Intelligence Surveillance and Reconnaissance Asset Assignment for Optimal Mission Effectiveness

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PART I

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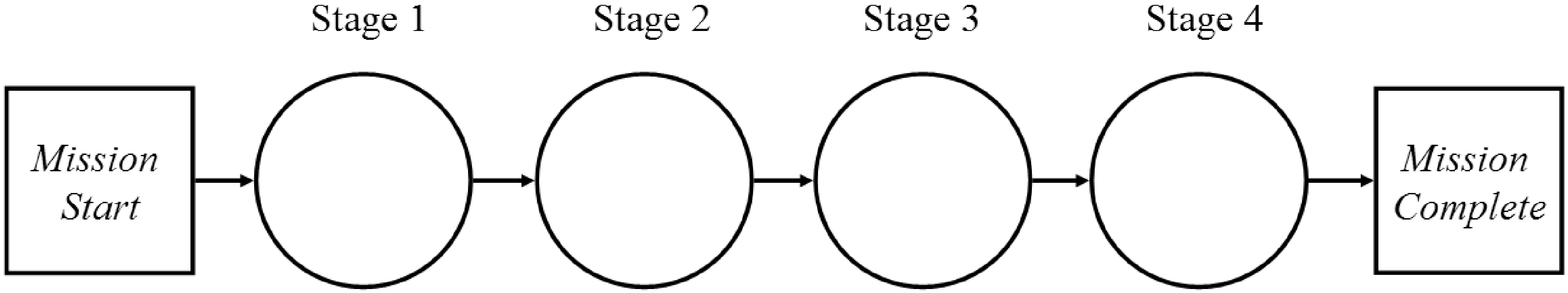
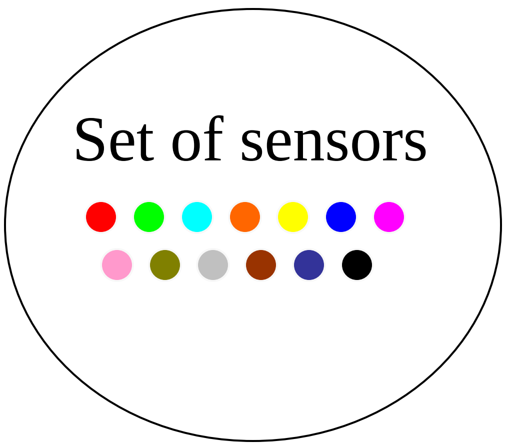
Problem Statement

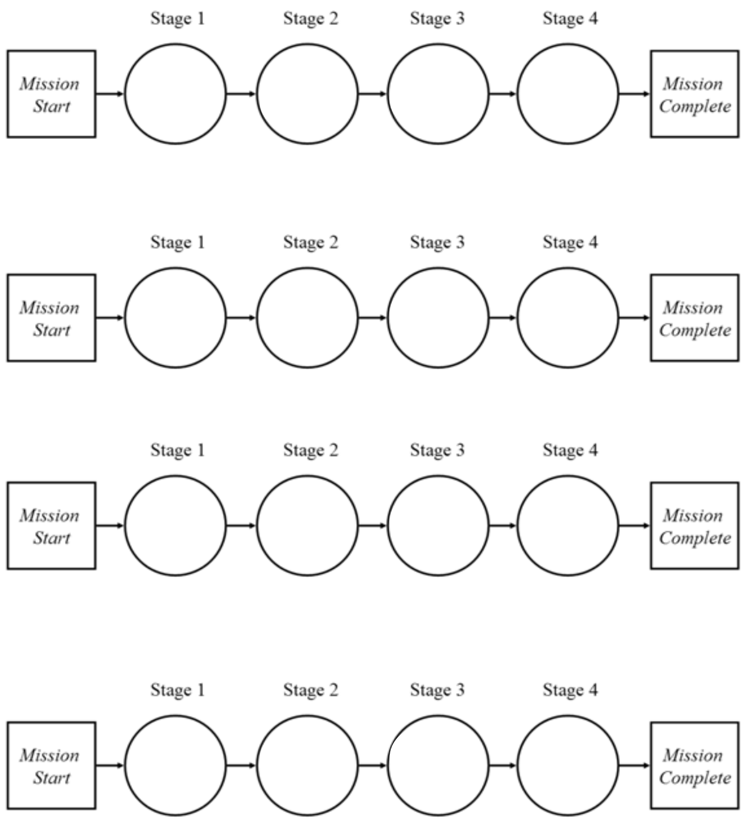
- USSTRATCOM has requested assistance assigning sensors to multi-stage missions
- Each mission has several stages, and some sensors may be shared between missions
- Each sensor has a distinct probability of success at a unique mission's stage
  - These probabilities are not always known until just prior to tasking



Problem Example



Set of missions



General Mathematical Description

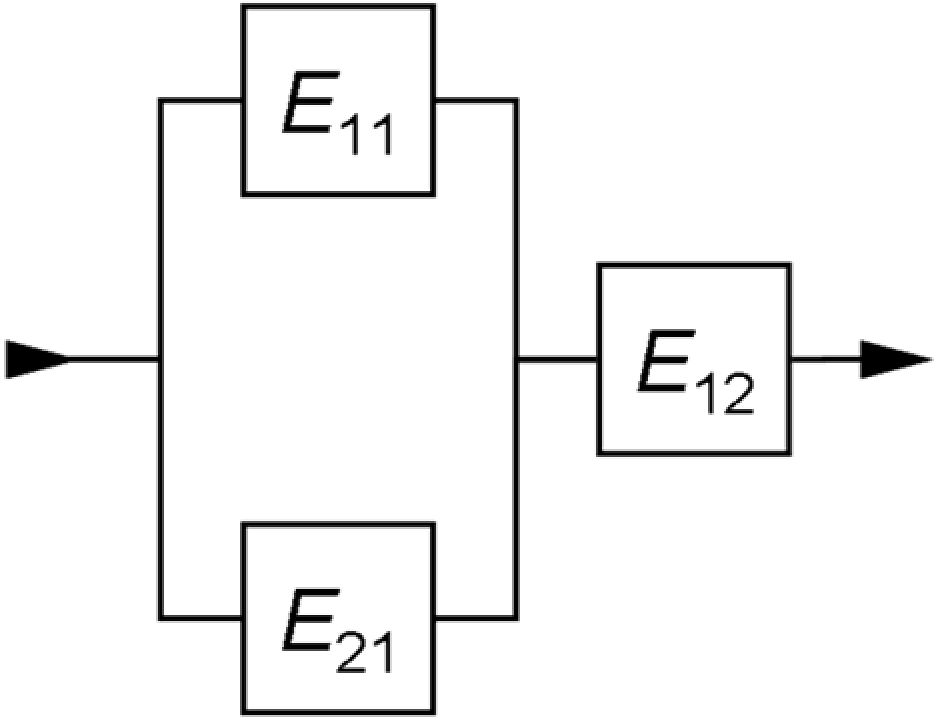
$$\max_{\mathbf{x}\in\Omega} F(\mathbf{x}),$$

$$\mathbf{x} \in \mathbb{B}^n$$

$$F(\mathbf{x}) \in \mathbb{R}^p$$

- This research seeks to
  - Define $\mathbf{x} \in \mathbb{B}^n$, $\mathbf{x}\in\Omega$, and $F(\mathbf{x})$
  - Find techniques to Maximize $F(\mathbf{x})$

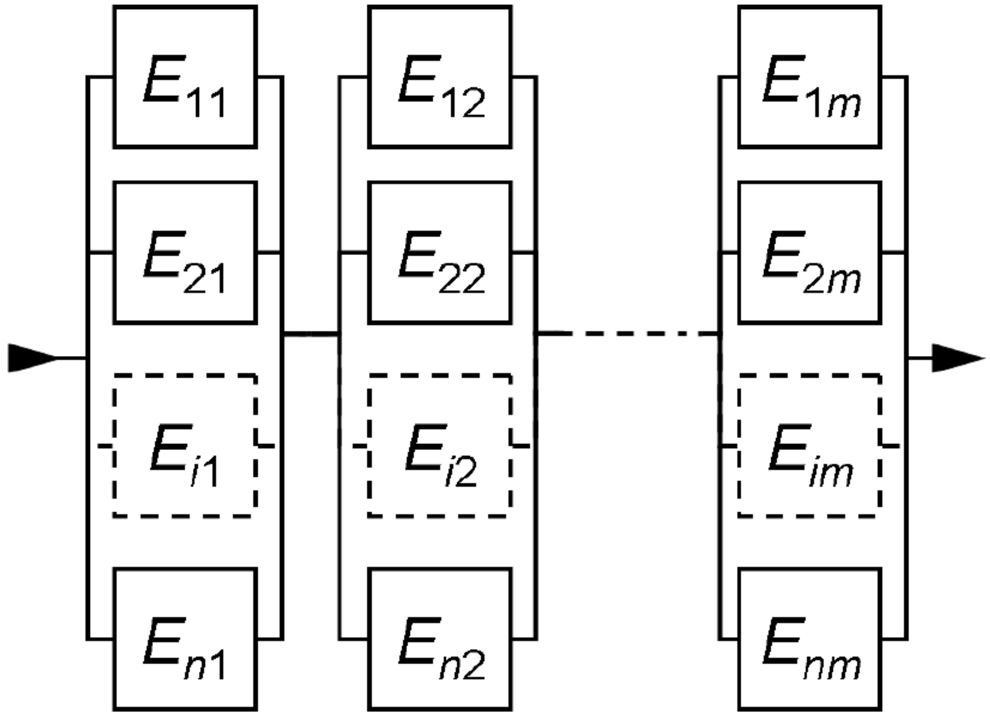
Reliability Theory



$$R = [1 - (1 - P(E_{11}))(1 - P(E_{21}))][P(E_{12})]$$

- Basic bridge structure network
  - Assuming independent failures of elements, calculations are simple

Reliability Theory



$$R = \prod_{j=1}^{m} \left(1 - \prod_{i=1}^{n} (1 - P(E_{ij})) \right)$$

- General bridge network
  - System is called a series-parallel redundant system

Simple Resource Allocation

$$\max \sum_{j=1}^{n} f_j(x_j),$$

subject to

$$\sum_{j=1}^{n} x_j \leq b$$

$$\mathbf{x} \in \mathbb{Z}^n$$

- $f_j(x_j)$ is concave, increasing, and non-linear
- Problem is NP-Complete

Weighted Sum Scalarization

$$\max_{\mathbf{x}\in\Omega} \sum_{k=1}^{p} \lambda_k f_k(\mathbf{x}),$$

$$\mathbf{x} \in \mathbb{B}^n$$

$$f(\mathbf{x}) \in \mathbb{R}$$

- Converts a multi-objective function into a single objective function
- Answers are guaranteed to be efficient

Methodology

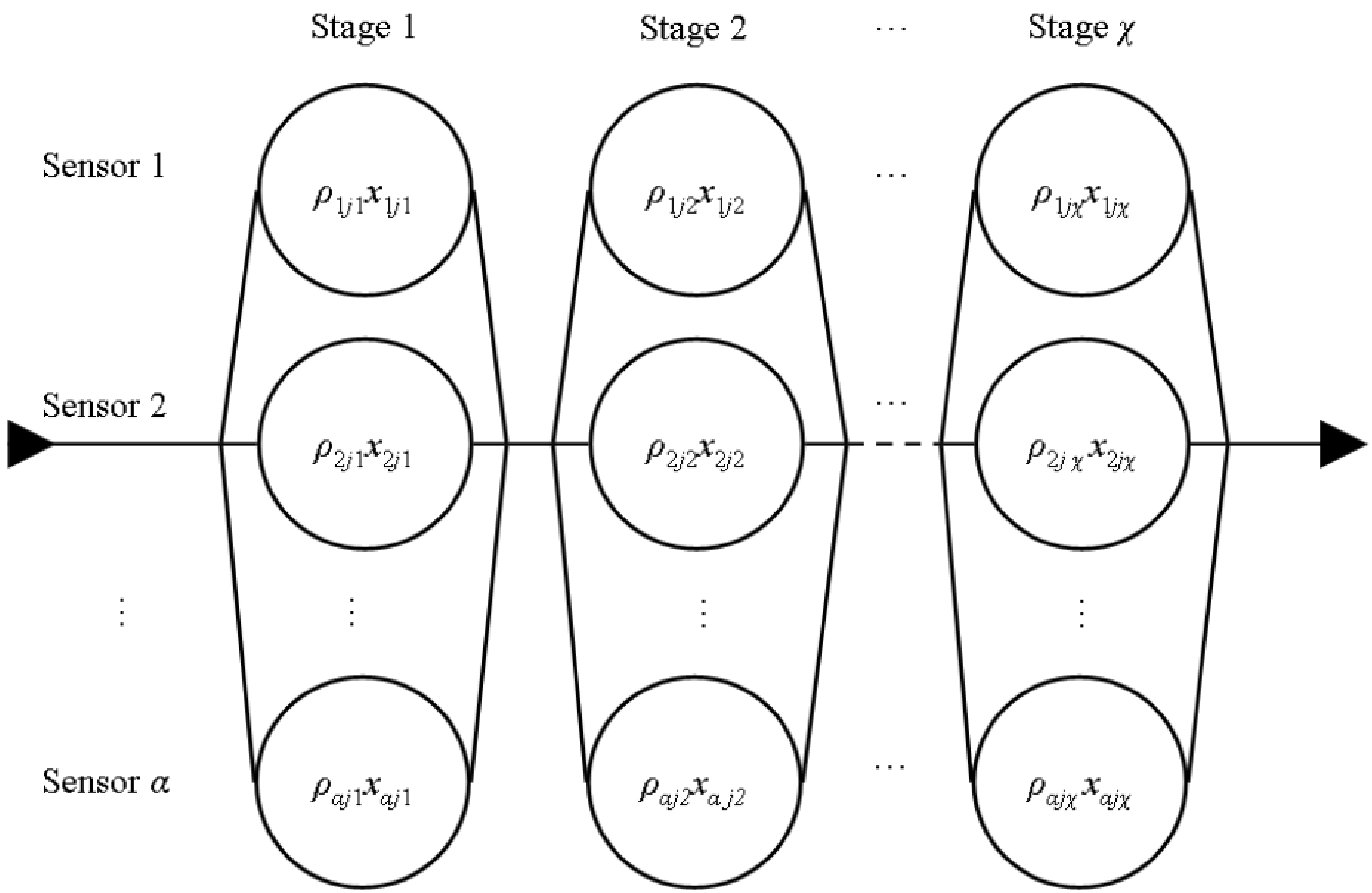
- Formulation of Maximum Utility Sensor Assignment Problem (MUSAP) as an IP
- Solution techniques
  - Explicit enumeration
  - Heuristics (Simulated Annealing)

Model Formulation

$$x_{ijk} \equiv \begin{cases} 1 & \text{if sensor } i \text{ is assigned to mission } j \text{, at stage } k \\ 0 & \text{otherwise.} \end{cases}$$

- Decision Variables
  - Current formulation assumes any sensor can do any mission at any stage
  - Each assignment has a probability of success, ρ_{ijk}

Building the Objective Function



- General bridge structure network for a single mission
  - Assumes independence of stages and sensors

Building the Objective Function

$$1 - \prod_{i=1}^{\alpha}(1 - \rho_{ijk}x_{ijk})$$

Probability of success at an individual stage

$$\prod_{k=1}^{\chi}\left(1 - \prod_{i=1}^{\alpha}(1 - \rho_{ijk}x_{ijk})\right)$$

Probability of success at an individual mission

$$\sum_{j=1}^{\beta} w_j \left(\prod_{k=1}^{\chi}\left[1 - \prod_{i=1}^{\alpha}(1 - \rho_{ijk}x_{ijk})\right]\right)$$

Mission probabilities aggregated into a weighted-sum scalarized objective function

Constraining the Space

$$\sum_{i=1}^{\alpha}\sum_{j=1}^{\beta} x_{ijk} \leq \alpha \ \ \forall\, k = 1, 2, \ldots, \chi$$

Do not assign more sensors than are available at a given stage

$$\sum_{j=1}^{\beta} x_{ijk} \leq 1 \ \ \forall\, i = 1, 2, \ldots, \alpha, \ \ k = 1, 2, \ldots, \chi$$

Do not assign a sensor to more than one mission at a given stage

Complete Formulation of MUSAP

$$\max \sum_{j=1}^{\beta} w_j \left(\prod_{k=1}^{\chi} \left[1 - \prod_{i=1}^{\alpha} (1 - \rho_{ijk} x_{ijk}) \right] \right)$$

subject to:

$$\sum_{i=1}^{\alpha} \sum_{j=1}^{\beta} x_{ijk} \leq \alpha \quad \forall \quad k = 1, 2, \ldots, \chi$$

$$\sum_{j=1}^{\beta} x_{ijk} \leq 1 \quad \forall \quad i = 1, 2, \ldots, \alpha, \quad k = 1, 2, \ldots, \chi$$

$$x_{ijk} \in \{0, 1\} \quad \forall \quad i = 1, 2, \ldots, \alpha, \quad j = 1, 2, \ldots, \beta, \quad k = 1, 2, \ldots, \chi$$

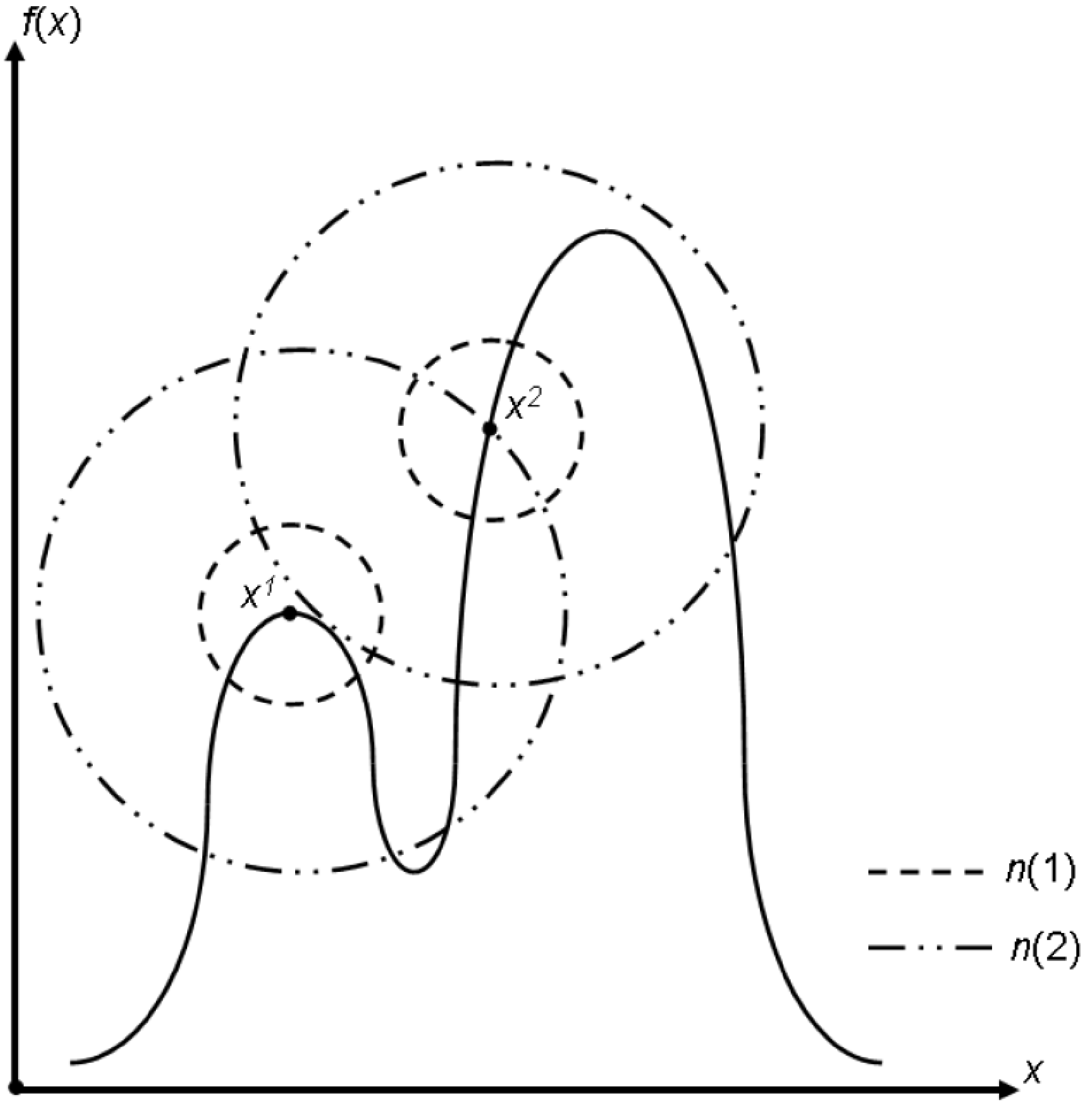
Intractability of test Problems

sensors	missions	stages	number of points
10	4	4	1.05×10^6
10	7	4	2.82×10^8
20	8	4	1.15×10^{18}
20	14	4	8.37×10^{22}
30	12	4	2.37×10^{32}
30	21	4	4.64×10^{39}
40	16	4	1.46×10^{48}
40	28	4	7.70×10^{57}

Heuristic Techniques

- Construction Heuristics
  - Greedy Individual and Greedy Marginal
- Local Search
  - Simulated Annealing (with several parameter settings)
- Combining Greedy Construction algorithms with Local search is a method called GRASP (Feo and Resende 1989)

Neighborhoods



Experimental Settings

Experimental Factors			
neighborhood	γ	starting point	diversify after
1-swap	0 (Simple Ascent)	marginal	50%
2-swap	0.9 (Simulated Annealing)	individual	75%
3-swap	0.8 (Simulated Annealing)	-	never
-	0.7 (Simulated Annealing)	-	-

- 72 total algorithms

  (3 x 4 x 2 x 3 = 72)

Full Enumeration

- Provides a baseline from comparison of heuristics techniques
- Generally takes a large number of function evaluations
  - Every point must be examined
- Not practical for implementation

Simulated Annealing Implimentation

Aggregate Results												
	Diversification Rule			Neighborhood			γ				Construction	
dist	50%	75%	never	1-swp	2-swp	3-swp	0.9	0.8	0.7	0	Mrg	Ind
10%	94.9%	94.8%	94.9%	91.2%	95.6%	97.9%	99.0%	96.6%	95.0%	88.9%	95.0%	94.8%
5%	86.6%	86.9%	87.8%	82.9%	89.1%	89.4%	88.4%	88.2%	87.2%	84.7%	86.9%	87.4%
1%	12.9%	14.2%	17.4%	16.1%	17.8%	10.6%	9.8%	14.0%	15.3%	20.1%	13.5%	16.1%

Table B.3 Aggregate results for problem size 10×4×4

Aggregate Results												
	Diversification Rule			Neighborhood			γ				Construction	
dist	50%	75%	never	1-swp	2-swp	3-swp	0.9	0.8	0.7	0	Mrg	Ind
10%	7.1%	7.3%	7.4%	3.8%	8.2%	9.7%	9.6%	5.0%	3.4%	10.9%	6.7%	7.7%
5%	0.4%	0.4%	0.5%	0.1%	0.5%	0.6%	0.5%	0.2%	0.2%	0.8%	0.3%	0.5%
1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Table B.5 Aggregate results for problem size 10×7×4

Sensor sparse networks have much worse results

Initial Results

- 10 x 4 x 4 network does well
- 10 x 7 x 4 network does poorly
  - Even with 7x the iterations
- Re-evaluating the SA algorithm
  - If the last sensor is removed from any individual mission's stage, the mission fails
  - A failed mission is very difficult to recover to a successful stage
  - Many local optima are created
  - Move evident in "sparse" vs. "saturated" networks
- Modification prevents "auto-fails" the every mission and stage has at least one sensor
  - This eliminates the "greedy individual constructions"
  - Only 36 algorithms to consider

Modified Algorithm (Saturated Network)

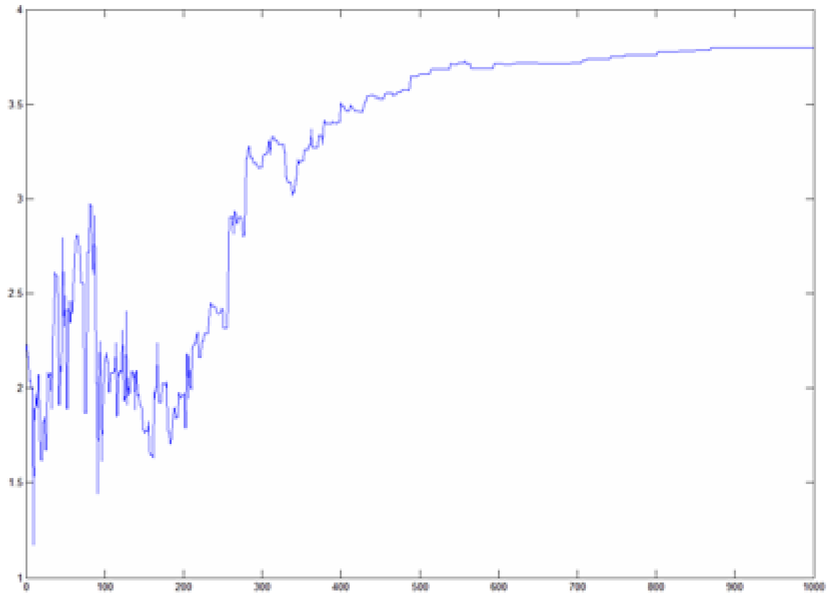
Aggregate Results										
	Diversification Rule			Neighborhood			γ			
dist	50%	75%	never	1-swp	2-swp	3-swp	0.9	0.8	0.7	0
10%	99.6%	99.7%	99.7%	99.3%	99.9%	99.8%	99.6%	99.6%	99.7%	99.7%
5%	91.1%	91.6%	92.2%	89.7%	93.5%	91.7%	89.7%	90.5%	91.8%	94.5%
1%	12.2%	14.2%	17.1%	15.7%	18.2%	9.7%	9.9%	14.7%	16.1%	17.3%

Table B.7 Aggregate results for problem size 10×4×4: Algorithm Modification

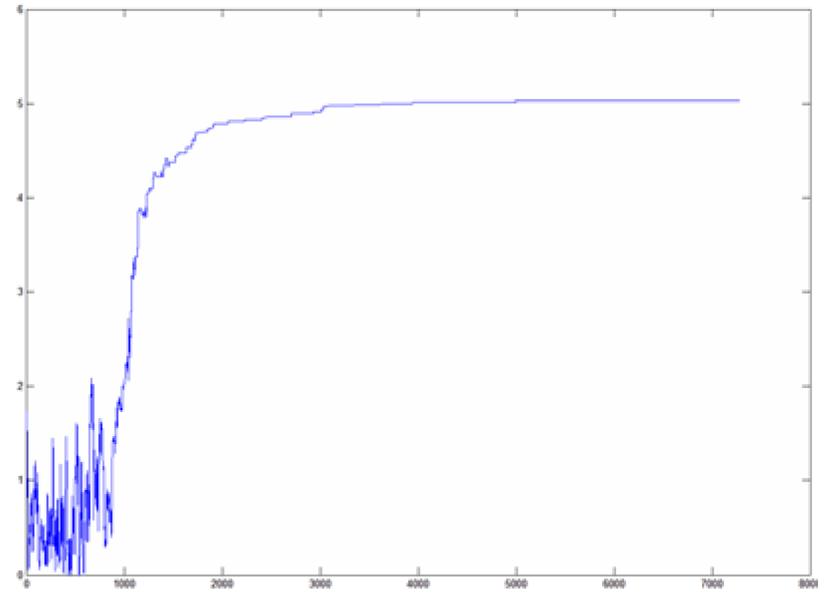
Aggregate Results										
	Diversification Rule			Neighborhood			γ			
dist	50%	75%	never	1-swp	2-swp	3-swp	0.9	0.8	0.7	0
10%	60.5%	60.2%	61.3%	47.8%	71.0%	63.1%	63.9%	60.7%	60.0%	58.0%
5%	21.5%	21.7%	24.4%	16.3%	31.2%	20.0%	23.4%	21.9%	22.2%	22.5%
1%	0.6%	0.8%	1.2%	0.5%	1.5%	0.5%	0.7%	0.7%	0.8%	1.1%

Table B.9 Aggregate results for problem size 10×7×4: Algorithm Modification

Simulated Annealing Convergence



10x4x4 Network



10x7x4 Network

Overall Heuristics Observations

- Algorithm Type and Cooling Schedule
  - SA with a cooling schedule of 0.9 produces the highest quality results only in the sparse networks
  - In saturated networks, the Simple Ascent algorithm is more effective at returning high quality solutions.
  - May be because sensor saturated networks have far less local optimal than the sensor sparse networks

Overall Heuristics Observations

- Neighborhood Functions
  - 1-swap and 2-swap neighborhoods proved to be the best neighborhoods by consistently performing well in the test problems
  - Larger neighborhoods performed very poorly, especially in the larger problem sizes
  - In the larger neighborhoods, there are many different points to search with higher n-swap neighborhoods such that the probability of finding improving moves is smaller
  - In this case, the simpler methods are better.

Overall Heuristics Observations

- Diversification Rules
  - “Never diversify” is the best rule
  - Implication for MUSAP is that starting off with a strategy and utilizing it throughout, the algorithm performs much better than attempting to switch midstream.
  - Does not rule out the possibility of using a different type of diversification strategy that doesn't use the "switch after certain percentage of iterations" rule.

Conclusions

- This research has formulated the USSTRATCOM's sensor assignment problem as a type of resource allocation problem.
  – Shown the utility of simulated annealing and simple ascent (iterative improvement) to solve that formulation.
  – As the problems became more complex, simulated annealing with geometric cooling schedules emerged as the most effective algorithm

Recommended Future Research

- Inserting Dependant Probabilities
  - Another effort has created this function
- Simulated Annealing Parameter Specification
  - 10x outer loop / inner loop ratio could be changed
- Varying Weights
  - Mission Drop thresholds
- Other Heuristics Techniques
  - GA has been successful in the single variable case