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Data Science as an Enabler: Integrating Business Intelligence (BI) Tools with Artificial Intelligence (AI) for an Ever Evolving Industry

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The evolution of industrial revolutions has been marked by the increasing use of data and information to improve productivity and efficiency. Industry 3.0 introduced automation and digitalization, which generated a lot of data from various sources and processes. This data was mainly used for monitoring and controlling the industrial activities, such as production, quality, and maintenance. Industry 4.0 leveraged this data to generate insights and intelligence, using technologies such as cloud computing, big data analytics, and the Internet of Things (IoT). These technologies enabled the integration and communication of data across different levels and domains of the industrial system, such as machines, products, processes, and services. Industry 4.0 also introduced the concept of smart factories, which are self-organizing, adaptive, and learning systems that can optimize their performance and efficiency. Industry 5.0 aims to enable human-robot collaboration and artificial intelligence [1], creating a more personalized and sustainable industrial system. Industry 5.0 focuses on enhancing the human capabilities and creativity, rather than replacing them with machines. It also emphasizes the social and environmental aspects of industrial development, such as customer satisfaction, worker well-being, and resource conservation. Industry 5.0 envisions a human-centric and eco-friendly industrial paradigm, where humans and machines work together in harmony and synergy.

One of the sectors that can benefit from the convergence of business intelligence (BI) and artificial intelligence (AI) is the energy industry, which faces challenges such as increasing demand, environmental regulations, and market volatility. By combining BI and AI, energy companies can unlock value from their data and optimize their operations, such as production, distribution, and consumption. BI helps energy companies to collect, store, analyze, and visualize data from various sources, such as sensors, meters, devices, and systems. BI enables energy companies to monitor and manage their assets, processes, and performance, as well as to identify and solve problems, improve efficiency, and reduce costs. AI helps energy companies to augment and automate their decision making, using techniques such as machine learning, natural language processing, computer vision, and deep learning. AI enables energy companies to generate predictions, recommendations, and insights from their data, as well as to optimize their operations, such as scheduling, dispatching, pricing, and trading. AI also helps energy companies to create new products and services, such as smart grids, smart meters, smart homes, and smart cities. By combining BI and AI, energy companies can create a data-driven and intelligent energy system, which can respond to the changing needs

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and preferences of customers, stakeholders, and regulators, as well as to the dynamic and uncertain market conditions.

This paper discusses the approach of complimenting the established business intelligence (BI) process with Artificial Intelligence (AI) in order to optimize gas production in an oil field in the south of Sultanate of Oman, it details the facts, observations, and insights the multidisciplinary authors have captured throughout the progress of this work, as well as general industry insights and BI process description.

Introduction

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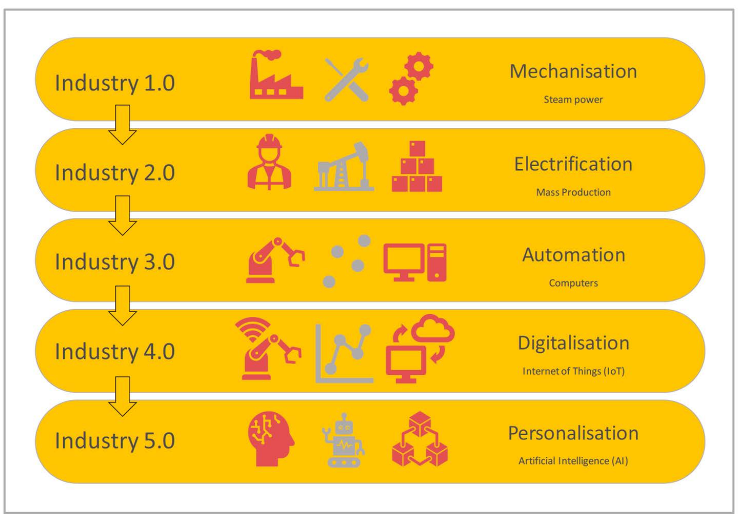

Figure 1—Industry Evolution and path towards AI

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predictions, recommendations, and insights from their data, as well as to optimize their operations, such as scheduling, dispatching, pricing, and trading. AI also helps energy companies to create new products and services, such as smart grids, smart meters, smart homes, and smart cities. By combining BI and AI, energy companies can create a data-driven and intelligent energy system, which can respond to the changing needs and preferences of customers, stakeholders, and regulators, as well as to the dynamic and uncertain market conditions.

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Business Intelligence & Artificial Intelligence

A conventional business intelligence process starts by gathering and compiling data from multiple sources, usually a dedicated tool or a piece of software, which is logically followed by organizing it into a sensible model, with a varying relationship between those data sets, with a person, who is usually a business analyst, or a similar role, running queries on them to establish trends and make sense of those data sets. Those sets are in turn visualized, reported, and dashboards created in a number of many ways, leading the decision makers to make informed and better decisions using those very same data sets, basically, turning data into information. This process must be repeated whenever there's new data to be looked at and analysed. One of the things this paper discusses is to try and compliment this pre-existing business intelligence process [2] with Artificial Intelligence [3], leaving only the last bit of the decision making for the decision makers, enabling more efficiency and streamlining the process.

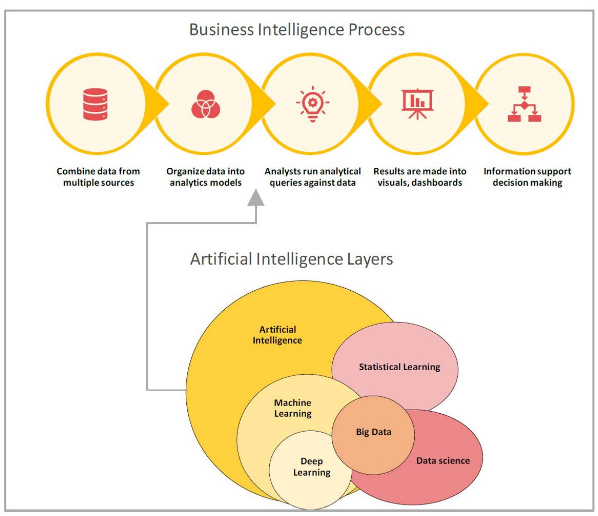

Figure 2—Complimenting the BI Process with AI

To expand on this, we can explain how Artificial Intelligence can enhance the business intelligence process in different stages. First, Artificial Intelligence can help to organize and model the data, using techniques such as data cleaning, data integration, data transformation, and data mining, to ensure the quality, consistency, and validity of the data, as well as to discover hidden patterns, associations, and anomalies in the data. Second, Artificial Intelligence can help to run queries and generate insights from the data, using techniques such as machine learning, deep learning, and reinforcement learning, to build predictive and prescriptive models, as well as to learn from feedback and adapt to changing situations. Fourth, Artificial Intelligence can help to visualize, report, and create dashboards from the data, using techniques such as natural language generation, data visualization, and conversational agents, to present

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the data and insights in a clear, concise, and interactive way, as well as to answer questions and provide explanations. By using Artificial Intelligence, the business intelligence process can become more automated, intelligent, and adaptive, reducing the human effort and error, and increasing the speed and accuracy of the decision making.

Problem Statement

The reservoir under study is initially undersaturated, meaning that the reservoir pressure is higher than the bubble point pressure, and the oil is free of gas bubbles. The wells are producing oil with associated gas, which is either exported, re-injected, or flared, depending on the market and environmental conditions. The facility is operating at full gas capacity, meaning that it cannot handle any more gas production without compromising the safety and efficiency of the operations. The wells have surface pressure and temperature gauges, which are used to monitor the well performance and detect any anomalies. However, there is no recurrent testing of wells, which makes it difficult to "see" the gas increase per well and estimate the reservoir parameters, such as gas-oil ratio, oil saturation, and relative permeability. The modelling of the reservoir is not accurate, due to the lack of data and the complexity of the fluid and rock properties. There is a big uncertainty in the reservoir behavior and the future production potential. A reactive approach is followed to "cream" wells, meaning that the wells are produced until they reach their economic limit, without any optimization or intervention. This may result in suboptimal recovery and premature abandonment of the wells. Figure below showcases an example of a well that is part of this study, that has exhibited the behavior explained earlier, and simply not tested at regular intervals for early identification of increased Gas production, and even decreased oil production.

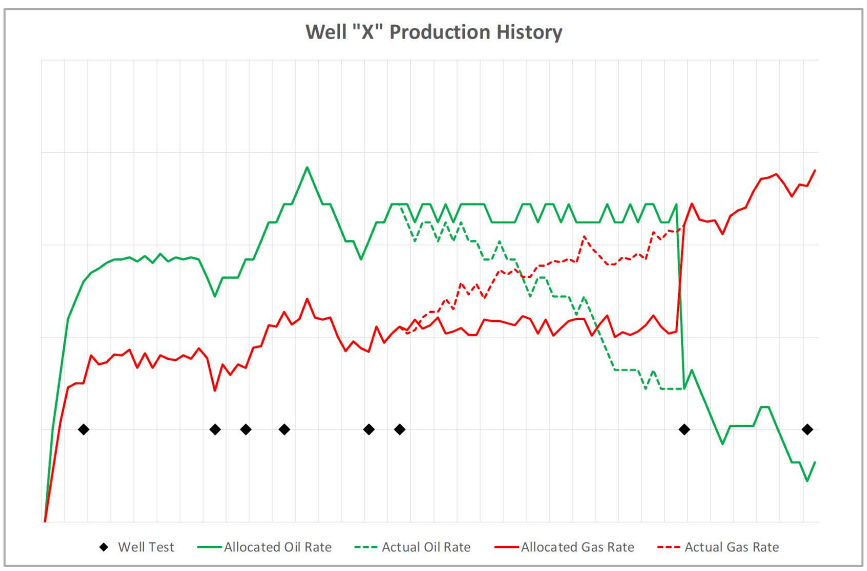

Figure 3—Well "X" Production History Example

Methodology

Imagine a future where oil field operations are revolutionized by artificial intelligence (AI). This research delves into such a future, proposing a system that integrates AI with Business Intelligence (BI) processes to automate gas detection in oil wells [4]. By leveraging readily available tools like Microsoft Power BI and Python, this approach aims to develop a machine learning code that identifies early signs of gas increases based on existing surface readings.

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The proposed system analyzes four key variables: wellhead temperature, pressure, oil flow rate, and gas flow rate. Additionally, it factors in seasonal weather variations that can influence surface measurements. This comprehensive approach ensures accurate predictions and minimizes false alarms.

Boosting BI dashboards with AI

Integrating AI directly into the Power BI dashboard empowers operators with real-time insights and proactive recommendations. Based on data analysis, the system generates predictions and suggests optimal actions, aiding informed decision-making.

Learning from the past

The secret sauce lies in historical data. The system draws knowledge from historical data points collected from other wells that have experienced gas increases in the past. This data, encompassing around 50 wells, is used to train and validate the machine learning code, ensuring its effectiveness in diverse scenarios.

Visual risk monitoring

Beyond predictions, the system prioritizes safety by incorporating visual cues. It employs color codes and symbols to highlight potential risks, making critical information readily understandable for operators. This visual representation enables swift action in case of anomalies.

Rigorous testing and validation

After training, the system undergoes rigorous testing on 50 different wells. This repetition helps reproduce results, evaluate performance, and refine the code's accuracy for real-world application.

Optimizing production and minimizing impact

Ultimately, this AI-powered approach aims to optimize gas production while minimizing operational costs and environmental impact. By identifying early signs of gas increase, the system empowers responsible surveillance teams to make proactive adjustments. This allows focusing on oil extraction while minimizing wasted gas that would otherwise be flared, contributing to a more sustainable and efficient operation.

While this approach represents a relatively simple application of AI, its significance lies in its potential to inspire further research and exploration. It serves as a springboard for researchers in the field to develop even more sophisticated and impactful AI solutions for the oil and gas industry.

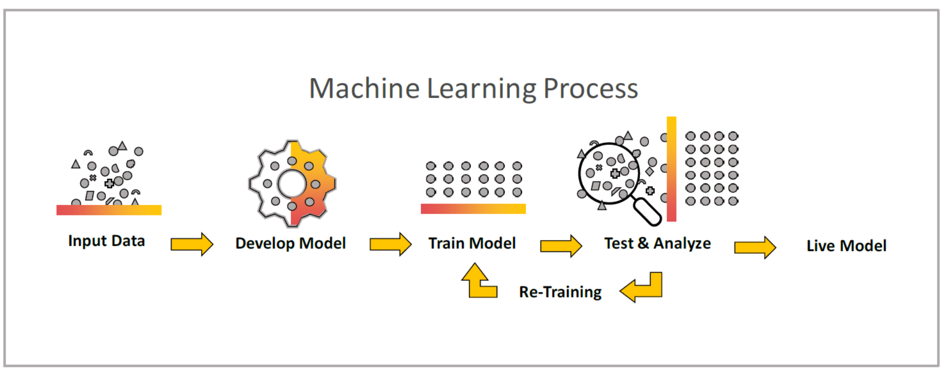

Figure 4—Machine Learning process

Machine learning, a subfield of artificial intelligence, has revolutionized computing by granting machines the ability to learn from data. Imagine computers not just following instructions, but adapting and improving based on experience! This translates to remarkable abilities like recognizing faces, analyzing vast datasets, and even predicting future events.

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At the heart of machine learning lie algorithms trained on massive datasets. These algorithms learn patterns and relationships within the data, allowing them to make informed predictions on new, unseen data. Like a student studying countless examples, the machine "learns" to generalize its knowledge to new situations.

Think about the personalized recommendations you see online, or the spam filter catching suspicious emails. These are just a few examples of machine learning in action. Its reach extends to tasks like self-driving cars, translating languages in real-time, and even composing music.

However, while machine learning excels at pattern recognition and prediction, it doesn't truly grasp the "why" behind things. Unlike humans, who can reason and understand contexts, machine learning models operate within the boundaries of the data they're trained on. This limitation becomes evident when faced with new situations outside the learned patterns.

Enter Deep Learning, a more advanced form of machine learning inspired by the structure and function of the human brain. With complex neural networks, Deep Learning models can achieve impressive feats like recognizing complex objects in images or generating human-quality text.

But even Deep Learning faces challenges[5]. It often requires vast amounts of data and can be computationally expensive. And, like all machine learning models, it suffers from a lack of true understanding and the potential for bias based on the training data.

So, while machine learning has transformed our world, the quest for artificial intelligence that truly thinks continues. The future may hold machines that combine the adaptability of machine learning with the reasoning power of Deep Learning, truly blurring the lines between human and machine intelligence. Until then, let's explore and responsibly develop these technologies, ensuring they benefit humanity at large.

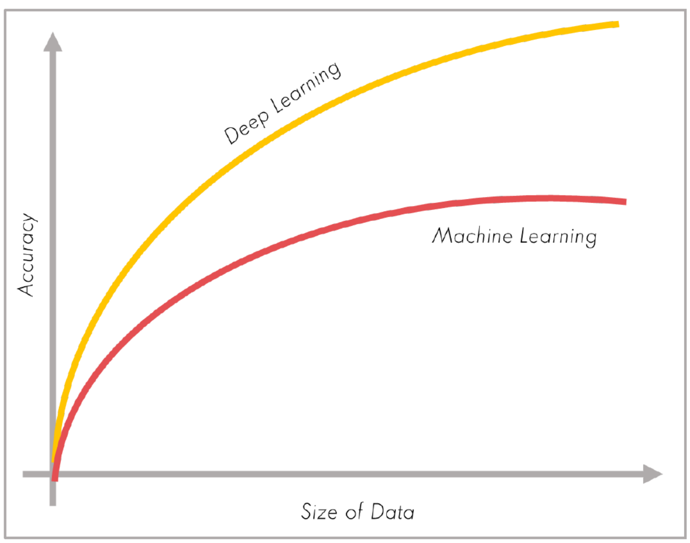

Figure 5—Depp Learning vs machine Learning

Results

The newly developed model has shown promising results in predicting gas increase within oil wells, with an accuracy hovering around 50%. While this may seem moderate, the model shines in its ability to deliver higher accuracy for wells with longer breakthrough times, offering valuable insights for proactive risk management. This innovation eliminates the need for repetitive manual data analysis whenever new information arrives. Instead, the model automatically scans incoming data sets, essentially acting as an extra layer of surveillance for the team. This shift from reactive to proactive monitoring significantly improves operational efficiency and allows personnel to focus on other crucial tasks.

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However, it's important to remember that machine learning models rely heavily on the quality and quantity of their training data. This model utilizes a relatively simple approach, considering only four variables: wellhead temperature and pressure, alongside oil and gas flow rates. While effective, this simplicity also comes with limitations. Assumptions of uniform subsurface conditions introduce a degree of inaccuracy, highlighting the constraints inherent to machine learning. This is not to say the model isn't valuable. Its primary purpose is to stimulate discussion and encourage continuous improvement in how we approach operational practices within this vital sector. It opens the door for further exploration and refinement.

So, how does this model function? At its core, it ingests the four mentioned variables and employs a machine learning algorithm, like linear regression, to unearth patterns and connections between these inputs and the occurrence of gas increase. Following this, the model provides a prediction for each well, accompanied by a confidence interval to gauge its own certainty. Additionally, it triggers visual alerts and color-codes potential risks, ensuring timely attention to critical situations.

Currently, the model has been trained and validated using historical data from 50 wells that have previously experienced gas increase. To assess its effectiveness in real-world scenarios, it's further tested on another set of 50 wells.

Looking ahead, exciting possibilities lie in pushing the boundaries of this model's capabilities. By incorporating more data from diverse sources like sensors, meters, and various monitoring systems, the model can capture a broader picture and reduce uncertainties. Expanding the range of variables considered, such as reservoir pressure, fluid properties, and rock characteristics, would enable it to account for the complex and heterogeneous nature of subsurface environments. Finally, leveraging more sophisticated machine learning techniques, like neural networks, could enable the model to capture the non-linear and dynamic nature of the system, further enhancing its accuracy and reliability.

Ultimately, refining this model can lead to significant improvements in operational efficiency and safety. By anticipating gas increase with greater precision, we can optimize production processes, minimize risks, and ensure the responsible management of this valuable resource. This example serves as a stepping stone towards a future where data-driven insights power our decision-making, leading to a more sustainable and efficient oil and gas industry.

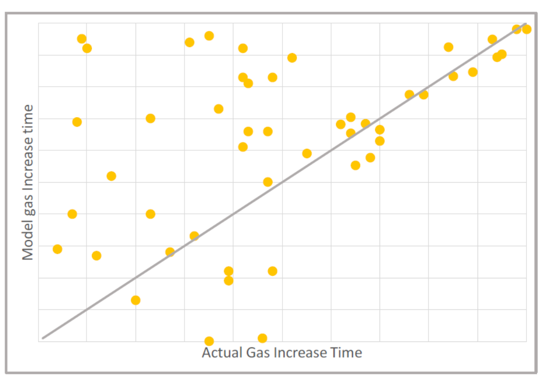

Figure 6—Main Results for 50 tested wells

Conclusions

- **Beyond Oil & Gas:** The authors believe this project's insights transcend the specific case of gas prediction in oil wells. They emphasize the **widespread applicability of data science and AI across diverse industries**, urging professionals to explore similar digitalization approaches for efficiency gains. This project serves as a valuable **thought leadership example**, inspiring others to adopt and adapt such techniques in their fields.

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- **Building Better Models:** To enhance the gas prediction model and adapt it for broader applications, several key considerations are highlighted:
  - **Feature Engineering:** Leveraging domain knowledge and statistical analysis, creating **new features** can capture hidden patterns and improve model performance.
  - **Hyperparameter Tuning:** Experimenting with **key parameters** within the chosen model algorithm can **fine-tune its accuracy** and effectiveness.
  - **Model Selection:** Exploring alternative algorithms like **Support Vector Machines or Gradient Boosting** might identify models better suited to specific datasets or tasks.
  - **Addressing Seasonality:** If **seasonal trends** significantly impact the data, incorporating **time-based features or specialized models** is crucial for better predictions.
- **Understanding Limitations:** Recognizing the model's limitations is essential for responsible implementation:
  - **New Wells:** This model primarily relies on historical data, making it unsuitable for **newly drilled wells lacking production history**.
  - **Surface Interference:** Wells experiencing frequent **changes in operating conditions** due to surface interferences might not match the model well, requiring specialized approaches.
  - **Future Changes:** Anticipating **future events like workovers** is crucial. Resetting the history start time based on such interventions ensures the model accurately reflects post-change trends.
  - **Data Quality:** Maintaining **data accuracy and consistency** is vital to avoid model biases and ensure reliable predictions.
- **Deployment and Beyond:** Integrating the model into **production systems** enables **real-time monitoring and prediction**, driving operational improvements.
  - **Collaboration & Knowledge Sharing:** Fostering **cross-disciplinary collaboration** and **knowledge sharing** can accelerate the development and adoption of advanced AI-driven solutions.
  - **Continuous Improvement:** Ongoing **refinement and improvement** of the model based on new data and insights is essential for maintaining its effectiveness and expanding its applicability.
  - **Advanced AI Exploration:** Investigating **cutting-edge AI techniques** holds promise for further advancements, enabling more complex and nuanced predictions, ultimately leading to greater efficiency and safety across various industries

Abbreviations and Acronyms

AI	Artificial Intelligence
BI	Business Intelligence
IoT	Internet of Things
ML	Machine Learning
P	Well Head Pressure
Qg	Gas rate
Qo	Oil rate
T	Well Head Temperature
TEnv	Environmental Temperature

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Appendix

The below is the summarized steps of the utilized Python© code for references. The gas rate variable is referred to as Qg, well head temperature is T, well head Pressure is P, and Oil rate is Qo, with the environmental Temperature referred to as TEnv.

1. Import necessary libraries:
   ```
   import pandas as pd
   from sklearn.model_selection import train_test_split
   from sklearn.preprocessing import StandardScaler
   from sklearn.ensemble import RandomForestRegressor
   from sklearn.metrics import mean_absolute_error
   ```
2. Load and pre-process data:
   ```
   # Load the 50 datasets
   data = pd.read csv("data.csv")
   # Separate features and target variable
   X = data[["T", "P", "Qo", "TEnv"]]
   y = data["Qg"]
   # Split data into training and testing sets
   X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
   # Scale the features
   scaler = StandardScaler()
   X_train = scaler.fit transform(X_train)
   X_test = scaler.transform(X_test)
   ```
3. Create and train the model:
   ```
   # Instantiate the model
   model = RandomForestRegressor()
   # Train the model on the training data
   model.fit(X_train, y_train)
   ```
4. Make predictions and evaluate performance:
   ```
   # Make predictions on the testing data
   y_pred = model.predict(X_test)
   # Evaluate the model's performance
   mae = mean absolute error(y_test, y_pred)
   print("Mean Absolute Error:", mae)
   ```
5. Identify gas increase indications:
   ```
   # Define a threshold for significant gas increase
   threshold = 0.2 # Adjust as needed
   # Apply model to new data to detect gas increase
   new_data = pd.read csv("new data.csv")
   new_X = new_data[["T", "P", "Qo", "TEnv"]]
   new_X = scaler.transform(new_X)
   new_y_pred = model.predict(new_X)
   # Identify time of increase
   increase_indices = np.where(new_y_pred > threshold * np.mean(new_y_pred))[0]
   increase_times = new_data["Time"].iloc[increase_indices]
   print(["Gas increase detected at:[", increase_times)
   ```

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