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Perspective

Artificial intelligence in oil and gas upstream: Trends, challenges, and scenarios for the future

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HIGHLIGHTS

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ABSTRACT

We analyze how artificial intelligence changes a significant part of the energy sector, the oil and gas industry. We focus on the upstream segment as the most capital-intensive part of oil and gas and the segment of enormous uncertainties to tackle. Basing on the analysis of AI application possibilities and the review of existing applications, we outline the most recent trends in developing AI-based tools and identify their effects on accelerating and de-risking processes in the industry. We investigate AI approaches and algorithms, as well as the role and availability of data in the segment. Further, we discuss the main non-technical challenges that prevent the intensive application of artificial intelligence in the oil and gas industry, related to data, people, and new forms of collaboration. We also outline three possible scenarios of how artificial intelligence will develop in the oil and gas industry and how it may change it in the future (in 5, 10, and 20 years).

1. Introduction

Artificial intelligence (AI), as the most important general-purpose technology of today [1,2], is rapidly entering industries, creating significant potential for innovations [3] and growth [4]. In healthcare, transportation, retail, media, and finance, AI already triggered substantial changes and transformed the competition rules. Instead of relying on traditional and human-centered business processes, companies from these industries create value using AI solutions [5]. Advanced algorithms trained on large and useful datasets, and continuously supplied with new data drive the value creation process. That is how Gero.ai fights Covid-19, Amazon sets prices for products it offers, InboxVudu prioritizes mails, and Yandex moves (autonomous) cars.

However, not only companies from digital-savvy industries are profiting from AI. Oil and gas, mining, and construction companies are the latecomers to digitalization [6,7], but they are also getting more and more dependent on AI solutions. Although the first applications of AI in the oil and gas industry were considered in the 1970s [8], the industry has started to look more proactively for AI application opportunities several years ago [9,10]. It coincides with the exponential growth of AI capabilities and the industry's movement towards the Oil and Gas 4.0 concept, whose core goal is to achieve higher value utilizing advanced digital technologies [11].

As oil and gas companies are much quicker to adopt new technologies than to experiment with and change their business models [12], their AI's primary target (and other digitalization) efforts are to improve efficiency. In practice, that typically means to accelerate processes and reduce risks [8,11,13]. This paper aims to discuss in detail and demonstrate how AI is transforming the oil and gas upstream. We will mainly focus on the following three questions:

- what de-risking in the oil and gas industry means and how AI is helping with it;
- which processes can be accelerated by applying AI and how much;
- what has been already done and what are the expected advancements in the following years.

As the oil and gas industry is complex and diverse, we situate and focus our discussion on the upstream sector. The upstream covers crude oil and natural gas production. It includes searching for potential underground or underwater crude oil and natural gas fields, drilling exploratory wells, and subsequently drilling and operating the wells used to lift the crude oil or raw natural gas to the surface. The upstream is of particular interest as it is the most capital-intensive and important of the three segments in the oil and gas business [13]. Companies from the sector deal with enormous uncertainties handled manually and relied on expert knowledge, not the actual data. The saying "one rock, two geologists, three opinions" tells a lot about the high uncertainties and risks oil and gas companies have to deal with. The uncertainties need handling

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Table 1
Non-confidential summary of projects performed with the direct involvement of the authors.

Upstream activity	Developed tool	AI approach	Main effect	
			Acceleration	De-risking
Geological assessment	Tool for automated mapping of reservoir rock properties over an oil region	None gradient optimization + interpolation techniques	Speeded up the manual mapping procedure from several weeks to several seconds	Removing human errors causing wrong mapping = making a more accurate definition of right hydrocarbon targets
	Tool for extracting the geological information from well logs	Gradient boosting	100+ times speedup	
	Tool for rock typing based on images of rock samples extracted from the wells	Deep neural networks	~1.000.000+ times speedup	
Drilling	Tool for detecting the drilled rock type and potential failure using real-time drilling telemetry	Combination of machine learning algorithms	Up to 20% time saving and up to 15% money savings at well construction	Maximizing the contact between the wellbore and the pay zone
Reservoir engineering	Tool for accelerating the conventional reservoir simulations	Deep neural networks	Accelerating by a factor of 200 to 2000	Making it possible to screen through much more field development scenarios for selecting the most optimal one
Production optimization	Data-driven tool for an objective forecast of efficiency of well treatment campaigns	Gradient boosting + expert based feature selection	100+ times faster estimation of the well treatment effect	Up to 20% growth of marginality of the investments to the campaigns

when making multibillion decisions on where and how to invest in the coming 5–20 years. However, despite the complex and uncertain nature of management problems in the sector, the single-criterion approaches have historically dominated decision-making [14]. To use existing field data to account for uncertainties associated with practitioners' subjective perception and decision-making based on experience, the first steps in using artificial intelligence and machine learning in the upstream are made, becoming increasingly popular [13].

The paper utilizes learnings from dozens of AI projects performed with the authors' involvement over the last three years for leading oil and gas upstream companies worldwide. The projects covered AI solutions for the whole spectrum of the upstream activities – geological assessment of the reservoirs, drilling optimization, reservoir engineering/field development, and production optimization. More details are in Table 1.

The paper is organized as follows. In Section 2, a big picture of the need for using AI in the upstream oil and gas industry sector is outlined. Based on an in-depth analysis of possibilities for applying AI and already existing applications, in Section 3, we review the most recent trends in developing AI-based tools for the sector and identify their effects, primarily on accelerating and de-risking processes in the industry. Section 4 briefly reviews AI approaches and algorithms used in solutions, while Section 5 in detail analyzes the role and availability of data in the sector. Further, in Section 6, we discuss the main challenges the intensive application of AI faces in the industry, focusing on new requirements related to data, people, and collaboration. Finally, we conclude by outlining three possible scenarios of how AI will develop in the industry and how it may change it in the future (5, 10, and 20 years) in each of the scenarios.

2. The problem and need for AI

The dominance of "difficult-to-recover" oil and gas reserves over the last ten years [15] dictates the necessity of new operational approaches and business models in the exploration and production of hydrocarbons, oriented towards ensuring appropriate profitability of oil and gas production. The latter is true for both well-developed (*brownfields)* and newly discovered (*greenfields*) subsurface hydrocarbon reservoirs.

Even though the vast majority of the brownfields are relatively big in terms of their geometrical sizes and rather good in terms of transport and storage properties (porosity and permeability), the amount of oil and gas recoverable with cheap waterflooding is very small. In principle, all conventional brownfields are producing more water than oil [16]. To keep production levels, the operating companies have to spend a sufficient amount of money for one of the following operations: extra drilling, well treatment (e.g., hydraulic fracturing), or field-scale enhanced oil recovery procedures (e.g., increasing the mobility of remaining oil in the reservoir with an injection of chemical cocktails). In many cases, money invested in these actions does not pay off, leaving the brownfields in a slow process of dying.

The situation is not better for new discoveries neither. Nearly all of the newly discovered hydrocarbon reservoirs are also difficult. They might be [17]: (1) located in places with harsh environmental conditions (e.g., in Arctic's shelf); (2) complex in terms of geometry (e.g., thin and winding layers of oil-saturated rocks with lots of cracks); (3) under the very thick layer of seawater and salt minerals (e.g., offshore Brazil); or (4) poor in terms of permeability (so that the hydrocarbon is nearly immobile within the reservoir rock). The development of these greenfields requires expensive technologies and makes the profitability of further oil production questionable.

The decision-makers handle uncertainties related to long term and high-value investments in the oil and gas upstream manually and based on expert knowledge, not the actual data enormous . There are two major questions they need to answer in this context. First – is this a particular asset perspective? Shall we spend money on geophysical studies to assess the potential of the asset? Typically, this question is answered with the geological modeling and reservoir modeling workflow, which takes several months to several years, depending on the necessity of additional geophysical surveys and the complexity of the in-company procedures. The second question is – shall I spend money on enhancing the oil production at my asset? If so, what technologies are worth investing? This question is dominantly handled by experts and supported, at some level, by conventional reservoir modeling tools. Strong dependence on expert opinion and the insufficiency of appropriate input data for the traditional modeling tools result in biased and uncertain answers.

For both questions, AI systems, trained with the right field data, can offer significant help by speeding up the asset assessment process and making it more objective or expert-independent. The first steps in this direction and future possibilities are discussed in the next section.

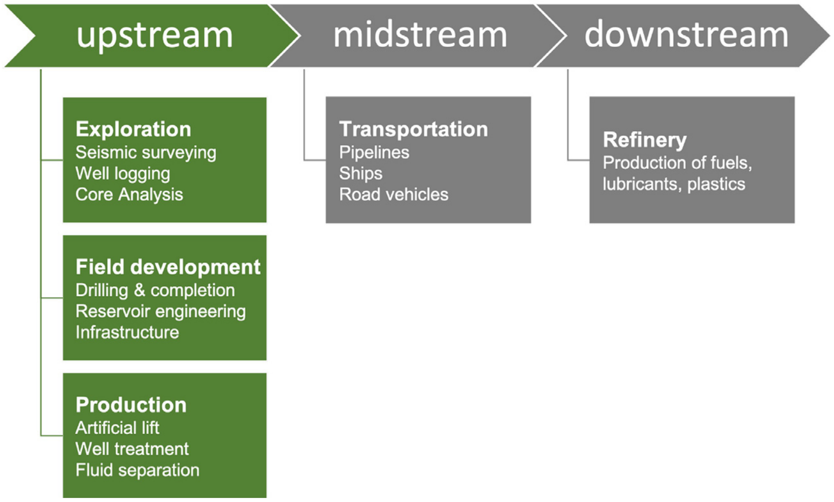

Fig. 1. Division of the oil and gas industry into sectors.

3. How AI is changing the upstream

The petroleum (oil and gas) industry divides into upstream, midstream, and downstream (see Fig. 1). The upstream summarizes the subsurface (mining) part of the industry, including exploration followed by the field development and production of the crude oil/gas. Midstream stands for transportation of oil and gas, and downstream is for refinery i.e., production of fuels, lubricants, plastics, and other products. Explaining in detail many of the upstream activities, we discuss points where AI solutions are already applied and their results. We also highlight where we expect AI to be used and what results can come out of its application.

3.1. AI-aided exploration

Exploration of oil and gas reserves is a set of operations resulting in a 3D geological model of an oil/gas field or reservoir. The operations include geophysical and petrophysical studies and processing of the data acquired during the studies. Geophysical and petrophysical studies typically consist of 1) reservoir-scale seismic surveying, 2) well logging, and 3) lab core analysis and (in some very specific cases) digital core analysis.

Seismic surveying produces a set of sensor recordings called seismic traces. The traces are time series representing the strength of elastic waves initiated by a vibrator at the surface and reflected from boundaries dividing various subsurface formation layers. These recorded time series together with spatial coordinates of the corresponding sensors and the vibrator are put to a special reconstruction algorithm resulting in noisy 3D images illustrating some of the reflecting boundaries. The reconstruction process is strongly offline due to very significant requirements for high-performance computing. AI-focused studies are aiming to speed up this stage [18].

The 3D images are called seismic cubes. The seismic cubes are studied by seismic interpreters, which can also be involved in setting the previous reconstruction phase parameters. The interpreters segment the 3D images by selecting the points, lines, and surfaces within the 3D cube, which are "definitely" related to the boundaries between the various layers in the subsurface formation. We quote "*definitely"* as there are no objective criteria for defining these points, lines, and surfaces. The whole process, starting with reconstruction to the 3D cube segmentation, is very time consuming and expert dependent. The entire survey data processing can take more than a year for a precise seismic study, as geologists decide, based on the segmented 3D cubes, where to drill the first set of exploration wells to refine the understanding of the subsurface specifics.

Modern pattern recognition techniques based on deep learning have started to dive into this seismic-related operation, accelerating the interpretation by a factor of 10–1000 [19]. There is a low probability that the AI techniques will optimize the physical part (i.e., amount, cost, and placement layout of sensors) of the first seismic surveying at an asset. Still, they add value in the optimization of the secondary surveys at the same asset. The mathematics of recommender systems [20] and interpolation capabilities of machine learning algorithms will enable proper recommendations on making the secondary surveys cheaper with a minor loss in the value of acquired information.

While seismic images provide a big scale (covering tens of kilometers) low resolution (down to tens of meters) information about reservoirs topology and its elastic properties, the well logging is used to get more precise information about various physical properties of the subsurface along a wellbore. The resolution of well logging is down to centimeters. The well logging sensors can measure electrical resistivity, natural gamma-ray intensity, response to magnetic excitation (nuclear magnetic resonance study), neutron density, and some others. Results of the well logging are vectors of properties along the wellbore. Petrophysicists use well logging data for their interpretation routine, including rock typing along the wellbore, estimation of porosity and permeability along the wellbore, and estimation of relative fluid saturation (amount of oil vs. the amount of gas and amount of water) along the wellbore.

The petrophysical interpretation is a rather time-consuming process, and the result of the interpretation depends strongly on the interpreter (i.e., expert). The authors faced this when developing an automated interpretation algorithm based on machine learning for oil companies. The algorithm, trained on historical well logging data, was applied to the data from new wells. The accuracy of ML interpretation versus manual interpretation was 92%. The ML interpretation was about 1000 times faster than the manual. Then we have decided to make another manual interpretation of the same data with the same experts. Interestingly enough, the second manual interpretation versus the first manual interpretation showed an accuracy of 91%.

In this view, the AI-aided technologies are the obvious way to accelerate and, maybe even more critical, to exclude the subjective part of the interpretation process [21,22]. Moreover, internal trials we did for industrial partners demonstrate that a solid portion of the well logging measurements could be easily reconstructed with ML. That would enable the utilization of machine learning to build the recommendation systems helping the oil companies spend less on the physical part of well logging. A similar acceleration is possible with core analysis [23,24].

The results of the petrophysical interpretation are then used to refine seismic interpretation. Geologists and petrophysicists extrapolate the acquired properties from near-wellbore zones into the seismic cube, saturating the 3D segmented cube with porosity, permeability distribution, and values of fluid saturation. This interpolation is probably the most time consuming and subjective part of the whole geology modeling workflow. With all the tuning exercises, the process can take from a couple of months to a couple of years. We expect that, if properly trained on multiple manually conducted extrapolation exercises, generative architectures of deep neural networks can accelerate the process by a factor of 1000+. Although it is hard to expect that in the near future, geologists and decision-makers will accept the automatically generated 3D geological model as the absolute truth, the automation with deep learning is an excellent opportunity for suggesting the expert-independent and fast variant for further fine-tuning and decision-making. Putting it simply, we foresee that the final decision-making could be performed much faster with the AI enablers.

3.2. AI-aided field development

Once the initial geological model is built, it goes to reservoir engineers. The reservoir engineers build a reservoir model from the geological model. Typically, they perform upscaling [25], which reduces the amount of the 3D cells describing the reservoir properties by increasing the size of the cells from the geological model. After the upscaling, the reservoir engineers use reservoir modeling software [26] to model the reservoir flows at various field development schemes. The field development scheme contains the plan for well drilling and well operation.

The result of each of the reservoir modeling runs is a forecast of oil/gas production for forthcoming years (typically 10 to 25 years) for a particular field development scheme. Performing many runs, the reservoir engineers select the optimal field development scheme and field development plan. The word *optimal* has different meanings for different companies. One group of companies, typically mid to large-scale companies, look for keeping the long-term production at some appropriate level at a fixed investment to field development and production operations. The second group, typically small to mid-scale companies, looks for a maximal outcome in producing oil/gas at minimal drilling costs over a couple of years. The third group may want to ensure that the asset or the field can be sold at a reasonable price after some time of field operation. Mathematically speaking, different companies have different target functions to optimize.

The reservoir engineering exercise is not done only for the greenfields, but for brownfields as well. The brownfields have production history, which helps correct the initial models via history matching [27] and reduce uncertainties in the production forecast. Theoretically, the history matching is an inverse problem with no unique solution, but there are practical workflows to handle this in application to reservoir engineering.

We see three major opportunities for applying AI in reservoir engineering. The first is related to computations done with conventional reservoir modeling tools. The tools perform numerical solutions of partial differential equations describing the physics of reservoir flows. The computations are performed on the 3D grid containing, typically, from 1 million to a couple of billions of cells. The computations are rather lengthy, even with the modern workstations and HPC servers, limiting the number of possible runs. The latter, in order, limits the optimization ability for proper field development planning. The acceleration of reservoir modeling is one of the obvious directions for AI technologies. Modern surrogate reservoir models with a new computation engine based on deep neural networks compress the mathematical problem dimensionality and approximate the time derivatives promise 100–1000 times the conventional models' speedup while keeping similar functionality [28,29].

The second opportunity is in upscaling (i.e., bringing the information gained from various scales of geophysical studies to a single geological and then hydrodynamical reservoir models). The upscaling process has a significant portion of art within. There is no single scientifically adequate framework for upscaling [30–32], and many reservoir engineers

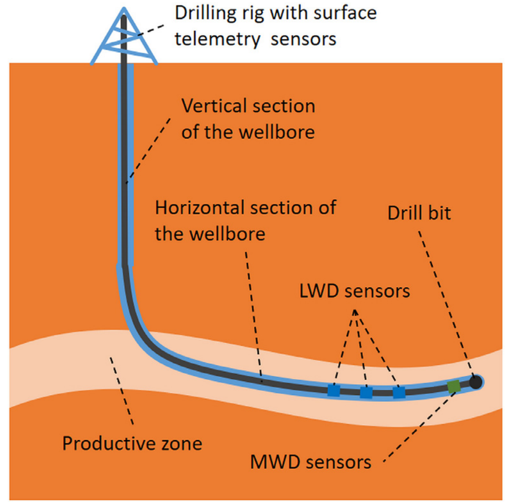

Fig. 2. Schematics of the well construction. Modern wells often have a horizontal section which needs to follow the geometry of the productive layer thoroughly.

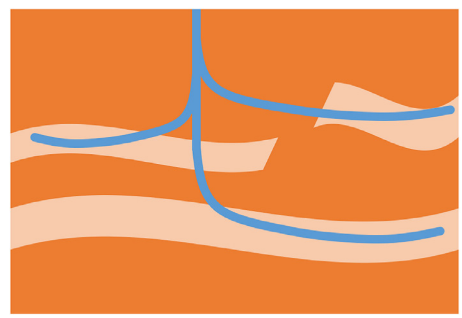

Fig. 3. The layout of multilateral wells. The wells drilled from the same point at the surface can reach several target hydrocarbon reservoirs.

use tricks to perform it in a way that seems correct to themselves. It introduces a strong bias to the reservoir model. As there is no single correct and objective procedure for the upscaling, one could think of increasing objectiveness by summing up the multiple experiences with a smart tool. This could be done well with a deep learning algorithm trained on multiple cases of manual upscaling. The outcome here would not be only the increased objectiveness but also the increased speed of the upscaling process.

The third opportunity is similar to upscaling but touching the history matching. The procedure here could be the same: trying to involve a machine or deep learning to make history matching faster and less biased.

As we have mentioned in the introduction, most greenfields have reservoirs that are complex in terms of its geometry and geological features. The latter requires building high tech wells with horizontal parts and multilateral completions (see Figs. 2 and 3).

Well construction at field development is the most cost-intensive operation at field development. For high investment in the drilling and completion of the well to pay off, it is essential to use all the drilling sensors' information. The aim is to ensure the best contact between the wellbore and the productive part of the formation, and maximal rate of the whole well construction process at minimal risk of failure and so, minimal non-productive time.

Modern drilling is a data-rich process. There are three types of sensors. First are the sensors on the surface that record the mechanical parameters of the drilling process in real-time. Second are the logging-while-drilling (LWD) sensors, recording physical parameters of the formation behind the drilling bit. Third are mechanics-while-drilling (MWD) sensors recording mechanical data from the bottom hole assembly. All the sensors generate a time series that can be used to manage the drilling itself and update the oilfield's geological or reservoir model. There are multiple approaches for making the drilling process faster [33], safer [34], and more precise [35]. We expect a significant reduction of the non-productive time down to 20–40% on average with a considerable decrease in failures down to 90% with the development and implementation of AI-aided drilling support systems working with real-time drilling telemetry.

3.3. AI-aided production

Producing reservoirs are attractive for AI-aided tools as well as the green fields. There are obvious machine learning applications for various pumps to implement predictive maintenance and select the optimal operation regimes concerning operational costs vs. production. Many of the pumps, including electric submersible pumps, pumps for injection wells, hydraulic fracturing, and other well treatment pumps, are equipped with a high number of sensors measuring pressures, temperatures, vibrations, flow rates, etc. There are many examples when an entirely data-driven or a hybrid model containing physics-driven and data-driven math helps optimize the regimes, prevent unexpected failures, and save on maintenance-on-schedule [36,37].

Apart from these apparent applications for equipment maintenance, we foresee the well treatment as another area with high cost-saving potential. The well treatment operation is produced to stimulate the inflow of hydrocarbon to an old well or increase the starting flow rate of a newly drilled well. The most popular well treatment procedures are hydraulic fracturing [38] and chemical treatment [39]. The well treatment costs are significant and comparable with the cost of well construction. The investments to the well treatment campaigns are always at high risk because of two things. The first relates to the fact that physics-driven models for predicting the well treatment effect produce very rough estimates due to the lack of precise knowledge of the near-wellbore formation's physical properties. The second relates to the experts' bias involved in figuring out the final selection of the well treatment procedures for a particular set of wells. The bias is mainly because of standard procedures of assessment of marginality levels of the procedures in operating companies. Many of the standards assume fixed levels of marginality, which are targeted by the experts to get the investments for the well stimulation jobs.

There is an excellent opportunity to reduce the investment risks by accumulating the data from already produced well treatment jobs. Pioneering efforts on predicting the efficiency of hydraulic fracturing jobs [40] and ML-based analysis of injectivity issues [41] have already been made. We expect that further development of algorithms based on optimization math and programming will enable full-scale recommending systems. The recommending systems will help select the particular well treatment design for a particular well and plan the well treatment campaigns.

3.4. AI for safety

Apart from the AI application for cost reduction and de-risking, we should mention its extraordinary impact on safety measures. Operations on the oilfields are risky for personnel as there are several risk factors, including heavy equipment, non-covered rotary equipment, high pressure, high-temperature operations, and aggressive chemicals. There are many IT systems based on deep learning helping the safety officers spot safety protocols' violence. Pattern recognition utilizing deep learning allows and video streams recorded with cameras to alarm if an employee is not adequately dressed for the particular set of operations. Moreover, predictive analytics alarm the operators on the equipment's health state, enabling pro-active actions to prevent a catastrophe with the consequences to health, safety, and environment.

4. Algorithms in the oil and gas upstream

Classical machine learning and deep learning are dominant approaches used in AI applications in the upstream sector and the whole oil and gas industry [8]. They are used in solving classification, clustering, or regression types of problems. Machine learning and deep learning algorithms are black-boxes – there is no obvious formula that describes why systems based on them do what they do or how they work. These algorithms contain very complex multi-dimensional algebraic expressions. Coefficients within these expressions are defined to fit the input and output data describing the system, object, or process. This fitting process is called training. Once trained on known data, the algorithms can generate novel insights based on new inputs.

Additionally, hybrid modeling, where physics-driven models are used together with machine learning algorithms, is present in industrial applications. There is a distinction between physics-dominated hybrid models and data-dominated hybrid models. In physics-dominated hybrid models, machine learning is used to tune the equation's coefficients to the actual data generated by an object of interest. On the other hand, in data-dominated hybrid models, the physics-driven model is used for generating large amounts of training data, based on which (+real-life data) the ML model learns the physics of the problem and helps in solving it [42].

Finally, the first applicators involving AI planning – the set of optimization and machine learning methods to plan some actions to achieve a goal, typically executed by autonomous robots, intelligent agents and crewless vehicles – are emerging in the oil and gas industry.

In-depth analysis of AI and machine learning algorithms used in the oil and gas industry can be found in several recent reviews, including [8,43–45].

5. Data in the oil and gas upstream

Common to all mentioned AI approaches is that without access to large and good enough training data, AI algorithms are significantly less useful, sometimes useless. "Good enough" means that data must be diverse enough to cover all events, activities, and behaviors of interest [46]. For example, to build a successful predictive maintenance solution, the dataset must contain enough recorded failures to be useful for learning from it. On the other hand, what is a "large enough" dataset is less clear, as the size of the needed dataset depends on the context of the problem that is being addressed (and the tempo of algorithm development). Goodfellow, Bengio, and Courville [47] estimated that to achieve somehow acceptable performance levels with the most interesting form of today's AI (i.e., supervised deep-learning), around 5000 labeled examples are needed for training. While to match or exceed human-level performance, at least 10 million labeled samples are required.

The oil and gas industry is very data-rich [48]. Table 2 summarizes its sources, formats, size, generation rate, and application areas in the upstream.

AI is bringing a new approach in developing the oil and gas fields, one in which data is key. Before this transition, the development of the oil and gas fields and related data usage has passed through three major stages. The beginning of the oil century (late XIX to early XX century) was characterized by the logic, which can be formulated as: "There is a hill, and there is a producing well at the neighbor hill. Let's drill this hill as soon as possible". To identify and develop the oil and gas fields, people were using an entirely empirical approach based on analog cases. Sensors, measurements and data were not used.

This changed when Schlumberger brothers updated the empirical decision-making with subsurface physical properties measurements starting from electrical resistivity from the surface and then from the wellbores. These measurements introduced sensor data to the decision-making process of detecting oil and developing an oilfield.

Further development came with adding numerous data sources and using data to characterize and analyze the fields through different sim-

Table 2
Upstream data.

Data Source	Data format	Size	Generation rate	Used for
Seismic surveys	Time series, 2D images, 3D images	Up to 100 TB for a field	One to several times in 25 years	Geological modeling
Well logging	Vectors, spreadsheets	Up to a 10 TB for a field	Several times in 25 years	Petrophysical and geological modeling
Core analysis	Spreadsheets, 2D images, 3D images	Up to 500 TB for a field (assuming digital rock study with X-ray microtomography)	Several times in 25 years	Petrophysical and geological modeling
Fluid analysis	Spreadsheets	Up to 500 MB for a field	Several times in 25 years	Reservoir Engineering
Drilling telemetry	Time series	Up to 100 MB for a well	Up to several numbers per second during drilling	Real-time drilling management
Drilling reports	Spreadsheets, unstructured text	Up to 2 MB for a well	Once a day for each drilled well	Offline drilling management
Logging while drilling	Time series	Up to 100 MB for a well	Up to a number per second during drilling	Real-time drilling management/ geosteering
Well testing	Time series	Up to 100 MB for a well	Up to several numbers per minute	Reservoir engineering and production management
Production rates	Time series	Up to 100 MB for a well daily	Up to once per hour	Reporting, production management, reservoir engineering
Well treatment data	Spreadsheets, unstructured text	Up to 0.5 TB for a well treatment job	Several times over a wellbore life	Reservoir engineering, production management

ulation and modeling exercises. At this third stage, experts use the data in three ways typically. Seismics, well logging, core and fluid data are used mainly to construct a reservoir geological model followed by constructing a reservoir model used in reservoir engineering for scenario modeling to plan field development. This modeling is a key input to the most cost-intensive decision making in oil and gas upstream. Some portions of the data, like drilling telemetry, well treatment job telemetry, and production rates, are used for the operational management of various technical processes happening at the oilfield. And some of the data (like production rates) is used for reporting. That describes the current situation with oil and gas field data acquisition and management.

Nowadays, we are in a transition period in-between stage three, which utilizes a lot of data-intensive practices, like conventional reservoir engineering, drilling engineering, and geo-modeling towards the stage four, where data is the key, and modern AI developments will help to overcome some of the challenges not tackled previously. It is essential to highlight that AI is not just technology that enables some processes to be done faster or cheaper or with higher quality. AI-tools exclude people from many processes and lead to numerous possibilities for operational and business model innovations, making it possible to do things differently at the architectural level.

6. Key challenges and enablers

While some oil and gas companies, like BP, Shell, Saudi Aramco, and Gazprom Neft are jump-starting their AI initiatives by investing aggressively in startups and R&D, several challenges are preventing them to massively and rapidly implement AI in the exploration and production of oil and gas. That is not an oil and gas specific problem, but a commonplace in applying AI at this stage of its development [49]. Based on our evidence, the critical challenges are related to the (new) profile of people the industry requires, the central importance of data, and the need for open collaboration. We discuss these three issues below.

6.1. People

The success of artificial intelligence critically depends on human intelligence. AI solutions are not generic – they cannot be just bought. Even when developed by third parties (and given for free, like Google's TensorFlow) AI solutions have to be customized to the business context and data a company has [46]. Thus, to actively use AI in processes and products, companies must grow in-house teams composed of data and AI specialists. These teams should be able to support development of AI infrastructure (algorithms and datasets) and, at least to customize tools that companies will later utilize in their operations. Yes, that means that oil and gas companies will become (partially) data-driven companies and, that AI specialists will become irreplaceable in supporting almost all innovation efforts in oil and gas companies in the next 10 years. However, finding and retaining AI talent is a very challenging task. There is a significant shortage of AI talent on the job market [50,51], and with more and more companies getting into AI and forming their own AI groups, prospects are not good for the next decade. This is especially true for oil and gas companies. Next, to compete with tech giants like Google, Yandex, IBM, and Amazon, leading universities and cool startups worldwide over the same talent – oil and gas companies have to fight negative attitudes toward fossil fuel industries. That is not an easy neither a cheap task.

Although AI's entrance into the oil and gas industry announces "*the end of petroleum engineering as we know it*" [52], petroleum engineers will not disappear. Just their role and required skillset will change. To successfully innovate in the AI-era, next to data scientists oil and gas companies will need petroleum engineers with a strong sense of data science and the ability to identify and design tasks to be solved by AI. Their role will be to ensure that the right problems are identified for applying AI, that the right data is collected and that solutions fit the physical and process reality. Over time, this will become a crucial role, as otherwise the wrong questions may be asked and existing human mistakes amplified, as it happened in the case of Google's breast cancer detection solution based on mammograms [53]. So, it is not that just data science and AI skills are in demand due to the adoption of AI, but a new way of thinking about problems oil and gas companies face, rooted in deep understanding of the processes and the core logic of tasks. Thus, the new role of petroleum engineers will be more and more critical. To prepare the next generation of petroleum engineers for it, some universities like Skolkovo Institute of Science and Technology (Russia) and West Virginia University (US), already started implementing special educational programs that are a healthy mix of data science and petroleum studies.

Next to working more with data and data scientists, petroleum engineers will have to learn how to work with AI assistants – products similar to Alexa and Siri, but focused on industry applications. In these new partnerships, the challenge will be to combine best from the two sides – AI's ability to deal with a lot of data, find patterns and relations, and petroleum engineers' deep industry domain knowledge [54]. Although AI is expected to be dominantly used by humans to augment their decision-making abilities rather than replace them [49], this will be a challenging task as many questions related to trust and fear of losing jobs may arise. There is an unsolved issue also related to people – the legal view on AI's recommendations. There could be cases when an AI tool recommends an action leading to a loss in money, production, or even severe health or environmental issues. In this case, we have no clear understanding of responsibility-sharing between the AI algorithm itself, the AI algorithm user, or the AI algorithm developer. With the development of AI tools, this question will rise more and more often. So the parallel establishment of the legal base is expected here. The practice says that the algorithms and their developers are not responsible, but the responsibility is still with the decision-makers getting the advice from the AI and AI users. Thus, to benefit from the opportunity to extend decision-making capabilities significantly, companies will have to create not only strategies *for AI*, but strategies *with AI* [55] as well.

6.2. Data

AI tools need the good quality data of a suitable volume to be trained and then to work properly in the operational mode. While using smarter algorithms may help in getting better results from datasets of limited size, no manipulation can help with bad data [56]. Thus, access to big and quality data is a crucial enabler and barrier for AI applications' successful development. Oil and gas fields generate large amounts of raw data. Still, it is not a guaranty for success as there are known issues with the quality and accuracy of field data and overall lack of large volumes of labeled data in the oil and gas industry [48]. Training datasets have to be carefully collected through the well-planned workflow- and situation-specific multi-year procedure [57]. One of good examples is Ambyint, a VC-funded AI-driven startup focused on oil and gas production optimization, which has spent over a decade to build its repositories of high-quality production and optimization data that is used to train and improve their solutions [58].

To enhance the value of data oil and gas companies possess or can access, they will have to redesign and adjust their organizational structures and processes. Oil and gas companies are not known for their agile, lean, and bottom-up development approaches but for strict jurisdiction division and waterfall processes and procedures – that has to be changed. Also, data storage should be centralized into one or a small number of data warehouses to allow people and AI software easy access and usage [57].

Data challenges (across industries, not only in the oil and gas) drive technical efforts in improving AI systems and their further practical usage in the exploration and production of oil and gas. One of the key directions here is small data learning [59] that enables training the AI algorithms with a small number of examples. The small data learning attracts the serious attention of researchers worldwide, but there is no substantial progress as of now. The second direction is about the efficient adaptation of the already trained models for the new datasets generated by similar but not the same objects, processes, or systems. Capability to update the pre-trained model on-the-fly will significantly increase the applicability envelope for the AI-aided tools. Such quick adaptation studies are also under intensive research [60,61].

6.3. Open collaboration

Artifical intelligence is born in open and collaborative environment as a consequence of academia being a leading force in AI research for decades, almost without any business influences. This created culture of free sharing (e.g. GitHub) and open publishing (e.g. arXiv), which companies across industries (and across the globe) had to embrace as a standard to succeed in the era of AI [62,63] once they joined the race.

While open innovation is becoming standard in the tech sector, oil and gas companies are not famous for their joint industry projects, especially between competitors and especially not in strategic domains such as AI [48]. Even though many companies announce bringing some of their data to the open-source and claim the necessity of cross-company and cross-border data sharing, the reality is rather pessimistic now. We have very few sources of geophysical and production data, and they are of questionable quality. The UK's oil and gas National Data Repository is one of the first large oil and gas open data releases. It contains 130 terabytes of geophysical, infrastructure, field, and well data, covering more than 12,500 wellbores, 5000 seismic surveys, and 3000 pipelines [64]. The opportunities for machine learning and artificial intelligence applications based on available data are highlighted [65].

Next to data access, the need to acquire the latest AI technology and talent are additional reasons for oil and gas companies to adopt open collaboration. The ability to question everything and efficiently experiment with data allows AI-born startups to attract attention and record investments. In 2019 AI-related companies in the U.S. raised $18.5 billion, almost 2 billion more than in 2018 [66]. The largest oil and gas companies are active in acquiring AI startups. For example, GE and Statoil jointly invested in Ambyint [58]. Saudi Aramco invested in Earth Science Analytics, a startup developing the next generation of petroleum geoscience AI software [67]. BP invested in Belmont Technology, a startup aiming to boost the company's AI and digital capabilities in its upstream offshore business [68]. Shell, Saudi Aramco, and Chevron invested together in AI startup Maana, which partnered with Microsoft to use its cloud computing platform Azure [69].

University labs are another important source of novel AI technology and AI talent [51]. Thus, oil and gas companies should re-think strategies for collaborating and interacting with universities. But, not only with them. All three challenges related to succeeding in the era of AI – data access, acquisition of new technologies, and talent attraction – ask companies across industries (including those from the oil and gas industry) not only to move from close to open innovation but to move from partnerships towards ecosystem approach.

The AI-related oil and gas ecosystem comprises many different players – companies and organizations from different sectors, with different AI development stages, different strategies, and priorities. The first group, mainly consisting of major international oil companies, is focused on building the first modern data storage infrastructure (e.g. company-wide data lakes) and then AI solutions, on top of them, e.g. [70]. The second group, typically represented by the smaller field operating companies, is trying to leverage whatever helps speed up their business and technological processes as soon as possible, figuring out the issues of relevant data storage and IT infrastructure in parallel, e.g. [71]. The third group represents the emerging hi-tech sector – startups (e.g. Ambyint), universities (e.g. Stanford University), and technology-oriented oil service companies (e.g. Digital Petroleum) developing new AI-aided tools for oil companies (those from the first two groups). The fourth group represents IT companies that mainly supply oil companies with digital platforms and data storage capabilities. For example, Microsoft's Azure platform is selected by Shell as a base infrastructure for enabling rapid scalability and replication of AI applications across its enterprise [72]. The fifth group represents regulators. Many other interested parties are engaged in AI development, like banks, telecom operators, and many others. For example, Gazprom Neft joined forces with some of the Russian largest tech companies (i.e. Yandex, Mail.ru, MTS and Sberbank), aiming to spur the development of AI solutions and facilitate the development of a dynamic AI market [73].

This new interconnected network of partners, with frequently very limited experience of previous collaborations, has to learn how to manage new interdependences, how to create, appropriate and share value. Data's central role and growing convergance will drive the nature of connections between members of the evolving and enlarging oil and gas ecosystem, defining how risk should be managed, value distributed and collaboration orchestrated.

Table 3
Scenarios of AI penetration in the oil and gas upstream.

Scenario	Key inputs	5Y	10Y	20Y
Positive	Data sharing approved Proper data platforms are in place	Active testing of AI for various cross-company problems Growing trust level to the black box technologies	AI tools support decision making at nearly each of the cost-intensive decision Up to 40 to 50% cost savings at E&P	AI tools support decision making at 90% of operations Oil century is extended due to AI-aided support of E&P margins
Realistic	Data sharing is a problem Proper data platforms are in place	Active testing of AI for various local problems Growing trust levels to the black box technologies	AI tools are accepted as the objective expert 10 to 15% cost savings at E&P	Hybrid "AI + physics" tools take over Strategic investments in E&P continued with some support of AI technologies
Negative	No data sharing agreements between the companies and countries	Poor overall performance of Ai tools due to lack of appropriate training data A negative perception of the AI developments in E&P	AI tools help in some local problems a bit No significant growth of margins at E&P processes	Nuclear, solar, and wind start dominating

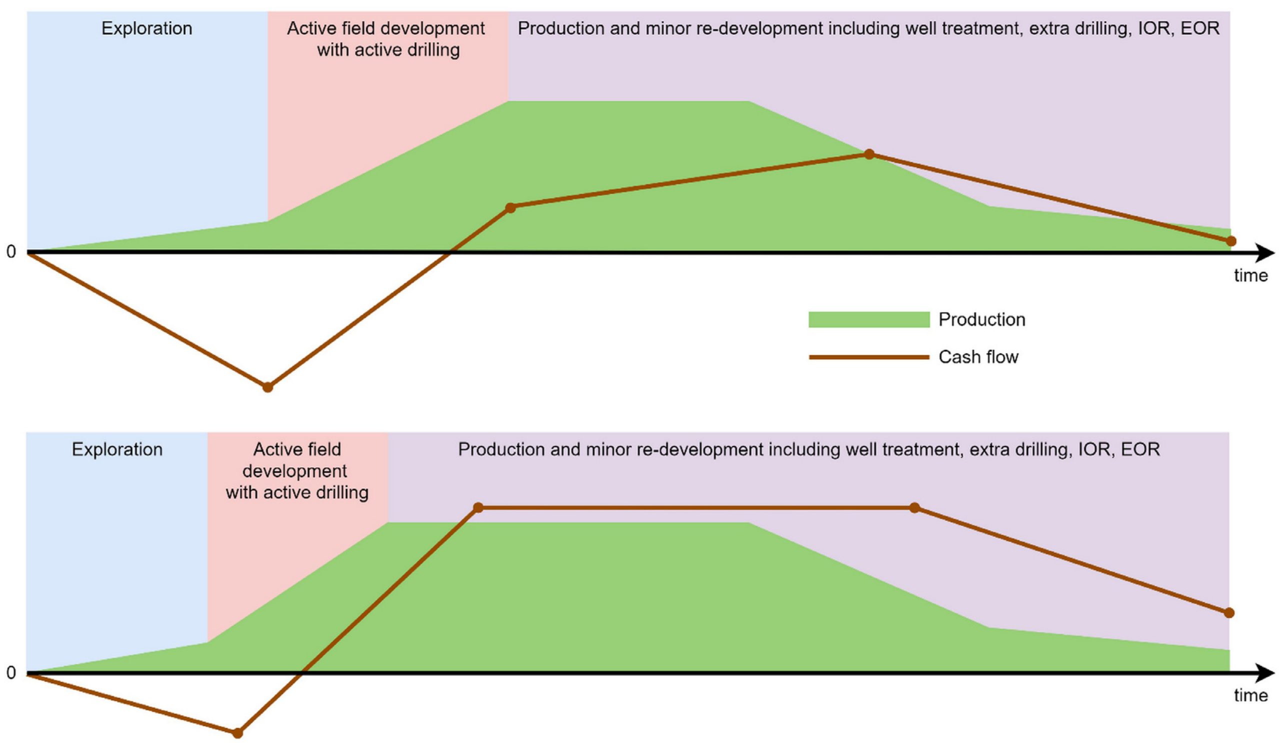

Fig. 4. The lifecycle of an oilfield in the pre-AI era (top) and AI era (bottom). IOR stands for improved oil (gas) recovery; EOR is for enhanced oil (gas) recovery techniques.

7. Discussion

Succeeding in the digital competition is not about technology only [12]. AI initiatives will not fail because of bad algorithms, but rather because of lack of vision, late or even no changes in the organization's operational and business model, due to lack of high-resolution data and poor collaboration. Thus, strategy plays a key role and is a driving force of digital transformation [7], and top management commitment is essential to assure the success of AI and other transformative efforts [74].

This may be one of the core problems for the oil and gas industry famous for its risk-averse culture and poor innovation management practices [48]. *The flavor of failing* that industry experienced two times in the last five years, especially the last one (April 2020) in which oil prices went negative, maybe the right trigger to start transforming their business models [75]. Otherwise, there is a very high risk that initially good results in using AI for a single purpose will be misleadingly understood as the final goal [7]. This could lead companies to invest more only into technology, which will result just in marginal, not transformative improvements [12]. However, this is not a specific problem of the oil and gas industry – only 8% of firms engage in core practices that support the widespread adoption of AI. At the same time, the majority of initiatives are ad hoc pilots focused on a discrete business process [76].

Assuming the absence of the major technological breakthroughs within the energy area and social storms affecting current energy demand trends in the coming years, we can visualize three possible scenarios of AI spreading in the oil and gas upstream. Here we assume that *Covid-19 crisis* will not permanently change the main postulates of the industry. The scenarios are classified as positive, realistic, and negative in terms of usage of the potential of AI developments (Table 3).

The positive scenario is based on a globally spread understanding that cross-company and cross-border data sharing is crucial. Assuming strong and committed leadership in the key companies and that good data platforms are in place, one may expect very rapid growth of AI capabilities for the upstream applications followed by AI tools for decision making at various levels. Here we can bravely foresee huge potential in the growth of marginality of the oil and gas upstream business due to very significant savings on costs and monetized losses due to non-optimal decisions reaching 50% of the current levels. There is also a big portion of the environmental effect present here [77]. If AI penetrates the industry this way, many opportunities minimize the negative footprint of the upstream's hardware technologies. For example, one can use a proper AI model to minimize hazardous components at well treatment jobs or re-utilize the produced water in a way that keeps the recovery factor on an appropriate level.

The realistic (neutral) scenario is when the IT platforms are in place, but the progress on data sharing agreements is limited. Limited means that there are some additional sharing opportunities concerning what we have now (like sharing between groups of the companies within a country). Some AI tools will be accepted as useful advisors, and the focus within AI developments will be shifted towards grey box hybrid models, where the physics-driven part will compensate for the absence of access to a fair amount of the actual field data. We foresee this as the most realistic case, with an overall impact on the upstream margins being two-three times lower than in the positive scenario.

The negative scenario is all about the blockage of data sharing. Our forecast here is as simple as the end of the oil century in 20-30 years due to continuously dropping the whole upstream domain's margins.

In the positive or realistic scenario, the overall effect on an oilfield lifcycle should change as schematically shown in Fig. 4. The lifecycle of an oilfield in the pre-AI era (top) and AI era (bottom). IOR stands for improved oil (gas) recovery; EOR is for enhanced oil (gas) recovery techniques Fig. 4. The lifecycle of an oilfield in the pre-AI era (top) and AI era (bottom). In general terms, AI should make exploration and active field development faster and cheaper while keeping the production margins higher on a longer-term.

8. Conclusion

We discussed the development of practical tools based on artificial intelligence for oil and gas upstream. It is clear that even though artificial intelligence is an emerging trend in oil and gas, there are applications that have already brought countable value. We have provided several examples of how artificial intelligence helps speed up and de-risk many business processes associated with the exploration of hydrocarbon resources, the development of oil and gas fields, and raw hydrocarbons production. There is an on-going experiment on the scalability of artificial intelligence across the whole industry. Here we have discussed not only the technical drivers of such scalability but the non-technical factors as well. We evaluated the influence of education, organizational attitude, and data availability on the speed and direction of artificial intelligence penetration to oil and gas upstream. Basing on this analysis, we derive three possible scenarios on how artificial intelligence could spread within the oil and gas in the coming five to twenty years.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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