Spatial Clustering and Reservoir Analysis: An Expert-Guided Synergy Dynamic Time Warping (DTW) Machine Learning Technique on Volve and Norne Fields[1]

Jakub Marek Cebula[1] (✉), Mohamed Hassan Abdalla Idris[1 2], Shamsul Masum[1], Jebraeel Gholinezhad[1], Edward Smart[1],

[1] University of Portsmouth
[2] Sudapet Co. Ltd.

Abstract: This study introduces an expert-guided application for clustering production wells using Machine Learning (ML), focusing on the Volve and Norne Field datasets to optimise reservoir analysis and decision-making. The Dynamic Time Warping (DTW) algorithm was employed for clustering and further enhanced by spatial visualisation through Voronoi polygons on topographic maps. The study presents a workflow, integrable before reservoir characterization, significantly reducing time for spatial property distribution analysis. The findings indicate that DTW, especially integrated with domain expertise, emerges as an efficient method, offering flexibility and quick results within this workflow. The approach was validated using the Silhouette Score as a reliable clustering metric guide. Alternative methods like K-Shape Clustering and Frequency Domain Aggregated Clustering (Wavelet and FFT) were also examined. Although offering distinct insights, DTW was preferred for its flexibility in capturing temporal shape similarity directly and its better integration into the proposed expert-guided synergistic workflow, despite known computational considerations. The study highlights the potential application of these techniques in different reservoirs of various geological settings.

Keywords: Clustering, Reservoir Characterization, Dynamic Time Warping (DTW), Production Profile, Silhouette Score, Domain Knowledge Expertise

1 Introduction

Increasingly, Machine Learning (ML) and Artificial Intelligence (AI) are being adopted in the oil industry, from classifying operational Non-Productive Time (NPT) to forecasting oil and gas rates in both conventional and unconventional fields [1]. This research focuses on addressing a specific challenge: the significant time traditionally required to determine the optimal number of parameter clusters based on physical reservoir characteristics. By utilising large volumes of temporal (time series) data, the study aimed to substantially reduce this process time. It presents a clustering methodology that enhances reservoir analysis and modelling by grouping wells based on their production history and time-dependent trends. This approach employs ML techniques for clustering production wells using the publicly available Volve and Norne Field datasets under their respective academic licences.

The variety of ML techniques aims to cluster wells based on their similarity, proposing a versatile approach applicable to different fields. Implementing this approach successfully in oil and gas upstream leads to more effective well grouping and clusters, better understanding of the reservoir and more precise volumetric estimates and hence future wells' placement. This study specifically introduces a workflow combining robust clustering techniques with spatial visualization and expert guidance, enabling a synergistic approach to reservoir analysis.

1.1 Related Works

Cai [2] applied K-Means clustering to classify 50 tight gas wells using production performance indices (e.g., rates, pressure), refining gas well management. This methodology, tailored to tight gas reservoirs, may not directly suit conventional oil wells. Weber [3] used a statistical approach to identify gas wells operating below economic thresholds. The ML model's predictive capacity was crucial for early identification of declining wells, aiding decommissioning decisions. Similarly, Saputra et al. [4] applied a hybrid statistical model to Bakken shale, developing unique well prototypes from extensive production data to categorize wells by reservoir characteristics. This identified productive zones, informing drilling and exploration.

Temizel et al. [1] highlighted varied ML applications in oil and gas, including PVT prediction, unconventional reservoir characterization, and well completion optimization. ML models showed to cluster reservoir data by similarity, unveiling patterns of reservoir behaviour and heterogeneity for more accurate models. Sircar et al. [5] emphasized ML's necessity for analyzing the vast technical data in the oil and gas industry. The study explored ML applications in upstream sectors: Reservoir Engineering (integrating seismic, well log, core analysis with past performance using ANN, Genetic Algorithms, RSM) and Production Engineering (analyzing production history, forecasting, correcting well logs, ensuring fluid quality). ANNs for price volatility prediction and linear regression for crude oil economics were also discussed. A Duvernay Formation case study used Bayesian Optimization to predict cumulative production, underscoring spatial feature analysis (e.g., TOC, GOR) for model enhancement, though feature significance can vary by production period and field.

Unsupervised learning (clustering, dimensionality reduction, rule engines) is crucial for reservoir analysis. Specifically, unsupervised clustering is key for conventional oil reservoirs to identify patterns in complex multivariate time series where manual labelling is impractical.

Kheirollahi's study aligns closely with the focus of this research, illustrating the integration of traditional clustering algorithms with advanced techniques such as genetic algorithms and particle swarm optimization. The approach was applied to 24 wells in a conventional oil reservoir, focusing on the decline curve analysis (DCA) to classify wells into groups based on similar production decline characteristics [6]. The DCA equation can be seen in (1).

$$D = kq^b = -\frac{1}{q}\frac{dq}{dt} \tag{1}$$

where

- D = decline rate, 1/day
- q = well production rate, bbl/day (barrels per day) for oil and MCF/day (thousand cubic feet per day) for gas
- t = time period of production, days
- k, b = empirical constants depending on well decline characteristics.

The value of b in the traditional decline curve analysis can be assigned to the declines of:

- Exponential decline: $b = 0$
- Hyperbolic decline: $0 < b < 1$
- Harmonic decline: $b = 1$

Kheirollahi [6] incorporated K-Means with Genetic Algorithm and Particle Swarm Optimization, achieving stable clustering. This improved DCA fit and showed ML's potential in augmenting traditional reservoir analysis. However, its applicability across diverse reservoir environments needs cross-validation for generalisation.

Integrating ML with DCA is promising for automatic well clustering in conventional reservoirs, but DCA has limitations [7]. It applies to conventional reservoirs only under specific assumptions [8]: depletion drive without external support, boundary-dominated flow (no well interference), and constant bottom-hole pressure

While these studies highlight various ML applications, a gap exists in providing a flexible, expert-guided workflow that directly integrates temporal production pattern similarity with spatial reservoir context for conventional fields, which this study aims to address.

2 Methodology

The Volve dataset [9] was sourced from the Eclipse Model using SLB Petrel E&P software. The data originally exhibited inconsistencies in recording frequency—daily data intermingled with 2–3-day gaps, likely due to operational efficiencies. The data was reprocessed accordingly to exhibit daily frequencies using KNNImputer function from the 'scikit-learn' library. The inclusion of simulated bottom-hole pressures, while offering a comprehensive reservoir perspective, came with cautions regarding the dynamic model's fidelity and the absence of real-world anomalies in the simulation. Such considerations were critical in preparing the dataset for subsequent clustering analysis.

Key features for production well clustering, chosen for relevance to reservoir dynamics and production characteristics, included:

- Production Rates: Historical Oil Production Rate (OPR_H), Historical Water Production Rate (WPR_H), and Historical Gas Production Rate (GPR_H), which reflect the well's output and are indicative of reservoir performance.
- Reservoir Pressures: Historical Bottom Hole Pressure (BHP_H) and simulated bottom hole pressures (_BHP), with the assumption of constant reservoir pressure due to water injection supporting secondary recovery mechanisms.

Features were selected based on physics (per Productivity Index relationship), as Volve's reservoir pressure was maintained above bubble point to prevent multi-phase flow and extend production. The relationship between these features and hydrocarbon production is captured by Darcy's Law and the Productivity Index (PI) [10]. Darcy's law explains fluid flow via parameters like permeability (k) and area (A), which, with porosity (φ), N/G, viscosity etc., influence flow rates, allowing indirect reservoir assessment through production data. The PI equation refines this, differentiating undersaturated/saturated conditions, with non-linear IPRs (Vogel's, Fetkovich) for saturated reservoirs [11], guiding understanding of pressure differential effects on production.

Clustering these physics-based features offers insights into reservoir behaviour, production characteristics, depositional patterns, connectivity, and compartmentalization. This analysis can optimize reservoir modelling and management by identifying similar well patterns, influencing drilling and recovery strategies. To identify patterns in multivariate time series production data from oil wells, this research explores several algorithms. Chosen methodologies are evaluated for effectiveness and versatility; the best is visualized and compared against reservoir data for accuracy. Methodology robustness and applicability are tested on a different field's data, with optimal cluster numbers determined by the Silhouette score.

2.1 K-Shape Clustering

K-Shape clustering, effective for time series, was chosen for its shape-based distance measure suitable for well production data [12]. The process (data normalization, grouping wells by production patterns, group refinement) is noise-robust and yields interpretable, shape-based well behaviour patterns.

2.2 Frequency Domain Approach

Both Wavelet and Fast Fourier Transform (FFT) methods were used for their frequency domain approach in extracting components from production data. Wavelet analysis, advantageous for capturing sudden changes in non-stationary data [13] and FFT, useful for identifying dominant frequencies in well data [14], provided comprehensive insights into the periodic components of well production.

2.3 Dynamic Time Warping (DTW)

Dynamic Time Warping (DTW) was chosen to measure similarity between evolving temporal sequences like well production data [15]. The methodology (normalization, alignment by production patterns, pairwise distance matrix computation) accommodates multivariate data, grouping wells with similar temporal behaviours.

2.4 Model Evaluation

Validating the methods in this research was crucial to ensure that wells with similar characteristics were appropriately grouped by the ML model. Unsupervised learning, and specifically clustering, differs from supervised learning as it doesn't use direct metrics like accuracy or precision for evaluation. Instead, the primary validation relied on the Silhouette Score [16]. While other metrics such as the Davies-Bouldin Index and the Calinski-Harabasz Index were also considered, they were not systematically applied in this study. The synergy nature of the proposed methodology, which allows for multiple realisations guided by expert input, meant there wasn't a single definitive answer for the optimal number of clusters determined solely by metrics. The Silhouette Score served primarily as a quantitative guide within this framework to inform the decision on the suitability of the clusters for the reservoir model, acknowledging that a single metric may not capture all aspects of cluster quality. The tool's importance is emphasised in the context of reservoir modelling, especially when dealing with static model facies and properties distribution in different sedimentary environments. The right number of clusters for modelling facies and sedimentary environments in a reservoir is often ambiguous due to uncertainties, and the proposed tool provides quick, fairly accurate solutions that can be systematically tested for optimal results.

3 Results and Discussion

A reservoir horizon and corresponding well locations were exported from the Eclipse Model [17, 18, 9]. Only producing wells (PF-1C, PF-5, PF-11B, PF-14, PF-15, PF-15C) were considered for clustering and plotted; injection or pilot wells were excluded. Their spatial arrangement is shown on the Volve Field Contour Map Figure [1].

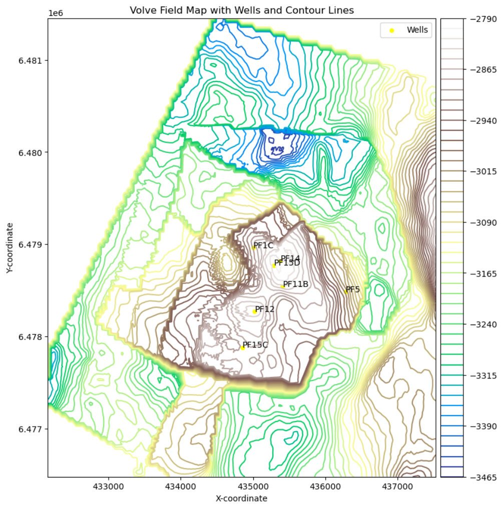

Figure 1: Volve Field Contour Map

The first statistical approach resembled traditional well grouping by Oil-Water (OW) Ratio at various production stages. Historic water and oil rates for each Volve Field well were aggregated from 2008 until production ceased in 2016. Yearly pie charts per well (Figure [2]; green: cumulative oil, blue: cumulative water) show OW ratios and were plotted spatially on the Volve Contour Map.

This statistical method could be equally repeated for the quarterly, monthly, or weekly periods, reflecting their respective operating reports. The resultant OW ratios can be used as a prevention and remedy measure for treating wells with high water cuts, analysing early water breakthroughs, and revealing dynamic properties of the reservoir. This method closely relates to the reservoir surveillance literature of Cai et al [2] as it focuses on the ratios in the given period, and thus could be clustered together using the K-Means or any other unsupervised algorithm. Contrarily, the method does not consider the individual's lifetime. The wells which were producing longer are statistically more likely to produce higher water rates resulting in higher water cuts and water ratios, introducing uncertainty and bias. Moreover, some wells which were not producing at all in the given year are completely neglected, eliminating them from the potential clustering. The method is valid, easy and can be very quickly implemented and monitored by the operating companies, however it does not capture the temporal behaviour of the data and thus was not further explored in the research.

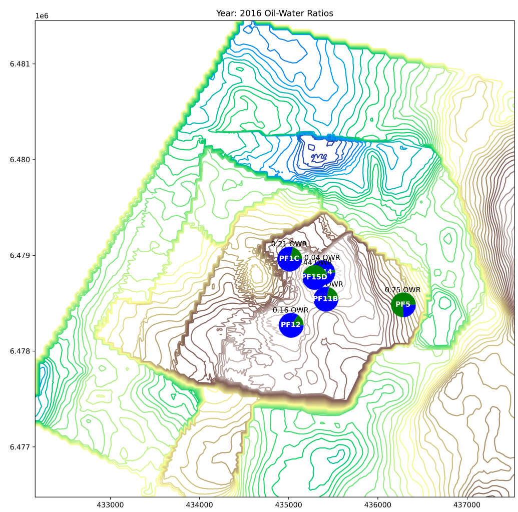

Figure 2: Volve Field: Contour Map with cumulative ratios plotted.

3.1 K-Shape ML Clustering

The K-Shape algorithm was executed with a default model parameter of 10 iterations and the number of clusters chosen was equal to the number of wells, resulting in a total of 7 clusters. However, this K-Shape method results were not ideal for clustering the wells together based on their similarity as the algorithm clustered the individual parameters such as the OPR_H and GPR_H together from the same wells. The clustering was principally based on the features' respective lengths. The resultant approach did not reflect any distinct reservoir behaviours or depositional sedimentology. The method has been replicated only concerning the (OPR_H) feature. The optimal number of clusters was determined using the silhouette score metric which is used to evaluate how good clustering results are in data clustering. The Silhouette Score was achieved using a loop that considers between 2 – 7 clusters as per well number. The optimal number of clusters based on the silhouette score was found to be 3 (Table [1]). The efficiency and performance for clustering with other features i.e. WPR_H, GPR_H and BHP_H or any combination of them was not tested and not within the current study scope.

Table 1: Clustering results for k-Shape model based on the OPR_H features.

K-Shape Results (OPR_H features)	
No of Clusters	3
Cluster 1	PF12, PF14
Cluster 2	PF11B, PF15D
Cluster 3	PF15C, PF1C, PF5

3.2 Frequency Domain Aggregated ML Clustering

An alternative frequency-based approach, the Wavelet Approach, grouped wells by transforming time series data (db1 wavelet) and extracting statistical features (mean, variance, skewness, kurtosis). Aggregated features were input to K-Means, which iteratively found the optimal cluster number by maximizing the silhouette score.

The first wavelet approach used fluid features (GPR
H, OPR_H, WPR_H); BHP_H was excluded due to missing PF-5 well data. The algorithm derived statistical features (mean, variance, skewness, kurtosis) using the db1 wavelet. Extracted features were aggregated by mean well values. K-Means was then applied iteratively with varying cluster numbers, calculating the silhouette score per iteration to evaluate clustering quality. The highest score indicated the optimal cluster number.

Table 2: Wavelet Clustering Results based on just OPR_H features.

Wavelet (OPR_H Features)	
No of Clusters	2
Cluster 1	PF12, PF14
Cluster 2	PF11B, PF15D, PF15C, PF1C, PF5

The flexible wavelet clustering method, capturing patterns at various scales, presents challenges: selecting the wavelet, decomposition level, and cluster number. Required data science, signal processing, and reservoir engineering knowledge for informed decisions can be excessive without prior wavelet expertise. Its complexity might reduce practicality for routine use. Though Wavelet successfully clustered wells (optimal cluster number via silhouette score), model implications and validation require further study.

Similarly, the Fast Fourier Transform (FFT) clustering approach, applied to well OPR_H features, extracted spectral features capturing frequency domain aspects. Features like peak magnitude, spectral centroid, and spectral flatness provide a comprehensive view of the signal's frequency distribution, from dominant frequencies to noise-like characteristics [19]. For oil production, peak magnitude indicates the most significant periodic trend; spectral centroid, the average rate of production changes; and spectral flatness, the frequency distribution's evenness (predictability/variability) (Table [3]). The silhouette score determined the optimal K-Means cluster number; iterating cluster numbers and computing silhouette scores yielded n=3 as optimal (score 0.434).PCA was used to visualize results and understand spatial cluster distribution.

3.3 DTW ML Clustering

Dynamic Time Warping was the last clustering approach conducted in this research. The DTW algorithm was utilised for all the fluid and pressure features. This included both simulated features as well as the more desirable historic features (OPR_H, WPR_H, GPR_H, BHP_H). The algorithm realised the shortest DTW distance between each sequence. The DTW distance represents the sum of distances along this optimal warping path between two time series. A smaller distance indicates that the two series are more similar. Traditional clustering methods (e.g., K-Means) struggle with temporal misalignment in production data. DTW addresses this by warping time series to align patterns, making it ideal for reservoirs with varying production timelines or transient behaviors. As this process is computationally intensive, the 'Numba' jit library was used to optimise and compile the process faster, although scalability to extremely large datasets remains a consideration for practical deployment. The outcome of the algorithm resulted in a matrix containing the pairwise distances between all features, which formed the basis for subsequent clustering analysis. The resultant DTW Clusters Matrix was not further aggregated concerning the production wells due to the multiple features being empty i.e., the bottomhole pressure of the PF-5 well. Thus, the sensitivity analysis of the clustering was conducted based only on the following features:

- Fluid Features of OPR_H, GPR_H and WPR_H columns which have been aggregated together.
- Historic Oil Production Feature of OPR_H.

3.3.1 DTW Clustering Approach using the Aggregated Historic Fluid Features

In the first clustering approach, the DTW Distance Matrix was visualised using Hierarchical Clustering based on the OPR_H in (Figure [3]).

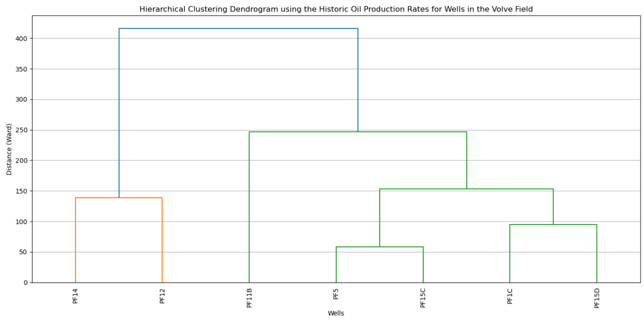

Figure 3: Hierarchical Clustering Dendrogram for Volve using only Historic Oil Production Rates.

The hierarchical clustering was achieved using the 'ward' linkage method [20], implemented via standard scientific computing libraries in Python. The method was used to minimise the variance within clusters and combined clusters based on how similar their DTW distances are, ensuring that each merge results in the least increase in total variance. The strength of the 'ward' method is evident in its robustness in handling clusters of varying sizes. Wells PF14 and PF12 are the most similar, forming the first cluster, followed by wells PF11B and PF15, which also show high similarity. Wells PF15C and PF11C group together with moderate similarity, and well PF13D joins this cluster but with less similarity. The final large cluster, formed at a high distance, indicates an overall low similarity among all wells.

From the dendrogram visualisations (Figure [3]), a critical decision was choosing where to set the clusters number. This was achieved with the highest silhouette. The silhouette score optimization revealed an optimal cut-off distance of 253.49. At this specific distance, the clustering algorithm determined there to be 2 distinct clusters based on the OPR_H features.

This was further clarified in (Figure [4]), which illustrates the silhouette scores at varying cut-off distances. The peak of this plot, indicating the highest silhouette score, substantiated the choice of 253.49 as the optimal cut-off distance for the OPR_H hierarchical clustering.

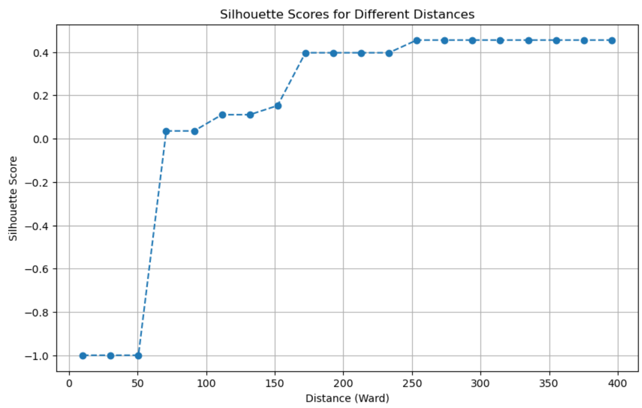

Figure 4: Silhouette Scores at different cut-off distances for the Hierarchical Clustering using the Historic Oil Production Rates.

The two clusters identified provide a structured separation of wells based on their historic oil production rates. This distinction can serve as a foundation for various further analyses, from understanding the geology driving these production behaviours to planning differential strategies for production optimization. The main advantage of focusing on strictly the historic oil production rates is its broad availability in the oil fields globally.

Moreover, the 'ward' hierarchical clustering method demonstrated in this approach can be quickly and effectively deployed in other fields. It provides a standardised approach to initial field analysis, especially when diving into new and unexplored datasets which is of great use when creating the numerical static and dynamic reservoir models.

3.3.2 DTW Clustering Approach using the Aggregated Fluid Features

For the subsequent approach, the focus was directed towards the DTW clustering of the aggregated historic fluid features in the Volve Field. This involved a thorough aggregation of production features, namely OPR_H, WPR_H, and GPR_H, using an additive approach that cumulated the DTW distance of the features in each well. The aggregation of the fluid features did not rely on summing up the individual time series of the fluid features which would heavily bias the results due to their differences in magnitudes and different units. It was achieved by cumulating the DTW distances corresponding to these features within the same well. This means that for each well, the DTW distances calculated for features like OPR_H, WPR_H, and GPR_H were combined to provide a consolidated distance metric. The presented approach emphasised not just the fluid production trends but also their temporal alignments and deviations. This aggregated distance matrix was then used for hierarchical clustering.

Using the aggregated fluid feature set, the 'ward' linkage hierarchical clustering was employed once again. (Figure [9]) shows the dendrogram visualisation for the Volve Field. Similarly, to the previous method, the silhouette score played a pivotal role, and its analysis revealed an optimal clustering distance of 1585.68. Moreover, the aggregated features resulted in a dendrogram of the same structure as for the standalone OPR_H dendrogram in (Figure [3]). This cut-off recognized two distinct clusters for the aggregated fluid features.

The DTW-based hierarchical clustering, especially with the aggregated fluid features, offered a blueprint that's replicable across other fields. For fields with essential fluid production data, this clustering method can be swiftly replicated, ensuring that insights are derived rapidly, even in diverse geological settings.

Regardless of the features used, the silhouette score has remained an essential clustering metric. Its consistent role in determining the optimal clustering cut-off, as evidenced in this phase with two clusters, underscores its reliability in the clustering approach.

3.3.3 Synergy Clustering and Spatial Visualization

Building upon the spatial visualisation presented in (Figure [1]), the Volve Field's contour map was further improved by including the geological faults which were previously extracted from the Volve's Reservoir Model. Geological faults play a critical role in reservoir dynamics as they act as conduits, altering the hydrocarbon production or leading to a division of reservoir segments with different pressure systems [21].

To visualise the potential interaction between neighbouring wells, Voronoi polygons were incorporated. These polygons partition the reservoir space, attributing distinct areas to each well based on its proximity. At its core, a Voronoi polygon divides a space into distinct regions based on a set of points. Together, the enhanced contour map, the overlay of geological faults, and the Voronoi polygons provide a deeper, spatial insight into the DTW results and their implications in the context of the Volve Field's geological complexities.

The static analysis approach, especially in the case of unsupervised clustering often fails to cater for the clustering dynamic requirements of reservoir engineers, geologists, and production engineers. Thus, the DTW clustering was further improved by implementing a synergy approach that enables the user to choose the number of clusters.

While machine-driven cluster identification has its advantages, the experience, and domain-specific knowledge of reservoir professionals can lead to nuanced interpretations. By allowing for a manual clusters' selection, the algorithm introduces an element of domain expertise into the novel clustering approach. (Figure [5]) captures this, showcasing a Hierarchical Clustering Dendrogram for the Volve Field with a user-specified cluster count of n = 5 based on the OPR_H features.

The clusters can be then visualised spatially where each well's corresponding Voronoi polygon is colour-coded based on its cluster. Reservoir geologists and engineers could refine reservoir models, enhance prediction accuracy, and optimise production strategies based on the clustering of different realisations.

The spatial representation, as illustrated in (Figure [10]) and (Figure [11]), merges the ML output of the Hierarchical Clustering with spatial geological data of the field, integrating the underlying faults, and the clustered Voronoi polygons for n = 2 and n = 5. The clusters signify areas that are similar in terms of production profiles of the wells, reflecting the reservoir's heterogeneity. By clustering the production profiles, reservoir geologists and engineers can identify regions with similar characteristics.

The difference between the two clusters in (Figure [10]), where PF-12 and PF-14 are grouped together, and the multiple clusters in (Figure [11]), is due to the granularity and scale of the hierarchical cut-off selected. (Figure [10]) represents a broader categorization with fewer clusters, while (Figure [11]) shows a more detailed segmentation with a higher number of clusters.

The 3D static models, specifically showcasing the well trajectories of PF12 and PF14 in (Figure [6]) act as the validation benchmark. As derived from the clustering results, these wells have been the longest active producers of the Volve Field and are equally located at the most elevated points in the reservoir. Being at the given depths implies that they were the first to interact with hydrocarbons. The fact that these two wells were grouped together in the clustering results is most likely due to their similar geo-spatial elevation on the horizon map which could have had an impact on the reservoir thickness and N/G ratio affecting their production. Furthermore, these 2 wells have been the 2 major producers of the field which the clustering results equally reflect.

It is also essential to understand that there are many more aspects to consider in a reservoir that may affect their productivity and respective clustering outcomes. The key elements like porosity permeability, Gas-Oil Ratio (GOR), pressure gradient, reservoir thickness, and temperature gradient play significant roles in determining how the reservoir functions. Each of these factors contributes uniquely to the overall reservoir behaviour. When combined with the clustering results,

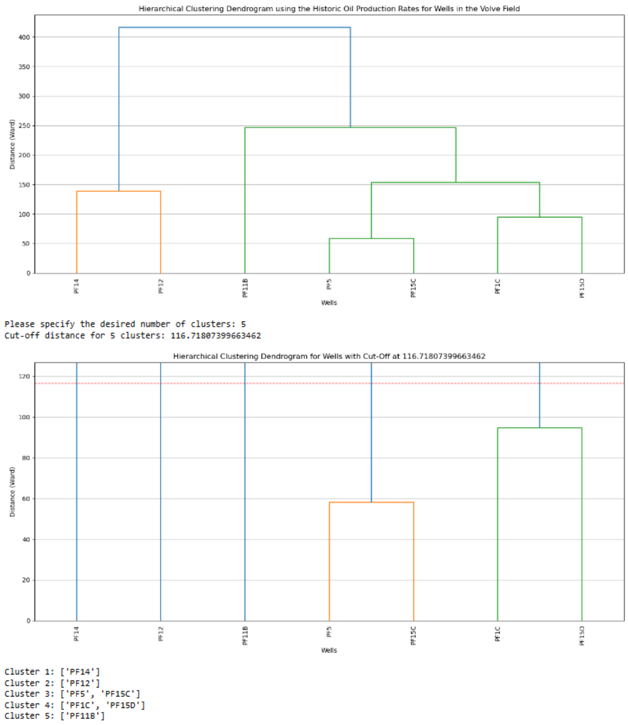

Figure 5: Hierarchical Clustering Dendrogram for Volve Field following the manual selection of desired clusters, n = 5.

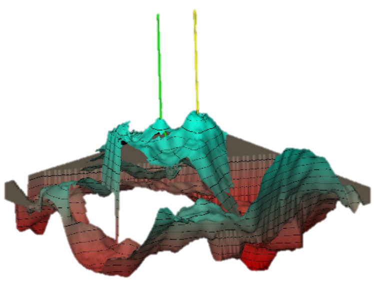

Figure 6: 3D Static Model showing PF12 and PF14 well trajectories.

they provide a comprehensive picture of the reservoir's dynamics and potential productivity areas. In terms of the modelling approach, it's essential to keep validating the dynamic ML model results against the established static models. This ensures that the new insights and findings align with historical data and the specific characteristics of the field.

3.3.4 Model Deployment – Norne Field

In the exploration of the Volve Field, it's clear that expanding the model's application to other reservoirs, like the Norne Field, enhances its robustness and offers further validation. The same DTW methodology was applied, focusing on the Historic Oil Production Rates (OPR_H). The resulting dendrogram for the OPR_H features is illustrated in (Figure [7]). Based on the silhouette score analysis, the optimal number of clusters was identified as two (n = 2). In contrast, when considering the aggregated fluid features, the optimal distance for clustering was determined to be at the cut-off of 10362.28, resulting in three distinct clusters. The BHP_H features were excluded from the analysis due to their complete absence for all producing wells in the Norne dataset to keep the constancy with the Volve Field.

The clusters derived from the OPR_H features of the Norne Field were spatially represented using Voronoi Polygons, as showcased in (Figure [8]). Clusters of 3, and 4 classes were displayed. Although these clusters have not been compared with any specific reservoir properties, their visualisation highlights the method's efficiency, rapidity, and ease of deployment.

The process of hierarchical clustering in reservoir engineering and geosciences can be associated with grouping wells or

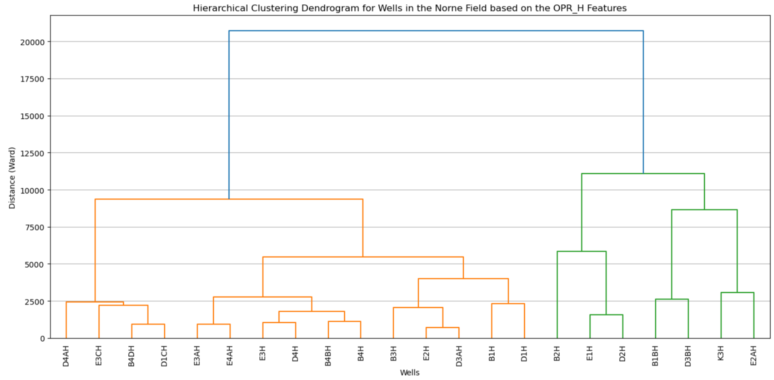

Figure 7: DTW Hierarchical Clustering Dendrogram for Norne Field using Historic Oil Production Rate features.

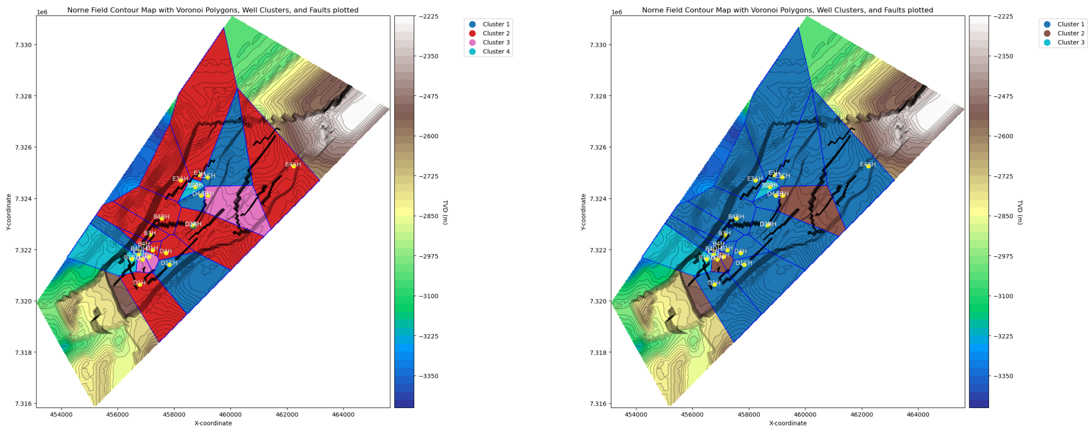

Figure 8: Norne Field Spatial Representation of the DTW Clustering using Voronoi Polygons for 3 and 4 clusters.

formations based on their similarity in certain attributes. These can range from petrophysical properties, seismic attributes or as the case for this project the historical production histories. The resulting dendrogram provides a visual representation of the similarities and the level (or distance) at which the groupings occur.

Clustering based on the historic production data might signify a threshold at which wells have similar decline rates, or perhaps similar water-cuts. In such scenarios, the cut-off would segregate high-performing wells from underperforming ones. Further application might cover, targeted well intervention strategies that could be designed or optimised by identifying clusters of wells with similar production behaviours. Moreover, understanding the spatial distribution of clusters could enhance resource allocation and efficient risk mitigation.

4 Comparison with Previous Studies

Although the DTW results were validated using the Silhouette Score metric, its output is still primarily dependent on the desired user input as the method resembles a synergy multiple realisation approach. The Silhouette Score metric was chosen, due to its clear interpretation and versatility with any distance metric. This might not be the case with other clustering metrics i.e., Dunn index, Hopkins statistic and Similarity measure (SMC) which are sensitive to outliers, noise, and binary data. It is acknowledged that the comparison between DTW and the alternative methods (K-Shape, Frequency Domain) presented is primarily qualitative and lacks a rigorous quantitative evaluation under identical conditions; such detailed benchmarking is suggested for future work.

Comparing the findings to the study of H. Kheirollahi et al., the DTW methodology did not heavily rely on the DCA Apr's Equation which is dependent on numerous assumptions [6]. Furthermore, in Kheirollahi's study, not all Decline Curve Analyses were optimally aligned with the findings analysing strong clusters between the wells but not validating them in any way such as spatially or relating them to any static or dynamic reservoir properties. His study emphasised on selecting pilot wells and determining EOR injection patterns, whereas the DTW method conducted in this work already accounts for any EOR mechanism. Their effect would be reflected in the production patterns and thus the approach could be used in both mature fields at the end of their life as well as during the field development stages. Both methods, however, considered the temporal nature of the oil decline, one directly extracting the decline curve exponents and, this work, directly comparing the fluid production trends between each other. This study focuses on the similarity of the overall production shape rather than explicitly modeling the temporal decline parameters.

The study of Z. Cai et al. is even less comparable with this work as his study classified wells using a supervised classification method [2]. This makes this method tailored and only viable to the given unconventional tight gas field. The DTW method conducted in this study presents a generalised approach which could be applied regardless of the field while not requiring the determination of various threshold classes or labelling. Cai's study also focused on the average production output such as the daily average output of a well, the average gas-liquid ratios, the average casing pressure or the average oil pressure in a given time period [2]. The outcome of the study resembles the O-W statistical approach that was conducted at the beginning of the Results and Discussion Chapter. However, this approach was not continued as it would not reveal any sedimentary depositional patterns and facies as it did not consider the whole temporal nature of the production data.

At last, none of the above literature studies discussed, clustered or classified wells within Volve or Norne Fields substantially limiting the comparison of the findings. The clustering approaches were conducted with respect to unconventional fields with only H. Kheirollahi et al. study focusing on the conventional field, presenting a novel unsupervised approach.

The DTW method employed, found to satisfy the generalisation concept in terms of deployment regardless of the type of field. The method compared the production trends of the wells between each other under the feature selection assumptions of Darcy's Law and Productivity Index. The selection was based on fundamental reservoir engineering principles, though exploration of alternative or additional features could provide further insights.

5 Conclusion

The primary objective of the project was achieved by developing and applying a workflow for grouping wells based on their similarity in historical production data using multiple clustering methodologies. The DTW distance hierarchical clustering method, integrated within a synergistic framework allowing expert input and spatial visualisation using Voronoi polygons, emerged as a particularly robust and adaptable approach for this task.

The proposed clustering workflow offers industry experts rapid insights into reservoir behaviours, positioning it as a valuable tool for initial reservoir analysis, guiding subsequent detailed modelling efforts, and facilitating multiple realisation studies. The deployment of the DTW model on the Norne Field dataset demonstrated the potential of the clustering algorithm in analysing well production data efficiently across different assets. While various clustering methodologies offer unique insights, the DTW-based hierarchical clustering method stands out due to its effectiveness in capturing temporal similarities and its flexibility within the synergy workflow. The ability to integrate domain-specific knowledge makes it a practical tool for reservoir analyses. The consistent use of the silhouette score provided a quantitative guide for cluster assessment within this framework.

5.1 Recommendations and Further Research

This article suggests oil and gas upstream specialists to adopt advanced clustering algorithms like DTW in various tasks as needed, for instance to analyse well production data, offering deeper insights and aiding in effective well management, optimization strategies, and reservoir modelling. The proposed method, a synergy model combining hierarchical clustering and DTW, needs validation in actual producing fields. Future research should focus on systematically correlating the obtained clusters with detailed static (e.g., porosity, permeability maps) and dynamic (e.g., pressure interference tests) reservoir properties to further validate their geological and engineering relevance. Additionally, exploring the integration of other machine learning clustering techniques with DTW could enhance capabilities, particularly in geological settings and production scenarios different from those of the Volve and Norne fields.

CRediT authorship contribution statement

Jakub Marek Cebula - Conceptualization, Data curation, Formal Analysis, Methodology, Software, Writing – original draft **Mohamed Hassan Abdalla Idris -** Conceptualization, Data curation, Formal Analysis, Software **Shamsul Masum -** , Validation, Writing – review and editing **Jebraeel Gholinezhad -** Supervision, Validation, Writing – review and editing **Edward Smart -** Validation

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6 Appendices

Table 3: Clusters and Spectral Features of the FFT analysis for the OPR_H parameters of all wells.

FFT Parameter	Peak Magnitude	Peak Frequency	Spectral Centroid	Spectral Spread	Spectral Skewness	Spectral Kurtosis
PF11B_OPR_H	1.18E+06	0	0.081134	0.138127	22.984869	579.187022
PF12_OPR_H	4.59E+06	0	0.086606	0.142567	25.711856	739.954671
PF14_OPR_H	3.95E+06	0	0.096331	0.147792	26.741718	818.069266
PFI5C_OPR_H	2.92E+04	0	0.166562	0.162476	6.112632	41.22449
PFI5D_OPR_H	1.45E+05	0	0.130602	0.163692	19.251118	435.146957
PFIC_OPR_H	1.71E+05	0	0.118672	0.146536	11.114433	164.103938
PF5_OPR_H	4.32E+04	0	0.097994	0.145725	9.870572	102.537779
FFT Parameter	**Spectral Slope**	**Bandwidth**	**Spectral Contrast**	**Spectral Flatness**	**Spectral Rolloff**	**Cluster**
PF11B_OPR_H	-0.549117	0.499687	1.18E+06	0.318887	0.249218	**0**
PF12_OPR_H	-0.491188	0.499687	4.59E+06	0.333319	0.272358	**0**
PF14_OPR_H	-0.480738	0.499687	3.95E+06	0.369288	0.293934	**0**
PFI5C_OPR_H	-0.388958	0.499687	2.92E+04	0.59927	0.3793	**1**
PFI5D_OPR_H	-0.395159	0.499687	1.44E+05	0.482863	0.370231	**1**
PFIC_OPR_H	-0.666219	0.499687	1.71E+05	0.508162	0.312695	**2**
PF5_OPR_H	-0.548006	0.499687	4.32E+04	0.400635	0.287054	**2**

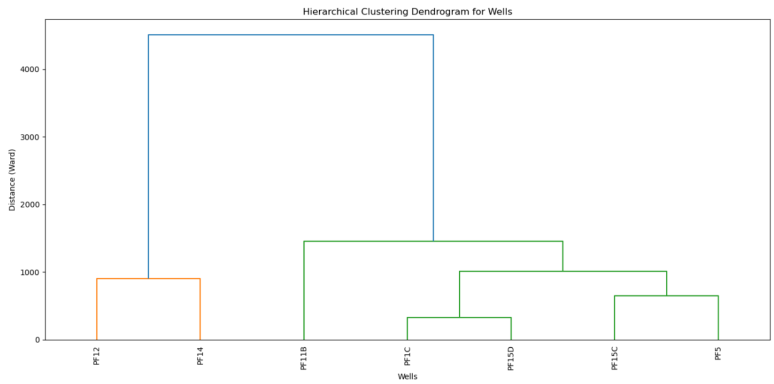

Figure 9: Hierarchical Clustering Dendrogram for Volve using aggregated Fluid Features of OPR_H, WPR_H and GPR_H.

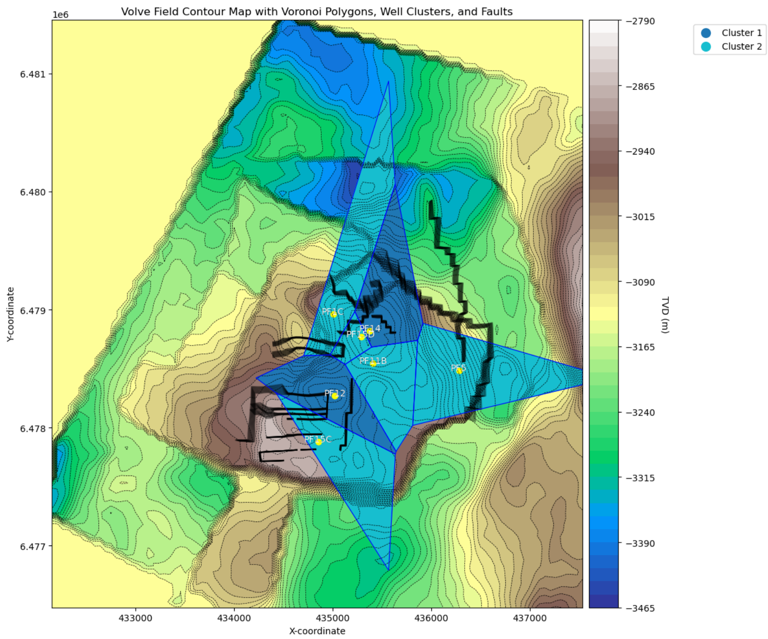

Figure 10: Volve Field Contour Map with visualised Faults and Voronoi Polygons assigned to the clusters of n = 2.

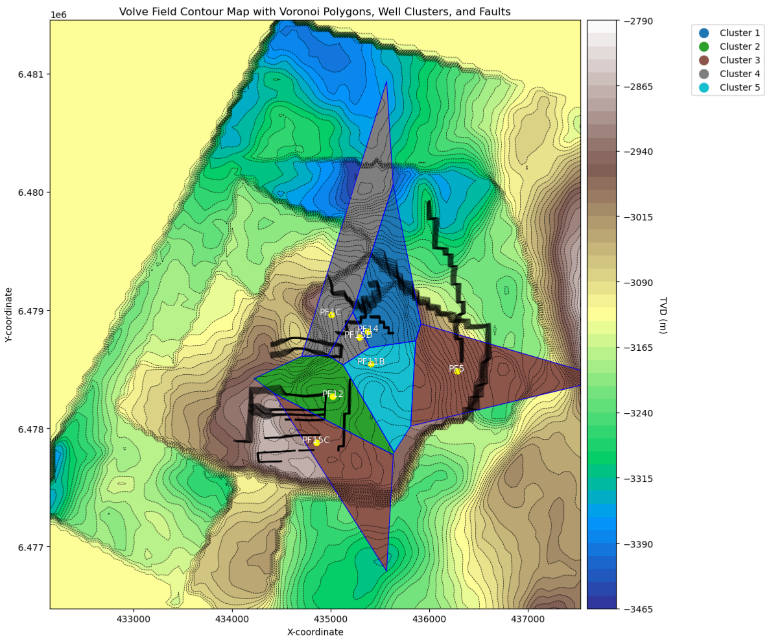

Figure 11: Volve Field Spatial Representation of the DTW Clustering using Voronoi Polygons assigned to the clusters of n = 5.