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# CGD-GA: A graph-based genetic algorithm for sensor network design

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**Abstract**

The foundations and implementation of a genetic algorithm (GA) for instrumentation purposes are presented in this paper. The GA constitutes an initialization module of a decision support system for sensor network design. The method development entailed the definition of the individual's representation as well as the design of a graph-based fitness function, along with the formulation of several other ad hoc implemented features. The performance and effectiveness of the GA were assessed by initializing the instrumentation design of an ammonia synthesis plant. The initialization provided by the GA succeeded in accelerating the sensor network design procedures. It also accomplished a great improvement in the overall quality of the resulting instrument configuration. Therefore, the GA constitutes a valuable tool for the treatment of real industrial problems.


*Keywords:* Combinatorial optimization problem; Process system engineering; Process-plant instrumentation design; Genetic algorithm; Observability analysis

## 1. Introduction to sensor network design

The research field recognized as sensor network design (SND) aims at determining the type, amount and location of measuring devices that are to be placed in an industrial plant so as to get complete knowledge of its functioning conditions. A satisfactory SND is definitely advantageous since it results in a better control, significant savings, a safer operation and a cleaner environment.

One of the most broadly used approaches to accomplish this task is based on the construction and analysis of a suitable steady-state mathematical model that contains information about the fundamental physico-chemical principles that govern the process. The mathematical model is a set of strongly non-linear algebraic

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equations that correspond to mass and energy balances, including the relationships employed to estimate thermodynamic properties like densities, enthalpies, and equilibrium constants. Based on the equation system, the SND is usually carried-out in two main analysis phases: observability and redundancy [20]. The observability analysis (OA) provides information on the amount of knowledge about the industrial process that can be obtained from a set of measurements and from the mathematical model. The redundancy analysis (RA), which is very valuable for control purposes, helps in finding the necessary redundancy degree to detect measurement errors, and to ensure that when a fault occurs the system can still be functional.

Bearing in mind the high complexity of the SND process, a decision support system (DSS) [28] was proposed to assist the engineer during the whole task. By interacting with the DSS, the process engineer (PE) defines the instrumentation by means of an incremental refinement procedure. Traditionally, the analysis begins from an initial sensor network with a few instruments chosen by the PE based on his skills and experience. Then, an iterative process takes place; the PE runs the tools in the DSS and refines the configuration until he achieves a satisfactory instrumentation. In the case of complex industrial processes, a complete iteration entails a great deal of expert examination and several executions of the analysis software tools included in the DSS. For this reason, it is desirable to reduce the amount of iterations required to obtain the final fitting sensor network.

In this context, the initiative of developing an *intelligent* initialization module emerged, so as to obtain a good initial sensor configuration. In this way, we have hypothesized that an initial configuration suggested by a computational strategy would be closer to the final sensor network than an instrumentation defined by the PE, who bases the choice only upon his expertise, and who is naturally able to manage neither huge amounts of information nor several objectives simultaneously. Then, this tool would be useful to drastically reduce the total number of iterations required to converge on a satisfactory sensor network design.

In the last few years various stochastic approaches have been introduced to solve sensor network design problems. In this sense, the use of artificial intelligence (AI) strategies constitutes a promising course and, in particular, genetic algorithms (GAs) are especially suitable to tackle multi-objective optimization problems [23,25]. Moreover, GAs are high-speed robust algorithms, being this feature very valuable in the case of initialization techniques. In addition, they yield a set of several good solutions, allowing the PE to make the final decision on the initialization that best satisfies his needs.

In this paper, we propose a genetic algorithm for initialization purposes in the context of sensor network design problems. The main contribution of this work is the development of a new multi-objective fitness function that uses procedures based on graph theory. It is important to note that even though this function was ideated to tackle the instrumentation task, it could also be adapted to any problem belonging to the class of *spatial allocation problems*, thus extending the potential application range of our method.

The rest of the article is structured as follows. A literature survey of the state of the art in our problem instance is presented first. The definition of a standard GA and its underlying principles are introduced next. An overview of the DSS is described afterwards, together with a discussion about the advantages of incorporating an automatic initialization module into its frame. Then, the details of the GA implementation and its interaction with the rest of the DSS are presented, followed by a performance analysis, where the usefulness of the proposed method is discussed on a relevant industrial example. Finally, some conclusions and guidelines for future research work are put forward.

## 2. Literature survey: sensor network design and evolutionary computing

Instrument allocation problems are typically solved by means of an analysis of the steady-state model. A comprehensive review of the various SND strategies can be consulted in [3]. Kretsovalis and Mah [14] developed methods based on linear algebra in order to design sensor networks and quantify the effects of estimated variables for mass-flow processes. In turn, Maquin et al. [16] and Madron and Veverka [15] used the same approach, but aiming at a minimum cost configuration. However, methods naturally become more efficient when the structure of the model equations is exploited as part of the design strategy. Vaclavek and Loucka [26], Ali and Narasimhan [1] and Bansal et al. [4] made use of graph theory for this purpose. The aforementioned algorithms focus on the optimization of a single objective, and furthermore, they all work on linearized models of local validity, thus being dependent on the operating point.

When several metrics need to be taken into account, the traditional approach is to regard one of them as the objective to be either minimized or maximized, while the others are considered as problem constraints. For example, Bagajewicz [2] presented a method that looks for an optimum-cost sensor network with restrictions concerning maximum accuracy, error-detection capacities, resilience and availability.

In the last few years, some stochastic approaches were introduced to solve sensor network design problems. A complete survey on evolutionary algorithms in control systems engineering can be found in [12]. In particular, genetic algorithms (GAs) are especially suitable to tackle multi-objective problems. On the basis of graph theory, Sen et al. [22] developed a GA for SND that can be used to deal with three objectives associated with cost, reliability and accuracy. However, they do not solve an actual multi-objective optimization problem; rather, they propose a method that has to be used in a similar manner to take into account each of those objectives. In contrast, Summanwar et al. [24] introduced a multi-objective GA that treats all the constraints as objective functions and handles the different goals using the concept of Pareto dominance. Nevertheless, they start the analysis from a linear equation system representing the problem. Another similar linear approach to sensor network design and retrofit for evaluating several reliability objectives of process variable estimations, such as hardware reliability or by means of a GA, is proposed in [5]. Recently, Carnero et al. [7] addressed the problem of designing non-redundant linear sensor networks by means of a GA that simultaneously considers two objectives respectively related to cost and system reliability.

Even when the mentioned methods constitute an improvement in this area, rigorous multi-objective sensor network design techniques *based on non-linear models* of the process are lacking in the scientific literature. In this sense, the DSS [28], which will be briefly described in Section 4, represents the first software tool able to deal with strongly non-linear process models. The GA presented in this paper constitutes the initialization module of this decision support system.

## 3. Genetic algorithms: definition and philosophy

Genetic algorithms are stochastic adaptive global search and optimization methods, founded on the principles of natural selection and population genetics. The population is comprised by several individuals that represent potential solutions to the problem. The basic operations first carried out by a GA are the generation and evaluation of an initial population. Subsequently, a main loop of operations that include selecting the best

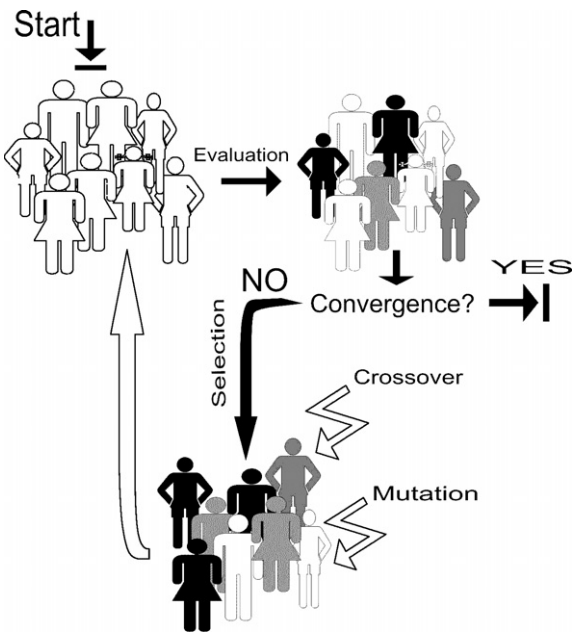


Fig. 1. Genetic algorithm's philosophy.

individuals, crossing them and applying mutation on every locus (string position) is performed. The population evolves within this loop and the best string present in the final population is considered to be the solution, as convergence is reached. The progress of the population in the classic GA is represented in Fig. 1.

The main computational effort in a traditional GA resides in the evaluation of the strings quality, i.e. the estimation of the fitness function. An ideal fitness function should correlate closely with the algorithm goal, and yet should be computed quickly. The execution speed is very important, as each generation of the genetic algorithm must be iterated many times in order to produce a useable result for a non-trivial problem. Usually, the fitness function is a complex mathematical function with many parameters, while the operators like selection, mutation, crossover and replacement are of linear complexity, often working at constant rates for a given problem.

## 4. The decision support system: problem formulation

Due to the complexity of the SND task, the development of automatic decision-support tools for this purpose has become a challenge. As it was aforementioned, we are currently working on the design and implementation of a complete software package, the DSS that includes various tools to carry out the analysis with an original non-linear approach [28]. The end user of the package is the PE, who interacts at various points of the procedure in order to incorporate heterogeneous physical constraints and requirements that should be present in the final sensor configuration.

The DSS functioning, with the addition of the proposed GA, is illustrated in Fig. 2. First, the PE introduces information about the process under stationary operating conditions through a module called Model Generator [27]. This tool generates the mathematical model that consists of a set of algebraic equations corresponding to mass and energy balances, as well as relationships employed to estimate thermodynamic properties like densities, enthalpies, and equilibrium constants. The rigorous model involves not only linear functionalities, but also many non-linear equations.

On the base of the equation model, the initial instrument configuration is traditionally delineated by the PE. However, in view of the complexity of this task, we propose the use of a GA that suggests various configurations. Then, the PE chooses, among the different candidates, the initial sensor network. It is important to mention that the final decision on the initial configuration has to be taken by the PE, since there are several subjective features and constraints that are not feasible to be modeled by a computational tool.

As soon as the starting sensor network is defined, the observability analysis (OA) is performed. It consists in determining which unmeasured variables will be observable, i.e. which ones may be calculated by means of model equations, fixing the measurements as constant-values. Once this analysis has finished, the PE decides whether the information achieved from the configuration is satisfactory or not. A classification is not satisfactory if it contains indeterminable variables of interest. If that is the case, the sensor network needs to be refined – more instruments are included – and the analysis must be repeated. As a result, the OA constitutes an iterative process that includes the execution of software tools together with the analysis work performed by the

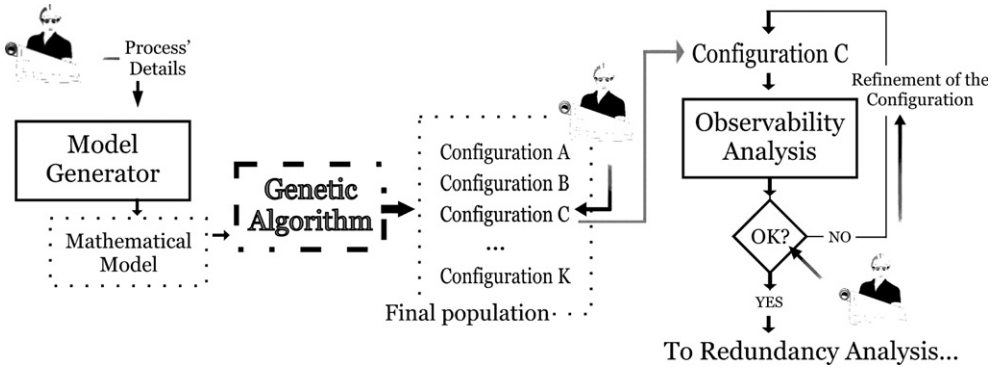


Fig. 2. Proposed DSS's scheme.

expert. Both the OA efficiency and the results strongly depend on the initial instrument configuration, and they therefore benefit from a careful initial choice of sensors.

The whole SND procedure also entails the classification of the measurements, namely redundancy analysis (RA) [11], which is carried out after a satisfactory OA is achieved. Although the initialization policy indirectly affects the RA, for the sake of simplicity, in this work we have focused on the effect of the GA initialization on the OA.

## 5. GA for SND initialization

In this section, the GA proposed in this article will be described. First, a brief description of the well-known standard features is introduced. Then, the ad hoc implemented properties are discussed and finally, a detailed explanation of a novel fitness function based on graph theory is presented.

### 5.1. Standard features

Individuals' chromosomes in the GA are binary strings of length $\ell$, where each allele represents the presence (a 1-value) or absence (a 0-value) of a sensor for measuring the variable that corresponds to that position in the mathematical model, and $\ell$ is the amount of variables in the mathematical model. This representation of the genotype is shown in Fig. 3, where a small academic equation system consisting of seven variables is exemplified. For this sample case, the configuration modeled by the binary string suggests that variables corresponding to positions 1, 4, 6 and 7 should be measured.

The population is randomly generated except for some special positions of the chromosome that are set to 0 values and remain fixed during the complete procedure, as it will be described in the next subsection. Its size remains fixed during the whole evolution process. Binary tournament is used to decide which individuals will qualify for the new population, maintaining the best up-to-the-moment individual with an elitist approach. As regards the generational model, each individual survives for exactly one generation due to the fact that the entire set of parents is replaced by the offspring. Consequently, the generation gap, i.e. the proportion of the population that is replaced, is 1.0. One-point crossover and bit-flip mutation are the operators used to improve exploitation and exploration, respectively.

One-point crossover is particularly suitable for this problem instance since its performance depends on the order in which variables have been arranged in the representation. This operator is more likely to keep together genes that are near each other (in the neighborhood) and it never maintains together genes from opposite ends of the string. This feature constitutes an important advantage because nearby variables have, in general, a stronger relationship in the equation system than those at opposite positions. Thus, with one-point crossover the aim is to keep together those variables that are more likely to form an assignment subset.

### 5.2. Special technical features

The fact that some locations cannot be physically measured restricts the decision about the choice of sensors to be placed in an industrial plant. However, these locations cannot be eliminated from the model because these variables are taken into account in the observability analysis [17,18]. Hence, the genes corresponding to those variables in the chromosome must be fixed to a 0-value. Individuals are specially treated according to this requirement in two phases of the algorithm. Firstly, when the initial population is generated, the positions of non-measurable variables are always assigned a 0-value. After that, as new gene information is only

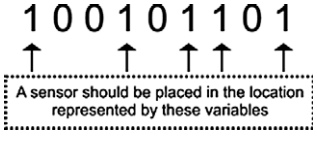


Fig. 3. Genotype's meaning.

introduced by the mutation operator, this operator was expressly implemented so that it never generates non-feasible individuals.

Despite the fact that the mutation operator is traditionally implemented, except for the special treatment of non-feasible individuals, it has both dynamic and adaptive properties. The rates employed when applying mutation vary during the algorithmic run in two different ways. Its starting value is $1/\ell$ [10] and as the evolution proceeds it becomes smaller. The decrease is based on the idea of having a vast exploration at the beginning of the procedure, while reducing it as convergence is reached. In addition, this rate is combined with the fitness of the individual so that better individuals get less chance of changing their gene information than those unfit. The parameter control was implemented because this feature succeeded in improving the GA performance [10].

On the subject of the termination condition, a genotypic criterion was employed. The algorithm stops when there is a very small probability that new gene information will be introduced in the population if evolution continues. This design choice was founded on the properties of schemata mainly addressed by Radcliffe [19], who states that as the GA progresses the population will tend to converge on some schema and eventually, that schema will be an instance of the solution to the problem. Also the criterion was chosen based on the review on convergence criteria developed by Safe et al. [21].

### 5.3. Fitness function

As stated above, the selection of sensors to be placed in an industrial plant constitutes a multi-objective problem. The fitness function presented here takes into account three objectives associated with configuration costs, measurement errors and number of observable variables. The first two terms are calculated in a straightforward manner from two vectors that respectively store information about purchase prices and sensor reliability. They are computed as a linear function that simply adds every value of the corresponding vector stored in a position where there is a non-zero in the individual. The observability term (OT) is more complex and therefore, as the main computational effort in a GA resides in the evaluation of the fitness function, its detailed description represents the core of this section.

The OT basically estimates the number of variables that would become observable starting from a configuration represented by the chromosome of the individual, i.e. the binary string. For initializing purposes, estimated values suffice since a more accurate procedure is computationally too expensive to be included as a term of the fitness function. Moreover, it should be clear that the GA is considered as an initialization tool, and the final SND will be obtained after the whole OA is performed.

As the OT plays a fundamental role in the initialization for the OA, for consistency reasons, it is built following the same philosophy of the procedures that comprise the observability analysis module. The main idea with this respect is that the genetic algorithm will yield a configuration (binary string) based on the results of a simplification of the rigorous observability method, capturing the fast stages from it so as to obtain a bound on the number of observable variables. Two techniques for the structural observability analysis, namely, GS-FLCN [18] and Direct Method [17], have been devised.

The GS-FLCN is a combinatorial procedure that classifies unmeasured variables into observable and unobservable. This task is performed by means of a structural rearrangement of the occurrence matrix corresponding to the equation system that represents the plant's behavior. It proved to work properly for small and medium-size problems. However, as a result of its combinatorial nature, the GS-FLCN methodology results inadequate to tackle the observability analysis in the case of large industrial processes mainly since its computing times grow exponentially with problem size. Therefore, it became necessary to devise a new technique that would overcome this drawback, and the development of the Direct Method (DM) constituted the follow-up [17]. This strategy rearranges the process occurrence matrix $\boldsymbol{O}$ to a specific block lower-triangular pattern by means of bi-graphs and digraphs. The algorithmic core is constituted by a new node classification proposed by Ponzoni et al. [17], which is based on Dulmage–Mendelsohn decomposition [9].

On the base of the Direct Method, we have designed a novel procedure that estimates the OT of the fitness function. As a prologue, a reduced occurrence matrix $\boldsymbol{O}'$ is built by deleting from $\boldsymbol{O}$ all the columns that correspond to variables in the genotype of the individual under analysis that have 1 value. Then, as in the first step of the DM, a bi-graph $\boldsymbol{B} = (\mathscr{R}, \mathscr{C}, \mathscr{E})$ associated with the occurrence matrix $\boldsymbol{O}'$ is constructed, where

the two disjoint node sets $\mathscr{R}$ and $\mathscr{C}$ represent the matrix rows and columns, respectively. The edge set, $\mathscr{E}$, represents non-zero entries of the occurrence matrix, in other words, an edge between $r_i$ and $c_j$ indicates that row $i$ contains a non-zero element in column $j$. Then, a coarse-grain decomposition (CGD) of $\boldsymbol{B}$ is carried out. This decomposition involves two consecutive steps: a search for a maximum matching in $\boldsymbol{B}$, followed by a node classification procedure. A matching $\boldsymbol{M}$ of a bi-graph $\boldsymbol{B}$ is a subset of $\mathscr{E}$, whose edges have no common end-points. The number of edges in $\boldsymbol{M}$ is called *cardinality of matching*. In particular, $\boldsymbol{M}_i$ is a maximum matching for $\boldsymbol{B}$ if there are no other matchings $\boldsymbol{M}_j \neq \boldsymbol{M}_i$ in $\boldsymbol{B}$ whose cardinality is higher than $\boldsymbol{M}_i$'s.

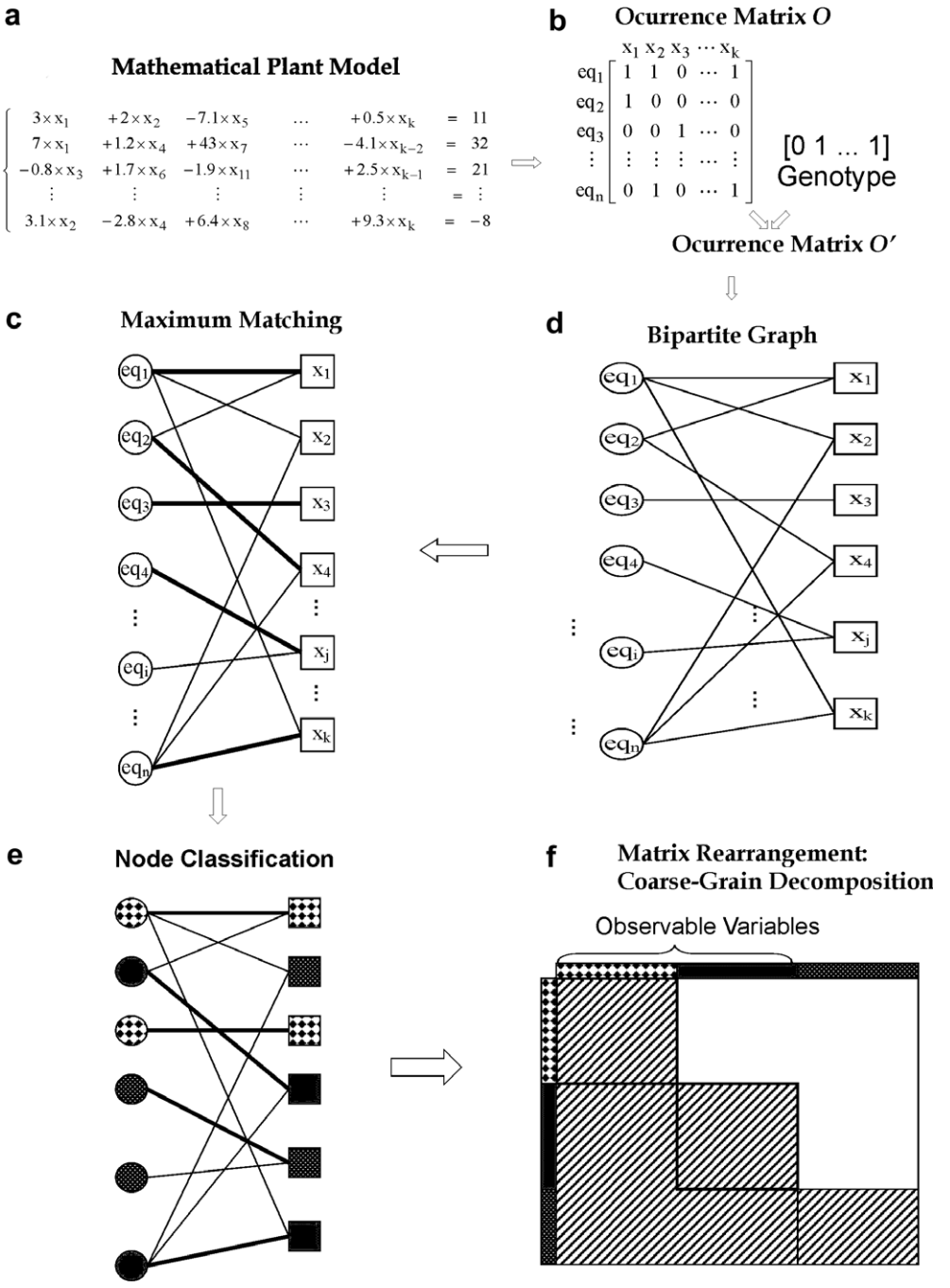


Fig. 4. Fitness function: estimation of the OT.

Fig. 4 illustrates these stages applied to a brief academic example. Starting from the mathematical model (Fig. 4a), the occurrence matrix $\boldsymbol{O}$ is built. From the genotypic information of the individual being evaluated and $\boldsymbol{O}$, the reduced occurrence matrix $\boldsymbol{O}'$ is built (Fig. 4b). Then, the corresponding bi-graph is obtained from this matrix (Fig. 4c), and a maximum matching for this bi-graph is calculated (Fig. 4d). In order to calculate a maximum matching, CGD-GA employs Hopcroft–Karp's algorithm [13] whose execution time is $O(n^{3/2}\tau)$ in the worst cases, where $n$ and $\tau$ are the number of nodes and edge elements in $\boldsymbol{B}$, respectively. Later, a node classification takes place (Fig. 4e). For this step, CGD-GA uses a new way of categorizing $\boldsymbol{B}$'s nodes devised by Ponzoni et al. [17]. The technique partitions the sets $\mathscr{R}$ and $\mathscr{C}$ into disjoint subsets by means of an analysis of the maximum matching $\boldsymbol{M}$. In Fig. 4e the classes are indicated by filling the nodes with different patterns. This node taxonomy allows identifying the matrix blocks corresponding to the coarse-grain decomposition of the occurrence matrix (Fig. 4f) obtained by the Direct Method.

Despite the details of this classification procedure, which are carefully explained in [17], it is important to note that the variables associated with the two squared blocks on the diagonal of the rearrangement matrix (Fig. 4f) constitute the potential set of observable variables. Moreover, even though the fine decomposition stage of the Direct Method will probably identify a small percentage of these variables as unobservable, this initial set constitutes a good approximation to the actual observable variable set. For this reason, the aforementioned novel procedure was implemented to calculate the OT of the CGD-GA, in order to achieve a good estimation of the number of observable variables.

As soon as the three objectives are calculated, the values obtained for each of them have to be normalized and combined into a single function, since the implementation was designed based on an aggregating approach, as shown in Eq. (1):

$$\boldsymbol{F}(\boldsymbol{i}) = \boldsymbol{N}_{\mathrm{R}}(\boldsymbol{i}) + \boldsymbol{N}_{\mathrm{Obs}}(\boldsymbol{i}) + 1 - \boldsymbol{N}_{\mathrm{C}}(\boldsymbol{i}), \tag{1}$$

where $\boldsymbol{N}_{\mathrm{R}}(i)$, $\boldsymbol{N}_{\mathrm{Obs}}(i)$ and $\boldsymbol{N}_{\mathrm{C}}(i)$ are the normalized values corresponding to the reliability, observability and cost terms, respectively. The aggregating approach constitutes an appropriate strategy to tackle the initialization task since it is well known that these techniques perform satisfactorily on combinatorial optimization problems [8].

The genetic algorithm aims at maximizing $\boldsymbol{F}$, which ranks between 0 and the amount of objectives to be reached. Because of the manner it was designed, Eq. (1) can be straightforwardly extended to Eq. (2), for the case when more objectives are pursued.

$$\boldsymbol{F}(\boldsymbol{i}) = \sum_{p=1}^{n} NOM_p + m - \sum_{q=1}^{m} NOm_q, \tag{2}$$

$\boldsymbol{n}$ and $\boldsymbol{m}$ are the amounts of objectives to be maximized and minimized respectively, $NOM_p \in [0..1]$ is the $p$th normalized objective to be maximized, $NOm_q$ is the $q$th objective to be minimized, and $\boldsymbol{F}(\boldsymbol{i})$ ranks in the interval $[0..n+m]$. The optimum situation arises when $\boldsymbol{F}(\boldsymbol{i})$ becomes equal to $\boldsymbol{n} + \boldsymbol{m}$, i.e. all the terms for the objectives to be maximized produce a 1-value, and the ones to be minimized yield a 0-value.

## 6. CGD-GA: performance in industrial applications

In this section a detailed analysis on the impact of including the CGD-GA as an initialization module into the DSS for sensor network design is performed. For this experimental study a realistic industrial process plant was employed.

### 6.1. Industrial example: an ammonia synthesis plant

The industrial plant chosen as a realistic example to assess the performance of this software component was designed by Bike [6] for the production of 1500 tons/day of anhydrous liquid ammonia at 240 K and 450 kPa with a minimum purity of 99.5%. This method, known as the Haber–Bosh separation technology, consists in

producing ammonia through synthesis at medium pressure, prior to its recovery by absorption with water. Fig. 5 shows a simplified flow sheet of the plant. The product of the catalytic reactor is fed to a flash whose gas output stream is the feed of the absorber, while its liquid output stream feeds a distillation column that yields ammonia at specification conditions as its top product.

A sound plant instrumentation design should take into account all the critical variables with special care. As a result of the instrumentation analysis, all the variables of this kind should be classified as either redundant measurements or observable variables to be calculated as functions of redundant measurements exclusively. In this way, the presence of the critical variables in the data reconciliation subset can be ensured. This implies that they can be monitored with accuracy, since it will be theoretically possible to corroborate their value continually during plant operation.

The criteria for the selection of the critical variables depend on the peculiar features of the specific process under analysis, mainly comprising plant economy objectives, safety requirements and controllability considerations. The operating temperatures and pressures of the major items of equipment are always very important. In this case, in particular, the presence of inert gases should also be controlled carefully because they do not only tend to accumulate, but also to affect the main reaction by reducing the ammonia content at equilibrium. Besides, both the reaction speed and the product purity should be guaranteed.

In view of the aforementioned considerations, the next variables were labeled as critical:

- Operating temperatures and pressures of the main items of equipment, namely the reactor, the flash, the absorber and the distillation column.
- Feed temperature, pressure and composition.
- Composition of the feed stream that enters the reactor in order to control the rate between the main reactants, as well as the presence of inert gases, which poison the reaction.
- Composition of the output from the reactor in order to control the reaction conditions.
- Composition of the gas stream that constitutes the top product from the distillation column in order to control plant production strictly.
- Composition of the gas purge in order to make sure that the desired fraction of hydrogen is being recovered.

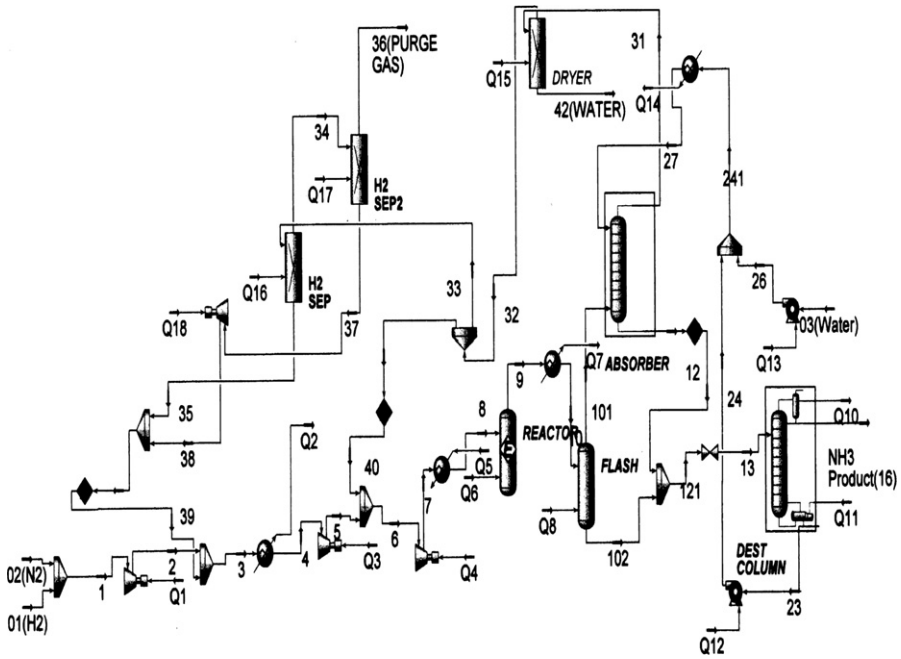


Fig. 5. Ammonia synthesis plant's flow sheet.

### 6.2. Experimental results

The mathematical model used for the experiments corresponds to the ammonia synthesis process, where all the compositions and critical variables were set as measured. The reason for this decision was that it is not trivial to calculate the price of measuring one component on a stream, since it is the same to measure a single one or all the components that comprise that stream. Also, the other critical variables were measured for all the cases because it was mandatory to have them measured as the OA finished. As a consequence, the emphasis was focused on the observability degree rather than on the kind of variables that were suggested to be instrumented. This modification led to a model with 333 variables.

Another important issue consists in the recollection of the actual data about the cost and reliability of every sensor. In this sample case, several manuals and magazines were consulted for that purpose, and finally the information published on the magazine "Cole-Parmer International" (Cole-Parmer International, USA, fax: (847) 549-1700) was picked.

The experimentation devised to validate the CGD-GA's efficacy was organized in two phases. In phase 1 a configuration thrown by a CGD-GA run was randomly picked, from a set of 100 trials, to initialize and execute the OA algorithm. Then, the results obtained in phase 1 were used as reference for the experimentation in phase 2, where the initialization of the OA was performed by the PE without computational assistance.

#### 6.2.1. Phase 1

Step 1: CGD-GA suggests measuring 11 variables.
Step 2: Those 11 variables are measured.
Step 3: One global sweep of the OAA is performed on the mathematical model.

*Results*: 62% of the variables turned out to be observable. The cost and reliability of the configuration amounted to US$ 5000 and 99.8%, respectively.

The observability percentage – 62% – will be used as a threshold in phase 2.

#### 6.2.2. Phase 2

Step 1: An initialization consisting in 11 measurements is defined by the PE considering the same factors as those pursued by the GA.
Step 2: An OAA global sweep is performed.
Step 3: As the information thrown by the OA is not satisfactory according to the threshold defined in phase 1, new measurements are added to the plant.
Step 4: Step 2 is repeated until the observability percentage reaches 62%.

*Results*: The last configuration contained twenty two measurements. The cost and reliability of the final configuration were US$12,500 and 99.7%, respectively. Nine OA algorithmic global iterations were necessary in order to obtain the same observability level as the one achieved by a single global sweep of the OA algorithm with CGD-GA initialization. Each global cycle takes an average of an hour; it comprises several runs of the OA algorithm interleaved with analysis stages that aim at aggregating constraints related to forbidden subsets. The time reported for each global sweep is approximate, and tends to decrease as the analysis advances.

Fig. 6 summarizes the layout and results of this experimentation, which confirms that the CGD-GA accelerates the convergence of the sensor network design, and moreover, it improves the results of the observability analysis algorithms in terms of cost, reliability and observability of the final configuration. In particular, with the CGD-GA there was a cost saving of 60%, and a smaller amount of time (8 h less) was needed to complete the whole observability analysis.

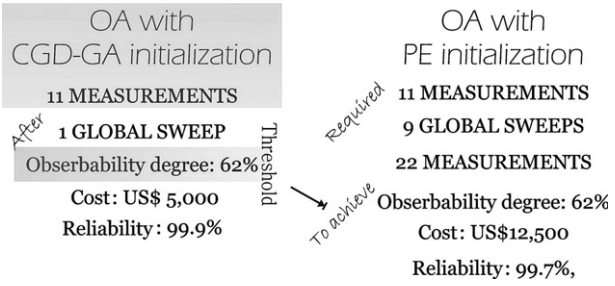


Fig. 6. CGD-GA's impact verification.

## 7. Conclusions and future research work directions

A graph-based genetic algorithm used in process plant instrumentation problems is presented in this paper. The algorithm is called coarse-grain decomposition based genetic algorithm (CGD-GA). The proposed method finds a configuration of sensors to be considered as the most convenient initial instrument setting for the OA algorithm. The CGD-GA fitness function is implemented as an aggregation function that combines three objectives, namely cost, reliability and observability. The CGD-GA exhibits outstanding features such as a dynamic adaptive mutation operator, a genotypic convergence criterion and special treatment for unfeasible individuals.

In order to assess the behavior of the technique in speeding up the observability analysis procedure, a comparative study between OA behavior with and without CGD-GA initialization was carried out. The CGD-GA proved to accelerate the convergence of the OA, and what is more, it produced a better final configuration in terms of cost as well as reliability. Approximately eight hours of analysis and algorithmic execution were saved by initializing the OA with the configuration suggested by the CGD-GA. Moreover, the software component could be used independently to carry out the entire instrumentation design procedure. This constitutes an interesting topic for future research.

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