A risk-based method for optimizing process plants layout

A.C. Caputo*, Mario Palumbo**, P.M.Pelagagge**, P.Salini**

*Department of Engineering, University of Roma Tre, via della Vasca Navale 79, 60100, Roma – Italy (acaputo@uniroma3.it)

** Department of Industrial Engineering, Information and Economics, University of L'Aquila, Zona industriale di Pile, 67100, L'Aquila – Italy (mario.palumbo@univaq.it, paolo.salini@univaq.it)

Abstract:

Purpose

This paper presents an automated method for optimizing process plant layout factoring in risk of mutual damage deriving from accidents to process equipments.

Design/methodology/approach

The relative location of main process units is determined to minimize an annual cost function including land cost, the cost of material transfer between process units (piping and pumping costs), as well as the expected annual loss resulting from damage to each secondary unit caused by primary accidents occurring in nearby process units. A genetic algorithm is used to minimize the objective function. In the paper, after discussing the structure of the annual cost function and describing the working logic of the layout generating algorithm, a case study is developed to demonstrate the effectiveness of the proposed methodology.

Originality/value

This method is an improvement over previous attempts to optimize process plant layout. In fact, earlier methods neglected pumping costs and included safety issues by evaluating the infringement of predefined safety distances only. In this approach, instead, the operating cost of material transfer is included and the likelihood of accidents is taken into account, as a function of equipment distances, thus providing good practical solutions to the plant layout problem by incorporating more realistic cost functions and constraints.

Keywords: Process plant safety, Genetic algorithm, Plant layout, Risk reduction, Layout optimization.

1. Introduction

The process plant layout problem consists in defining the optimal spatial arrangement of a set of facilities and the required connections among them within a plant site. The location of process units and plant facilities is chosen in order to reduce land use and the costs of the piping interconnecting each units pair, as well as to organize more efficiently the production and increase the plant safety. Such requirements frequently give rise to conflicting goals. If, on the one hand, material transfer cost and occupied area are reduced by placing interrelated units at a short distance, on the other hand safety concerns ask for minimum safety distances between process units to be maintained. Process plant layout design is an activity usually carried out by human designers (Mecklenburgh, 1985). Computer-aided layout planning methods were instead scarcely adopted in the past in this sector owing to the difficulty in minimizing a number of different objective functions simultaneously in a realistic manner. Nevertheless, there is a growing need to develop computer-aided methods to support process plant engineers in the rapid generation of alternative chemical plants layouts. Heuristic techniques were suggested at first (Amorese et al., 1977; Gunn and Al-Asadi, 1987; Suzuki et al., 1991), offering computational efficiency but no guarantee on the optimality of the solution. Jaykumar and Reklaitis (1994) in alternative formulated a graph partitioning problem to allocate equipment to sections created by aisles or corridors. These attempts were followed by mathematical programming approaches aimed at reaching optimal solutions. Mixed integer linear programming formulations were developed by Georgiadis et al. (1999) to allocate items to candidate locations onto a grid or, in the continuous domain, for single or multiple-floor problems by Papageorgiou and Rotstein (1998), Patsiatzis and Papageorgiou (2002a, 2003), Ozyruth and Realff (1999), Barboza Pavoa (2001).
Attempts to incorporate safety issues in computer-aided layout optimization procedures have been also carried out adopting heuristic, mathematical programming and stochastic optimization techniques. Fuchino et al. (1997) adopt a heuristic approach where the equipment modules are divided into groups and then sub-arranged within groups according to safety requirements. Suzuki et al. (1991) rely on a set of heuristics supporting a facilities interchange procedure based on a cost function calculated from unit separation distances. Georgiadis and Macchietto (1997) analyse the layout of multifloor production facility of equally sized units. Penteado and Ceric (1996) adopt a mixed integer non-linear programming technique to optimize cost and safety of circular or elliptical process units layout. In this approach, the cost of a layout is a function of piping cost, land cost, financial risk, and protection devices cost. The financial risk term captures the risk of unsafe plants and can be expressed as the expected losses if major accidents happen (i.e., fires or explosions). Patsiatzis and Papageorgiou (2002b) suggest a MINLP model by adopting rectangular shapes and rectilinear distances, including risk related to accidents propagating from a source to a target utilizing the equivalent TNT method. Patsiatzis et al. (2004) extend previous continuous domain process plant layout mathematical models to include safety aspects and economic loss by utilizing the Dow Fire and Explosion index. Castell et al. (1998) consider a process layout including oriented rectangular facilities and adopt a non differentiable objective function, utilizing Genetic Algorithms (GA) for its optimization. In their approach safety is modelled by the Mond fire and safety index which specifies the preferred minimum distance between process units. The extent to which these constraints are violated determines, although not explicitly, the safety cost of the layout. Jung et al. (2011) adopt a MINLP approach together with probit method to estimate probability of damage to equipment to be factored as a potential structural damage cost in the overall cost function including land cost and interconnection cost. Finally, some authors (Vazquez-Roman et al., 2009; Garcia-Sánchez et al., 2013; Vazquez-Roman and Mannan, 2010) suggest a MINLP layout cost minimization model associated to a probabilistic analysis performed by Monte Carlo simulation to account for uncertainties in accident scenarios. However, the previous approaches neglect operating cost of the pipe network related to overcoming friction losses, and often consider safety costs either indirectly or, when explicitly, in a substantially deterministic manner. Therefore, it can be concluded that although in recent time the problem of optimal process plant layout has attracted the attention of a number of researchers, there is still a need for an approach combining process plant layout and detailed risk assessment. With this aim a genetic algorithm based optimization approach to the plant layout problem in the continuous domain is presented in this work which includes in a realistic manner all relevant costs, including land use, piping investment and operating expenses, as well as economic loss from potential accidents evaluated in a probabilistic manner.

In the paper, the layout problem is formulated at first and an objective cost function is derived. Then the encoding of analytical formulation into the genetic algorithm structure is described as well as the solutions adopted to comply with the layout problem constraints. An industrial case study concludes the paper by exemplifying the method application and its capabilities.

2. Layout problem formulation

According to Mecklenburgh (1985) a good layout is associated to low pipework cost, a small plant area, and a safe design. To account for these requirements layout optimization is here carried out by minimizing the objective function of (Eq. 1) representing the layout-related total annual cost of the plant TC (€/yr)

$$ TC = PIC + POC + EAL + LC $$  

(1)

where PIC is the equivalent annual piping investment cost, POC is the annual pumping-related operating cost for overcoming friction losses in the piping, EAL is the expected annual loss from accidents, and LC is the equivalent annual land cost. All costs are expressed as annual costs (€/yr) and computed as indicated below.

2.1 Piping cost

To compute piping investment cost it is assumed that all pipes run from the centre point of a process unit and that the pipe length between two interconnected units \(i\) and \(j\), having centre points coordinates \((x_i, y_i)\) and \((x_j, y_j)\) respectively, is the rectangular distance

$$ L_{ij} = |x_j - x_i| + |y_j - y_i| $$  

(2)

It is also assumed that the cost per unit length \(C_{ij} (€/m)\) of the pipe interconnecting units \(i\) and \(j\) is known from a preliminary sizing which enabled the designer to set the technical specification of each pipe line, including pipe diameter \(D_{ij}\), material, and wall thickness.

The overall equivalent annual cost of piping investment is therefore

$$ PIC = \frac{C_{ij}}{2} \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} \delta_{ij} C_{ij} L_{ij} $$  

(3)

where factor \(\frac{1}{2}\) avoids counting two times the same pipe line, \(N\) is the number of facilities to be allocated, and \(\tau\) is the capital recovery factor \(\tau = [s(1+s)^T]/[(1+s)^T-1]\), being \(T\) is the plant life span (years) and \(s\) the interest rate (%/year), while \(\delta_{ij}\) represents the connectivity matrix and is defined as follows: \(\delta_{ii} = 1\) when unit \(i\) and \(j\) are connected, \(\delta_{ij} = 0\) when units are not connected.

2.2 Pumping costs

The annual energy cost for overcoming friction losses is computed as follows. At first the pressure drop \(\Delta p_{ij}\) (Pa) in the pipe connecting units \(i\) and \(j\) is computed knowing the fluid density \(\rho_i\) (kg/m$^3$) and the flow velocity \(v_{ij}\) (m/s)
\[ v_{ij} = \frac{Q_i 4}{\pi D_{ij}^2} \]  
(4)

\[ \Delta p_{ij} = \frac{P_{ij} V_i^2}{2} \int_{D_{ij}}^{} \]  
(5)

where \( Q_i \) is the flow rate \((\text{m}^3/\text{s})\) between units \( i \) and \( j \), while \( f \) is the friction factor. The corresponding pumping power \( P_{ij} \) is

\[ P_{ij} = \frac{Q_i \Delta p_{ij}}{\eta} \]  
(6)

being \( \eta \) the pump mechanical efficiency. The total annual operating cost for pumping losses \( POC \) is

\[ POC = C_{e} \frac{H}{2} \left( \sum_{i=1}^{N} \sum_{j=1}^{N} \delta_{ij} P_{ij} \right) \]  
(7)

being \( C_{e} \) \((\text{€/Wh})\) the energy cost, and \( H \) the annual operating hours \((\text{hr/yr})\).

### 2.3 Safety cost

The expected annual loss is computed as the summation of the expected monetary loss related to each process unit or facility in the plant \( \text{EAL}_{i} \)

\[ \text{EAL} = \sum_{i=1}^{N} \text{EAL}_{i} \]  
(8)

The expected annual loss for the generic \( i-\text{th} \) process unit is computed as the sum of expected monetary loss due to damage to the equipment, and the expected loss due to fatalities of people involved in equipment operation and maintenance.

\[ \text{EAL}_{i} = p_{\text{CD},ij} \left( CF_{i} EV_{i} \right) + N_{pi} P_{pi} FL \]  
(9)

The expected value of production interruption is not included in this model, as it is case specific and may even occur in case of damage of a single equipment irrespective of layout design. In Eq. 9 \( p_{\text{CD},ij} \) is the cumulative annual probability that the considered unit has of being damaged from the other process units in the plant owing to loss of containment or mechanical failure (an equipment self-damage unrelated to accidents occurring to other equipment is not relevant as far as layout design is concerned), \( EV_{i} \) is the economic property damage value of the \( i-\text{th} \) process unit, \( CF_{i} \) is a credit factor (usually set at 1, but can assume any user specified value in the \([0,1]\) range) which accounts for any safety measure or protection device able to limit the actual property damage cost to the unit. The cost of such additional safety measure can be included in equipment value \( EV_{i} \), \( N_{pi} \) is the average number of people standing by the equipment for operational and maintenance purpose, \( P_{pi} \) is the probability that people actually stay near the equipment when the accident occurs (this depends from work shift organization and the needs for local manned supervision), while FL is the economic value of a fatality (usually about 2x10^6 $/fatality according to the statistical value of life approach).

In (Eq. 9) the term \( p_{\text{CD},ij} \) is evaluated as a probability complementary to that of not being damaged by any other unit.

\[ p_{\text{CD},ij} = 1 - \left( \prod_{j=1}^{N} \left( 1 - p_{\text{AD},ij} \right) \right) \]  
(10)

The probability that the \( i-\text{th} \) unit has of being actually damaged by a generic other unit \( j \) is

\[ p_{\text{AD},ij} = p_{ij} \]  
(11)

where \( p_{ij} \) is the probability of an accident occurring in unit \( i \), while the probability \( p_{ij} \) of damage to unit \( i \) caused by unit \( j \) is computed resorting to a probit model of the kind

\[ Y = k_{1} + k_{2} \ln (D) \]  
(12)

where probit coefficients \( k_{1}, k_{2} \), and the dose \( D \) computed at the actual rectilinear distance between units \( i \) and \( j \) are defined according to the type of accidental event (Leese, 1996; Van den Bosh and Weterings, 1997). From the probit value \( Y \) then the corresponding probability of damage can be easily obtained. As an example, in the case of damage caused by overpressure, Cozzani and Salzano (2004) suggest the following probit equations for different kinds of target process units, where the dose is expressed in terms of peak overpressure \( \Delta P \)

- atmospheric vessels: \( Y = -18.96 + 2.44 \ln (\Delta P) \)  
(13)

- pressurised vessels: \( Y = -42.44 + 4.33 \ln (\Delta P) \)  
(14)

- elongated equipment: \( Y = -28.07 + 3.16 \ln (\Delta P) \)  
(15)

- small equipment: \( Y = -17.79 + 2.18 \ln (\Delta P) \)  
(16)

If accident modes other than explosion may occur in the process units (i.e. pool fire, jet fire, fireball, flash fire, mechanical explosion, BLEVE, vapour cloud explosion) the same analysis is carried out each time referring to a different class of initiating event. In this case for each \( k-\text{th} \) class of initiating event occurring at the \( j-\text{th} \) unit and affecting the \( i-\text{th} \) unit the damage probability \( p_{\text{AD},ijk} \) is computed as above described, and the overall value of \( p_{\text{CD},ij} \) follows as

\[ p_{\text{CD},ij} = 1 - \left( \prod_{j=1}^{N} \left( 1 - p_{\text{AD},ijk} \right) \right) \]  
(17)

If a more detailed analysis is required then the damage area boundary can be computed by resorting to specific consequence models (Leese, 1996; Van den Bosh and Weterings, 1999; CCPS, 2000) to evaluate the radius where a given threshold value of the physical effect is obtained (Cozzani et al., 2006).

### 2.4 Land cost

The annual equivalent cost of the land, which is assumed to have a rectangular shape enclosing all process units and a unit cost \( ULC \) \((\text{€/m}^2)\) is
being $t$ the capital recovery factor, while $l_j$ is the length of a process unit side parallel to the x axis, and $w_i$ is the length of the side parallel to the y axis. The facilities locations, chosen randomly by the genetic algorithm, define the distances $L_{ij}$ between process units as well as the size of the land area, thus allowing to compute the objective function value.

3. The genetic algorithm solution method

In discrete and combinatorial optimization problems, or when non differentiable objective functions occur, stochastic optimization techniques such as Genetic Algorithms (GA) may be successfully utilized (Goldberg, 1989, Davis, 1991). GA have been already applied to process plant layout problems, where they have generally proved to largely outperform other heuristic algorithms and metaheuristics. GA is a stochastic global search method that mimics the process of natural biological evolution. It operates on a population of individuals, each one described as a string composed by binary genes and representing a candidate solutions to the problem, and applies the principle of survival of the fittest to produce better performing individuals in subsequent evolutionary generations of the examined population. At each generation, individuals are selected according to their level of fitness and then are bred together. This process leads to the creation of individuals better suited to their environment than their parents. In practice a GA operates starting with a population of random individuals. Thereafter each string, i.e. an individual of the population, is evaluated to find the fitness value. Then individuals of the new population are generated including the best individual(s) copied from the previous generation (the so called Elite Count); new individuals obtained by crossover recombination of couples of selected individuals of the previous generation, where the probability of an individual of being picked for breeding depends from its fitness level; new individuals randomly generated, mutant individuals obtained by randomly changing some of their genes; migrant individuals from past generations. The process stops when a convergence criterion establishes that the fittest individual has been found or a maximum number of iterations is reached. The minimization problem in this paper is solved resorting to a GA coded by the authors that, given a set of N facilities to be allocated onto a plant layout, generates the physical location and orientation of each unit until an optimal layout is found corresponding to a minimum of the objective function $TC$ (Eq. 1). In the genetic representation of this problem each individual of the population represents a candidate plant layout arrangement and is coded as a binary string made of N substrings, each one coding the location of a single process unit in terms of centre point coordinates $(x_i, y_j)$ and an additional bit $O_i$ representing unit orientation. If the orientation bit is 0 the unit has the longest side parallel to the y axis, if it is 1 the longest side is parallel to the x axis. The fitness level of each individual is inversely proportional to the total cost associated to the layout represented by the individual. A major problem when solving layout problems with GA is that of generating feasible solutions in the population during the stochastic evolution process and to ensure that the offspring of two parents representing feasible solutions still is a feasible solution. In fact, neglecting geometrical constraints resulting from facilities overlapping or from the assignment of more than one equipment to the same physical location, the GA would inevitably generate infeasible individuals and the number of feasible solutions in a randomly generated population would rapidly go to zero preventing the solution of the layout problem. Therefore infeasible solutions can not be allowed in the population, as discussed for example by Suresh et al. (1995) and new genetic operators or “repair operators” may be required to ensure feasibility of the generated individuals (Al-Hakim, 2000).

In the implemented model the GA chooses the coordinate of equipment centre points $(x_i, y_j)$ on a grid of predefined width. In case the grid pitch is chosen smaller than the maximum side length of the largest process unit it may happen that in a candidate layout two or more units overlap. In this case the GA discards the unfeasible individual.

To solve the problem one must know the units connection matrix $\delta_{ni}$, the size of process units (expressed as length of the two sides $A_i$ and $B_i$ of their rectangular footprint), the probabilities of accidents of each process unit $P_{ai}$, the economic property damage value of each process unit $EV_i$, the values of $Q_{ni}$, $C_{ULC}$, $D_{ni}$, $\rho_{ni}$, for each pipe connecting two process units, the values of constants $T$, $s$, $C_{ni}$, $H$, $ULC$, $FL$, $P$, $N$. After obtaining a new generation, for each candidate individual the values of distances $L_{ij}$ are computed, the values of $\Delta P_{ni}$, $P_{ij}$, $P_{Cij}$ are computed, the cost functions $PIC$, $POC$, $LC$, $EAL$ are computed, the value of the objective function $TC$ is computed. Then the individuals for the successive generation are created and the process is repeated until termination. When the stopping rule is reached the best fit solution (i.e. minimum $TC$) is chosen which corresponds to the searched optimal layout expressed as a string of coordinates of process units centre points and their orientation in the plane.

4. Application example

In order to show the application of the method a case study is examined. Reference is made to a Nitric acid production plant as described by Ray and Johnston (1989). The process scheme is shown in Figure 1, while plant technical details can be found in the referenced textbook.

This plant processes several hazardous substances, namely ammonia, reaction gasses, tail gas and reaction acid. Following a preliminary sizing of process units their economic value has been estimated as shown in Table 1. The Table also shows the assumed accident probability, the process conditions, and the radius of the damage area.
The genetic algorithm has been coded with a 5+5+1 bits substring structure. Therefore both the x and y center points coordinate of each process unit can assume 1024 different values. This means that the layout is basically built on a 32 x 32 grid. The grid spacing has been assumed 10 m. Plant life was 10 years and the yearly discount rate was $s = 5\%$, $C_e = 0.1 \text{€/kWh}$, $H = 6000 \text{ h/yr}$, $ULC = 20 \text{ €/m}^2$. The GA parameters were set as follows: maximum number of iterations $N_{\text{MAX}} = 500$, crossover probability 0.7, mutation probability of 0.001, population including 100 individuals.

Figure 2 shows the safety cost reduction using the proposed approach.

In order to show the working process of the GA, Figure 3 shows how the prospective layout changes as the GA runs. Cost reduction was obtained through a progressive reduction of the distance between process units and inversion of units positions in order to avoid an excessive increase of expected accident cost, as shown in the sequence of layouts generated by the GA. In the figures the circles represent the damage areas of the process units.

### Figure 1: Nitric acid production process plant scheme

#### Table 1: Plant data.

<table>
<thead>
<tr>
<th>Process Unit</th>
<th>Economic Value (€)</th>
<th>Accident Probability MTBA (yr) (%)</th>
<th>Damage Radius (m)</th>
<th>Inventory (kg)</th>
<th>Volume (m³)</th>
<th>Pressure (kPa)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AT</td>
<td>1460.000</td>
<td>100</td>
<td>1.0%</td>
<td>-</td>
<td>337280</td>
<td>6018</td>
</tr>
<tr>
<td>AVS</td>
<td>210600</td>
<td>50</td>
<td>2.0%</td>
<td>1673.0</td>
<td>15</td>
<td>3</td>
</tr>
<tr>
<td>MR</td>
<td>408800</td>
<td>20</td>
<td>5.0%</td>
<td>2049.4</td>
<td>15</td>
<td>10</td>
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<tr>
<td>ECI</td>
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<td>20</td>
<td>5.0%</td>
<td>825.9</td>
<td>10</td>
<td>3</td>
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<tr>
<td>CWSW</td>
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<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>IEU</td>
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<td>-</td>
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</tr>
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<td>1.26</td>
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</table>
Finally, Figure 4 show the results of the overall optimization process where the objective function to be minimized includes all cost items.

Figure 3: Layout evolution during GA run

Figure 4: Total cost evolution during GA run

5. Conclusions

In this paper a novel methodology for optimizing the layout of unequal area rectangular-shaped facilities considering safety issues is presented. The proposed methodology adopts a genetic algorithm formulation and is specifically tailored for generating layouts for process plants. It is based on the minimization of the total annual cost explicitly including land cost, investment and operating expenses for the piping network connecting the process units and safety costs related the potential loss from accident in process units. Respect previous attempts to include safety aspects in the optimal layout problem, this method explicitly adopts a probabilistic approach to models expected annual cost of accidents. Furthermore, it includes operational expenses in the form of pumping cost which are generally neglected by other authors, and adopt a genetic algorithm procedure instead of a mixed integer linear programming formulation as happens in most of the related literature concerning process plant layout. In fact, the adoption of a genetic algorithm enables to consider any degree of complexity in the definition of the objective function and in the estimation of safety risk, which is usually prevented in more traditional mathematical programming approaches. This allows a more realistic solution of the layout optimization problem.
References