Modeling Supervisory Control in the Air Defense Warfare Domain with Queueing Theory[1]

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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.

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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.

Stepwise Model Approach

- **GOMS = Goals Operators Methods Selection Rules**

What is it?

A computational modeling approach developed by ONR research based on Visual, Cognitive, Auditory & Psychomotor VCAP "step-wise" human task definition.

What does it do?

Defines human VCAP functions with respect to *impact of a design on the performance* of those functions - predicting performance outcome.

GOMS Components

Goals: What Must be Accomplished

Operators: Elementary Perceptual, Motor, or Cognitive Acts.

Methods: Step by Step Procedure for a Goal

Selection Rules: Basis for Choosing Methods

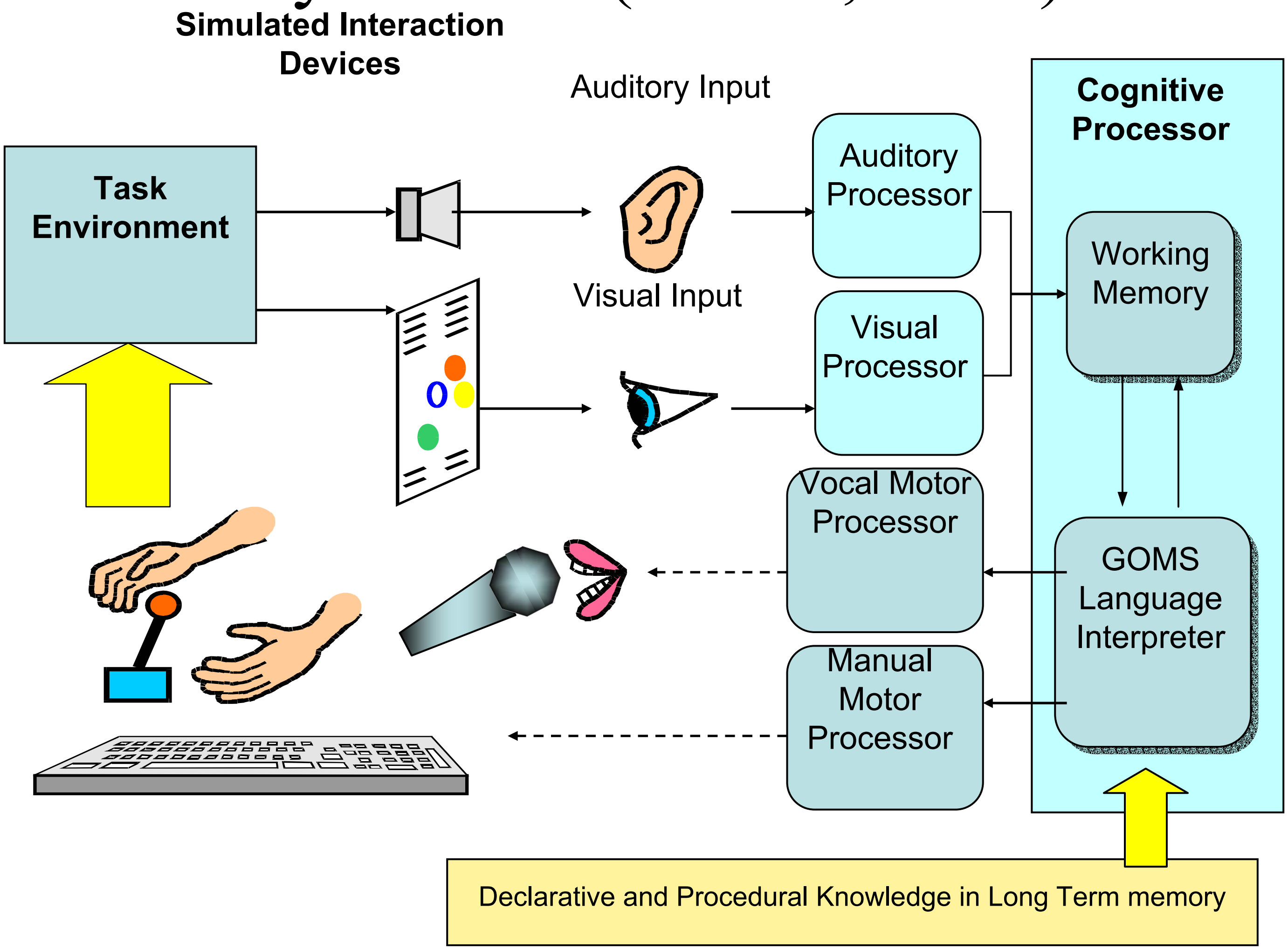
Based upon Stepwise models as defined in: Psychology of Human-Computer Interaction, Card, Moran, and Newell (1983).

How is Modeling Done…

- Models are constructed by creating “building blocks” of each subtask component.
- Each subtask is used as a step in a task sequence.
- Connections of subtasks describe how operators interact with a given human-computer interface.
- When constructed the models can be used to predict performance and workload of a system.

To accomplish this a modeling language was developed…

GLEAN: GOMS Language Evaluation and Analysis Tool (Kieras, 1997)



Modeling Procedure

1. Do a Task Analysis
   - Define the Goals:
   - How are they accomplished ?
   - How might they be accomplished?
   - What are the alternatives?

2. Write The Methods in GOMSL

3. Build the HCI and Task Environment in C++

4. Run the Scenario(s)

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.**

Task Manager & Status Display

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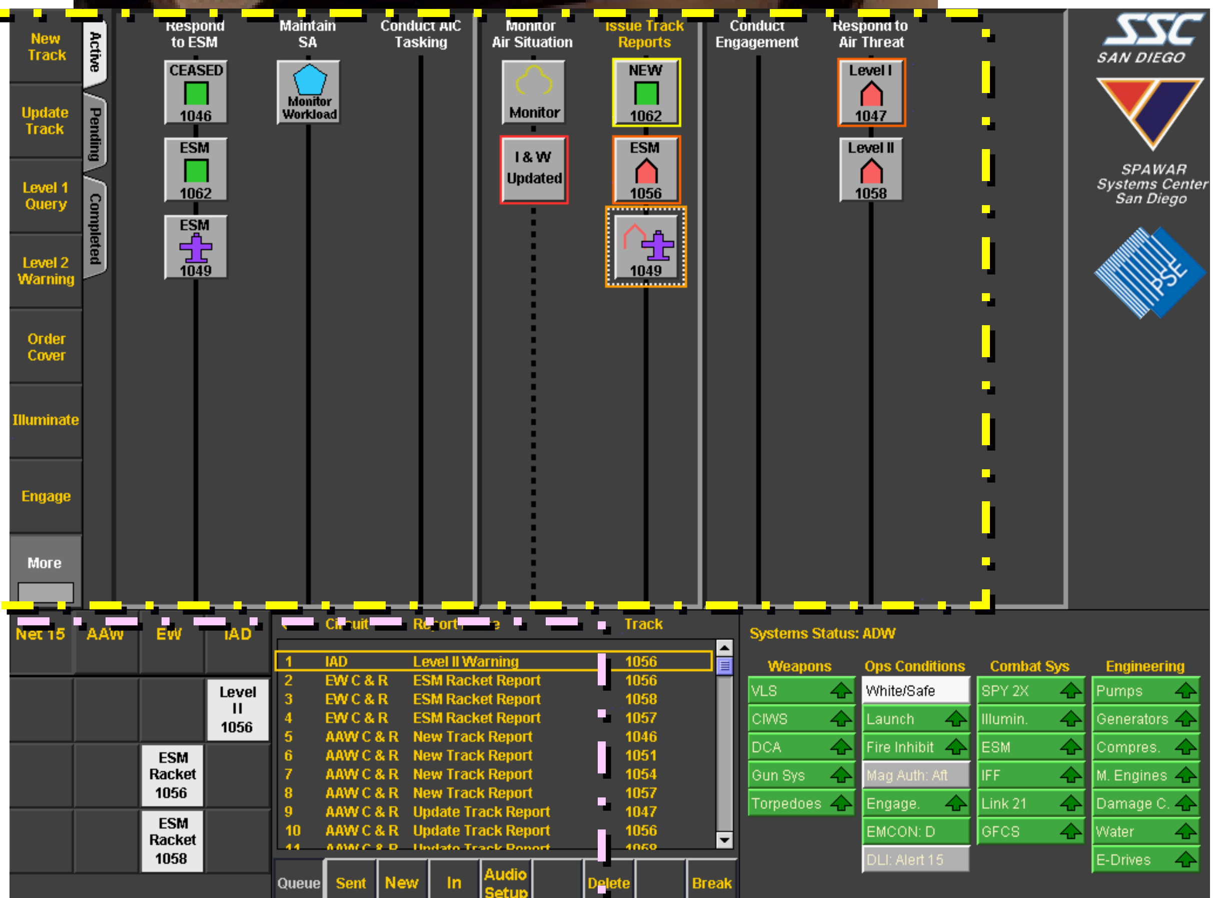
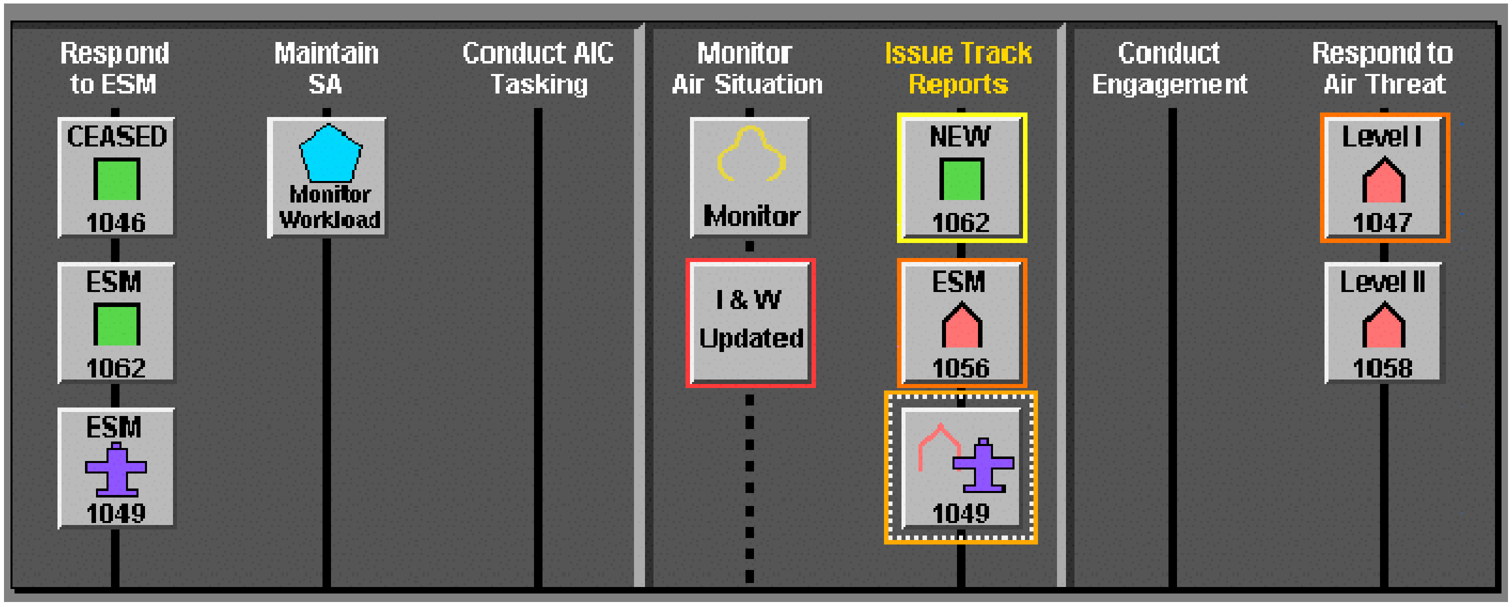
Task Manager Task Queue



Communications

Systems Status

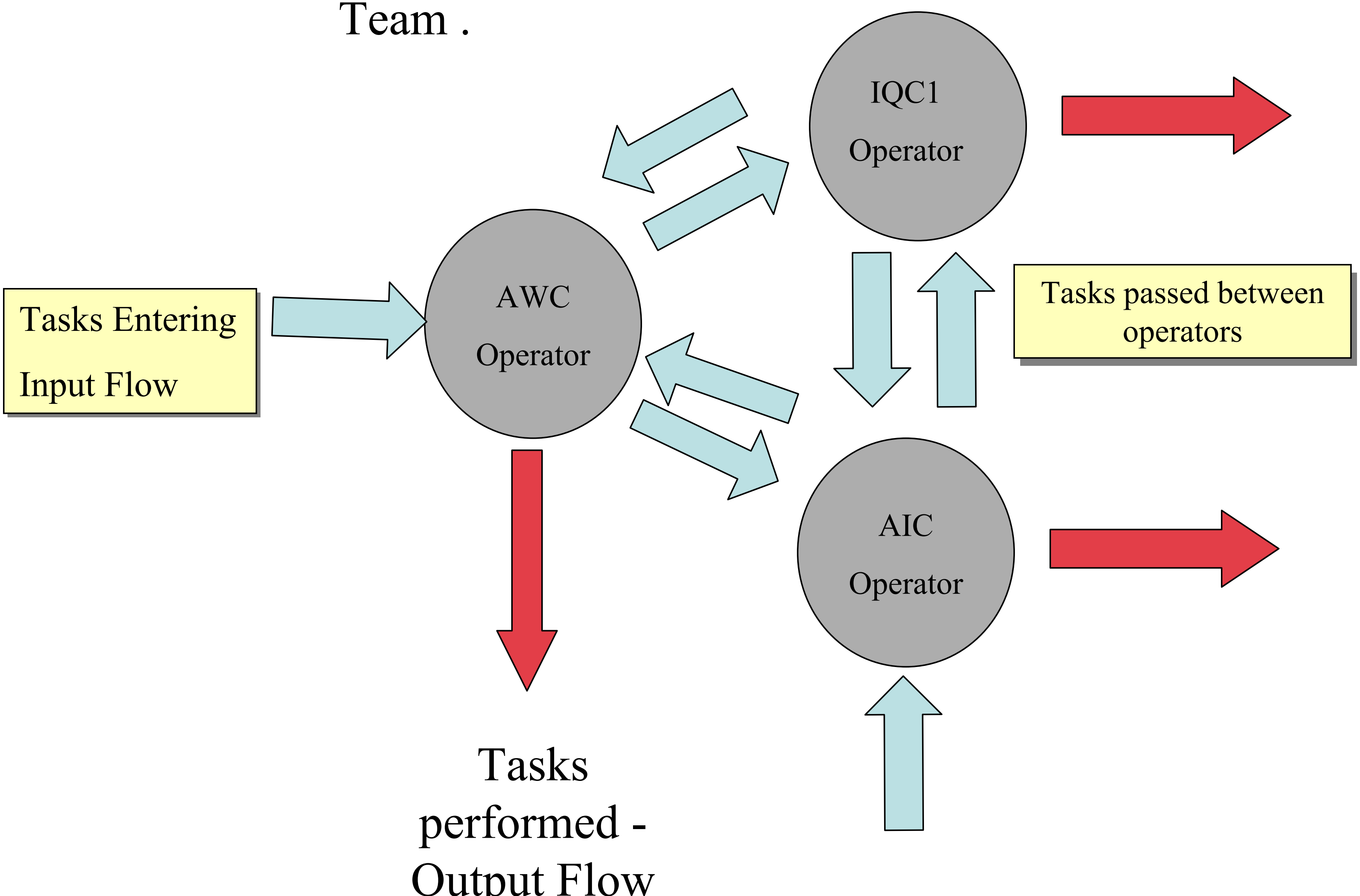
Air Defense Warfare Task Monitoring



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.

General Network Queueing Model of Air Defense Warfare Team .



Components of Queueing Model

1. **The Input or Arrival Process**

2. **The Service Mechanism**

3. **The Queueing Policy**

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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, λ,** is the reciprocal of the mean inter-arrival time of customers.
- For the Poisson distribution with parameter λ, 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 μ :

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

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 expontentially 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,** ρ**,** to a queueing system is defined to be the **ratio** of the rate of **arrivals,** λ. to the rate of **service,** μ **:**

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

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

$$N = \lambda T$$

Vital Statistics of a Queueing System

- Average number of customers, N:

$$N = \frac{\rho}{1-\rho} = \frac{\lambda}{\mu - \lambda}$$

- Average Time spent in the system, *T*:

$$T = \frac{N}{\lambda} = \frac{\rho}{\lambda(1-\rho)} = \frac{1}{\mu - \lambda}$$

- Average Waiting Time, W:

$$W = T - \frac{1}{\mu} = \frac{\rho}{\mu - \lambda}$$

Adventures of the Vacationing Server

- No tasks present - **server is idle**; hopefully, this is **not the case with human operators**.
- When there were no tasks on the TM displays, operators examined the map – the TACSIT display.
- **Non -TM tasks must be taken into account** in order to quantify system performance because they will have an impact on the queueing statistics.

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Adventures of the Vacationing Server

- A queue with **"Service Vacations"** (Takagi, 1991) can be adapted to **Supervisory Control**.
- If the **operator** has no tasks on the TM display he **"takes a vacation"** by analyzing information on the TACSIT display. When he is done looking at the TACSIT display he **"returns from vacation"** to see if there are any tasks on the TM display.
- We assumed operator's 'vacation times' and service times were both exponentially distributed however the **parameters v and μ** for vacation time and service time, respectively, are not necessarily equal.

Vital Statistics of a Queueing System with Vacationing Server

- Average number of customers, N:

$$N = \frac{\rho}{1-\rho} + \frac{\lambda}{\nu}$$

- Average Time spent in the system, *T*:

$$T = \frac{1}{\mu - \lambda} + \frac{1}{\nu}$$

- Average Waiting Time, W:

$$W = \frac{\rho}{\mu - \lambda} + \frac{1}{\nu}$$

- These equations can be adapted to reflect Prioritization

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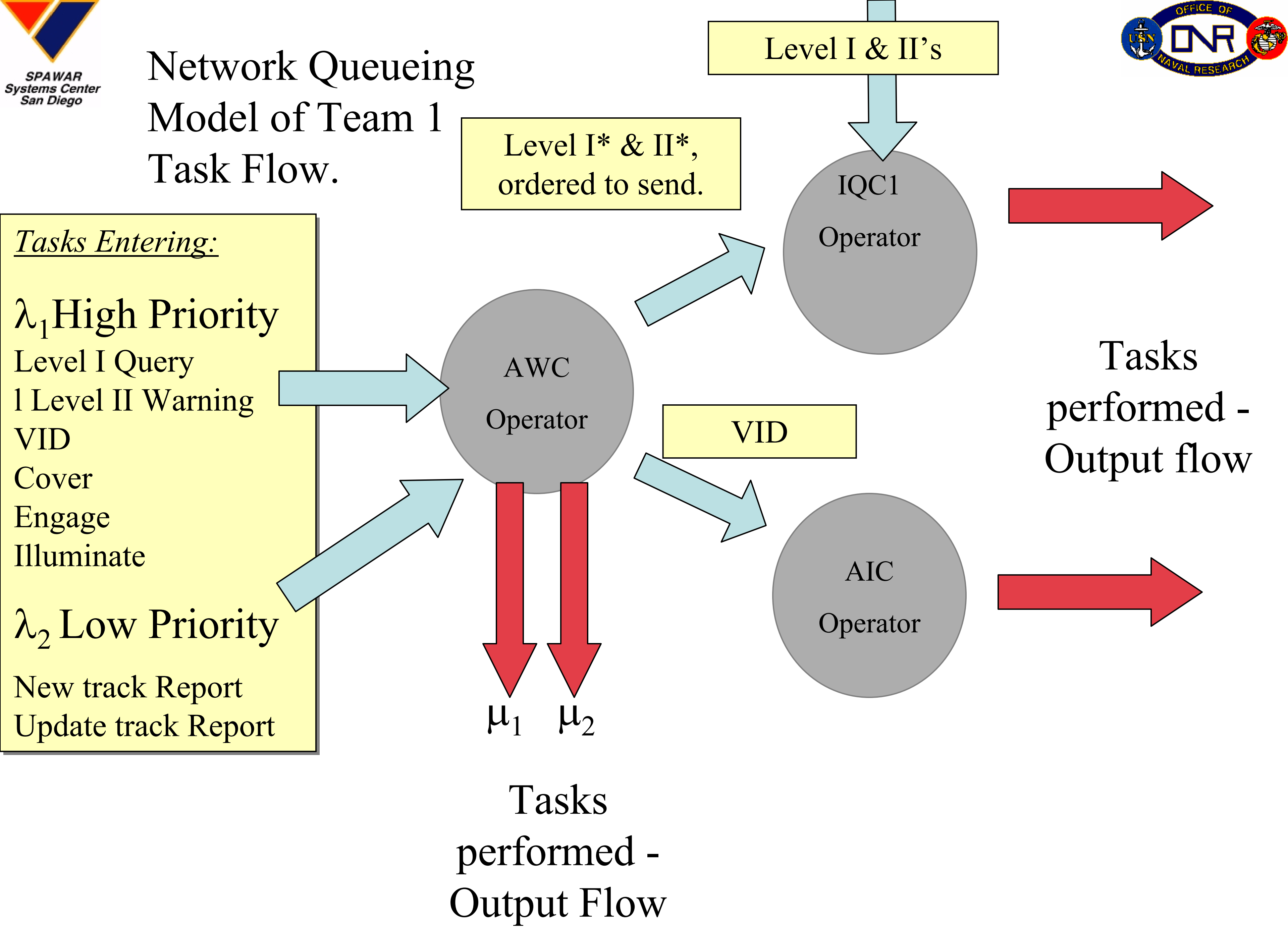
Air Def. Warfare MMWS Experiments

- 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.

Network Queueing Model of Team 1 Task Flow.



Queueing Parameters GOMSL and Actual Data

	GOMSL High	GOMSL Low	Actual Data
λ_1	**1/252.57**	**1/252.57**	**1/252.65**
λ_2	**1/49.88**	**1/49.88**	**1/50.51**
λ	**1/41.65**	**1/41.65**	**1/42.10**
set-up$_1$	**1/2.46**	**1/2.44**	**1/2.46**
set-up$_2$	**1/3.76**	**1/3.79**	**1/3.76**
set-up	**1/3.56**	**1/3.58**	**1/3.56**
μ_1	**1/22.06**	**1/15.19**	**1/7.95**
μ_2	**1/21.58**	**1/9.47**	**1/18.59**
μ	**1/21.66**	**1/10.41**	**1/16.81**
v	**1/8.46**	**1/7.76**	**1/8.46**

Queueing Statistics

AWC Server Node

	N – Mean # of tasks	T – Mean lifetime	W – Mean wait time
GOMSL high	1.232	54.06	28.27
Actual	0.936	40.919	20.27
GOMSL low	0.642	27.84	13.9

GOMSL model data for the AWC compared to actual Team 1 AWC data.

Queueing Statistics

AWC Performance: M/E_2/1 Model, Task Prioritization Queueing Policy

	N – Mean # of tasks	T – Mean lifetime	W-Mean wait time
Predicted Queueing	1.067	44.9	24.55
Actual AWC	0.936	40.919	20.27
% Error	12.24	8.86	17.42

Queueing Model predictions compared to actual AWC Team 1 data.

Queueing Statistics

- **Source of Error:** the **service time distribution** was assumed to be a **2-stage Erlang distribution**.
- The first stage consisted of the set-up time – estimated using the GOMSL model. The distribution was assumed to be exponential.
- The second stage represents the actual average reaction time of the AWC operator to perform tasks. We assumed that the distribution for stage-two service times was exponential.
- Comparing the second moment of the actual data, to that of the assumed exponential, there is a large difference:
  - $\overline{x_O^2}$ **= 397.61 versus** $\overline{x_E^2}$ **= 565.15 or 42% error**
- **Solution:** Model the distribution of reaction times with an **r-stage Erlang distribution that minimizes the error** between, and the Erlang distribution's second moment, (Kleinrock, 1975).
- r is adjusted – stages are added or deleted- until the error is minimized.

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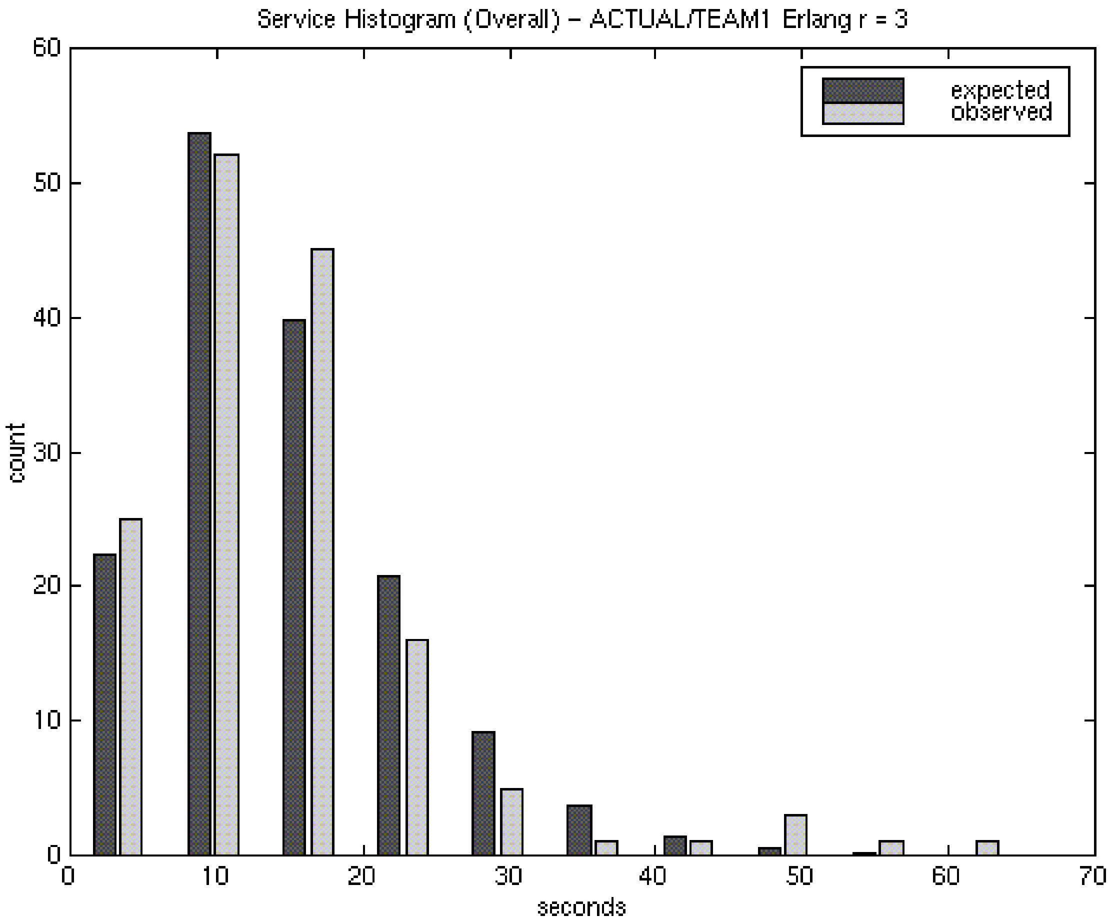
Queueing Statistics

Fitting Actual Service Time Data with r- stage Erlang Distributions

	r	$\overline{x^2_E}$	$\overline{x^2_O}$	% Error	N
High Priority Tasks	1	126.34	159.77	26.47	7
Low Priority Tasks	4	431.81	440.30	1.97	39
FCFS Tasks Combined	3	383.86	397.61	3.58	46

Best fitting r-stage Erlang distributions that minimize second moment error.

Queueing Statistics



Histogram of Actual data service times versus 3-stage Erlang distribution.

Queueing Statistics

AWC Performance: M/E_r/1 Model, Task Prioritization Queueing Policy

	N – Mean # of tasks	T – Mean lifetime	W-Mean wait time
Predicted Queueing	0.966	40.668	20.314
Actual AWC	0.936	40.919	20.27
% Error	3.11	0.62	0.27

Queueing Model predictions compared to actual AWC Team 1 data.

Queueing Statistics

AWC Performance: M/E_r/1 Model, FCFS Queueing Policy

	N – Mean # of tasks	T – mean lifetime	W-Mean wait time
Predicted Queueing	0.969	40.794	20.44
Actual AWC	0.936	40.919	20.27
% Error	3.41	0.31	0.83

Queueing Model predictions compared to actual AWC Team 1 data.

Conclusions

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

- The GOMSL and Queueing Models, together, provided effective predictions of actual operator performance.

Conclusions

Lessons Learned:

- Why not compare Queueing theory predictions with GOMSL data?
  - Distribution of reaction times in GOMSL model not realistic. Thus queueing analysis of GOMSL data becomes an exercise in modeling the GOMSL model's arbitrary distribution of service times.

- The Constraints that modeling imposes reveals gaps in real time operator data collection.
  - Queueing theory requires an accountability of every aspect of the server's (operator's) time.
  - GOMSL modeling provides that accountability - fills in those gaps in time not accounted for in the data.

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Work in Progress

- **Extend analysis to a team of operators – the other nodes of the queueing network.**
- **In addition, to predicting the performance of each operator in a manner similar to the AWC predictions, derive a model with predictions of team/system performance.**
- **Modify Model to allow for a more general arrival process of tasks (Markov Modulated Arrival Processes)**
- **Different team structures alter the flow of tasks through the network.**
- **Can queueing models predict previously observed differences in team performance?**