

## OPTIMAL PLACEMENT OF FLAME DETECTORS IN PETROCHEMICAL FACILITIES

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### *Abstract*

Flame detectors provide an important layer of protection for personnel in petrochemical plants, but effective placement can be challenging. A mixed-integer nonlinear programming formulation is proposed for optimal placement of flame detectors while considering probabilities of detection failure. We show that this approach allows for the placement of fire detectors for a fixed sensor budget while under uncertainty and outperforms deterministic models that do not account for imperfect detection. We demonstrate the effectiveness of this formulation on a 100 sq. ft. test case and on a real-world dataset.

### *Keywords*

Optimization, Fire Detection, Process Safety

### **Background**

In petrochemical facilities, gas and flame detectors provide an important layer of protection for personnel (Legg et al., 2012). Flame detectors, as opposed to smoke or heat detectors, however, are optical sensors that utilize information from a visual field to detect flames and can respond faster and more accurately. For successful and reliable detection, flame detectors require a visual path to the fire, free of obstructions. Petrochemical facilities, however, are typically characterized by complex physical geometries arising from the large number of valves, pipes, tanks, and reactors in the plant. There is a significant number of additional factors and uncertainties to consider when trying to determine the optimal placement of detectors, including: visual field decay, unknown obstructions, sensor outages, and cost limitations.

Numerical optimization methods (Farahani et al., 2012) provide opportunities to overcome these challenges and determine effective detector placement. Yang et al., (2012) investigated placement of visual fire detectors using a color classification method and an exhaustive search algorithm.

In this paper, we present a mixed-integer nonlinear programming (MINLP) formulation for determining the optimal plant-specific placement of flame detectors by maximizing expected coverage of the space with consideration to probability of detection failure. This formulation is related to the class of problems defined as Maximal Expected Coverage Problems (MECP) (Camm et al., 2002, Daskin 1983). A convex relaxation using linear under-estimators is used to solve the MINLP. We show that this probabilistic formulation, with consideration of uncertainties, outperforms the corresponding deterministic version that places detectors assuming perfect detection.

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## Problem Formulation

The mixed-integer nonlinear programming formulation for optimal detector placement, assuming imperfect detection, and denoted as Probabilistic Coverage Formulation (PCF), is given by

$$\begin{aligned}
 & \text{maximize} && \sum_{e \in E} \sigma_e w_e \\
 & \text{s. t.} && \sum_{l \in L} x_l \leq k \\
 & && \sigma_e = 1 - 1 \left[ \prod_{l \in L_e} (1 - p_{l,e} x_l) \right] \quad \forall e \in E \\
 & && x_l \in \{0,1\} \quad \forall l \in L \\
 & && 0 \leq \sigma_e \leq 1 \quad \forall e \in E
 \end{aligned} \tag{1}$$

where  $E$  denotes the set of entities to be observed,  $L$  denotes the set of all candidate detector locations,  $L_e$  denotes the set of candidate detector locations that can observe entity  $e$  (pre-processed from data),  $x_l$  is a binary variable denoting whether a detector is built at location  $l$ ,  $k$  is a parameter denoting the detector budget limit,  $\sigma_e$  is the expected coverage of entity  $e$  (i.e. probability of an event at entity  $e$  being detected),  $p_{l,e}$  is the probability of a detector at location  $l$  successfully detecting an event at entity  $e$ , and  $w_e$  is the weight of entity  $e$ . The nonlinear product within the expected coverage constraint can be reformulated to produce a convex MINLP which is then solved as an MILP using linear under-estimators for the convex nonlinear constraint, as follows

$$\begin{aligned}
 & \sigma_e = 1 - \gamma_e \quad \forall e \in E \\
 & \bar{\gamma}_e = \sum_{l \in L_e} x_l \ln(1 - p_{l,e}) \quad \forall e \in E \\
 & \gamma_e \geq \exp(\bar{\gamma}_{e,m}^*) (\bar{\gamma}_e - \bar{\gamma}_{e,m}^* + 1) \quad \forall e \in E, m \in M_e
 \end{aligned} \tag{2}$$

where  $\gamma_e$  is the probability that an event at entity  $e$  is not detected (represents the product term in the second constraint of Eq. 1),  $\bar{\gamma}_e$  is an auxiliary variable denoting the log-transform of  $\gamma_e$ , and  $\bar{\gamma}_{e,m}^*$  are points along the domain of  $\bar{\gamma}_e$  where linear under-estimators are placed.

## Results and Conclusions

We test the placement formulation on a 100 sq. ft test case with 45 candidate detector locations. We run both the deterministic placement formulation (maximizing coverage) and the probabilistic formulation. Fig. 1 shows the percent improvement of using the proposed Probabilistic Coverage Formulation versus using a deterministic coverage model under imperfect conditions (i.e. assuming imperfect detection as defined by probabilities of successful detection  $P=0.5, 0.7$ , and  $0.9$ ). As detection becomes less reliable, this discrepancy becomes more pronounced. However, even a 10% confidence in

successful detection yields a non-trivial improvement by using PCF to optimally place flame detectors.

An analysis of the proposed formulation using a real-world dataset provided by Kenexis Consulting Corporation will be discussed in detail in the poster presentation.

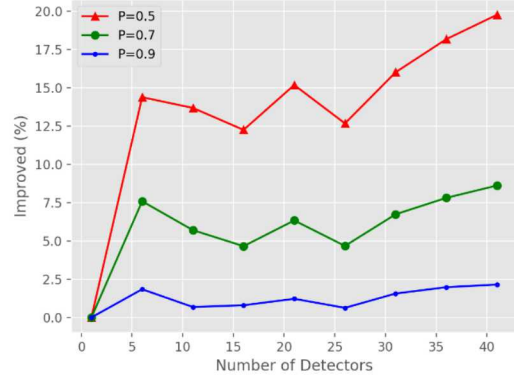


Figure 1. Percentage improvement of PCF solutions against DCF solutions for probabilities of successful detection  $P=0.5, 0.7$ , and  $0.9$ .

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