Process Refinement using Biosensor Location Problem

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Abstract - Complex biological sensor performance drives the decisions of which sensors to include into the tiered testing approach of a combined sensor system to achieve high confidence results. The goal is to decrease the “time to confirmation” while increasing confidence in the test results. This research develops a mathematical formulation for solving the Biosensor location problem derived with an Ontological approach toward Sensor Management. Initially an Integer Programming formulation is developed in order to obtain an optimal sensor allocation for a given area utilizing the Ontology information of the biosensors. However, due to the combinatorial nature of the problem, the storage and solution time requirement to solve the IP Model grows exponentially with the size of the problem. We have developed two heuristic models to obtain good solutions to the sensor location problem. Then we have statistically analyzed the various parameters on sensor locating cost and heuristic running time.

Keywords: Biosensor Location Problem, Ontology, Process Refinement, Heuristic, Statistical Analysis, Design of Experiment (DOE).

1 Introduction

The high level objective of the proposed research is to investigate and provide a proof-of-concept demonstration of how to approach the Biosensor Fusion process as a Systems Optimization. Recent work on Biosensor Fusion is disjointed and compartmentalize at each technical challenge of a very complex problem. For example the Biosensor designers might not consider the communication bandwidth issues and fusion algorithms might not take into account the human decision-makers processing limitations. So we will try to take a systems approach in deciding the following questions: Where to locate sensors? What sensors to locate? How to configure sensors? When to locate the sensors or extract the data? The answer to all these questions will be done by trying to consider all aspects of the Fusion process.

To be able to answer a number of questions on Biosensors, we need to be able to have a clear understanding on the sensors themselves. In particular, the understanding of the capabilities of the sensor suite, will enable us to develop more meaningful and useful fusion algorithms to aid the decision makers. So the first thing we will develop under this program is an Ontology of Biosensors.

Then we will develop a mathematical model that will maximize the different dynamic variables of sensors (i.e. where to locate, how to configure, when to extract) subject to a number of constraints. This process will take into account a number of conflicting system requirements that need to work together to attain a solution that will satisfy a multi-criteria decision-making process. Some of the factors that will be included in the model are:

- Type of sensors and class of agents that can be detected.
- False Positives and False Negatives
- Spoofing Vulnerability
- Response Time
- Power Consumption
- Sensitivity
- Pedigree

2 Biosensor Ontology

The first thing we developed in this research program is an Ontology of Biosensors. The objectives of this task in this endeavor is to decompose the Biosensors to understand a schema that will be applicable to existing sensors as well as allow for the inclusion of future developed sensors. It will help us to have a clear understanding on the sensors themselves. In particular, the understanding of the capabilities of the biosensor suite will enable us to develop more meaningful and useful fusion algorithms to aid the decision makers.

Biological weapons (also known as biological agents) include bacteria (e.g. anthrax), viruses (e.g. smallpox) and toxins (e.g. ricin) that are spread deliberately in air, food or water to cause widespread damage and destruction. Hence timely detection of the presence of these agents is very important for prevention of bioterrorist attacks. Based on the data available [1][2][3] for existing biosensors, 33 biosensors were identified for the Ontology. Based on their mobility type, there were 8...
handheld biosensors, 9 Mobile Lab biosensors, 12 Fixed Site biosensors and 4 Standoff biosensors.

In this research we use OWL Ontology with Protégé-OWL editor and reasoned called “RACER”. OWL (Noy and McGuinness, 2001) is a web Ontology language intended to be used when the information contained in documents needs to be processed by applications, as opposed to situations where the content only needs to be presented to humans. Protégé is a free, open source ontology editor and knowledge-base framework.

3 Biosensor location problem

The Biosensor Location problem is a part of Sensor Location Problem (SLP) which has been extensively studied in the literature. Sensor Location Problem (SLP) is the problem of choosing an appropriate mix of sensors and decide where to locate them for best protection and early warning. Early warning is critical and this is a crucial factor underlying the plan to place networks of sensors to warn of a bioterrorist attack.

The SLP is being addressed in literature by many authors. It has been applied by Cavalier et al. [4] to locate sensors while minimizing the maximum probability of non-detection. This problem is very popular in traffic Network applications [5][6][7]. Some researchers consider sensor location problem in wireless networks [8][9][10]. Sensor technology is changing rapidly and sensors come with a variety of characteristics. A good sensor location methodology should not be dependent upon particular sensor technologies.

Some of the questions which we want to answer are: Given a mix of available sensors and a fixed budget (cost), what mix will best accomplish our goals? Will the methods we develop be independent of today’s technology? How to take care of the differences among sensors, like: response time, accuracy and reliability, stationary vs. mobile, constraints on their location, cost, etc. How is the sensor data reported, do humans physically examine collection devices or is the data electronically reported? Do the sensors report data discretely or continuously? Some other modeling issues to be considered are probability of release at different locations, geography, buildings, weather, population distribution, etc. These are some of the questions which we will try to address while formulating the Biosensor location problem in Section 4.

4 Problem Formulation

To solve the problem of Biosensor Location we develop an optimal mathematical model which is an Integer Problem (IP). The Integer formulation is not described here to conserve space. The details of the formulation are described in our past research papers [11][12][13][14]. The mathematical model developed fails to generate a solution within a reasonable amount of time for large instances of the problem; therefore we have developed a heuristic approach to allocate sensors.

4.1 Heuristic

The objective of the heuristic remains the same; minimizing the cost of allocating sensors to the region under consideration while satisfying the sensitivity constraints. We have developed two heuristics, I and II, which are respectively further described in sub-sections 4.2.1 and 4.2.2.

4.1.1 Heuristic I

We would like to allocate the appropriate mix of sensor combination to the region under consideration with minimum cost while satisfying the sensitivity constraints with respect to the attack probability of all potential agents. The steps of the allocation method are described below. For each grid over the area of consideration, a sensor preference list is created. This list ranks the available sensors based on the sensor cost versus the incremental coverage benefit obtained by allocating that particular sensor into the grid under consideration.

Notation

Sets:
P = sensor preference list for a grid,
S = set of sensors,
A = set of agents,
G = set of grids,

Heuristic Steps:
1. Get a grid k’ that has not visited yet and initialize the preference list P as empty set.
2. Set the available sensor set S as entire sensor list.
3. Set the available agent set A as entire agents considered.
4. Develop the preference list of the grid k’ according to the subroutine below:
   a. Get a sensor i’ from the available sensor set S and set its priority value (pv) to 0.
   b. Get agent j’ from the agent set A.
   c. For grids l’ that are neighbor grids of k’ within the range of sensor i’, check \( \alpha_{i'j'k'} \geq \alpha_{i'j'k} \).
   d. Each time the inequality is satisfied, increase pv by 1.
   e. Iterate through the entire agent list A.
   f. Calculate the preference index of the sensor k’ as \( \frac{C_{ik'}}{pv} \).
   g. Locate sensor into preference list according to its preference index value; sensors are ranked in the preference list in ascending order of pv values.
   h. Remove sensor i’ from S and restart the subroutine until all sensors are evaluated.
5. Rank grids under consideration in a descending order according to their $P_{ij}$ values into grid set $G$.
6. Get first entry $k$ from $G$.
7. Assign sensors from the preference list of $k$ until all the coverage requirements are met.
8. Remove $k$ from set $G$
9. If $G$ is empty, terminate the procedure. Otherwise, return to step 6.

### 4.1.2 Heuristic II

Three criteria should be considered when selecting and locating a sensor.

- **Cost**
- **Coverage area**
- **Sensitivity for agents**
- **Life time**

A good sensor is considered to have a low cost, large coverage, high sensitivity for almost all agents, and long life time. Under this consideration, a critical value is developed, which is $v(i, k) = \frac{\sum_{j,l} \alpha_{ijkl}}{C_{ik}} \sum_{j} \delta_{jl} LT_{i} - \text{penalty}$. From the critical value formulation, each $(i, k)$ is evaluated. A $(i, k)$ is a scenario, meaning sensor $i$ is located at cell $k$. If the critical value for $(i, k)$ is a large value, the scenario of locating sensor $i$ at cell $l$ is considered to be a good selection. If an agent in a cell, which is denoted by $(j, l)$, is already covered by a sensor, we do not have to consider this $(j, l)$ when calculating critical values for $(i, k)$s. In this sense, we should modify the formulation of critical value a little, which is:

$$v(i, k) = \frac{\sum_{j,l} \alpha_{ijkl}}{C_{ik}} \sum_{j} \delta_{jl} LT_{i} - \text{penalty}$$

where $(j, l)$ SET is a set of $(j, l)$ which is not covered by any sensor. **Penalty** is to be used to guarantee the feasibility of our heuristic if the problem has at least a feasible solution. Therefore, the procedure is simply to select the $(i, k)$ whose critical value is the highest among all $(i, k)$ and which satisfies two constraints as follows:

$$\alpha_{ijkl} \geq \alpha'_{j} \frac{P_{ij}}{P_{n}} \quad (1)$$

$$\frac{24}{T_{ijkl}} \geq \frac{24P_{ij}}{P_{n}} \quad (2)$$

**Notation**
- Sets:
  - $W^{n}$ = set of $(j, l)$ combination which is not covered by any sensor yet at iteration $n$,
  - $L^{n}$ = set of $(j, l)$ where all constraints are satisfied by a $(i, k)$ pair at iteration $n$
- Decision variables:
  - $Q_{ijkl}$ = number of times we sample for sensor $i$ which is located at cell $k$ for cell $l$ in order to detect agent $j$,
  - $y_{ikl}$ = number of times we take samples at cell $l$ for sensor $i$ which is located at cell $k$,
  - $\overline{y}_{ki}$ = number of times we take samples at cell $l$ for all sensors which are located at cell $k$.

**Heuristic Steps:**
1. **Initialization.**
   a. Iteration number $n=1$.
   b. $W^{1}$ involves all $(j,l)$ pairs.
   c. $L^{1} = \Phi \forall n$.
   d. $X_{ik} = 0, Q_{ijkl} = 0, y_{ikl} = 0, \overline{y}_{ki} = 0, \forall i,j,k,l$.
2. Calculate the critical value

$$v(i, k) = \frac{\sum_{j,l} \alpha_{ijkl}}{C_{ik}} \sum_{j} \delta_{jl} LT_{i} - \text{penalty}$$

for each $(i, k)$ pair at $n$.

where

$$\text{penalty} = \begin{cases} \text{a large number} & \text{if constraints (1) and (2)} \text{ are not satisfied for all } (j, l) \in W^{n} \\ 0 & \text{otherwise} \end{cases}$$

3. Pick up the $(i, k)$ pair with the highest critical value among all the $(i, k)$ pairs and denote it by $(i*, k*)$. Set $x_{i*,k} = 1$.
4. Check Constraints 1 and 2 for each $(j, l)$ pair.

If both Constraints 1 and 2 are satisfied for a $(j, l)$ pair, then include $(j, l)$ pair in set $L^{n}$.
5. $Q(i*)j(k*)l = \left\lfloor \frac{24P_{ij}}{P_{n}} \right\rfloor \forall (j, l) \in L^{n}$.
6. $W^{n+1} = W^{n} - L^{n}$
   - If $W^{n+1} = \Phi$, STOP. Set $\overline{y}_{ki} = \max_{i,j,k,l}(Q_{ijkl})$.
   - Otherwise, $n = n + 1$.
7. If $n = \text{number of agents*number of cells}$, STOP.

Infeasible solution. Otherwise go to step 2.

The total cost obtained from the heuristic is

$$\text{Total Cost} = \sum_{i} \sum_{k} \frac{C_{ik}}{LT_{i}} x_{ik} + \sum_{i} \sum_{k} (SC_{ijkl} \overline{y}_{ki})$$

**Lemma:** Heuristic II can find a feasible solution if only if the problem has at least one feasible solution.

**Proof:** Base on the critical value formula, if there exists a feasible solution, the largest $v(i, k)$ is positive at each iteration before the termination of Heuristic II, which means, at each iteration, at least one $(j, l)$ is covered. The procedure continues until all $(j, l)$s are covered, meaning a feasible solution is found. The largest possible number of iteration is agents number * cells number if the problem is feasible.

**Computational Complexity:**
Define
- $I$: number of sensors type
- $J$: number of agents type
- $K$: number of cells within the map

Computational time is $O((IJK)^{2}P)$
5 Solution Analysis

The two heuristics are applied over the complete Biosensor Ontology developed in Section VII, and we obtain a feasible solution in less than a minute. We can obtain an optimal solution of location problem (PLo) by CPLEX 9.0, which is $6172.2/day. Heuristic I provide a weak solution, which is $8181.0, and the optimality gap between the optimal solution ($6172.2/day) is 32.6%. Heuristic II provides a much better result. The location cost is $6370.2 with a 3.1% optimality gap and the total cost including location and sampling is $14462.5. The solution of sensors location is shown in Figure 1. The small case shown in section VI is also solved by Heuristic II. The solution is obtained in 1 second. The sensor location cost is $142.2 with a 0.2% optimality gap and the total cost including locating and sampling is $2022.5 which is better than $2061.1, a feasible solution found by CPLEX using 3893 seconds. The reason why Heuristic I works weakly is that the preference of a particular sensor for a particular grid is not updated in the process of assigning.

Heuristic Solution.

5.1 Computational Test

We increase the number of grid size and perform a computation test for both small examples (i.e. 2 agents and 4 sensors) and ontology information examples (i.e. 23 agents and 33 sensors). All the computational tests are performed based on parameters setting shown in Table 1. The results of the test are shown in Tables 2 and 3. From Table 2, we can conclude that Heuristic II works well although in some cases the optimality gap is a little high. From Table 3, it is very clear that Heuristic I works inferiorly, while Heuristic II works pretty good and the optimality gap is about 4%. The improvement from Heuristic I to II is huge.

Table 1. Parameters Setting for Computational Test.

<table>
<thead>
<tr>
<th>Grid Size</th>
<th>CPLEX Solution</th>
<th>Heuristic II Solution</th>
<th>% Optimality Gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>2*2</td>
<td>13.6</td>
<td>16.6</td>
<td>18.07</td>
</tr>
<tr>
<td>3*3</td>
<td>13.6</td>
<td>13.6</td>
<td>0.00</td>
</tr>
<tr>
<td>4*4</td>
<td>52.2</td>
<td>56.7</td>
<td>7.94</td>
</tr>
<tr>
<td>5*5</td>
<td>54.4</td>
<td>60.6</td>
<td>10.23</td>
</tr>
<tr>
<td>6*6</td>
<td>54.4</td>
<td>54.4</td>
<td>0.00</td>
</tr>
<tr>
<td>8*8</td>
<td>122.5</td>
<td>128.6</td>
<td>4.74</td>
</tr>
<tr>
<td>10*10</td>
<td>213.3</td>
<td>226.7</td>
<td>5.91</td>
</tr>
<tr>
<td>15*15</td>
<td>340.3</td>
<td>340.3</td>
<td>0.00</td>
</tr>
<tr>
<td>25*25</td>
<td>1092.5</td>
<td>1128.1</td>
<td>3.16</td>
</tr>
</tbody>
</table>

Table 2. Computational test for small examples (4 sensors, 2 agents).

<table>
<thead>
<tr>
<th>Grid Size</th>
<th>CPLEX Solution</th>
<th>Heuristic II Solution</th>
<th>% Optimality Gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>2*2</td>
<td>13.6</td>
<td>16.6</td>
<td>18.07</td>
</tr>
<tr>
<td>3*3</td>
<td>13.6</td>
<td>13.6</td>
<td>0.00</td>
</tr>
<tr>
<td>4*4</td>
<td>52.2</td>
<td>56.7</td>
<td>7.94</td>
</tr>
<tr>
<td>5*5</td>
<td>54.4</td>
<td>60.6</td>
<td>10.23</td>
</tr>
<tr>
<td>6*6</td>
<td>54.4</td>
<td>54.4</td>
<td>0.00</td>
</tr>
<tr>
<td>8*8</td>
<td>122.5</td>
<td>128.6</td>
<td>4.74</td>
</tr>
<tr>
<td>10*10</td>
<td>213.3</td>
<td>226.7</td>
<td>5.91</td>
</tr>
<tr>
<td>15*15</td>
<td>340.3</td>
<td>340.3</td>
<td>0.00</td>
</tr>
<tr>
<td>25*25</td>
<td>1092.5</td>
<td>1128.1</td>
<td>3.16</td>
</tr>
</tbody>
</table>

5.2 Sensitivity Analysis

If we change the threshold for population contaminated (P"), the total cost will change as well. If we tighten the population contaminated threshold, i.e. reduce the number of population contaminated we can accept, the total cost tends to increase. If the constraint is too tight, the problem could be infeasible. Because we need some time at least for analyzing the sample, the population contaminated over analyzing time should be acceptable if the problem is guaranteed to be feasible. If we relax the threshold to some degree, the total cost tends to decrease. We perform the sensitivity analysis for the population contaminated threshold based on Buffalo area in which ontology information is obtained and all parameters setting is kept same in section VI. This result is shown in Table 4. In the table, Total Cost is the cost of locating sensors and sampling. From the result, we can conclude that with the increasing of the value of P", the total cost including location of sensors and sampling decreases and finally reaches the lowest value, 8578.3.

6 Wind Effect to Solution

If wind effect is considered, the parameter α'jl increases. Figure 2 illustrates an example of southern wind at Buffalo area. Note that the value of α'jl without wind effect is 0.73 for all cells. In Figure 2, the value of α'jl in north part of Buffalo area increases.
Table 3. Computational test for Ontology information (33 sensors, 23 agents).

<table>
<thead>
<tr>
<th>Grid Size</th>
<th>CPLEX Solution (1)</th>
<th>Heuristic I (2)</th>
<th>% gap ((2)-(1))/(2)</th>
<th>Heuristic II (3)</th>
<th>% gap ((3)-(1))/(3)</th>
<th>Improvement ((2)-(3))/(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2*2</td>
<td>561.1</td>
<td>612.4</td>
<td>8.38</td>
<td>584.7</td>
<td>4.04</td>
<td>4.52</td>
</tr>
<tr>
<td>3*3</td>
<td>561.1</td>
<td>1133.3</td>
<td>50.49</td>
<td>584.7</td>
<td>4.04</td>
<td>48.41</td>
</tr>
<tr>
<td>4*4</td>
<td>952.8</td>
<td>2244.4</td>
<td>86.56</td>
<td>937.6</td>
<td>4.04</td>
<td>59.74</td>
</tr>
<tr>
<td>5*5</td>
<td>952.8</td>
<td>3301.3</td>
<td>52.97</td>
<td>999.9</td>
<td>4.71</td>
<td>69.71</td>
</tr>
<tr>
<td>6*6</td>
<td>3301.3</td>
<td>32.01</td>
<td>100.00</td>
<td>2338.7</td>
<td>4.03</td>
<td>79.61</td>
</tr>
<tr>
<td>8*8</td>
<td>NFSF</td>
<td>6685.9</td>
<td>NA</td>
<td>3031.6</td>
<td>NA</td>
<td>54.66</td>
</tr>
<tr>
<td>10*10</td>
<td>NFSF</td>
<td>11360.8</td>
<td>NA</td>
<td>4078.7</td>
<td>NA</td>
<td>64.96</td>
</tr>
<tr>
<td>15*15</td>
<td>NFSF</td>
<td>35077.9</td>
<td>NA</td>
<td>7727.8</td>
<td>NA</td>
<td>77.97</td>
</tr>
<tr>
<td>25*25</td>
<td>NFSF</td>
<td>110077.9</td>
<td>NA</td>
<td>23235.3</td>
<td>NA</td>
<td>78.89</td>
</tr>
</tbody>
</table>

Table 4. Sensitivity analysis.

<table>
<thead>
<tr>
<th>P&quot;</th>
<th>Location</th>
<th>Total Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>infeasible</td>
<td>Infeasible</td>
</tr>
<tr>
<td>25</td>
<td>6370.2</td>
<td>14462.5</td>
</tr>
<tr>
<td>30</td>
<td>6370.2</td>
<td>14382.5</td>
</tr>
<tr>
<td>35</td>
<td>6370.2</td>
<td>13069.6</td>
</tr>
<tr>
<td>40</td>
<td>6370.2</td>
<td>12096.8</td>
</tr>
<tr>
<td>45</td>
<td>6370.2</td>
<td>12096.8</td>
</tr>
<tr>
<td>50</td>
<td>6370.2</td>
<td>10863.9</td>
</tr>
<tr>
<td>55</td>
<td>6370.2</td>
<td>10863.9</td>
</tr>
<tr>
<td>60</td>
<td>6370.2</td>
<td>10863.9</td>
</tr>
<tr>
<td>65</td>
<td>6370.2</td>
<td>10783.9</td>
</tr>
<tr>
<td>70</td>
<td>6370.2</td>
<td>10783.9</td>
</tr>
<tr>
<td>75</td>
<td>6370.2</td>
<td>9891.2</td>
</tr>
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<td>100</td>
<td>6370.2</td>
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<tr>
<td>200</td>
<td>6370.2</td>
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<td>8578.3</td>
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<tr>
<td>INF</td>
<td>6370.2</td>
<td>8578.3</td>
</tr>
</tbody>
</table>

$6800.8/day (> $6370.2).

Figure 2. Parameter value with southern wind.

Base on values of parameter $\alpha'_j$ in Figure 2, the heuristic solution is shown in Figure 3. The objective value is $6800.8/day (> $6370.2).

Figure 3. Heuristic solution with southern wind.

7 DOE for biosensor location problem

7.1 Introduction and factors setting

For a biosensor location problem, the locating cost for sensors, which are responsible for detecting biological attacking agents, is the objective to be minimized within a threshold of population sacrifice. Due to the large size and computational complexity of the problem, a heuristic is developed. Heuristic can find a “good” solution with a small optimality gap in a short time. The running time is another issue we concern. There are some factors which could affect the locating cost and heuristic running time. The situation where a factor is significant or not for cost and time should be explored, which motivates to do a design of experiment (DOE).

In our problem, there are altogether five factors: population importance, population sacrificed per hour, wind impact, attacking probability, and map size. There are two responses in our design, which are locating cost and heuristic running time. The following shows the responses, factors, and factor levels in DOE. Note that if
wind impact is at high-level, there are eight wind directions that could occur. We use these wind directions as replications of DOE. Therefore, there are 256 (2^8) runs with 8 replications per treatment level.

Response:
1. Locating Cost
2. Heuristic Running Time

Factors:
1. \( P \): population importance
2. \( P \): population sacrificed per hour
3. wind impact
4. \( \alpha' \): attacking probability
5. map size

Factors 2-level setting

\[
\begin{array}{ll}
\text{Low Level} & \text{High Level} \\
\hline
P & \text{Unif}(0,0.3) \quad \text{Unif}(0.5,0.8) \\
P & \text{Unif}(0,3) \quad \text{Unif}(5,8) \\
\text{wind} & \text{No} \quad \text{Yes} \\
\alpha' & \text{Unif}(0,0.3) \quad \text{Unif}(0.5,0.8) \\
\text{map size} & 6*6 \quad 12*12 \\
\end{array}
\]

Minitab statistical software is used in our analysis. The results are separated by different response (i.e. cost and running time) and shown as follows based on 95% confidence interval.

### 7.2 Results and Analysis

#### 7.2.1 Result I (Response: Locating Cost)

The ANOVA table for locating cost is not shown here for lack of space. If \( p \)-value is less than 0.05, the corresponding effect is significant, otherwise it is not significant. Bases on the table above, only interactions:

- \( \text{wind*alpha pri*P} \)
- \( \text{wind*mapsize*alpha pri*P} \)
- \( \text{wind*alpha pri*P_bar*P} \)
- \( \text{wind*mapsize*alpha pri*P_bar*P} \)

are insignificant. The normal probability plot in Figure 1 shows the significant effects.

The following plots show the main effects and interactions. In Figure 5, cost increases as you move from the low level to the high level of the factor. The increase due to mapsize factor is the greatest, while the increase due to population sacrificed is the smallest. Since almost all interactions are significant, we should be sure to understand this interaction before making any judgments about the main effects. Figure 6 shows the two-way interaction plot. The angle that two lines makes represent the degree of significance of this two-way interaction. For example, the interaction of alpha pri*P_bar is greatly significant. If alpha pri is at low-level, there is almost no increase of cost if we move from low-level to high-level of P_bar. But if alpha pri is at high-level, there is a large increase of cost in response to the moving from low-level to high-level of P_bar.

![Figure 4. Normal Probability Plot for Locating Cost.](image1)

![Figure 5. Main Effect Plot for Locating Cost.](image2)

![Figure 6. Interaction plot for Locating Cost.](image3)
7.2.2 Result II (Response: Running Time)

The ANOVA table for running time is shows that most of the effects are significant which is similar with the situation where the DOE response is cost. Again, we use normal probability plot (Figure 9) to clearly show the significant effects.

From Figures 10 and 11, we can conclude that the results from response locating cost and response running time are very similar due to the heuristic mechanism. The heuristic allocates sensors one by one. If more sensors are located, a larger cost is incurred and running time is increased as well.

8 Conclusions

It’s not easy to locate sensors, since networks of sensors are expensive. The ways to locate them to maximize “coverage” and expedite an alarm are not easy to determine. To study the overall performance of a Biosensor system we study in depth; capabilities of the sensor suite, which will enable us to develop more meaningful and useful fusion algorithms to aid the decision makers. From this a mathematical framework is created to evaluate the system level performance of an integrated suite of sensors to determine the sensitivity and specificity of the system. The mathematical model maximizes the different dynamic variables of sensors subject to a number of constraints. This process takes into account a number of conflicting system requirements that need to work together to attain a solution that will satisfy a multi-criteria decision-making process. Based on the
analysis on locating cost and heuristic running time with respect to factors of population importance, population sacrificed per hour, wind impact, attaching probability, and map size, all factors are significant to locating cost and heuristic running time by a 95% confidence interval. Furthermore, those five factors are highly interactive significantly. Results of the holistic methodology we have adopted would contribute towards mitigating biological threats and help us in emergency preparedness and response areas.

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References


