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Optimizing Seismic Sources for Cost-Effective Petroleum Exploration

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Abstract : This paper presents a decision-making framework for optimizing seismic source deployment in 3-D land exploration campaigns, a critical challenge for cost management in the oil industry. The framework seeks to balance two often conflicting objectives: achieving high-quality geophysical data (coverage, offset, azimuth) and improving operational efficiency (logistics, productivity, equipment use). A comprehensive mathematical programming model was developed to integrate the various cost components and operational constraints. To address the complexity of the solution space, several optimization techniques were investigated. In addition to classical methods such as Genetic Algorithms and Simulated Annealing, an innovative hybrid approach was introduced, combining Constraint Programming with GRASP and VNS heuristics. Extensive simulations and sensitivity analyses validate the effectiveness of the proposed framework, showing its ability to deliver solutions that are both technically robust and economically efficient. The study thus provides a valuable tool for the planning and execution of large-scale seismic surveys.

Keywords: Seismic exploration; Source deployment optimization; Mathematical programming; Metaheuristics; Genetic Algorithm; Simulated Annealing; Particle Swarm Optimization; Greedy Randomized Adaptive Search Procedure; Variable Neighborhood Search

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1 Introduction and Background

The world's energy security is heavily influenced by hydrocarbon-rich nations, whose economic growth depends largely on the effective monetization of their vast oil and gas reserves. These countries are therefore continuously confronted with both technical and economic challenges.

One of the most critical challenges in petroleum exploration lies in the inherent trade-off between the high cost of 3-D land seismic acquisition and the demand for high-resolution subsurface data. While this technique is indispensable for identifying potential reservoirs, it entails substantial logistical and financial burdens [1]. The design of 3-D land seismic surveys is thus a pivotal stage in the Exploration and Production (E&P) lifecycle, aiming to generate high-fidelity subsurface images that reduce the risks associated with drilling. The underlying principle is to illuminate geological targets using acoustic energy from seismic sources, with the reflected wavefield captured by an array of receivers.

The success of such surveys depends on meeting specific geophysical objectives, particularly those concerning fold coverage, offset, and azimuth distributions. These factors collectively ensure adequate sampling of the subsurface. However, achieving these objectives often conflicts with operational and economic constraints. For example, increasing the density of sources and receivers enhances the signal-to-noise ratio and image resolution, but it also escalates costs, logistical complexity, and environmental footprint.

This cost-quality dilemma has long been recognized as the central challenge in seismic survey design, prompting extensive research into methodologies capable of delivering optimal acquisition geometries under strict budgetary and operational constraints. A vast body of literature addresses this issue, exploring approaches to reduce costs while maintaining data integrity (see, for instance, [2, 3, 4].

The core optimization problem can therefore be formulated as strategically reducing the number of seismic shot points-the primary driver of cost and time-while rigorously preserving seismic image fidelity and ensuring comprehensive survey coverage.

This paper situates itself at the intersection of operations research and energy logistics by presenting an in-depth study on the optimization of seismic source deployment. It demonstrates the effectiveness of advanced metaheuristic frameworks in tackling this computationally complex problem in oil exploration: the strategic reduction of seismic source points while preserving the quality of acquired geophysical data. The findings highlight the potential of operations research methodologies to enhance decision-making and improve cost efficiency within the capital-intensive energy industry.

2 Three-Dimensional Onshore Seismic Acquisition

This section outlines the technical principles of seismic acquisition in petroleum exploration. It begins with the fundamental concepts and objectives of this geophysical method. A detailed description of the essential components of a seismic acquisition system, including sources, receivers, and shots, is then presented. Emphasis is placed on the critical role these elements play in ensuring the quality of the acquired data. The main stages of the acquisition process are subsequently reviewed, from logistical planning through to data interpretation. The section concludes by addressing the optimization of seismic surveys, considering the technical, economic, and operational constraints that influence both the quality of subsurface imaging and the overall cost of the survey.

2.1 Seismic Acquisition

Seismic acquisition is a geophysical method used to map subsurface structures through the analysis of seismic waves. A seismic source, such as a vibroseis truck or an explosive charge, generates waves that propagate through geological layers. As these waves encounter interfaces between different rock formations, they are reflected or refracted. By analyzing the travel times of the waves recorded by surface receivers, known as geophones, it is possible to reconstruct a detailed image of the subsurface. This information provides valuable insights into geological structures and the types of formations present.

2.2 Acquisition System Components

A seismic acquisition system relies on the interaction of several essential components: seismic sources, receivers (or geophones), the generated waves, and the recorded seismic traces. Each of these elements has a direct impact on the quality of the acquired data, the resolution of subsurface images, as well as the cost and operational feasibility of the survey [5, 6, 7]. Figure 1 illustrates the spatial arrangement of sources and receivers in a two-dimensional linear acquisition geometry.

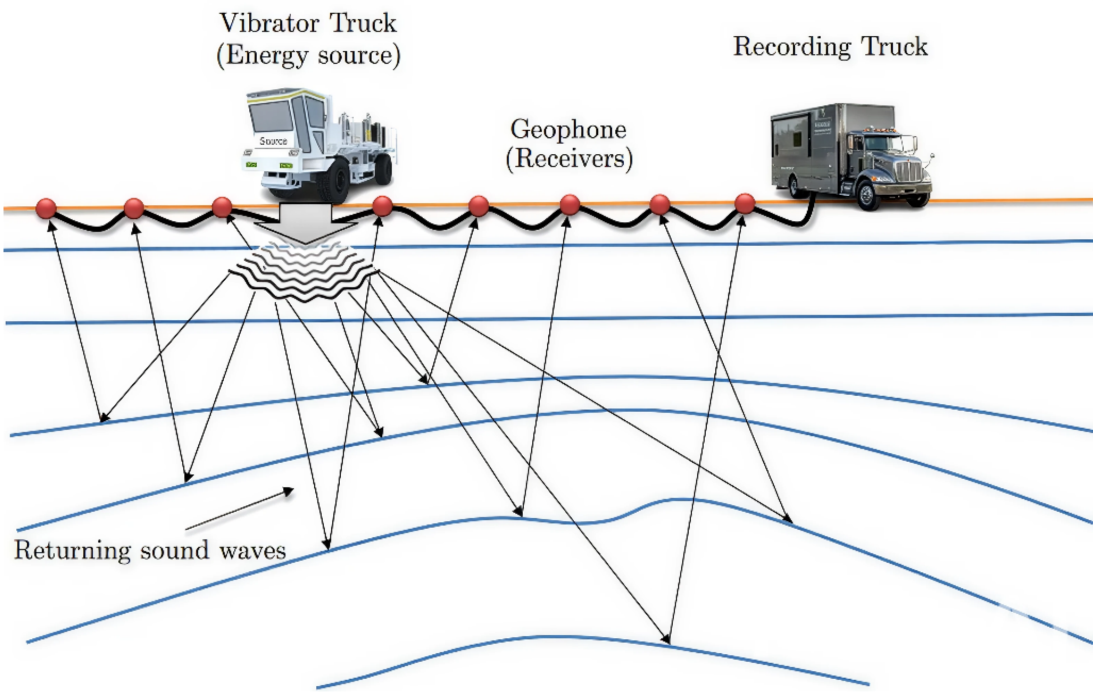

Figure 1: Workflow of the Seismic Data Acquisition Process.

The principal objectives of seismic acquisition include:

- **Geological Characterization:** To produce a detailed seismic image of the subsurface in order to precisely delineate structural and stratigraphic traps capable of hosting hydrocarbon accumulations.

- **Uncertainty Mitigation:** To reduce exploration risk by constraining geological models and providing a clearer understanding of subsurface formations, which is critical for guiding well-placement decisions.

- **Economic Optimization:** To maximize the economic return of exploration campaigns by identifying high-potential zones, thus optimizing drilling programs and enhancing the probability of commercial success.

Three-dimensional seismic surveys, which distribute sources and receivers in a grid-like geometry (Figure 2), are designed to achieve homogeneous subsurface coverage and high-resolution data. In a typical orthogonal layout, for instance, geophones are deployed in parallel lines while source points are positioned on perpendicular lines. Every aspect of this design, such as positioning sources between receiver lines to optimize azimuthal distribution, directly influences both data quality and survey expense. Therefore, the fundamental challenge in seismic acquisition design is to achieve an optimal trade-off between minimizing source and geophone costs while ensuring the fidelity of the acquired geophysical data.

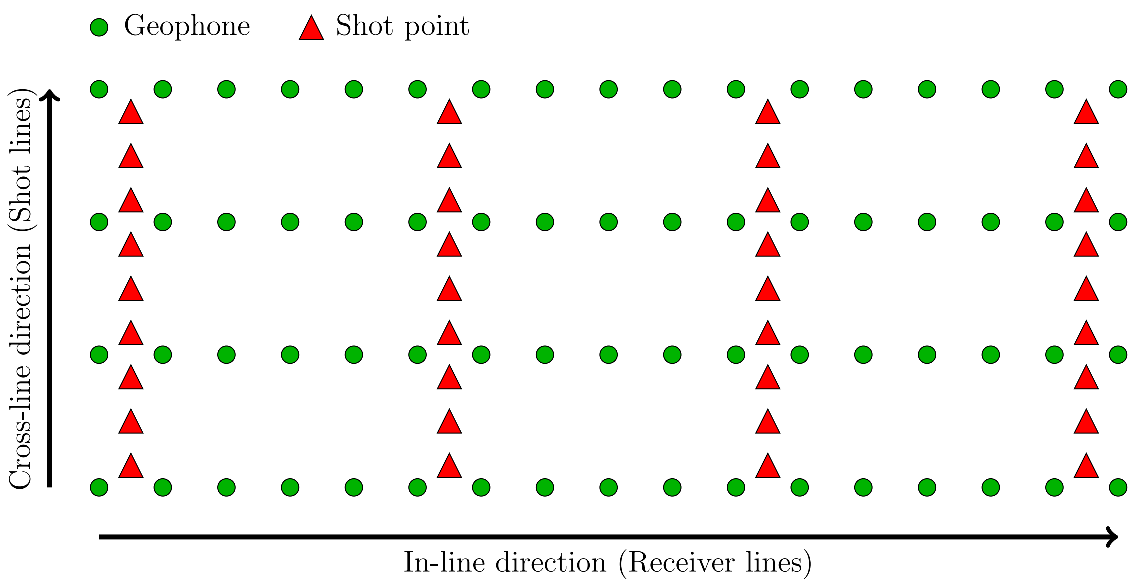

Figure 2: Schematic of an orthogonal 3D seismic acquisition geometry.

For the subsequent analysis, we adopt an orthogonal split-spread geometry for the source and receiver layout as depicted in Figure 3 see Douglas J. Morrice et al. [8].

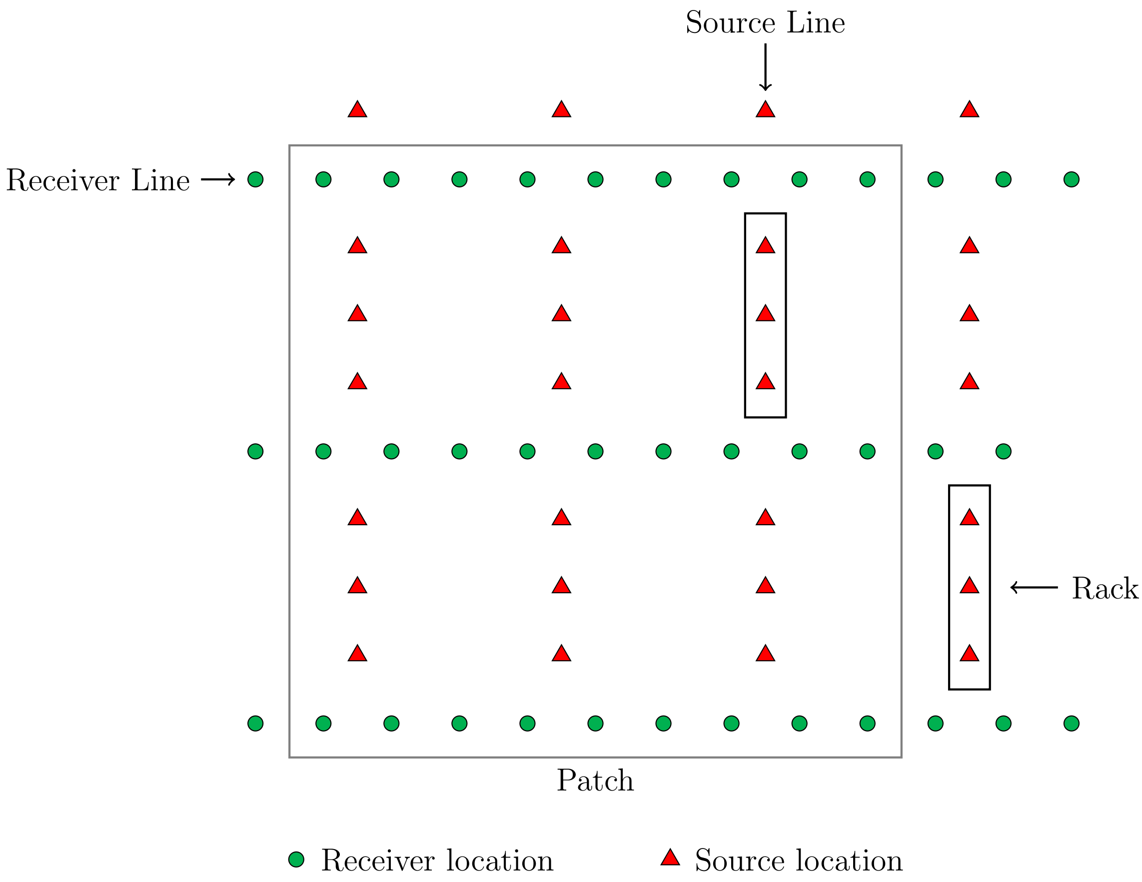

Figure 3: Illustration of the patch and a source rack.

3 Related Work

Current research in seismic acquisition optimization can be broadly classified into two categories: *physics-driven modeling approaches* and *combinatorial optimization methods.*

(I) Physics-driven approaches rely on geophysical forward models and inversion techniques to determine acquisition geometries that maximize subsurface image quality. Classical methods include ray-tracing based modeling [16, 17] and wave-equation simulations [18], which provide accurate estimates of illumination and resolution. More recent studies incorporate Bayesian formulations to quantify uncertainty and optimize acquisition under prior geological knowledge [19, 20]. While these approaches are physically rigorous, they are computationally expensive and often impractical for large-scale 3D surveys, where millions of potential shot and receiver positions must be evaluated. Furthermore, their reliance on precise velocity models makes them sensitive to modeling errors.

(II) Combinatorial optimization methods, on the other hand, directly explore the discrete design space of possible source and receiver placements. Metaheuristics such as Genetic Algorithms [21, 22], Simulated Annealing [23], and Particle Swarm Optimization [24] have been widely applied to maximize coverage, minimize acquisition cost, and satisfy operational constraints. For example, [25] applied a GA-based framework that iteratively refines survey geometries by combining and mutating candidate layouts, selecting those that maximize illumination uniformity. Similarly, [24] used PSO to balance imaging quality with logistic constraints such as terrain accessibility. More recently, hybrid methods combining constraint programming with metaheuristics have been proposed to handle multi-objective settings [25, 26]. These approaches are more scalable and flexible, yet they may converge to suboptimal local solutions and often require careful parameter tuning.

4 Mathematical Formulation and Analysis

To address the critical challenge of designing cost-effective onshore seismic surveys, we present a mathematical optimization model. This model is engineered to guarantee sufficient geophysical coverage while simultaneously minimizing overall expenses. Our methodology, adapted and slightly modified from the established framework of Morrice et al. [8], seeks to achieve an optimal equilibrium between geophysical quality and economic viability. This is accomplished by meticulously determining the ideal values for key decision variables, such as geophone line spacing, the number of shots, and receiver mobility. These determinations are made subject to a comprehensive set of geometric, operational, and logistical constraints. The ultimate goal is to define a source and receiver layout that is both geophysically effective and economically sound. Table 1 provides a detailed specification of these decision variables, while Table 2 enumerates the symbols representing the problem data, which are presumed to be fixed and known for any given problem instance.

4.1 Objective function

The first step involves defining the objective function, which is to minimize total acquisition costs per km^2. This can be further subdivided and reformulated as: Minimize (Total cost of geophones + Total cost of shots + Total crew cost).

- The total cost of deploying geophones consists of:
  - Geophone installation cost: $C_{\text{inst}} = C_{\text{dep}} \times \dfrac{1}{x_2 x_3}$,
  - Daily operating cost of active geophones: $C_{\text{active}} = C_{\text{day}} x_5 (1+I)\dfrac{x_8}{x_9}\cdot$
- The total shooting cost: $C_{\text{shots}} = (C_{\text{shot}} + C_{\text{surv}})x_8$,
- The total crew cost: $C_{\text{crews}} = C_{\text{crew}} \times \dfrac{x_8}{x_9}$,

where $\dfrac{1}{x_2 x_3}$ and $\dfrac{x_8}{x_9}$ represent the number of geophones and the number of days required to complete the coverage per km^2, respectively.

By combining the three different costs to minimize, the objective function can be expressed as follows:

$$\text{Min } C_{\text{total}} = C_{\text{inst}} + C_{\text{active}} + C_{\text{shots}} + C_{\text{crews}}. \tag{1}$$

Symbole	**Description**
x_1	Shot line spacing
x_2	Receiver line spacing (or Geophone line spacing)
x_3	Receiver interval (in-line)
x_4	Shot interval (in-line)
x_5	Total number of active receivers
x_6	Number of active receiver lines
x_7	Number of receivers per line
x_8	Shot density (shots per km^2)
x_9	Number of shots per day
x_{10}	Number of receivers moved per day
x_{11}	Half the number of active receiver lines

Table 1: Definition of Decision Variables

Symbole	**Description**	**Symbole**	**Description**
C_{dep}	Deployment cost per receiver	OIN_{min}	Minimum inline offset
C_{day}	Daily cost per active receiver	OCR_{min}	Minimum crossline offset
C_{shot}	Cost per shot	O_{min}	Minimum diagonal offset
C_{surv}	Surveying cost per shot	O_{max}	Maximum diagonal offset
C_{crew}	Daily crew cost	T_{max}	Maximum number of shots per day
I	Inflation factor	G_{max}	Maximum number of receivers moved per day
B_x	Inline bin size	C_{max}	Maximum available receiver capacity
B_y	Crossline bin size	a_i	Lower bound for decision variable x_i
F	Fold (seismic coverage)	b_i	Upper bound for decision variable x_i

Table 2: Model Parameters

4.2 Problem constraints

The comprehensive set of constraints can be categorized into four primary groups: Seismic Image Quality constraints, Operational constraints, Geometric Consistency constraints, and General constraints.

4.2.1 Seismic Image Quality constraints

- *Fold*: $x_5 x_8 B_x B_y \geq F$.

  This ensures a minimum fold value, F, to guarantee sufficient signal-to-noise ratio and improve the resolution of the subsurface image.

- *Offset maximal inline*: $\dfrac{x_5}{x_6} \times \dfrac{x_3}{2} - \dfrac{x_3}{2} \geq OIN_{min}$.

  This ensures that the maximum distance between a source and a receiver in the inline direction is greater than or equal to a threshold OIN_{min}. This condition enables the capture of deep signals with a sufficient offset.

- *Offset maximal crossline*: $\dfrac{x_6}{2} \times x_2 - \dfrac{x_4}{2} \geq OCR_{min}$.

  This ensures a minimum distance between receivers and sources in the perpendicular (crossline) direction, in order to guarantee adequate lateral coverage.

- *Offset radial maximal*: $\left(\dfrac{x_5}{x_6} \times \dfrac{x_3}{2} - \dfrac{x_3}{2}\right)^2 + \left(\dfrac{x_6}{2} \times x_2 - \dfrac{x_4}{2}\right)^2 \geq O_{max}^2$.

  This ensures that the maximum diagonal distance (radial offset) between a source and a receiver is sufficiently large, reaching the threshold O_{max}, which is necessary for exploring greater depths.

- *Offset radial minimal*: $x_4^2 + x_3^2 \leq O_{min}^2$.

  This ensures that the minimum diagonal distance between sources and receivers remains below a threshold O_{min}, which is essential for capturing shallow signals.

4.2.2 Operational constraints

- *Daily shot limit*: $x_9 \leq T_{max}$.

  This limites the number of seismic shots per day to the production team's maximum capacity, in order to comply with human and technical constraints in the field.

- *Daily shot limit*: $x_{10} \leq G_{max}$.

  This restrictes the number of geophones that can be relocated daily, depending on the available logistical resources (vehicles, operators, time, etc.).

- *Activity synchronization*: $x_9 x_4 x_1 = x_{10} x_3 x_2$.

  Ensuring synchronization between seismic shots and geophone relocation, in order to maintain continuous production without logistical interruptions.

- *Capacité maximale des équipements*: $(1+I)x_5 \leq C_{max}$.

  This verifies that the total number of geophones used, adjusted for the technological inflation factor I, remains less than or equal to the maximum capacity of the equipment available on site.

4.2.3 Geometric Consistency constraints

- *Inline bin size*: $x_3 \leq 2B_x$.

  This ensures that the spacing between geophones along a line does not exceed a value compatible with the inline bin size B_x, in order to guarantee homogeneous seismic coverage in the receiver line direction.

- *Crossline bin size*: $x_4 \geq 2B_y$.

  This ensures that the spacing between sources is sufficiently large relative to the crossline bin size B_y, in order to achieve regular coverage perpendicular to the receiver lines.

- *Shot density*: $x_8 = \dfrac{1}{x_4 x_1}$.

  This ensures a regular shot density per km^2, by balancing the spacing between sources and the distance between shot lines.

- *Geometry of geophone lines*: $x_5 = x_6 x_7$.

  This defines the total number of geophones as the product of the number of lines and the number of geophones per line, thereby ensuring a regular structure of the receiver network.

- *Geophone line parity*: $x_6 = 2x_{11}$.

  This imposes that the number of geophone lines is even, which is essential to obtain symmetric coverage during acquisition.

4.2.4 General constraints

- *Decision variable bounds*: $a_i \leq x_i \leq b_i, \ \forall i \in \{1, \dots, 11\}$.

- *Real variable domain*: $x_i \in \mathbb{R}_+^*, \ \forall i \in \{1, 2, 3, 4\}$.

- *Integer variable domain*: $x_i \in \mathbb{N}^*, \ \forall i \in \{5, \dots, 11\}$.

The complete mathematical formulation is given by:

$$
\begin{cases}
\text{Min } C_{\text{total}} = \dfrac{C_{\text{dep}}}{x_2 x_3} + C_{\text{day}}(1+I)\dfrac{x_5 x_8}{x_9} + (C_{\text{shot}} + C_{\text{surv}})x_8 + C_{\text{crew}}\dfrac{x_8}{x_9}, \\
\text{s.t.} \quad x_5 x_8 \geq \dfrac{F}{B_x B_y}, \\
\dfrac{x_3}{2}\left(\dfrac{x_5}{x_6} - 1\right) \geq OIN_{min}, \\
\dfrac{x_2 x_6 - x_4}{2} \geq OCR_{min}, \\
\left(\dfrac{x_3 x_5}{2x_6} - \dfrac{x_3}{2}\right)^2 + \left(\dfrac{x_2 x_6 - x_4}{2}\right)^2 \geq O_{max}^2, \\
x_4^2 + x_3^2 \leq O_{min}^2, \\
x_9 \leq T_{max}, \quad x_{10} \leq G_{max}, \\
x_1 x_4 x_9 - x_2 x_3 x_{10} = 0, \\
x_5 \leq \dfrac{C_{max}}{1+I}, \\
x_3 \leq 2B_x, \\
x_4 \geq 2B_y, \\
x_1 x_8 x_4 = 1, \\
x_5 - x_6 x_7 = 0, \\
x_6 = 2x_{11}, \\
x_i \in \mathbb{R}_+^*, \ \forall i \in \{1, \dots, 4\}, \quad x_i \in \mathbb{N}^*, \ \forall i \in \{5, \dots, 11\}.
\end{cases}
$$

The proposed optimization model falls into the class of Mixed-Integer Nonlinear Programming (MINLP) problems, characterized by integer decision variables, quadratic constraints, and nonlinear fractional terms. It can be interpreted as a constrained covering problem, where the objective is to ensure adequate coverage of the study area with a minimal number of seismic shots while adhering to geometric, technical, and operational requirements. Owing to its inherently non-convex structure, the problem belongs to the NP-hard complexity class, which makes the search for exact solutions computationally intractable for large-scale instances. To overcome these difficulties, we rely on heuristic and approximation approaches, particularly metaheuristics, which are well-suited to generating high-quality feasible solutions within reasonable computational times.

Our optimization strategy is specifically designed to reduce the number of seismic shots by enlarging the spacing between shot lines. To compensate for the resulting decline in coverage, selective densification of receivers is introduced. This trade-off-between fewer sources and denser receivers-substantially increases the number of discrete variables, thereby intensifying the combinatorial complexity of an already challenging problem.

5 Solution Approaches

Exact methods aim to provide guaranteed optimal solutions for a given problem; however, their applicability is often limited when dealing with large-scale instances or complex constraints, such as those arising in the optimization of seismic acquisition campaigns. In such contexts, approximate methods-and in particular metaheuristics-emerge as a relevant alternative. They are capable of producing satisfactory solutions within reasonable computational times while adapting effectively to the operational specificities of the field.

Metaheuristics are flexible optimization frameworks inspired by natural processes, designed to deliver high-quality solutions through a balance of global exploration and local exploitation [9]. Their strength lies in their ability to address complex optimization problems where traditional methods struggle.

In this study, four complementary approaches are investigated: Genetic Algorithm (GA), Improved Particle Swarm Optimization (IPSO), Simulated Annealing (SA), and a hybrid CP-GRASP-VNS method. Each of these techniques brings specific mechanisms for handling mixed variables, satisfying structural constraints, and efficiently exploring vast and intricate search spaces.

The remainder of this section is structured as follows. Subsection 1 presents the Genetic Algorithm, highlighting its population-based search and genetic operators. Subsection 2 introduces the Improved Particle Swarm Optimization, focusing on its enhancements over the classical PSO. Subsection 3 describes the Simulated Annealing method and its probabilistic acceptance mechanism. Subsection 4 details the proposed hybrid CP-GRASP-VNS approach, combining constructive and local search strategies for improved performance. Finally, a comparative discussion is provided to underline the complementarities and potential synergies among these approaches.

5.1 Genetic Algorithm (GA)

The origins of Genetic Algorithms go back to the 1960s with the pioneering work of Holland, later extended and popularized by Goldberg [10]. GA is a stochastic global optimization approach inspired by the mechanisms of natural evolution. It relies on the principle of "survival of the fittest" to progressively refine candidate solutions, without requiring strong assumptions such as continuity or unimodality. Owing to this flexibility, GA has been widely applied to complex optimization problems, where it often outperforms traditional techniques, particularly in landscapes with multiple local optima. In a GA, a population of potential solutions is maintained, with each individual represented as a chromosome. Once decoded, the quality of each chromosome is assessed using a fitness function. Based on these evaluations, selection operators-often using a biased roulette wheel-identify promising candidates that undergo genetic operations such as crossover and mutation, which emulate evolutionary processes. Newly generated offspring with higher fitness replace weaker individuals from the previous generation. This iterative process continues until a predefined termination condition is satisfied. In the proposed approach, each candidate solution is represented as:

$$X = \big(\underbrace{x_1, x_2, x_3, x_4}_{\text{real-valued}}, \underbrace{x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}}_{\text{integer-valued}}\big),$$

where the first subset corresponds to real variables, while the second subset is associated with integer ones. The crossover and mutation operators are simultaneously applied to both subsets, with each type of variable processed independently.

The main parameters governing the algorithm can be summarized as follows: a population of size N, in which all individuals respect the prescribed bounds, dependencies, and the variable types (real or integer); the number of generations; the crossover probability P_c; the mutation probability P_m; and the selection strategy (e.g., tournament or roulette). The overall procedure of the genetic algorithm is summarized in Algorithm 1.

Algorithm 1 Genetic Algorithm

Input: Population size N, crossover probability P_c, mutation probability P_m, stopping criterion
Output: Best individual found
Initialize the population P_0 of size N
Evaluate the fitness of each individual
$t \leftarrow 0$
while stopping criterion not met **do**
    Select parents: $P_{\text{parents}} \leftarrow \text{Selection}(P_t)$
    $P_{\text{offspring}} \leftarrow \emptyset$
    while $|P_{\text{offspring}}| < N$ **do**
        Select two parents $p_1, p_2 \in P_{\text{parents}}$
        if rand() $< P_c$ **then**
            $(o_1, o_2) \leftarrow \text{Crossover}(p_1, p_2)$
        else
            $(o_1, o_2) \leftarrow (p_1, p_2)$ ▷ No crossover, parents become offspring
        end if
        $o \in \{o_1, o_2\}$
        if rand() $< P_m$ **then**
            $o \leftarrow \text{Mutation}(o)$
        end if
        Add o to $P_{\text{offspring}}$
    end while
    Evaluate the fitness of $P_{\text{offspring}}$
    $P_{t+1} \leftarrow \text{Replacement}(P_t, P_{\text{offspring}})$
    $t \leftarrow t + 1$
end while
return best individual from P_t

5.2 Improved Particle Swarm Optimization (IPSO)

Building upon the standard Particle Swarm Optimization framework [14], the Improved PSO (IPSO) is designed to overcome premature convergence and stagnation in local optima. Unlike the conventional model, which updates particle velocities using fixed linear operators, IPSO introduces adaptive non-linear parameters and integrates mutation mechanisms inspired by evolutionary algorithms. These modifications enhance the balance between exploration and exploitation, thereby improving convergence stability and robustness, especially for non-convex and high-dimensional optimization problems. A key improvement lies in the adaptive inertia weight w, which governs particle behavior: higher values encourage exploration, while lower values promote exploitation. To accelerate convergence, w is dynamically reduced across iterations according to:

$$w(t) = w_{\max} - \left(\frac{w_{\max} - w_{\min}}{T_{\max}} \right) t,$$

where, $w(t)$ denotes the inertia at iteration t, $w_{\max}$ and $w_{\min}$ are its initial and final values, and $T_{\max}$ is the total number of iterations.

Furthermore, if a particle fails to improve its position over $S_{\max}$ consecutive iterations, a random mutation is applied. To reinforce diversification, the swarm is also divided into subgroups, each exploring distinct regions of the search space. The IPSO procedure is summarized in Algorithm 2.

Algorithm 2 Particle Swarm Optimization (PSO)

Input: swarm size N, iterations T, inertia w, cognitive c_1, social c_2, search space X
Output: best solution $gbest$
Initialize x_i (positions), $v_i = 0$ (velocities) for $i = 1, \ldots, N$
Evaluate $f(x_i)$, set $pbest_i \leftarrow x_i$
$gbest \leftarrow \arg\min f(pbest_i)$
for $t = 1$ to T **do**
    for each particle i **do**
        Generate $r_1, r_2 \sim \mathcal{U}(0, 1)$
        $v_i \leftarrow wv_i + c_1 r_1 (pbest_i - x_i) + c_2 r_2 (gbest - x_i)$
        $x_i \leftarrow x_i + v_i$
        if x_i valid **then**
            Evaluate $f(x_i)$
            if $f(x_i) < f(pbest_i)$ **then** $pbest_i \leftarrow x_i$
            end if
            if $f(x_i) < f(gbest)$ **then** $gbest \leftarrow x_i$
            end if
        end if
    end for
end for
return $gbest$

5.3 Simulated Annealing (SA)

Simulated Annealing is a probabilistic metaheuristic inspired by the metallurgical annealing process [15], where a material is heated and gradually cooled to minimize structural defects and reach a low-energy state. Analogously, the algorithm explores the solution space by occasionally accepting solutions of inferior quality. This controlled acceptance mechanism, particularly effective at high "temperatures", enables the search to escape local optima. The acceptance probability is governed by a temperature parameter, which decreases according to a predefined cooling schedule. As the temperature decreases, the algorithm progressively shifts from extensive exploration to focused exploitation of promising regions. Due to its conceptual simplicity and theoretical guarantees of global convergence, SA has proven effective for tackling complex combinatorial optimization problems, such as the traveling salesman problem and VLSI design. The main parameters governing the algorithm can be summarized as follows: the initial temperature T_0, which must be sufficiently high to allow the acceptance of about 80% of degrading moves at the beginning; the final temperature T_f, typically set to $0.01 \times T_0$ to ensure convergence; the length of the plateau $L(T)$, corresponding to the number of iterations performed at each temperature, often proportional to the problem size; and the cooling coefficient α, which controls the rate of temperature decrease and influences the trade-off between solution quality and computational time. The main steps of SA are summarized in Algorithm 3.

Algorithm 3 Simulated Annealing

Input: Objective function f, initial temperature T_0, cooling schedule α, stopping criterion
Output: Best solution found S_{best}
Generate an initial solution S_0
Initialize the temperature T_0
$S_{\text{current}} \leftarrow S_0$, $S_{\text{best}} \leftarrow S_0$
$k \leftarrow 0$
while stopping criterion not met **do**
  for $i = 1$ **to** $L(T_k)$ **do**
    Generate $S' \in N(S_{\text{current}})$ (neighbor)
    Compute $\Delta f = f(S') - f(S_{\text{current}})$
    if $\Delta f \leq 0$ **then**
      $S_{\text{current}} \leftarrow S'$
      if $f(S') < f(S_{\text{best}})$ **then**
        $S_{\text{best}} \leftarrow S'$
      end if
    else
      Generate $r \sim U(0,1)$
      if $r < \exp(-\Delta f / T_k)$ **then**
        $S_{\text{current}} \leftarrow S'$
      end if
    end if
  end for
  $k \leftarrow k + 1$
  Update the temperature: $T_k = \alpha^k T_0$, with $0.8 \leq \alpha \leq 0.99$
end while
return S_{best}

5.4 Hybrid Method based on CP-GRASP-VNS

The CP-GRASP-VNS hybrid method integrates the complementary strengths of Constraint Programming (CP) [11], the Greedy Randomized Adaptive Search Procedure (GRASP) [12], and Variable Neighborhood Search (VNS) [13] into a unified optimization framework. First, CP is employed to generate feasible initial solutions by rigorously enforcing the structural and logical constraints of the problem. Next, GRASP introduces adaptive randomness through a greedy yet randomized constructive process, which enhances solution diversity and mitigates the risk of premature convergence. Finally, VNS systematically explores a sequence of neighborhood structures to balance intensification and diversification, thereby improving the overall solution quality. By combining these three strategies, the CP-GRASP-VNS method offers a robust and flexible approach, particularly well suited for large-scale and combinatorial optimization problems where traditional exact methods and standalone heuristics often prove insufficient. Algorithms 4 and 5 detail the *GRASP_Construct* and *VNS* subprocedures, while Algorithm 6 presents the overall method.

Algorithm 4 GRASP-Construct Algorithm

Input: Constraint Programming model (CP), parameter α
Output: Constructed solution S_c
$S_c \leftarrow \emptyset$
while the solution is not complete **do**
    Generate the Restricted Candidate List (RCL)
    Select a random element from the RCL (guided by α)
    Add the element to the solution and propagate CP constraints
end while
return S_c

Algorithm 5 Variable Neighborhood Search (VNS)

Input: Initial solution S_0, neighborhoods $\mathcal{N} = \{N_1, \ldots, N_k\}$, stopping condition
Output: Best solution S_{best}
$S_{\text{best}} \leftarrow S_0$
while stopping condition not met **do**
    $i \leftarrow 1$
    while $i \leq k$ **do**
        $S' \leftarrow \text{Shake}(S_{\text{best}}, N_i)$
        $S'' \leftarrow \text{LocalSearch}(S')$
        if $f(S'') < f(S_{\text{best}})$ **then**
            $S_{\text{best}} \leftarrow S''$
            $i \leftarrow 1$
        else
            $i \leftarrow i + 1$
        end if
    end while
end while
return S_{best}

Algorithm 6 CP-GRASP-VNS Algorithm

```
Input: Constraint Programming model (CP), GRASP parameters, VNS parameters
Output: Best solution found S_best
S_best ← ∅
Generate an initial feasible solution with CP S_0
for i = 1 to I_Max do
    S_curent ← GRASP_Construct(CP, α)
    S_curent ← VNS(S_curent, CP)
    if S_curent is better than S_best then
        S_best ← S_curent
    end if
end for
return S_best
```

6 Implementation and Results

This section outlines the implementation of the GA, SA, PSO and CP-GRASP-VNS algorithms, along with computational experiments based on real-world data from the "2023-IFT-3D" project conducted by SONATRACH in In Amenas, upstream concession, located in the Illizi Basin in southeastern Algeria (see Table 3). The study area, extending over 1720.39 km^2, is characterized by smooth terrain with flat to gently undulating surfaces, well-suited for deploying seismic equipment and facilitating field operations. Strategically, it is of high petroleum interest due to potential hydrocarbon-rich reservoirs in the Devonian and Ordovician formations, and forms part of a large-scale seismic exploration program aimed at improving subsurface knowledge and optimizing drilling plans.

We first describe the experimental setup, including the problem instances, parameter configurations, and implementation environment. The subsequent analysis assesses the efficiency and robustness of the proposed approaches in this specific context.

The computational findings are presented in the following subsections, where the performance of the algorithms is examined in detail. In addition, the proposed optimization model was solved using the `LINGO` solver, which is particularly suited for Mixed-Integer Nonlinear Programming (MINLP). The resulting spatial configuration of seismic sources satisfied all operational and technical constraints, confirming both the feasibility of the solutions and the field applicability of the approach. Overall, these results validate the model's effectiveness and highlight its potential as a decision-support tool in real industrial settings.

Table 4 reports the numerical values of the decision variables obtained from the model solution.

The computational experiment yielded a solution within 0.27 seconds, achieving an objective function value of **3,552,433,311 DZD**. All tests were performed on a personal computer running an Intel® Core™ i7-5600U CPU @ 2.60 GHz with 8 GB of RAM.

A dedicated software application was also developed to provide a flexible experimental framework for testing heuristic and metaheuristic approaches. This platform integrates the implementation of three well-established algorithms—Genetic Algorithm (GA), Parti-

Parameter	Value
C_{dep}	250
C_{day}	120
C_{shot}	5000
C_{surv}	1500
C_{crew}	800000
I	0.3
B_x	0.015
B_y	0.015
F	348
OIN_{min}	0.0075
OCR_{min}	0.0075
O_{max}	0.6
O_{min}	0.035
T_{max}	3000
G_{max}	5000
C_{max}	48000

Table 3: Input data

Domain	Variable	Value
Continuous variables		
$[0.150, 0.20]$	x_1	0.15
$[0.060, 0.10]$	x_2	0.10
$[0.007, 0.01]$	x_3	0.01
$[0.030, 0.04]$	x_4	0.030
Integer variables		
$[1500, 7000]$	x_5	7000
$[30, 60]$	x_6	40
$[100, 250]$	x_7	175
$[200, 500]$	x_8	221
$[1000, 2800]$	x_9	1105
$[3000, 5000]$	x_{10}	5000
$[15, 30]$	x_{11}	20

Table 4: Values of the decision variables using `LINGO`

cle Swarm Optimization (PSO), and Simulated Annealing (SA)—together with the hybrid method CP-GRASP-VNS. The unified environment ensures consistent testing conditions across all methods, enabling a fair and systematic comparison of their performance.

The application is structured into four main modules: (i) a *multi-method optimization* module, designed to compare the performance of the different algorithms under identical conditions; (ii) an *advanced visualization* module, allowing the exploration of outcomes through interactive graphics and detailed comparative tables; (iii) a *customized parameter management* module, which provides full flexibility to configure, store, and reuse algorithmic settings; and (iv) a data management and reporting module, enabling the systematic organization of input data and the generation of reproducible experimental reports. Together, these modules form a comprehensive tool that ensures both methodological rigor and practical usability in real-world experimental settings.

6.1 Obtained Results

The computational experiments conducted through the developed application provided a comprehensive evaluation of the proposed methods. Each algorithm was executed under identical conditions and on the same real-world data previously tested with LINGO, thereby ensuring the fairness of the comparison. The multi-method optimization module enabled a direct confrontation of the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and the hybrid CP-GRASP-VNS, while the advanced visualization module facilitated an in-depth analysis of the obtained solutions. A summary of the main numerical results is reported in Table 5, which provides a detailed comparison of solution quality and computational effort across the tested algorithms.

The results indicate that the hybrid CP-GRASP-VNS consistently outperforms the classical metaheuristics in terms of both solution quality and robustness, particularly when addressing large-scale and complex instances. Moreover, the parameter management module proved to be an essential feature, as it allowed fine-tuning and reproducibility of the experimental configurations. These findings confirm the relevance of the developed application as both a decision-support tool and a research framework for the systematic assessment of metaheuristic optimization strategies.

Variable	LINGO	GA	SA	PSO	CP-GRASP-VNS
Continuous variables					
x_1	0.15	0.19	0.16	0.15	0.20
x_2	0.10	0.10	0.10	0.10	0.10
x_3	0.01	0.01	0.01	0.01	0.01
x_4	0.03	0.04	0.04	0.03	0.04
Integer variables					
x_5	7000	6130	5944	7000	1500
x_6	40	59	30	40	40
x_7	175	222	221	175	100
x_8	221	200	200	221	200
x_9	1105	2576	2800	1105	2772
x_{10}	5000	4992	4785	5000	3000
x_{11}	20	17	15	20	15
Objective function (DZD)	35 524 333.11	29 011 919.65	28 788 593.37	35 524 330.29	**27 949 676.76**
Execution time (s)	0:27	0.76	0.16	1.53	3.59

Table 5: Comparison of results obtained by LINGO and the proposed algorithms

7 Results Analysis

As summarized in Table 5, the comparative analysis highlights the relative performance of the investigated algorithms in terms of both solution quality and computational efficiency. Beyond these technical outcomes, the financial dimension of the project remains central, since it defines the contractual framework within which the proposed optimization approaches are applied. The results clearly demonstrate the decisive impact of reducing the number of seismic shots on both total cost and project duration. The Hybrid Method, which optimized not only the number but also the spatial distribution of shots, yielded the lowest total cost of **27 949 676.76 DZD**, compared with the **4,023,869,268.34 DZD** initially projected in the SONATRACH contract. This corresponds to a saving of more than **774 million dinars**, representing a substantial financial benefit for the project.

Scenario	Total Cost (DZD)	Savings (DZD)
Initial Contract Estimate	4,023,869,268.34	–
Hybrid Optimization Method	27 949 676.76	774,710,053.82

Table 6: Comparison of total project costs

In addition to cost reduction, the decrease in the number of shots significantly shortened the overall project duration, from **241 days** to **190 days**. This gain of more than **50 days** results directly from the reduced volume of field operations, particularly the daily shooting activities, while still maintaining satisfactory geophysical coverage.

Table 7: Comparison of project duration

Scenario	Duration (days)	Reduction (days)
Initial Contract Estimate	241	–
Hybrid Optimization Method	190	51

It is worth noting that, to balance the reduced number of shots, the number of geophones was slightly increased. However, despite this additional deployment of sensors, the overall cost still decreased. This confirms that the number of seismic shots is the dominant factor shaping the final cost of a seismic survey.

Taken together, the economic and temporal gains underline that the number of shots constitutes a strategic lever in the planning of seismic acquisition campaigns. A well-calibrated reduction of this variable, combined with an efficient sensor layout, enables optimal results without compromising data quality.

These findings highlight the importance of incorporating advanced optimization approaches into survey design, as a means of simultaneously improving operational performance and ensuring economic profitability.

8 Conclusion

This paper has presented a decision-making framework for optimizing seismic source deployment in 3-D land exploration campaigns. By formulating a mixed mathematical programming model and investigating advanced optimization techniques, including a novel hybrid approach, the study has demonstrated the ability to balance geophysical data quality with operational efficiency. The results confirm that such optimization methods provide technically robust and economically efficient solutions, offering valuable guidance for large-scale seismic survey planning in the oil industry.

Beyond its immediate application, the proposed framework also contributes to the broader field of operations research by illustrating how metaheuristic strategies can be tailored to address complex, real-world industrial challenges. The integration of cost, time, and data quality considerations highlights the versatility of the approach and its potential for adaptation to other domains requiring large-scale resource allocation and planning.

Furthermore, this study reinforces the importance of bridging theoretical optimization models with practical implementation, ensuring that advanced mathematical techniques translate into tangible benefits for industry. The findings not only provide actionable insights for practitioners but also open avenues for future research, particularly in extending hybrid optimization methods to multi-objective contexts and dynamic operational environments.

Overall, this work underscores the strategic role of optimization in modern geophysical exploration, demonstrating that carefully designed mathematical models can drive both scientific progress and economic value in the energy sector.

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