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APPLICATION OF ARTIFICIAL INTELLIGENCE IN PETROLEUM INDUSTRY

Siddhant Garje* & Dr. Anita Kumari**
* Student, Thadomal Shahani Engineering College, Bandra West, Mumbai, Maharashtra
** Professor of Chemical Engineering Department, Thadomal Shahani Engineering College, Bandra West, Mumbai, Maharashtra

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Abstract:

Artificial intelligence (AI) has been widely applied to optimization challenges in the petroleum exploration and production industry in recent years. With the new industry interest and enthusiasm for smart wells, intelligent fields, and real-time analysis and interpretation of enormous amounts of data for process optimization, our industry's need for powerful, resilient, and intelligent technologies has expanded dramatically. This survey provides a thorough literature analysis based on various types of AI algorithms, their application areas in the petroleum sector, and the geographical regions where they are being developed. To that end, AI methods are divided into four categories: evolutionary algorithms, swarm intelligence, fuzzy logic, and artificial neural networks. Furthermore, these types of algorithms in terms of their applications in petroleum engineering are investigated. Furthermore, the hybridization and/or combination of multiple AI techniques can be successfully used to address critical optimization problems and achieve superior results.

Key Words: Artificial Intelligence; Genetic Algorithm; Particle Swarm Optimization; ANN; Fuzzy Logic; Differential Evolution; Petroleum Engineering; Digital Transformation

1. Introduction:

As the most important general-purpose technology of today, artificial intelligence (AI) is rapidly infiltrating industries [1, 2], generating huge opportunities for innovation and growth. AI has already sparked significant changes and modified competitive norms in healthcare, transportation, retail, media, and finance [3,4]. Companies in these areas create value utilising AI solutions rather than traditional and human cantered business methods [5]. The value creation process is driven by advanced algorithms that have been trained on vast and meaningful datasets and are constantly fed new data. Gero.ai fights in this manner. Amazon determines goods prices, Inbox Vudu prioritises emails, and Yandex moves (autonomous) automobiles, according to Covid-19. Based on recent advances, it is apparent that our sector has recognised the enormous potential presented by intelligent systems. As petroleum professionals, they spenddays combating very complex and dynamic situations and making high-stakes judgements. Furthermore, with the introduction of new sensors that are permanently installed in the wellbore, very significant amounts of data including critical and necessary information are now available.

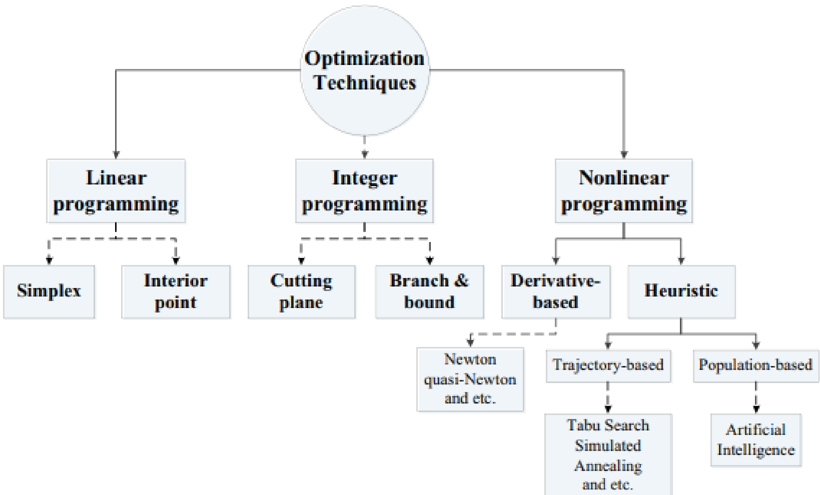

Figure 1: Classification of optimization techniques [6, 7]

To make the most of these unique hardware instruments, access to appropriate software to process data in real time is required. Intelligent systems in all their varieties are the only practical methodologies capable of providing real-time analysis and decision-making power to the new hardware. A search of the commercially available intelligent software tools for the oil and gas industry reveals that, while some software applications barely scratch the surface of intelligent system capabilities (and should be commended for their contributions), the software tool that can effectively implement integrated intelligent systems in our industry has not yet made it to the commercial market.

Optimization methods were first used in the petroleum exploration and production (E&P) sector in the 1940s and have since been widely used to anticipate, estimate, and determine various operational parameters. These techniques are divided into three categories: linear, integer, and nonlinear programming techniques. Linear programming is most commonly employed when both the objective function and the restrictions are linear. The linear approach is illustrated via the simplex algorithm and the interior point algorithm. Despite its popularity, this method has one significant drawback: it requires a high number of iterations to converge. In contrast, the integer programming technique is appropriate to problems in which all unknown components are discrete or mixed continuous and integer (e.g., coupled well control and placement optimization). Scholars typically utilise two ways to address these issues: the cutting plane technique and the branch and bound method. Because no systematic study of the applications of various AI algorithms to diverse challenges in the oil and gas industries has been done, this summary of the most relevant literature on the subject is provided. The remainder of this review is structured as follows.

2. The Problem and Need for AI:

The domination of "difficult-to-recover" oil and gas reserves over the last ten years [16] necessitates the development of new operational approaches and business models in hydrocarbon exploration and production, aimed at assuring adequate profitability of oil and gas production. This is true for both established (brownfields) and freshly found (green fields) subterranean hydrocarbon reserves. Despite the fact that the vast majority of brownfields are relatively large in terms of geometrical size and have adequate transport and storage qualities (porosity and permeability), the amount of oil and gas recoverable with low-cost waterflooding is fairly little. In general, traditional brownfields produce more water than oil. To maintain production levels, operating businesses must invest sufficient funds in one of the following operations: more drilling, well treatment (e.g., hydraulic fracturing), or field-scale enhanced oil recovery processes (e.g., increasing the mobility of remaining oil in the reservoir with an injection of chemical cocktails). In many situations, the money invested in these measures does not pay off, and the brownfields die slowly.

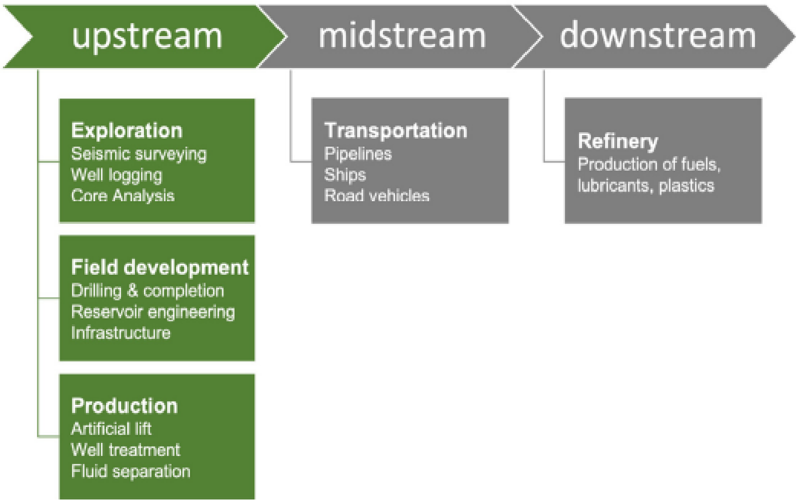

Figure 2: Division of the oil and gas industry into sectors.

3. How AI is Changing the Upstream:

The petroleum (oil and gas) sector is divided into three components: upstream, midstream, and downstream, as shown in the figure above. The term "upstream" refers to the subsurface (mining) sector of the industry, which includes exploration, field development, and crude oil/gas production. Midstream refers to the transportation of oil and gas, whereas downstream refers to the manufacture of fuels, lubricants, polymers, and other products. Points where AI solutions have already been used and their results, explaining many of the upstream processes in depth are covered. Also, where AI to be employed is expected and what effects it can produce is discussed.

4. Evolutionary Algorithms:

Many species have evolved to adapt to varied settings over millions of years, according to Darwinian evolutionary theory. Similarly, if we regard the environment as a form of the problem and EA as an adaptation of the population to suit the best environment, the same principle may be applied to numerical optimization. The fundamental principle of EA is to evolve a population of candidate solutions through a selective process similar to natural selection, mutation, and reproduction until superior answers are discovered. Specifically, parent solutions are joined using successful search algorithms to yield child solutions that may be evaluated and may produce offspring. The continuation of the generation cycle results in improved solutions to search, optimization, and design issues. EA encompasses a wide range of algorithms, including evolutionary programming, genetic algorithms, evolution methods, and evolution programmes. Because of the exceptional performance of Genetic Algorithms (GA) and Differential Evolution (DE) in dealing with solutions to a wide range of engineering problems, this category of techniques has become extremely popular in engineering applications, and they are thus discussed in greater detail in the following section.[7]

5.1 Genetic Algorithm (GA):

The genetic algorithm was introduced as a natural evolution of biological species based on the premise of "survival of the fittest." This stochastic optimization approach is highly efficient, adaptable, and well-suited to multi-objective optimization situations. Although GA was initially proposed as an academic tool for studying biological processes, it is currently used in a variety of engineering domains due to its capacity to handle numerous conflicting objectives.[8]

5.1.1 To Apply GA to Any Problem, Three Key Parameters Must be Defined:

- Encoded variable strings on chromosomes (representations of control vectors with n unknowns) (or sometimes called genes). Each gene is a parameter (an unknown), and each chromosome is a trial (or a possible solution).
- A vast number of chromosomes (genotype) that represent the people in a GA population.
- A vast number of chromosomes (genotype) that represent the people in a GA population.[9]

5.1.2 GA Advantages Include the Following:

- It requires fewer parameter sets and begins with a population of parameters rather than a single parameter.
- Instead of deterministic transition rules, probabilistic ones can be utilised.
- Rather than dealing with each individual parameter, a chromosome or a control vector is considered entirely.
- Instead of performing derivative calculations, direct function evaluations can be performed.
- The ability to combine with other algorithms to boost optimization efficiency.
- The capacity to easily parallelize for efficient computation time.[10]

5.1.3 Some Disadvantages of GA Include:

- Choosing regions at random from an initial population may result in the selection of incorrect regions. As a result, the evolution process is heavily reliant on the founding members' ideals.
- For complex optimization tasks, GA has a slow convergence speed. [11]

5.2 Differential Evolution (DE):

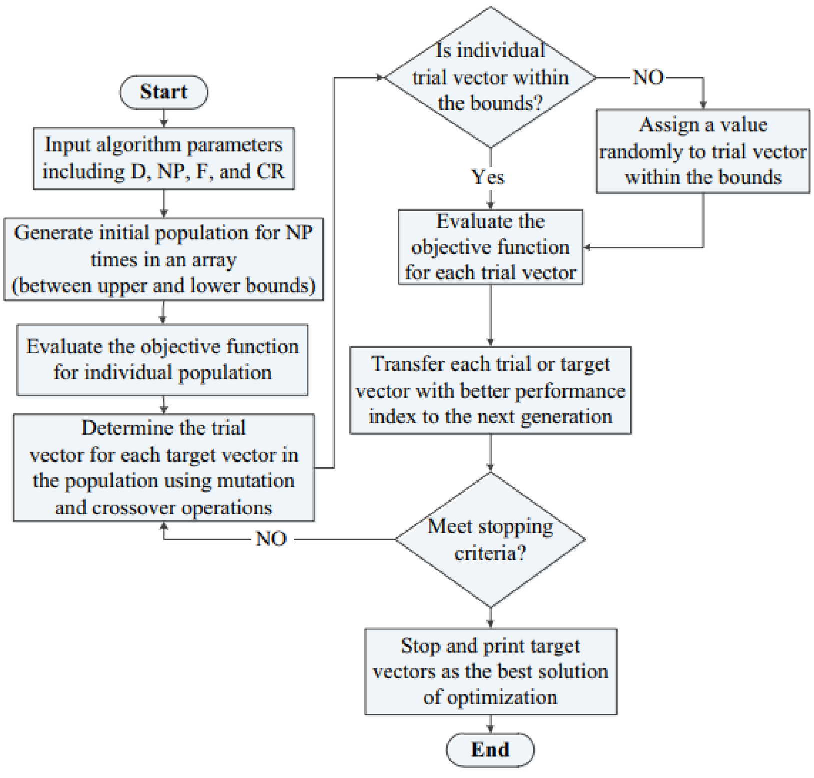

Figure 3: The flow chart of DE algorithm [13]

DE is a population-based method that finds the global minimum of the objective function by combining a real-coded GA with an adaptive random search (ARS) and a normal random generator. The primary distinction between GA and DE is that GA relies on crossover operations to discover the optimal solution, whereas DE relies mostly on mutation operations. DE, like all evolutionary algorithms, has four stages: initialization, mutation, crossover, and selection. During the initialization step, a population/generation with a fixed number of candidate solutions (NP) is formed by using minimum and maximum values for each defined variable as well as a uniform random value in the range of 0 to 1. The starting population is then evolved, with each solution mutated by adding the difference of two random solutions from the current population to a new picked random solution scaled by a factor F. The crossover probability rate is then used to create diversity in the newly generated candidate solutions throughout the crossover phase (CR). Below diagram shows different steps of the DE algorithm. [12]

6. Swarm Intelligence:

Swarm intelligence (SI) is a novel intelligent optimization technique that simulates the social and collective behaviour of swarms of ants, bees, fish schools, and insects while they search for food, communicate with one another, and socialise in their colonies. SI models are distinguished by their self-organization, decentralisation, communication, and cooperation behaviours among members within the group in the absence of a central governing mechanism. Although these individual interactions are basic at first, they eventually evolve to complex global behaviour, which is at the heart of SI. Many SI-based methodologies have been proposed in recent years, covering a wide range of study disciplines. The idea of PSO is discussed here, followed by its chronological application in the petroleum business.

6.1 Particle Swarm Optimization (PSO):

The PSO approach is based on a natural pattern of flocking birds or schooling fish. PSO algorithm, like GA technique, starts with a randomly created population, utilises a fitness function value to evaluate the population, and updates the population and search with random procedures. The PSO technique, on the other hand, does not employ crossover and mutation operators. It takes into account particles with two major parameters: a vector relating to a unique place in the search space and a velocity for the particle's motion. The convergence behaviour and performance of three different PSO algorithms were explored to optimise oil recovery from a heavy oil reservoir. The results showed that conventional PSO produced the best objective function.

7. Fuzzy Logics:

FL is a strong mathematical tool for describing information uncertainty in the actual world by generalising any specific theory from a crisp (discrete) to a continuous (fuzzy) form. Each FL variable generally comprises of a truth value that varies from 0 to 1 and between totally true and completely false.

7.1 The Benefits of FL Can be Summarized as Follows:

- FL is simple, fast, durable, and indifferent to changing conditions.
- FL explains systems using a combination of numeric and symbolic notation
- FL represents systems as a blend of numeric and symbolic data.
- FL addresses problems with very limited circumstances or without exact answers.

7.2 Despite the Obvious Benefits of FL, There are Some Scenarios in Which FL Does Not Work Effectively:

- In cases where adequate mathematical descriptions and solutions exist, the use of FL may be justified only when computational power constraints prevent a thorough mathematical implementation.
- In most cases, proving the features of fuzzy systems is challenging due to a lack of formal descriptions (e.g., in the area of stability of control systems).

FL and neural network models can be employed to calculate bubble point pressure as a function of gas specific gravity, oil gravity, solution gas oil ratio, and reservoir temperature. To avoid trapping in local minima and increase the accuracy, they utilized models optimized with GA.

8 Artificial Neural Networks (ANN):

An artificial neural network (ANN) is made up of a collection of simple processing units that communicate with one another via a large number of weighted connections. The following is a list of its characteristics:

- a collection of processing units (neurons),
- a state of activation y_k for each unit that corresponds to the unit's output,
- links between units; in general, each connection is specified by a weight w_{jk} that specifies the influence of unit j's signal on unit k.
- a propagation rule for determining a unit's effective input s_k,
- an activation or transfer function F_k for determining the new level of activation based on the effective input s_k (t),

- an external input (bias, offset) Θ_k for each unit used to improve the neural network model's fit to the real one.

8.1 ANNs Have the Following Advantages Over Other Models:

- ANNs are a reasonably simple learning method
- They can outperform other models when high-quality data is available
- They can approximate any function, regardless of its linearity
- ANNs can be utilised in applications where formulating a non-linear connection is difficult or impracticable.

8.2 ANNs Have a Number of Important Disadvantages:

- Because ANN models are "black box" prediction engines, they are difficult to understand and interpret; however, with the new tools on the market, this difficulty has been eased.
- ANNs are prone to overtraining, which means they just memorise their training data and are incapable of generalisation. Commercial-grade neural networks have prevented overtraining in recent years by monitoring test vs training errors and "bootstrapping holdout (test) samples."
- Their estimates are unacceptably inaccurate for tiny data sets.

In chronological sequence, some ANN applications in the oil industry below are presented: [14] Described a model based on back-propagation ANN and fractal geo statistics to solve the optimal bit selection problem for multiple wells in a carbonate field using real rock bit data, gamma ray data, and sound log data. [15] Introduced an ANN model to predict MMP of pure and impure CO2 and oil systems. The molecular weight of the C5+ fraction, reservoir temperature, and concentrations of volatile (methane) and intermediate (C2-C4) fractions in the oil were all utilised in this method.

9. Conclusion:

A general resource allocation for AI algorithms by dividing it into four groups, i.e., EA, SI, FL, and ANN and specified the most popular techniques for the first two categories was presented. The research shows that the application of AI methods has demonstrated outstanding performance in prediction, estimation, and optimization of different objective functions (e.g., minimum miscibility pressures, oil production rate, asphaltene precipitation around wellbore, well placement, and reservoir characterization). This review focuses on the employment of GA, DE, and PSO approaches in Evolutionary computation and SI algorithms, although future work could incorporate other methods such as Ant Colony Optimization. The creation of viable artificial intelligence-based solutions for oil and gas upstream was discussed. Even though artificial intelligence is still a new trend in the oil and gas industry, there are applications that have already proven to be valuable. How artificial intelligence may assist speed up and de-risk numerous commercial processes involved with hydrocarbon resource exploration, oil and gas field development, and raw hydrocarbons production is shown.

10. Compliance with Ethical Standards Acknowledgments:

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11. Disclosure of Conflict Of Interest:

No conflict of interest.

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