

# Modeling Supervisory Control in the Air Defense Warfare Domain with Queueing Theory, Part II<sup>1</sup>

Joseph DiVita, PH D, Robert Morris, Glenn Osga, Ph D  
San Diego Systems Center, Space and Naval Warfare



<sup>1</sup>This work was sponsored by the Office of Naval Research, Cognitive, Neural and Social Science Division. research Area: Decision Support Systems and Models for Intelligent Mission Management.

CCRTS June 2006, San Diego CA

# Decision Support Systems and Models for Intelligent Mission Management

## Background

- Multi-mission, multi-tasking, optimally manned CICs will require greater reliance on automation.
- Operators will require resource management tools and planning aids to meet mission requirements - these *must* reduce workload in the planning and execution process



## GOALS

1. **Model** individual operator and team performance.
2. **Simulate** and quantify the effects of increasing and decreasing team size providing a model of manning and automation requirements.
3. **Test** the nature of task allocation and dynamic task reallocation schemes among team members and autonomous agents.
4. Develop methods to dynamically predict team performance.
5. Develop displays to depict actual team performance dynamically to team leaders and methods to recommend changes towards optimization.
6. Discover behavioral results of team performance awareness with regard to team self-monitoring and correction.

# Purpose of Modeling



- Predict impact of design on human performance - before system is built.
- Compare alternative designs.
- Compare alternative job structures, positions, team definitions.
- Predict and compare performance results for design reference missions.
- Reduce design risk.
- Identify design changes and corrections before costly mistakes made.

# Modeling Approaches

## 1. GOMSL Modeling (Micro):

- Explicitly represents the strategies an individual operator and teams of operators may use to perform tasks.
- Quantifies operator performance based on these strategies.

## 2. Queueing Modeling (Macro):

- Quantifies large-scale aspects of system performance: **workload, input, output and work throughput**
- Represents dynamic **flow of tasks** among a team of operators.
- These statistics represent **emergent characteristics** of a system that are not directly modeled by GOMSL.

# Queueing Theory and Supervisory Control

- **Multimodal Watchstation (MMWS)**
- **Land Attack Weapons Systems (LAWCS)**

The increased automation of combat weapon systems is changing the role of the **human operator** from that of **controller to supervisor**.

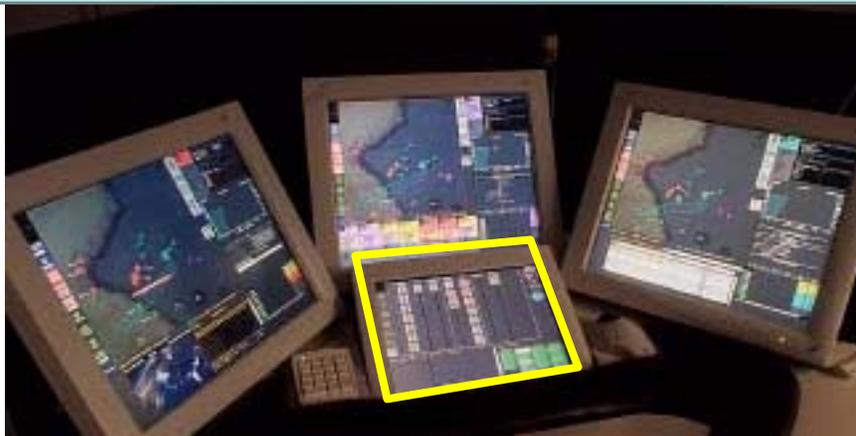
As a supervisor, the operator is responsible for monitoring and performing **multiple tasks**.

**Task Manager Display Supports** multitasking activity associated with **supervisory control**.



SPAWAR  
Systems Center  
San Diego

# Task Manager & Status Display



Task  
Manager  
Task  
Queue

Task Manager Interface:

- Active:** Respond to ESM (CEASED 1046), Maintain SA (Monitor Workload), Monitor Air Situation (Monitor, I & W Updated), Issue Track Reports (NEW 1062, ESM 1056, 1049), Conduct Engagement (Level I 1047, Level II 1058).
- Pending:** Respond to ESM (ESM 1062).
- Completed:** Respond to ESM (ESM 1049).



Communications

Communications Table:

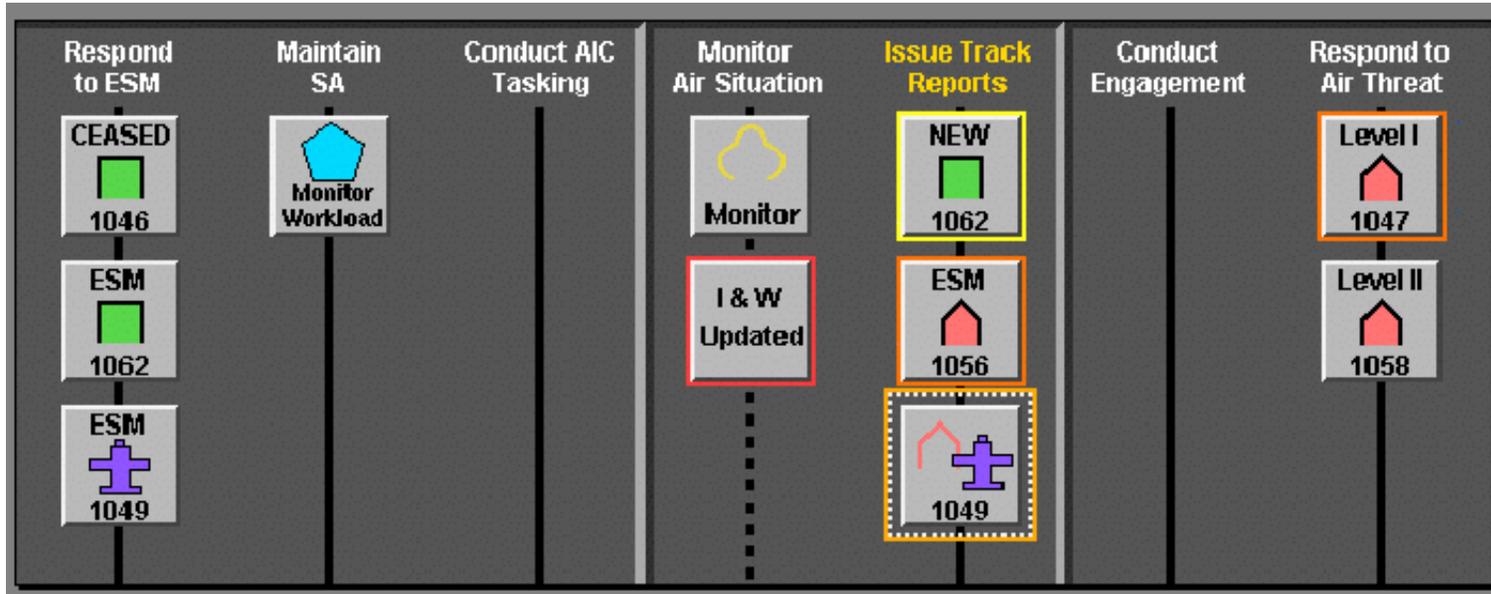
Net	AAW	EW	IAD
15			Level II 1056
		ESM Racket 1056	
		ESM Racket 1058	

Systems Status: ADW

Weapons	Ops Conditions	Combat Sys	Engineering
VLS	White/Safe	SPY 2X	Pumps
CIWS	Launch	Illumin.	Generators
DCA	Fire Inhibit	ESM	Compress.
Gun Sys	Mag Auth: Alt	IFF	M. Engines
Torpedoes	Engage.	Link 21	Damage C.
	EMCON: D	GFCB	Water
	DLI Alert 15		E-Drives

Systems  
Status

# Air Defense Warfare Task Monitoring



Representation of work in terms of tasks servers as a trace - enables designers to track workload and flow of tasks among team members.

Posting of Task analogous to customers arriving at a queue for service: Model Teams with Queueing Theory and Queueing Networks.



# Network Queueing Model of Team 1 Task Flow.

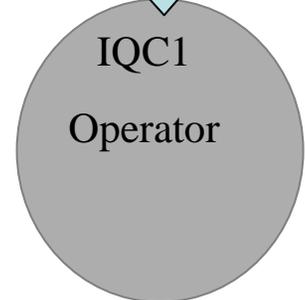
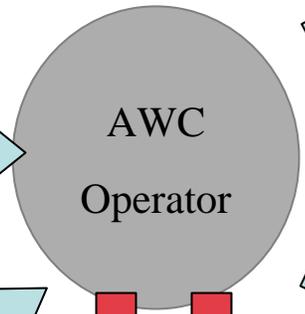
Tasks Entering:

$\lambda_1$  High Priority  
 Level I Query  
 Level II Warning  
 VID  
 Cover  
 Engage  
 Illuminate

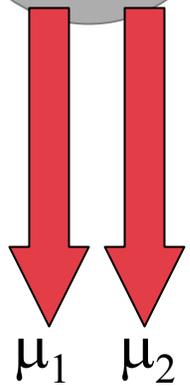
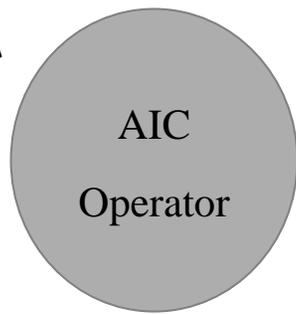
$\lambda_2$  Low Priority  
 New track Report  
 Update track Report

Level I\* & II\*,  
 ordered to send.

Level I & II's



VID



Tasks performed -  
 Output flow

Tasks performed -  
 Output Flow

AWC = Air Warfare Coordinator  
 IQC = Information Quality Control  
 AIC = Air Intercept Controller

# Components of Queueing Model

- 1. The Input or Arrival Process**
- 2. The Service Mechanism**
- 3. The Queueing Policy**

# Components of Queueing Model

## The Input or Arrival Process:

- The **arrival** of customers to a queue is often **unpredictable**, so arrival is modeled as a **random process**.
- The arrival process is often assumed to be **Poisson** in nature where **arrival rate,  $\lambda$** , is the reciprocal of the mean inter-arrival time of customers.
- For the Poisson distribution with parameter  $\lambda$ , the probability,  $P_k$ , that  $k$  arrivals occur in the time interval  $(0,t)$  is given by:

$$P_k(t) = \frac{(\lambda t)^k}{k!} e^{-\lambda t}$$

# Components of Queueing Model

## The Service Mechanism:

- Service refers to the **number of "servers"** and the lengths of time the customers hold servers.
- In our case this is the number of operators and the distributions of **reaction times it takes operators to perform various tasks.**
- Service time is modeled by a continuous random variable,  $x$ , exponentially distributed with parameter  $\mu$  :

$$f(x) = \mu e^{-\mu x}$$

# Components of Queueing Model

## The Service Mechanism:

- **Human reaction time** to various tasks, and task components, are **exponentially distributed** (see Townsend & Ashby, 1984).
- **Service time** may be modeled and shaped. For example, service may be viewed as composed of **several serial stages** each of which is exponentially distributed.
- In this case, an **Erlang distribution** is used to model service time ( $r$  represents the number of stages):

$$b(x) = \frac{r\mu(r\mu x)^{r-1} e^{-r\mu x}}{(r-1)!}$$

# Components of Queueing Model

## The Queueing Policy

- Entails the method by which the system selects customers for service:
  - First-Come-First-Served (FCFS)
  - Last-Come-First-Served (LCFS)
  - Priority
  - Random.

Queueing Policies for this research: **FCFS** and **Priority**

# Vital Statistics of a Queueing System

- The **Load** or **Intensity**,  $\rho$ , to a queueing system is defined to be the **ratio** of the rate of **arrivals**,  $\lambda$ , to the rate of **service**,  $\mu$ :

$$\rho = \frac{\lambda}{\mu}$$

- **Little's Theorem:** The average number of customers to the system,  $N$ , is equal to the product of the rate of flow of customers,  $\lambda$ , and the average time spent in the system,  $T$ :

$$N = \lambda T$$



# Air Def. Warfare MMWS Experiments



- Four 5-member ADW teams were tested on a 2 hour Scenario - Sea of Japan (SOJ).
- Tactical Action Officer, Air Warfare Coordinator, Information Quality Control (2), Air Intercept Controller.
- Operators were assigned **Primary and Secondary Tasks**.
- All system recommended tasks were presented on a **Task Manager (TM) Display**.
- All Teams “**self-organized**” - were “free” to allocate tasks amongst themselves - not told how or when to reallocate.
- Only support for allocation was visual - **listing of tasks** on the TM display.

The results provide a basis for building team models.

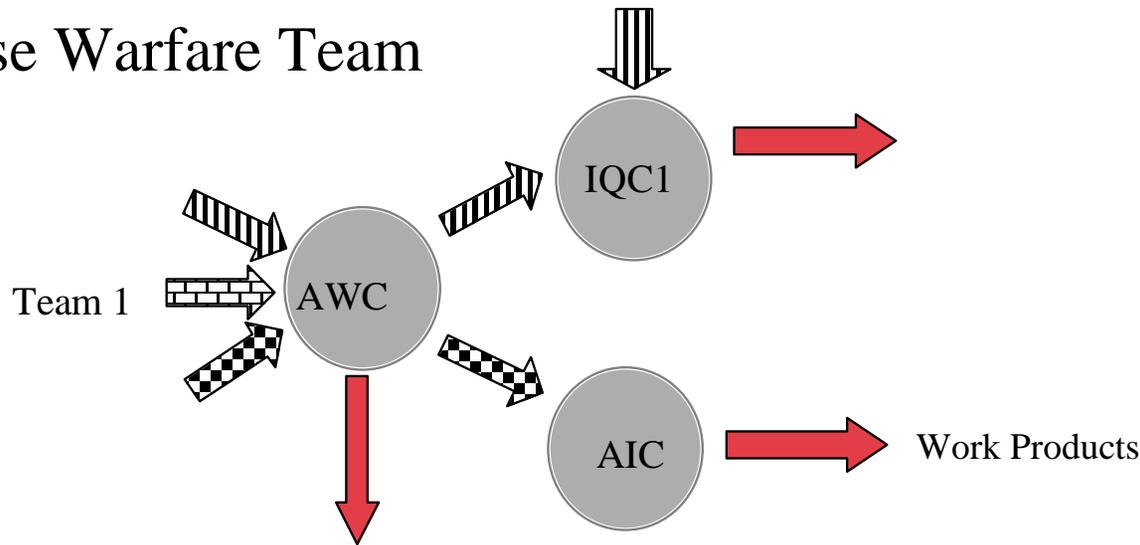
Results show a contrast between team performance outcomes.

# C2 Team Modeling Problem

Problem: The rate at which tasks arrive on the Task Manager display varies - there is a “Rush Hour” Effect - But Rush Hour comes and goes.

Tasks Entering Team

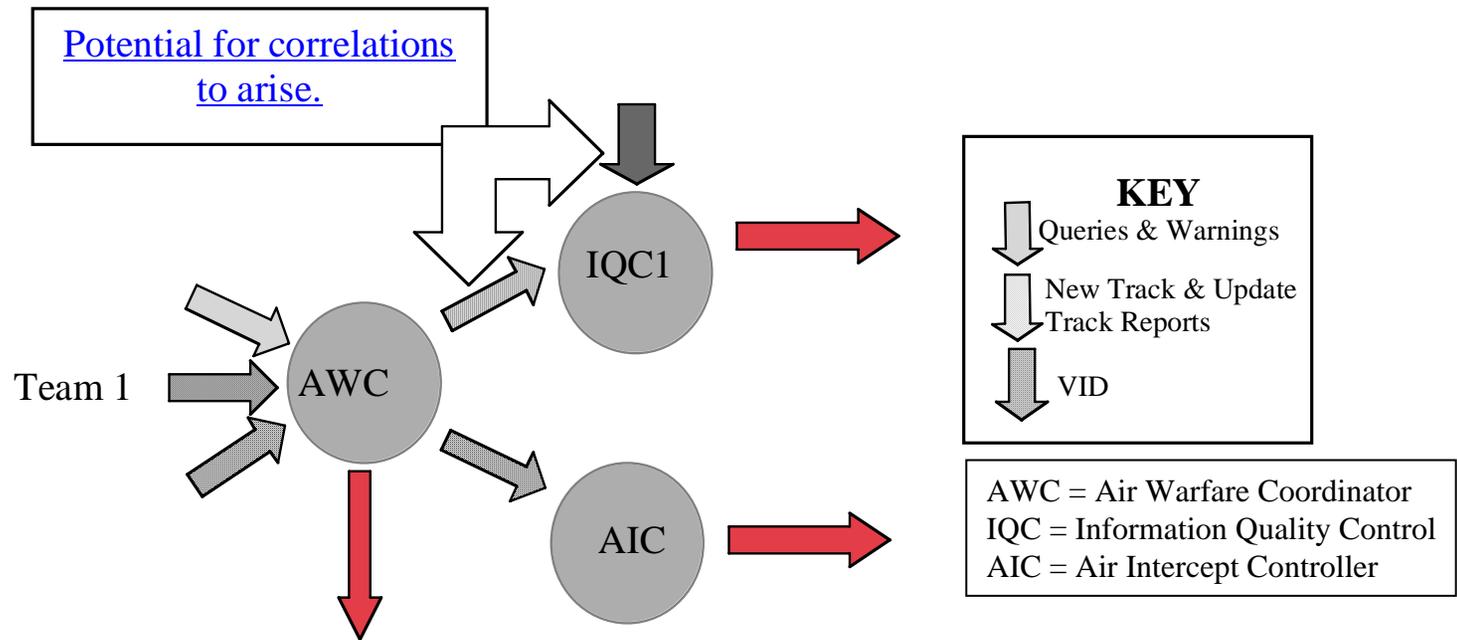
Air-Defense Warfare Team



AWC = Air Warfare Coordinator  
IQC = Information Quality Control  
AIC = Air Intercept Controller

# C2 Team Modeling Problem

PROBLEM: Correlations between arrivals when tasks are passed between operators.  
Model has to account for these correlations.



## Queueing and GOMSL Models

## **Arrival Process:**

This arrival process creates a challenge for queueing theory predictions since, tasks “back-up” during periods of high task flow, but then are completed as the flow of tasks subsides.

## **Varying Workload:**

The C2 mission impact for performance during time critical events must be addressed within the context of varying periods of high and low workload.

## **Varying Team Demands:**

During periods of low workload the system may be over-staffed, but during periods of high workload the system runs the risk of being under-staffed.

The Markov-Modulated Poisson Process (MMPP) captures the ebb and flow of the task arrivals and their impact on the performance of a queueing system.

These are “Doubly Stochastic” Processes:

Two Task Arrival Rates (which are stochastic):

“Rush Hour” & “Non-Rush Hour”.

But how long Rush Hour and Non-Rush Hour lasts also varies and is itself stochastic - hence this combination of variable processes is called *doubly stochastic*.



# Addressing the Correlation Problem



(Arrival Time Distribution/Service Time Distribution/# of servers)

*Using a simplistic M/M/1 modeling approach prediction error is high...*

In this Table we present the results of comparing the predictions for an M/M/1 queue to that of a matlab simulation of the Information Quality Control 1 operator (IQC1) in our queueing network. As can be seen, the predictions are rather poor. This is because Automation delivered tasks to the IQC1 and the AWC also manually delivered tasks.

$\lambda_{outside} = \lambda_{inside} = 1/152.4$ $\mu = 1/15.0$ $V = 1/13.3$	<b>N</b> (average # of tasks)	<b>T</b> (average lifetime)	<b>W</b> (average lifetime)
Predicted Queueing	0.420	31.976	16.976
Observed IQC1	0.455	34.464	19.430
% Error	8.41	7.78	14.45

# Addressing the Correlation Problem

*Using The Markov-Modulated Poisson Process (MMPP) % error  
Is substantially reduced...*

$\lambda_{outside} = \lambda_{inside} = 1/152.4$ $\mu = 1/15.0$ $V = 1/13.3$	<b>N</b> (average # of tasks)	<b>T</b> (average lifetime)	<b>W</b> (average lifetime)
Predicted Queueing	0.455	34.478	19.478
Observed IQC1	0.455	34.464	19.430
% Error	0.03	0.04	0.25

Table 9: MMPP/M/1 Queueing model predictions compared to observed IQC1 correlated arrival simulation.

# Addressing the Rush Hour Effect...

## From M/E<sub>R</sub>/1 to MMPP/E<sub>R</sub>/1 Model...

To review: Our previous model handled the first 33 minutes of the Sea of Japan Scenario and incorporated several features:

1. The Service Time function was generalized to an 6 stage Erlangian.
2. The server took “Vacations” when there were no tasks on the Task Manager Display.
3. The Tasks were prioritized: high and low.

### M/E<sub>R</sub>/1 Model Results

$\lambda_1 = 1/332.52$ $\lambda_2 = 1/48.66$ $\mu_1 = 1/16.72$ $\mu_2 = 1/16.79$ $V = 1/17.73$	<b>N<sub>1</sub></b>	<b>N<sub>2</sub></b>	<b>N</b>	<b>T<sub>1</sub></b>	<b>T<sub>2</sub></b>	<b>T</b>	<b>W<sub>1</sub></b>	<b>W<sub>2</sub></b>	<b>W</b>
	<i>Mean number of Class 1 tasks</i>	<i>Mean number of Class 2 tasks</i>	<i>Mean number of tasks in system</i>	<i>Mean total time for Class 1 tasks in system</i>	<i>Mean total time for Class 2 tasks in system</i>	<i>Mean total time for a task in system</i>	<i>Mean waiting time for Class 1 tasks in system</i>	<i>Mean waiting time for Class 2 tasks in system</i>	<i>Mean waiting time for a task in system</i>
<b>Predicted</b>	0.096	0.867	0.964	32.077	42.198	40.906	15.362	25.406	24.124
<b>Observed</b>	0.098	0.787	0.884	32.467	39.602	38.651	15.752	22.496	21.616
<b>% Error</b>	1.22	9.28	8.23	1.22	6.15	5.51	2.54	11.45	10.39

# MMPP/M/1 Model and the Rush Hour Effect

**Needed to extend model to entire 1 hour and 45 minute scenario:**

**Several obstacles first had to be overcome:**

**1) The data capture didn't specify start and end times of many tasks.**

- use estimates of task times derived with GOMSL models and
- viewed hours of time stamped video tapes of the scenario to accurately capture begin and end times.

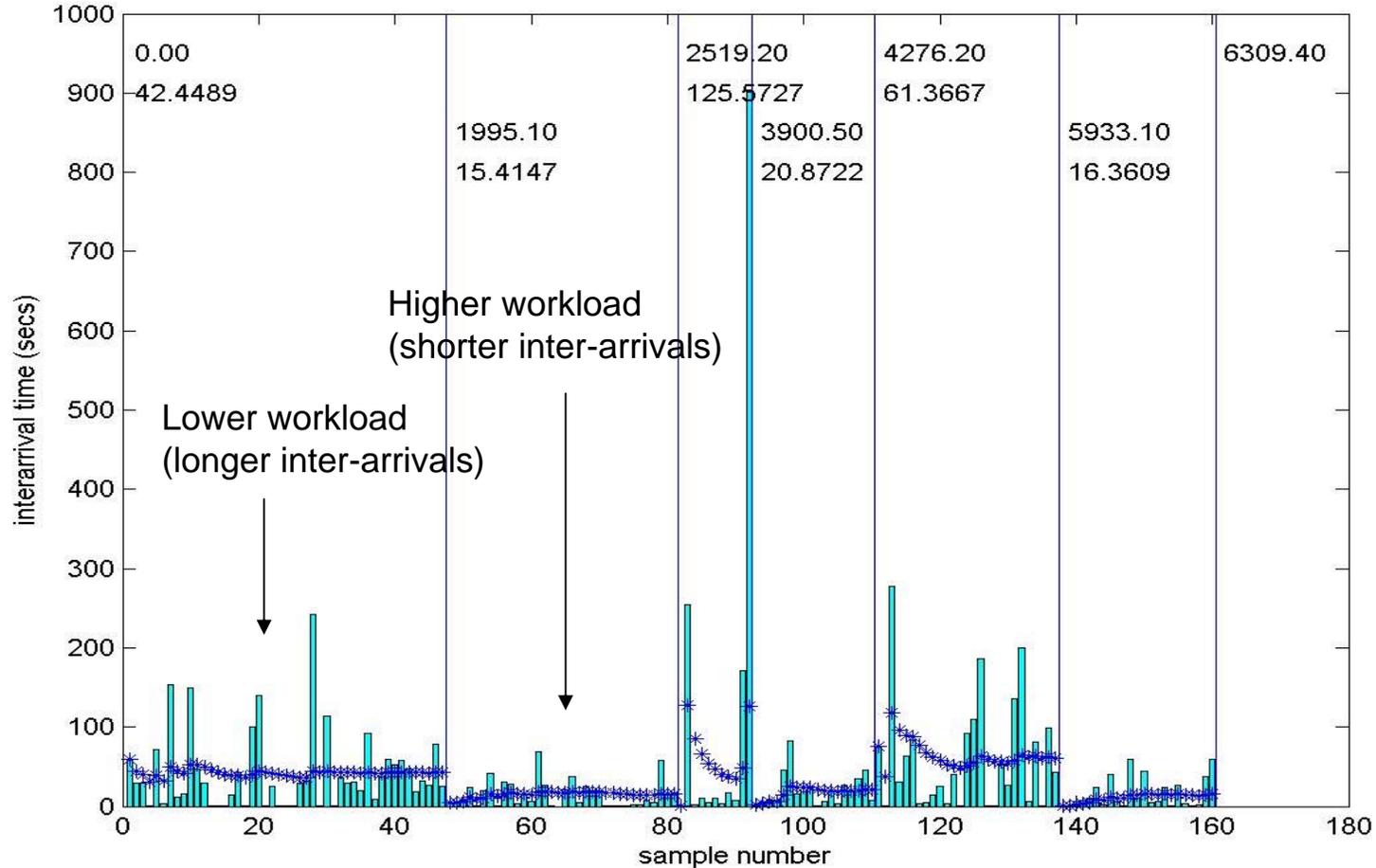
**2) The change in task arrival rate had to be captured.**

- implement a Change Point Analysis and an entirely different algorithm found in the literature (Meier-Hellerstern).

**Both of these Algorithms have their flaws; they give comparable results but not the same answer.**

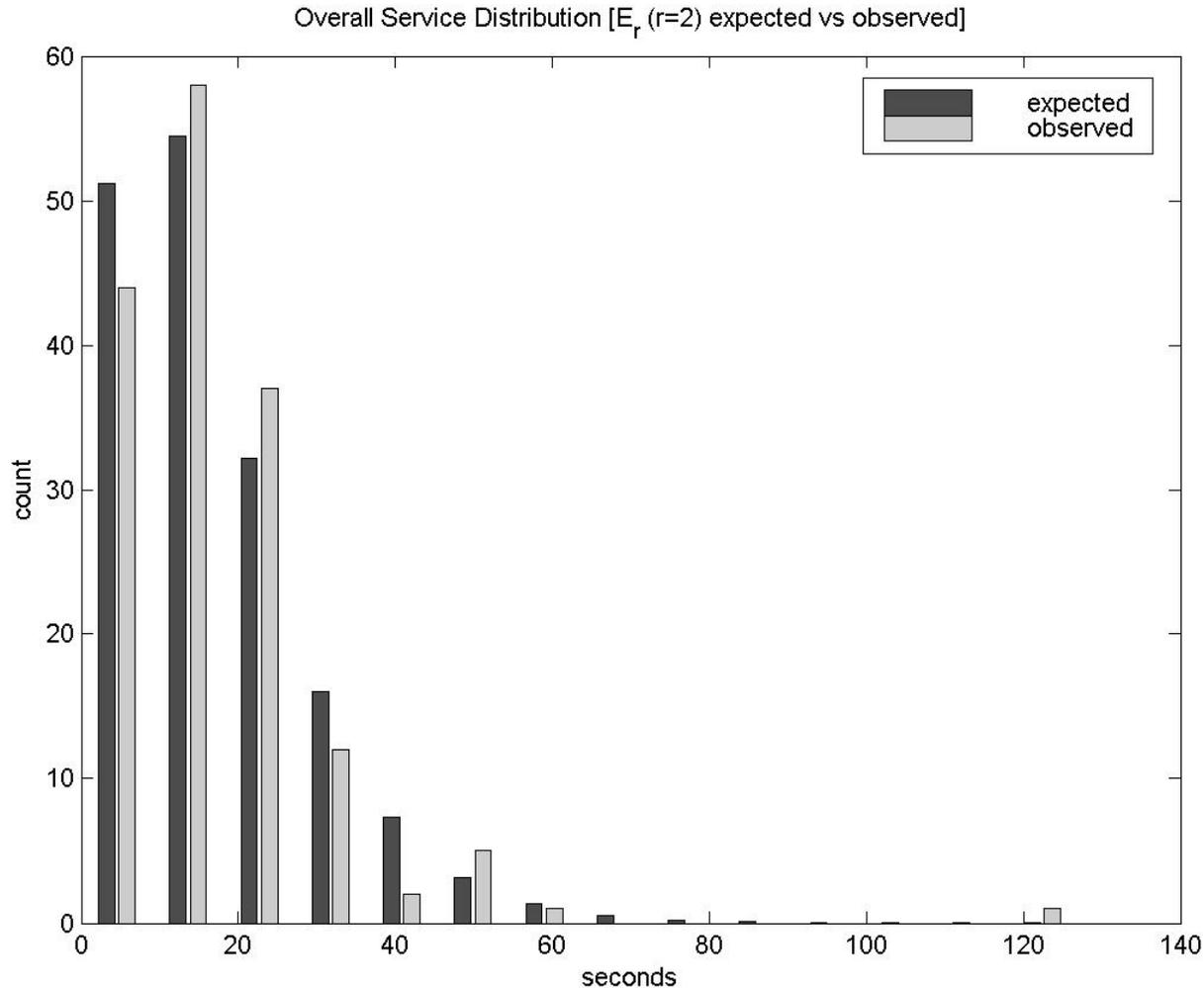
**The question:** C2 task flow varies but is it best represented with a 2-stage MMPP?

## Task Inter-arrival times



Change point analysis based on the inter-arrival time between AWC tasks for the entire scenario. Asterisks represent the running average.

# Reducing Prediction Error



Erlangian 2-stage service minimizes second moment error - model predictions compared to AWC data for the entire scenario.

# Reducing Prediction Error

$1/\lambda_{\text{tot}}$ : 39.434  
 $1/\mu$ : 17.500  
 $\rho$ : 0.444

$1/\lambda_1$ : 59.215  
 $1/\lambda_2$ : 17.015

$1/r_1$ : 1677.767  
 $1/r_2$ : 425.3667

Type	Mean Waiting Time of Tasks in System	Mean Number of Tasks in System	Mean Total Time of Task in System
Predict	43.75	1.553	61.250
Observe	39.708	1.443	57.256
Error	4.042	0.110	3.993
% Error	9.239	7.104	6.520

MMPP/ $E_r/1$ : 2-state MMPP queueing model predictions (Fischer and Meier-Hellstern, 1992) compared to AWC data for the entire scenario.

# Resolving MMPP/M/1 Model Limitations

## Issues:

- Need to incorporate generalized service distribution (Done).
- Need to add vacationing server.
- Need to add Prioritization.

We found a discrepancy between our calculated predictions and another algorithm we recently found and implemented from the literature (Fischer and Meier-Hellstern)

The two methods agree only over certain values of the parameters:  $\lambda_1$ ,  $\lambda_2$ ,  $r_1$ ,  $r_2$ ,  $\mu$  -

This has to be resolved... (FY06 effort)

# Conclusions

- Queueing Statistics characterize operator and system performance. Allows for summarization and quantification of system performance.