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Preliminary communication

A Review of Chan Plot Application and Recent Advanced Models for Diagnosing Excessive Water Production

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Abstract

Water is one of the major fluids associated with the operational cycle of the oil industry that must be carefully considered due to its environmental, treatment facility, and economic impacts. Over the years, various methods have been developed to identify excessive water production. These methods range from reliable and expensive ones, such as well-logging records, to less accurate methods that utilize available production and water-oil ratio data, such as the Chan plot. The Chan plot emphasizes that well production can exhibit various patterns of excessive water production, including constant water-oil ratios, normal displacement, channeling, and coning. However, manual interpretation of these plots is often confusing due to the noise present in the actual data. Machine learning models have improved interpretation accuracy, but limitations remain in detecting evolving water production patterns. This paper reviews the application of Chan plots and their integration with existing diagnostic tools for diagnosing excessive water production. It then focuses on a recent advanced model that leverages machine learning specifically designed to improve the interpretation of Chan plots. The review highlights the limitations of traditional interpretation techniques and explores how the recent advanced model can address these limitations. Additionally, the paper briefly discusses the potential of an interactive model for the continuous monitoring of water production patterns. Finally, the paper offers recommendations for future research directions.

Keywords:

excessive water production; water oil ratio; diagnostic plot; well log; machine learning

1. Introduction

Throughout the history of oil production, an increase in water is typically expected over the life of a reservoir as it is one of the favorable driving mechanisms. Although the production of water is essential for simultaneous oil production, water breakthroughs in the reservoir can occur in various ways, due to unfavorable impacts on mobility and subsequent bypassing of oil, resulting in a reduced recovery factor. The major contributors to excessive water are:

- A natural water drive or flood,
- External causes, such as casing leaks or cementing failure,
- Mess-completion (Poor perforation).

Historically, economic assessments deemed high water or gas ratios and elevated production rates as acceptable. However, contemporary realities dictate that water associated with hydrocarbons must adhere to stringent environmental regulations dictating its disposal methods and locations. With daily production reaching 250 million barrels there is an urgent need to address excessive water problems (**Haneef et al., 2020**). The management of disposed-produced water now poses a substantial financial challenge for numerous companies. This challenge manifests in reduced income, diminished production levels, and escalating costs associated with upgrading water treatment facilities and disposal systems (**Rabiei et al., 2009**). The expenses incurred in this process vary from 5 to more than 50 cents per water barrel (**Dahl et al., 1992**), and they soar even higher, reaching $4 for every barrel of oil, when dealing with wells producing an 80% water cut (**Bailey et al., 2000**). Moreover, recent studies estimated produced water treatment and disposal costs ranging from $5 to $100 per cubic meter depending on the process and region (**Zolfaghari et al., 2022**). Clearly, significant investment in innovative water management technologies is necessary.

To mitigate the risk of water-related issues, the sources of unwanted water should be accurately diagnosed. Traditional diagnostic techniques, such as well logs, production logging, and pressure transient analysis (PTA), have been used (**Bhagavatula et al., 2015**; **Wang et al., 2023**;

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Yaakob et al., 2017). However, these techniques have limitations, including high costs, time-consuming manual analysis, and limited sensitivity to specific water production patterns. For instance, while well logs provide static formation properties, they lack reservoir dynamic information about water production patterns (**Lai et al., 2024**). Similarly, while production logging captures downhole data, it is often expensive and limited in temporal resolution. Additionally, PTA, while useful for reservoir characterization, may not be specifically sensitive to water production alone.

One commonly used analytical tool, Chan plots, visually represents water-oil ratio (WOR) changes over time, offering valuable insight into excessive water production patterns. However, Chan plots application have limitations such as subjective manual interpretation and human error (**Egbe & Appah, 2005**; **Garcia et al., 2019**; **Mukhanov et al., 2018**; **Rabiei et al., 2009**). To confirm a diagnosis, Chan plot is often used in conjunction with other diagnostic tools such as well logging and simulation. However, the recent involvement of artificial intelligence in the oil and gas industry offers a promising solution to overcome the challenge of mislabeling, such as machine learning approaches which improved diagnosing accuracy (**Foster et al., 2021**; **Garcia et al., 2019**; **Mukhanov et al., 2018**). While the well can exhibit more than one pattern in the production cycle, the model developed by Garcia in 2019 was able to detect only one pattern, either constant WOR, normal displacement, or channeling. This limitation is addressed by developing a computer vision application based on a Convolutional Neural Network (CNN) to distinguish all possible Chan patterns a well might exhibit (**Abdelaziem et al., 2022**). However, the model requires the entire plot as an image input, meaning it can only identify the pattern after it fully develops.

This review highlights a new approach to improve Chan plot interpretation through an interactive model, that incorporates time series functions. This model enhances diagnostic accuracy and efficiency, enabling early detection of water production problems. The model can integrate with current production surveillance tools, allowing for real-time tracking of water production patterns, minimizes economic losses and environmental damage associated with excessive water production.

The subsequent sections of this paper are structured as follows: the next section explores the causes and repercussions of excessive water production, thoroughly investigating these aspects. The examination extends to traditional diagnostic tools, with a focused analysis on Chan plot applications and their standalone efficacy, as well as their integration with other tools explored in the following sections. Subsequently, the paper scrutinizes recent advancements aimed at refining Chan pattern detection. Moreover, a novel methodology is discussed, incorporating time series functions. In conclusion, a summary of the key points is provided, and potential avenues for future research directions in the field of Chan plot interpretation are outlined.

2. Causes of Excessive Water Production

Water is typically found at the bottom or edges of an oil zone, existing in equilibrium as part of a unified system. When the pressure decreases during oil production, water moves to replace it by filling the pore volume, thus maintaining the pressure system. This process can occur naturally through an active aquifer source or be induced artificially by injecting water into the reservoir for pressure maintenance and secondary recovery (**Alexis, 2010**). Consequently, water production is essential for oil extraction, unavoidable, and ceasing it would lead to reserve losses (**Egba et al., 2018**; **Kabir et al., 1999**).

In the initial stages, water saturation exceeds the critical saturation, sweeping oil from the reservoir at a nearly constant water-oil ratio. This leads to stable displacement, consistent production performance with a plateau time, and minimal observable water. Subsequently, interactions between the formation matrix, water, and oil occur through macro and micro displacement in the system. Gradually, water increases and recovers oil from the reservoir. In this scenario, water is deemed beneficial. The flow of water is mainly influenced by water properties, saturation, rock wettability, mobility ratio, and production strategy.

However, as the process progresses, oil displacement becomes unstable due to inefficient micro movements, resulting in oil being trapped in pore spaces. This instability leads to earlier, excessive, and faster-than-anticipated water breakthroughs, classifying the water as detrimental or "bad water". (**Ayeni et al., 2018**; **Kabir et al., 1999**; **Saleh et al., 2019**) have noted that excessive water recirculation, as discussed in their studies, does not contribute to pressure support in the area and results in either minimal or no oil production. Over time, wells experiencing such conditions will inevitably exhibit water-related challenges. The serious impact of excessive water production on the oil production cycle has adverse effects on surface equipment integrity (**Al-Shahrani et al., 2007**). This includes escalated costs in oil production due to higher expenses related to lifting, separation, and disposal, as well as scaling issues in the wellbore, tubing, flow lines, and processing facilities. Additionally, it contributes to the corrosion and deterioration of completion and flow lines.

Moreover, excessive water weight increases hydrostatic pressure on the formation, which reduces the pressure needed to transport oil to the surface. Frequently, wells become inactive as a result of the excessive water output from the deposit. Water-related problems can be broadly categorized as either reservoir-related or well-related issues, stemming from various wellbore conditions such as leakage, flow behind casing, gravity segregation, moving oil-water contact (OWC), channels, and

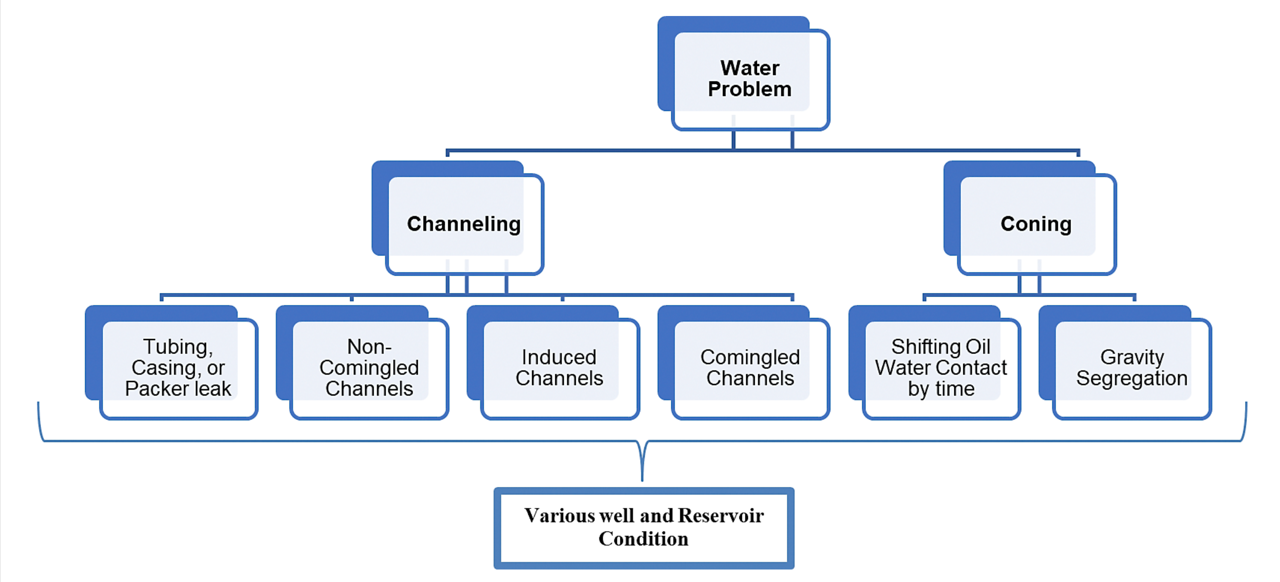

Figure 1: General summary of Water problem types

coning. A single well may experience one or more of these issues.

Various criteria have been used in the literature to classify water production problems, depending on the authors' interests and the specific focus of their work. They have been categorized based on their complexity and the ease of implementing shut-off treatments, ranging from simple to complex solutions (**Bailey et al., 2000**; **Seright et al., 2003**).

Based on the well production profile, water problems classified into three categories, with notable main problems being water coning, multilayer channeling, and near-wellbore issues (**Chan, 1995**). This chapter will separately discuss the first two problems. It's important to note that these categories do not contradict the previously mentioned conditions, as each problem can arise for various reasons. **Figure 1** summarizes the main water problems and their condition.

2.1 Channeling

The phenomenon of channeling commonly occurs as a result of reservoir heterogeneity and the presence of high permeability layers. Due to variations in mobility ratio and wettability, water has a tendency to migrate towards zones of high permeability and large pores, bypassing the oil and leaving less permeable areas unswept. Consequently, the water's permeability increases during subsequent flow, resulting in elevated water-oil ratios throughout the lifespan of the well or project (**Reynolds, 2003**).

Channeling can occur in three diffrent forms. Firstly, when there is a shale layer present between, above, or below these multilayer systems, without any crossflow within the reservoir. Secondly, when highly permeable layers communicate without any shale in between to impede crossflow. In this case, high crossflow leads to a pressure balance between the layers, reducing the chances of oil resaturation in the depleted high permeability zone and causing increased water crossflow (**Jahanbani Ghahfarokhi et al., 2016**). Thirdly, fractures or deposits subjected to high pressure from external injection waterflood designs can quickly break through into producing wells. Even with natural barriers, such as thick shale layers, dividing the fluid zones and a reliable cement job, the shales may experience cracking and fracturing near the wellbore due to production. The pressure difference between these shales facilitates the movement of fluids down the wellbore. This breakthrough form is often associated with stimulation attempts (**Reynolds, 2003**).

Viscous fingering, which is considered to be induced fractures during heavy oil flooding projects, is another contributing factor, that can lead to varying water-oil ratio values (**He et al., 2023**).

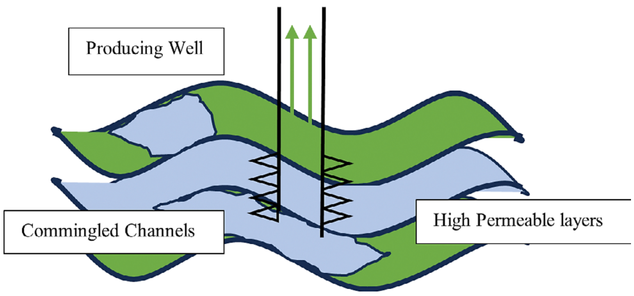

Figure 2: Comingled Channels (Bailey et al., 2000)

2.2 Coning

Coning refers to the upward movement of water into the well perforation, driven by its least resistance path (**Ahmed, 2001**). This phenomenon occurs when the pressure in the wellbore exceeds the gravitational forces due to the density difference between oil and water. As a result of the disruption in equilibrium between viscous and gravitational forces, oil flows towards the perforated gap. This imbalance favors the viscous force, resulting in a significant increase in flow rate and, eventually, a fromation of cone-like shape (**Bournazel & Jeanson, 1971**; **Chaperon, 1986**; **Moawad et al., 2013**). Although the perforations are located above the original water-oil contact, their proximity allows the undesired fluid to be produced more easily and quickly through coning or cresting (**Reynolds, 2003**). However, the coning phenomenon causes less increase in water flow than the channeling. This is owing to the cone's radial expansion compared to its vertical expansion; when the horizontal permeability exceeds the vertical permeability, the cone extends radial.

Conversely, the speed of water flow in channels increases due to permeability parameters and fluid saturation distribution (**Shabibi & Sahraei, 2021**). The water cone reaches its maximum when the circular expansion of the cone base (oil-water contact) reaches the drainage radius.

The coning phenomenon is directly influenced by production methods and strategies. Employing Electric Submersible Pumps (ESP) as an artificial lift method to reduce sub-hydrostatic reservoir pressure often leads to excessive drawdown pressure and water coning, especially at high well rates (**Al-Azmi et al., 2022**). A common approach to mitigate coning in the early stages involves controlling the critical coning rate. This rate represents the maximum amount of oil that can be produced without forming a cone and is often economically challenging to achieve (**Bailey et al., 2000**).

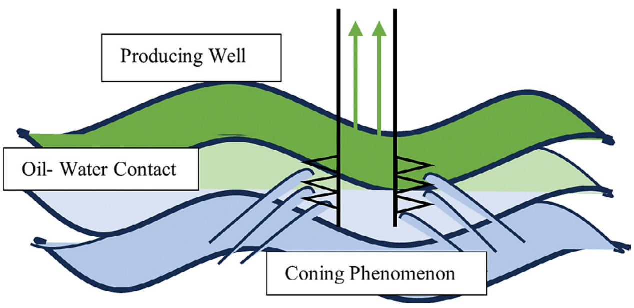

Figure 3: Coning phenomena reproduced (**Okon et al., 2017**)

3. Excessive Water Diagnostic Methods

There are several methods for diagnosing excessive water production varying from traditional ones to the recent advanced and analytical approaches. Here, we will address the common methods used in the industry. It is generally recommended to monitor water production in each well by regularly analyzing samples and establishing a baseline. This provides valuable information in the event of unexpected changes in production or well conditions. For example, increases in chloride or Total Dissolved Solids (TDS) can serve as indicators, enabling us to identify potential issues and determine whether the produced water originates from the reservoir or an external source. This method is considered a quick and effective diagnostic approach (**Weschenfelder et al., 2015**).

Additionally, well logs are capable of recognizing downhole issues that may contribute to undesirable water production and quantify the fluid production within the wellbore. Cement leaks, cement channels, coning and watered-out reservoirs represent common sources of undesired water, that can be identified through well logs such as the Production Logging Tool (PLT), Pulsed Neutron, and casing/Cement Bond Log assessment (CBL). These tools provide insight into cement integrity, zone production sharing, and help identify cross-flow behind the casing (**Wyatt, 2000**). However, it's important to note that well logs are confined to evaluating conditions exclusively within the wellbore and do not extend to the assessment of reservoir-related issues.

Well log interpretation has recently been enhanced through the integration of advanced technologies. This includes combining various logs to locate and measure excessive water sources behind the casing. This improvement extended the diagnosing surveys to the reservoir by identifying flowing zones and detecting undiscovered breaches (**Bhagavatula et al., 2015**). For instance, PLT could be an efficient tool for investigating well integrity diagnosing, and discovering leaks, rather than production allocation, particularly in open-hole completion (**Yaakob, 2017**). Additionally, the water flow log has evolved as a viable standalone approach for locating tubing leaks and tracking water flow within and behind casings or tubing (**Saxen et al., 2013**). However, the cost of running High Precision Temperature logging (HPT), Spectral Noise Logging (SNL), Spinner (Flow Meter Logs), and PLT is too high for each well and it is sometimes necessary to suspend production while logging, which impacts the cash flow. Furthermore, log data processing, evaluation, and interpretation are frequently sophisticated, demanding, expensive, and time-consuming (**Nikravesh & Aminzadeh, 2001**). Moreover, the constraints restriction in deviated wells limit PLT application, citing complex flow dynamics that make monitoring downhole fluid velocities and liquid holdups challenging (**Al Hasani et al., 2008**).

On the contrary, analytical tools, such as production data analyses, are the most often utilized approaches for analyzing reservoirs, individual well performance, and water management. The recorded percentages of produced oil and water, acquired at normal periods, are the most important component of the production data (usually daily). Alongside the produced oil and water rates, the water-to-oil (WOR) ratio is also taken into consideration. These approaches can be summarized as recovery plots and production history plots. For instance, but not limited to, water cut versus time, is frequently used to illustrate the growth and severity of excessive water

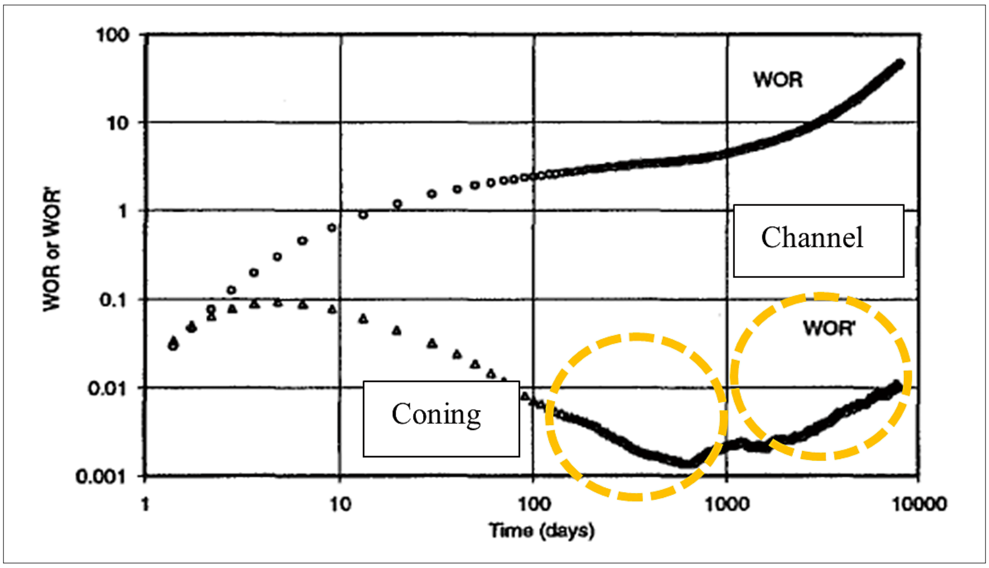

Figure 4: WOR-D Shifting from Coning to late time Channeling (**Chan, 1995**)

(**Bailey et al., 2000**). Another technique, the X-plot, is an extension of the water-cut plot (**Ershaghi & Omorigie, 1978**). It establishes a linear relationship between cumulative oil (Qo) and variable water-cut features. Furthermore, decline-curve analysis, which is one of the most common methods for evaluating well performance during normal depletion, involves identifying a straight decline bar for each well from production data. Any deviation in the bar could indicate water or other issues (**Bailey et al., 2000**). However, these analytical methods of production plots have limited diagnostic capabilities and do not provide information about the underlying reasons for excessive water production, as the shapes of the plots appear similar. These plots can be useful for assessing production efficiency, but they do not reveal any data on reservoir flow characteristics (**Chan, 1995**).

4. Chan Diagnostic Plot

The Chan plot is a simple representation of the water-oil ratio (WOR) and its derivative (WOR-D) on a logarithmic scale. This plot effectively captures changes in the WOR, making it a valuable tool for identifying excessive water production mechanisms. Additionally, the integration of the WOR-D allows for the determination of whether the water problem is due to coning or multilayer channeling. Chan demonstrated his theory by using a three-dimensional, three-phase black oil reservoir simulator to showcase WOR plots for various drive mechanisms and waterflood scenarios. He observed three behavioural periods for coning and channeling. The WOR remains constant for both mechanisms throughout the first phase until water breakthrough, after which the departure time begins. While the WOR sharply increases for channeling, it gradually rises for coning until it reaches a constant value (**Chan, 1995**). Usually, Coning takes less time than channeling.

Moreover, the WOR-D exhibits a distinct visual characteristic when tracking the slope of the WOR-D points. It demonstrates a relatively positive slope for channeling and a declining slope for coning (**Chan, 1995**). **Figure 4** presents an ideal plot that effectively portrays coning and channeling behaviour in a well.

It can be inferred that Chan's diagnostic plot provides a more thorough understanding and information for evaluating performance. This plot can be used for the whole well life or a specific phase, such as the waterflood phase. The analytical results offer valuable insight into reservoir flow dynamics, enabling a comprehensive understanding of the key mechanisms behind excessive water production when combined with a complete workover history. Furthermore, the WOR and WOR-D slope switch indicates the various patterns, including normal displacement production behaviour, multilayer water breakthrough behaviour, fast layer depletion, coning, and water recycling activity (**Chan, 1995**).

However, the application of Chan's method poses challenges for engineers due to the presence of noise and interruptions in actual production data. In many cases, the visual interpretation of the slope can be misleading, making it difficult to differentiate between different patterns (**Mukhanov et al., 2018**). The slope feature typically exhibits growth for multilayer channeling, resulting in various slopes compared to a single slope observed for channeling behaviour. Additionally, distinguishing between straight and horizontal lines for Constant WOR and Normal Displacement patterns can be challenging (**Mukhanov et al., 2018**). Although the inclusion of generated points along the log cycle may be an additional feature, the limited number of points within the log period may not be comprehensive. Additionally, WOR and WOR-D are highly sensitive to production changes and field characteristics. Therefore, it is necessary to rely on comprehensive information from reliable and periodic data sources in order to trust the results. To address these challenges, Chan's plot has been included in water management workflows, combined with other tools to diagnose excessive water production.

5. Coupling Chan Plot Interpretation with Other Diagnostic Tools

Chan plots have been widely used as a standalone diagnostic tool in various case studies. It has been applied to Jake's oil field in Sudan (**Mahgoup & Khair, 2015**). By comparing the results to Chan's standard plot, they were able to discern the distinction between channeling and coning in each well. The study revealed that channeling was the primary factor contributing to water production in wells containing high-permeability sandstone zones. Also, Chan's diagnostic plot was applied to examine the excessive water production in Aswad Oilfield, Libya (**Abdulmaein Bin Younus, 2020**). Three wells were selected for diagnosis, exhibiting water rates of up to 88% per day. In conclusion, the Chan plot effectively identified channeling as the main driver of water production. Recently, the Chan plot was utilized with two diagnostic methods: conventional plotting of water-cut over time and well card data, to identify causes of water production (**Hazarika et al., 2022**). The Chan plot effectively identified multilayer channeling and coning as the underlying causes of excessive water production. The findings underscore the crucial role of the Chan plot in accurately pinpointing water sources and guiding remedial operations to prolong oil production. Evidently, in sandstone reservoirs, the two forms of channeling signature and coning to some extent appear readily as slope changes instantly for the various watered-out permeable layers. Similarly, the Chan model was employed for diagnosis and concluded that inadequate well surveillance and deficiencies in well reservoir and facility management were present (**Nmegbu et al., 2020**). Following this identification of water-related issues, a shutoff plan was implemented, resulting in an increase in oil production for both of the tested wells, along with a 1% reduction in water production.

However, in order to address the limitations of Chan's plot, such as potentially misleading results and the lack of reliable WOR records, engineers have integrated Chan's plot with other diagnostic tools to confirm the causes of excessive water production. **Reyes et al. (2010)** introduced a Reliability-Based Systemic Method that incorporates the Six Sigma tool. This method combines Chan's plot with logging tools to identify the source of excessive water production and classify water as either desired or undesired. This comprehensive approach evaluates the entire system, including both surface and subsurface components, and examines how they interact to influence water production using a probability index. While Chan's plot serves as a primary diagnostic tool, it is important to note that the accuracy of the results may be compromised if crucial data and testing information are missing. Additionally, running this workflow may also require a significant amount of time.

Another inclusive workflow was proposed to understand water breakthrough mechanisms and prioritize well remediation (**Dokhon et al., 2020**). The Chan correlation was their essential analytical tool, while the secondary investigative tools were PLT and ionic-produced water analysis. This systematic method can be effectively applied without the need for the PLT step. Five out of seven wells were successfully diagnosed by combining geological features with the Chan plot and comparing initial water salinity with current salinity. The change in water quality due to pressure and temperature is relatively small, making it easy to analyze excessive water production source. This approach has assisted engineers in gaining a deeper understanding of reservoir communication, especially in the context of injection projects. However, in order to reduce the noise in actual data, a workflow was recommended involving reservoir numerical simulation to smooth the data by matching the actual production trends (**Alexis, 2010**). This roadmap increased confidence in using Chan's plot, as the modeled patterns closely resembled Chan. Furthermore, the slope growth feature was examined using X-plots to diagnose the multilayer channeling pattern and identify the dominant layer contributing to water production (**Alexis, 2010**). In the same context, the X-plot was used to detect layering in multilayering systems based on the slope changes due to various permeability layers contrast **Nabila et al. (2022)**.

The numerical simulation was used once again as a verification tool in the Asmari reservoir within the Abu Ghirab oilfield, located southeast of Iraq (**Mohammed et al. 2020**). Despite the geological complication and missing 70% of production data from 1980 to 2011, Chan's analytical results were identical to simulation results, showing that the channeling is the cause of water production due to high permeability zones, high water saturation zones, and faults or fracturing. Their integration assisted in confirming the appearance of reservoir geological features of channeling and fracturing detected by Chan's signature and observing the change in the water flow path in the model as the water chose the shortest path (**Shabibi & Sahraei, 2021**). However, all the above workflows assisted in overcoming the need for running additional costing tools and helped in determining the geological structure, especially the fractures that developed after production. However, the major drawback of the X-plot is its applicability solely to high water-cut wells, particularly for addressing channeling. While coning behaviour can be studied and verified by numerical simulation, it is time and effort-consuming, requiring an extensive data set. A single study may take months for history matching, requiring continuous updates for the producing wells.

Other investigations have explored the suitability of Chan's diagnostic plot across different well and reser-

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Table 1: Summary of studies on Chan plot Integration with other diagnostic tools

Diagnostic Tools	Advantages	Disadvantages	Reference
• Production History • Chan plot • PLT • Pressure • Temperature log	By methodically assessing each component of the production system and supporting the suggestion of several solutions to increase productivity, Six Sigma offers a solid framework for a water production analysis. This approach helps the identification of underlying issues and streamlines the process of thoroughly investigating the system.	The developed workflow is operationally oriented and explains the general integration of tools, but it lacks a specific technical focus on diagnosing the water problem. It overlooks considerations such as tool availability and the time and cost required for running these tools.	**Reyes et al., 2010**
• Chan correlation • PLT for determining the water entry zone • Lab analysis for ionic concentration	The introduction of lab analysis combined with the Chan plot is an efficient way to address water problems and understand reservoir communication easily and quickly. Also, the workflow can identify the excessive water qualitatively and quantitatively.	Any use of a Production logging tool will directly affect the overall operation costs. Additionally, without initial properties of produced water, benchmarking for the future, especially in the context of any injection project, becomes challenging.	**Dokhon et al., 2020**
• Numerical simulation • Chan's Diagnostic plot • X-Plot • Hall and the Hearn Plots	The proposed workflow involves incorporating numerical simulation for the reservoir, enhancing the confidence in interpreting diagnostic plots after history matching. The successful integration of the X-plot with Chan proved to be an effective module for diagnosing multilayer channeling behaviour.	Time-consuming and requiring ongoing effort, it needs to be updated for as long as the well is in production to align with the production and Water-Oil Ratio (WOR) data.	**Alexis, 2010**
• X-Plot • Chan's Diagnostic Plot • Decline Curve Analysis	While the noisy data posed challenges in interpretation, the integration of the X-Plot and the Chan plot in the case study assisted in verifying and confirming the patterns detected from the Chan plot.	The methodology can be efficient for multilayer channeling problems but may not be suitable for addressing other issues, such as coning.	**Nabila et al., 2022**
• Chan's Diagnostic Plot	Chan demonstrates its applicability as a standalone diagnostic tool that accurately differentiates between channeling and coning problems accurately, especially after remediation took place.	The noise in the actual production data, challenges in interpreting the first derivative order of Water-Oil Ratio (WOR), and irregularities in the production profile due to various activities.	**Mahgoup & Khair, 2015**; **Nmegbu et al., 2020**; **Abdulmaein Bin Younus, 2020**; **Mekunye & Ogbeide, 2021**
• PLT • Water-oil-ratio (WOR) plots • 3-D simulation model	This contribution examined and confirmed the application of Chan in horizontal wells, showing a high degree of alignment with Chan's published work. It considered various types of artificial lift influence on the plot interpretation for both coning and channeling signatures.	Yet, the work needs to demonstrate its practicality using actual production data for horizontal wells.	**Al Hasani et al., 2008**
• Chan diagnostic plots • Permeability • PLT • PTA	A new method of integrating permeability & FZI profiles with Chan plot for advanced dynamic interpreting by segmenting well life cycle into early, middle, and late time to predict watered-out layers and water breakthrough, and this is confirmed by PTA & PLT in a complex carbonate reservoir.	Predicting the permeability of carbonate reservoirs is challenging due to natural fractures acting as secondary porosity. The analysis of transient pressure data necessitates sophisticated techniques, and the associated costs for conducting both Pressure Transient Analysis (PTA) and Production Logging Tool (PLT) can be substantial.	**AlOtaibi et al., 2019**

voir conditions in their research. One study investigated the application of Chan plots to horizontal wells in the Oman oil field (**Al Hasani et al., 2008**). The limitations of PLT in these wells motivated this exploration. Flow dynamics and gravity effects on the flow pattern within horizontal wells often lead to complex PLT interpretations. A 3D simulation model consisting of one horizontal and three vertical wells was developed to explore the impact of the coning and channeling through a fracture on the plot signature (**Al Hasani et al., 2008**). In conclusion, the results agreed with Chan's published work, even considering the impact of using artificial lifts for oil production. However, this study modeled the channeling behaviour by modifying the layer's permeability in homogenous strata and neglecting the reservoir environmental deposition, that could lead to induced fractures and geological features like carbonate reservoir, as studied later. **AlOtaibi et al. (2019)** articulate the effectiveness of using the Chan diagnostic plot in these complex reservoirs. The approach involved segmenting the well into early, middle and late time periods, using a Flow Zone Indicator (FZI) for rock typing to reflect the permeability profile and Pressure Transient Analysis (PTA) to study the flow around the wellbore. This methodology emphasized that FZI can affect the upward slope shift of the WOR trend rather than the simple permeability variation for the same layers. This phenomenon can be due to the dominating flow unit within the reservoir in specific areas. Therefore, this may broaden the integration of Chan's interpretation in understanding the reservoir geocomplexity by addressing the variations in rock types within the reservoirs, in addition to detecting fractures and fault communication.

From the literature, the Chan plot has been validated for many fields through numerical simulation and logging tools for various excessive water problems. Additionally, Chan's applicability has been demonstrated in both sandstone and carbonate reservoirs, exhibiting a reasonable degree of matching with Chan's published work on sandstone, besides vertical and horizontal wells. However, the developed workflows and the coupling with other tools are both economically and technically exhausting, requiring a substantial amount of time for interpretation. Therefore, machine learning and artificial intelligence have the potential to become powerful tools for standardizing and automating Chan plot interpretation, thereby reducing the associated challenges. Below is a literature summary showing the tools combined with Chan to diagnose excessive water production.

6. Chan Plot Improvement

Artificial intelligence (AI) has already sparked significant changes in the oil and gas industry and assisted in solving many problems. Although the earliest applications of AI in the oil and gas business were studied in the 1970s, the industry has recently begun to seek AI application potential more consciously (**Li et al., 2021**). All the described AI techniques have one thing in common: without access to vast and high-quality training data, AI algorithms are much less helpful, if not unusable. "Good enough" indicates that the data must be wide-ranging enough to cover all relevant events, actions, and behaviours (**Ng, 2016**). The oil industry is full of data based on correlation that require feature engineering procedures to establish a good relationship between the input variables, for instance, geological correlation, log correlation, and rock typing, as well as plot interpretation. In general machine learning (ML) can be classified into two supervised and unsupervised machine learning depending on the data set and the objective of the study. Unsupervised learning focuses on clustering and grouping the data by identifying the common relationship from the given sets, while in supervised learning the model is trained from given labeled data and tested its performance in test sets. Based on the problem the models can be utilized either for regression or classification.

Chan's interpretation can be considered a multiclass classification problem as the plot can have two or more classes. These plots are difficult to simply address as ML problems because, in terms of the data set, there is no specific range for WOR & WOR-D values for various patterns for example the normal displacement with high water rate values is quite identical to the channeling problems. In addition, relevant data such as production rate, water-cut percentages, and artificial pump data don't help the model extract any specific features. However, in terms of visualization signature, slope is the basic concept of the Chan plot and in order to be captured by the ML model, an effort should be made to remove outliers and feature engineering parts. Outliers may either be removed manually before labeling or be detected using different advanced models. Some models use the point distance from the mean to remove nonconformist points. However, this approach may remove representative points, in short-period patterns. Additionally, time series models can be used for outlier detection in two forms, an overall or neighbouring threshold to extract abnormal points, or a sequential pattern to remove abnormal behaviour, in the two cases they are difficult to apply, as the former, will smooth the point and become blurred to obtain the slope, while the latter can't be applied as Chan is not in form of series data and sequence pattern. For example, unsupervised methods could be statistical, such as Z-score, Modified Z-score, and Interquartile Range (IQR), or ML-based such as Angle-Based Outlier Detection (ABOD), Isolation Forest, K-Nearest Neighbours (KNN), and Local Outlier Factor (LOF). ABOD was used for detecting outliers from production time-series data to develop a computer vision that interprets Chan's signature (**Abdelaziem et al., 2022**). However, the algorithm operated on the whole production data from the well start to the abandonment stage, which means after the water problem pattern is fully developed

Table 2: Summary of Chan's Improvement Attempts

Study	Methodology	Findings	Reference
Noise associated with the analysis of diagnostic plots involving fluctuating and random functions in the time domain.	• Spectral Analysis	The developed software aimed to mitigate the high noise in Water-Oil Ratio (WOR) data points by exploring autocovariance and autocorrelation, providing insight into the frequency of WOR in the time domain. The results indicate that coning can be reasonably closely modeled as a low-order autoregressive process with a narrow spectrum. However, the model's capability is limited to distinguishing between coning and non-coning issues, especially in normal high WOR scenarios.	**Egbe & Appah, 2005**
Classification of Excessive Water Production Issues and WOR Deficiencies	• WOR vs RF Reservoir characteristics • Tree-based ensemble classifiers	Considering three scenarios—pre-water production, post-water production with static reservoir features, and post-water without static reservoir characteristics—the Water-Oil Ratio-Reservoir Factor (WOR-RF) plot demonstrates accurate forecasting rates of at least 90%, 93%, and 82%.	**Rabiei et al., 2009**
Artificial Neural Network Models for Diagnosing Water Production	• Data obtained after simulation was used to develop two artificial neural network models • Artificial Neural Network (ANN)	While the data noisiness poses challenges for developing a diagnostic model, the neural network model successfully forecasted the water cut for the well's last four years of production, achieving a high regression coefficient of 0.9985.	**Shola, 2017**
Support Vector Machine for Pattern Recognition in Water Control Diagnostic Plots	• Supervised machine learning (ML) technique, • Support Victor Machine (SVM)	The model was developed efficiently to distinguish the various Chan's signature of water problems, with an accuracy of 78%.	**Mukhanov et al., 2018**
Practical Machine Learning Approach for Identifying Chan Plot Signatures	• Machine learning (Multiclass classification problem)	By simplifying features and improving the data quality used in the Chan plot signature recognition challenge, the accuracy of the Machine Learning (ML) model increased. The Radial Basis Function (RBF) Support Vector Machine (SVM) algorithm achieved an estimation of 0.90, while the nearest neighbour model achieved the highest f1-score of 0.93.	**Garcia et al., 2019**
Recognition of Multiple Chan Signatures in Wells Exhibiting Diverse Mechanisms Across Lifecycle	• Chan plots as images • CNN (Convolutional Neural Network) • YOLO as an Object detector	The application is considered a novel, as it is the first to identify different Chan signatures and patterns that a well can exhibit during production with an accuracy exceeding 80%.	**Abdelaziem et al., 2022**

and does not track the outliers as active learning. More effort can be made to improve outlier detection for future recommendations. So, the choice of removing manual outliers can be a good option for now, particularly for very low and high abrupt changes in water-oil ratios (WOR) due to any changes in the well production environment. In addition, the feature engineering part should be well designed as WOR&WOR-D alone can't be enough to detect patterns even if it's normalized. The slope used as a special added feature instead of WOR points, but only for detecting single pattern (**Garcia et al., 2019**). Still a need for unique features that can easily be captured when the slope trend changes with time, below is a review of all the previous attempts to improve Chan plot interpretation. **Table 2** summarizes the significant work done to improve Chan diagnostic plot interpretation.

One of the earliest efforts to find a solution for the disorderly data associated in the Chan diagnostic plot employed spectral analysis, particularly Fourier transformation, to overcome the high noise in WOR data points (**Egbe & Appah 2005**). Their approach involved investigating autocovariance and autocorrelation to understand the frequency of WOR in time domine. However, their model could only differentiate between the coning and non-coning problems, mainly normal high WOR scenarios. This led to the question of whether the model could identify channeling problems, given the similar WOR frequency; and potential changes in the production profile due to any operational activities that reflected in WOR change.

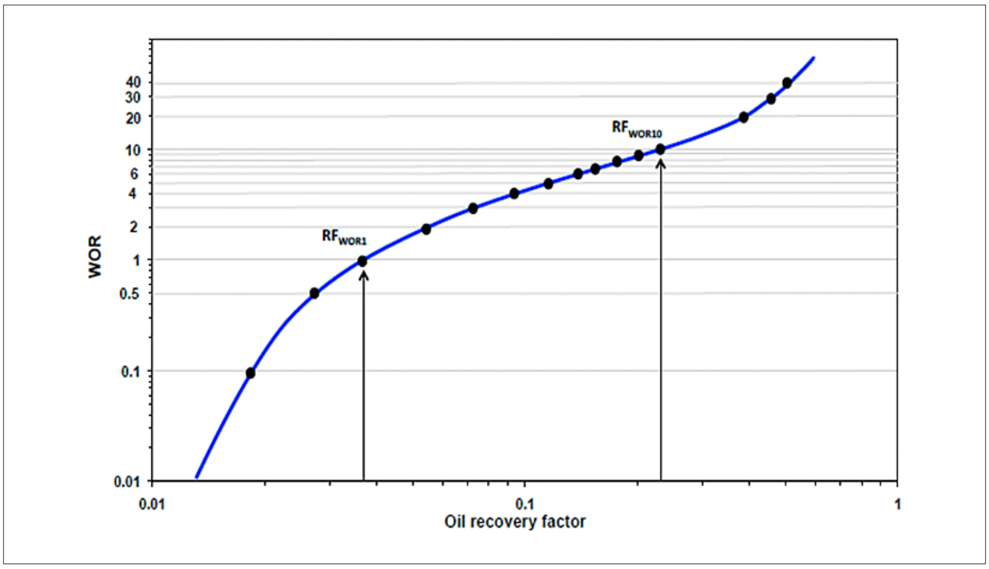

Figure 5: WOR vs RF (Rabiei et al., 2009)

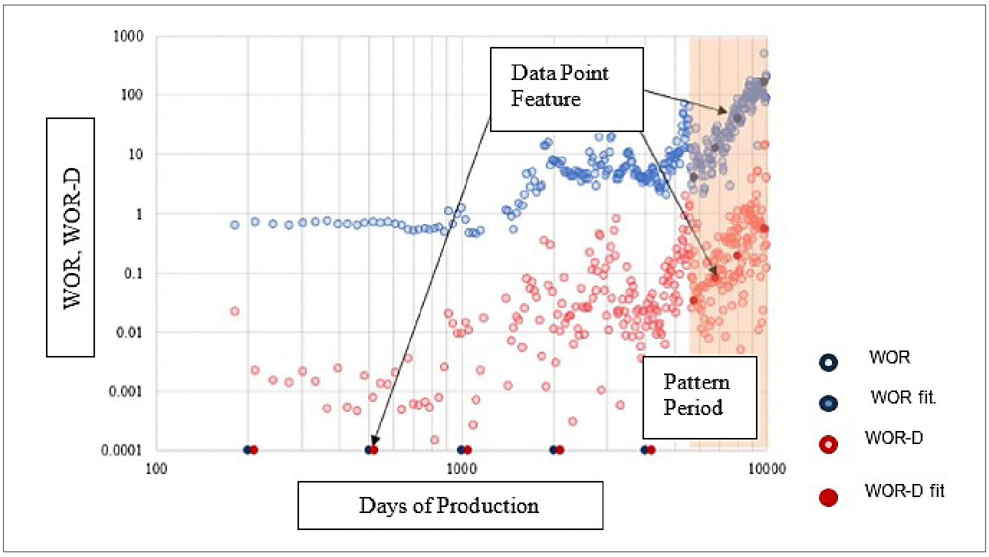

Figure 6: Fitted WOR points used as a feature by (Mukhanov et al. in 2018)

Another effort addressed the limitation of the Chan diagnostic plot, especially for the coning cases (**Rabiei et al., 2009**). This work noticed a disagreement in the WOR-D slope compared to the Chan idealistic result. In response, they proposed a WOR vs. Recovery Factor (RF) plot to identify the different water problems originating from multiple reservoir parameters models. They achieved this by extracting hidden predictive data points from the plot using Tree-Based Ensemble classifiers and a Logistic Model Tree, aiming for more improvement. They considered three scenarios, pre-water production and post-water production with static reservoir characteristics, and post-water production using only dynamic data (WOR Points). They extracted a total of 15 new dynamic points corresponding to RF, as shown in **Figure 5**, and simulated various water patterns. The Analysis of Variance (ANOVA) technique was used to examine the mean for these parameters, resulting in accuracy rates of at least 90%, 93%, and 82%, respectively for each scenario (**Rabiei et al., 2009**). However, this model has limitations regarding the utilization of static reservoir features, which are not always available and comprehensive. Additionally, using static reservoir characteristics alone to identify the water problem is theoretically weak, due to the changes in relative permeabilities by the means of saturation and mobility variation because of pressure drop. Furthermore, the modifications in the reservoir geomechanics resulting from production impact water flow behaviour within the reservoir and contribute to post-production water problems. In addition, the simulated data appear smoother compared to the actual production data, explaining the lower accuracy reported when relying solely on dynamic surface WOR points, as actual data poses greater challenges.

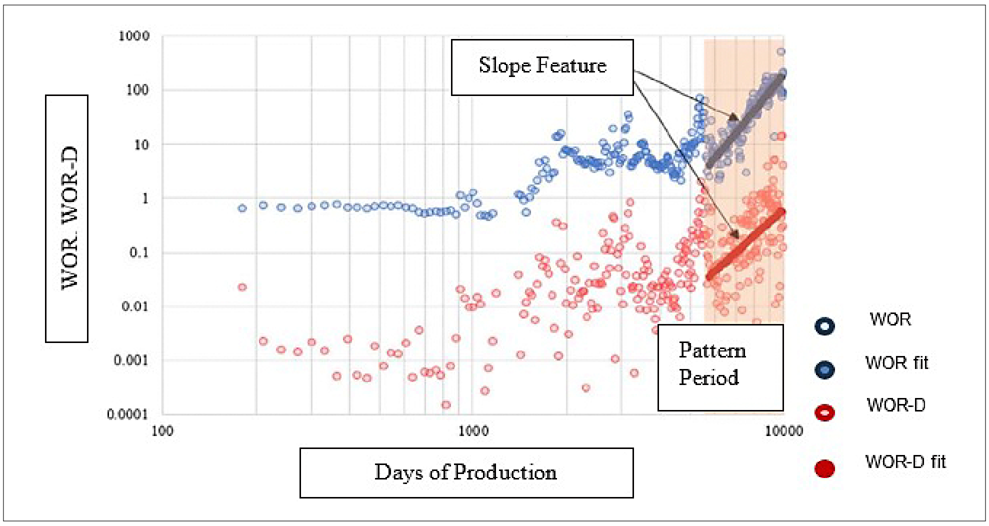

Figure 7: Slope used as a feature by (Garcia et al., 2019)

Additionally, deep learning, specifically Artificial Neural Networks (ANN), were applied to diagnose water problems (**Shola, 2017**). Unfortunately, Chan's signatures were not distinguishable from the real production data. However, a breakthrough was made by introducing Chan plots as a multi-class classification problem using supervised machine learning techniques, specifically support vector machine algorithm (SVM) (**Mukhanov et al., 2018**). They used around 10,000 actual completion data sets. The model identified four patterns (Constant WOR, Normal Displacement, Multilayer channeling, and Rapid channeling) with an accuracy of 78%. However, this model ignored the coning problem and used fitted WOR points as a scaled one-dimensional (1D) vector (features), presenting a fixed number of points per pattern (20) points. This approach neglected the pattern period variation without capturing the whole signature.

A novel approach was demonstrated by **Garcia et al. (2019)** to improve **Mukhanov et al. (2018)** work by applying the slope as a feature instead of the WOR points. The number of features was reduced from 20 to two per pattern, with slope coefficient extracted from the polynomial equation after matching the WOR data point instead of the fitted data points method. This approach significantly increased the accuracy to more than 90% across various applied algorithms (nearest neighbour, naïve Bayes, liner SVM, and RBF) (**Garcia et al., 2019**). **Figure 6** and **Figure 7** present the WOR data point and slope approaches as features for model development.

However, all the models mentioned above could detect only one pattern over the well life cycle and couldn't identify and capture the change in the slope directly to mitigate the problem before it entirely occurs. This limitation addressed by developing a computer vision application based on a Conventional Neural Network (CNN) to distinguish the different Chan patterns that the single well can exhibit during its production life. Using the You Only Look Once (YOLO) algorithm for object detection, they detected channeling and coning patterns with a confidence score higher than 80% accuracy, inputting Chan plot as an image (**Abdelaziem et al., 2022**). However, the YOLO algorithm may struggle with detecting many objects in a single image, especially small objects like scatter point trends, due to its rigid approach and limited capacity. Therefore, it may not accurately detect and classify many objects. Additionally, the model captures the patterns from the image after they are fully materialized which does not help in tracking and early problem determination. This explains the need for an interactive model that tracks every point and warns if there is any pattern change to mitigate any complication early on. Moreover, presentation of the Chan plots as images for deep learning requires a large set to enhance the accuracy. They initially scored 67% from the first patch, but after using additional data and applying active learning, accuracy increased to more than 80%. Another issue is the failure to consider other changes that affect the well production profile and WOR trend such as, depletion, drawdown, stimulation, and any addition or removal of perforation within the well life cycle it didn't take into account while labeling.

Furthermore, this review aims to contribute to the improvement of Chan's diagnostic plot as a more precise, rapid, and real-time surveillance tool for water production problems. Building upon the slope model (**Garcia et al., 2019**), this review proposes an interactive model that employs a fixed-size "partition" that slides (rolls) over a time series or sequence of data points. Within each window, a polynomial fit calculates the slope and intersection, allowing the model to track changes in these values over time, as illustrated in **Figure 8**. This technique has the advantage of identifying abnormal points in slope shifts with greater accuracy, influenced by the chosen window size and intersection values. Notably, the suggested model's features (WOR, WOR-D,

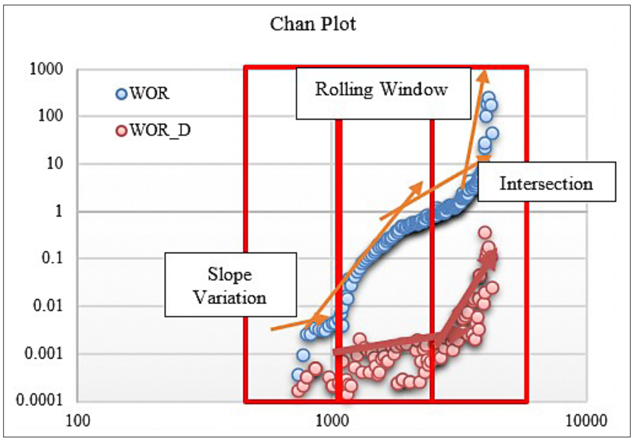

Figure 8: Rolling Window with fixed size detecting slope and intersection

slope, and intersection) form a matrix, making it insensitive to the pattern period.

7. Future Directions

Suggestions for future research directions to address gaps identified in the review include:

[1] Development of a real-time model capable of continuously tracking slope changes in Chan patterns. This model should leverage a fusion of Water-Oil Ratio (WOR) data points and temporal analysis techniques, such as time series and rolling windows functions. The goal is to enable the early detection of water-related issues, facilitating timely mitigation of water problems and increasing the potential for higher oil recovery.

[2] Development of Interactive algorithms for detecting outliers sensitive to WOR and its derivative WOR-D points.

[3] Conducting a comprehensive examination of the coning behaviour interpretation based on empirical field data. This research should include integrating coning behaviour into the learning process to enhance the model's ability to capture a broader spectrum of patterns.

[4] Leveraging slope shifting in the layering system to enhance reservoir characterization. This involves discerning the presence of permeable layers and induced fractures post-production. The approach integrates Chan›s interpretational framework with geological attributes from the core and 4D-seismic data. This integrative approach is particularly pertinent for addressing reservoir geocomplexity issues, such as faults and channel communication, and determining flow units. It holds significance within the context of enhanced oil recovery (EOR) projects.

8. Conclusion

In conclusion, this paper addressed the causes and effects of excessive water in both well integrity and facility scale and recovery factor at the reservoir scale. Excessive water mechanisms were classified and discussed. The Chan diagnostic plot was deliberated in detail, emphasizing its application as standalone and integration with other tools based on their availability and complexity of the water production problem. Additionally, future directions for improving Chan's interpretation were outlined. Consequently, the following conclusions can be drawn.

[1] The review highlights the traditional diagnostic methods for excessive water production, underscoring the significance of regular sample analysis and baseline establishment. While well logs are reliable, there are technical and economic drawbacks associated with them. Efforts to expedite the logging process and enhance analysis should be prioritized to extend their applicability to reservoir water problems.

[2] The review also emphasized the effectiveness of Chan plots in diagnosing water influx mechanisms like channeling and coning across various reservoir and well conditions. Furthermore, it highlighted the value of integrating Chan plot interpretation with existing tools like well logs and simulations for a more comprehensive identification of water production patterns.

[3] The review focused on recent advancements in Chan plot interpretation using machine learning models. These models offer significant advantages by automating plot interpretation, leading to increased accuracy and efficiency in identifying water production issues. While these models offer substantial benefits, future research should focus on developing models that excel at early pattern detection through real-time data analysis and interactive capabilities. Such models have the potential to revolutionize water production management by enabling proactive intervention strategies, ultimately leading to improved well productivity and overall production efficiency.

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List of Acronyms:

Acronyms	Expansions	Acronyms	Expansions
ML	Machine learning	ANOVA	Analysis of variance
WOR	Water Oil Ratio	IQR	Interquartile range
WOD-D	Water Oil Ratio Derivative	SVM	Support Vector Machine
FZI	Flow Zone Indicator	KNN	K-nearest neighbours
HPT	High Precision Temperature	LOF	local outlier factor
SNL	Spectral Noise Logging	CNN	Conventional Neural Network
PLT	Production Logging Tool	ABOD	Angle-based outlier detection
ANN	Artificial Neural Networks	YOLO	You Only Look Once
EOR	Enhanced Oil Recovery		

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SAŽETAK

Pregled primjene Chanova dijagrama i nedavno razvijenih naprednih modela za utvrđivanje prekomjerne proizvodnje slojne vode

Slojna voda jedan je od glavnih fluida povezanih s proizvodnim ciklusom u naftnoj industriji, koji je potrebno pažljivo razmatrati zbog utjecaja na okoliš, izgradnje postrojenja za obradu fluida i ekonomskoga utjecaja. Tijekom godina razvijene su različite metode za otkrivanje uzroka prekomjerne proizvodnje slojne vode. Te metode obuhvaćaju cijeli niz metoda, od pouzdanih i skupih, kao što su karotažni podatci, do manje točnih metoda, koje se koriste dostupnim podatcima o proizvodnji te podatcima o vodo-naftnom faktoru (eng. *Water-Oil Ratio*, WOR), kao što je Chanov dijagram. Iz Chanova dijagrama vidljivo je da tijekom proizvodnje ugljikovodika do prekomjerne proizvodnje slojne vode dolazi zbog različitih uzročnika uključujući konstantan WOR, istiskivanje fluida, kanalno strujanje (strujanje istiskujućega fluida) i konusiranje. Međutim, ručna interpretacija ovih dijagrama često dovodi do zbunjujućih rezultata zbog pogrešaka (šumova) prisutnih u stvarnim podatcima. Modeli strojnoga učenja poboljšali su točnost tumačenja, no još uvijek ostaju ograničenja vezana uz otkrivanje obrazaca proizvodnje vode koji se pritom razvijaju. Ovaj rad daje pregled primjene Chanovih dijagrama i njihove integracije s postojećim dijagnostičkim alatima za otkrivanje uzročnika prekomjerne proizvodnje vode. Rad je fokusiran na nedavno razvijen napredni model koji se koristi strojnim učenjem posebno osmišljenim za poboljšanje interpretacije Chanovih dijagrama. U ovome su preglednom radu istaknuta ograničenja tradicionalnih metoda tumačenja Chanovih dijagrama i istraženo je kako nedavno razvijen napredni model može riješiti ta ograničenja. Dodatno, u radu se ukratko raspravlja o potencijalu interaktivnoga modela za kontinuirano praćenje uzroka prekomjerne proizvodnje slojne vode. Na kraju, rad daje preporuke za buduće smjerove istraživanja.

Ključne riječi:
prekomjerna proizvodnja slojne vode, vodo-naftni faktor, karotažni dijagram bušotine, strojno učenje

Author's contribution

Ahmed Hamdoon (1) (Msc student, Petroleum Engineer) conducted the literature review systematically and wrote the manuscript. **Mohammed Mohammed (2)** (AP, Dr., University of Emirate) provided the data that helped derive the gab concept and a novel methodology for further research. **Khaled Elraies (3)** (AP, Dr., Chair of Petroleum Engineering Department at UTP) supervised the study and provided result analyses.