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Artificial Intelligence Models for Flowing Bottomhole Pressure Estimation: State-of-the-Art and Proposed Future Research Directions

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***Abstract*— Flowing bottom hole pressure (FBHP) is an important parameter during evaluation of conventional and unconventional oil and gas resources and is mainly used for production optimization, calculation of productivity index and assessment of well performance. FBHP in an oil well is a multifaceted parameter that has a number of factors affecting it. It is characterized by high stochasticity, non-linearity and non-stationarity. Traditionally, production engineers rely on physics-based models and empirical correlations calibrated with measurements from offset wells to calculate FBHP. However, in recent times, there has been a significant shift towards the use of cutting-edge artificial intelligence (AI) algorithms. The present study is designed to provide a historical account of past and present models developed with AI algorithms for estimating FBHP. To achieve this, a deep bibliographic survey was conducted using various peer reviewed journals and relevant oil and gas conference papers. The results of the review have been presented in tables to avoid ambiguity. To make the review novel, the merits and demerits of each of the AI models for FBHP prediction are highlighted and discussed in detail. In this direction 54 models were isolated from the literature. The findings indicate that artificial neural network is the preferred algorithm by several researchers. However, the transparency and interpretability issues associated with the neural network algorithm has propelled researchers to explore the possibility of deploying physics informed machine learning techniques to model FBHP. This review would serve as a valuable reference for production engineers seeking information on AI models for FBHP estimation.**

***Keywords*—Artificial intelligence; flowing bottomhole pressure; predictive models; oil and gas.**

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I. INTRODUCTION

In evaluating the productivity of oil and gas wells, the flowing bottomhole pressure remains an indispensable parameter for this purpose [1]. For instance, production monitoring is possible using the FBHP [2]; the design of well facilities, such as tubing size and well head, can be assured using FBHP [3]; the operational management of downhole equipment is possible by the FBHP [4]; the reduction of oil cost per barrel [5], etc. Despite the significant role of FBHP in the production of oil and gas, its accurate determination from an engineering perspective remains unsatisfactory. This inadequacy can be attributed to the intricate interactions among numerous variables influencing FBHP. The complexity arises because hydrocarbons are rarely produced as single-phase fluids; instead, they exist as multiphase fluids consisting of oil, gas, and water. These multiphase fluids exhibit distinct flow regimes, rendering the entire flow process intricate and challenging to comprehend. Due to the complicated nature of multiphase flows, the computation of flowing bottom-hole pressure becomes a convoluted task.

One method commonly utilized to evaluate bottom-hole pressure involves the utilization of down-hole gauges capable of recording vast quantities of bottom-hole pressure data. Despite the merits of this approach, two limitations arise the associated expenses that are prohibitively high and their poor performance in processing noisy data [2]. In practical terms, when a well is operated with deep-pumping equipment, the calculation of BHFP becomes the preferred method of determination [6]. To this end, production engineers utilize empirical correlations and physics-based models calibrated with real physical observations from offset wells to determine

FBHP [7]. It should be noted that these correlations and models were predominantly developed and validated within specific operating conditions. Consequently, their performance may be compromised when applied beyond these boundaries [8].

In recent years, there has been a growing trend in the utilization of artificial intelligence (AI) based methods within the field of petroleum engineering [9]. These methods have successfully tackled various traditional and non-conventional problems, including FBHP. Given the difficulty faced by the mechanistic models and the deficiencies of downhole pressure gauges, the prediction of FBHP is more likely to be achieved using AI-based modeling frameworks capable of handling nonlinear relationships between FBHP and other wellbore parameters. While numerous AI-based models exist for predicting FBHP, there appears to be no universal model. Furthermore, it is observed that despite the avalanche of AI-based predictive models for FBHP estimation, no work has yet done a comprehensive review and critique of these models. The current study is aimed at surveying past and recent literature on the applicability of AI methods for FBHP modeling with the primary aim of critiquing the models.

To critique the models, the merits and demerits of each AI-based FBHP model are highlighted, and recommendations for future research are made. These recommendations are necessary to help researchers break new ground that can advance past and current progress on AI-based models for FBHP estimation. To this end, this work is a veritable source of information regarding AI-based models for FBHP estimation.

The remaining sections of this review are structured as follows: Section 2 describes the strategy adopted for the review. Subsequently, section 3 highlights the FBHP prediction models and provides a critical analysis of them. Section 4 highlights the review's main findings, and section 5 offers conclusions and suggestions for further research based on those findings.

II. Materials and Methods

Five databases were searched methodically to find the publications used for this review: Google Scholar, Scopus, SPE OnePetro, Web of Science, and ScienceDirect. Three primary themes were identified in this search process: (a) literature discovery and screening, (b) data extraction and analysis, and (c) Literature review creation. The literature search was carried out without regard to language, period, or publication kind by combining different phrases and free text words in the right order. The articles were chosen in two stages using a predefined set of inclusion and exclusion criteria. In addition to the electronic searches, manual screening of references discovered in the included studies was done to reduce the possibility of missing relevant studies that were not located during the original search. The number of studies found, screened, and approved or rejected at each stage of the study selection procedure is shown in the flow diagram in Fig. 1.

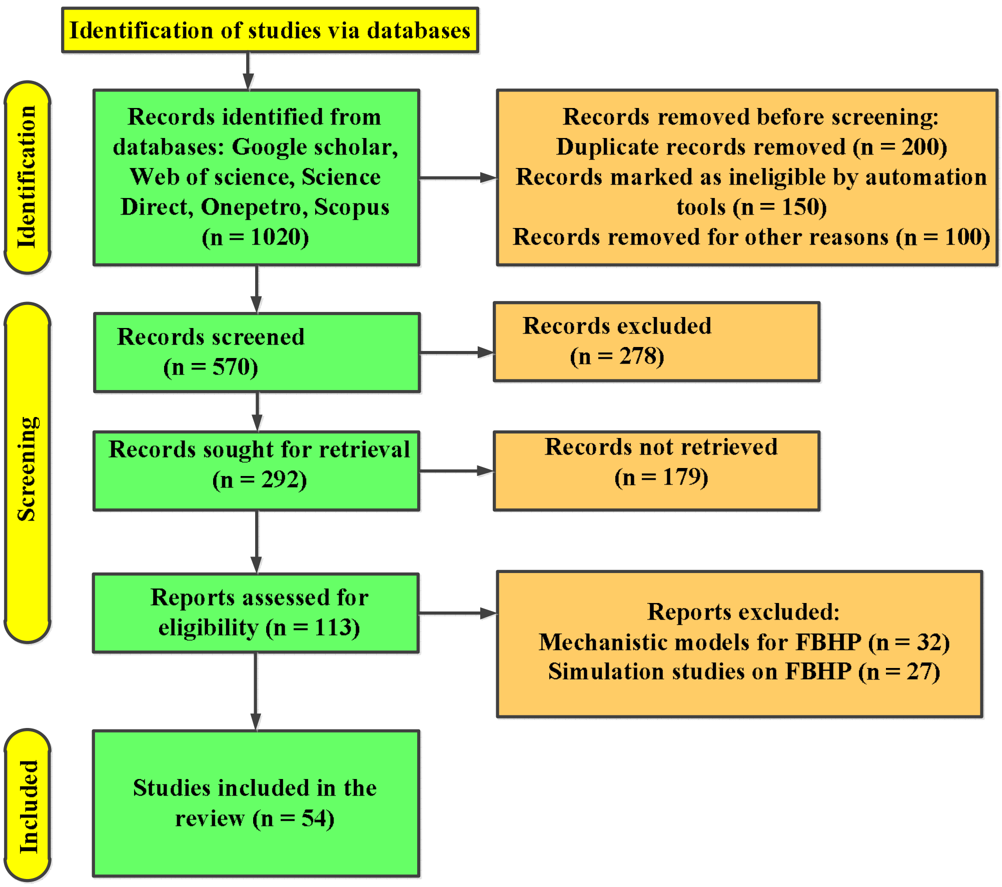

Fig. 1 Literature search flowchart

III. RESULTS AND DISCUSSION

This study section examines previous studies that deployed AI-based models for estimating FBHP. The summary is presented in Table I, which comprises 5 columns. Each column provides essential information about the respective models. The data in the table has been arranged chronologically based on the publication year to identify any trends in the modeling techniques over time. In total, 54 papers focusing on FBHP modeling with AI algorithms were identified, and their attributes, including strengths and weaknesses, were documented in the table. A closer examination of the table reveals the following points, shedding further light on the characteristics of the models.

Interpretability of the FBHP models: Of the 54 models isolated from the literature and presented in Table I, it is observed that about 91% of the models need more interpretability. But what exactly does machine model interpretability mean? Because of the subjective nature of interpretability, there is no consensus around its definition or its measure [10]. However, this work would stick to the definition of interpretability proposed by Murdoch et al. [11], wherein they asserted that interpretable machine learning is a vital generic terminology that expresses the "extraction of vital knowledge from an ML model about relationships either domiciled in data or learned by the model. According to Vellido et al. [12], interpretability is a crucial feature that AI methods should strive to gain for practical application. According to Molnar [13], the interpretation of machine learning models may be intrinsic or post hoc. On the one hand, inherent interpretability refers to AI models deemed interpretable arising from their non-complex structure achieved by limiting the complexity of the AI model. An example is the learned weights and biases of a neural network model. On the other hand, posthoc interpretability involves applying methods that evaluate the model post-training. An example is feature or parametric importance.

The interpretability mechanisms used as a basis for the critique of the FBHP models in this work include:

Model explicitness: This involves using internal weights and biases, kernels, support vectors, dual coefficients, etc., generated by the algorithm to write a visible equation relating the inputs and the outputs. By writing out a model explicitly, the model and its results can be reproduced. For the FBHP models in Table I, it is observed that about 91% of the models needed to be explicitly presented. The few that made their models explicit were Ayoub et al. [14], Tariq et al. [5], Al-Shehri et al. [15], Zolfagharroshan and Khamehchi [16] developed with algorithms such as group method of data handling (GMDH), hybrid of neural network and particle swarm optimization (ANN-PSO), artificial neural network and genetic programming respectively. Furthermore, some of the models that showed some details, such as the weights and biases of the neural network model, were too complex in their network architecture that it was challenging to write the model to show the relationship between the inputs and the output, e.g., the models by Okoro et al. [17]; Nwanwe et al. [18] and Nwanwe and Duru [19], etc.

Feature selection or parametric importance: Feature selection before training a model helps a modeler to forecast which inputs will have the most predictive power for the chosen label. Applying feature selection before training boosts the ML model's performance in efficient learning and accurate prediction [20]. Feature selection can equally be used after training a model to find which features the model learned to be most important. This review focuses on the latter and deals with feature selection after model training. This involves showing how each input affects the prediction of the output and in what manner and direction it does so. This tool can aid in reducing the dimensionality of the models if some of the inputs are observed to contribute infinitesimally to the output prediction. According to Molnar [13], feature importance is only meaningful if visualized, and a table would be a wrong choice. Examples of tools that can show the parametric importance of input variables to a machine learning model include partial dependence plots, the use of Garson's or connection weights algorithm, etc. For the FBHP models in Table I, a large percentage of the models did not show the inputs' relative contribution or parametric relevance.

Use of trend analysis: Trend analysis helps assess the physical validity of a developed model [21]. It also helps explain how well the developed machine-learning model conforms to the realities of a given phenomenon. With respect to the FBHP models in Table I, to the best of the authors' knowledge, none of the works carried out a trend analysis of the model they developed.

Datasets size: Irrespective of the machine learning algorithm used for predictive modeling, data and lots of it are the basic raw material on which the robustness of the models thrives. This is why they are called data-driven methods. According to Althnian et al. [22], dataset size is crucial in determining how well or otherwise an ML model performs. A large dataset tends to guarantee a broader range of coverage by the developed model. In contrast, a small dataset tends to limit the application range of the model and may trigger overfitting [23]. In the review of FBHP models developed using machine learning algorithms, it is observed that the data sizes used varied from one researcher to the other. For instance, the most extensive dataset size was 3,400,000 data points by Firouzi and Rathnayake [24], while the least was 16 data points by Di et al. [25]. These data, as Table I shows, were obtained from different sources and are graphically presented in the funnel chart in Fig. 2. This figure shows the sources where the researchers' dataset for developing FBHP models was obtained and their respective percentages. It is observed that about 40% of the researchers failed to state the source of their data.

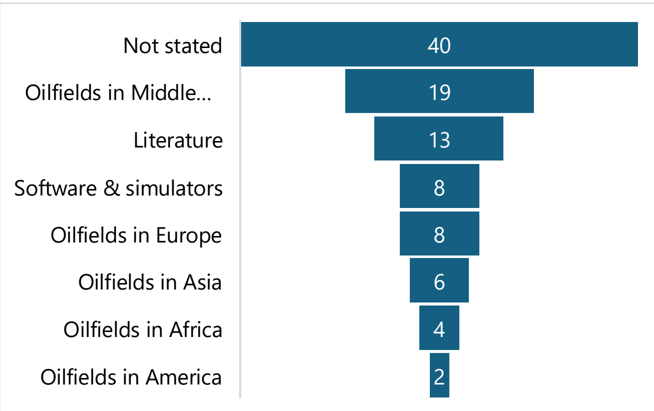

Fig. 2 Sources of data used by researchers for FBHP model development

The computational cost burden of developed models: According to Gomez-Carmona et al. [26], the computational cost of machine learning models is essentially measured as the necessary time taken for the machine learning algorithm to perform the task for which it was deployed, e.g., classification or predictions. This time is essentially a function of the complexity or otherwise of the model architecture or design and the number of inputs to the model. For instance, a neural network with a single hidden layer would have a low computational cost compared to a deep neural network with many hidden layers. The model evolved eventually from a complex architecture would equally lead to higher computational cost when the model is deployed for practical use. A simple way of computing computational cost is the number of multiply add operations a model needs to carry out before producing an output. This is known as the MACCs number. It is observed that none of the FBHP models reviewed took into account the computational cost of the models they developed.

Adaptability of developed FBHP models: The relationship between FBHP and its driving factors may change over time. This is primarily due to variations in downhole conditions that impact fluid flow. Consequently, the predictive model created using static historical data becomes outdated relatively quickly and begins to yield erroneous results. In such cases, periodic monitoring is advisable, although this necessitates additional resources and contributes to project management costs. Thus, there is a need to develop adaptable models. A machine learning model is considered adaptable if it can adapt and enhance its performance as it encounters more data. In recent years, the forward-rolling method has been employed to render AI prediction models adaptable to changes in the input-output relationship. Based on the review, it was found that 96% of the data used by researchers to develop AI-based FBHP models consisted of static historical data, resulting in the development of non-adaptable models. However, the studies conducted by Spesivtsev et al. [27] and Ignatov et al. [28] utilized time series data, to some extent enabling their models to adapt to parameter changes over time.

Input variable selection: A multitude of factors impact FBHP. Consequently, the predictive modeler has access to numerous input variables. The wide range of factors influencing FBHP is illustrated by the diversity and number of input variables presented in column 4 of Table I. For instance, Li et al. [29] utilized 15 input variables, while Okoro et al. [17] and Zhang et al. [30] employed 12 input variables, each with their own unique set of input variables. Due to these variables' extensive and varied nature, selecting and combining them for FBHP modeling poses a challenge [31]. Additionally, some researchers resorted to using a limited number of input variables; for example, Memon et al. [32], Yin and Zhang [33], and Marfo et al. [34] relied on only three input variables. In contrast, about 7% of the researchers failed to disclose the inputs to the models they developed. This issue of selecting and combining input variables likely contributes to the absence of a universal model for FBHP estimation.

Type of machine learning algorithm: Various researchers have adopted and used a wide array of machine learning algorithms for FBHP modeling, as shown in Table I. Fig. 3 shows the distribution of these algorithms and how the researchers deployed them. It is observed from the figure that a more significant number of researchers used the single neural network. Hybrids of neural networks with evolutionary algorithms were also highly utilized. Still, there is an emerging trend towards the use of physics-informed neural networks due to the issues of interpretability and trustworthiness of conventional machine learning algorithms. It is also observed that algorithms that evolve mathematical relationships automatically and present them as explicit models, such as multivariate adaptive regression splines (MARS), multigene genetic programming (MGGP), and group method of data handling (GMDH), were sparingly used. This underscores the findings by Agwu et al. [35], wherein they asserted that algorithms such as MARS had yet to be widely adopted for predictive modeling purposes in petroleum engineering despite the numerous advantages it offers. Furthermore, it was also observed that newer algorithms, such as M5Prime, were also emerging.

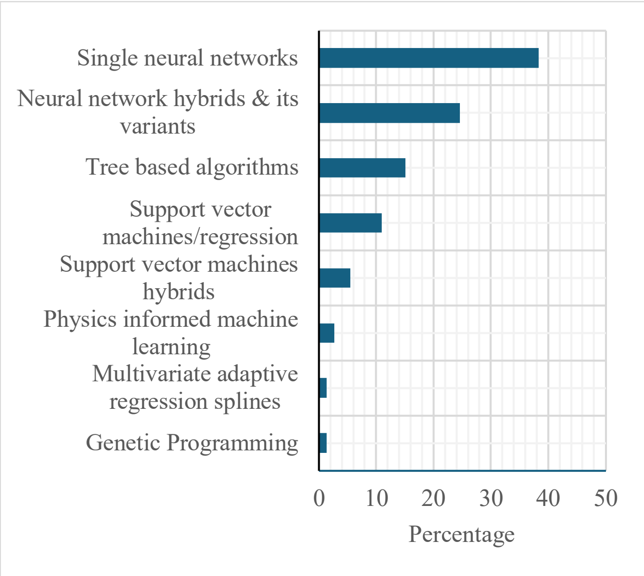

Fig. 3 Distribution of types of AI algorithms used for FBHP modeling

TABLE I
SNAPSHOT OF EXISTING AI BASED MODELS FOR FBHP ESTIMATION

Reference	**AI algorithm**	**Inputs**	**Merits of model**	**Demerits**
Ayoub [14]	Neural Network [9-6-3-3-1]	Gas flow rate, oil API gravity, oil flow rate, pipe length and diameter, surface temperature, water flow rate, WHP, WHT	Ideal for vertically oriented wells with natural fluid flow.	Lack of model explicitness
Osman et al. [21]	Neural Network [9-6-3-3-1]	Gas flow rate, oil API gravity, oil flow rate, pipe length and diameter, surface temperature, water flow rate, WHP, WHT	Applicable to naturally flowing, vertically orientated wells.	Model lacks explicit presentation

Reference	AI algorithm	Inputs	Merits of model	Demerits
Mohammadpoor et al. [36]	Neural Network	BHT, gas rate, hole diameter, oil API, oil rate, well depth, well location coordinates, WHP, WHT,	Ideal for wells that are vertical. Model outperforms both mechanistic& empirical models.	Model lacks explicit presentation
Ashena et al. [37]	Neural Network	Not stated	Ideal for slanted wells drilled in underbalanced situations	Model lacks explicit presentation
Salcedo et al. [38]	Neural Network	Not stated	Beneficial for estimating FBHP in vertically oriented wellbores	Lack of explicit model & sensitivity analysis
Al-Shammari [39]	Adaptive Neuro-Fuzzy Inference System (ANFIS)	Flowing WHP, gauge depth, GOR, liquid rate, oil API, reservoir temperature, tubing ID diameter, water cut %,	Beneficial for forecasting FBHP in two-phase flow in vertically oriented wells	Dearth of explicit model & sensitivity analysis
Ashena and Moghadasi[40]	Hybrid of neural network and ant colony optimization (ANN-ACO) [7 – 7 – 1]	Casing pressure, injected gas and liquid flow rates, liquid density at surface, MD, Surface temperature, TVD	Beneficial for forecasting BHP of two-phase drilling fluid in underbalanced drilling operations	Model lacks explicit presentation
Jahanandish et al. [41]	Neural network [9-20-15-10]	BHT, Gas rate, GOR, oil API gravity, Oil rate, pipe length, surface temperature, Water rate, WHP.	Beneficial for FBHP forecasting in vertically oriented wells. Sensitivity analysis carried out.	Model lacks explicit presentation
Nasimi et al. [42]	ANN-Ant colony optimization [7-5-1]	Casing pressure, injected gas flow rate, liquid density at surface, liquid flow rates, MD, Surface temperature, TVD	Appropriate for forecasting BHP during underbalanced drilling	Model lacks explicit presentation
Li [43]	Neural network [10-28-1]	Absolute roughness, BHT, gas rate, inclination angle, MD, oil API gravity, oil rate, separator pressure & temperature, specific gravity of produced gas, Tubing ID, water rate, water salinity, WHP, WHT,	For easy FBHP computation, a Windows application with a graphical user interface was created.	Model lacks explicit presentation
Adebayo et al. [44]	Neural network [8 – 30 – 1] Support vector machines	Gas rate, oil API gravity, oil rate, reservoir temperature, tubing ID, TVD, water flow rates, WHP	Applicable to predicting FBHP in conventional vertical wells	Dearth of explicit model & sensitivity analysis
Bello and Asafa [45]	Neural network	API gravity, depth, gas rate, GOR, oil rate, tubing pressure, tubing temperature	Model works well with vertically producing wells.	Model lacks explicit presentation
Ayoub et al. [46]	Group method of data handling (GMDH)	Gas rate, oil gravity, oil rate, pipe length, surface temperature, tubing ID, water rate, WHP	There is an explicit model provided.	Model developed is complex
Li et al. [29]	Neural network Slug flow: [10-30-1] Mist flow: [10-28-1]	Average pressure, average temperature, gas viscosity, gas-liquid surface tension, inclination angle, liquid & gas superficial velocity, liquid density, liquid viscosity, specific gravity of free gas	Model takes flow regime impacts into account. Independent field datasets were used to validate the model.	Lack of an explicitly presented model. High model complexity
Memon et al. [32]	Radial basis neural network	Permeability, porosity, productivity index	Ideal for predicting dynamic FBHP	Lack of explicit presentation of model
Awad [47]	Neurofuzzy algorithm	BHT, gas rate, oil API, oil rate, surface temperature, tubing ID, tubing length, water rates, WHP	Model exhibits more precision in predicting outcomes than both empirical & mechanistic models.	Lack of explicit presentation of model
Awadalla and Yousef [48]	Neural network [12-68-1]	BS&W, formation GOR, gas rate, liquid rates, motor current, oil rate, oil specific gravity, pump discharge pressure, pump intake, THP, TVD, water rate, water specific gravity	Applicable to FBHP prediction in wells supported by ESPs. Analysis of input sensitivity is available	Model lacks explicit presentation
Di et al. [25]	Support vector machines	Gas compressibility factor, gas flow rate, gas relative density, mean wellbore temperature, well depth, WHP.	Applicable to FBHP estimation in gas wells	Model lacks explicit presentation

Reference	AI algorithm	Inputs	Merits of model	Demerits
Antonelo et al. [49]	Recurrent neural networks (RNN) trained with Echo state networks	Gas lift flow rate, pressure before and after production choke, SDV, temperature before production choke, temperature before SDV	Ideal for FBHP estimation in gas-lift wells.	Model lacks explicit presentation
Chen et al. [50]	Support vector regression	Average well temperature, casing pressure, gas compressibility factor, gas rate, gas relative density, water rate, well depth	Ideal for estimating gas well FBHP. Field data is used to validate the model.	No explicit model
Spesivtsev et al. [27]	Neural network [80-100-50-1] [80-500-150-1]	Gas rate, MD close to surface, measured depth (MD), oil rate, time series of WHP, true vertical depth, water rate	Applicable to diverse well trajectories	Lack of an explicitly presented model. High model complexity
Ignatov et al. [28]	Extreme gradient boosting; Random forest	Gas rate, MD close to the surface, measured depth (MD), oil rate, time series of WHP, true vertical depth, water rate	Scalable system with a strong capacity to withstand noise	Lack of an explicitly presented model
Bahaa et al. [51]	Neural network [7-6-2]	Gas injection pressure, gas injection volume, GOR, reservoir pressure, water cut, WHP, WHT.	The model can be utilized to establish an integrated production model.	Lack of an explicitly presented model
Tariq [52]	A hybrid of neural network & particle swarm optimization (PSO-ANN) [9-20-1]	BHT, depth, gas rate, oil API gravity, oil rate, perforation depth, surface temperature, tubing diameter, water rate, WHP	An explicit model was presented. Applicable to vertical wells. The model was cross-validated using an “unseen” data set	Complex model. Input sensitivity not done.
Akinsete and Adesiji [53]	Neural network	Annulus pressure, BHT, bore oil volume, choke differential pressure, choke size, mean values of downhole pressure, tubing pressure differential, well depth, WHP, WHT.	The model has a higher predictive capacity than mechanistic models	Lack of an explicitly presented model
Firouzi and Rathnayake [24]	Neural network; Linear Regression (LR)	Casing pressure, gas rate, pump speed, pump torque, tubing pressure, water rate from the separator, and water rate from the tubing.	Applicable to FBHP forecasting in coal seam gas wells	Lack of an explicitly presented model
Ahmadi and Chen [8]	Neural network	Bottom hole temperature, depth, gas flow rate, oil API, oil rate, surface temperature, tubing diameter, water flow rates, WHP.	Ideal for FBHP forecasting in vertical wells	The model lacks explicit presentation
Amar and Zeraibi [54]	Hybrid of support vector regression (SVR) optimized with firefly algorithm	Depth, gas gravity, gas rate, GOR, oil gravity, oil rate, tubing ID, water flow rate, WHP, WHT.	Ideal for FBHP forecasting in vertical wells	Model lacks explicit presentation
Baryshnikov et al. [55]	Neural network [11-32-32-1]	Diameter number, gas-to-liquid density ratio, inclination angle, non-slip liquid holdup, relative pipe roughness, Reynolds & Froude number, velocity & viscosity numbers for gas and liquid.	Ideal for forecasting FBHP in deviated wellbores	Model lacks explicit presentation
Al-Shehri et al. [15]	Artificial neural network; Functional Networks; Long short-term memory (LSTM)	Chloride content, fluid rates, fluid specific gravity, TVD, water cut, water gas ratio, WHP, WHT.	The model was explicitly presented. Its applicability includes gas condensate, tight sand, and fractured wells. The model has been cross-validated with an “unseen” dataset.	Sensitivity analysis of input variables was not done
Zhang et al. [56]	Support vector regression	Not stated	Field and simulated data were used to validate the model.	Lack of an explicit model
Krishna et al. [57]	Neural network [6-10-16-1]	Hole diameter, mud weight, pipe OD, pipe velocity, plastic viscosity, yield point,	Ideal model for forecasting surge & swab pressure while tripping	A dearth of explicit model
Tariq et al. [5]	Hybrid of neural network & particle swarm optimization (PSO-ANN) [9-20-1]	BHT, gas rate, oil API gravity, oil rate, perforation depth, surface temperature, tubing diameter, water rate, WHP	The model was explicitly presented. Model fit for vertical well geometry. The model was cross-validated.	Complex model. Lack of input sensitivity analysis

Reference	AI algorithm	Inputs	Merits of model	Demerits
Khamehchi and Bemani [58]	Extreme Learning Machine (ELM), Gradient tree boosting (GTB)	Average angle, average deviation, gas rate, measured depth, oil rate, TVD, water flow rates, WHP	Appropriate for estimating BHP in two-phase flow situations in vertical and deviated wells. Analysis of sensitivity is available.	A dearth of explicit model
Liang et al. [59]	Support vector regression – simulated annealing (SVR-SA)	Not stated	Applicable for FBHP estimation in managed pressure drilling conditions	A dearth of explicit model
Marfo et al. [34]	M5 prime	Gas rate, oil flow rate, tubing head pressure,	The model is robust enough to estimate FBHP	The dearth of explicit model
Yin and Zhang [33]	Radial basis neural network	Permeability, porosity, productivity	Model appropriate for horizontal wells with fractures	The dearth of explicit model
Eltahan et al. [60]	Support vector regression ensemble; Random Forest; Linear ensemble	Empirical FBHP, gas rate, gas-lift injection rate, GLR, GOR, oil rate, surface flowing pressure, water flow rates, water oil ratio	It is ideal for several fractured horizontal wells that flow naturally or with artificial lift. The model has high precision as a result of using multiple models	The dearth of explicit model
Molinari and Sankaran [61]	Physics-augmented features, physics-informed machine learning, residual model & domain knowledge-based regularization	Gas specific gravity, GLR, liquid rate, oil gravity, solution GOR, tubing depth (at MD, TVD), tubing head pressure, tubing ID, water cut, water salinity	The model is interpretable as it combines the physics of the FBHP process with artificial intelligence algorithms	The dearth of explicit model & sensitivity analysis
Sami and Ibrahim [1]	Random forest; K-nearest neighbor; Neural network	Oil gravity (API), oil rate, tubing ID, water rate, well perforation depth, WHP	The model applies to FBHP prediction in vertically oriented wells	The model lacks explicit presentation
Gorbachev et al. [62]	Support vector regression	Casing pressure, fluid flow rates, fluid PVT properties, gas lift valve installation depth, gas lift flow rate, GOR, length & diameter of casing & tubing, water cut, WHP.	Applicable to estimating FBHP in gas-lift wells	The dearth of explicit model & sensitivity analysis
Zolfagharroshan and Khamehchi [16]	Neural network (Radial Basis); Least square support vector machines (LSSVM); Genetic Programming (GP)	BHT, gas rate, gas specific gravity, oil API gravity, oil rate, surface temperature, tubing ID, water flow rate, well depth, WHP.	The model developed using the GP algorithm was explicitly presented	Models developed using ANN & LSSVM are not explicitly presented.
Baki and Dursun [7]	ANN; SVR; Extreme gradient boosting	Basic sediments & water (BS&W), chlorine content, choke size, condensate gas ratio, downstream pressure, gas rate, condensate rate, water rate, WHP, WHT.	FBHP model applicable to horizontal wells	Lack of an explicitly presented model
Rathnayake et al. [63]	Multiple linear regression; Linear mixed effects modeling; Extreme gradient boosting	Casing pressure, gas flow, pump torque, speed of pump, tubing pressure, water flow	Ideal for forecasting FBHP in coal seam gas wells	Lack of an explicitly presented model
Olamigoke and Onyeali [64]	Support vector regression; Random Forest; Long short-term memory (LSTM)	Average oil rate, BHP, BHT, choke size, differential tubing pressure, gas rate, percentage of choke open, production hours, water flow rates, WHP, WHT.	A variety of models have been provided so that users can make choices.	Lack of an explicitly presented model
Zhu et al. [65]	Back propagation neural network (BPNN); Long short-term memory (LSTM); Convolutional Neural Network	Back pressure pump flow rate, funnel viscosity, inlet flow rate, mud weight, outlet density, outlet flow rate, riser pressure, rotary speed, sand content, total pool volume, TVD, and well depth.	Beneficial for predicting BHP in managed pressure drilling operations.	Lack of an explicitly presented model
Jin et al. [66]	Physics-based neural network Data-based ANN	*Physics-based ANN inputs* GLR, hydrocarbon fluid properties, liquid flow rate, temperature gradient, TVD, water-oil ratio, WHP, WHT. *Inputs for data-based ANN* GLR, liquid flow rate, TVD, water-oil ratio, WHP	It is beneficial for estimating the FBHP of unconventional wells supported by gas lift.	Lack of an explicitly presented model

Reference	AI algorithm	Inputs	Merits of model	Demerits
Okoro et al. [17]	A hybrid of neural network and Imperialist competitive algorithm (ANN-ICA)	Average BHT, average WHP, bore gas volume & bore oil volume, bore water volume, mean annular pressure, mean choke size, mean tubing pressure differential, permeability, porosity, pressure differential in chokes, and stream hours.	The model considers the impact of permeability and porosity on FBHP	Lack of an explicitly presented model. High model complexity.
Goliatt et al. [31]	Extreme Learning Machine (ELM); Support vector machines; Extreme gradient boosting; Multivariate adaptive regression splines	BHT, gas rate, oil API gravity, oil rate, surface temperature, tubing ID, water rates, well depth, WHP.	Ideal for wells supported using artificial lift mechanisms	Lack of an explicitly presented model
Nwanwe et al. [18]	Neural network [8-20-15-15-1]	Gas rate, oil API gravity, oil flow rate, tubing ID, water rate, well BHT, well perforation depth, WHP.	Availability of an explicit model. Ideal for FBHP prediction for vertically oriented wells.	High model complexity
Nwanwe and Duru [19]	Adaptive neuro-fuzzy inference system (ANFIS)	Gas rate, oil API gravity, oil flow rate, tubing ID, water rate, well BHT, well perforation depth, WHP.	Availability of an explicit model.	High model complexity
Zhang et al. [30]	Convolutional Neural Network & Gate Recurrent Unit [12 – 60 – 60 -1]	Back pressure pump flow rate, funnel viscosity, inlet & outlet flow rate, mud weight, outlet density, riser pressure, rotary speed, sand content, total pool volume, TVD, and well depth.	A large data size was used to develop the model.	Lack of an explicitly presented model
Sun et al. [67]	Extreme Gradient Boosting algorithm	Gas injection rate, gas rate, GOR, oil rate, water cut, water injection rate, water production rate.	Ideal for FBHP forecasting in carbonate reservoirs	Lack of an explicitly presented model
Jin et al. [68]	Neural network	GLR, liquid production rate, water-oil ratio, well depth, and wellhead pressure.	It is beneficial for estimating FBHP for unconventional wells produced via gas lift.	There is no explicit model. Complex network architecture

The analysis in this section focuses on evaluating the performance of models developed using various AI algorithms. The models have been categorized based on the AI algorithms employed for their development to provide an objective assessment. The evaluation is conducted by considering the reported performances presented by each researcher in their respective studies. Three statistical error metrics have been selected for this assessment, namely the coefficient of determination (R^2), the mean square error (MSE), and the average absolute percentage error (AAPE). The categorized groups include Artificial Neural Networks (ANN) and their hybrids and variants, Support Vector Machines (SVM) and their hybrids and variants, and tree-based algorithms.

Table II presents the FBHP models developed using artificial neural networks (ANN) and its various hybrids and variants. The table arrangement is based on the mean square error metric descending order. It is noteworthy to observe that the ANN models showcasing superior performance were the variants, including recurrent neural networks (RNN), convolutional neural networks (CNN), and hybrids, such as the neural network—ant colony optimization algorithm (ANN-ACO).

TABLE II
COMPARISON OF THE PERFORMANCE OF FBHP MODELS DEVELOPED USING ANN

Reference	AI Method	R^2	MSE	AAPE
Antonelo et al. [49]	RNN	Not available	9.48E-06	Not available
Ashena and Moghadasi [40]	ANN-ACO	0.9888	2.85E-04	Not available
Nasimi et al. [42]	ANN-ACO	0.9916	2.1E-04	Not available
Mohammadpoor et al. [36]	ANN	Not available	0.00074	2.064
Zhang et al. [30]	CNN & Gate Recurrent Unit	Not available	0.001444	0.025
Nwanwe et al. [18]	ANN	0.8154	0.0022	Not available
Ahmadi and Chen [8]	ANN-PSO	0.9757	0.0024275	Not available
	ANN-HGAPSO	0.9934	0.002982	
Ashena et al. [37]	ANN	Not available	0.004	15.81%
Akinsete and Adesiji [53]	ANN	0.99997	0.00548	Not available
Zhu et al. [65]	BPNN	Not available Not available	0.013689	0.156
	LSTM	Not available	0.011236	0.148
	CNN		0.065025	0.27
Sami and Ibrahim [1]	ANN	0.8649	2.5%	Not available
Okoro et al. [17]	ANN-ICA	0.9985	0.119	0.011

Reference	AI Method	R^2	MSE	AAPE
		0.9989	0.1347	
Awadalla and Yousef [48]	ANN	0.994	1.96	Not available
Awad [47]	Neuro-fuzzy algorithm	0.9645	3.853	2.929
Ayoub [14]	ANN	0.9477	7.84	2.165
Osman et al. [21]	ANN	0.9477	7.84	2.165
Bello and Asafa [45]	ANN	0.99	13.54	
Spesivtsev et al. [27]	ANN	Not available	31.36	3.4
Ayoub et al. [46]	GMDH	0.923	34.34	4.46
Yin and Zhang [33]	RBNN	Not available	42.25	13.6
Jahanandish et al. [41]	ANN	0.7378	46.7856	4.719
Memon et al. [32]	RBNN	Not available	62.41	14.66
Baki and Dursun [7]	ANN	0.994	2937.64	Not available
Khamehchi and Bemani [58]	ELM	0.999	6556.14	Not available
Firouzi and Rathnayake [24]	ANN	Not available	131044	Not available
Zolfagharroshan and Khamehchi [16]	ANN	0.8417	640,864.29	28.98
Krishna et al. [57]	ANN	0.987	2225765.61	
Al-Shehri et al. [15]	ANN	0.999	Not available	0.09%
	Functional Networks	0.9865		0.4%
	LSTM	0.9992		0.07%
Tariq [52]	PSO-ANN	0.98	Not available	3.1%
Li et al. [29]	ANN	Not available	Not available	3.1%

Table III showcases the FBHP models developed using support vector machines (SVM) and their various hybrids and variants. As in Table 2, the arrangement of the table is based on the mean square error metric descending order. Notably, the SVM models showcasing superior performance were the variants, including SVR ensemble and SVR-simulated annealing (SVR-SA).

TABLE III
COMPARISON OF THE PERFORMANCE OF FBHP MODELS DEVELOPED USING SVM

Reference	AI Method	R^2	MSE	AAPE
Eltahan et al. [60]	SVR Ensemble	NA	0.000655	Not available
Liang et al. [59]	SVR – Simulated Annealing	0.9998	0.004624	Not available
Zhang et al. [56]	SVR	NA	<0.01	< 0.2%
Olamigoke and Onyeali [64]	SVR	0.81	104.04	3.02
Baki and Dursun [7]	SVR	0.999	3003.04	26.45
Zolfagharroshan & Khamehchi [16]	LSSVM	0.9969	12,670.924	7.754
Goliatt et al. [31]	SVR	0.197	61,206.76	8.66%
Amar and Zeraibi [54]	SVR-firefly algorithm	0.9917	Not available	6.65%

*NA = Not Available

Table IV shows the FBHP models developed using tree-based algorithms such as random forest, extreme gradient boosting, M5 Prime etc. The table is arranged in decreasing order of the mean square error (MSE) metric. It is noteworthy to observe that the random forest algorithms performed better than extreme gradient boosting (XGBoost) in terms of the MSE metric but the XGBoost algorithm showcased superior performance when the R^2 metric is used as basis.

TABLE IV
PERFORMANCE COMPARISON OF FBHP MODELS DEVELOPED WITH TREE BASED ALGORITHMS

Reference	AI Method	R^2	MSE	AAPE
Eltahan et al. [60]	Random forest	NA	0.00046	0.0183(MAE)
Sami and Ibrahim [1]	Random forest (RF)	0.6889	4%	
Olamigoke and Onyeali [64]	Random forest	0.7	158.76	3.87
Baki and Dursun [7]	XGBoost	1	213.16	8.089 (MAE)
Khamehchi and Bemani [58]	Gradient Tree Boosting	1	298.769	0.72 (MRE)
Goliatt et al. [31]	XGB	0.852	11,929.008	3.53%
Rathnayake et al. [63]	XGBoost	MARE = 0.07	13,225	11.7%
Zolfagharroshan & Khamehchi [16]	GP	0.9859	57,302.78	12.458
Marfo et al. [34]	M5 prime	0.985	Not available	0.3

From this review, the following can be inferred there is no universally applicable artificial intelligence (AI) model capable of capturing all features related to the FBHP phenomenon. This limitation arises from the inherent constraints imposed by the algorithms employed and the specific input features related to FBHP. This assertion is substantiated by the vast array of input variables employed by different researchers in their respective studies. The issue of model interpretability remains a significant concern, as most of the FBHP models have yet to be explicitly presented. Moreover, most researchers have yet to conduct sensitivity and trend analysis, and the literature lacks a discussion of the computational cost burden.

Unlike other AI algorithms such as ANN, SVR, and tree-based algorithms, GMDH, Genetic Programming, and MARS can autonomously evolve explicit mathematical relationships between the factors that influence FBHP and FBHP. However, their accuracy is significantly lower when compared to other algorithms developed with hybrid systems (e.g., ANN-ACO, SVR-SA, ANN-PSO, etc.). The adoption of physics-informed machine learning algorithms is gradually gaining traction due to its ability to offer explanations to the developed models, unlike conventional machine learning algorithms. Though FBHP is a dynamic parameter that changes with time and conditions, it is observed that most of the data used by the researchers to develop the FBHP models were static historical data. This may cause the models to become obsolete with time if conditions different from the one that was used to generate the data are presented to the model.

IV. Conclusion

The present study was undertaken to provide a comprehensive overview of the FBHP models developed using AI algorithms. Data was collected from peer-reviewed journals and SPE conference papers from 2004 to 2024. The bibliographic analysis revealed the utilization of numerous AI algorithms in the predictive modeling of FBHP, resulting in the identification of 54 models. While not exhaustive, the list of AI algorithms includes neural networks and their variants and hybrids, support vector machines and their variants and hybrids, genetic programming, tree-based algorithms, spline-based algorithms, and fuzzy logic, among others. The review isolated key components within existing FBHP models, such as the algorithm type used for development, the dataset size and source, the input variables, and the strengths and limitations of each model.

As part of the recommendations, Fig. 4 depicts the proposed research directions for FBHP modeling. The figure highlights five key areas of research concern. Firstly, the modeling process begins with data acquisition and the selection of inputs. As a diverse range of factors influences FBHP, a well-defined method for input selection should be outlined, and the relative importance of each input should be ranked. Generally, since a model is a simplified representation of reality, the FBHP model should be designed with readily obtainable inputs through sensors or surface facilities. Secondly, while conventional AI algorithms have been extensively tested, exploring the capabilities of different ensemble learning algorithms is essential. Thirdly, future research should focus on developing adaptable models, incorporating a dynamic data stream. This is crucial because well conditions change over time, and models should be able to adjust to new situations or datasets. Fourthly, models developed for FBHP estimation should be cross-validated using independent datasets to ensure their generalization ability. Fifthly, for a model to be helpful, it must be efficient regarding computational resources. Thus, future work should include determining the computational cost of the models relative to the scope of their studies. Finally, the utility of any model can only be ascertained when implemented in real-life conditions. Hence, future studies must provide clear proposals on how the model can be implemented in a real oil and gas production system. This final step provides a pathway to potential users for the model's field deployment.

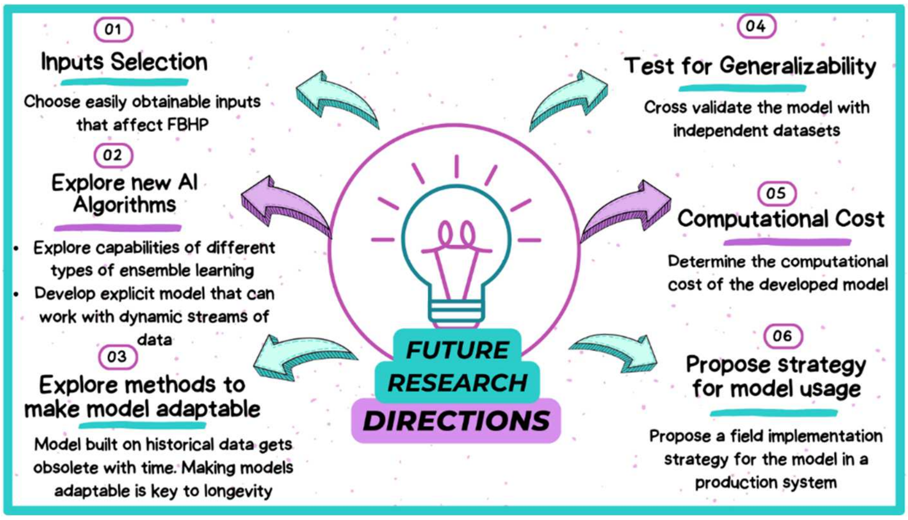

Fig. 4 Proposed future research framework for FBHP modelling studies

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