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Critical Review of the Percentage of Cumulative Oil Production with Artificial Intelligence Methods for Gas lifted Wells

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***Abstract**: Gas lift optimisation is critical to sustaining production and economic viability in mature oilfields, particularly brownfields where reservoir pressure decline impairs natural hydrocarbon flow. As conventional assets age, the complexity of maintaining production intensifies, with gas lift systems offering a viable solution despite their highly nonlinear dynamics, inter-well dependencies, and operational uncertainties. Traditional optimisation methods often underperform under such high-dimensional, real-time constraints. In response, recent advances have embraced artificial intelligence (AI) as a transformative paradigm for full-field gas lift optimisation. This review presents a technical evaluation of AI-driven strategies, focusing on machine learning (ML), meta-heuristic algorithms, and fuzzy logic systems. ML models, especially artificial neural networks (ANNs), capture nonlinear input-output relationships from historical data, enabling fast production forecasting and control, though they are limited by data quality and computational demands. Meta-heuristic techniques, including genetic algorithms, particle swarm optimisation, and ant colony optimisation, excel in exploring complex, multimodal search spaces but face challenges with scalability and convergence efficiency. Fuzzy logic systems offer resilience in uncertain, data-sparse environments by integrating heuristic knowledge, yet suffer from subjectivity and limited scalability. Recognising the limitations of individual approaches, the study underscores the emergence of hybrid AI frameworks that synergise multiple AI paradigms or integrate AI with physics-based and statistical models. These composite systems enhance robustness, scalability, and interpretability while dynamically adapting to evolving reservoir conditions, injection constraints, and economic objectives. The review concludes that the future of gas lift optimisation lies in intelligent, adaptive hybrid AI systems capable of real-time field-wide optimisation, offering a pathway to improved efficiency, extended field life, and maximised economic returns in the upstream oil and gas sector.*

Keywords— Artificial intelligence, machine learning, optimization, gas lift, oilfields

1. INTRODUCTION

In many mature petroleum reservoirs, the natural pressure is insufficient to sustain the weight of the fluid in the wellbore and overcome the frictional forces against its movement. The gas lift process is widely used to enhance production from oil fields that cannot produce under natural pressure [25], [27]. In this process, high-pressure natural gas is injected into the wellbore to reduce the density of the fluid column, allowing the reservoir pressure to push the fluid to the surface [3]. In gas lift operations, production results from the pressure drop at the bottom hole, meaning higher oil production occurs as the bottom hole pressure drop increases. Gas has two distinct effects on oil: it facilitates easier oil movement toward the surface due to the expansion of gas within the oil phase, and it reduces viscosity, thereby diminishing the oil column pressure, allowing oil to move upward more easily. However, at a certain point, the benefit of increased production due to decreased static head pressure is offset by the increase in frictional pressure loss from the large gas quantity present [25]. This increases bottom-hole pressure and reduces fluid production [57]. Therefore, each well has an optimal gas-lift injection rate (GLIR). When considering the entire gathering network, however, the optimal gas-lift injection rate differs from that which maximizes individual well production due to the back pressure effects imposed by connected wells further downstream.

Maximizing long-term field production may require adjusting the lift gas injection rate and/or oil–gas separator pressure in response to changing reservoir conditions over time. Establishing the optimal gas injection rate, separator pressure, and tubing diameter constitutes a complex optimization problem that necessitates efficient models capable of tracking spatial and temporal changes in flow rate and hydrocarbon fluid composition in every element of the gas lift process [93]. The gas lift process is inherently transient, and the model must account for changes in the flow rate and composition of the reservoir feeding the gas-lifted well. The performance of the gas lift system is highly composition-dependent, and this must be explicitly accounted for in the model, especially for describing multiphase flow in the gas-lifted wellbore [46]. Due to the time-varying nature of model parameters and the feedback loop caused by re-compression and re-injection of the lift gas, this optimization problem is complex with many local minima [83]. This complexity often rules out traditional optimization algorithms, making global optimization techniques like artificial intelligence more suitable. These methods include the heuristic and meta-heuristic techniques, the machine learning techniques, the fuzzy logic techniques and the statistical model techniques

Heuristic and metaheuristic optimization techniques have been developed to address the limitations of traditional numerical methods [57]. A heuristic is designed to solve problems more efficiently when traditional methods prove too slow, while a metaheuristic operates at a higher level, seeking or generating heuristics to provide satisfactory solutions to optimization problems [93]. These approaches aim to handle challenges such as nonlinearity, multi-objectivity, and uncertainty [83], offering flexibility and the capability to attain global solutions more readily.

These newer optimization techniques rely on random initial populations, employing probabilistic theory to obtain global solutions. Examples of such methods include genetic algorithms (GA), ant colony optimization (ACO), particle swarm optimization (PSO), artificial bee colony (ABC), etc [57]. GA, for instance, can provide multiple solutions but requires careful tuning of parameters such as mutation, crossover, and reproduction, and it can be computationally intensive for simulation-optimization-based applications [59], [93]. ACO is robust for non-uniform, complex, and non-linear problems but faces challenges with explicit or implicit stochastic problems and requires tuning parameters [16]. PSO is known for its simplicity, fast convergence, and low computational cost, though it necessitates parameter tuning [39]. ABC, while flexible and robust, operates relatively slowly in sequential processing and requires tuning parameters [58], [31].

Furthermore, machine learning (ML) techniques have been introduced as data-driven approaches. These methods, including artificial neural networks (ANNs), effectively handle nonlinear and high-dimensional data for production optimization [40], [42], [31]. ML models analyze production data using algorithms to make predictions and optimizations without explicit knowledge of reservoir or wellbore properties [9]. Response surface methodology is a statistical model, served as a proxy model for evaluating well performance, relying on a sequence of design of experiments for optimal responses. While RSM is not standalone and requires NODAL analyses for accurate data, it offers efficient performance as available data increases. In this study, comprehensive review of artificial intelligence methods for gas lift optimization has been conducted. Emphasis has been given to their principles, application, merits and demerits for gas lift optimization applications [34].

2. GAS LIFT OPTIMIZATION

Optimization in gas lift process involves efficient allocation of resources to achieve specific goals, such as maximizing production or net present value (NPV), or minimizing injected gas [3].

The determination of the optimal gas injection volume for a set of wells is a critical optimization problem. This is significant as the injected gas is a valuable and costly resource. Injecting gas into a well initially increases oil production by reducing hydrostatic pressure and fluid density in the tubing. However, excessive injection can lead to a drop in production due to frictional losses [77], [88]. This creates a characteristic gas-lift performance curve (GLPC), resembling a dome. According to the GLPC, insufficient gas injection decreases oil production, while excessive injection reduces oil production and increases operational costs due to elevated friction pressure gradient. Thus, accurately calculating the optimal gas injection rate is crucial for maximizing oil production [34].

When considering the entire network, the optimal gas-lift injection rate for individual wells may differ due to backpressure effects, which result from pressure drops in the flow lines caused by downstream tiebacks connecting multiple wells [109]. Gas lift operations also face constraints such as gas-injection rate, injection pressure, availability of lift gas, compressor capabilities, and water handling facilities. Addressing these constraints is essential during the optimization process to achieve the best allocation of lift gas injection rates for each well within a network [97]. Various gas-lift optimization methods have been developed to allocate the injection rate of lift gas optimally, considering specific facility constraints [10]. In gas allocation problems, many parameters are fixed due to prior selection and installation, leaving only the gas injection rates adjustable. Implementing optimization techniques during the design phase allows for the optimization of parameters such as injection depth, tubing diameter, and compressor facilities [51].

3. WELL-BASED AND FIELD-BASED GAS LIFT OPTIMIZATION

Optimizing production can be approached at the well-based or field level. Well-level optimization involves physical tests, such as fluid composition and PVT tests, along with step-rate gas injection tests to accurately describe fluid production variations with changes in lift gas injection [54]. Single-well production optimization focuses on modeling individual well behavior considering parameters like completions, fluid composition, pressure, and temperature at both the reservoir and wellhead [84]. Analysis techniques, whether using complex computational fluid descriptions or simple black-oil models, provide effective lift performance curves for gas-lifted wells [84].

However, single-well considerations may not offer a complete understanding of field performance, especially where gas allocation poses challenges [55]. Complex field network solutions often start with individual wells, using network simulators to couple the behavior of single wells through a common gathering network [53]. Nodal analysis, based on multi-phase flow concepts, is useful for solving field network solutions, integrating shared field facilities and constraints [84]. In the absence of step-rate tests, lift performance curves are generated to aid in gas lift optimization. For steady-state solutions, these curves can be updated to address well interdependence during field-based optimization [54]. However, errors may arise when using lift performance curves during pseudo-state solutions. Complete steady-state solutions are derived from network simulators, balancing pressure over nodes after allocating lift gas to wells [43]. Optimal allocation of lift gas is crucial for the entire field, considering facility constraints [56].

Nodal analysis techniques or gas lift performance curves (GLPC) are well-established but may not provide a complete solution for field gas lift optimization [87]. Numerous researchers have explored solutions for well optimization. Vazquez-Roman and Palafox-Hernandez (2005) developed a well-based model grounded in mass, momentum, and energy balance, utilizing a hybrid interior algorithm for injection depth, pressure, and gas injection amount. Their results were more accurate than the standard nodal approach and were suggested for field-wide studies.

Mantecon [65] focused on redesigning individual wells based on well site data to enhance oil production, addressing injection pressure, depth, packer installation, and gas lift valve size, and considering a shift from continuous to intermittent gas lift. While these enhancements improve well stability and steady production, optimal allocation remains crucial, particularly when operational resources and handling facilities are constrained. Dutta-Roy and Kattapuram [22] studied lift gas introduction to a single well using nodal analysis techniques, considering back-pressure effects of gas injection into two wells before investigating a 13-well network. They found that analyzing production networks of many gas-lifted wells individually is inadequate for achieving optimal solutions for the entire field network, recommending the use of a general network solver to address interdependencies. Bahadori and Zeidani [8] emphasized accurate lift gas injection and liquid production for field-wide optimization, insisting on computer simulations to capture interactions between wells in a field, where conditions in one well affect connected wells.

Field-wide gas lift optimization considers multiple interconnected wells, requiring a sophisticated optimization procedure to address interrelated well allocations [84]. Field-based optimization encompasses the entire field network, including interconnected wells and surface facilities like separators, chokes, valves, manifolds, flowlines, compressors, processing, and storage units. Single well analysis provides an incomplete picture of overall field performance, especially for optimal gas-lift allocation. The back pressure resulting from lift gas injection in one well impacts production from all connected wells. Therefore, optimal production requires suitable lift gas allocation, considering well interactions. Additionally, constraints such as water production and handling volume in facility operations may only be effectively addressed when the entire field network model is considered [84].

Multi-well field optimization presents several challenges, including gas allocation issues due to limited availability, back pressure effects, surface equipment and handling facilities limitations, production difficulties in some wells, and problems arising from well shut-in and workover. Among these challenges, gas allocation to wells has garnered significant attention [84]. In gas allocation optimization, most parameters cannot be altered due to previous design, making the gas injection rate the controllable parameter. The goal is to maximize total field oil production and/or profit, identifying the best allocation that maximizes profit by allocating more gas to wells with higher production potentials while adhering to constraints imposed on the interconnected field [30].

Gas is allocated to wells based on their gas-lift performance curve, illustrating the oil rate vs. the gas-lift injection rate. In scenarios with gas availability constraints and well interconnections, the gas injection rate for each well can be determined using optimization algorithms [30]. Gas allocation optimization typically occurs after the design stage when wells are already in existence and altering certain well parameters, such as tubing size and injection depth, is not possible. Various optimization techniques, classified as numerical methods or heuristic methods, have been employed in addressing gas allocation optimization problems [68].In wells, the injection rate plays a crucial role in determining fluid production. Typically, an increase in the injection rate leads to higher oil production until an optimum injection rate is surpassed, resulting in a decline due to gas slippage. Many optimization problems incorporate a maximum limit for the injection rate, considering constraints on surface facilities to manage produced fluids [86]. If facilities handling water cut are constrained, fluid production may decrease. Water cut, a significant production limitation, must be controlled to avoid exceeding a maximum value and to meet surface handling capacity [69].

Optimization of this nature often considers limitations imposed by separator capacity. Without accounting for separator capacity, there might be no restriction on liquid production volume, and water cut may not have a maximum imposed value. However, in real situations, separator capacity limitations impact the volume of liquid (oil and water) and gas the separator can handle, setting a maximum production rate for the field [75].Rashid [84] addressed a lift-gas allocation problem with gas constraints, considering the effects of interactions between wells. He developed an algorithm iterating until convergence on wellhead pressures, utilizing a simulator in the loop for result validation, test pressures, and curve generation. However, separation constraints were not taken into account. Buitrago et al. [12] were among the pioneers proposing a global optimization algorithm for lift-gas allocation, considering compression restrictions. Their algorithm combines stochastic domain exploration and heuristic calculation of a descent direction to avoid suboptimal solutions. They particularly focused on wells that do not respond instantaneously to gas injection.

4. ARTIFICIAL INTELLIGENCE OPTIMISATION METHODS

Artificial Intelligence (AI) techniques encompass a broad range of methods that leverage computational power to mimic human-like cognitive processes such as learning, reasoning, and problem-solving. AI learns, reasons and self-corrects by utilising logic and decision trees which target to develop systems that are highly intelligent and can be deployed to perform complex tasks. AI systems are applicable to structured, semi-structured and unstructured data [37], [100]. These techniques have found widespread application in optimization problems, including gas lift optimization, by providing innovative approaches to solving complex, nonlinear, and high-dimensional challenges. AI optimization methods include machine learning methods, heuristic and meta-heuristic methods, fuzzy logic methods and statistical methods. Figure 1 gives a general classification of AI optimization methods.

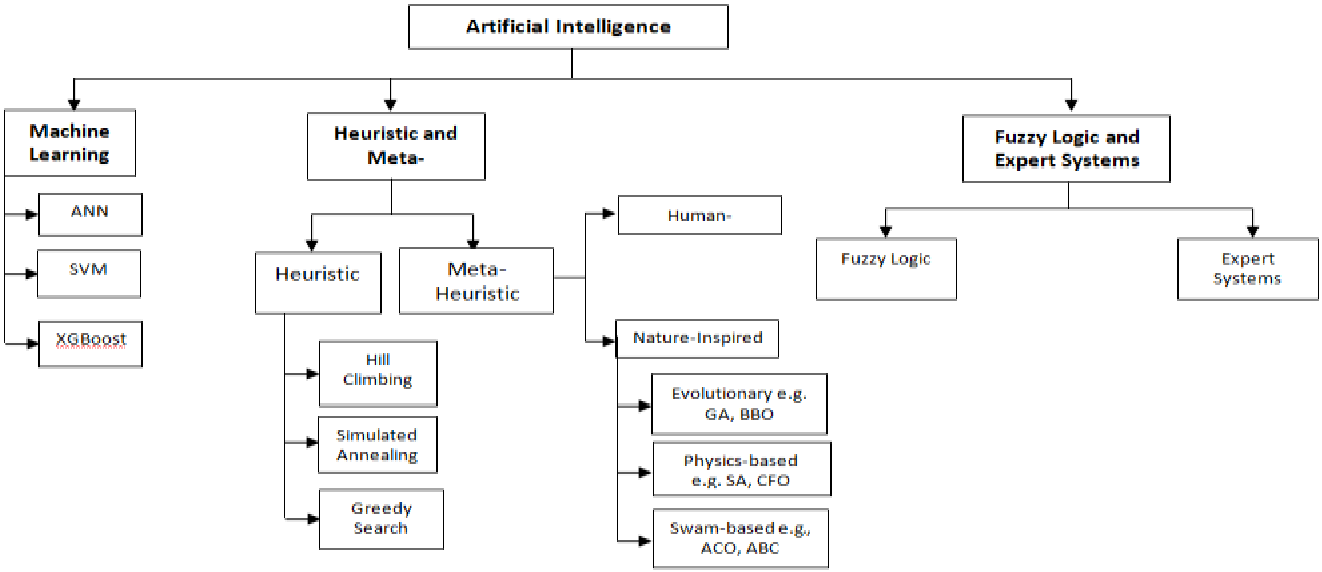

Figure 1: Classification of artificial intelligence optimization methods

4.1 Machine Learning Models for Gas Lift Optimisation

Machine learning (ML) is a branch of artificial intelligence focused on teaching systems to identify patterns and make predictions or decisions based on data, without requiring explicit mathematical models or programming [37]. ML models enhance their performance by learning from data inputs, allowing them to classify, predict, optimize, or forecast based on learned patterns [94]. In gas lift optimization, machine learning techniques represent advanced, data-driven methods. Data-driven models use system data to establish relationships among input, internal, and output variables, evolving from traditional statistical methods to overcome limitations related to strict probability distribution assumptions [14], [107]. With the rise of big data and artificial intelligence, these models offer valuable insights and predictions based on historical data, utilizing techniques such as regression, classification, and clustering algorithms for analysis [73]. Machine learning models including support vector machines (SVMs), artificial neural networks, and decision trees, undergo training with labeled, unlabeled, or mixed data. These models have proven effective in gas lift optimization modeling, adapting to changing conditions by learning from new data [73]. Their capacity to handle large datasets and identify patterns enhances accuracy and forecasting reliability. However, successful implementation demands substantial training datasets, robust computing infrastructure, and careful validation [14].

4.1.1 Support Vector Machines

Support Vector Machines (SVMs) are powerful supervised learning models used for classification and regression tasks. They have gained popularity due to their robustness in handling high-dimensional data and their ability to find an optimal hyperplane that maximizes the margin between classes. While SVMs are primarily used for classification, their regression variant, Support Vector Regression (SVR), is particularly relevant for optimization modeling, including gas lift optimization [23].

One of the main advantages of SVMs in optimization modeling is their robustness to overfitting. SVMs use a regularization parameter (C) to control the trade-off between maximizing the margin and minimizing errors, which is crucial in optimization problems where the model must generalize well to unseen data [99]. Additionally, SVMs can handle non-linear relationships using kernel functions such as polynomial and radial basis functions, allowing them to model complex relationships in data [99]. This flexibility is essential in gas lift optimization, where the relationship between variables can be highly non-linear. SVMs also perform well in high-dimensional spaces, making them suitable for scenarios with many input variables. In gas lift optimization, numerous parameters such as gas injection rate, pressure, and reservoir characteristics need to be considered. The dual problem formulation in SVMs allows them to work efficiently with kernel tricks, facilitating the transformation of data into higher-dimensional spaces where a linear separation is more feasible.

In gas lift optimization, SVR can be used to predict the outcome of different gas lift injection rates. By training on historical production data, an SVR model can estimate the production rate for various injection scenarios, helping to identify optimal injection strategies [99]. SVMs can also classify different operational states of wells, such as optimal, suboptimal, or failure states, based on input features like pressure, temperature, and flow rates. This classification can guide operators in adjusting parameters to maintain optimal production conditions. SVM models can be used to understand the sensitivity of different parameters affecting gas lift performance [45]. By analyzing the support vectors and weights, operators can identify which parameters have the most significant impact on production, aiding in more focused optimization efforts. Furthermore, SVMs can be integrated with other optimization algorithms such as genetic algorithms to enhance their performance. For instance, an SVM model can provide initial estimates or constraints for a genetic algorithm searching for the optimal gas lift injection rates [48].

Support vector regression plays a significant role in addressing gas allocation optimization problems in gas lift operations. Gas allocation optimization aims to determine the most efficient distribution of available gas among multiple wells to maximize oil production, minimize costs, or achieve other operational objectives. The complexity and non-linear nature of these problems make SVMs an invaluable tool. Firstly, SVMs excel in handling non-linear relationships, which are common in gas allocation optimization. The relationship between gas injection rates and oil production is inherently non-linear due to factors like reservoir characteristics, fluid dynamics, and interaction effects between wells. SVMs, with their ability to use kernel functions, can model these complex non-linearities effectively. This capability ensures more accurate predictions of production outcomes based on varying gas injection rates, leading to better-informed decision-making.

Moreover, SVMs are robust to overfitting, a crucial feature when dealing with real-world data that often includes noise and outliers. In gas allocation optimization, the model's ability to generalize well to unseen data is vital for ensuring consistent performance under different operational conditions. By maximizing the margin between support vectors, SVMs maintain high predictive accuracy even with limited and noisy data, which is common in field operations [48]. Another critical advantage of SVMs is their efficiency in high-dimensional spaces. Gas allocation optimization involves numerous variables, including injection rates, well pressures, temperatures, and production rates. SVMs can handle these high-dimensional datasets effectively, capturing the intricate relationships between variables without suffering from the curse of dimensionality. This makes SVMs particularly suitable for optimizing complex, multi-well gas lift systems [99].

In gas allocation optimization, SVMs can be used to develop predictive models that estimate oil production rates for different gas injection scenarios [95]. By training these models on historical production data, operators can simulate various allocation strategies and identify the optimal distribution of gas that maximizes production or profit. This predictive capability is invaluable for planning and operational adjustments, especially in dynamic reservoir conditions [82]. SVMs also contribute to understanding the sensitivity of different parameters in gas allocation optimization. By analyzing the support vectors and model coefficients, operators can identify which factors have the most significant impact on production outcomes [44]. This sensitivity analysis helps prioritize operational adjustments and resource allocation, focusing efforts on the most influential variables. Furthermore, SVMs can be integrated with other optimization techniques, such as genetic algorithms, to enhance their performance in gas allocation problems. For instance, an SVR model can provide initial estimates or constraints for a genetic algorithm optimizing gas injection rates. This hybrid approach leverages the strengths of both methods, combining the accurate predictive power of SVMs with the global search capability of genetic algorithms to find optimal solutions more efficiently [95].

However, there are challenges and considerations to keep in mind. Choosing the right kernel and tuning hyperparameters such as C, epsilon, and kernel parameters can be complex and computationally expensive. Cross-validation is often required to find the optimal settings, which can be resource-intensive. SVMs also require a sufficient amount of labeled data to train effectively, and collecting high-quality and comprehensive data from wells can be challenging and costly [82]. While SVMs are effective at modeling complex relationships, they are often considered black-box models. Interpreting the results and understanding the underlying relationships between variables can be difficult, which might hinder their adoption in some operational settings. Additionally, training SVMs on large datasets can be computationally demanding. For large-scale gas lift optimization problems involving many wells and parameters, this can become a bottleneck [95].

Despite their advantages, it is essential to recognize the challenges associated with using SVMs in gas allocation optimization. Selecting the appropriate kernel and tuning hyperparameters can be complex and computationally expensive, requiring careful cross-validation [99]. Additionally, the interpretability of SVM models can be limited, making it challenging to understand the underlying relationships between variables fully. Therefore, integrating SVMs with domain knowledge and other optimization techniques is often necessary to maximize their effectiveness.

1. Equations for SVM

Support Vector Machines (SVMs) aim to find the optimal hyperplane that separates two classes of data points

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with the maximum margin. The formulation for SVM can be described as follows [101]:

Primal Formulation

Given a training dataset $\{(x_i, y_i)\}_{i=1}^{n}$ where $x_i \in R^d$ is the input vector and $y_i \in \{-1,1\}$is the corresponding class label, the primal form of the SVM optimization problem is:

$$min_{w,b,\xi} \frac{1}{2} |w|^2 + C \sum_{i=1}^{n} \xi_i \qquad 1$$

Subject to

$$y_i(w^{\top x_i} + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, \ldots, n \qquad 2$$

Where, w is the weight vector, b is the bias term, ξ_i are slack variables that allow some data points to be on the wrong side of the margin, and C is the regularization parameter that controls the trade-off between maximizing the margin and minimizing the classification error.

Dual Formulation

The dual form of the SVM optimization problem is:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j x_i^{\top x_j} \qquad 3$$

Subject to

$$\sum_{i=1}^{n} \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C, \quad i = 1, \ldots, n \qquad 4$$

Here, α_i are the Lagrange multipliers.

Decision Function

The decision function for a new input vector x is given by:

$$f(x) = \text{sign}(\sum_{i=1}^{n} \alpha_i y_i x_i^{\top x} + b) \qquad \mathbf{5}$$

2. Support Vector Regression (SVR)

Support Vector Regression (SVR) extends SVM to regression problems. It aims to find a function that deviates from the actual observed targets by a value no greater than ϵ and at the same time is as flat as possible.

Primal Formulation:

Given a training dataset $\{(x_i, y_i)\}_{i=1}^{n}$, the primal form of the SVR optimization problem is:

$$min_{w,b,\xi,\xi^*} \frac{1}{2} |w|^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \qquad 6$$

Subject to

$$y_i - (w^{\top x_i} + b) \leq \epsilon + \xi_i,$$

$$(w^{\top x_i} + b) - y_i \leq \epsilon + \xi_i^*,$$

$$\xi_i, \xi_i^* \geq 0, \quad i = 1, \ldots, n$$

Here, ϵ is the margin of tolerance, $\xi_i$and $\xi_i^*$are slack variables that measure the deviation from the ϵ-tube.

Dual Formulation:

The dual form of the SVR optimization problem is:

$$\min_{\alpha,\alpha^*} \quad -\frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) x_i^{\top x_j} - \epsilon \sum_{i=1}^{n} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{n} y_i (\alpha_i - \alpha_i^*) \qquad 7$$

Subject to

$$[\sum_{i=1}^{n} (\alpha_i - \alpha_i^*) = 0,] \qquad 8$$

$$[0 \leq \alpha_i, \alpha_i^* \leq C, \quad i = 1, \ldots, n]$$

Here, α_i and α_i^* are the Lagrange multipliers.

Decision Function:

The regression function for a new input vector x is given by:

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) x_i^{\top x} + b \qquad 9$$

3. Kernel Trick

For both classification and regression, SVMs can handle non-linear relationships by mapping the input data into a higher-dimensional feature space using a kernel function $K(x_i, x_j)$. Common kernels include:

- Linear kernel: $K(x_i, x_j) = x_i^{\top x_j}$
- Polynomial kernel: $K(x_i, x_j) = \left(x_i^{\top x_j} + 1\right)^d$
- Radial basis function (RBF) kernel: $K(x_i, x_j) = \exp(-\gamma |x_i - x_j|^2)$
- Sigmoid kernel: $K(x_i, x_j) = \tanh\left(\kappa x_i^{\top x_j} + \theta\right)$

Using these kernel functions, the decision functions for SVM classification and SVR become:

$$f(x) = \text{sign}(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b) \qquad 10$$

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x) + b \qquad 11$$

These formulations enable SVMs to model complex, non-linear relationships, making them suitable for various optimization problems, including gas lift optimization.

4.1.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) stand as one of the most widely employed and rapidly advancing artificial intelligence techniques globally [35]. Over the past decades, researchers have increasingly directed their focus towards ANNs, successfully applying them to diverse applications, including pattern recognition, system identification, and classification problems. Operating as computational models, ANNs simulate the structure and functional aspects of biological neural networks, mirroring the organization of the human brain [73].

ANNs are comprised of interconnected processing units, or neurons, functioning in a manner similar to biological neurons. These networks rely on connections represented by input values and weights, with the output value being a function of the summed input value and weight. Neurons receive data from neighboring neurons, conduct computations, and transmit results to others [35]. The connections between neurons possess associated weights, facilitating the transmission of signals from one artificial neuron to another. As information traverses the network, the structure of the ANN evolves, learning from input and output data.

The strength of ANNs lies in their ability to learn from past experiences, generalize to provide new outputs, and abstract main properties from inputs. This capacity renders ANNs valuable for solving complex problems through logical and analytical techniques [80]. ANNs can capture intricate relationships between inputs and outputs, identify patterns in data, and exhibit better adaptability to data compared to conventional statistical analysis methods. They automatically adjust their weights to optimize behavior [96].

Trained using a defined dataset, ANNs learn input patterns until they achieve the best representative outputs, accurately predicting target data. Once adequately trained, ANNs can handle new patterns for prediction or classification, making them suitable for various applications, such as nonlinear regression, discriminant analysis, and nonlinear time series [32]. Their adaptability allows the modeling of complex non-linear systems, especially those lacking conceivable relationships between input and output, which might be challenging or impossible to model using conventional statistical tools [91].

Various ANN architectures exist, including multilayer perceptron (MLP), backpropagation (BP), radial basis function network (RBF), and recurrent neural network (RNN) [71]. ANNs can be categorized based on the direction of information flow within the network, with "feed-forward" ANNs having a forward flow of information and "backpropagation" ANNs involving backward information flow [71]. Simultaneous (parallel) learning occurs when information is obtained instantaneously, allowing for the immediate update of process parameters [89].

The ANN model is constructed by weights and biases**.** The neuron output is calculated by the summation of weighted inputs with a bias through a transfer function as follows.

$$f_n = f\left[\left(\sum_{i=1}^{k} w_i\, x_i\right) + b\right] \quad 12$$

Where k, wi, b, and f(n) are the number of elements in the input vector xi, the interconnection weight, the bias for the neuron (n), and the neuron output, respectively. ANN model in has several network architectures, training models, transfer functions, and optimal number of neurons [4]. The ANN model implemented in this study comprises feed-forward neural network architecture based on the back propagation learning principle. According to feed-forward ANN model which is the most suitable transfer function for training non-linear functions such as those observed in many chemical processes is the tangent sigmoid transfer function (tansig). The general formula for the tansig transfer function is given as

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \quad 13$$

1. Levenberg-Marquardt (LM) Training Algorithm

The Levenberg-Marquardt algorithm is an optimization method that combines the gradient descent and Gauss-Newton methods to minimize the cost function.

The weight update rule in the LM algorithm is given by [81]:$[\Delta w = -(J^\top J + \lambda I)^{-1} J^{\top e}]$

Where:

(w) is the vector of network weights, (J) is the Jacobian matrix of the network error with respect to the weights, (λ) is the damping factor that controls the transition between gradient descent (λ large) and Gauss-Newton (λ small) methods, (e) is the vector of errors for all training examples.

The Jacobian matrix J is defined as:

$$J = \frac{\partial e}{\partial w} \quad 14$$

Each element (J_{ij}) represents the partial derivative of the error (e_i) with respect to the weight (w_j).

The error vector (e) is defined as:

$$[e = y - \hat{y}] \quad 15$$

Where y is the vector of target outputs, and $\hat{y}$ is the vector of network outputs.

The weights are updated iteratively using the following steps:

1. Compute the Jacobian matrix J
2. Compute the error vector e.
3. Update the weights using the LM weight update rule:

$$w^{(k+1)} = w^{(k)} + \Delta w$$

Here, ($w^{(k)}$) is the weight vector at the k-th iteration.

2. Bayesian Regularization Training Algorithm

Bayesian regularization aims to improve the generalization of the neural network by incorporating a prior distribution over the network parameters (weights and biases) and updating this distribution based on the training data.

The cost function E with Bayesian regularization combines the mean squared error (MSE) and the regularization terms:

$$[E = E_D + \alpha E_W]$$

Where:

E_D is the data error term (mean squared error):

$$E_D = \frac{1}{2}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Here, y_i is the target output, and ($\hat{y}_i$) is the network output for the i-th training example.

E_W is the weight decay term (sum of squares of the weights):

$$E_W = \frac{1}{2}\sum_{j=1}^{m} w_j^2$$

Here, (w_j) represents the weights of the network, α is the regularization parameter that balances the trade-off between fitting the data and keeping the weights small.

Ranjan, Verma & Singh [83] applied Artificial Neural Networks (ANN) to optimize daily hydrocarbon production by determining optimal lift gas rates. The approach utilized well test information and calculations of vertical two-phase flow behavior, incorporating nodal analyses, gas lift databases, and gas lift monitoring systems. Various ANN models were trained and tested by adjusting the number of neurons in each layer, learning rate, training type, epoch, and minimum error. The results confirmed that their ANN model exhibited superior accuracy and performance compared to models previously published in the literature.

Khan et al. [50] employed artificial intelligence (AI) techniques to establish robust correlations for predicting oil rates in gas-lift wells. The AI techniques included Artificial Neural Network (ANN), artificial neuro-fuzzy inference systems, support vector machines, and functional networks. ANN was further utilized to develop a physical equation for predicting oil flow rate. The study collected separator test dataset from multiple wells operating on continuous gas lift, performing extensive data analytics before applying algorithms. The developed AI models were compared among themselves and with conventional empirical models, demonstrating the newly developed AI model's exceptional accuracy in predicting oil rates, exceeding 98%.

Abdollahi et al. [2] proposed an integrated model considering parameters like separator pressure, wells' bottom-hole pressure, and gas injection rates to define the entire system. The integrated system, incorporating PROSPER, REVEAL, and GAP, demonstrated enhanced accuracy by considering both surface and sub-surface aspects simultaneously. Additionally, an Artificial Neural Network (ANN) was employed to model the data, revealing the intricate relationship between bottom-hole pressure, separator pressure, and cumulative oil production. The ANN demonstrated effective modeling capabilities with a minimum average absolute relative deviation percent (AARD %) of 3% during training and 2% during testing subsets.

Elgibaly et al. [26] utilized conventional nodal analysis models and Artificial Neural Network (ANN) models based on gas lift databases to predict optimization parameters and optimize gas lift systems. Their study introduced a new theory regarding the relative importance of gas lift system inputs on output parameters. ANN models were trained and tested against nodal analysis models, showcasing the effectiveness of ANN in predicting optimization parameters.

Khan et al. (2019) proposed the use of machine learning (ML) algorithms, including Artificial Neuro Fuzzy Inference Systems (ANFIS) and Support Vector Machines (SVM), along with Artificial Neural Network, to develop a correlation for accurately predicting oil rates in artificial gas lift wells. The developed ANN model demonstrated remarkable accuracy, achieving a 99% prediction accuracy, outperforming empirical correlations and previously developed AI models. This work not only provides a highly accurate prediction model but also offers a functional equation for broader applicability in the field, simplifying the use of artificial intelligence in production reconnaissance schemes.

Marfo et al. [66] investigated the impact of artificial lift (gas lift) in the Jubilee Field on future production performance. Using historical production data, they predicted future inflow and outflow performances as well as tubing head pressure with PROSPER software and artificial neural networks. After applying gas lift, there was a notable increase in the future deliverability of all wells, with an 83.63% increment for Well A and a 61.64% increment for Well B. Additionally, Radial Basis Function Neural Network (RBFNN) and Backpropagation Neural Network (BPNN) models were developed to predict Tubing Head Pressure (THP). RBFNN showed superior performance during testing, exhibiting a correlation coefficient (R) of 0.96290 and Mean Absolute Percentage Error (MAPE) of 0.02134, outperforming BPNN with R of 0.96118 and MAPE of 0.02764 and the best computational time.

Khamehchi et al. [47] autilized artificial neural networks to determine the optimum gas lift injection rate. Their models incorporated data from production flow and well tests.

Mahdiani et al; [62] addressed instability in gas allocation optimization, emphasizing the consideration of instability as a constraint in the optimizer. Their results demonstrated that accounting for instability led to placing the optimal point in a stable zone with minimal production loss.

Tavakoli et al. [98] employed artificial neural networks (ANN) for modeling gas lift operation and genetic algorithms (GA) for gas allocation optimization among wells. They reported that ANN outperformed classic methods in creating Gas Lift Performance Curves (GLPC) and highlighted that optimizing an increased number of wells may not necessarily linearly increase the economic production capability.

Miresmaeili et al. [68] conducted a study on gas-lift operations, exploring the potential application of an Artificial Neural Network (ANN) using Bayesian Regularization (BR) and comparing its performance with the Levenberg–Marquardt (LM) back-propagation training algorithm. The study also employed the Teaching–Learning-Based Optimization (TLBO) algorithm to optimize well-rate and gas-lift allocation under injection capacity constraints. The efficiency of TLBO was assessed in terms of convergence rate and solution quality, comparing it with the Genetic Algorithm (GA).The study utilized extensive published data for model development and comparison. The proposed prediction and optimization model was tested in a gas-lift system over a specific reservoir life period. The BRNN and LMNN models achieved prediction accuracies of 99.9% and 99.5%, respectively, indicating strong predictive capabilities. Results showed that the BR model was more robust and efficient than the LM model. In terms of optimization, TLBO outperformed GA in gas allocation mapping for continuous gas-lift systems. The results demonstrate that BRNNs are more efficient and robust compared to classical back-propagation neural networks. TLBO, a recently proposed algorithm based on the teaching-learning process, showed satisfactory performance compared to the classical Sequential Quadratic Programming (SQP) method and the popular GA technique, particularly in terms of convergence and efficiency. A significant advantage of TLBO is its lack of additional algorithm parameters. While convergence rate depends on the function being optimized, TLBO exhibited superlinear convergence for the studied problem. TLBO is relatively easy to implement and proved promising for solving gas-lift optimization problems in this study.

The performance of an algorithm depends on the nature of the problem, and for the specific problem addressed in this paper, TLBO outperformed both GA and SQP. The approach used reservoir pressure as a representative parameter for the time-elapsing aspect of the system. The results indicate that the proposed scheme can achieve acceptable accuracy in modeling and optimizing production systems.

Choubineh et al. [18] examined the relationships commonly used to determine liquid critical-flow rates through wellhead chokes in producing oil wells. These relationships typically consider wellhead pressure, choke size, and gas-liquid ratio. The study proposed improving these correlations by incorporating three additional variables: gas specific gravity, oil specific gravity, and temperature. They introduced novel models for predicting liquid critical-flow rates, combining artificial neural networks (ANN) with teaching-learning-based optimization (TLBO) algorithms, using both three and six input variables. These models showed improved accuracy compared to nonlinear regression models, traditional ANN models, and existing correlations.

The accuracy of the developed models was assessed statistically using a dataset of 113 wellhead flow tests from oil wells in South Iran, with the complete data set included. Among the computational intelligence models developed, those using fuzzy logic (FN) and ANN were the most optimal. However, FN provided variability within the range of ±30 barrels per day (bpd), slightly higher than ANN's ±20 bpd, and was computationally more expensive. The ANN model achieved an R^2 of 0.99 and an average absolute percentage error (AAPE) of 2.56%. The developed AI model was validated by producing the lowest AAPE among all created AI models and other tested empirical models. The six-parameter ANN-TLBO model was the most accurate, yielding the best liquid critical-flow rate predictions for that dataset, with a coefficient of determination of 0.981, a root mean square error of 714, an average relative error of 2.09%, and an average absolute relative error of 6.5%. The six-parameter models outperformed the three-parameter models without overcomplicating functionality, justifying the use of all six input variables for improved predictions of wellhead choke liquid critical-flow rates. Relevancy factors calculated for the six-parameter ANN-TLBO model indicated that choke size and gas-liquid ratio had the maximum and minimum influence on determining liquid critical-flow rates, respectively.

Elgibaly et al. [26] conducted conventional nodal analysis models using Pipesim software to predict optimization parameters based on well flow surveys, reservoir and well parameters, and multiphase flow behavior calculations. Additionally, artificial neural network (ANN) models were developed using gas lift databases and gas lift monitoring systems. The ANN models were trained to determine the optimum structure and then tested against Pipesim models. The paper also introduced a new theory regarding the relative importance of gas lift system input data in predicting optimum parameters for gas lift systems. The study concluded that ANN has excellent capability for gas lift optimization prediction compared to conventional methods and can be used interchangeably. This technique can significantly aid in the immediate optimal design of gas lift wells.

Monyei et al. [70] provided a comprehensive characterization of oil wells and gas allocation for both limited and unlimited scenarios, presenting a cost-effective means for gas allocation in the oil and gas industry. Unlike earlier works that considered characterization and allocation separately, this study combined both processes, using generated values from characterization for gas allocation. A mathematical model was developed for characterizing gas allocation and oil production for the wells. Wells 1 and 2 were characterized using a quadratic equation, while the rest were characterized using linear curve fitting techniques. The combined MANN-MIGA approach was extensively applied to establish a relationship between gas allocated and oil produced for the six wells. These values were then used to compute the optimum gas allocation per well. The results demonstrated remarkable allocation efficiency using this approach. The mild intrusive property of the GA arises from its ability to allocate the minimum necessary gas for maximum oil production, avoiding gas values that exceed the optimal level. The MIGA generated optimized values that met the given conditions and yielded improved economic returns. The MANN-MIGA approach proves beneficial to the oil and gas industry, providing characterized equations and allocating gas based on preset conditions.

Okorocha et al. [79] investigated the impact of artificial neural networks (ANN) on gas lift optimization to enhance crude oil production. Data were collected from two wells and trained using the MATLAB 7.9 neural network toolbox. The data were divided into three parts: training (60%), validation (20%), and testing (20%), and a 20 hidden neuron multi-layer feed-forward neural network was utilized. The results indicated that the data from both wells were well-trained for accurate optimal prediction, as evidenced by an R-value close to 1 and a very low Mean Square Error (MSE). The average error between the actual and predicted data was minimal, even with a small subset of the general data.

The behavior of both wells followed the same pattern, leading to the conclusion that optimal production involves reduced wellhead parameters and gas compressor suction pressure, along with a higher gas compressor injection pressure. This study demonstrated the significant impact of artificial intelligence on optimizing crude oil production using gas lift. By examining the parameters affecting the production rate of the wells, the study confirmed that ANN significantly improves the accuracy of gas lift optimization predictions, thereby enhancing oil production rates for both wells.

The minimal MSE and R-values close to 1 for training, validation, and testing indicated a very good fit. Both wells exhibited similar trends for the properties considered, except for the gas compressor suction pressure, which remained constant for well 2. Overall, the study concluded that to achieve optimal production, it is necessary to reduce wellhead parameters and gas compressor suction pressure while increasing gas compressor injection pressure. This conclusion was drawn from the observed trends in both the predicted and actual data.

Shokir et al. [92] developed an artificial neural network (ANN) model using data extracted from PROSPER1 software, production logging tool (PLT) reports, and test separator data. Initially, the ANN model was trained and tested with synthetic data generated from PROSPER1 software. Subsequently, the model was validated using a set of test points collected from PLT reports. The ANN model accurately predicted well flowing bottom-hole pressure (P_{wf}) and well fluid rate (Qf).

To create an integrated production model (IPM) using GAP2 software, the values of Pwf and Qf for each well were utilized. The aim was to perform various gas lift optimization scenarios. Some wells were properly modeled in PROSPER using reliable PLT data, and all available well test data at the time were considered for quality assurance. These modeled wells provided a large synthetic data set for developing the ANN model. The ANN model was built with seven input variables (WHP, WHT, GOR, WC, IG, D/S, and GOR), one hidden layer with six neurons, and two output variables (P_{wf} and Qf). The developed ANN model was tested with separate PLT values that were not used in the training process, yielding highly accurate results. The model was then used to predict P_{wf} and Qf values for each well in the study field. The optimization processes resulted in an increase in oil production by 2,260 barrels of oil per day (BOPD) and a reduction in gas injection volume by 2.2 million standard cubic feet per day (MMSCF/day) in the field under study.

4.2 Meta-heuristic Algorithms

Heuristic and meta-heuristic optimization methods are widely used in various fields, including engineering and operations research, to find approximate solutions to complex optimization problems where traditional methods may be inadequate or infeasible. Heuristics are particularly useful for large-scale, combinatorial, and non-linear optimization problems [38. These methods rely on practical, experience-based techniques that exploit the problem’s structure and use rules of thumb to guide the search process. While they do not guarantee an optimal solution, they often produce sufficiently good solutions within a reasonable timeframe. Below is a more exhaustive discussion on various heuristic optimization methods, including their principles, applications, and limitations. Examples of heuristic methods include the greedy algorithm, which makes the locally optimal choice at each step with the hope of finding a global optimum, and the hill-climbing algorithm, which iteratively improves the solution by making small changes [17].

Meta-heuristic optimization methods are high-level strategies designed to find near-optimal solutions to complex optimization problems by exploring the search space more extensively and effectively than traditional heuristics. These methods are particularly useful for solving large-scale, non-linear, and combinatorial optimization problems where exact methods are impractical [36]. Meta-heuristics provide a general framework that can be adapted to various types of optimization problems, often incorporating multiple heuristics and using mechanisms inspired by natural processes, social behaviors, or physical phenomena. Below is an exhaustive discussion on various meta-heuristic optimization methods, including their principles, applications, and limitations. Examples of meta-heuristic methods include Genetic Algorithms (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) etc [104], [36]. These methods use mechanisms such as selection, mutation, crossover, temperature schedules, and swarm behavior to guide the search process. These methods can be broadly categorized into two main groups. The first comprises those inspired by nature (physical or biological phenomena), further classified into evolution-based, physics-based, and swarm-based methods [38]. The second category includes algorithms inspired by human phenomena [17].

In gas lift optimization, both heuristic and meta-heuristic methods are employed to enhance the allocation of gas to wells, thereby maximizing oil production. Heuristic methods can provide quick, initial assessments to identify promising regions within the solution space. For instance, a heuristic rule might allocate gas based on historical production rates and well performance, offering a straightforward way to prioritize gas distribution. Meta-heuristic methods, on the other hand, offer more robust and versatile solutions for gas lift optimization [17]. Genetic Algorithms (GAs), for example, evolve a population of potential solutions over several generations. Through processes of selection, crossover, and mutation, GAs explore a diverse set of possible configurations, allowing for a thorough search of the solution space. This approach helps in finding a near-optimal solution that effectively balances gas injection rates across multiple wells, taking into account the complex interactions and dependencies inherent in the system.

4.2.1 Genetic Algorithm for Gas Lift Optimization

The Genetic Algorithm (GA) is a prominent metaheuristic algorithm introduced by Holland in 1975, falling under the category of evolutionary algorithms commonly applied in Artificial Intelligence (AI) and computing [60]. As an optimization technique, GA addresses both unconstrained and constrained optimization problems through a natural selection process inspired by evolutionary biology. The fundamental processes of selection, crossover, and mutation guide the algorithm in establishing and adjusting a population of potential solutions. Unlike traditional approaches that focus on a single point or solution, GA explores a range of solutions by iteratively modifying the population, selecting random individuals as parents, and generating the next generation of children. Over successive generations, the population evolves towards an optimal solution, marking a departure from conventional optimization methods [5].

However, the GA method has a drawback, as it requires a significant number of function evaluations, making it a computationally expensive process. To address this, various variations and extensions have been developed to enhance convergence speed, maintain population diversity, and avoid binary string encoding [84], [98].

Okorocha et al. [79] conducted a comprehensive review of gas lift optimization methods, emphasizing strategies based on artificial intelligence (AI) and machine learning (ML). Their review highlighted the potential benefits of implementing optimization strategies in gas lift operations, including enhanced profitability, reduced operational costs, and extended well life.

Martinez et al. [67] described the application of a genetic algorithm (GA) to optimize production in oil fields utilizing the gas lift method. The computational methodology proved effective and efficient, assisting production engineers in assigning optimum gas-injection rates to individual wells while considering the available total gas supply for the field. The GA-based gas-lift optimization system, integrated into a computer-aided analysis and optimization system for gas lift wells, facilitated an intelligent search in the gas-injection rate space, providing a distribution of gas-injection rates compatible with field constraints and maximizing total liquid production.

Ray and Sarker [86] proposed an evolutionary algorithm based on genetic algorithms to solve practical gas lift optimization problems in oil production. Gas lift involves injecting gas into oil wells to facilitate oil extraction from the tubing. The challenge lies in determining the optimal amount of gas to inject into each well, considering constraints on daily gas availability and maximum injection volumes for individual wells. The objective is to maximize daily oil production from the reservoir. Their study introduced a multiobjective formulation, offering improved solutions over existing practices and demonstrating significant enhancements.

Ebrahimi and Khamehchi [23] presented a support vector machine (SVM) approach for gas lift optimization, replacing reservoir simulation software with a trained SVM to achieve faster run times. The optimization process for a real field was performed using particle swarm optimization (PSO) and genetic algorithm (GA). PSO was employed to determine optimal SVM parameters, and Taguchi experiment design helped identify optimum GA and PSO parameters.

Binder [11] proposed decision support tools to increase production from a subsea production system. The approach involved well models, numerical optimization, and both static and dynamic optimization, addressing complex MINLP problems. Static optimization showed potential for increased oil production, while the dynamic approach yielded inconclusive results. The methods, implemented in MATLAB, were tested on predefined scenarios, emphasizing the potential of static optimization for enhancing overall production.

Zerafat, Ayatollahi, and Roosta [108] addressed gas rate distribution using genetic algorithms (GA) and ant colony algorithms, solving a problem with five wells. Their method yielded more precise results compared to previous approaches.

Mahdiani et al. [62] developed a model using modern heuristic algorithms for optimal control of a gas-lifted field. Initially, a reservoir and well model for a gas lift well was developed, and the best-fitted correlations were selected using experimental data points. Four optimization algorithms were then employed: two common heuristic algorithms (genetic algorithm and simulated annealing) and two recently introduced algorithms (Moth Swarm Algorithm and Grasshopper Optimization Algorithm) to determine the optimal injection lift gas rates for the wells.

The results of these four algorithms were compared with each other and with other allocation scenarios. Various aspects of the injection and production rates for different wells, along with their cumulative rates and net present value (NPV) paths, were analyzed. The findings illustrated that the Moth Swarm Algorithm (MSA) achieved an optimal point with higher production. Additionally, MSA identified a specific control path that required less lift gas and a smaller compressor, differing significantly from the control paths found by other optimization algorithms.

Furthermore, the study observed a new long-term instability in flow, which was attributed to the drainage area of each well. The control path for each well was discussed, and it was concluded that the genetic algorithm (GA) could identify the most stable path.

Al-Masonry et al. [6] assessed the feasibility of using the genetic algorithm (GA) technique to optimize the distribution of continuous gas-lift injection flows in the Zubair oil field, which comprises 10 gas-lift injected wells. This optimization was achieved through numerical simulation and modeling studies. The overall production rate of the field increased significantly from 15,767 STB/day to 19,847 STB/day as a result. The study included sensitivity analyses of reservoir pressure and water cut to examine their potential impacts on well performance and efficiency throughout the field's lifecycle. By incorporating examples from economic analyses, the research provides a deeper understanding of the technical and economic benefits of employing gas lift techniques. Although the use of GA for this purpose is not new, this work discusses GA-based optimization methodologies specifically for enhancing oil production rates through gas lifting in the Zubair oil field. The study outlines a step-by-step model for optimizing gas injection rates assigned to specific wells within the network, even when gas injection rates are limited. This model is designed to be straightforward and practical, serving as a useful guide for front-line production technicians involved in the development and design of gas-lift systems.

Namdara and Shahmohammadi [72] developed models to optimize the amount of injected gas in a heavy oil reservoir in western Iran using Excel Solver software. The results were compared with optimization methods using genetic algorithm (GA) and particle swarm optimization (PSO) algorithm. To improve the accuracy of calculating oil production relative to gas injection amounts, the empirical correlations were modified to fit the gas lift performance curves, and a new correlation was developed. The results indicate that the model developed by the authors has the highest accuracy compared to other methods. Furthermore, the results demonstrate that the accuracy of Excel Solver software is comparable to that of GA and PSO algorithms.

Ray and Sarke [86] introduced a practical gas lift optimization problem and addressed both single and multi-objective versions using their multi-objective (MO) evolutionary algorithm. Their method demonstrated superior results compared to previous reports for both the six-well and fifty-six-well problems. For the six-well problem, their solution achieved an additional 35 BPD (equivalent to 12,775 barrels annually), and for the fifty-six-well problem, their solution provided an additional 243 BPD (equivalent to 88,695 barrels annually) compared to the results reported by Buitrago et al. [12].The study was extended to include the results of multi-objective formulations, highlighting additional benefits derived from using their MO evolutionary algorithm. The consistency and efficiency of the algorithm were demonstrated through multiple runs. The MO approach is particularly attractive as it eliminates the need for daily optimization of gas lift operations. Unlike methods that rely on functional or slope continuity of the objective or constraint functions, this approach can easily be coupled with functional approximation models or surrogate models of oil extraction versus gas usage for each well. Given the nonlinear nature of oil extraction versus gas usage, which varies across wells, the authors are exploring the possibility of automatically creating surrogate models based on data. These models would then be used within the optimization framework to derive optimal gas allocation for maximum oil extraction from the field.

Ghaedi et al. [29] employed a hybrid genetic algorithm (HGA) to optimize gas allocation across groups of wells in three different fields. The HGA proved to be an efficient optimization method, demonstrating significant improvements in gas lift allocation: an increase of 9.3 STB/day for a field with 6 wells and 2,741 STB/day for a field with 56 wells, relative to the best previous results. This study clearly illustrates the impact of gas lift optimization on field production rates. For example, in an Iranian field, optimal injection of 100 MMSCF/day of gas led to a production rate increase of 280.6%, from 6,502 STB/day to 18,249.67 STB/day. These applications highlight the benefits of optimal gas allocation. The results suggest that stochastic optimization methods like HGA are particularly effective when managing a large number of wells, as evidenced by the substantial improvements in the field with 56 wells. The HGA demonstrated superior gas allocation to the wells compared to previous methods, highlighting its effectiveness in maximizing field oil production rates.

Miresmaeili et al. [68] introduced an economic approach addressing the gas-lift allocation problem in a time-dependent manner using an estimation of distribution algorithm (EDA), alongside a simple genetic algorithm (GA) and particle swarm optimization (PSO). The aim was to optimize injection profiles and gas-lift start times to maximize the net present value (NPV) of the project. The optimization procedure was tested on a four-well production system with a typical reservoir model over five years of production. The performance of the EDA was compared with GA and PSO. Despite the stochastic nature of evolutionary algorithms, which can lead to variations in results across multiple runs, each algorithm generally converged to a local solution. The EDA demonstrated superior performance, showing a 17.3% increase in profit compared to the base case, which did not consider gas-lift start times as a decision variable. This underperformance highlighted the importance of incorporating start times in the optimization process. For the four-well field, the EDA-optimized schedule led to significant profit gains, suggesting that larger fields with more wells could see even greater benefits from such optimization. The nonlinear nature of the problem caused GA and PSO to get stuck at local optima, while the EDA, with its knowledge-based nature, was able to find better solutions. This highlighted the limitations of fixed optimization operators in GA and PSO for high-dimensional problems and demonstrated the advantages of using a more intelligent and efficient optimization algorithm like EDA.

Rasouli et al. [85] introduced a novel method called surrogate integrated production modeling, which leverages an artificial neural network (ANN) to predict gas-lift performance based on a database of oil production. This approach combines the neural network with a genetic algorithm (GA) for long-term optimization of gas-lift allocation in a group of wells, considering real constraints. The study focused on an Iranian oil field with volatile oil and a reservoir pressure of 3500 psi, using a synthetic model due to security reasons and lack of access to geological maps.

The simulation was conducted with varying gas injection rates, ranging from 0 MMSCF/day to 10 MMSCF/day in 1 MMSCF/day intervals. The results included numerous parameters such as oil and water production rates, reservoir pressure, and temperature profiles, presented in both graphical and tabulated formats. The simulation outputs were fed into the surrogate integrated production model to predict oil and water production at different gas injection rates over time. High water cut was identified as a significant issue in the field, leading to the selection of gas lift to enhance production rates. The hybrid GA optimizer software, which integrates ANN with GA, was used to solve the complex gas-lift long-term non-linear programming (NLP) problem, optimizing the model throughout the project's life. Although the algorithm did not find the global optimum, it achieved a near-optimum solution. The ANN predicted oil production for each well, serving as the fitness function for the genetic optimizer. The key characteristic of gas-lift injection performance-production rate increasing with gas injection up to a certain limit and then declining was validated by the simulation output. The ANN section of the developed software predicted oil production with an average relative absolute error of about 3%, indicating good predictive accuracy. The simulation outputs were fed into the hybrid optimizer, which used the back-propagation model for the ANN. Custom code was written to couple ANN with GA, using production cash flow as the fitness function, calculated based on constant oil price and production rate at the start of each year. The genetic optimizer was configured with a population size of 500, a crossover rate of 0.5, and a mutation rate of 0.1. ANN training utilized 120 production data points, which could be adjusted during optimization.

In each optimization step, GA generated a population with different gas injection rates, and the fitness function required oil production calculated by ANN. The results of the optimization for controlling gas injection rates over a 10-year production life were presented, demonstrating the method's effectiveness in indirectly predicting gas-lift performance curves (GLPC) using ANN and limited simulation software output. This procedure can be applied to optimize gas-lift operations in similar fields and manage other uncertain parameters, such as compression costs, providing a guideline for nonlinear continuous production optimization problems with real constraints.

Ghassemzadeh and Pourafshary [30] developed a novel approach that incorporates the time factor into the gas lift optimization process. They employed a piecewise cubic Hermite function to model gas lift performance, utilizing a Genetic Algorithm (GA) for optimizing gas allocation to multiple wells. This model was used to investigate the impact of gas lift initiation time on reservoir life and net present value (NPV). Their calculations revealed that initiation time significantly influences the optimization procedure and should be considered a crucial factor in gas allocation problems for real fields. The study presented a new methodology for assessing the effect of gas lift initiation time on the optimization process. A procedure was developed to determine the best initiation time for gas lift operations to maximize profit for a naturally producing, depleting reservoir. The proposed optimization algorithm was compared with previous models and its accuracy was validated. By integrating this algorithm with an economic model and calculating the NPV for different initiation times, the optimal time for starting gas lift operations was identified. The approach was applied to a large field under gas lift, demonstrating that, for typical oil and gas discount rates, delaying the operation by just six months resulted in a $12 million benefit. This study, distributed under the terms of the Creative Commons Attribution License, allows for unrestricted use, distribution, and reproduction in any medium, provided the original authors and source are credited.

Namdar and Shahmohammadi [72] proposed a new correlation to address two key aspects of gas lift optimization: 1) fitting the gas lift performance curve (GLPC) and 2) optimizing the allocation of gas between wells. To enhance the speed and accuracy of solving gas allocation optimization problems, improvements in both steps were necessary. For the first step, a new correlation was introduced, which not only increased the fitting accuracy but also improved optimization speed by reducing the number of constants in the correlation. To enhance the performance of the second step, the water cycle optimization algorithm was utilized and its results were compared with those from previous studies using the teaching–learning-based optimization (TLBO) algorithm, continuous ant colony optimization (CACO) algorithm, genetic algorithm (GA), and particle swarm optimization (PSO) for solving the five-well Nishikiori index problem. The findings suggested that the water cycle optimization algorithm performed excellently in terms of convergence rate, avoiding local optima, and repeatability. As a novel application, the gas allocation between the wells of a heavy oil field in southwest Iran was optimized with predetermined oil production rates. The goal was to minimize the amount of gas required to achieve these predetermined oil rates using the water cycle optimization algorithm. The results indicated that optimization is particularly critical at lower oil production targets, leading to higher additional oil production. The GA algorithm showed high dependency on population size and tended to get trapped in local optima at lower populations, whereas the water cycle and PSO algorithms demonstrated less population dependency and better repeatability. In terms of convergence rate, the water cycle algorithm significantly outperformed the PSO and GA algorithms. At higher populations, the performance of the PSO and GA algorithms notably decreased in speed. The PSO algorithm converged to the optimal solution faster than the GA algorithm in smaller populations. In optimization problems aiming for a predetermined oil production amount, the closer the target oil production rates are to the maximum oil production rate in the gas lift process, the less additional oil can be produced through optimization. Consequently, optimization is more critical and yields more extra oil at lower production targets.

4.2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) is a metaheuristic algorithm inspired by the collective behavior of animal swarms, particularly the flocking of birds. Kennedy and Eberhart introduced this algorithm in 1995 [34]. PSO iteratively enhances candidate solutions, mimicking the movement and interactions of a swarm. Despite being faster and more cost-effective than similar evolutionary algorithms, PSO has some drawbacks. Its convergence rate does not necessarily improve with more iterations, and the quality of solutions depends on weighting coefficients and algorithm parameters. In a study focused on gas lift optimization for five oil wells in Iran, PSO was employed, recommending a new gas lift performance curve-fit for faster and more efficient computation [34].

4.2.3 Ant Colony Optimization

Ant Colony Optimization (ACO) is another metaheuristic algorithm inspired by the foraging behavior of real ants. Ants deposit pheromones to mark favorable pathways for other colony members. ACO employs a similar mechanism to solve optimization problems. It is known for being cost-effective and fast. Continuous Ant Colony Optimization algorithms have been utilized to optimize gas allocation for wells in different fields, demonstrating superior performance compared to other optimization methods in terms of gas allocation [29], [72].

4.3 Fuzzy Logic

Fuzzy logic is an approach to computing that operates on "degrees of truth" rather than the traditional binary true/false values. This concept is particularly useful in dealing with uncertainty and imprecision, making it a valuable tool in optimization modeling, especially in complex and uncertain environments like gas lift optimization. Fuzzy logic systems (FLS) use fuzzy sets to handle uncertain and imprecise information. These sets define a membership function that assigns a degree of membership ranging from 0 to 1. In optimization, fuzzy logic helps model problems where variables and constraints are not precisely known but are instead fuzzy. This is crucial in scenarios like gas lift optimization, where many parameters are not sharply defined due to the inherent variability in reservoir conditions [5].

There are several types of fuzzy logic methods, each with distinct characteristics and applications. Type-1 Fuzzy Logic Systems (T1FLS) use crisp membership functions for fuzzy sets and are applied in simpler fuzzy systems with clear, well-defined membership functions. Type-2 Fuzzy Logic Systems (T2FLS) use fuzzy membership functions where each element has a range of membership values, providing more robustness in handling higher levels of uncertainty and imprecision [83]. Fuzzy Inference Systems (FIS) come in different forms, such as Mamdani FIS, which uses fuzzy sets for both the antecedent and consequent parts of rules; Sugeno FIS, which uses fuzzy sets for antecedents but a crisp function for consequents; and Tsukamoto FIS, which uses fuzzy sets for antecedents and outputs fuzzy sets with monotonically changing membership functions. Neuro-Fuzzy Systems combine neural networks with fuzzy logic to learn membership functions and rules from data, making these systems adaptive and capable of improving performance over time. Fuzzy Decision Trees use decision nodes and leaf nodes to represent fuzzy rules and fuzzy sets, respectively, and are used for classification and regression tasks with fuzzy inputs and outputs [68].The Adaptive Neuro-Fuzzy Inference System (ANFIS) integrates the learning capabilities of neural networks with the qualitative approach of fuzzy logic, creating a powerful tool for modeling complex systems where precise mathematical models are difficult to develop [50]. ANFIS is structured so that each layer of the system corresponds to a specific operation in the fuzzy inference process, such as fuzzification, rule evaluation, and defuzzification [49]. It typically uses a hybrid learning algorithm that incorporates both backpropagation (for optimizing premise parameters associated with the membership functions) and a least-squares method (for optimizing consequent parameters associated with the linear combination in the fuzzy rules).

In the Input Layer, values are passed to the next layer. The Fuzzification Layer represents membership functions, transforming input values into fuzzy values. The Rule Layer represents fuzzy rules, performing fuzzy AND operations to determine the firing strength of the rules. The Normalization Layer normalizes the firing strengths from the previous layer. In the Defuzzification Layer, nodes are associated with rule consequents and compute weighted consequent values. Finally, the Output Layer sums the outputs from the defuzzification layer to produce the final output [13].

ANFIS stands out from traditional fuzzy logic systems (e.g., T1FLS, T2FLS, Mamdani, Sugeno, Tsukamoto) due to its learning capability. Unlike traditional systems, ANFIS incorporates neural network learning algorithms to optimize membership functions and rules based on input-output data pairs. This adaptive learning capability makes ANFIS more powerful in modeling complex and dynamic systems [19], [20]. The hybrid structure of ANFIS combines the qualitative approach of fuzzy systems with the quantitative learning methods of neural networks. This dual approach allows ANFIS to handle both the imprecision of fuzzy systems and the adaptive learning of neural networks. ANFIS employs a hybrid learning method that combines back-propagation and least-squares estimation to optimize both the premise and consequent parameters, improving the model's accuracy and convergence speed [19]. In terms of application flexibility, while traditional fuzzy systems are generally rule-based and require expert knowledge to define the rules and membership functions, ANFIS can automatically generate these from data, making it more flexible and less reliant on expert input [28], [19].

In gas lift optimization, fuzzy logic offers several advantages. One significant merit is its ability to handle uncertainty, as gas lift optimization involves numerous uncertain parameters such as reservoir characteristics, fluid properties, and well performance [28]. Fuzzy logic effectively models these uncertainties, providing more robust optimization solutions. Its flexibility in modeling allows for the inclusion of expert knowledge and heuristic rules, which are often crucial in complex optimization problems like gas lift optimization. Additionally, fuzzy logic can capture the non-linear relationships between different variables in gas lift optimization, such as the relationship between gas injection rates, pressure, and oil production rates [7]. The rule-based framework of fuzzy logic is also easy to understand and implement, making it straightforward to incorporate rules like "If gas injection rate is high, then oil production rate is likely high" into the model. Moreover, ANFIS can model the complex, non-linear relationships between gas injection rates, pressures, and oil production rates more effectively than traditional fuzzy systems. Its adaptive learning capability allows it to continuously improve and adjust the model based on new data, ensuring more accurate predictions and optimal control strategies [76], [7]. The integration of expert knowledge with data-driven learning in ANFIS provides a balanced approach to handling the inherent uncertainties and complexities of gas lift operations, offering robust and reliable optimization solutions.

Despite these advantages, fuzzy logic also has limitations. One challenge is the potential for rule explosion, where the number of rules can grow exponentially in complex systems with many variables, making the system difficult to manage and interpret. Another limitation is the subjectivity involved in defining appropriate membership functions and rules, which can affect the robustness and accuracy of the model [63]. Computational complexity is another concern, especially with advanced fuzzy logic systems like Type-2 FLS, which can be computationally intensive. This may be a limitation for real-time optimization in gas lift operations [76]. Integrating fuzzy logic with other methods can address these challenges. ANFIS also has its limitations include computational complexity, scalability issues, dependency on high-quality data, susceptibility to local minima, interpretability challenges, sensitivity to initial parameter choices, risk of overfitting, and limited handling of dynamic systems [63]. These limitations need to be carefully considered when applying ANFIS to complex optimization problems, such as gas lift optimization, to ensure that the model remains practical and effective. Generally, while fuzzy logic is powerful, it often needs to be combined with other optimization techniques, such as genetic algorithms or neural networks, to handle complex optimization problems efficiently.

Table 1 summarizes some of the notable artificial intelligence optimization methods, their principle, and applicability to gas lift optimization, their advantages and limitations.

Table 1: Summary of artificial intelligence optimization methods [41]

Type of Optimization Method	Principle	Application to Gas Lift Optimization	Advantage	Limitation
Artificial Neural Networks (ANN)	Mimics the human brain's network of neurons to model complex patterns and relationships in data.	Used to predict production rates based on historical data, optimizing gas injection rates.	Can model complex, non-linear relationships; adaptable to changing data.	Requires large datasets and significant computational resources; can be a "black-box" model, difficult to interpret.
Genetic Algorithm (GA)	Uses principles of natural selection and genetics to evolve solutions to optimization problems over generations.	Optimizes gas allocation by evolving a population of solutions, balancing gas injection rates across wells.	Explores a diverse set of solutions; good for complex, multi-modal problems.	Computationally expensive; may converge to local optima; requires careful parameter tuning.
Fuzzy Logic	Utilizes degrees of truth rather than binary logic to handle uncertainty and approximate reasoning.	Models uncertain and imprecise information in gas lift systems, optimizing operational parameters.	Handles uncertainty well; provides interpretable rules and reasoning.	Can be less precise; requires expert knowledge to define membership functions and rules.

5. Overview of Artificial Intelligence Optimisation Techniques Applied to Gaslifted Oil Fields

Several AI techniques have been deployed to gaslifted oilfields with notable production improvement and field oil recovery. Table 2 below summarises the well-known examples in literature on the successes of AI techniques in enhancing oil production in gaslifted oilfields.

Table 2: Summary of AI Techniques Applied to Gaslifted Oilfields

Technique	No of Wells	Optimized Cumulative Oil (%)	References
GA	1300	2%	Movaheed et al., 2024
ANN/GA	30	5%	Miao et al, 2024
DRL	200	25%	Docharty et al., 2022
RBFNN	2	72.64%	Marfo et al., 2024
PSO	56	3%	Lopez et al., 2019
GA	56	3.2%	Lopez et al., 2019
TLBO	56	4.23%	Miresmaeili et al., 2019
GA	10	25.88	Al-Mansory et al., 2024

GA	43	187%	Al-Juboori et al., 2020
GRG	5	1.28%	Zerefet et al., 2009
GA	5	1.17%	Zerefet et al., 2009
ACO	5	1.16%	Zerefet et al., 2009
GA	56	1.12%	Ray and Sarker, 2007
HGA	6	0.25%	Ghaedi et al., 2017
GA	5	35.55%	Tavakoli et al., 2017
GA	4	17.06%	Miresmaeili et al., 2019
PSO	4	17.06%	Miresmaeili et al., 2019
EDA	4	17.21%	Miresmaeili et al., 2019
GA	3	57.9%	Namder, 2019
GABC	10	0.93%	Fadilah et al., 2019
GA	56	69.88%	Ghassemzadeh and Pourafsharay, 2014

The data presented in Table 2 and plotted in figure 1 reveals a comparative overview of different optimization techniques applied to oil well production, highlighting both the number of wells involved and the resulting percentage increase in optimized cumulative oil production, along with their respective references.

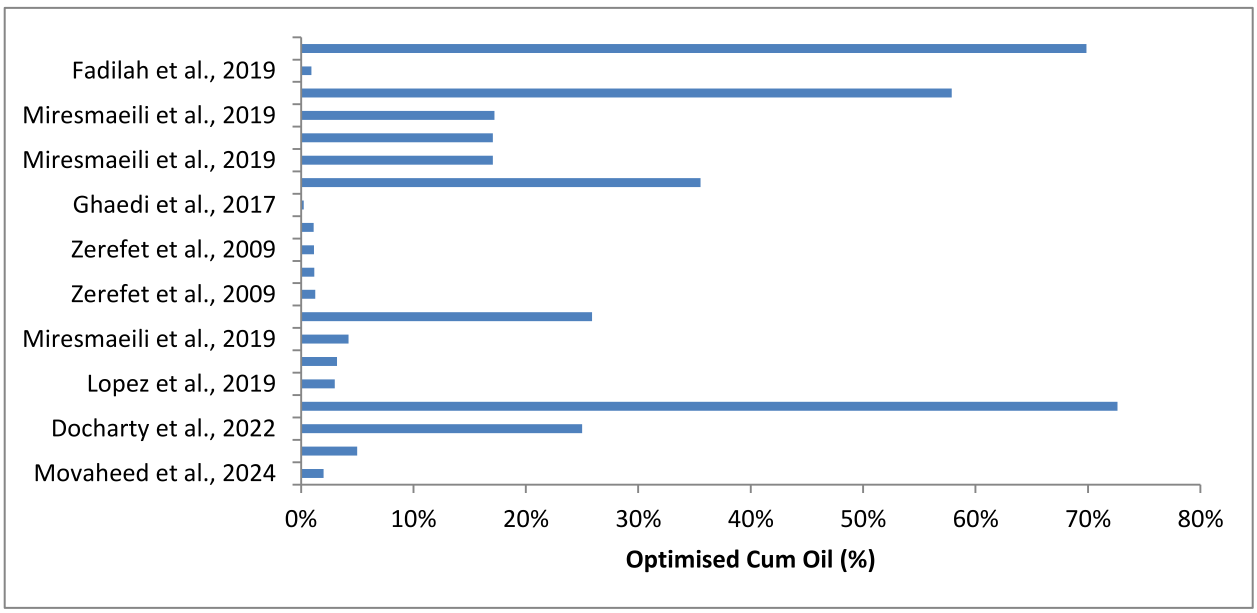

Figure 1: Optimised cumulative oil recovery percentage from utilization of AI techniques in gas lift field optimisation

Movaheed et al. [64] reported a modest 2% improvement in cumulative oil production using Genetic Algorithm (GA) across a substantial dataset of 1300 wells, suggesting that while GA was applied at scale, the performance gains were minimal, potentially due to limitations in convergence or the complexity of the problem at such scale. In contrast, Miao et al. (2024) employed a hybrid approach combining Artificial Neural Networks and Genetic Algorithms (ANN/GA) on just 30 wells, achieving a more impressive 5% gain, reflecting the strength of hybrid models in capturing nonlinear behaviors in well performance.

Docharty et al. [21] demonstrated a significant leap in performance with Deep Reinforcement Learning (DRL), achieving a 25% increase over 200 wells, indicating the effectiveness of DRL in handling dynamic decision-making and optimization in complex reservoir systems. Even more notable is the result by Marfo et al. [66], who utilized Radial Basis Function Neural Networks (RBFNN) on just two wells and reported a staggering 72.64% improvement, although the small number of wells raises questions about generalizability and whether the result reflects localized optimization rather than scalable efficacy.

Lopez et al. [60] evaluated both Particle Swarm Optimization (PSO) and Genetic Algorithm on 56 wells each, with PSO yielding a 3% improvement and GA slightly outperforming it at 3.2%, suggesting a marginal benefit of evolutionary strategies over swarm-based methods in this context. Miresmaeili et al. [68] explored the Teaching-Learning-Based Optimization (TLBO) method, reporting a 4.23% improvement over the same set of 56 wells, highlighting TLBO's comparative strength. Al-Mansory et al. [6] applied GA on 10 wells and achieved a 25.88% gain, reflecting better performance possibly due to problem-specific tuning or favorable reservoir conditions.

A particularly extraordinary result is observed, where GA was used on 43 wells and delivered a 187% increase in cumulative oil, an outlier that may stem from a baseline with very low initial production or highly inefficient previous operations. Zerefet et al. [100] compared multiple methods on a consistent set of five wells: Generalized Reduced Gradient (GRG) achieved 1.28%, GA gave 1.17%, and Ant Colony Optimization (ACO) showed 1.16%, suggesting minimal variation in outcome across these classical optimization methods, with GRG slightly ahead.

Ray and Sarker [86] applied GA to 56 wells and reported a low improvement of 1.12%, perhaps reflecting suboptimal parameterization or a highly constrained optimization scenario. Ghaedi et al. [29] used a Hybrid Genetic Algorithm (HGA) on six wells and attained only a 0.25% gain, indicating limited effectiveness, possibly due to poor hybridization strategy or algorithmic inefficiency. Tavakoli et al. [98] recorded a more impressive 35.55% gain from GA applied on five wells, while Miresmaeili et al. [68] found that GA, PSO, and Estimation of Distribution Algorithm (EDA) each achieved roughly 17% optimization when applied on four wells, suggesting comparative efficacy across these different algorithmic approaches on the same problem set.

Namder & Shahmohammadi [72] reported a 57.9% increase with GA on just three wells, again raising issues of scalability and reproducibility. Finally, Ghassemzadeh and Pourafsharay [30] achieved a high 69.88% increase using GA on 56 wells, pointing to a successful application of the algorithm, possibly due to a well-calibrated model or optimization of a field with substantial room for production gains.

Overall, the data highlights significant variability in the effectiveness of optimization methods depending on factors such as the technique employed, the number of wells, data quality, and the baseline production levels. While advanced methods like DRL, RBFNN, and some GA applications yield substantial gains, others provide marginal improvements, underlining the importance of context-specific algorithm selection and tuning.

5. CONCLUSION

The optimization of gas lift operations remains a fundamental aspect of enhancing oil production efficiency and ensuring economic sustainability in petroleum engineering. Conventional optimization techniques, primarily based on deterministic and numerical methods, have shown limited effectiveness in addressing the intrinsic complexity, non-linearity, and high-dimensional nature of gas lift systems. These methods often suffer from computational inefficiencies, sensitivity to initial conditions, and difficulties in navigating multi-modal solution landscapes—factors that collectively contribute to suboptimal system performance in real-world applications.

In recent years, artificial intelligence (AI) techniques have gained prominence as promising alternatives to traditional approaches due to their capacity to model non-linear systems, handle noisy data, and adapt to evolving operational dynamics. Among these, artificial neural networks (ANNs) have demonstrated strong predictive performance by capturing hidden patterns in historical production and injection data. However, ANNs require extensive training datasets, high computational power, and often operate as black-box models, making them challenging to interpret and validate in operational settings where transparency and explainability are critical.

Meta-heuristic algorithms such as genetic algorithms (GAs) offer adaptive search capabilities and global optimization potential by simulating evolutionary processes. These methods are particularly suited for navigating the vast solution spaces associated with multi-well, multi-constraint gas lift optimization problems. Nonetheless, they are computationally intensive and prone to premature convergence to local optima if not carefully tuned. Their performance is highly sensitive to algorithmic parameters such as crossover rates, mutation probabilities, and population diversity, necessitating extensive experimentation for optimal configuration.

Fuzzy logic systems provide a viable mechanism for incorporating expert knowledge and handling the inherent uncertainty and imprecision of gas lift operations. By employing linguistic rules and membership functions, fuzzy inference systems can make interpretable decisions in environments characterized by ambiguous or incomplete information. However, the formulation of effective fuzzy models is heavily reliant on domain expertise, and their resolution is often limited by the granularity of the rules and membership definitions.

Recognizing the limitations of these individual AI approaches, there is a clear impetus toward the development of hybrid intelligent models that synergistically combine the strengths of machine learning, meta-heuristics, and fuzzy systems. Such hybrid frameworks aim to leverage the predictive modeling capabilities of ANNs, the exploratory power of GAs, and the decision reasoning structure of fuzzy logic to produce more robust, scalable, and interpretable optimization solutions. For example, neuro-fuzzy systems augmented with genetic tuning mechanisms can dynamically adapt fuzzy rules and membership functions while learning from real-time data, thereby improving performance under varying reservoir and surface conditions.

Future research should prioritize the formulation, training, and deployment of these hybrid models within integrated digital oilfield environments. Emphasis should be placed on multi-objective optimization strategies that balance production efficiency, energy consumption, and equipment wear. Furthermore, the integration of real-time data acquisition systems, advanced sensor technologies, and edge computing will enable continuous model refinement and faster decision cycles.

To ensure practical relevance and adoption, collaboration between academia and industry is essential to provide domain-specific insights, facilitate field validation, and address issues related to model generalizability, robustness, and interpretability. By embracing AI-driven hybrid optimization techniques, the petroleum industry can significantly enhance gas lift efficiency, reduce operational costs, and contribute to the long-term sustainability of hydrocarbon resource development.

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