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Optimal placement of omnidirectional sensors in a transportation network for effective emergency response and crash characterization

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ABSTRACT

Rapid motor vehicle crash detection and characterization is possible through the use of Intelligent Transportation Systems (ITS) and sensors are an integral part of any ITS system. The major focus of this paper is on developing optimal placement of accident detecting omnidirectional sensors to maximize incident detection capabilities and provide ample opportunities for data fusion and crash characterization. Both omnidirectional sensors (placed in suitable infrastructure locations) and mobile sensors are part of our analysis. The surrogates used are acoustic sensors (omnidirectional) and Advanced Automated Crash Notification (AACN) sensors (mobile). This data fusion rich placement is achieved through a hybrid optimization model comprising of an explicit–implicit coverage model followed by an evaluation and local search optimization using simulation. The compound explicit–implicit model delivers good initial solutions and improves the detection and data fusion capabilities compared to the explicit model alone. The results of the studies conducted quantify the use of a data fusion capable environment in crash detection scenarios, and the simulation tool developed helps a decision maker evaluate sensor placement strategy.

1. Introduction

The US Department of Transportation (DOT) is planning for a future wherein, the transportation system will be equipped with automated sensor systems that sense unsafe driving conditions and take action to prevent crashes thereby decreasing fatalities. In those cases in which a crash is not preventable, the systems will automatically detect and characterize incidents through interoperable, wireless networked communications among vehicles, infrastructure and travelers personal communication devices. The Connected Vehicle Program launched by the DOT envisions this future system and aims to achieve the required sensor technology, vehicle and infrastructure connectivity to transform the US transportation system.

Sensors play a crucial role in this future transportation system, monitoring and measuring every change on the road. The next generation of Intelligent Transportation Systems (ITS) sensors will add wireless networking capabilities to the last generation of sensors and new technology to improve current state of the road conditions. ITS have long been helping traffic managers with incident detection and provide a means to monitor traffic.

One area that is expected to benefit from the next generation of ITS is emergency response to motor vehicle crashes. Emergency medical personnel refer to the 60 min following traumatic injury as the "Golden Hour" (Lerner and Moscati,

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2001). The exact impact of providing emergency care during the golden hour on survivability has not been clearly quantified. However, it is generally agreed that shortening the time to definitive care will improve chances of survival for many crash victims (American College of Surgeons, 2004). Many motor vehicle crashes on roads go undetected, delaying the delivery of emergency services and thereby result in higher morbidity and crash-related fatalities. To improve the situation, there is a need to quickly identify motor vehicle crashes and characterize them. ITS systems with incident detection capability fill this need.

The focus of this paper is to study the use of omnidirectional sensors in a future ITS system where every sensor has wireless communication capabilities. This study includes developing a general approach for optimally placing these sensors to maximize detection capabilities and provide higher quality crash assessment. Acoustic sensors are one type of omnidirectional sensor, which we expect to have a functional role in a future transportation system. We use them in this paper as a representative sensor type and as a proxy for all omnidirectional sensors. Some key papers and patents that use acoustic sensors (mobile and stationary) (Harlow and Wang, 2002; White et al., 2011; Lagassey, 2008; and Kuhn et al., 1998). These studies demonstrate clear potential for application of acoustic sensors in transportation systems.

Our primary goal is to study the impact of stationary omnidirectional sensors while exploring the benefits of using mobile sensors data along with existing infrastructure sensors. To this end, we note that there are many advances in sensor technology for automobiles; one of the most prominent is Advanced Automated Crash Notification (AACN). AACN systems combine the information from in-vehicle sensor suite (GPS, accelerometers, rollover sensors, etc.), to detect a crash and transmit (via cell phone communication) a crash report with crash location. In this paper, we use AACN sensors as a secondary sensor system to the omnidirectional acoustic sensors to understand and demonstrate the utility of a data fusion environment.

The distinguishing features/contributions of our paper are as follows:

- The use of data fusion in locating omnidirectional sensors.
- Evaluates the performance of a data fusion capable omnidirectional sensors network using a simulation of a road network.
- Provides insight on the number of omnidirectional sensors needed for a required detection level.
- Considers the use of multiple sensor types and quantifies the use of sensors independently and together.
- Uses simulation as an evaluation and optimization framework.

The organization of the remainder of this paper is as follows: Section 2 presents the literature survey and background on the sensors considered for the study. Section 3 introduces the node and path based formulation and the solution methodology comprising of an implicit and explicit model. Section 4 presents the simulation model used to evaluate the solution methodology, the simulation-based optimization framework and the improvements possible with the proposed solution methodology. In Section 5, we present how omnidirectional and mobile sensors work in a data fusion environment and evaluate the simulation with both sensor types. Finally, in Section 6, we present our concluding remarks.

2. Background on sensor location problem and sensors considered in our study

Advanced transportation sensor systems typically include a variety of sensors, some mobile (i.e. drones, in-vehicle sensors) and some fixed. The fixed sensors can be directional (e.g. cameras, with a fixed line of sight) and non-directional or omnidirectional (e.g. chemical, radiation and some radio frequency antennae). For the analyses reported in this paper, we choose to consider a set of omnidirectional fixed sensors (i.e. acoustic sensors) and a set of mobile sensors (i.e. AACN sensor). We note that at present AACN sensors are part of onboard sensors in a small subset of vehicles whereas acoustic sensors are not widely used in transportation systems. However, the potential effective use of acoustic sensors in transportation systems is discussed in Harlow and Wang (2002), White et al. (2011), Kuhn et al. (1998) and Lagassey (2008). Section 2.1 presents the literature review on sensor location problem and its applications in road transportation systems. Section 2.2 introduces acoustic sensors and explain in detail their functional capabilities and shortcomings. Section 2.3 introduces AACN sensor and the role of AACN as a complementary sensor to the acoustic sensors.

2.1. Sensor location problem

The fixed/infrastructure sensors performance in an incident detection system depends on both the sensors and location/placement of sensors. This necessitates the need of a systematic approach to place the sensors. This placement also needs to consider the data fusion opportunities that arise from multi sensor coverage. There is a large resource of research in this field of sensor placement that we can use to solve the omnidirectional sensor placement.

Sensor location problems typically refer to placement of sensors in a large distributed sensor network. These problems tend to maximize or minimize a certain performance measure depending on the problem. For example (Li and Ouyang, 2011) proposes the use of linear programming model to determine effective sensor placement for vehicle ID inspection stations to determine O–D flow count and travel time estimation. Linear programming model proposed assumes that all the vehicles are equipped with RFID technology and can be used to detect each car passing the detection stations. The model assumes that the detection stations can be erroneous and may even fail to work. The authors propose the use of lagrangian relaxation approach to solve the linear program. Danczyk and Liu (2011) presents a mixed integer linear program model to place point sensors to measure traffic parameters similar to traffic volume and travel time. The objective of the model is to minimize the error in parameter estimation with a limitation on the number of available sensors. Danczyk and Liu (2011) is similar in approach to the study presented here. The key differences being (Danczyk and Liu, 2011) study is limited to highway corridors and considers only sensors that are similar whereas we propose limitation on the type of the road and consider multiple sensor types both mobile and stationary.

Other papers in sensor placement problem arena present algorithms to solve sensor location problems. In Dhillon and Chakrabarty (2003), authors proposes two algorithms for effective placement of sensors in a sensor field modeled as a grid. The aim of the paper is to optimize the number of sensors and determine the placement of sensors in a distributed sensor network. Nie et al. (2007) addresses the problem of locating bomb detecting sensors in a grid setup, aimed at solving the problem of locating sensors in an airport or mall area to counter an attack from terrorists. Gentili and Mirchandani (2005) presents a location of sensors in a traffic environment for applications like flow measurements and time to travel a path. The problem is formulated as a set covering problem and devises a heuristic algorithm to approximately solve the NP-hard (non-deterministic polynomial-time) problem.

Maximal coverage location problem was proposed (Church and ReVelle, 1974) with an objective function to maximize the coverage of a given number of facilities. A sensor location problem and maximal coverage problem share similar features and the mathematical formulation in certain applications look identical. In this work we use mathematical models that are typical in coverage problems. Most sensor coverage problems model the demand as occurring at nodes, c.f. the papers (Megiddo et al., 1983; Daskin and Stern, 1981). However, these mathematical models may not be useful in modeling demand from crashes. Road crashes are typically separated into two categories. The first type occurs at specific crash-prone locations. The second type occurs at random points on crash-prone road segments. Erdemir et al. (2008b) uses a formulation based on explicit model found in Erdemir et al. (2008a), for crashes, which allows the demand to occur on both paths and nodes. Our paper applies the same path and node based formulation to the placement of omnidirectional sensors.

2.2. Acoustic sensors

Acoustic sensors can monitor traffic and be able to detect a crash using the high amplitude noise generated in a crash, if these events happen inside the detection radius of the sensor. Even though acoustic sensors are very useful and have advantages over other sensors, the cost and maintenance of these sensors is significant (though not as high as a video image processor). The limited number of acoustic sensors available need judicious placement to maximize detection capability of future crashes. In this work, we use past crash location data from FARS (The Fatality Accident Reporting System) to guide the sensor placement. As an illustration of the data used to run our model, refer to Fig. 1, which presents a road network and the set of crashes near the University at Buffalo, North Campus for the period 2004–2009.

Acoustic sensors can also aid in assessing the severity of a crash. Acoustic sensors can detect if there are multiple impacts in a crash (Whitney and Pisano, 1995). Multiple impacts from a crash have significant influence of the passenger's safety. Multiple impact crashes increase the chance of serious injury to vehicle occupants (Augenstein et al., 2001), making the information on multiple impacts a higher priority for emergency service providers. Similarly, acoustic sensors are also capable of detecting a rollover during a crash (SmarTek Systems Inc, 2002). Thus acoustic sensors not only aid in crash detection but also aid in crash characterization.

Acoustic sensors also differentiate themselves from the other sensors by their capabilities in bad weather conditions. Every sensor deployed in the field experiences interference from severe weather and traffic conditions. The acoustic sensors are not immune to the interferences but are capable of still functioning though at a higher error rates. Observing the benefits and capabilities of acoustic sensors, we can assert that an array of acoustic sensors deployed on a road network will provide enhanced crash situation assessment.

2.3. Advanced Automated Crash Notification (AACN) system

Advanced Automated Crash Notification (AACN) systems consist of multiple electronic sensors inside the vehicle, which can detect and characterize a crash, assemble a crash message and transmit the message to the appropriate public safety agency. In many cases, the AACN system automatically forwards the initial message to a private call center, which then forwards the message to the appropriate public safety agency (i.e. 9–1–1). In almost all cases, an in-vehicle cell phone transmits the message. GM's OnStar™ system, which is available on most of its models, is an example of a commercially available AACN system. The OnStar AACN crash message contains GPS reported position of the car and crash characteristics, e.g. crash delta velocity, principal direction of force, rollover and multiple impact information (OnStar, 2012).

In this paper we assumed that an AACN sensor consists of a set of contact sensors, accelerometers and a GPS sensor to estimate number of impacts, detect a crash and estimate of the crash location respectively. Similar to every sensor deployed in traffic systems, we assumed that all the sensors working in tandem in AACN have inherent detection errors. The assumptions are listed as follows:

- AACN sensor can detect a crash in 95% of the crash scenarios (Lahausse et al., 2008).
- GPS estimate of the crash location is within 10 meters of the actual location of the crash (Hubrich and Curran, 2009).

Fig. 1. All police reported crash data on road network near University at Buffalo, North Campus from 2004–2009 from NHTSA database.

- Contact sensors can estimate the number of impacts with 80% accuracy.

3. Optimally locating omnidirectional sensors

3.1. Problem description

Although this paper presents placement of acoustic sensors, the general approach presented here for placement can be extended to other omnidirectional sensors as well (e.g., chemical vapor or environmental sensors). In order to detect every crash which occurs on a road segment a large number of acoustic sensors are required, which is not practical and often limited by the availability of financial resources. With this motivation, this paper addresses the problem of locating a given number of acoustic sensors on a set of possible locations (the number of possible locations is far greater than the available sensors). The two objectives are to maximize detection capability and to improve the quality of information through the application of data fusion techniques.

A crash can occur in any part of the road, some more than others. From observing the crash data we can segment the location of crashes into crash nodes and crash paths. The locations on the road more prone to crashes, like an entry/exit ramp, a merging lane on a highway and a busy intersection are segmented as crash nodes. On the other hand, crash paths correspond to road segments on which crashes occur at some location on the path, not at a specific location. A crash occurring on any of the crash nodes or paths constitutes demand to be serviced by the set of deployed acoustic sensors. Erdemir et al. (2008a) use the same approach of demand arising from nodes and paths, in the problem of locating cell phone base stations to cover demand arising from customers who are traveling on a road as well as stationary customers.

3.2. Solution methodology

The solution methodology employed in this paper is similar to Erdemir et al. (2008a), which proposes an explicit and implicit model to solve the coverage problem with demand arising from both nodes and paths. The major additions in this paper are the use of simulation as an evaluation method and complementing the stationary sensors with mobile sensors in incident detection. Erdemir et al. (2008a) is proposed to solve the coverage problems for mobile phone coverage, that have a very large coverage radius compared to the short coverage ranges expected in accident detection sensors. The explicit model formulates the problem as a quadratic maximal coverage problem and the implicit model uses a pure geometric approach to solve the problem. The implicit method to solve the problem lets the decision maker decide what percentage of the path should be overlapped. In the acoustic sensor problem, we will use the implicit method, so that we can fix the percentage of a path that should be overlapped. This overlap area is a good source for collecting more data and improves the quality of information through data fusion.

The implicit model is a heuristic procedure developed using geometric concepts. This heuristic procedure in Erdemir et al. (2008a) is started using the solution from the explicit model. The omnidirectional sensor placement problem will also follow the same procedure and use the explicit model as a starting solution to the implicit model.

As illustrated in Fig. 2 after arriving at a solution from the implicit model, a simulation based optimization procedure is used. This simulation based optimization procedure will use a local search procedure to generate more solutions that are feasible. Then the simulation evaluates all the generated feasible solutions. Solutions that result in favorable solutions will iteratively use local search to reach better solutions. In the next section, we present the details of the explicit and implicit models.

3.3. Explicit and implicit coverage models

Erdemir et al. (2008a) suggested two models encompass nodal and path demand in a coverage problem. The explicit model develops a mathematical formulation for the maximal expected covering location problem based on both nodal and path demand. The implicit model considers service requests from paths and nodes implicitly via multiple coverage. In our paper, we use both models. We first use the explicit model to generate an initial solution. This initial solution is a starting point for the implicit model and used to create an improved solution with higher data-fusion capabilities. Simulation evaluates the solution from the implicit model and uses a neighborhood search heuristic to iteratively evaluate (via simulation) and improve. The addition of simulation-based optimization to a coverage problem is unique and to the best of our knowledge never tried before. The simulation-based optimization framework is discussed separately in Section 4.1.

3.3.1. Explicit location model: maximizing coverage of nodal and path demand

The explicit model formulates the acoustic sensor placement problem as a quadratic maximal coverage location problem (qMCLP). The qMCLP formulation includes consideration of demand arising from nodes and paths. The specific objective of the formulation is to maximize the coverage with a constraint on number of sensors.

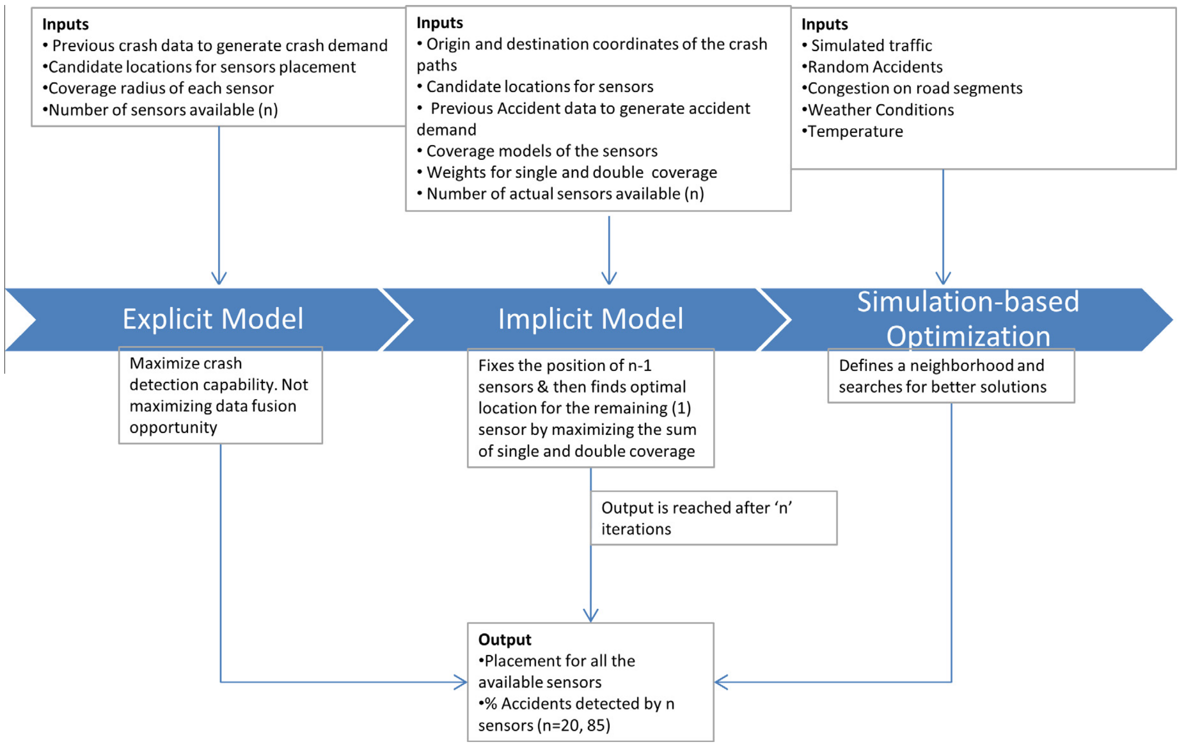


Fig. 2. Solution methodology complete with input and output data.

The model inputs are: (i) node and path demands (in our case, calculated using previous crash data); (ii) candidate locations for omnidirectional sensors (in our case, a set of feasible sensor locations on infrastructure with access to power); (iii) a common coverage radius; and (iv) the number of sensors available. The output of this model is the location of the available sensors.

To construct node and path demands, we use previous crash data. In our case study, there were 3600 crashes that occurred in a 5 year period. To determine the nodes we identified locations where 20 or more crashes occurred in very close proximity. There were 11 such locations with 784 total number of crashes between them. The weight (demand) of a node was set equal to the number of crashes that occurred at the node divided by the total number of crashes. The remaining 2816 crashes occurred on road segments (paths). The weight (demand) of a path was set equal to the number of crashes on the path divided by the total number of crashes. For our case, we had 760 paths, of these 760 paths, 208 had zero demand.

To construct candidate locations we assumed that each end of a path was a candidate location (which yielded 400 locations). We also generated 469 additional locations by first randomly selecting 469 paths and then for each selected path specifying a random location in the interior of these selected paths.

The constraints of the model ensure that the coverage of nodal and path demand is accurately captured. A node is covered if it is in the coverage radius of at least one sensor. A path is covered if each point on the path is in coverage radius of at least one sensor.

We now proceed by introducing relevant notation, followed by the model formulation. Our model is identical to the one found in Erdemir et al. (2008a) except that a single period case is considered.

The input data for this model is as follows: (a) M = set of potential acoustic sensor locations; (b) N = set of nodes; (c) P = set of paths; (d) S = set of nodes; (e) p = total number of sensors to be located; (f) H_j = weight of node j; (g) H_k = weight of path k; (h) $A = \{A_{i,j}\}$, where $A_{i,j} = 1$, if sensor i covers node j, and 0, otherwise; (i) $B = \{B_{i_1,i_2,k}\}$, where $B_{i_1,i_2,k} = 1$, if sensors at i_1 and i_2 cover path k, and 0, otherwise.

The outputs of the model are as follows: (a) $x_i = 1$, if a sensor is located at i, and 0, otherwise; (b) $z_j = 1$, if node j is covered, and 0, otherwise; (c) $l_k = 1$, if path k is covered, and 0, otherwise.

The formulation of the model is as follows:

Maximize

$$Max. \sum_{j \epsilon N} H_j * z_j + \sum_{k \epsilon P} H_k * l_k \tag{1}$$

Subject to:

$$\sum_{i \epsilon M} x_i \leqslant p \tag{2}$$

$$\sum A_{ij} * x_j \geqslant z_j \ \forall j \epsilon S \tag{3}$$

$$\sum B_{i_1,i_2,k} * x_{i_1} * x_{i_2} \geqslant l_k \ \forall k \epsilon P \tag{4}$$

$$x_i \epsilon \{0,1\} \tag{5}$$

$$z_j \epsilon \{0,1\} \tag{6}$$

$$l_k \epsilon \{0,1\} \tag{7}$$

In the model, the objective function (1) maximizes the total coverage, first term maximizing the coverage from the nodes and the second term maximizing the coverage from the path. Constraint (2) limits the number of acoustic sensors to p. Constraint (3) defines node coverage and declares that a node j is covered if and only if at least one acoustic sensor covers node j. Similarly, constraint (4) defines path coverage and declares a path covered if at least one pair of acoustic sensors covers it. This constraint can be easily converted into a linear equation. Constraints (5)–(7) ensure that the decision variables are all binary.

Erdemir et al. (2008a) designed a Greedy Paired Adding Heuristic (GPAH) method for large scale problems, to solve this quadratic maximum coverage location problem (qMCLP). Observing the complexity involved in MCLP, we apply GPAH heuristic to solve qMCLP. The GPAH solution is shown in Erdemir et al. (2008a) to be within 6.6% of the optimal in the computational tests performed. Since the GPAH algorithm performs well on large-scale problems, we use it for our situation to obtain a starting solution for the implicit model. In Fig. 3 we present the performance of the GPAH algorithm. The results presented in Fig. 3 show that weight of crashes covered increases as we increase the number of sensors. In Fig. 4, we show the sample solution of the explicit model on the case study chosen near UB North Campus with an '*n*' value of 55. GPAH algorithm was developed in JAVA® and runs under 15 min using Intel® Core™ 2 Duo with clock speed of 3.17 Hz and 4 Gb RAM for the case study chosen in Section 4.3.

Note that objective function or constraints in the explicit model do not include terms dealing with the data fusion capabilities. The implicit model detailed in the next section captures this aspect.

3.3.2. Implicit location model: maximizing a weighted combination of single and double coverage

The implicit model in Erdemir et al. (2008a) is an alternative method to solve the coverage problems with demand originating from both nodes and paths with application in location of cell phone base stations. This model allows the cell phone service providers the flexibility to adjust single, double and triple coverage. We adopt their model but only utilize

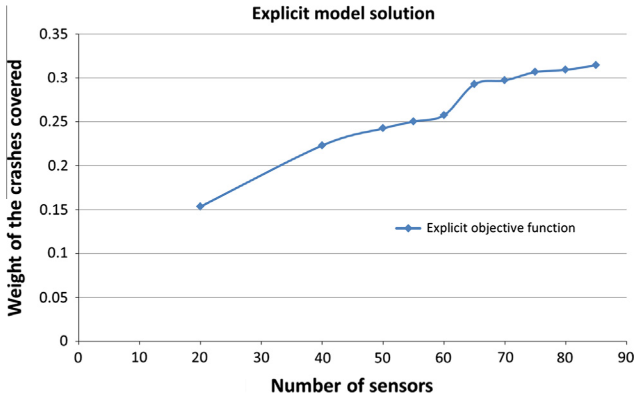


Fig. 3. Weight of the accident data covered through explicit model with different number of sensors.

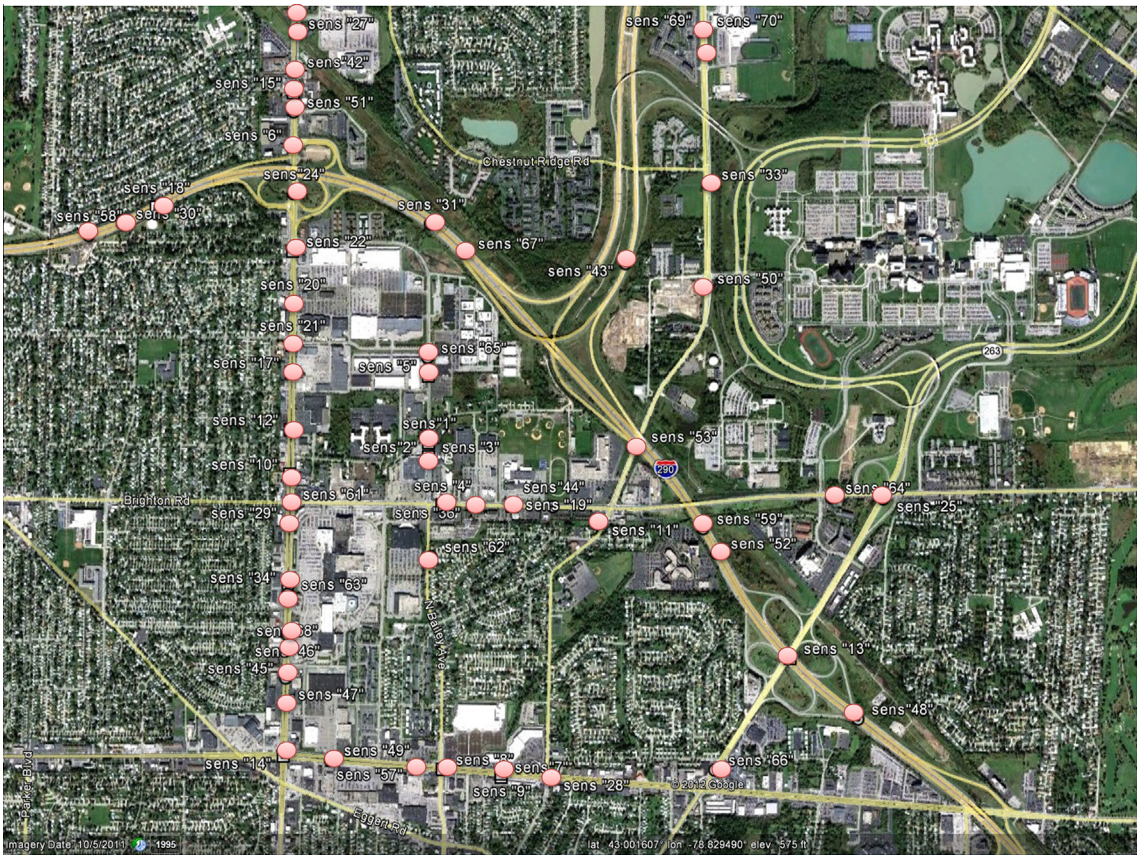


Fig. 4. Map of the case study with explicit model solution for 55 sensors.

single and double coverage. In the acoustic sensor location situation, double coverage implies coverage of the same path by two sensors. If there is a crash in the area covered by two sensors, each sensor makes an observation of the same event. This double coverage has many advantages over just single coverage. Every sensor deployed in the field has a detection rate inside its detection range, the true positive probability. Suppose a sensor's true positive probability is 0.9. That is if there is a crash in its detection area, it will detect it 90 times out of hundred. However, if the crash happens in a region which is covered by two sensors (assuming the acoustic sensors have the same detection rate and are independent), the combination of data from two sensors observes 99 crashes out of 100, which is an improvement of 9%. The advantage double coverage provides is through the application of data fusion techniques on information obtained through multiple sensors. There is a direct correlation between the performance of the incident detection system and the double coverage. The other advantage double coverage provides is better characterization of crash.

The implicit model is a pure geometric approach to solve the problem. It takes a geometric approach to measure the coverage achieved by a particular placement of sensors on every path and every node. For example consider a node A with an crash demand of 0.01. Suppose that in a specific sensor placement strategy 3/4th of the path is covered by at least one sensor and 1/4th of the path is covered by 2 sensors and we assign a weight of 0.7 to single coverage and 0.3 to double coverage, this path contributes $(0.01 * (3/4 * 0.7 + 1/4 * 0.3))$ to the objective function.

The objective function of the implicit model is defined as:

$$max\ f[(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)] = \begin{cases} \alpha_1 s_1[(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)]+ \\ \alpha_2 s_2[(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)] \end{cases} \tag{8}$$

s_1 : Function of single coverage α_1:weight of single coverage.
s_2 : Function of double coverage α_2:weight of double coverage.

The objective function defined in (8) maximizes the sum of single and double coverage with associated weights. The decision variables are the location of sensors $(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)$.

In Erdemir et al. (2008a) the authors use a heuristic solution methodology to solve the implicit model. The heuristic model fixes the position of n-1 sensors and then finds the optimal location for the remaining sensor using the objective function (8). For this heuristic to work effectively, the authors start the heuristic with the solution from the GPAH algorithm. We adapt the same solution methodology.

The inputs for the implicit model are: (i) the coordinates of the two end points of the paths; (ii) coordinates of potential sensor locations; (iii) mean demand per unit length of a crash path; (iv) coverage radius of the sensors; (v) weights for single and double coverage and (vi) the number of actual sensors available. Output for the implicit model is the coordinate locations of omnidirectional sensors.

The heuristic algorithm used to solve the implicit model is an iterative search process. Each step has to evaluate a large number of feasible solutions before choosing the best solution. Fig. 5 compares the results of implicit model objective and explicit model objective for different number of sensors. The implicit model objective shows improvement in weight of the crashes covered as the number of sensors increase. However, the improvement in objective decreases as the number of sensors increase (diminishing returns as more sensors added) as expected. We observe that there is a large improvement in the weight of crashes covered by the implicit model compared to the explicit model. This sharp discrepancy can be explained as follows. First, the implicit model uses, as its starting solution, the result obtained from the explicit model. Hence, it has opportunity to improve it. Second, and much more significant, is the difference in the method by which path coverage is accounted for in the two models. The explicit model considers a path covered only if one or more sensors cover the entire path. On the other hand, the implicit model measures partial coverage.

Fig. 6 presents the implicit model solution on the same case study. Comparing Figs. 4 and 6, it is evident that sensor placements in the implicit model solution are clustered (i.e. several sensors located nearby) whereas the explicit model solution has scattered placement of sensors. The clustering of sensors in the implicit model allows for multiple coverage and significant data fusion opportunities (see Fig. 7).

From a computation perspective, this implicit model is developed in JAVA® and using the explicit model solution as a starting strategy, takes a computation time of 3 h using Intel® Core™ 2 Duo with clock speed of 3.17 Hz and 4 Gb RAM, compared to the computation time of under 15 min for the explicit model. These computation times reported here are for the case study presented in Section 4.3.

4. Evaluation and improvement of sensor location through simulation

A simulation environment is necessary to evaluate a strategy for this sensor placement. A sound generated by the crash and received by the acoustic sensors is dependent on the location of the crash, traffic conditions, weather and the distance from the sensor. Therefore, a random crash creates a random input for the sensors. This signal, when interpreted using

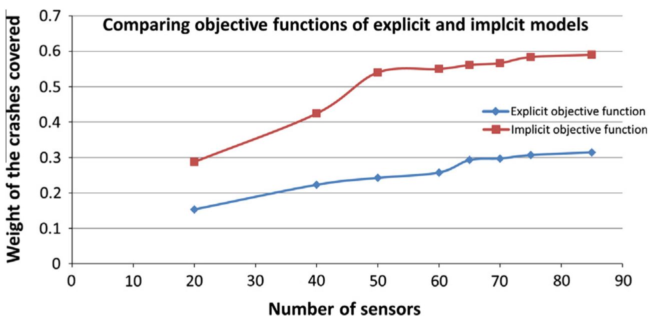


Fig. 5. Comparing the weight of the crash covered in implicit and explicit model.

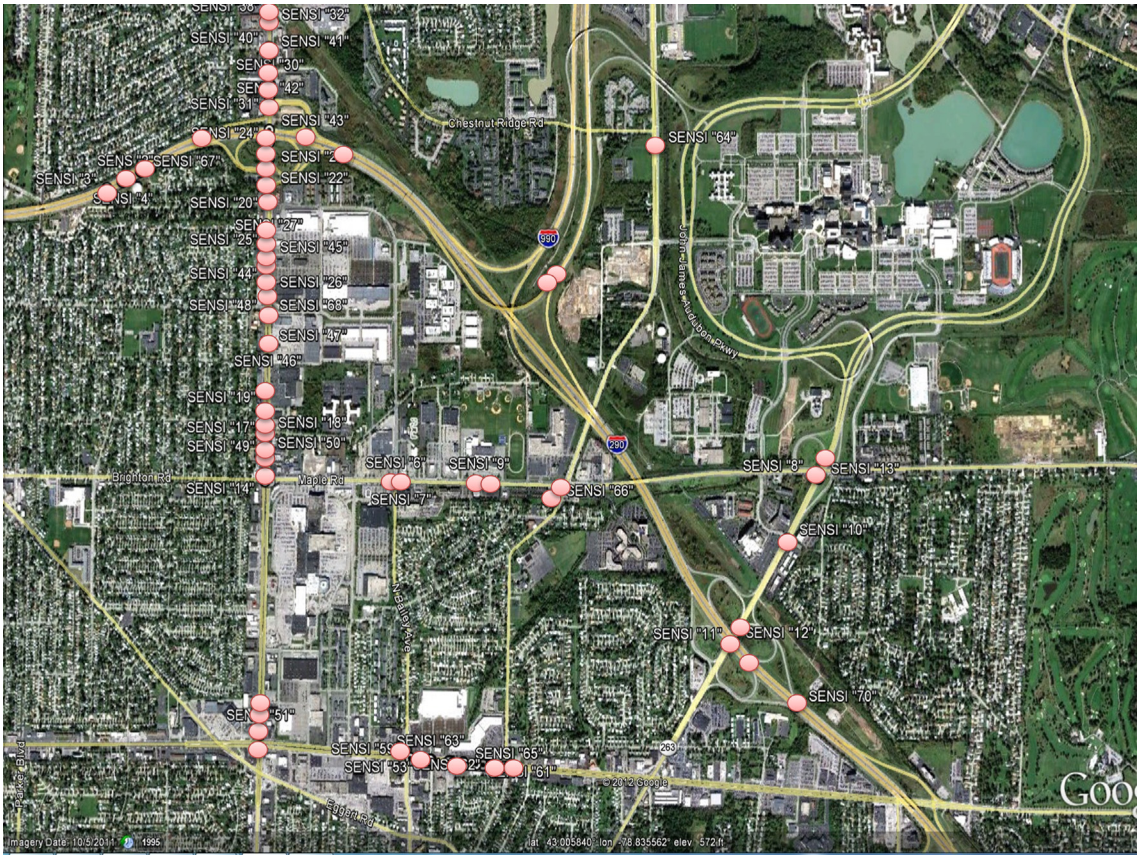


Fig. 6. Map of the case study with implicit model solution for 55 sensors.

appropriate data fusion techniques, creates an output that is virtually impossible to capture in an objective function. Whereas a simulation can capture data necessary to evaluate a sensor placement and test multiple sensor placement strategies without investing in the sensors. In this section, we propose a simulation model to evaluate the performance of placing acoustic sensors at specified locations.

4.1. Simulation framework

To evaluate a sensor placement strategy in simulation, the simulation model should replicate a real road network. This simulated road network should include all the traffic interactions that we see on road segments like intersections, traffic lights, highway exit and entry points, one-ways and speed limits to just name a few. On top of it this simulation model should capture the sensor detection capabilities and signal processing. There needs to be a way to include all the road interaction and signal processing together. There are several factors influence the incident detection capability of acoustic sensors. Any source of sound on the road segment causes interference and creates error in monitoring crashes for acoustic sensors. Some well-known sources of sound affecting the incident detection capabilities are road sound (from traffic), and weather conditions (snow, rain and wind). When vehicles travel on road they generate sound that is observed to increase as the flow of traffic increases. Similarly, when there are extreme weather conditions like snow and rain the acoustic sensors observe a higher noise level. Both the above-mentioned factors are observable by signal processors and influence crash detection capability. However these traffic and weather conditions are hard to replicate in a simulation environment. An alternative and practical approach would be to add signal noise to the acoustic sensor information in simulation. This signal noise is kept at minimal for all of our case studies.

Observing all the needs of simulation model a simulation model is developed (Henchey et al., in press), as a part of a Automated Situation Awareness Platform (ASAP) with inputs from our sensor location problem. The simulation model developed in Henchey et al. (in press) is adapted to include acoustic and AACN sensors. The simulation model consists of three modules. The first "traffic generation" module creates a traffic network with a random traffic generator, which includes real world variations based on expected traffic flow as a function of the time of day, type of vehicle and weather. This module integrates all the traffic elements like the road segments, traffic lights etc., mirroring the real road network. The purpose of this module

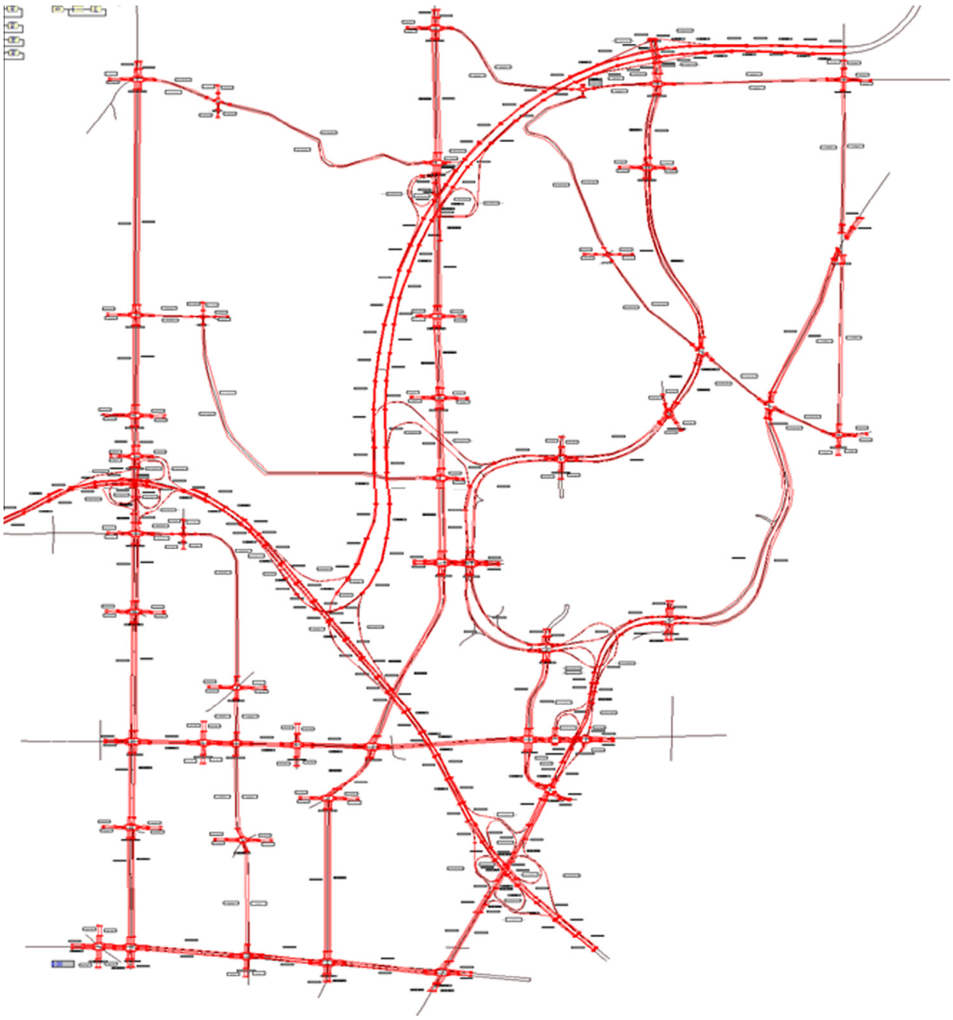


Fig. 7. Simulation model of the road network near University at Buffalo, North Campus in Arena®.

is to create traffic, which is representative of real traffic environments. This module includes the traffic signal template, stop sign, effects of congestion and weather on traffic flow. For example during a heavy rain condition, the simulation automatically decreases the traffic speed on the roads to model traffic movement in severe weather conditions. To validate this simulation (Henchey et al., in press) uses real emergency response times for a set of previous crashes and compares them with the simulation calculated times. The study indicates that the simulation is a good representation of the real-traffic network.

The second "crash creation" module creates a random crash on the road network. This module first chooses a crash location using the weights associated with each path and node, which is based on past crash data. Then the crash creation module creates a random crash and all the associated parameters, e.g. number of vehicles involved, number of people in each vehicle, delta velocity (deltaV) of the impact, number of impacts, primary direction of force (PDOF) and acoustic signature of the crash.

The third module is the sensor module. This part of the simulation is developed specifically for the acoustic sensor placement problem. This module imitates a real sensor in a data fusion environment. Significant functions of the sensor module are to observe ground truth conditions generated by the traffic creation and crash generation module and create an acoustic signature for every acoustic sensor. After the crash generation module creates the crash and its characteristics, the acoustic sensor module evaluates the crash. For example if the crash generation module generates a random crash at (43.024592, −78.798994) with an acoustic signature, the acoustic sensor located at (43.026178, −78.800012) receives the acoustic signature from the crash. The sensor module calculates the distance between the crash and the sensor location. Through the traffic module, the sensor collects the congestion information on the particular road on is 600 vehicles/hr and the weather condition is input as sunny and clear. Using all this information the sensor module calculates sound decay in the acoustic signature. A new acoustic signature with decay incorporated is used to observe for sound amplitudes beyond a threshold for a short period, indicators of an crash. If the crash is detected it will also calculate the error rate in its reading. The simulation-based optimization begins with the solution of sensor locations from the implicit model. Each acoustic sensor module makes the necessary calculations of sound decay from the acoustic signature of the crash and then uses a threshold detection value to sense the crash. More details about the traffic generation module and crash modules can be found in Henchey et al. (in press).

Each simulation starts by creating traffic on a road network modeled in the simulation on a regular day from 7:00 AM to 9:00 PM, with a predefined location of acoustic sensors. The crash creation module creates a random crash on this network, from the crash-weights given to each road segment from past data. Once the crash generation module creates a crash and the sensor module provides sensor signals, the model collects the sensor data from nearby acoustic sensors and stops the simulation. This acoustic data obtained from the nearby sensors is analyzed using signal processing techniques and the data is fused using data fusion algorithm. This output from the data fusion generates information regarding a crash, e.g. crash location and data regarding multiple impacts. To gather statistically significant performance measures like percentage detection and quality of data from data fusion, the simulation is run multiple times generating random crashes every time, keeping the position of the sensors unchanged.

4.2. Neighborhood search procedure

As noted in the problem definition, there are 869 candidate sensor locations and 20–85 sensors to be placed. The number of possible ways to locate the sensors is a combinatorial large, e.g. ${}^{869}C_{20}$ solutions exist for 20 sensors, far too many for any enumerative algorithm to evaluate. Note that each solution would need multiple simulation runs to reach statistically significant results to compare. Given these constraints, the goal of the neighborhood search is to identify a few solutions with potentially better performance than the initial solution (obtained by placing sensors from implicit model as shown in Fig. 6 for the case study).

A neighborhood search procedure should generate potential solutions close to the present solution and move in the direction of improved objective/performance measures. This is an exploratory method and there is typically no guarantee that this method will generate a better solution. To generate a feasible set of neighbor solutions we propose a cluster-based exchange.

A cluster of sensors refers to a geographically close set of sensors. In the cluster-based exchange, we move a sensor from one cluster to an unoccupied potential sensor location in another cluster as shown in Fig. 8.

To implement the above cluster-based exchange, we first need to divide the set of potential sensor locations occupied by sensors into clusters. For the case of 75 sensors we select 6 clusters. The reason for selecting 6 clusters is that we expect roughly 12 sensors per cluster. The clusters are identified using Lloyd's algorithm (Lloyd, 1982). Fig. 9 illustrates the 6 clusters obtained by applying Lloyd's algorithm on the 75 sensor problem for our case study. We note that the number of sensors in each cluster varies significantly. To proceed with generating a neighboring solution, we select a sensor geographically distant sensor (from the center of one cluster) and remove the sensor allocated to this location. A new potential sensor location is chosen (preferably closer to the center of the cluster) from another random cluster and a sensor is allocated to this new location.

There are other methodologies to create feasible neighbor solutions, however the cluster-based exchange, we believe preserves the data fusion opportunities provided from the explicit–implicit model.

4.3. Case study

As a case study, we chose a road network that covered a 9-mile square area near UB North Campus. This road network is an urban-arterial road network with an interstate running through it. The area chosen has a shopping mall, 3 schools and

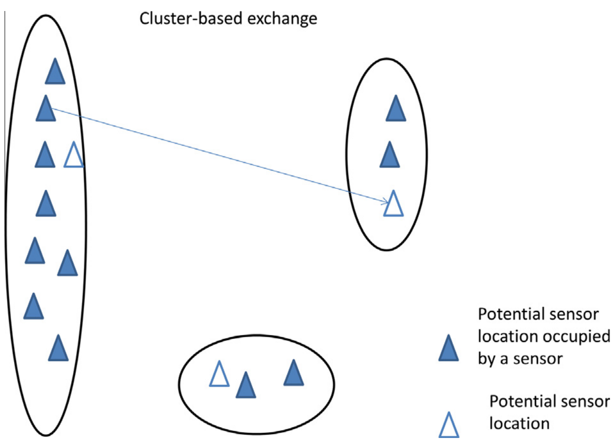
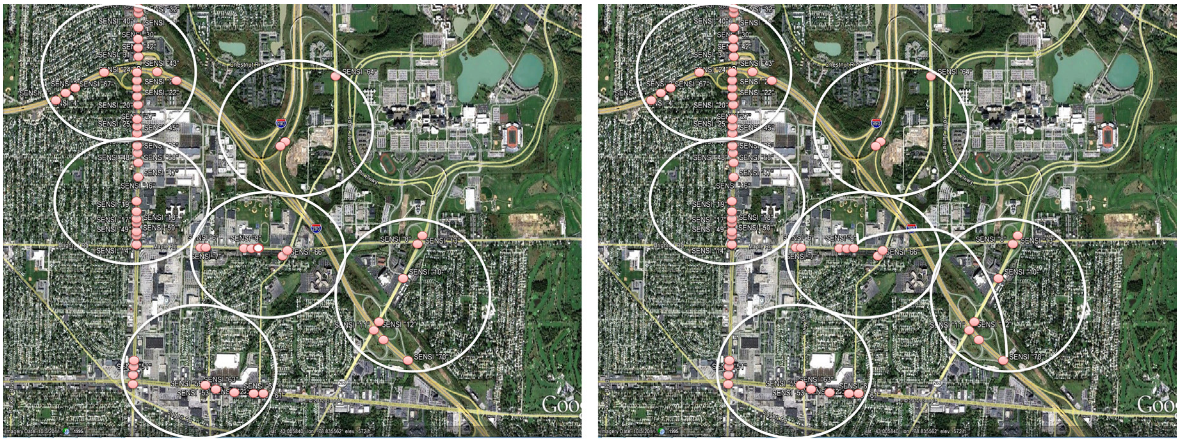


Fig. 8. A demonstration of cluster-based exchange.



(a) (b)

Fig. 9. Cluster-based exchange generating a neighbor solution.

other commercial areas. This area represents a road network with medium traffic flow with peak traffic typically in the mornings and evenings. The average annual traffic data (Greater Buffalo-Niagara, 2010) is used as a reference to recreate the traffic flow inside the simulation. The area chosen is ideal to understand and test the placement of acoustic sensors, as it is without any hilly terrain and large industries which tend to cause errors in signal processing. We consider road noise from the traffic, the most influential on signal processing, in this paper.

From the simulation case study we are interested in two important performance measures. The first measures the "percentage of crashes" detected by the acoustic sensors with a given location strategy. The second performance measure we are interested in is "% crashes detected by two acoustic sensors". This performance measure indicates the level of data fusion opportunity resulting in having multiple sources of crash data.

There are several factors which influence these performance measures chosen for the simulation study. One such factor is the placement of the sensors, which influences both the performance measures. So far in this study we have three placements of the acoustic sensors, first the explicit model, second the implicit model and third, the best of the neighbor solutions obtained through simulation-based optimization.

Explicit and implicit models need key inputs to determine a feasible placement for the sensors. These key inputs also serve as factors influencing both the performance measures. The four inputs/factors we have chosen to analyze in this paper are: (1) number of sensors '*n*', (2) weights of primary/single and secondary/double coverage, (3) detection radius of acoustic sensor, (4) past crash data, which is used as demand data.

Table 1 presents a tabular form of the performance measures chosen using the simulation and Table 2 presents factors affecting the performance measures. In Section 4.5, each of the affecting factors are studied closely to understand their effects on the performance measures.

From Table 1, the performance measures collected from the simulation are "% crashes detected" and "% of crashes detected by two sensors". All the experiments on simulation will collect both the performance measures. The % crashes detected performance measures, measures the number of crashes detected as a percentage of the total number of crashes.

4.3.1. Preliminaries related to computational experiments

In order to derive statistically significant estimates for the performance measures we run 20 experiments for each acoustic sensor placement considered. Each experiment consists of 50 simulation runs. After the conclusion of each experiment, the performance measures are collected. For example, if the first experiment results in the observation of 14 crashes by the acoustic sensors, the performance measure for the % of crashes detected is 14/50 or 28%. This experiment is repeated 20 times generating 19 more observations for the "% of crashes detected" performance measure. In total, we run 1000

Table 1
List of performance measures focused in the study.

Performance measures	How calculated	Implication
% of crashes detected	$\frac{\#\ \text{of crashes detected} * 100}{\text{Total}\ \#\ \text{crashes}}$	Measures the effectiveness of placement in detecting a crash
% of crashes detected by 2 sensors	$\frac{\#\ \text{of crashes detected by 2 sensors} * 100}{\#\ \text{of crashes detected}}$	Measures the data fusion opportunity

Table 2
List of factors affecting the performance measures.

Factors effecting the performance measures
Detection radius of each sensors
Weights of single and double coverage
Number of sensors
Input crash data
Placement of sensors

simulation runs for each acoustic sensor placement. Running this Arena® simulation using Intel® Core™ 2 Duo with clock speed of 3.17 Hz and 4 Gb RAM, takes on average 45 s to complete a simulation run and takes on average 12.5 h to complete evaluation of a single placement of sensors.

Three points of classification are necessary regarding our experiments. First, since the computation time for evaluation of a single placement of sensors is 12.5 h only a few evaluations of additional sensor placement possibilities is possible during the neighborhood search procedure. Second, it is necessary to start each simulation run with a different random number seed in Arena; this ensures that the values of each performance measure collected by repeat performances of the experiment are statistically independent. Third, the fact that we execute 20 experiments and each generates statistically independent value for every performance measure studied, allows us to generate 95% confidence intervals for the performance measures.

4.4. Results

This section presents the results of the solution methodology proposed in Section 3. Section 4.5.1 compares the simulation results of explicit model and the implicit model. Section 4.5.2 presents the impact of increasing the number of sensors on the performance measures. Section 4.5.3 presents the results of neighborhood search procedure described in Section 4.2.

4.4.1. Explicit model vs implicit model

In this section, we compare the results of the explicit and the implicit model. Explicit model and implicit model are two different approaches to solve the acoustic sensor placement problem. We use simulation model presented in Section 4.1 to evaluate both the performance measures for explicit and implicit model. For this comparison, we place 75 sensors using the explicit and the implicit model.

From the results, implicit model generates solutions that show improvement in both the performance measures considered. For the "% of crashes detected" performance measure, explicit model placement has a mean of 23.1% and the implicit model has a mean of 43.5%. Examining the 95% confidence intervals in Fig. 10, the explicit model has a higher variance in "% of crashes detected" performance measure. Similarly, for "% of crashes detected by 2 sensors" the explicit model placement has a mean of 0.3% and implicit model placement has a mean of 11.2%. These results are as expected, since the implicit model uses the explicit model solution as the starting point and uses iterative scheme to improve the solution.

4.4.2. Implicit model performance with different number of sensors

One of the important factors that will affect the performance measures in the implicit model is "number of sensors". Ideally, the budget allocated for the sensor deployment determines the number of sensors available. In this section, we explore the effect of changing the number of sensors on both the performance measures.

In Fig. 14, we present the 95% confidence intervals for the "% of crashes detected" performance measure. The impact of different number of sensors (50, 55, 60, 65, 70 and 75) on the performance measure are also presented in Fig. 11. The mean of "% of crashes detected" performance measure increases with the number of sensors. The improvement in the mean of "% crashes detected" performance measure is not diminishing as the number of sensors increase; in particular going from 55 to 60 sensors yields less improvement than going from 60 to 65 sensors. The solution the implicit model reaches is a function of explicit solution, we attribute this discrepancy to having a comparatively better starting solution going from 60 to 65 sensors.

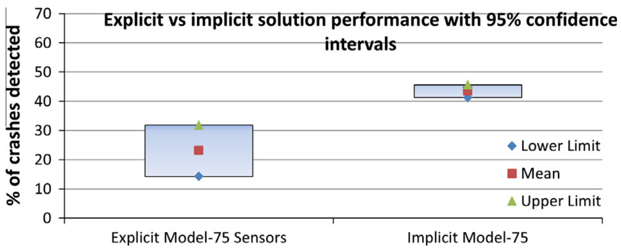


Fig. 10. Explicit solution compared with implicit solution.

4.4.3. Results of simulation-based optimization using a neighborhood search heuristic

Simulation-based optimization is a search for better solutions in the neighborhood of a particular solution. For the acoustic sensor placement problem, we have chosen a cluster-based exchange to provide neighbor solutions as described in 4.2.

We start the cluster-based exchange with the implicit model solution and generate 5 neighbor solutions and evaluate each solution using simulation. In Fig. 12, the neighbor solutions are around the implicit model solution. It is easy to observe that none of the neighbor solutions dominates the implicit model in both performance measures.

Since the implicit model solution is still one of the non-dominated solutions, we use this as the starting point for generating the next five neighbor solutions. The newly generated neighbors are evaluated using the simulation to observe both the performance measures. From the results in Fig. 12, the implicit model solution is still a non-dominant solution in both the performance measures after two iterations. It proves our intuition that the implicit model is a good solution for the acoustic sensor placement problem.

4.5. Exploration of three special cases: higher detection radius, solution robustness and single and double coverage weights

In this section, we explore three special cases of special interest. In Section 4.5.1, we present the change in performance measures if there is an increase in the detection radius of the acoustic sensors. Section 4.5.2 presents a robustness test to evaluate the implicit model solution. Section 4.5.3 presents the effects of changing single and double coverage values chosen in the implicit model on the two performance measures.

4.5.1. Evaluation of a sensor with higher detection radius

Improvement in detection radius for a sensor is an important factor as it usually has a direct impact on system performance measures. In the results of Section 4.4.2, a detection radius of 50 m was chosen (which is current specification for commonly available acoustic sensor). The impact of a higher detection radius (60 m, 70 m, 80 m and 90 m) is studied on the "% of crashes detected" and "% of crashes detected by 2 sensors" performance measures.

It can be noted from Fig. 13, that the increase in " % of crashes detected" performance measure, when the detection radius increases from 50 m to 90 m is about 4% whereas the increase in "% crashes detected by 2 sensors" is 26%. Having a higher detection radius, the sensors are able to increase the overlap region but considering the 9-mile square area chosen, the sensors are unable to cover a large part of the road segments previously uncovered by sensors with 50-meter detection radius. This explains increased gains in the "%crashes detected by 2 sensors" performance measure.

4.5.2. Solution robustness

One of the important inputs for both the explicit and the implicit model is the past crash data. The explicit and the implicit model use this past crash data to construct demand associated with each road segment. In this paper we assume that the past crash data serves as a good indicator for the future crash data to place the crash detecting sensors. There can be arguments made to support and reject the above assumption. In our study area, we found that 30% of the road segments had no crashes in the period 2004–2009, which clearly may have future crashes.

In order to alleviate some of the concerns with the assumption, we propose a robustness test, to understand the performance of the implicit model as a function of this assumption. We qualify the assumption made in this paper; past data completely predicts the future crash data and assign a value of ($p = 1$) to this assumption. In this section we test the performance of the placement suggested in Section 4.4.2 with different values of "p" ($p = 0.9$ and $p = 0.7$). If the value of "p" is chosen as 0.9, in that experiment 90% of the crashes happen on road segments where the crashes have occurred previously and 10% of the crashes occur on road segments that did not have an crash previously. Table 3 shows the construction of the demand for the two cases of $p = 0.9$ and $p = 0.7$. We construct a new path and node demand values and evaluate the placement suggested by the implicit model using 75 sensors.

The results shown in Figs. 14 and 15 indicate that when compared to the original ($p = 1$) results with the robustness test ($p = 0.9$ and $p = 0.7$) both the performance measures decrease. The percentage of crashes detected by a single sensor

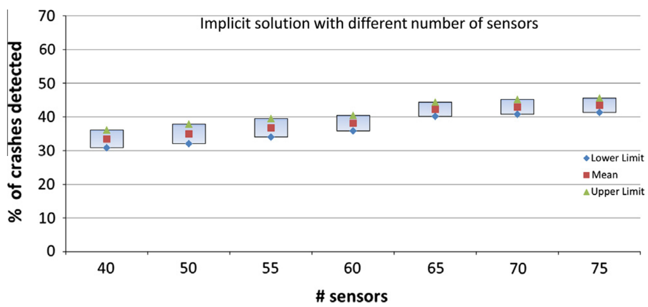


Fig. 11. Implicit model solution performance with varied number of sensors.

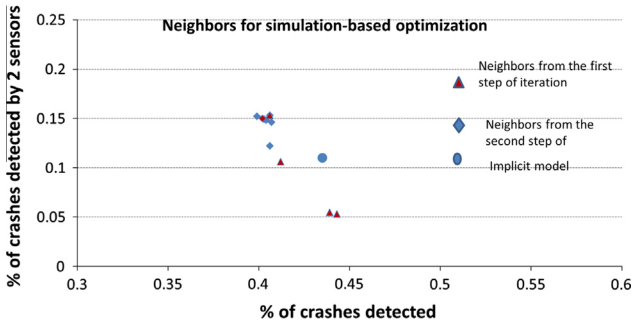


Fig. 12. Neighbor solutions in the simulation-based optimization.

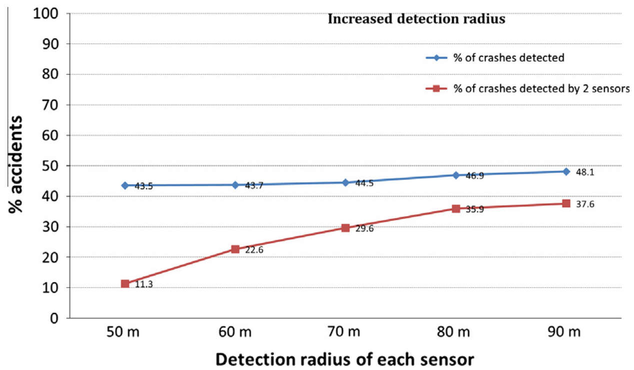


Fig. 13. Performance measures for increased detection radius.

decreases by 10% as the value of p decreases by 0.1. However, double coverage decreases drastically and as p value approaches to 0.7 there are just 1% of the crashes covered by two sensors.

These results also indicate to a user/practitioner that if 30% of future crashes happen on road segments which previously have no crashes, the data fusion opportunities are almost close to zero.

4.5.3. Effects of changing single/primary (α_1) and double/secondary coverage (α_2) on performance measures

The implicit model allows a practitioner/user to assign the importance of primary/single coverage and secondary/double coverage by choosing values for α_1 and α_2 in Eq. (8). This choice of single and double coverage weights will influence the placement of sensors and affect both the performance measures. In the results shown in Section 4.4.2, we selected $\alpha_1 = 0.7$ and $\alpha_2 = 0.3$. In this section, we explore the effect different values of α_1 and α_2 have on the performance measures.

In order to understand the effect of single and double coverage values, we chose three experiments with α_1 and α_2 values as shown in Table 4. For example, Experiment 1 assigns a weight of 0.4 to α_1 and 0.6 to α_2. Experiment 4 is used as a reference to the results.

From Fig. 16, it is clear that there is a positive correlation (except for Experiments 3 and 4) between the α_1 value and "% of crashes detected" performance measure and similarly there is a positive correlation between "% of crashes detected by 2 sensors" performance measure and α_2. Upon close inspection, there is very little variation in performance measures in experiments 3, 4 and a large overlap in the 95% confidence intervals of both performance measures, attributing this exception to random nature of the simulation. Understanding this relation between the weights for the implicit model and both the

Table 3
Shows the construction of new demand for nodes and paths for the robustness test.

Path/node	Probability of a crash	Robustness test ($p = 0.9$)	Robustness test ($p = 0.7$)
Path a	0.1	$0.1 * 0.9$	$0.1 * 0.7$
Path b	0.2	$0.2 * 0.9$	$0.2 * 0.7$
Path c	0.1	$0.1 * 0.9$	$0.1 * 0.7$
Node d	0.6	$0.6 * 0.9$	$0.6 * 0.7$
Node e	0	$(1 - 0.9)/2$	$(1 - 0.7)/2$
Path f	0	$(1 - 0.9)/2$	$(1 - 0.7)/2$

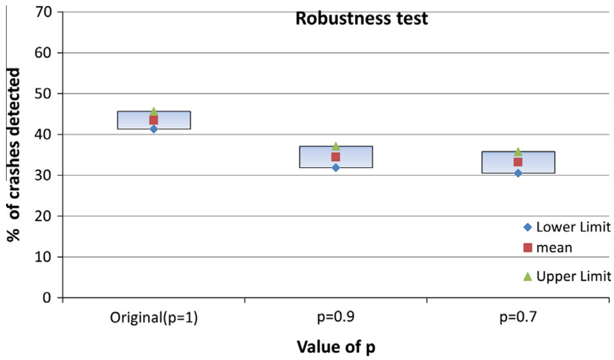


Fig. 14. Results of the robustness test with values of p = 0.7,0.9 and 1.0.

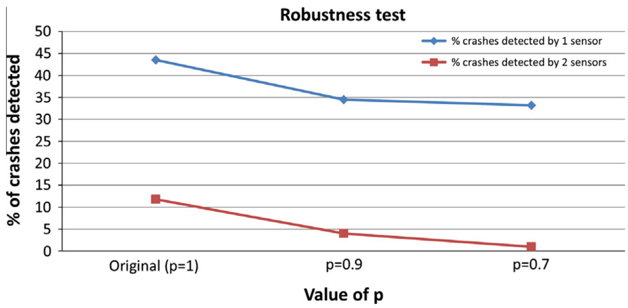


Fig. 15. A figure showing both the performance measures in robustness test with values of p = 0.7, 0.9 and 1.0.

performance measures should help the user/practitioner to select the appropriate weights before using the implicit model (see Table 5).

5. The impact of mobile sensors

We use AACN sensors as a representative sensor for mobile sensors. Both AACN and acoustic sensors use a signature crash characteristic to detect a crash. Acoustic sensors use the unique crash sound signature to detect a crash, whereas AACN sensors use accelerometers and contact sensors to detect a crash. Both the sensors are capable of detecting the following crash characteristics.

- Crash detection.
- Crash location.
- Crash time.
- Rollover.

For example, when a crash happens near an acoustic sensor and the automobile involved is equipped with AACN sensor, there is two sets of data of the above characteristics. The acoustic sensor receives a high amplitude noise for a short duration of time and detects a crash. Similarly, the AACN reports a crash when the accelerometers report crash like acceleration/deceleration. Since, a single acoustic sensor observes this crash, it cannot estimate the position accurately, however we assume that the acoustic sensor reports its position as a point estimate (sends its GPS location as an estimate for crash location).

Table 4
A table showing the different weights chosen for the 4 experiments to understand the relation between primary-double coverage split and performance measure.

	Single coverage (α_1)	Double coverage (α_2)
Experiment 1	0.4	0.6
Experiment 2	0.5	0.5
Experiment 3	0.6	0.4
Experiment 4 (Original)	0.7	0.3

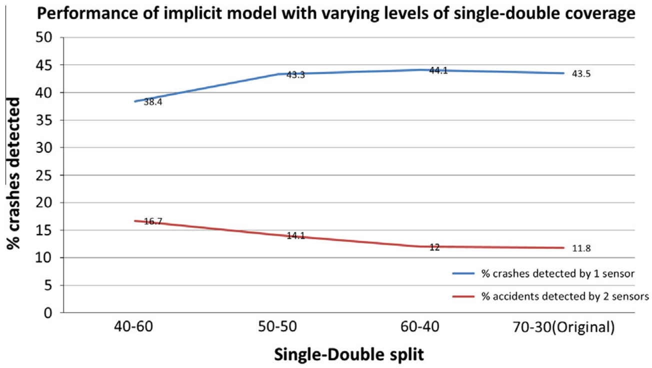


Fig. 16. Performance of implicit model with varying levels of single-double ratio.

Table 5
Improvements possible through data fusion.

	Acoustic sensors	AACN sensor	Acoustic sensors + AACN sensor
% of crashes detected	43.5%	16.9%	53.5%
Average error in position of accident	5.42 m	4.23 m	5.04 m

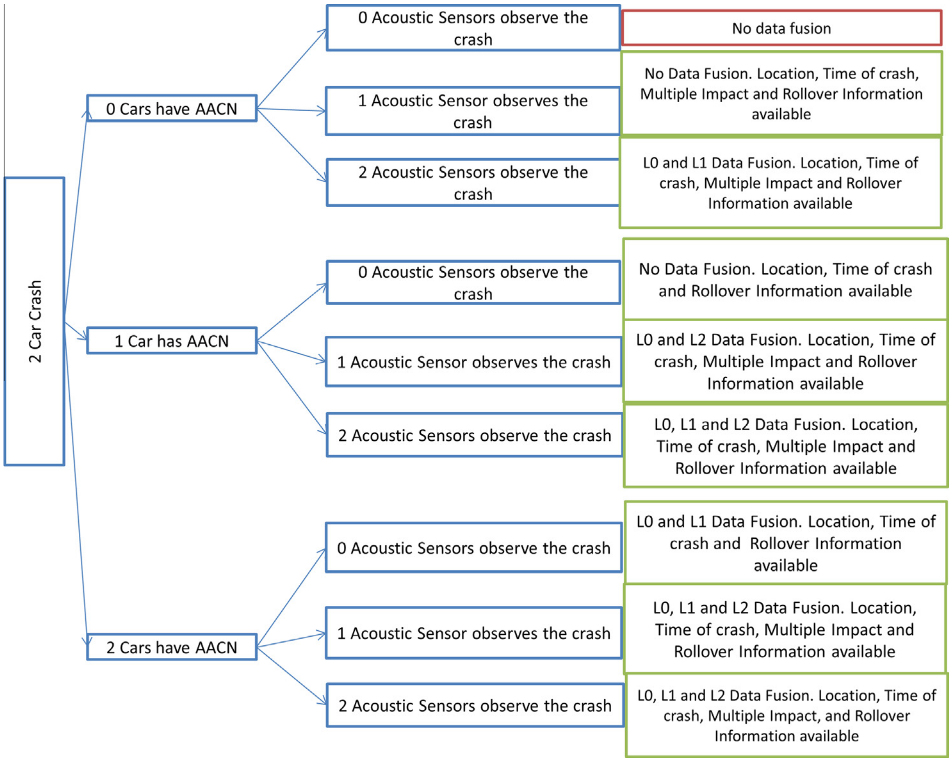


Fig. 17. Tree diagram identifying data fusion opportunities.

Every AACN has an inbuilt GPS sensor, which estimates the position of the crash. Acoustic sensor and AACN both report the crash time as the point where they first observe crash like high amplitude and high accelerometer readings respectively. The AACN uses 3-d accelerometers readings to identify a rollover. Once the two sets of data are available, the next step in the data fusion schema is to send this data from individual sensors to local data fusion motes.

We assume that there is a data fusion network capable of combining information from both acoustic sensors and sensors in the AACN system. The capability of the future system will help in combining the above crash information from both sensor

75 Acoustic Sensors and 10% of the Vehicles Equipped With AACN's				
Various Data Fusion Opportunities with Probabilities		Acoustic Sensor Data		
		0 Acoust. Sens	1 Acoust. Sens	2 Acoust.Sens
In a crash Number of Cars with AACN	0 Cars have AACN	No Data Fusion (prob=0.465)	No Data Fusion. Location, Time, MI, RollOver Info (prob=0.319)	L0 and L1 Data Fusion (prob=0.04)
	1 Car has AACN	No Data Fusion. Location, Time, MI, RollOver Info (prob = 0.08)	L0 and L2 Data Fusion (prob = 0.06)	L0,L1 & L2 Data Fusion (prob = 0.007)
	2 Cars have AACN	L0 & L1 Data Fusion (prob=0.006)	L0 , L1 & L2 Data Fusion (prob = 0.004)	L0,L1 & L2 Data Fusion (prob = 0.0005)

Fig. 18. Data fusion opportunity when 75 acoustic sensors and 10% of vehicles equipped with AACN.

types. In the following section, we demonstrate the data fusion opportunities arising in a crash situation, if there are both AACN sensors and Acoustic Sensors deployed.

5.1. Data fusion opportunity

Suppose there is a roadway incident involving two cars in a data fusion capable environment, populated with acoustic sensors and cars enabled with AACN. The tree diagram shown in Fig. 17 identifies the data fusion opportunities.

The tree diagram in Fig. 17, also identifies the levels of data fusion needed when acoustic sensors and AACN interact. Consider the case of a two car crash in which two cars are equipped with AACN. There are two acoustic sensors near the crash; crash data is available from 4 sensors making independent observations and the data is combined in three levels (Level 0, Level 1 and Level 2) using data fusion techniques to generate crash data useful for situational awareness.

Expanding upon Fig. 17, in Fig. 18 the data fusion opportunities with 75 acoustic sensors and assuming 10% of the vehicles are equipped with AACN are shown. In this case, the combined sensor system could detect 53.5% of the crashes. 75 acoustic sensors could detect 43.5% of the crashes in the same system without the aid of AACN sensors.

The improvements are not limited to percentage of detection alone; the combined system decreases the error in position and number of impacts sensed. By using AACN alone, the error in position of the crash is 4.23 meters in 169 crashes, whereas adding 75 acoustic sensors brings down the error in position down to 5.04 meters in 535 crashes. Similarly, using AACN and the acoustic sensor system, the error in detecting multiple impacts is down to 5%.

Using AACN and acoustic sensors together reduces the error in position to 5.04 m. This reduction may be significant in areas containing multiple road segments over bridges and underpasses. 5-m accuracy is close to lane level accuracy and very helpful in positioning the crash. The test case chosen assumes that the GPS sensors work with an error of 10 m and all the roads in the system have no tunnels and other form interruptions for GPS systems. Even in cases where there is a GPS interruption, we assert that a system with acoustic sensors and AACN will yield good estimates for position.

Both improvements demonstrate the positives of using a data fusion capable environment with different sensor types observing a crash. The simulation results point towards the improvements and the decrease in error in detecting both the position and number of impacts, which can be critical in assessing the crash.

6. Concluding remarks

In the absence of data fusion there is abundance of research in sensor placement problems, for both discrete and stochastic demand. This paper describes an omnidirectional sensor placement problem, where both primary coverage and double coverage are important in placement of sensors. double coverage is important because it provides an opportunity for data fusion.

The explicit–implicit model, followed by simulation-based optimization is a unique approach developed for this paper. The explicit–implicit model is mathematical model that approximates the real situation, and uses an objective that aims to cover crash demand from both paths and intersections where crashes are more likely to happen. The explicit model is a quadratic maximal coverage problem and the implicit model is a geometric approach to solve the sensor placement model. The implicit model uses the explicit model solution as a starting placement strategy. The simulation-based optimization starts using the implicit model solution. This combined approach has yielded good solutions to the omnidirectional sensor placement problem.

The simulation model adapted in this paper imitates a real road network and the functioning of omnidirectional (acoustic) sensors and mobile (AACN) sensors. The simulation model developed is unique in terms of creating an crash, measuring the performance of the sensors and takes into consideration the effects of weather, congestion and road noise. The simulation model developed here evaluates a placement strategy for the acoustic sensors. The main performance metrics considered are "% of crashes detected" and "% of crashes detected by 2 sensors".

Stochastic systems use simulation to evaluate the performance. This evaluation process combines well with an improvement procedure to an existing system by using a search procedure to evaluate some solutions and move in the direction of the improved solution. This approach has been useful here to evaluate the acoustic sensor placement strategy and provide more results for a decision maker to optimize their criteria. Though the method used here only yielded non-dominant solutions, the method is helpful in choosing a customized solution for every user.

This paper makes significant contribution in using simulation as a useful tool to answer questions pertaining to sensor deployment in a road network environment. We demonstrate that by strategically locating just 75 acoustic sensors that have a detection radius of 50 m, 43.5% of the crashes are observed by a single sensor and two sensors observe 11% of the crashes. The combined system of AACN and acoustic sensors detect 53.5% of the accidents and the average error in position of the crash is 5.04 m.

This paper evaluates the data fusion capable system with both acoustic and AACN sensors. Many papers discuss the capabilities of an advanced system involving multiple sensor types, but none has been able to evaluate the real world applications. This work demonstrates the effectiveness of such system and quantifies the improvements.

Several factors affect the overall performance of the sensor placement. Three factors explored in this paper are radius of detection, single and double coverage weights for the implicit model and the change in crash demand data. In Section 4, we evaluate all these factors individually to understand the relation between the factors and performance measures. A future research direction would be to explore the combined effects of changing multiple factors on the performance measures. Another future research direction is to extend this placement problem and adapt the implicit model to include other sensors that need not be omnidirectional.

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