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RESEARCH ARTICLE

Smart Oil Field Management System Using Evolutionary Intelligence

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ABSTRACT This research proposes a new flexible intelligent system that manages the inflow control valve to improve oil production. For the efficient management of the smart oil field, the use of optimization algorithms is required. Traditional optimization methods tend to be inefficient in solving such problems due to many variables and the numerous locally optimal solutions, besides the effort of reservoir simulation. Therefore, this work presents the development of a methodology that allows optimizing both the control and the positioning of the valves, maximizing the reservoir Net Present Value obtained through the operation management, and analyzing the deployment cost of intelligent wells and their operational returns. Decisions of inflow control valve placement and its operation, flow control, throughout the reservoir's life cycle are simulated to verify the efficiency of the methodology. In order to evaluate and validate the proposed intelligent system, the methodology was tested by building a new model with three evolutionary algorithms, allowing the placement and control of the flow (valve) as a single problem. The results demonstrated that the proposed approach has significant gains in the increased recovered oil volume and decreased water produced, indicating more efficient and sustainable oil production.

INDEX TERMS Intelligent fields, positioning problems, evolutionary computing, control valve flow management, decision support systems.

I. INTRODUCTION

Economic growth is essential in increasing the state capacity and the continuous supply of public goods for emerging and developed countries. One of the main sources of achieving economic growth is increasing the energy supply [1]. Oil is one of the main sources of energy in the world. Despite the growth in the use and production of renewable energy, petroleum has continuously been widely used in by-products, such as natural gas, naphtha, solvents, lubricants, asphalt, and others. Besides, it involves complex planning and decision-making and the development of new technologies [2], [3], [4].

In this sense, many investments in research, development, and innovation (RD&I) have been made, aiming at removing more and more oil from the reservoir or being able to span over for several decades the reservoir's production. Thus maintaining greater efficiency in production and reducing operating costs [5].

A commonly used practice in oil exploitation is the conventional secondary oil recovery method. In this method, the oil reservoir is supplemented with secondary energy by injecting certain fluids into selected wells. The practical objective is to increase recovery efficiency and accelerate production [6].

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These goals are the focus of the *i-fields* strategy. In order to achieve these objectives, several studies are working with the inflow control valves (ICV) [7], [8], [9], [10], [11], which contribute to the control of the water injection and of the oil flow that is extracted. Inflow control valves (ICV), as well as downhole sensing devices, are part of the intelligent completion technology that is a great solution to improve production performance by increasing cumulative oil recovery [12].

Thus, the petroleum area always seeks new technologies and methodologies to make its production more efficient [13], [14], [15]. The technological advance used in the oil production area allowed remote management systems, which enable real-time monitoring and actuation [16]. Besides, it results in greater oil recovery and the new concept, *i-fields* or *smart fields*.

The smart field in this study consists of intelligent wells (IW), which have sensors that receive the production data from certain well sectors and certain well equipment, such as the ICV. The ICV is an adjustable control valve used to maximize oil production. It can be adjusted automatically or with operator intervention. ICV control optimization has been a subject of research throughout the reservoir life cycle, although there are few studies on the optimization of valve placement.

In recent studies of ICV [10], [17], [18], [19], methodologies for optimal valves placement joint with ICV optimization were created, presenting a greater potential for actuation. Those approaches reduced the search space of the optimized solution by focusing the control valve in previously determined valve positions, which results in a guaranteed converge of the methodology but not necessarily an optimal global result.

In those cases, the problems of placement and control have been addressed separately, that is, using independent and subsequent steps [10], [17]. In the literature, only one simple case was found using a technique that addresses the problem in an integrated way, considering the optimization of both the control and the valves' placement, nonetheless using a very simple test case. Therefore, this work innovates by presenting a methodology capable of approaching the problem in an integrated way, both in control and in the valves' placement optimizations, validating complex cases with geological uncertainties. The other contributions of this work can be summarized as follows:

- Development of a new evolutionary optimization methodology capable of working with the representation of two problems, control and placement of valves, in smart fields;
- Creating a new hybridization algorithm, called Cooperative Coevolutionary Adaptive Genetic Research [20], which models a population for control and placement of producer wells valves and another for control and placement of injector wells valves (CCGeneAS-PIW);
- The utilization of objective function that seeks the maximization of the reservoir net present value NPV) by financially analyzing the cost of implementing smart fields and their operational return;
- Using a synthetic reservoir with simple geological characteristics to allow visual interpretation of the results and two real reservoirs: one is a subset of an aquifer reservoir with multilateral wells, and the other is a real reservoir with vertical wells; and
- Presenting an optimization with an uncertain geology reservoir for the aquifer reservoir to verify the behavior of the proposed methodology in situations where the geological information of the reservoir is uncertain.

This article is organized into six sections. Section II presents relevant definitions and a literature review in which the studies found in the area properly referenced are reported. Section III presents the proposed methodology, and mechanisms of representation and simulation, as well as validation and application methodologies. Section IV gives the mathematical foundation regarding the evolutionary algorithm that supports this work. Section V refers to the study case, presenting the outcomes obtained so far. Finally, the concluding remarks are presented in Section VI.

II. BACKGROUND AND RELATED WORKS

A. SECONDARY RECOVERY USING WATERFLOOD TECHNIQUE

This work aims to optimize secondary recovery using the waterflood technique supported by ICV. This technique injects water into the reservoir to push the oil through the production well. This results in a trade-off optimization of avoiding reservoir pressure drop and increasing oil production [21]. Figure 1 shows the analysis graph of the displaced oil volume curve in relation to the volume of water injected in the reservoir when performing the waterflood.

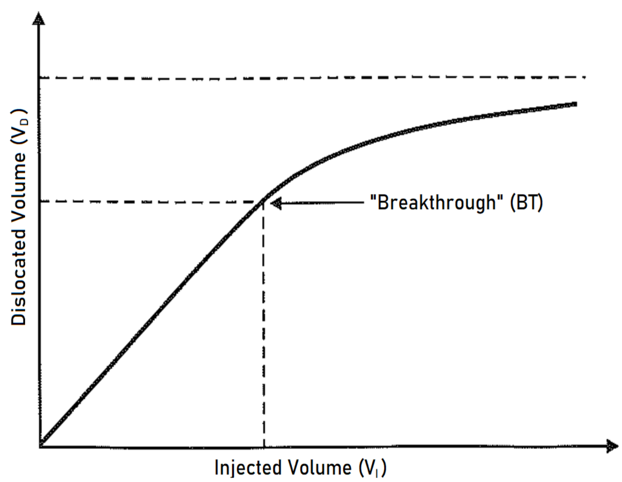


FIGURE 1. Displaced oil volume curve versus injected water volume in the reservoir (source: adapted of Rosa et al. [6]).

Note that the linear portion of Figure 1 means that the volume of injected water could displace the same oil volume. The beginning of water production is characterized at the point indicated as a breakthrough [6]. From this point, the volume of water injected is not equal to the volume of produced oil. That is, the part is retained in the reservoir, and the part is produced together with the oil. The fundamental milestone of this technique is to control the advance of the injected waterfront, which should avoid the premature arrival of water in the oil-producing well, resulting in the majority production of water.

Figure 2 shows a flat cross-section delimited by the injection and production wells. This figure represents the challenge of reservoirs with several layers of different permeability, stratified, the advance of water injected into the various layers occurs non-uniformly, where $k1 > k2 > k3$. This figure illustrates the non-uniformity caused by the continuous and uniform water flow in the layers with different permeability. The more complex it is the reservoir' composition (e.g., the geology and the permeability), the more complex the control of the waterfront uniformity.

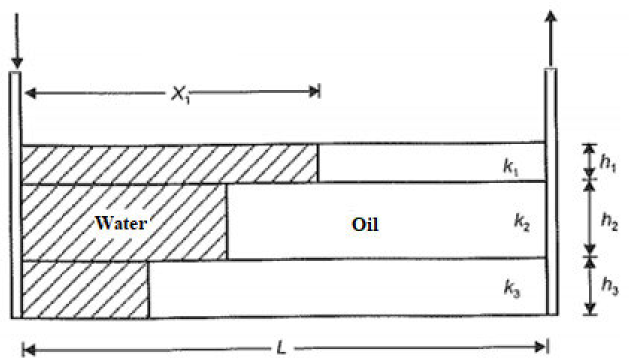


FIGURE 2. Vertical section of a stratified reservoir subject to water injection (source: Rosa et al. [6]).

B. RELATED WORKS

1) OPTIMIZATION PROCESS

Several studies used traditional methods to optimize control valves based on gradients [22], [23], [24], [25]. This approach converges to a local optimum, as opposed to some gradient-free techniques that can search for the global optimum. Besides that, obtaining the full gradient requires very large computational power, making it prohibitive for a realistic flooding optimization problem.

The simulated annealing algorithm was used in a simple case with only one horizontal producer well [26]. The objective of the problem was to maximize the accumulated oil, and the problem variables were the allocation of two valves and their control. Ensemble Kalman filter is another approach to optimize the reservoir, where Jansen et al. [24] performed a combination of optimization and data assimilation. Besides that, Chen et al. [25] used the novel ensemble-based optimization scheme (EnOpt) with the ensemble Kalman filter (enKF) to increase NPV.

A different approach, which applies evolutionary computation methods such as genetic algorithms, was published by Almeida et al. [7]. Their work presented a decision support system capable of optimizing the process control of intelligent wells considering technical failures and geological uncertainties. Another study proposing a bi-objective analysis in waterflood recovery is found in Isebor et al. [21]. Their method, called BiPSOMADS, uses a global search algorithm and a local search algorithm. The single-goal optimization was combined into two objectives, maximization of Net Present Value (NPV) and Cumulative Oil Production (COP). Besides that, a different analysis approach was used, a perspective of long and short-term performance maximization.

Chen and Reynolds [27] presented a water-alternating-gas (WAG) injection project that proposes an approach in which well control and ICV settings are simultaneously optimized. This study did not address the valve placement problem.

Furthermore, two recent studies regarding optimization methods that combine proactive valve control and valve placement are found in the literature. The first one seeks to reduce the number of simulations required. In this sense, the problem's search space is reduced [10]. This approach prioritizes regions only in producing wells where the use of the valve has better technical and economic indicators. These indicators reduce the number of variables, define restrictions applicable to each variable, and help in the initial seed composition for the optimization method. Their work presented a premise that the problem of ICV allocation is large and complex, and an optimized solution can be found by dynamic programming to evaluate a high number of valve allocation alternatives; The second work optimizes the valve placement and proactive control only in producing wells [17]. They used a deterministic analysis to decide whether the producer well would be smart or conventional and at which position the valve would be allocated. Then, the control optimization is performed using Fast Genetic Algorithm (FGA) combined with the local optimization method, the nonlinear conjugate gradient.

More recently, there have been works with new approaches to the stochastic search algorithm that presents optimization with geological uncertainty. Normally, their results have sub-optimal performance when applied to the full ensemble of possible realizations generated during an uncertainty study of the reservoir model [28], [29]. Some NPV optimization studies use proxy to approximate the reservoir-simulation model [30], [31], [32].

2) PROACTIVE CONTROL

The ICV operation can be performed through reactive or proactive control. Many studies have been developed to compare the benefits of proactive control in relation to reactive control [7], [8], [17], [33], [34]. Reactive control acts by controlling flow production or flow injection after an event has occurred. The proactive control foresees the event's occurrence and performs the action before its accomplishment [9].

In optimized cases, the IW strategy with proactive control is better than IW with reactive control. Besides, using both control strategies, Conventional Wells (CW) [34] is better than the standard alternative. Other works that addressed the production optimization problem in Smart Wells integrated digital models of reservoirs and used wells data for optimization.

Calvette et al. [18] used a Long Short-Term Memory (LSTM) neural network to build a proxy to forecast smart wells production, taking advantage of a large amount of data available in smart oilfields to minimize the use of computationally expensive simulations. It was tested in a simple synthetic box reservoir and a modified version of the PUNQ-S3 reservoir, achieving low errors in both cases. Temizel et al. [35] presented a review of literature and concepts on multilateral wells, optimization techniques, and applications, made a brief review of Enhanced Oil Recovery (EOR) techniques, and presented the economic and production advantages of "electrical resistive heating" as an EOR recovery method for heavy oil. Finally, they do a simulation to compare oil accumulation between models with active and passive devices.

The authors of Jia et al. [19] proposed an optimized model for water injections in oil reservoirs. This optimization has two parts: *(i)* model building and intelligent plan optimization, where the model construction uses static data from the reservoir and real-time data. Besides, the model is automatically assembled using "data assimilation" and adjusted using "ensemble Kalman filtering"; *(ii)* the intelligent optimization of the plan is carried out in 6 steps in which the use of "k-means clustering" is combined, a decision tree to analyze the water injection, and "particle swarm optimization" to optimize the injection plan.

As mentioned, this work presents a new approach to solving control and valve placement optimizations, validating complex cases with geological uncertainties. Several works in the literature proposed solutions to this problem. In order to summarize all mentioned works contributions in the literature, Table 1 compares state-of-the-art works and Table 2 presents another comparison emphasizing the control type and the case studies performed. In this table, the same works in Table 1 are compared. However, this comparison regards the type of control and case studies.

III. PROPOSED METHODOLOGY

The intelligent fields with ICV allow operational flexibility, monitoring, and interaction during oil production. Besides, it enables the integration of digital reservoir management models while making it more expensive [37], [38]. These wells require more careful evaluation since the potential benefits should be estimated considering uncertainties. A possible increase in cash flow may occur after a few years of production [17]. Thus, it is extremely important to anticipate the behavior of the reservoir throughout its life cycle.

The proposed optimization method can optimize the quantity and placement of the ICV and their control throughout the reservoir life cycle [11]. The ICVs are considered installed on the first day of optimization. Figure 3 illustrates the methodology that has the following steps:

- **Reservoir and alternative development description:** format accepted by the simulator IMEX is used [39]. Nonetheless, the ICV configuration is not accepted in the used version. Thus, the valve flow rate was tuned using the *keyword* ***FF**, as described in [40, pp. 47];
- **Optimization algorithm:** in the search for the best optimization result, 3 algorithms were used, and these will be described in sections Cooperative Coevolutionary Genetic Algorithms, A Genetic Adaptive Search (GeneAS) for Engineering Design, and Cooperative Coevolutionary Genetic Adaptive Search (CCGeneAS);
- **Valves Description:** The quantity and position of the ICV are optimized by the placement solution.
- **NPV Calculation (Financial Scenario):** the IMEX outputs the production curve. The curve makes it possible to extract information about NPV, and water production, among others.
- **Reservoir Simulator:** IMEX [39] reservoir simulation software; and
- **Geological Uncertainty:** the information is delivered to the simulated reservoir to appropriately generate the curve production.

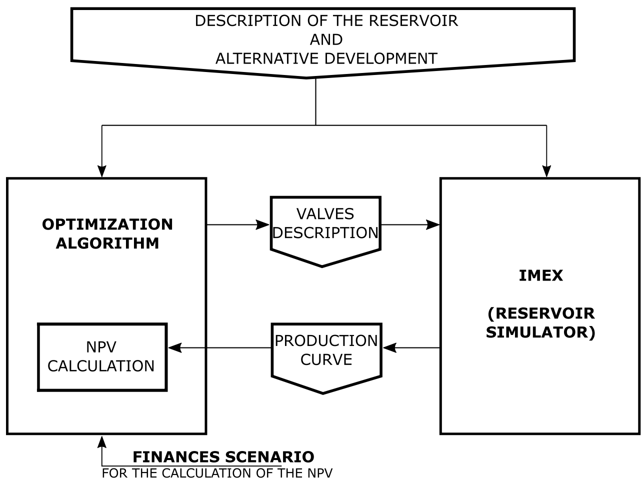


FIGURE 3. Dynamic Optimization Methodology.

A. DYNAMIC OF SMART FIELDS

The concept of smart fields aims for better control of the breakthrough and the uniformity of the waterfront advance. The smart fields are composed of IW and CW. IW uses the ICV to control the flow of oil production or water injection. Since CW is cheaper, they do not have flow adjustment control, and they are usually used in regions where IW contributes so little. It is important to mention that ICV is operated remotely (from the surface) through an electric hydraulic or electrohydraulic drive system [41].

B. DYNAMIC OPTIMIZATION METHODOLOGY

Figure 3 shows the dynamic optimization methodology. In this kind of problem, the many variables involved result in

TABLE 1. Comparison of the state-of-the-art with Search Methods.

Literature	Search for Placement Solution	Search for Control Solution
Barreto and Schiozer [10]	Performed through indicators	Free-Derivative variation of the steepest ascent method
Sampaio *et al.* [17]	Performed through reactive control strategy	FGA (Fast Genetic Algorithm) and Nonlinear Conjugate Gradient
Hasan and Foss [36]	NA	Gradient-based methods (optimal flow rate or bottom-hole pressure – BHP)
Isebor and Durlofsky [21]	NA	BiPSOMADS (Bi Particle Swarm Optim/Mesh Adaptive Direct Search)
Kharghoria *et al.* [26]	Simulated Annealing	
Sefat *et al.* [29]	NA	Simultaneous Perturbation Stochastic Approximation (SPSA) (Stochastically estimated gradient-based optimization algorithms)
Sie *et al.* [33]	NA	Integrated Simulation-Surface Network Modeling
Sampaio [34]	NA	Conventional genetic algorithm
This Work	Evolutionary Computation - CCGeneAS (Cooperative Coevolutionary Genetic Adaptive Search)	

TABLE 2. Comparison of the state-of-the-art between the Type of Well Control and the Case Studies Performed.

Literature	Control Solution	Study Case
Barreto and Schiozer [10]	Proactive (On/Off)	Simple Case Horizontal Well (GA) Brazil pre-salt layer (16 Vertical Well)
Sampaio *et al.* [17]	Reactive and Proactive (On/Off)	Namorado Reservoir – BR (4 PP e 4 PI)
Hasan and Foss [36]	Proactive (On/Off)	Uses Matlab Reservoir Simulator Toolbox (MRST) Case One: 1 Injector and 2 Producer Wells Case Two: 2 Injector and 2 Producers Wells
Isebor and Durlofsky [21]	Proactive (5 positions)	Reservoir with river system 3 Producers and 2 Injectors Wells
Kharghoria *et al.* [26]	Proactive (10 positions)	Simple Case 1 Horizontal Producers Well
Sefat *et al.* [29]	Proactive	Real North Sea field section
Sie *et al.* [33]	Proactive vs Reactive	Controls 2 injection wells with 6 valves in each well
Sampaio [34]	Proctive (On/Off)	Synthetic reservoir model (PUNQ-S3) with vertical wells: Deterministic cases without geological uncertainty (Inverted Five Spot) Case 1: lower heterogeneity and light oil Case 2: higher heterogeneity and light oil Case 3: higher heterogeneity and heavy oil
This Work	Proactive (11 positions)	Simple Case - 2 Vertical Wells (1 Producer and 1 Injector) Real Case with Aquifer - Multilateral Wells: 4 Producers and 4 Injectors Real Case with Aquifer - Horizontal Wells: 2 Producers and 1 Injector Real Case - 7 Producers and 7 Injectors Wells

a larger search space. It is important to stress the versatility of this approach since, unlike the mentioned state-of-art works, there is no separation of the problems in sequential steps nor a forced reduction of the search space [10], [17].

In this approach, both ICV optimization decisions (i.e., placement and control) are taken dynamically and continuously. This allows the search for space exploration for the optimal global solution. When using random search, there is access to the entire search space, and the convergence capability of the algorithm drives the exploration. The optimization result will find new ideas for better, more efficient, and longer production reservoir exploitation. It will also reinforce the initial analysis of the strategy chosen by the specialist [7].

C. DYNAMIC OPTIMIZATION ALGORITHM

In the search for a flexible algorithm capable of a more efficient convergence, comparisons were made between evolutionary algorithms. This research compared the single-population GeneAS algorithm [42] and the coevolutionary algorithms with two subpopulations: *(i)* CCGA [43] and *(ii)* CCGeneAS-PIW. In this comparison, the following execution parameters were used, aiming at a fair comparison:

1) The number of individuals in the GeneAS population is 200, and 100 individuals for each subpopulation of coevolutionary algorithms;
2) The initial population is composed of randomly generated individuals;
3) The composition of the individuals obeys the construction rules of the variables presented in sections Search Space on Placement Valves and Search Space on Control Valves;
4) The selection of individuals in the population is performed by Binary Tournament;

5) The elitism strategy preserves two copies of the best individuals in the population;
6) The genetic operators for binary individuals (placement) are: Single Point Crossover and Bit Flip Mutation;
7) The genetic operators for the real individuals (control) are: Simulated Binary Crossover and Polynomial Bit Flip;
8) The crossover probability is 90%;
9) The probability of mutation is 1 / chromosome; and
10) The stopping criterion is reached after a fixed number of evaluations, depending on the complexity of the reservoir used in the optimization. This is due to the high computational cost of simulation.

D. VALIDATION METHODOLOGY AND PROCESSING

There are two important points in the optimization methodology. The first point is the chosen evaluation function, that is, NPV, a methodology widely used in the literature [7], [10], [17].

The other point is the optimized solution validation. To validate the optimization of each reservoir, the NPV result is compared with the reservoir simulation using CW, known as the base case. In this evolutionary algorithm implementation for oil extraction optimization, the evaluation function is the most critical part of the code when considering the computational cost due to the IMEX Simulator time.

The framework used to implement the evolutionary algorithms is the JMetal framework [44], based on Java APIs. So, when evaluating a new individual's skills, the new individual's generation must be evaluated in parallel processing. Each one is queued and delivered to Java API that schedules each task (thread process) and notifies when it finishes.

Note that computers with multi-cores were used for the simulation. The number of cores in the computer is automatically identified, and a thread is routed to an idle core. The workstation used to reference the computational cost for the simulations is a machine with two Intel Xeon CPUs E5-2630 2.30GHz. Each processor has six cores of 2 threads each, totaling 24 threads for simultaneous execution, with 64 GB memory.

E. STRUCTURED DESCRIPTION OF VALVES

1) SEARCH SPACE ON PLACEMENT VALVES

The placement solution optimizes the quantity and position of the ICV. Any well position where there is completion is enabled to receive the ICV. To represent the position that the valve will receive, vector $\hat{l}$ is used. This variable contains all positions where there are completions. Each position is represented by $x^w_{n_w}$, where w is the well identifier and n_w is the completion position number in that well. This variable can receive values 0 or 1 to represent whether or not it has an ICV. Eq. 1 defines the vector l representing the location of valves.

$$\hat{l} = \left\{x^1_1, \ldots, x^1_{n_1}, \ldots, x^w_1, \ldots, x^w_{n_w}\right\}, \text{ where}$$

$$\begin{cases} x = \{b \in N \mid \mathrm{b} = 0 \text{ ou } \mathrm{b} = 1\} \\ w = \text{well id} \\ n_w = \text{completion id of the w-th well} \end{cases} \tag{1}$$

Eq. 2 presents an example of the vector $\hat{l}$ of a reservoir with two wells. Each well has two completions. In the example, the first well is not intelligent. However, the second well has ICV in both completions. The numeric results for the example are $\hat{l} = \{0, 0, 1, 1\}$.

$$\hat{l} = \left\{x^1_1, x^1_2, x^2_1, x^2_2\right\} \tag{2}$$

The placement vector $\hat{l}$ has a binary composition and the search space represents 2^{n_c}, where n_c is the number of well completions that may be eligible to receive valves.

2) SEARCH SPACE ON CONTROL VALVES

The modeling of proactive control of ICV follows the following criteria:

1) For the proactive control of the valves, 10 control interventions are performed (i_c) in the valves since the reservoir life cycle is of 20 years and the control interventions will occur every 2 years;
2) The chromosome has the configuration of a proactive control operation for all possible ICV in all possible time intervals of reservoir interventions;
3) If the well has at least one ICV, it is considered to be an IW. Otherwise, it is considered to be a CW. These definitions are important when considering the cost of deploying each well;
4) Each control variable can assume a real value in a [0, 1] range with one decimal point. Thus, the assumed values are 1.0 for fully open, 0.0 for fully closed, and 9 intermediate valve operating positions; and
5) The search space for the prediction of the control valve is defined by $11^{i_c * n_c}$, where i_c is the number of interventions defined and n_c is the number of completions that can receive ICV.

Eq. 3 defines the valve control vector $\hat{c}(t)$, which is composed of each intervention (i.e., Eq. 4). The $c(t)$ defines the aperture for all possible valve positions, w is a well id, and n_w is a completion id. Thus, $y^w_{n_w}$ identifies the aperture in a determined well and its completion. The intervention count in the reservoir cycle is t.

$$\hat{c}(t) = \left\{\hat{c}_1, \hat{c}_2, \ldots, \hat{c}_t\right\} \tag{3}$$

$$\hat{c}_i = \left\{y^1_1, \ldots, y^1_{n_1}, \ldots, y^w_1, \ldots, y^w_{n_w}\right\} \tag{4}$$

The control example is in Eq. 5. For the former placement, the example is in Eq. 2 can be $\hat{c} = \{1.0, 1.0, 0.5, 0.5\}$. Since the first well (CW) does not receive an ICV, the valve opening information data is 1.0, which is 100% of the capacity utilization of the completion flow. For the other well (IW), there is an opening information of 0.5, that is, 50% of valve capacity.

$$\hat{c_1} = \left\{y^1_1, y^1_2, y^2_1, y^2_2\right\} \tag{5}$$

The search space is 2^{n_c}, where n_c is the number of valves. In the simulation, the reservoir life cycle is 20 years and control intervention occurs every 2 years. For the proactive control of the valves, 10 control interventions (i_c) are performed on the valves on them. The search space: $11^{i_c \times n_c}$.

F. UTILITY FUNCTION

The NPV is the evaluation, or utility function, which has wide use in the literature [7], [10], [17]. In order to obtain the NPV, it is necessary to decode the location and control individuals in the information that describes reservoir wells. The information is formatted in a text input file for the reservoir simulator [39]. The simulator generates the oil production curve and water injection curve. Adding the curves with the text input file, it is possible to calculate the NPV for the reservoir lifecycle.

$$f(\hat{l}, \hat{c}(t)) = NPV \tag{6}$$

Eq. 6 shows the NPV obtained by evaluating the oil reservoir with the valves allocated and configured according to the information contained in the vectors $\hat{l}$ and $\hat{c}(t)$ previously described. NPV is the mathematical-financial formula capable of determining the current value of all discounted future cash flows at an appropriate interest rate minus the cost of the initial investment. The NPV is determined by the Present Value (PV) of the alternative (discounted cash flow) and the development cost of the valves (D_v) included in the alternative (i.e., Eq. 7) [7], [11].

$$NPV = PV - D_v \tag{7}$$

The cost of each component of the Intelligent Well is presented in Table 3. Eq. 8 shows the formula of D_v. It is interesting to note that the cost of the reservoir increases as the number of ICV increases. This highlights the relevance of ICV operation optimization to increase profit.

$$D_v = (C_v + C_p) \cdot n_v + C_{FP} \cdot n_w + C_{HPU}, \text{ where } \begin{cases} n_v = \text{quantity of ICV; and} \\ n_w = \text{quantity of intelligent wells.} \end{cases} \tag{8}$$

TABLE 3. Cost of Smart Well Components.

Hydraulic Power Unit (C_{HPU})	\$200.000/reservoir
Flat Pack (C_{FP})	\$177.00/well
Packer (C_p)	\$80.000/valve
Valve (C_v)	\$100.00

The Present Value (PV), in Eq. 9, is composed of the sum of the difference between the Revenue Value (RV) and Operating Cost (C_{op}) discounted at an interest rate (ρ = 10%), representing the current value of future payments.

The RV is the multiplication of the oil volume production ($Q(t_i)$) and the oil price (P_{oil} = \$20 barrel), Eq. 10. The C_{op} calculation considers the cost of water produced (C_{w_p} = \$3) and the cost of water injected (C_{w_i} = \$1). The first refers to the cost of separating the water from the extracted oil. The second to the cost of injecting the water. These costs are multiplied by the water flow produced ($W_p(t_i)$) and injected ($W_i(t_i)$), respectively, Eq. 11. These values are measured along the time of production (t_i) until reaching the end, where T is equal to 20 years.

$$PV = \sum_{i=1}^{T} \left[RV - C_{op}\right] \cdot e^{-\rho \cdot t_i} \tag{9}$$

$$RV = Q(t_i) \cdot P_{oil} \tag{10}$$

$$C_{op} = W_p(t_i) \cdot C_{w_p} - W_i(t_i) \cdot C_{w_i} \tag{11}$$

IV. EVOLUTIONARY ALGORITHMS

Optimization algorithms seek to find good solutions to complex problems in a reasonable amount of time. Evolutionary computation is the field of research inspired by evolutionary biology in order to develop, search, and optimization techniques to solve complex problems [45].

So far, it has not been proposed a solution to solve the problem considering the optimization of location and control of intelligent valves involving geological uncertainty. Thus, this work proposes to model three solutions with the objective of finding the one that presents the best performance for the problem: one using CCGA, one using Genetic Adaptive Search (GeneAS), and one based on both CCGA and GeneAS, called Cooperative Coevolutionary Genetic Adaptive Search (CCGeneAS-PIW). They will be described below.

In order to make significant comparisons regarding the best algorithm, some parameters were fixed for all, such as population initialization, selection form and elitism, crossover and mutation operators, operator rates, and stopping criterion. There is a resume in Table 4.

It is important to detail the operators, the crossover binary operator (Single Point Crossover and Bit Flip Mutation) and the mutation and the current mutation operator (SBCrossover and Polynomial Bit Flip), as they are the basis of comparison for the algorithms.

A. SINGLE POINT CROSSOVER AND BIT FLIP MUTATION

The crossover operation will only be performed after the probability rate for crossover execution is tested. If passed, two individuals (chromosomes) are selected (Binary Tournament) and a random cut point is chosen. From the cut-off point, there is the exchange of genes between the parents' individuals, generating the individual children [46].

The mutation operation also has its probability ratio tested for the operator execution on the child individuals generated in the crossover. The bit flip mutation performs bit inversion, that is, if the genome bit is 1, it is changed to 0 and vice versa [46].

B. SBX - SIMULATED BINARY CROSSOVER

Important properties that a self-contained real GA should have in its search engine [47]:

- The crossover operator must produce a child population that has the same mean as the parent population;
- The variance of the child population must be greater than the parent population.

The SBX operator generates solutions that are closer to each of the parents than solutions that are distant from the parents, SBX has two properties [47]:

- The extension of child solutions is proportional to the parent solutions;
- Solutions close to parents are probably more chosen as child solutions than solutions parents.

Self-adaptation is a phenomenon that makes evolutionary search algorithms flexible and closer to natural evolution. In crossover at the gene level, the recombination happens by variable, and in crossover at the chromosome level, the recombination happens vector by vector. The SBX is a crossover operator at the gene level, which is closer to the natural recombination processes [48]. The SBX was built to respect the single-point crossover properties in binary coding GA [42]. To compute child solutions $x_i^{1,t+1}$ and $x_i^{2,t+1}$ from the parents $x_i^{1,t}$ and $x_i^{2,t}$, a polynomial distribution approximation is used.

The value β_q is found so that the area under the probability curve 0 to β_q is equal to a random number chosen u. Eq. 12 shows that the distance between the children is proportional to the distance between parents to a factor β_q, and Eqs. 13 and 14 present the child solutions.

$$x_i^{(2,t+1)} - x_i^{(1,t+1)} = \beta_q \left(x_i^{(2,t)} - x_i^{(1,t)}\right) \tag{12}$$

$$x_i^{(1,t+1)} = 0.5\left[(1+\beta_q)x_i^{(1,t)} + (1-\beta_q)x_i^{(2,t)}\right] \tag{13}$$

$$x_i^{(2,t+1)} = 0.5\left[(1-\beta_q)x_i^{(1,t)} + (1+\beta_q)x_i^{(2,t)}\right] \tag{14}$$

C. EVOLUTIONARY ALGORITHMS - COOPERATIVE COEVOLUTIONARY GENETIC ALGORITHMS

CCGA is the algorithm based on cooperative coevolution between species populations. It suggests a new approach to evolving complex structures. To successfully apply evolutionary algorithms to problems of increasing complexity, it is necessary to introduce explicit notions of modularity in solutions to have reasonable opportunities to evolve in the form of co-adapted subcomponents [43].

In a CCGA, the decomposition of a complex problem is performed in interdependent subcomponents that will evolve in their own search space, uncoupled from others, in which each subcomponent is represented by an individual. Thus, individuals are separated into distinct populations according to their characteristics, enabling interaction between members of the same population or species. During the evaluation process, a complete solution is represented by the composition of an individual from each population. Figure 4 shows the flowchart of the algorithm.

The CCGA was used in this work to solve the optimization problem of the valves' placement and control. It uses a bio-inspired paradigm, in which species cooperate with each other and are genetically isolated. Individuals only evolve with members of their species. Thus, the placement problem (l) and the control problem ($c(t)$) are considered from different species. Besides, they are separated into different subpopulations, the former is a binary population and the latter is a real population, respectively.

D. A GENETIC ADAPTIVE SEARCH FOR ENGINEERING DESIGN

GeneAS is an algorithm based on binary-coded and real-coded genetic algorithms, it uses a natural coding schema to represent mixed variables [42]. Since the binary GA and real-coded GA cannot be used alone to efficiently handle different kinds of variables, GeneAS is a solution that seeks to solve this problem. The algorithm restricts its search only to variable values of a determined type, thus reducing the search effort in the convergence to the optimum solution.

The GeneAS was used in this work to solve the optimization problem of the valves' placement (l) and control ($c(t)$). The individual contains binary and real vectors in his chromosome. The real part of the chromosome uses the real operators, while the binary part uses the binary operators. Thus, GeneAS proposes a more flexible and efficient way of solving engineering problems with mixed variables, even though the operating principles of GA and GeneAS are the same.

Figure 5 shows the algorithm flowchart. The initial population is generated randomly. The genetic algorithm is generational, and the two best individuals are preserved for the next generation (elitism). The selection of the individuals' parents to perform the crossover and mutation is performed by the binary tournament [46].

E. COOPERATIVE COEVOLUTIONARY GENETIC ADAPTIVE SEARCH (CCGeneAS)

The CCGeneAS is proposed in this work as the implementation of a Cooperative Coevolutionary GeneAS. Figure 6 shows the use of two subpopulations. Each subpopulation uses individuals composed of both binary and real coding, as structured in GeneAS [42]. This new algorithm allows the problem to be broken and optimized.

This methodology was elaborated to solve the problem of valve optimization to enable the problem decomposition in other contexts of evolution. This decomposition is carried out following the idea presented in the work of Sampaio et al. [34] which makes use of the five-spot configuration using ICV only in the producing wells, in front of this, we understand it to be interesting to realize an optimization considering two groups one with producing wells and one with injector wells. As well this wells separation is presented in [26].

The initial population is generated randomly. The parents' selection is performed by the binary tournament [46] and the elitism operator is used for 2 individuals.

At the time of evaluation, the best individual of the one subpopulation is selected to compose the solution of all the individuals of the other subpopulation. Thus, the species

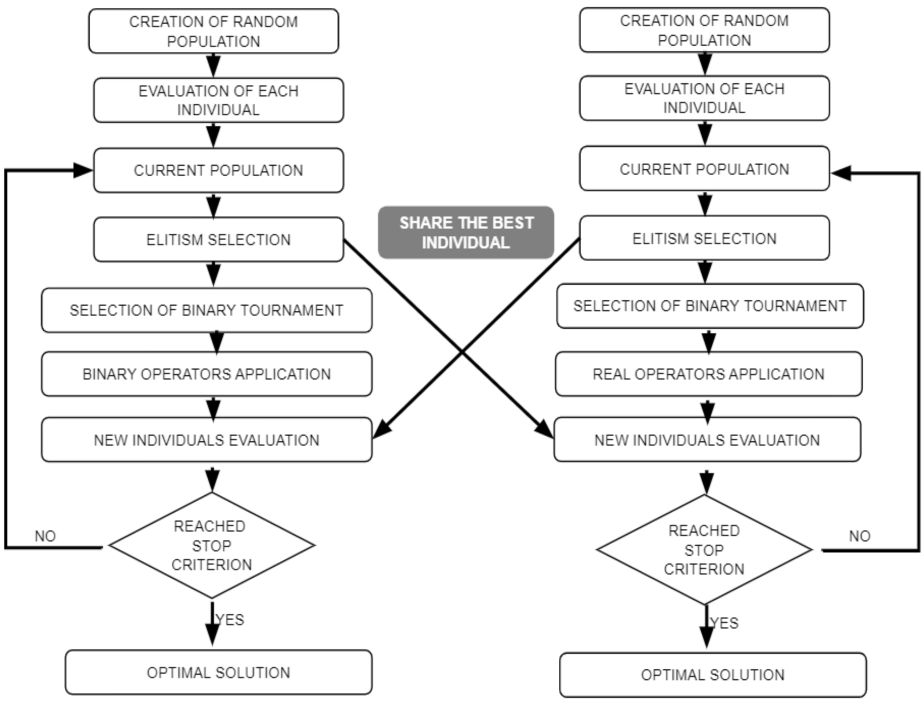


FIGURE 4. CCGA flowchart.

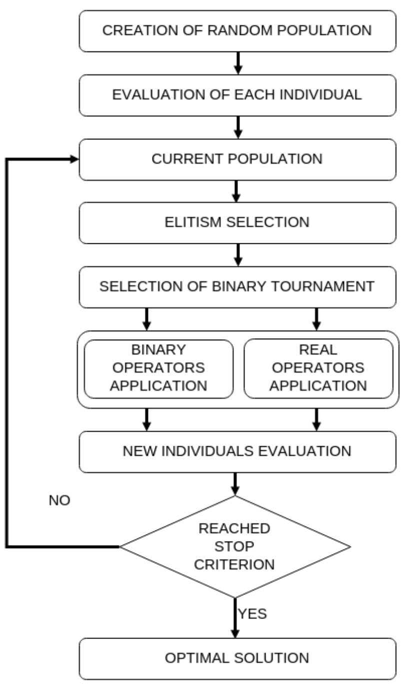


FIGURE 5. Flowchart of GeneAS.

interact with each other through the shared domain model and have a cooperative relationship [43]. If the stop criterion has not been reached, the process of evolution continues. In the end, the optimized solution is delivered.

This work proposes the CCGeneAS-PIW, which is the separation in subpopulations of production wells and injector wells. Figure 7 presents the coevolutionary model from the perspective of each species. To the left of Figure 7, it is performed the evolution of PW, which involves the selection of individuals' parents, crossover, and mutation operations. The same procedure is executed to perform the evolution of IW subpopulation, in the right of Figure 7. At the time of the evaluation, each subpopulation uses the best solution of the other subpopulation to compose a complete solution that can be evaluated through the NPV function.

After all, the reservoir is composed of both types of wells, production, and injection. After the completion of the first evolution cycle, the IW subpopulation on the right follows the same procedure.

V. RESULTS AND DISCUSSION

A. RESERVOIRS MODELS

Due to the cost of simulation and the complexity of the reservoirs, the stopping criterion of the algorithm was established in 21.000 simulations. It was verified empirically that the solution shows little evolution. At the end of each subsection that describes the reservoir, there is simulation time a description. Figure 8 illustrates a comparison of sequential and parallel runtime.

B. SYNTHETIC RESERVOIR

The synthetic reservoir [11] is composed of 3 layers isolated with shale barriers and with a development alternative of two vertical wells, where each with 3 ICV, one production, and one injection [7]. Note that this is a test protocol created by a specialist. The search space for this problem consists of 2^6 possibilities of receiving valve locations and $11^{10\times6}$

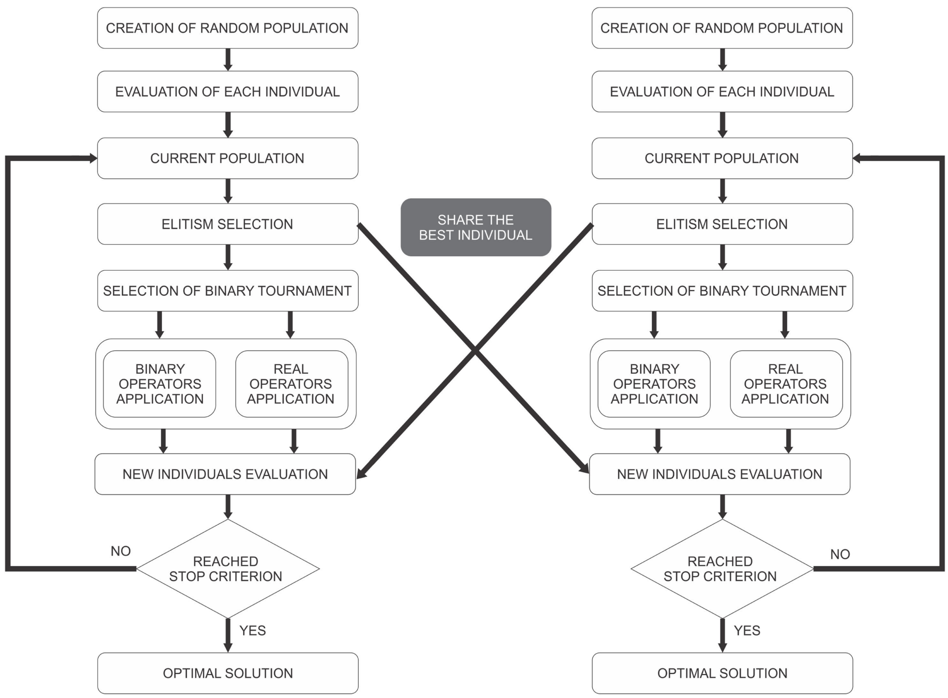


FIGURE 6. Flowchart of CCGeneAS.

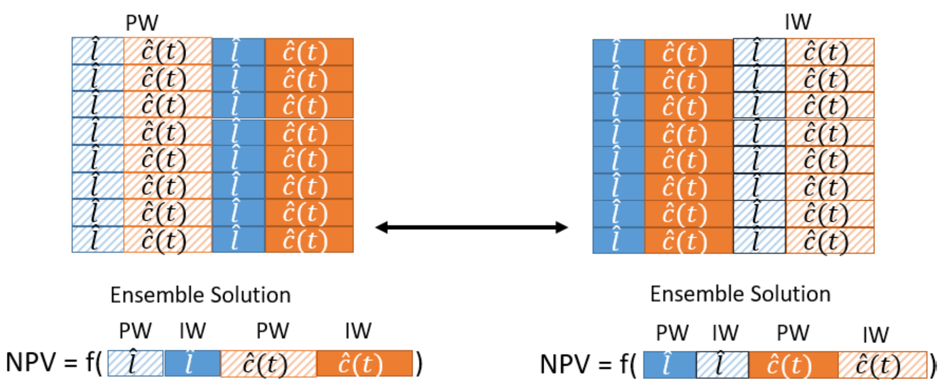


FIGURE 7. Ensemble Solution of CCGeneAS-PIW.

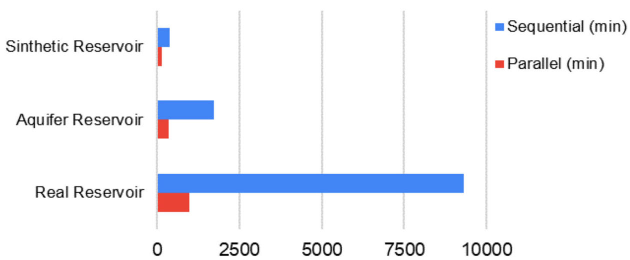


FIGURE 8. Comparison of Sequential and Parallel Runtime.

valve control possibilities in 10 interventions over 20 years. Thus, the total space consists of $2^6 \times 11^{10\times 6} \cong 1.95 \times 10^{64}$ possibilities.

The characteristics of the reservoir porosity are 0.2 and the permeability of the 1st layer is 500.0 (mD) in the i, j and 50.0 (mD) directions in the k direction; of the 2nd layer 800.0 (mD) in the directions i, j and 70.0 (mD) in the k direction; and of the 3rd layer of 1200.0 (mD) in the directions i, j and 120.0 (mD) in the direction k.

Simulation of the synthetic reservoir only costs 1.04 seconds. In a sequential execution of the algorithm, it would take around 364 minutes or 6 hours and 4 minutes. Performing parallel execution using thread, the simulation takes around 134 minutes or 2 hours and 15 minutes. The 30 runs for comparison with the non-parametric test take 2 days and 19 hours.

C. AQUIFER RESERVOIR

The aquifer reservoir is composed of 100% water saturation regions and other ones have a water saturation value of 25%. For this reservoir, the specialist created a restriction of the water cut reservoir; when the value of water production reaches 90%, the operation is suspended. This reservoir has a corner point type mesh grid of 33 × 57 x 3 blocks, whose block dimensions are 100.0 × 100.0 × 8.66 meters. These characteristics are important for optimizing the placement and control of the wells to ensure efficient production and injection of fluids in the reservoir. In addition, it has a permeability of 575.0 (mD) in the directions i, j and 57.40 (mD) in the k direction and a porosity of 0.229.

To improve oil production by increasing the contact area between the wellbore and the reservoir, which leads to higher oil recovery rates, a possible alternative is the development of multilateral wells, as shown in Figure 9. This reservoir has 4 well producers, two wells with seven completions and the other 2 with six completions; and four injection wells, with six completions each. The search space (placement x control) is $2^{50} \times 11^{(10\times50)}$.

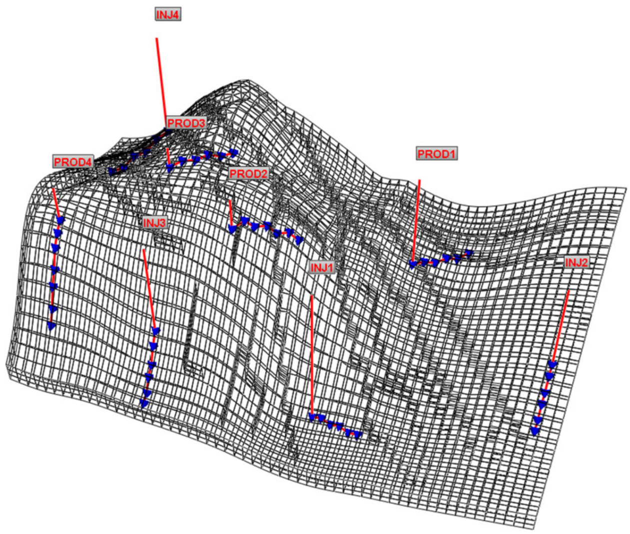


FIGURE 9. Aquifer Reservoir with multilateral wells. Note that this reservoir has four well producers, two wells with seven completions and the other two with six completions; and four injection wells, with six completions each.

The simulation of the aquifer reservoir only costs 4.88 seconds and the sequential execution of the algorithm is 28 hours and 28 minutes. The parallel execution (by threads) takes around 5 hours and 40 minutes. The 30 runs in parallel: 7 days and 2 hours; and executions of the 4 algorithms: 28 days and 8 hours.

D. REAL RESERVOIR

Figure 10 shows a real reservoir. It has a corner point type mesh grid of 43 × 55 x 6 blocks with block dimensions 100.0 × 100.0 × 10.0 meters. The reservoir geological values of permeability are variables, which means that the flow of fluids through the reservoir is not uniform and depends on the permeability of the different blocks. The field is divided into three regions, which are formed by layers 1 to 3; layers 4 and 5; and layer 6. However, it is important to note that, for optimization of valve placement, all 6 layers were considered. This means that the valves were placed in all layers of the field, taking into account the permeability values of the blocks in each layer to optimize the flow of fluids through the reservoir. The wells are all vertical: 7 production wells (3 wells with 3 completions, 3 other wells with 5 completions, and one well with 6) and 5 injection wells (1 well with 4 completions, 2 wells with 5, and 2 other wells with 6 completions). The search space: $2^{56} \times 11^{(10\times56)}$.

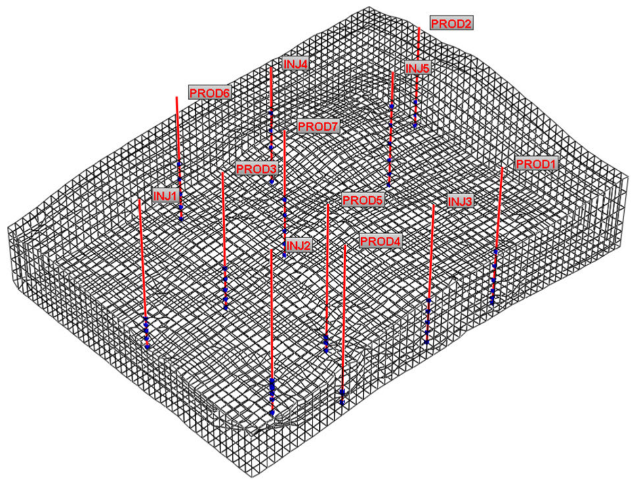


FIGURE 10. Real Reservoir with vertical wells. This field has a total of seven production wells, consisting of three wells with three completions, three wells with five completions, and one well with six completions. Additionally, there are five injection wells, with one well having four completions, two wells with five completions, and two other wells with six completions.

Regarding the synthetic reservoir, the simulation only cost 1.04 seconds. The simulation of the real reservoir took 26.61 seconds and the sequential execution of the algorithm, 6 days, 11 hours, and 14 minutes. The parallel execution (by threads) took around 16 hours and 10 minutes. The 12 executions in parallel: 8 days and 3 hours; and executions of the 4 algorithms: 32 days and 9 hours.

E. OPTIMIZATION TEST PARAMETERS

Table 4 shows the values of the GA main parameters for optimization.

TABLE 4. Optimization Test — Parameters.

Parameters	
Number of individuals	200
Initial Population	Random
Selection	Binary Tournament
Elitism	1%
Binary Crossover (BC)	Single Point Crossover
Rate BC	90%
Binary Mutation (BM)	Bit Flip Mutation
Rate BM	1/(chromosome size)
Real Crossover (RC)	SBCrossover
Rate RC	90%
Real Mutation (RM)	Polynomial Bit Flip
Rate TM	1/(chromosome size)
Stop Criterion	21.000 runs

F. SYNTHETIC RESERVOIR - VERTICAL WELLS

After performing the optimization methodology, the result presented has ICV in the last two completions of the injection well. Table 5 shows the optimized control values, where the values (0.0) represent the valve closed by the period. Figure 11 presents the performance results obtained through GeneAS, CCGA, and the proposed solution (CCGeneAS).

TABLE 5. Optimized Control Values of the Synthetic Reservoir.

Injector well	
Time (Year)	INJ1
0-2	1.0 0.2 0.0
2-4	1.0 0.1 0.1
4-6	1.0 0.0 0.1
6-8	1.0 0.5 0.5
8-10	1.0 0.2 0.1
10-12	1.0 0.2 0.1
12-14	1.0 0.1 0.0
14-16	1.0 0.1 0.1
16-18	1.0 0.9 0.1
18-20	1.0 0.2 0.1

Figure 11a shows the mean value of the optimized solution. The graph indicates that GeneAS has the best mean value of NPV, that is, better convergence throughout the evolution of the individuals.

Figure 11d presents the median and dispersion behavior of the optimization results. The GeneAS shows less dispersion of its results and rejects the null hypothesis with 99% confiability for all other algorithms (i.e., Wilcoxon tests). So, in this scenario, GeneAS presents a better performance.

Figure 11g shows the histogram of the optimized valves' quantity in 30 runs. The scenario presents the consistency of the GeneAS algorithm that always finds 2 ICV in the test model. Table 6 presents US$5,746,142 of profit in relation to the base case.

G. AQUIFER RESERVOIR - MULTILATERAL WELLS

The optimized solution considers the use of 5 conventional wells (CW): 4 production CW and 1 injection CW; and the use of 3 intelligent injection wells known as INJ2, INJ3, and INJ4. Table 7 shows the optimized control values. In INJ2, of the six zones, only the first two are completed with ICV, in INJ3 all the zones have valves except the third, and in INJ4 only the third zone is completed with ICV.

Table 8 shows an increase of almost US$ 6 million in NPV and an increase in accumulated oil production. There is also an increase in the water produced and the water injected. This is due to the extended operation of the optimized case in relation to the base case. Both simulations, base case and optimized, were suspended before the expected time due to the water cut restriction of 90% defined for this reservoir. However, the reservoir with the optimized solution operated longer and, therefore, extracted more oil.

Figure 11b shows the average of the aquifer reservoir. The graph indicates that GeneAS and CCGA have the best mean values of NPV, that is, the best mean convergences throughout the evolution of the individuals. In Figure 11e, the CCGA presents less dispersion. All samples were tested. They are from statistically different populations with a 99% of confidence interval. Since in this GeneAS's scenario has higher values of NPV than CCGA, GeneAS has a better performance. Figure 11h shows the valves' quantity. The GeneAS was capable of finding the best results with less ICV.

H. REAL RESERVOIR - VERTICAL WELLS

Figure 11c shows the average of the algorithms in the reservoir with the aquifer. The graph indicates that GeneAS has the best average values of NPV, that is, the best average convergences, throughout the individuals' evolution.

In Figure 11f, the CCGA presents less dispersion of its results. However, it shows the worst result of NPV. All samples were tested and they are from statistically different populations with a 99% of confidence interval. The GeneAS has the best performance.

Figure 11i shows the histogram of the number of valves. It can be seen that the number of valves found by the three methodologies is very close.

Table 9 presents the optimized control of IW. From the producing wells, PROD1 is completed with ICV in the first three zones, PROD3 and PROD4 wells have valves in all zones, PROD5 has ICV in the first two of three zones, and PROD7 has valves in the second and last zone, as shown in Table 9.

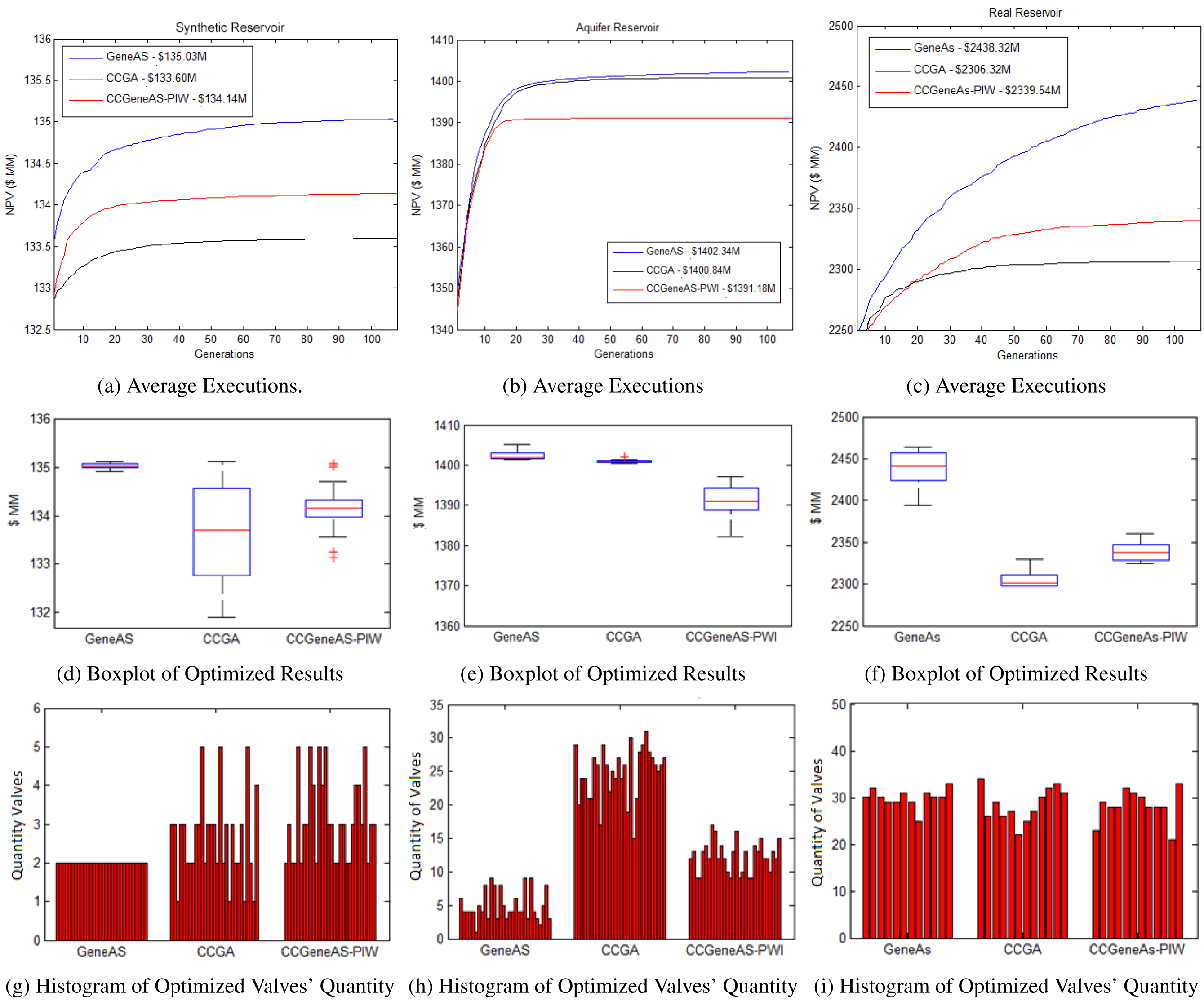
In the injection wells, INJ1 has no ICV in the last zone, and INJ2 has ICV valves in all zones except in the first and third. In INJ3, only the second and last receive a valve, INJ4 has ICV in the first three zones, and in INJ5 the last three zones have valves, as shown in Table 10.

Table 11 shows an increase of more than US$250 million in NPV, representing 12.08% concerning the base case. The accumulated oil produced increased by 9.33% concerning the base case. The optimized solution showed no change in the injected water. Nonetheless, it showed a reduction in the water produced.

Another reservoir behavior indicator is the mean reservoir pressure **(Figure 12).** It can be verified that the optimized case can control the drop in reservoir pressure, especially in the first half of the life cycle.

I. GEOLOGICAL UNCERTAINTY - AQUIFER RESERVOIR MODEL

Three scenarios have been specified by the oil company experts, aiming to evaluate the effectiveness of using intelligent wells in this reservoir in a very favorable and worst-case scenario. The experts have specified a degree of communication between the reservoir layers so that the control valves, which control the water injection to avoid the early arrival of the water flood in producing wells, could be evaluated. It is



(a) Average Executions. (b) Average Executions (c) Average Executions

(d) Boxplot of Optimized Results (e) Boxplot of Optimized Results (f) Boxplot of Optimized Results

(g) Histogram of Optimized Valves' Quantity (h) Histogram of Optimized Valves' Quantity (i) Histogram of Optimized Valves' Quantity

FIGURE 11. **Comparing optimized results obtained from GeneAS, CCGA, and CCGeneAS across three distinct reservoir types.**

TABLE 6. **Results of Optimized Reservoir of the Synthetic Reservoir.**

Case	NPV (US$)	Oil Prod. (m^3)	Water Prod. (m^3)	Water Inj. (m^3)	Δ NPV (US$)
Base	129,705,981	2,044,838	720,094	2,922,000	0
GeneAS	135,120,845	2,183,612	560,801	2,922,000	**5,414,863**
Δ %	**4.17%**	**6.79%**	**-22.12%**	**0.00%**	—

understood that the greater the communication between the layers, the harder it becomes to control the water injection through the valve since the flow of water from one layer can affect other layers, resulting in a slower response to an action in a given valve.

The geological scenarios were only available for the aquifer reservoir. The parameter of uncertainty involves the continuity of the layers of shales, in which:

- *Scenario 1:* Shallow shale-layer continuity;
- *Scenario 2:* Average shale-layer continuity; and
- *Scenario 3:* Continuous shale.

Table 12 presents the optimization result of each scenario and its cumulative metrics. As expected, in the best scenario, the NPV was higher. The interesting thing about this case study is that the applied methodology produces a considerable positive return even with various geological uncertainties.

Table 13 presents the comparative mean results in uncertainty geological aquifer reservoir, optimized and the base case the simulation without ICV. It shows an increase in the

TABLE 7. Optimized Control Values of the Aquifer Reservoir.

	INJECTOR WELLS		
Time (Year)	**INJ2**	**INJ3**	**INJ4**
0-2	0.7 0.5 1.0 1.0 1.0 1.0	0.9 0.8 1.0 0.6 0.7 0.3	1.0 1.0 0.2 1.0 1.0 1.0
2-4	0.2 0.4 1.0 1.0 1.0 1.0	0.6 0.6 1.0 0.0 0.8 0.3	1.0 1.0 0.2 1.0 1.0 1.0
4-6	0.7 0.7 1.0 1.0 1.0 1.0	1.0 0.2 1.0 0.2 0.6 0.7	1.0 1.0 0.5 1.0 1.0 1.0
6-8	0.8 0.0 1.0 1.0 1.0 1.0	0.3 0.9 1.0 1.0 0.9 1.0	1.0 1.0 0.9 1.0 1.0 1.0
8-10	0.9 0.6 1.0 1.0 1.0 1.0	0.9 0.2 1.0 0.8 0.7 0.3	1.0 1.0 0.6 1.0 1.0 1.0
10-12	1.0 0.4 1.0 1.0 1.0 1.0	0.8 0.3 1.0 0.1 0.8 0.9	1.0 1.0 0.7 1.0 1.0 1.0
12-14	0.3 0.7 1.0 1.0 1.0 1.0	0.4 0.2 1.0 0.6 0.5 0.2	1.0 1.0 0.8 1.0 1.0 1.0
14-16	0.2 0.4 1.0 1.0 1.0 1.0	0.3 0.1 1.0 0.7 0.5 0.6	1.0 1.0 0.4 1.0 1.0 1.0
16-18	0.9 0.0 1.0 1.0 1.0 1.0	0.1 0.1 1.0 0.2 0.1 0.0	1.0 1.0 0.2 1.0 1.0 1.0
18-20	0.8 0.6 1.0 1.0 1.0 1.0	0.3 0.4 1.0 0.1 0.0 0.1	1.0 1.0 1.0 1.0 1.0 1.0

TABLE 8. Optimized Reservoir Results of the Aquifer Reservoir.

Case	**NPV** (US$)	**Oil Prod.** (m^3)	**Water Prod.** (m^3)	**Water Inj.** (m^3)	**Δ NPV** (US$)
Base	1,399,401,031	19,342,021	46,613,201	65,732,194	0
GeneAS	1,405,147,173	19,945,503	50,969,020	70,522,978	**5,746,142**
Δ %	**0.41%**	**3.12%**	**9.34%**	**7.29%**	—

TABLE 9. Optimized Control Values in Production Well Real Reservoir.

	PRODUCTION WELLS				
Time (Years)	**PROD1**	**PROD3**	**PROD4**	**PROD5**	**PROD7**
0-2	0.9 0.5 0.7 1.0 1.0 1.0	1.0 0.9 1.0 0.2 0.0	0.2 0.3 0.9	0.1 0.1 1.0	1.0 1.0 1.0 1.0 0.4
2-4	0.0 0.1 0.5 1.0 1.0 1.0	0.2 0.2 0.1 0.0 0.2	0.2 0.1 0.2	0.2 0.2 1.0	1.0 0.6 1.0 1.0 0.9
4-6	0.1 0.2 0.4 1.0 1.0 1.0	0.6 0.1 0.1 0.0 0.0	0.6 0.6 0.5	0.5 0.1 1.0	1.0 0.6 1.0 1.0 0.2
6-8	0.3 0.2 0.1 1.0 1.0 1.0	0.1 0.1 0.6 0.8 0.3	0.3 0.4 0.0	0.1 0.1 1.0	1.0 0.6 1.0 1.0 0.4
8-10	0.3 0.1 0.6 1.0 1.0 1.0	0.8 0.7 0.4 0.6 0.3	0.2 0.9 0.4	0.1 0.2 1.0	1.0 0.7 1.0 1.0 0.8
10-12	0.8 0.0 0.3 1.0 1.0 1.0	0.1 0.4 0.3 0.3 0.8	1.0 0.9 1.0	0.7 0.3 1.0	1.0 0.1 1.0 1.0 0.0
12-14	0.7 0.1 1.0 1.0 1.0 1.0	0.6 1.0 0.6 0.8 0.2	0.7 0.9 1.0	0.3 0.0 1.0	1.0 0.5 1.0 1.0 0.7
14-16	0.6 0.8 0.8 1.0 1.0 1.0	0.6 0.1 0.1 0.1 0.6	0.5 0.9 0.8	0.9 0.2 1.0	1.0 0.8 1.0 1.0 0.3
16-18	1.0 0.2 0.5 1.0 1.0 1.0	0.3 0.5 0.9 0.4 0.6	0.6 0.7 0.7	0.0 0.4 1.0	1.0 0.3 1.0 1.0 0.8
18-20	0.3 0.7 1.0 1.0 1.0 1.0	0.1 0.6 0.5 0.4 0.2	0.6 0.3 0.8	0.3 0.3 1.0	1.0 0.4 1.0 1.0 0.0

TABLE 10. Optimized Control Values in Injection Well of the Real Reservoir.

	INJECTOR WELLS				
Time (Years)	**INJ1**	**INJ2**	**INJ3**	**INJ4**	**INJ5**
0-2	0.1 0.1 0.1 1.0 1.0	1.0 0.9 1.0 0.0 0.3 0.0	1.0 0.5 1.0 1.0 0.0	0.8 0.1 0.9 1.0	1.0 1.0 1.0 0.0 0.0 0.1
2-4	0.0 0.0 0.1 0.5 1.0	1.0 0.7 1.0 0.4 0.0 0.3	1.0 0.9 1.0 1.0 0.0	0.3 0.2 0.8 1.0	1.0 1.0 1.0 0.0 0.0 0.0
4-6	0.3 0.5 0.5 0.3 1.0	1.0 0.2 1.0 0.5 0.3 0.5	1.0 0.3 1.0 1.0 0.6	0.4 0.5 0.7 1.0	1.0 1.0 1.0 0.0 0.0 0.1
6-8	0.0 0.1 0.4 1.0 1.0	1.0 0.6 1.0 0.4 0.9 0.3	1.0 0.7 1.0 1.0 0.3	0.5 0.8 0.9 1.0	1.0 1.0 1.0 0.2 0.0 0.1
8-10	0.4 0.2 0.6 0.6 1.0	1.0 0.1 1.0 0.5 0.0 0.3	1.0 0.2 1.0 1.0 0.9	0.8 0.6 0.4 1.0	1.0 1.0 1.0 0.1 0.1 0.1
10-12	0.1 0.7 1.0 0.7 1.0	1.0 1.0 1.0 0.9 0.2 0.1	1.0 0.8 1.0 1.0 0.5	0.4 0.5 0.2 1.0	1.0 1.0 1.0 0.4 0.6 0.2
12-14	0.9 0.6 0.6 0.9 1.0	1.0 0.3 1.0 0.5 0.1 0.4	1.0 0.1 1.0 1.0 0.4	0.4 0.1 0.3 1.0	1.0 1.0 1.0 0.2 0.0 1.0
14-16	0.9 0.5 0.0 0.0 1.0	1.0 0.3 1.0 0.5 0.6 0.3	1.0 0.7 1.0 1.0 0.5	0.3 0.3 0.6 1.0	1.0 1.0 1.0 0.4 0.2 0.1
16-18	0.7 0.5 0.6 0.5 1.0	1.0 0.9 1.0 0.2 0.9 1.0	1.0 0.2 1.0 1.0 0.9	0.6 0.5 0.6 1.0	1.0 1.0 1.0 0.2 0.8 0.2
18-20	0.0 0.9 0.9 0.3 1.0	1.0 0.7 1.0 0.6 0.1 0.2	1.0 0.9 1.0 1.0 0.2	0.1 0.7 0.1 1.0	1.0 1.0 1.0 0.4 0.5 0.7

TABLE 11. Metrics of the Real Reservoir (Vertical Wells).

Case	**NPV** (US$)	**Oil Prod.** (m^3)	**Water Prod.** (m^3)	**Water Inj.** (m^3)	**Δ NPV** (US$)
Base	2,198,858,550	35,299,714	56,935,978	91,312,500	0
GeneAS	2,464,373,074	38,594,452	55,524,770	91,312,500	**265,514,524**
Δ %	**12.08%**	**9.33%**	**-2.48%**	**0.00%**	—

volume of oil produced by almost 24%. In addition, there was also an increase in the quantities injected and produced of water. This suggests a great potential for this reservoir exploitation. All of this reflects the increase, in the average case of geological uncertainty, of 18% of NPV or a little more than US$ 216 million.

TABLE 12. Geological Uncertainty of Aquifer Reservoir.

Case	NPV (US$)	Oil Prod. (m^3)	Water Prod. (m^3)	Water Inj. (m^3)	Δ %	Δ NPV (US$)
Scenario 1	1,405,745,721	16,726,622	22,990,787	37,242,720		
Base Scenario 1	1,146,243,000	12,947,570	22,124,431	33,518,005	**22.64%**	**259,502,721**
Scenario 2	1,421,050,127	16,873,523	23,711,158	37,942,668		
Base Scenario 2	1,216,873,927	13,823,491	21,248,507	33,198,746	**16.78%**	**204,176,200**
Scenario 3	1,455,258,500	17,457,299	22,817,829	37,307,267		
Base Scenario 3	1,270,875,197	14,617,501	22,098,168	34,554,926	**14.51%**	**184,383,303**

TABLE 13. Geological Uncertainty – Results of Optimized Aquifer Reservoir.

Case	NPV (US$)	Óleo Prod. (m^3)	Água Prod. (m^3)	Água Inj. (m^3)	Δ NPV (US$)
Average (Base Cases)	1,211,330,708	13,796,187	21,823,702	33,757,225	0
Average (Scenarios)	1,427,351,449	17,019,148	23,173,258	37,497,552	**216,020,741**
Δ %	**17.83%**	**23.36%**	**6.18%**	**11.08%**	

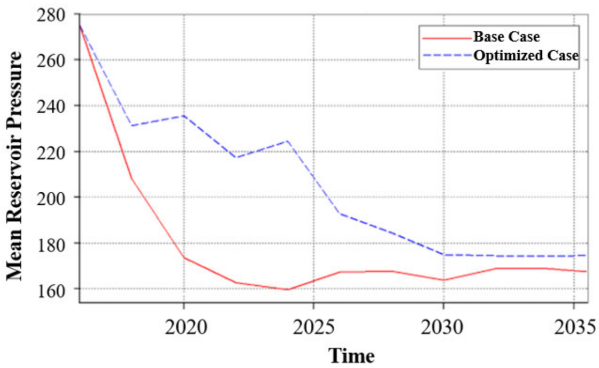


FIGURE 12. Average Pressure Curve of the Real Reservoir.

VI. CONCLUSION AND FUTURE WORK

This work presented a flexible optimization methodology capable of optimizing both the proactive control and the quantity and placement of the valves throughout the life reservoir cycle. Besides, this research efficiently compared the three evolutionary algorithms: GeneAS, CCGA, and CCGeneAS-PIW. The comparison outcomes showed a better convergence in the use of GeneAS. The values demonstrated in the presented simulations indicated significant gains in the recovered oil increase in the volume, and a decrease in water produced. This shows the gain in control of the advance of the waterfront in the reservoir.

The best convergence of the GeneAS algorithm has been demonstrated, providing solutions more stable regarding the number of ICVs than other algorithms. Probably, this is due to the better synergy of the iteration between the two forms of representing individuals. After all, the representations have no well-defined independence, causing a performance delay in any multi-population representation.

When evaluating the reservoir with geological uncertainties, it is observed that for all the scenarios (i.e., pessimistic, conservative, and optimistic), there is a generation of positive NPV. This shows that the simulation always predicts profit, reinforcing the advantage of Smart Field use.

In terms of evaluation, this research work opens up several future possibilities. For instance, improvements should be made to the allocation of Wells considering intelligent wells and the joint problem of valve allocation and control. Other possibilities cover the insertion of different market uncertainties, such as changes in production values over time, and the insertion of technical uncertainties, such as the failures in the operation of the valves, which was not done in order not to expand the optimization process. However, this would make the analysis complete; In addition to the black-oil type reservoir model, compositional simulation models could also be considered to analyze valves' performance when there is considerable gas production.

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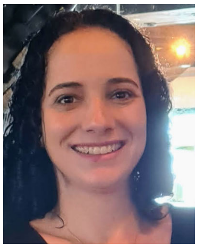

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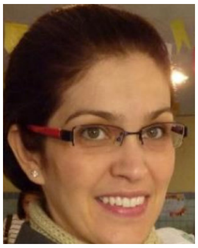

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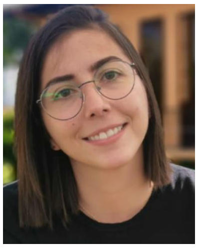

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