

A MODEL FOR CONSTITUTION OF AUDIT TEAMS: AN APPLICATION FOR THE GENERAL COMPTROLLER OF COLOMBIA REPUBLIC

UN MODELO PARA LA CONFORMACIÓN DE EQUIPOS DE AUDITORÍA: UNA APLICACIÓN PARA LA CONTRALORÍA GENERAL DE LA REPÚBLICA DE COLOMBIA

JAVIER PARRA PEÑA
DANIEL FERREIRA DE CASTRO
NELSON LEONARDO SEPÚLVEDA FLÓREZ

Resumen

En este artículo se soluciona el problema de constituir equipos interdisciplinarios y asignarlos a la realización de auditorías de carácter fiscal. Se presentan generalidades del proceso de auditoría, el estado del arte y los modelos propuestos; se finaliza con los resultados y conclusiones que de ellos se derivan. El problema de asignación de equipos de auditoría tratado es un problema de optimización combinatoria, para el cual se busca una asignación de equipos diferente en cada ejercicio.

Se propone un modelo lineal entero binario, y dos soluciones basadas en meta-heurísticas: algoritmos genéticos (GA) y enfriamiento simulado (SA), que permiten obtener buenas soluciones en un tiempo razonable. Como resultado principal se construye una herramienta informática basada en GA y SA que permite realizar la asignación requerida por la Contraloría General de la República, y con su aplicación se pretende eliminar los sesgos propios de la asignación.

Palabras clave: Asignación, Algoritmos genéticos, Enfriamiento simulado, Investigación de Operaciones, Meta heurística, Programación lineal entera mixta

Abstract

This article addresses the problem of constituting temporary interdisciplinary teams and their allocation to fiscal audits. First, we present generalities of the audit process and the literature review; second, we show the proposed models, and; we conclude with a presentation of results and conclusions derived from those models.

Constitution of audit teams; which require specific training, experience, and performance features; is a problem of combinatorial optimization that also requires a different allocation in each assignment.

We propose a Binary Integer Linear Programming model, and two solutions based on metaheuristics: genetic algorithms (GA) and simulated annealing (SA), to get solutions in a reasonable time.

As a result, we present an algorithm, based on GA and SA, which allocates people to audit teams as is required. Our methodology solves a specific problem of the General Comptroller of Colombia Republic, efficiently. It is expected that its application would reduce biases of audit tasks.

Key words: Allocation, Genetic Algorithms, Mixed Integer Linear Programming, Metaheuristics, Operations research, Simulated Annealing.

Introduction

Objectivity is a success critical factor in the process of micro fiscal control (audit), because it is a key factor to ensure safety in the work quality. The Technical Sectorial Committee of the General Comptroller of Colombian Republic (CGR by its Spanish abbreviation) in national level (or The Departmental Technical Committee, in territorial level) should organize and allocate audit personnel; these committees are also responsible of audit team evaluation and regular rotation of their associated personal. Audit teams should be constituted avoiding conflict of interests and/or disqualifications and/or incompatibilities.

The audit guide of CGR set to the context of the *Integrated System to the Audit Control (SICA by its Spanish abbreviation)*, is based on the *International Standards on Auditing (ISAs)* issued by the *International Federation of Accountants (IFAC)*, and their annual updates made by *International Auditing Practices Committee*. It also seeks to comply with *Generally accepted accounting principles (GAAP)*, the *Government Auditing Standards (NAGU)* and it is currently in implementation process of *International Standards of Supreme Audit Institutions (ISSAIs)* and the *Guidance for Good Governance of*

International Organization of Supreme Audit Institutions (INTOSAI GOV), and the notes of the *Latin American and Caribbean Organization of Supreme Audit Institutions (OLACEFS, by its Spanish abbreviation)*[1].

An audit is the systematic review of an activity or a situation in order to assess the law and norms performance relation with the objectives of the institutions. Moreover, public audit is “the audit done by a specialized government organism, like “*Contraloría*” in America or “*Intervención General del Estado*” and “*Tribunal de Cuentas*” in Spain.

The external audit objective is: [...] to express an opinion on the fairness of the financial statements and whether they conform to GAAP in all material respects [...] [to] provide the public with additional assurance – beyond managements' own assertions – that a company's financial statements can be relied upon (Securities and Exchange Commission –SEC-, 2010). The first audit functions are: ensuring a quality and validity of the financial reporting system, relying heavily on a common set of principles, standards, and selected procedures, following a systematic and disciplined approach when conducting their evaluations, developing, documenting; and following audit plans that meets the objectives of the audit, and relying heavily upon a common set of ethical standards [2].

For CGR, audit is “*a systematic process that assesses, in accordance with auditing standards generally accepted in effect, public policy and/or management and fiscal performance of the entities subject to fiscal control and plans, programs, projects and/or issues to be audited, by implementing fiscal control systems or special monitoring and control actions to determine compliance with the principles of fiscal management, service delivery or provision of goods public, and development of state constitutional and statutory purposes, which lets*

the Comptroller General of the Republic support their opinions and concepts.” [1].

In fiscal control that corresponds to the CGR, it may apply determined control systems, such as financial, legal, management, results, accounting reviewing and evaluation of internal control as well:

- *Financial control* is the examination made in order to establish if financial reports of an entity shows appropriately the results of its operations and changes in its financial conditions. It is verified that financial reports elaboration, transactions and operation were done in agreement with laws and rules established by national competent authorities about accounting, the principles of accounting universally accepted, or the prescriptions by the “*Contador General*”.
- *Legality control* is the verification to financial operations, administration operations, economic operations, and other operations of a public entity in order to establish if they were done in agreement with the applicable rules and laws.
- *Management control* is the examination about the efficiency and effectiveness of the public resources administration in an entity. It is done by the evaluation of its managing process, with the use of indicators of public profit and its behavior; with the profit identification, profit distribution, and their beneficiaries.
- *Results control* is the evaluation about the measure in which observed subjects achieve their objectives; the aims of their plans, programs and projects, in a time period.
- *Reviewing of accounts* is the specialized evaluation about the documents that support, legal, technical, financial and accounting, the operations done by the public resources responsible in a determinate period of time, in

order to evaluate the economy, effectiveness, efficiency and equity of their acts.

- *Internal control evaluation* is the analysis of entities control systems in order to determinate their quality, the level of confidence that should be assign to them, and to establish if they are effective and efficient in their objectives achievement.

CGR will make special surveillance and control activities, in accordance with the stated procedures, which are defined in current laws. The audit practiced by CGR aims at assessing the fiscal management of the entities subject to fiscal control through: evaluation of public policies, plans, programs, projects, processes or topics of interest, seen as a system or as its part; which have an interrelated resource set that are able to create, regulate and produce goods and/or services in accordance with State purposes.

The entities which are control fiscal object are: principal entities, checkpoints, surveilled resources, investments and individuals. Table 1 presents their principal features.

Literature review

The state of art related to our problem includes subjects like bias auditory, people allocation to tasks and, teams formation. The importance of mentioned issues is due to the sensitivity of the processes that are developed by them, which require an allocation of audit teams.

Allocation of people within teams has been studied from several diverse points of view: There exist requirements for effective function allocation within teams of human and automated agents. Allocation is a key design decision that should be made deliberately [5].

Auditors operate at the center of a complex interaction between heuristics and biases which tend to negatively affect the quality of judgement and decision-making and the applied level of

professional skepticism during the audit process. A positive contribution of joint audit arrangements on audit quality critically depends on the nature, aim and objective of its implementation, and specifically suggest that an application of joint audit which is not focussed on a proactive mitigation of bias during audit may be of limited value towards improving audit quality [6].

Allocation of workers to a task can be made individually or by teams. We explore both possibilities and present a review of cases studies that show the complexity of our problem. We present some ideas about worker's allocation, including multi-skilled workforces, and teams formation. They are based on a literature review.

Worker allocation problem consists in deciding who does what during the manual labor production. It is NP-Hard problem to find optimal solution as increasing worker number and enlarging production scale. A solution based in Genetic algorithms (GA) was considered as an alternative to solve this combinatorial optimization problem because any exhaustive search can take too much time to get a solution to assign people to jobs in a near optimal way, in a reasonable time [7].

In the scheduling problem with workers allocation (SPWA) the objective is to minimize the number of workers and the total time taken to perform all tasks (makespan). Two different mathematical programming models and a VNS-based multi-objective heuristic was proposed in [8]. Because of conflict between objectives, their proposed methods generate a set of efficient solutions, and the manager chooses which solution should be adopted

Multiskilling workforce strategy has been used to reduce indirect labor costs, improve productivity, and reduce turnover. A multi-skilled workforce is one in which the workers possess a range of skills that allow them to participate in more than one

work process. Its success depends on the foreman's ability to allocate workers to tasks and compose crews.

A linear programming model for allocating a multi-skilled workforce helps to optimize their assignment in a construction project. As a conclusion, the model should be used when there are not full employment conditions and, for short term allocation decisions [9].

The team formation problem can produce heterogeneous or homogeneous teams. The allocation of individuals to teams with the goal of maximize the overall expertise per team, or the formation of teams containing members that cover a set of specified skills while minimizing the communication costs. A homogeneous team formation algorithm, with the goal of grouping individuals into teams, each of which consists of members who fulfill the same set of pre-specified properties has been proposed in [10].

To find a team, subset of a group of individuals which compatibility is captured in a social network, in order to perform a specific task is known as team formation problem. In this case it is required that team has the required skills and that they can work effectively as a team. Two variants of this problem were studied in [11], [12].

A heuristic to form software development teams, considering the psychosocial profile of the students, was compared to random allocation of student to teams. Teams designed using the heuristic were more effective in terms of internal communication and coordination than the other teams, and their products had better quality [13].

A common practice is an adoption of Global Software Development (GSD) approach. Allocation teams to the set of software components, which are initially specified in the Software Production Lines (SPL) architecture and must be subsequently implemented [14].

Teams allocation phase aims to generate a set of recommended allocations to reduce communication needs between them. The recommended allocations are based on non-technical attributes of the teams, specified in teams non-technical description model, and the technical metrics received from the modules-teams mapping model. Evaluating the set of recommended allocations, the project manager may choose one that best fits the project goals. Teams allocation phase is divided into three steps: GSD priorities definition (geographical, temporal and cultural), non-technical analysis, and recommendation selection.

Due to prohibitive computational efforts required to evaluate all possible allocations, teams allocation phase can explore a heuristic approach based on genetic algorithms. Finally, the recommendation selection step consists of the choosing of allocation that best fits the project goals [14].

A decision support model for allocation of available rescue units to emergency incidents and schedule their attention, is formulated as a binary quadratic optimization problem. It minimizes the sum of completion times of incidents weighted by their severity. The problem, which includes both routing and scheduling, is a modification of both the Multiple Traveling Salesman Problem (mTSP) and the parallel-machine scheduling problem with unrelated machines, non-batch sequence-dependent setup times and a weighted sum of completion times as the objective function [15].

Objectives

The current work has the following objectives:

Analyze and solve the allocation problem of audit personal in the CGR, using a quantitative methods in order to reduce the biases in team formation.

Build a tool for allocation people using the proposed method.

We use operation research strategies to solve the allocation problem, and build an appropriated tool.

Methods

CGR should make different actions, under professionalism and objectivity, to achieve its missionary goals. We purpose the building and using of a properly mathematical model to allocate auditors in teams in order to reduce the biases associated to the team constitution.

There are a lot of works and algorithms to determine quantitatively how many people assign to each work or work journey, but none of the observed models can allocate specific personnel in teams as we need, to satisfy specific requirements of our problem.

The purpose of this work is to design a systematic process to allocate people in audit teams, in order to minimize the biases in which Sectorial Technical Committee would fail. As alternatives to solve the problem, optimization operation research techniques like a mathematical programming model and metaheuristics were used, because they let us to build teams in agreement with the requirements established in the audit guide of CGR in correspondence with its policies.

Initial assumptions considered in the purposed model are the followings:

- Team size should be four people in regular audits and three people in special ones; it is possible to change audit size team for each pair entity-audit if it would be necessary.
- Both, regular and special audits should have an accountant and an attorney, other people in the team should be preferably professionals of others areas.
- At least one member of the team should be “two degree” in order to develop the coordination and leadership functions in the team. In Colombian public function the

professional level has direct relation with experience.

- There should not have more than one employ with unsatisfactory grade, in the *performance evaluation system (SISED by the Spanish language abbreviation)*, in each audit team. It condition have the purpose of personnel development, by letting that a person who have a low grade in the evaluation system can work with people who have good behavior and, as a consequence, can learn from them.

Solution by a mathematical programming model

Firstly, we build a mathematical model to allocate auditors. This model is a set of linear constraints described previously as audit requirements.

Sets. We defined several sets in order to build a general model, these sets are:

- I Audit functionaries
- J Audits
- K Audits professions
- L Audit types
- R Subset of K, it includes the mandatory profession in the audit.

The indexes that represent an element in the set are written in low letters, respectively.

Parameters. Information associated to the audit personnel, their features, and the audit features is aggregated in the following parameters:

- $p_{i,k}$ Profession, it has the value 1 if person i has the profession k , and cero in other wise.
- g_i Rank, it has the value 1 if functionary i is in the two rank, and cero in other wise.
- s_i Evaluation, it has value 1 if evaluation of i functionary is satisfactory, cero in other wise.

- d_i Availability, it has value 1 if functionary i is available, cero in other wise.
- $m_{k,l}$ Quantity of functionaries, its value is the minimal quantity of functionaries of profession k in an audit of l type.
- h_l Rank 2 functionaries, its value is the minimal quantity of rank 2 professionals in an l audit.
- $t_{j,l}$ Kind of audit, its value is 1 if audit j is regular and cero in otherwise.
- a_l Audits, it is the quantity of audit people in a type l audit.

Decision variables. Decision variables are associated with allocation people in teams, they are:

- $x_{i,j}$ Binary variable which value is 1 if the i functionary is allocated to the j audit, cero in other wise.

Model do not have an objective function because its aim is satisfy the conditions in each auditory and, it can be achieved only with the constraints. It is possible to build a measure of allocation behavior as an objective function, if would be required.

Constraints. The conditions, established here as constraints, reduce biases in the allocation people in teams. The following constraints guarantee that teams achieve the features required:

$$\sum_{i \in I} p_{i,k} d_i x_{i,j} = \sum_{\substack{l \in L \\ \in R}} m_{k,l} t_{j,l} \quad \forall j \in J, \forall k \quad (1)$$

$$\sum_{i \in I} p_{i,k} d_i x_{i,j} \geq \sum_{\substack{l \in L \\ \in K}} m_{k,l} t_{j,l} \quad \forall j \in J, \forall k \quad (2)$$

$$\sum_{i \in I} g_i d_i x_{i,j} \geq \sum_{l \in L} h_l t_{j,l} \quad \forall j \in J \quad (3)$$

$$\sum_{j \in J} x_{i,j} \leq 1 \quad \forall i \in I \quad (4)$$

$$\sum_{i \in I} x_{i,j} = \sum_{l \in L} a_l t_{j,l} \quad \forall j \in J \quad (5)$$

$$\sum_{i \in I} (1 - s_i) x_{i,j} \leq 1 \quad \forall j \in J \quad (6)$$

$$x_{i,j} \in \{1, 0\} \quad \forall i \in I, \forall j \in J \quad (7)$$

Equations (1) and (2) let that all teams have the exact or minimal quantity of specific *k* profession people that is required in teams *j*, such quantity depends of the audit type specifications. In the equation (1), the right parameter is equal to attorney and accountant professionals without matter the kind of auditory and zero to others professionals. It is possible to design specific purpose audits that include a specific different profession, as example environmental audits or safety audits that include as a mandatory requirement a professional of a specific engineering area.

Equation (3) guarantees the presence of one professional of the rank 2, in agreement with audit guidelines and laws.

Equation (4) guarantees that each professional, allocated in an audit team, cannot be allocated in another audit team. A professional only can be allocated in one audit team.

Equation (5) limits the size of audit team, in agreement with specific audit requirements.

Equation (6) is responsible of the SISED evaluation grades in teams, and equation (7) is the constraint associated with the variables nature. Evaluated instance in MathProg language is showed in Appendix 1.

Problem solution using a genetic algorithm

In the firsts 70s, a group of researchers of the Michigan University, directed by John Holland professor, purposed the genetics algorithm as computer programs that emulate the natural

evolutionary process. This kind of software has a robust behavior in a variable and uncertainly environment [16].

Genetic algorithm (GA) building starts with an appropriate definition of a form of solution representation in a chromosome (individual). For this allocation problem, the chromosome is a vector subdivided in smaller ones. Each sub-vector represents an audit team that could be regular or special. At the end, there is a sub-vector of unallocated people. A chromosome example is showed in figure 1.

GA requires an objective function, called adaptation function (AF), which is a measure of the quality of the solutions represented by the chromosome.

Each part of the chromosome (figure 1) represents an audit team, which is composed by functionaries represented in each gen (or vector position). Here, gen is a code that represents a functionary who has attributes like: profession, rank, SISED evaluation and availability. A functionary in an upper rank will be responsible of manage the information about the audit functionaries; it is maintenance and actualization of the dynamic information about them. Figure 2 shows the structure of the purposed GA.

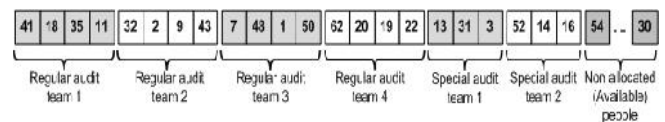


Figure 1. Chromosome of an individual for allocation of functionaries to audits, example

Source: Authors

Selection. There are different strategies to select the better adapted individuals, we use elitism and roulette ones. Independently of the used strategy, all genetic algorithms uses elitism, in the evolutionary process the best individual pass always to the next generation [17].

Adaptation function (AF). AF is a cumulated penalization function for violations to each of conditions established for audit teams. As a consequence of AF measure, an individual (chromosome) that has a lower AF value is better than other with a bigger one. Because of AF penalization sense, it is necessary to minimize adaptation function.

In the algorithm evaluation, we made penalizations of: one thousand units when a constraint related with accountants or attorney quantity were not satisfied or when there was not a professional of rank two in its; five thousand when there was more than one functionary with unsatisfactory SISED evaluation. In order to use *roulette selection strategy*, we gave a penalization of one unit when a condition is achieved, because it is a non-significant value if it is compared with values associated to violations, but it is necessary to guarantee that adaptation function is not zero for all the individuals.

Selection strategy. An *elitist selection strategy* was used in the evolutionary process. This strategy is based in the population sorting by adaptation function; so, there are two groups of individuals: *fraction of better fathers* and *fraction of non-better fathers*. A fraction of generated by better father individuals is the result of reproduction process between pairs of random selected better fathers. Population is completed with other fraction that is caused by reproduction by pairs of individuals without matter their adaptation function value, in order to avoid premature convergence to local optima values.

As another strategy of selection, we used *roulette selection*. A probability value is associated to each individual and a better individual has bigger probability to be selected. A probability of selection p_i is associated with the inverse of adaptation function value a_i of each individual as follow:

$$p_i = \frac{\frac{1}{a_i}}{\sum_{j \in Population} \frac{1}{a_j}} \quad (8)$$

Reproduction genetics operators

Crossover strategy. Reproduction process employed is based in natural sexual reproduction; two individuals called parents produce two individuals called sons by crossover between their gens. There are a lot of crossover strategies that can be used; however, we only considered several crossover strategies for permutations because the solution representation (chromosome) is a functionaries permutation and this kind of crossover strategies only produce “feasible” solutions which do not require reparation, it is a solution without repeated gens [18]. *In our problem, true feasibility is measured by AF that measures the penalization by constraints violation.*

The crossover strategies evaluated for solving the problem were: cycle crossover (CX), order crossover (OX), and partially mapped crossover (PMX). The implementation lets to select it when computational decision tool is used, it is one of the parameters to evaluate.

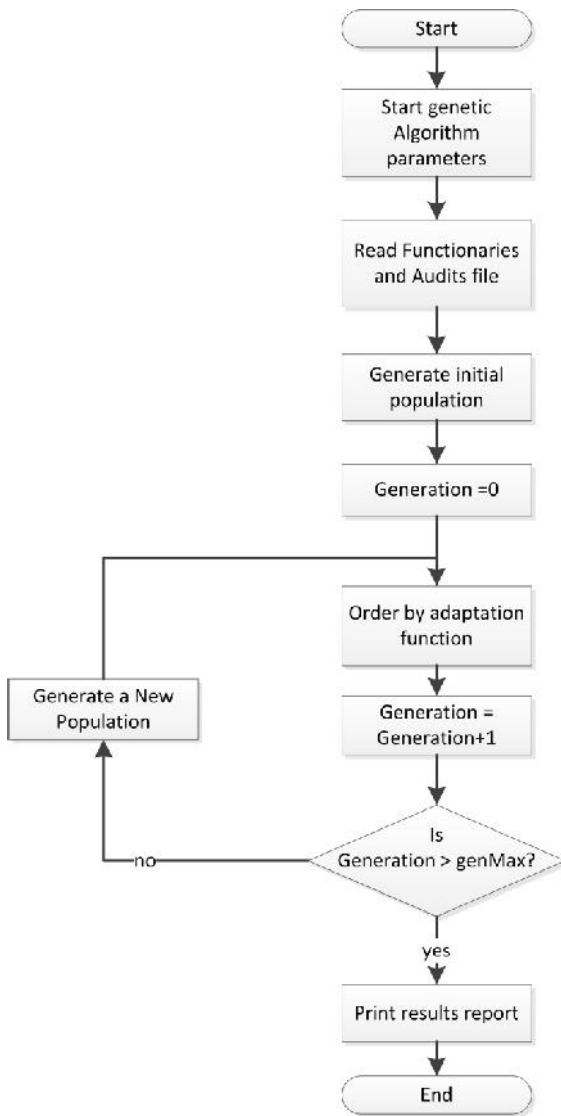


Figure 2. Purposed genetic algorithm structure.

Source: Authors

Mutation strategy. Mutation acts as a crossover complement in new population creation, it is like asexual reproduction because in it one parent produces one son. There are a lot of mutation strategies, too. In this genetic algorithm, we used mutation swap, the implementation consists in random selection of two points, and remove the gens between these two points, after that we have three chains, the first one in the first of the original chromosome, the second one that was extracted and the third one to the end of the original

chromosome; finally move the final chain next to the first one and the extracted chain at the final of the chromosome.

Improvement grew operator is an operator based in the Lixing and Jiyin paper, the idea is use it to produce improvement after an established number of generations without improve the solution. This operator is a local search procedure that starts in the best current individual; it is the interchange until find the pair of gens that produce the best improvement of the adaptation function. Grew operator guarantees an improvement of adaptation function in most of the cases [19].

Parameters evaluation. Parameters used in the algorithm are the result of an experimentation process. In a preliminary test, we changed the number of generations between 50 and 400, measure of the impact of generation number on the adaptation function; we found that 200 generations is enough to get satisfactory results.

Others parameters as fraction of better parents, the fraction generated by better parents, with elitist selection strategy, and the mutation probability were changed while we developed the experiment. Moreover we noted that the use of parameters suggested by De Jong and by Schaffer [18] did not produce better solutions to the obtained with values near to 10 percent.

Generated reports. The developed software produces reports, which contain the information associated with audit teams, in order to facilitate the allocation work.

Furthermore, convergence report let to observe the evolution of objective function after each generation.

Problem solution using a simulated annealing algorithm

Simulated annealing (SA) is a local search-based heuristic, which is featured by its capability of escape from be trapped into a local optimum by

accept, with small probability, worse solutions during its iterations. SA has been successfully applied to a wide variety of complex combinatorial optimization problems. It can start with a randomly generated initial solution or with a specific built one.

SA algorithm produces a new solution within the current solution neighborhood in its respective iteration. If new solution objective function value is better than the current solution, this new solution replaces the current solution from which the search process continues. However, in order to decrease the possibility of fail in a local optimal solution, it is possible to accept, with a small probability, a new solution with a worse objective function value as the new current solution. This feature let it to escape from local optimums [20]. Structure of Simulated annealing algorithm is showed in figure 3.

Solution representation. The representation of the initial solution is the same presented as a GA individual, (figure 1, in the previous subsection), in order to be able to hybridize both algorithms in only one in a near future, if it were required to achieve better behavior. Because of we use the same representation, objective function value is calculated like in GA section.

Neighborhood. This research use a standard SA procedure with a random neighborhood structure that includes several types of moves: swap, insertion, and inversion. Let $N(X)$ be the set of neighboring solutions of X current solution. At each iteration, a new feasible solution Y is selected from $N(X)$ using the type of movement selected.

Movements considered are the same established as mutation procedures in GA, so neighborhoods can be obtained by insertion, swap or another similar strategy of diversification based in a solution. After a movement is done, objective function is recalculated. The new solution is always feasible due to our solution representation scheme.

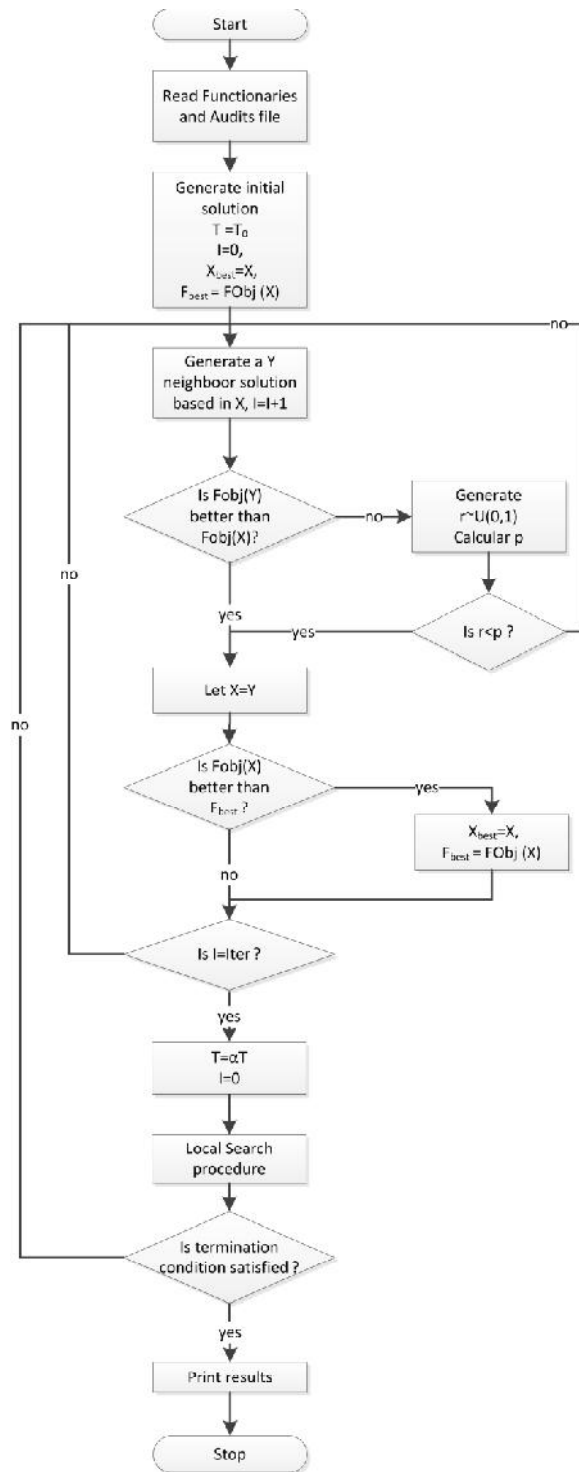


Figure 3. Flowchart for the SA Algorithm.

Source: Authors based in Lin and Yu (Lin & Yu, 2012)

Simulated annealing procedure. The SA heuristic requires four mandatory parameters: *initial*

temperature (T_0), iterations by temperature ($Iter$), minimal temperature (T_{min}), and cooling factor (α). It is possible to include an additional parameter: maxim number of temperature reductions without objective function improvement, as is presented in [20].

Initial conditions: Temperature T is set equal to T_0 and an initial solution X which can be randomly generated or obtained by another technique, like a genetic algorithm previously explained. The current best solution X_{best} and the best objective function value obtained so far, denoted by F_{best} , are set to be X and $obj(X)$, respectively.

Iterative procedure: in each iteration, a new solution Y is generated from the neighborhood of the current solution X , $N(X)$, and its objective function value is evaluated. If $obj(Y) < obj(X)$, this is Y is better solution than X , X is replaced by Y . Otherwise, the probability of replacing X with Y is p , see equation (9), X_{best} and F_{best} record the best solution and the best objective function value obtained so far, as the algorithm progresses.

Current temperature T is reduced after $Iter$ iterations, previous temperature decrease in agreement with α factor, how it is showed in equation (10). As Lin & Yu purposed (2012) we implemented a local search procedure to improve X_{best} after $Iter$ iterations, which is described as follow. Local search procedure implemented applies all possible swap moves to X_{best} , the best solution obtained replaces X_{best} because it only can be better or equal.

$$p = e^{-\frac{obj(Y)-obj(X)}{T}} \quad (9)$$

$$T = \alpha T, \quad 0 < \alpha < 1 \quad (10)$$

Finalization criteria: SA algorithm ends at achieving the minimal temperature or other additional ending criteria; the best solution is storage in X_{best} .

Results

Instances evaluated to try the purposed solutions have 149 functionaries, and a variable number of regular and special audits.

The purposed model was built using *MathProg* language and solved with *GLPK* (*GNU linear programming kit*) software in *GUSEK* (*GLPK under Scite Extended Kit*) interface. The software selection was made considering that this is *free software*, and it is enough to the size of the problem in Bogotá regional of CGR. *MathProg* is an algebraic modeling language that is a part of the *AMPL* software [21].

The model has 3874 binary variables and 513 constraints, and the obtained result is an allocation that achieves all the conditions required. Because of the solving process, this strategy gives us only one answer to the problem, from a big set of possible ones, in a normal use it is not a flexible tool and it is necessary change the order of functionaries list when an alternative allocation is required. It is important that a team allocated do not be the same as a quality team condition.

Genetic algorithm results after use elitist and roulette selection strategies, in combination with different crossover and different parameters, were acceptable. In general, we observed better behavior using elitism. Crossover strategies did not show significant differences.

Convergence report, in figure 4, shows AF values for ten replications. We did more than 100 replications for different parameters values with similar behavior, more than 50 percent of times, purposed algorithm achieve a solution that consider all of conditions required.

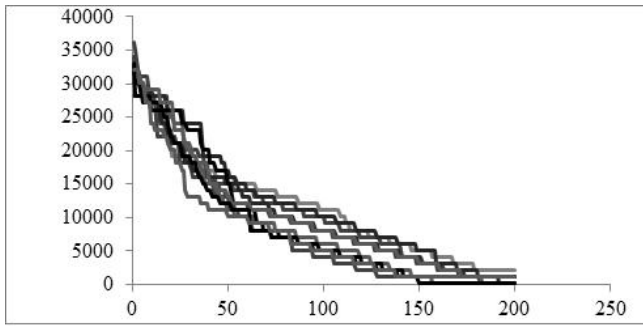


Figure 4. Convergence of genetic algorithm, using cx and elitism, and simulated annealing.

Source: Authors

In order to provide an agile tool to allocate people in audit teams, we generated a report of team allocation that presents all audits one by one, see table 1. It includes functionaries' information (names, rank, profession, SISED indicator) and audits information (audit identification and audit type). By confidence agreements the names of functionaries were replaced by letters.

So, allocation responsible will have a good solution as a basement of the final allocation. This allocation could not be considered as definitive in this kind of problem because it can be un-compatibilities among functionaries and entities. Un-compatibilities can be caused by relative and affinity relationships between auditors and audited entities functionaries, considered in Colombian law.

Both Genetic algorithm and simulated annealing algorithm, developed to solve the allocation people to audit teams problem, were coded in Microsoft Visual Basic for Applications 7.0 language programming, in an excel spreadsheet, which was used as input and output interface.

Table 1. Allocation teams generated example.

ID	Functionary name	Level	Profession	SISED	Audit	Type
33	A	1	Accountant	1	1	Regular
10	B	1	Lawyer	1	1	Regular

86	C	2	Manager	1	1	Regular
13	D	1	Computer Engineer	1	1	Regular
142	E	2	Accountant	1	2	Regular
139	F	1	Lawyer	1	2	Regular
15	G	1	Manager	1	2	Regular
39	H	1	Civil Engineer	1	2	Regular
4	I	1	Lawyer	1	3	Regular
85	J	1	Accountant	0	3	Regular
100	K	2	Manager	1	3	Regular
64	L	1	Manager	1	3	Regular
129	M	1	Accountant	1	4	Regular
110	N	2	Economist	1	4	Regular
12	O	1	Economist	1	4	Regular
57	P	1	Lawyer	1	4	Regular

Conclusiones

In spite of it is possible to get solutions manually; it is not easy to get them. Moreover, it is possible to make biased solutions when allocation is done by a manager.

Mathematical programming model gets a feasible allocation for each instance evaluated. But, it is not the best solution because all replications produce the same allocation.

Genetic algorithm generates satisfactory solutions to the problem almost all times, when it is running with more than 200 generations. Like genetic algorithm were the simulated annealing algorithm behavior, its results were satisfactory in the most of cases.

Moreover, we hybridize two algorithms getting satisfactory solutions in reasonable time. A growing routine, like the purposed by Lixing, et al.

(Lixing & Jiyin, 2002), lets achieve satisfactory solutions for all or almost all of teams, almost all times.

Best solution strategy is genetic algorithm enriched with growing routine because each time it makes a good and different solution as is required in audit team allocation people. Moreover, this solution always should be reviewed and adjusted to reduce incompatibilities.

In future researches it is possible to introduce soft constraints that let grade the achievement of better indicator for some of the features of the teams, as the heterogeneity of the professionals in them, with objective functions in which deviations of the goals be penalized.

Referencias

- [1] Contraloría General de la República de Colombia, “Guía de auditoría de la Contraloría General de la República.” May-2015.
- [2] Donald F. Arnold, Jack W. Dorminey, A.A. Neidermeyer, and Presha E. Neidermeyer, “Internal and external auditor ethical decision-making,” *Manag. Audit. J.*, vol. 28, no. 4, pp. 300–322, 2013.
- [3] Instituto de contabilidad y auditoría de cuentas, *Norma Técnica sobre Control de Calidad (BOICAC Número. 12, Marzo 1993)*.
- [4] Contraloría General de la República de Colombia, “Guía de auditoría gubernamental con enfoque integral - Audite 4.0.” de Diciembre de-2009.
- [5] K. M. Feigh and A. R. Pritchett, “Requirements for Effective Function Allocation,” *J. Cogn. Eng. Decis. Mak.*, vol. 8, no. 1, pp. 23–32, May 2013.
- [6] O. Marnet, E. Barone, and D. Gwilliam, “Joint audit: a means to reduce bias and enhance scepticism in financial statement audits,” 2016.
- [7] T. Sicong, Wei, Weng, and Shigeru, Fujimura, “Scheduling of Worker Allocation in the Manual Labor Environment with Genetic Algorithm,” Hong Kong, 2009.
- [8] G. Pantuza Júnior and Instituto Federal de Minas Gerais, Brasil, “Uma abordagem multiobjetivo para o problema de sequenciamento e alocação de trabalhadores,” *Gest. Produção*, vol. 23, no. 1, pp. 132–145, Mar. 2016.
- [9] J. E. Gomar, C. T. Haas, and D. P. Morton, “Assignment and Allocation Optimization of Partially Multiskilled Workforce,” *J. Constr. Eng. Manag.*, vol. 128, no. 2, pp. 103–109, Apr. 2002.
- [10] R. Brederick, T. Köhler, A. Nichterlein, R. Niedermeier, and G. Philip, “Using Patterns to Form Homogeneous Teams,” *Algorithmica*, vol. 71, no. 2, pp. 517–538, 2015.
- [11] T. Lappas, K. Liu, and E. Terzi, “Finding a team of experts in social networks,” in *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, Paris, France, 2009, pp. 467–476.
- [12] A. Majumder, S. Datta, and K. V. M. Naidu, “Capacitated team formation problem on social networks,” in *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, Beijing, China, 2012, pp. 1005–1013.
- [13] L. Silvestre, S. F. Ochoa, and M. Marques, *2015 34th Int. Conf. Chil. Comput. Sci. Soc. SCCC*, pp. 1–6, Nov. 2015.

- [14] T. A. B. Pereira, V. S. dos Santos, B. L. Ribeiro, and G. Elias, "A recommendation framework for allocating global software teams in software product line projects," in *Proceedings of the 2nd International Workshop on Recommendation Systems for Software Engineering*, Cape Town, South Africa, 2010, pp. 36–40.
- [15] F. Wex, G. Schryen, S. Feuerriegel, and D. Neumann, "Emergency response in natural disaster management: Allocation and scheduling of rescue units," *Eur. J. Oper. Res.*, vol. 235, no. 3, pp. 697–708, Jun. 2014.
- [16] Maroto Álvarez, Concepción and Alcaraz Soria, Javier, *Introducción a la investigación operativa en administración y dirección de empresas*. Valencia: Universidad Politécnica de Valencia, 2008.
- [17] Coello Coello, Carlos A, Lamont, Gary B., and Van Veldhuizen, David A., *Evolutionary algorithms for solving multi-objective problems*, 2. ed. New York, NY: Springer, 2007.
- [18] Coello Coello, Carlos A., *Introducción a la computación evolutiva*. México D.F.: CINVESTAP- IPN, 2016.
- [19] L. Tang and J. Liu, "A modified genetic algorithm for the flow shop sequencing problem to minimize mean flow time," *J. Intell. Manuf.*, vol. 13, no. 1, pp. 61–67, 2002.
- [20] S.-W. Lin and V. F. Yu, "A simulated annealing heuristic for the team orienteering problem with time windows," *Eur. J. Oper. Res.*, vol. 217, no. 1, pp. 94–107, Feb. 2012.
- [21] Andrew Makhorin, *GNU Linear Programming Kit, Modeling Language GNU MathProg*. Moscow, Russia: Department for

Applied Informatics, Moscow Aviation Institute, 2013.

INFORMACIÓN DE LOS AUTORES

Javier Parra Peña: Ingeniero Industrial – Universidad Distrital Francisco José de Caldas – Colombia. Especialista en Informática Industrial – Universidad Distrital Francisco José de Caldas – Colombia. Magíster en Ingeniería Industrial – Universidad de Los Andes – Colombia. Doctor en Ingeniería y Producción Industrial – Universitat Politècnica de València – España. Docente – Universidad Distrital Francisco José de Caldas – Colombia. – jparrap@udistrital.edu.co, jvparra@gmail.com

Daniel Ferreira de Castro: Possui graduação em Ciências Econômicas – Universidade Federal do Amazonas – Brasil. Especialização em Gestão pela Qualidade Total – Universidade Federal do Amazonas – Brasil. Mestrado em Engenharia da Produção – Universidade Federal do Amazonas – Brasil. Doctor en Ingeniería y Producción Industrial – Universitat Politècnica de València – España. Professor Parcial – Faculdade Metropolitana de Manaus e da Faculdade Martha Falção – Brasil. danmao@ufam.edu.br, dan.mao@hotmail.com.

Nelson Leonardo Sepúlveda Flórez: Ingeniero Industrial – Universidad Distrital Francisco José de Caldas – Colombia. Especialista en Higiene y Salud Ocupacional – Universidad Distrital Francisco José de Caldas – Colombia. Magíster en Gestión Ambiental – Pontificia Universidad Javeriana – Colombia. Coordinador de Gestión grado 2, Gerencia Departamental del Meta – Contraloría General de la República de Colombia – Colombia. – nelson.sepulveda@contraloria.gov.co, nlsepulvedaf@gmail.com