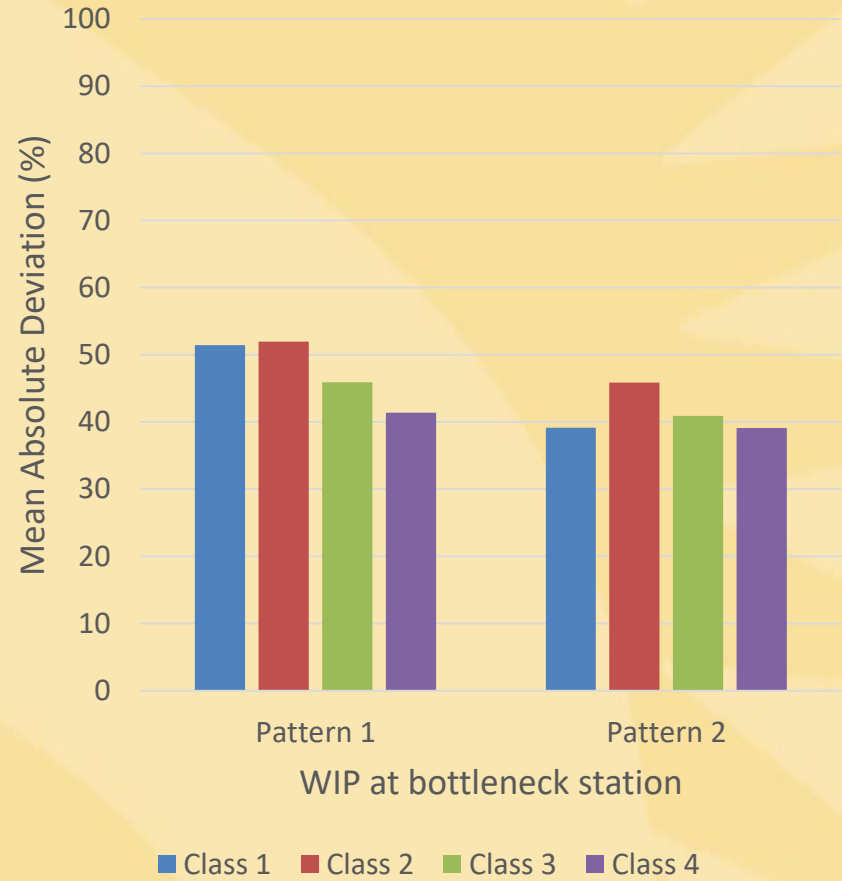
Pattern 2

# Large JobShop: Absolute Deviation

## Basic Model : Mean % Absolute Deviation



## ONBTM: Mean % Absolute Deviation





# Extensions

- This work will be extended to study:
  - other non-stationary demand patterns.
  - part priorities
  - product mix changes.
  - buffer sizing for workstations.
  - effect of different scheduling disciplines.
  - capacity/workstation availability conditions.
  - More memory efficient (single stage) WS level closed approximations.

# Conclusions

- All hope is not lost, we can tractably do rough cut estimation
- More work is needed

**Thanks for Listening**

**Questions?**