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A Computational Fluid Dynamics Approach for Optimization of a Sensor Network

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Abstract – *We optimize the placement of sensors for detecting a nuclear, biological, or chemical (NBC) attack in a dense urban environment. This approach draws from two main areas: (1) computational fluid dynamic (CFD) simulations and (2) sensor placement algorithms. The main objective was to minimize detection time of a NBC sensor network for attacks on a generic urban environment. To this end we conducted simulations in the generic urban environment using thirty-three (33) unique attack locations, thirty-three (33) candidate sensor locations, prevailing wind conditions, and the properties of the chemical agent, chlorine gas. A total of ninety-nine (99) simulated attack scenarios were created (three sets of thirty-three unique attack simulations) and used for optimization. Simulated surrogate agent concentration data were collected at each candidate sensor location as a function of time. The integration of this concentration data with respect to time was used to calculate the "consumption" of the network and the sensor placement algorithm minimized consumption to the network while minimizing the number of sensors placed. Our results show how a small number of properly placed sensors (eight(8), in our case) provides the best achievable coverage (additional sensors do not help).*

Keywords – *Homeland Security, Optimization, Sensor Networks, Sensor Placement, Computational Fluid Dynamics, Urban Dispersion.*

I. INTRODUCTION

Given recent heightened security concerns, a clear need exists for technologies to detect, classify and localize a nuclear, biological or chemical (NBC) attack in an urban environment. Currently, no such technology exists. The main objectives of the techniques described in this study are: (1) to provide accurate predictions of agent dispersion patterns following the onset of an attack; and (2) to optimize NBC sensor placement based on computational fluid dynamics (CFD) simulations.

Several U.S. government agencies have studied the design of sensor networks for homeland security purposes, most notably the Defense Threat Reduction Agency of the U.S. Army Nuclear and Chemical Agency [1]. Their efforts resulted in the development of several tools including SAFE (Sensor Analysis and Fusion Environment) and REASON (Response and Effects Analysis System for Operational Needs) [1]. CFD techniques have been widely studied for a variety of interests for the prediction of complex propagation [2] ranging from fire prediction [3], [4] aerodynamics, to air pollution systems and plasma processing [5]. The application of CFD for the prediction of NBC dispersion in urban environments is relatively new [6] and no previous research has been done on optimizing sensor placement based on the CFD simulations. By understanding how complex agents disperse in urban environments, cities will be better prepared to set up defenses against such attacks.

Using CFD for threat analysis, we present a robust placement methodology, optimized for an urban environment which aims to minimize the detection time for a contaminant in a network of sensors. The objectives are quick detection, classification, and neutralization of the threat. Our formulation takes into account detailed CFD simulations of potential attacks, the likelihood of these attacks, and total cost considerations.

The rest of the paper is organized as follows: Section II covers the background information on the sensor network design and the computational fluid dynamics. Section III explains the formulation of sensor placement algorithm. Section IV discusses the results of fallout dispersion of the CFD simulations and the optimized sensor configurations. Finally, conclusions are presented in section V. A symbol table is provided in section VI.

II. BACKGROUND

A. Sensor Network Design

Current sensor placement methodologies for target localization and surveillance applications often use grid based methods. These methods rely on the use of area sensors, which have an associated coverage area over which they are effective. Fixed sensors are deployed throughout a grid, or sensor field, such that at least one sensor covers each point in the area of interest. Chiu and Lin [7] focused on the placement of such sensors for target location based on the constraints of cost limitation and complete coverage. Dhillon's grid-based method

[8] operated under the constraints of cost limitation, imprecise detections, and terrain properties.

Our sensor placement algorithm is based on the research of Berry *et.al.* [9]. Their work employed an integer-programming based technique for sensor placement in municipal water systems. The aim of the placement methodology was to maximize the exposure of the network to potential contaminants, under cost and placement constraints. The placement constraints require perfect point sensors to be placed in the pipes and junctions of a municipal water network. Point sensors do not have an "effective area"; rather, in order to be detected the agent must pass physically through the location or "point" at which the sensor is placed. Although the propagation properties assumed in [9] differ from those of contaminants in our application, the mathematical framework is suitable for sensor placement for NBC detection of airborne contaminants (with an extension to account for the urban topology).

B. Computational Fluid Dynamics

The Department of Defense has funded the development of the FAST3D [10] and FEFLO [11] models by the Naval Research Laboratory. The Department of Energy's Lawrence Livermore National Laboratory has also developed a dispersion model called FEM3C [12]. These models are 3-dimensional CFD solvers explicitly developed for urban dispersion and transport modeling in complex geometries.

The National Institute of Standards and Technology has developed the Fire Dynamic Simulator (FDS) [13] a CFD software primarily designed to analyze fires. FDS is a multi-species, multi-variable boundary condition CFD solver that uses the large eddy simulation (LES) technique to solve the three dimensional flow. The flow is computed through a predefined mesh where agent dispersal is calculated from one mesh box to another. Accuracy of the flow can be further increased by refining the mesh size. However, there is a tradeoff between dispersal resolution and computation time. Lagrangian particles are used to visualize the flow in FDS and have been used to investigate particle-laden flows in many common industrial applications (such as atmospheric transport of pollutants). Although FDS was primarily designed to analyze fires, its predictive capabilities can be used for the simulation of chemical and biological agent dispersal [14], [15].

III. SENSOR PLACEMENT FORMULATION

We build upon the framework of Berry *et.al.* [9]. Consider a set of candidate sensor locations in an urban sensor network,

$$V = \{v_1, v_2, v_3, \ldots, v_N\}, \tag{1}$$

where N is the number of candidate sensor locations and $v_i \in V$ is a 3-dimensional position vector. Let τ be the set of discrete times for which NBC agent concentration data was recorded in the CFD simulator. A is the set of attacks, where each attack is uniquely specified by location and time. α_a is the probability that there will be an attack at $a \in A$, and

$$\sum_{a \in A} \alpha_a = 1 \tag{2}$$

For each attack, let $L_a \subseteq V$ correspond to the set of contaminated locations. This set of contaminated locations is determined from the CFD simulations by monitoring NBC agent concentration as a function of locations in the set V. We use the concentration data to determine $\omega_{a,j}$, the consumption. The symbol $\omega_{a,j}$ stands for the amount of NBC agent delivered by attack $a \in A$ to the network (i.e., all nodes in V) assuming that a sensor placed at node $j \in L_a$ was the first sensor to signal an alarm. To compute $\omega_{a,j}$, we use the initial time of attack $a \in A$, denoted by $t_{a,0}$ and the time, $t_{a,j}$, at which the attack is detected at node $j \in L_a$. Specifically, we define

$$\omega_{a,j} = \sum_{v \in V} d_v(t_{a,0}, t_{a,j}) = \sum_{v \in V} \int_{t_{a,0}}^{t_{a,j}} \gamma_{a,v}(t) dt \tag{3}$$

where $d_v(t_1, t_2)$ is the total amount of contaminant delivered to node $v \in V$ from time t_1 to t_2. $\gamma_{a,v}(t)$ represents the concentration of NBC agents, found by the CFD simulations, at node $v \in V$ during attack $a \in A$.

The decision variables for our optimization problem are: (1) the sensor placement index s_i which is 1 if a sensor is placed at node v_i and 0 if there is no sensor at that location; and (2) the first detector index $b_{a,i}$ which is 1 if a sensor at node v_i is the first sensor to react to attack $a \in A$ and 0 otherwise. A detection occurs at a candidate sensor location once the agent concentration reaches a predetermined concentration threshold. Given the above formulation, the objective function for sensor placement becomes

$$min \sum_{a \in A} \sum_{i \in L_a} \alpha_a \omega_{a,i} b_{a,i} \tag{4}$$

Subject to the following constraints:

$$\sum_{i \in L_a} b_{a,i} = 1 \quad \forall a \in A \tag{5}$$

$$b_{a,i} \leq s_i \quad \forall a \in A, i \in L_a \tag{6}$$

$$\sum_{j \in V} s_j \leq S_{MAX} \tag{7}$$

The objective function (4) minimizes consumption of NBC contaminants averaged over a set of attacks. The constraint in (5) enforces that there is exactly one best sensor for each attack. The constraint in (6) enforces that a sensor cannot be the best sensor for an attack if it is not installed, and the constraint in (7) enforces that at most S_{MAX} sensors are used.

IV. SIMULATION RESULTS

A. Fallout Dispersion

A simulation technique based on CFD was investigated in order to build a large database of attack scenarios for the urban environment. The scenarios differ by attack location and meteorological conditions. For our scenarios, FDS was used. The data collected from the simulations were then used to optimize our sensor placement algorithm.

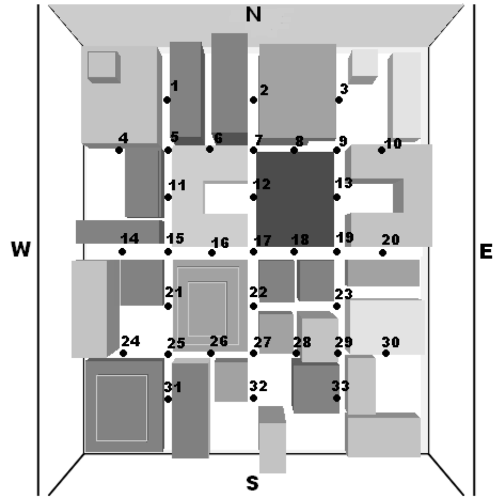
In order to optimize the sensor network, accurate predictive models are needed to compute the flow of gases and particles in the urban environment under given meteorological conditions. When studying urban air flow and dispersion, the modeling of the environment is critical to the type of results that can be achieved. An urban terrain can encompass hundreds of city blocks where the details of the environment (such as streets, buildings, and alleys) are extremely important in accurately modeling dispersion.

A generic urban environment (see Figure 1) was developed for the CFD simulator. Several observations were used to provide a realistic urban setting, namely: (1) The model contains structures of high importance that would reside in major cities, specifically: a city hall, skyscrapers, and a park; (2) The model contains residential buildings; (3) the rest of the model is occupied by generic buildings to account for stores, restaurants, and other common city structures. The environment was populated with thirty-three candidate sensor locations (see Figure 1a) placed in the streets and intersections to collect simulated concentration data as a function of time. The data were then used to compute the consumption, $\omega_{a,j}$, in order to determine optimal sensor configurations.

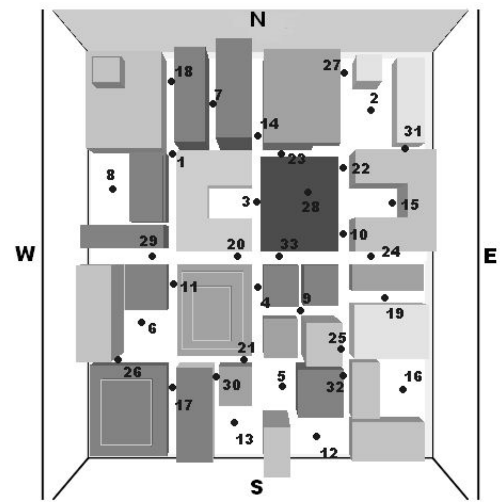
Chlorine gas was used as the chemical agent in all attack scenarios. Since chlorine is an industrial chemical, relatively easy to obtain, use, and often stored in or near large population centers..

Ninety-nine attack scenarios were simulated for 500 seconds each in the urban environment described above, under different meteorological conditions. The simulations were divided into three sets of 33 simulations each, labeled *Northwest (NW), Southwest (SW)* and *Random (RD)*. These labels corresponds to the prevailing wind condition. NW_i, where $(i = 1, 2, \ldots, 33)$, is the attack from the Northwest corresponding to the i^{th} attack location (see Figure 1b). The same labeling convention is consistent for the SW and RD sets. Each attack scenario has a unique attack location, but the attack location for NW_i, SW_i, and RD_i are the same.

Figure 2 is a series of snapshots taken from NW_9. The grey-scale bar to the right of each snapshot is a concentration scale of the agent in Kg/Kg (Kg of agent/Kg of air). While the wind is blowing from the northwest the contaminant remains in the southeast section of the environment. At the end of the simulation there are significant contaminant levels remaining in the atmosphere, reflecting the fact that this simulation used a low speed wind profile. High wind speed would accelerate the dispersion process, leaving little if any contaminant remaining.



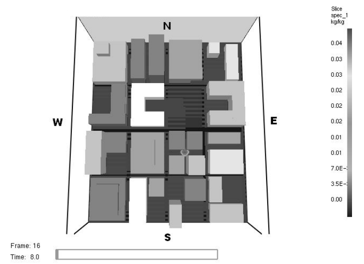
(a) Sensor Locations



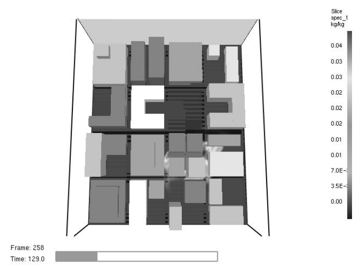
(b) Attack Locations

Fig. 1. Sensor Locations and Attack Locations

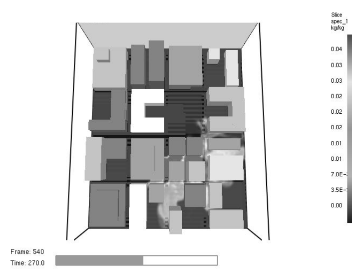
By simulating a high number of attack scenarios, we were able to create a large set of simulated data. These data were used for optimizing sensor placement. It also provided insight about dispersion behavior patterns coupled to the modeled environment. One example of a behavior pattern which was revealed is the dispersion vortex. The vortex is created when contaminant gets trapped in space found between buildings, where the walls form a barrier around the contaminated area, creating a tornado-like effect. The speed of the flow restricts the agent from escaping the area, allowing it to dissipate only upwards. This type of behavior can also be determined by analyzing concentration data at the candidate sensor locations. When a sensor has a constant concentration for an extended period of time, it is either near the attack location (directly in the flow of contaminant), or it is in an area where the agent is trapped. Regardless, the concentration data can show us where there are consistently high levels of contaminant, and, coupled with information from other sensors, provide information on the direction of the contaminant dispersion.



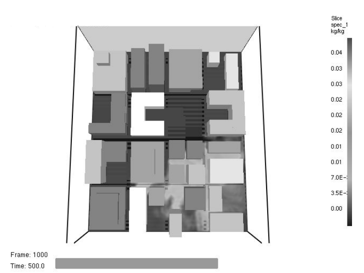
(a) Initial onset of attack



(b) at 129 seconds



(c) at 270 seconds



(d) Remaining Contaminant

Fig. 2. Progression of Agent Dispersion from NW_9 Attack Simulation

B. Sensor Configurations

We used AMPL and LPSOLVE [16] as our integer programming software to compute the optimal sensor locations for networks (containing up to twenty sensors). Figure 3 is a plot of consumption values versus the number of sensors placed. These results show that there is a limit to the effectiveness of adding sensors.

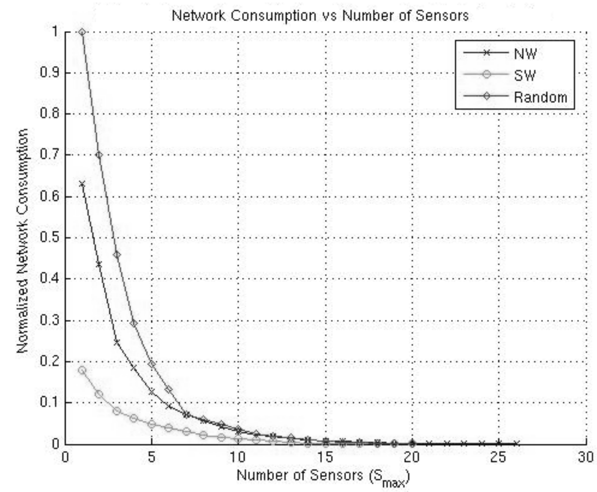


Fig. 3. Plot of Consumption versus Number of Sensors Placed

The placement algorithm was run for each set of attack scenarios to determine the optimal configuration respective to that set. We constrained our algorithm to place ten sensors, $S_{MAX} = 10$, for the first optimization and found the best configuration for each set. These configurations can be found in Table 1 below. S_{NW}, S_{SW}, and S_{RD} are the sensor configurations for their respective simulation set. The normalized mean consumption across these configurations was $\omega_{opt} = 0.0805$.

Table 1. Optimal Sensor Configurations with $S_{max} = 10$

Set	Configuration	Normalized Consumption
S_{NW}	5 12 13 14 19 22 24 26 29 31	0.032
S_{SW}	2 5 9 10 12 18 20 27 29 33	0.0125
S_{Rand}	3 5 9 12 17 19 21 23 26 29	0.0358
Common	5 12 29	

Next, we investigated the possibility of using any one of the optimized configurations across the union of all ninety-nine attacks. This was accomplished by computing the total consumption, ω, for the configurations (S_{NW}, S_{SW}, or S_{RD}) for all simulation sets (NW, SW, and RD). When the S_{SW} configuration was used in all three scenarios, the normalized mean consumption value, ω_{NW}, was found to be 0.334, which is approximately four times greater than ω_{opt}. By using the S_{NW} set or the S_{RD} set across all the scenarios, the normalized mean consumption values across all ninety-nine attacks were found to be $\omega_{NW} = 0.472$ and $\omega_{RD} = 0.157$, respectively.

We attempted to find a more robust sensor configuration by calculating a configuration of sensors to minimize consumption across the union of all three set of attacks (i.e. all 99 attacks, as opposed to each individual set of 33 attacks) where $S_{MAX} = 10$. We find

$S_{Merg} = \{5, 9, 12, 17, 19, 21, 23, 26, 29, 33\}$ by running our sensor placement algorithm over the set of all 99 attacks. This configuration represents a year-round fixed configuration and had a total normalized consumption of $\omega_{Merg} = 0.131$. While this consumption value is significantly greater than ω_{opt}, it is much lower than either ω_{NW}, ω_{SW} or ω_{RD}. Clearly when a fixed configuration of sensors is required the optimal configuration is less effective at minimizing consumption then when a seasonal configuration is used (calculated using seasonal prevailing wind conditions).

V. CONCLUSIONS

Our study determines that sensor placement for NBC detection is highly sensitive to the wind - wind is the primary motivator of agent dispersal. Consequently, it may be needed to use seasonal sensor configurations in urban environments to maximize early warning capabilities. The improvement in detection reached a saturation after a number of sensors were placed (in our case, eight) and additional sensor do not improve performance. The approach provides a consistent method to place sensors for NBC detection so that total network consumption is minimized.

VI. TABLE OF SYMBOLS

Table 2. Table of Symbols

Symbol	Meaning
$V = \{v_1, v_2, ..., v_N\}$	Set of candidate sensor locations
A	Set of attacks
$\alpha_a, \quad a \in A$	Probability an attack will occur at location a
L_a	Set of contaminated locations
$\omega_{a,j}$	Consumption as a results of attack a, with alarm j
$d_v(t_1, t_2)$	Total amount of contaminant delivered from time t_1 to t_2
$\gamma_{a,v}(t)$	Concentration of NBC agent as a function of time and location
$b_{a,i}$	First detector index
s_i	Sensor placement index (1 if placed, 0 otherwise)
S_{max}	Maximum number of sensors allowed to be placed
NW prevailing	Attack set with northwest wind conditions
NW_i	Attack i in attack set NW
S_{NW}	Optimal sensor configuration for attack set NW i
ω_{NW}	Consumption for all attack sets using NW attack set optimal sensor configuration
ω_{opt}	Consumption for all attack sets using prevailing wind condition optimal sensor configurations
S_{Merg}	Optimal sensor configuration for all attack sets combined
ω_{Merg}	Consumption for all attack sets using fixed sensor configuration,S_Merg

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