2020-IP12: Artificial Intelligence and CCS

The Oxford dictionary defines artificial intelligence (AI) as the 'theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages'. AI in general describes a programme that can sense, reason, adapt and interact. 'Machine learning' is an application of AI that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves. 'Deep learning' is a subset of machine learning in which multi-layered neural networks learn from vast amounts of data.

AI and machine learning are rapidly developing technologies with the ability to optimise processes and supply chains, to allow predictive maintenance and help identify and mitigate risks.

The ISO special focus report in late 2019 on 'The Age of Artificial Intelligence'[1] defines AI as the 'simulation of human intelligence processes through algorithms built into a dynamic data-driven environment', noting that it is not just a single technology, but 'a collection of hardware and software technologies and broad application domains' with the capability of doing precise jobs extremely quickly, generating huge time and cost savings. According to market research firm IDC, 'spending on AI technologies is projected to reach USD 52.2 billion by 2021' which demonstrates the promising potential for these types of programmes in generating strong economic growth opportunities worldwide whilst contributing to climate change mitigation (along with a several other important global issues) in a number of ways. The World Economic Forum also notes that 'the opportunity for AI to be harnessed to benefit humankind and its environment is substantial. The intelligence and productivity gains that AI will deliver can unlock new solutions to society's most pressing environmental challenges'[2] – including climate change.

IEAGHG have recently undertaken a study with Element Energy[3] on the 'Value of Emerging and Enabling Technologies in Reducing Costs, Risks and Timescales for CCS' which has been published in July 2020 (report 2020-05) and covers in detail the potential for technologies such as artificial intelligence that are already in use in the energy sector and looks at how these technologies can be transferred to help facilitate the large-scale worldwide deployment of CCS.

The study recognised that digital innovations (including AI) had several relevant applications for CCS, including process optimisation and automation, predictive maintenance, predictive analysis and simulation and virtual commissioning. These applications would have numerous benefits, including reduced costs, increased efficiencies, reduced downtime, lower failure rates and more effective (and therefore cheaper) maintenance through all aspects of the CCS chain (capture, transport and storage). The ability to collect data from multiple sensors and sources show significant opportunities for monitoring, and capture processes are suitable for the extension of current concepts to an AI-driven, autonomous system. Machine learning has also been applied to materials design for novel capture materials, with intelligent deep learning able to predict properties of materials meaning for faster analysis and evaluation time. Preventative maintenance is already in use in the oil and gas industry, with Baker Hughes using machine learning to develop a pump health monitoring systems and FOROIL

[1] *International Organization for Standardization*, **ISO*focus* November-December 2019**; **'the age of artificial intelligence'**, ISSN 2226-1095, 2019 https://www.iso.org/files/live/sites/isoorg/files/news/magazine/ISOfocus%20(2013-NOW)/en/2019/ISOfocus_137/ISOfocus_137_en.pdf

[2] *PwC & World Economic Forum (WEF)*, **Harnessing Artificial Intelligence for the Earth**, January 2018 https://www.pwc.com/gx/en/sustainability/assets/ai-for-the-earth-jan-2018.pdf

[3] **Element Energy** (UK), http://www.element-energy.co.uk/

has used historical production data to optimise oil recovery from brownfield sites; both of which are relevant and applicable to CCS projects.

In cost modelling carried out as part of the study, digital innovations were shown to have the potential to contribute the largest cost reductions in both capture and storage, with the greatest impacts resulting from robotics, drones and autonomous systems and novel sensors, which would require in part machine learning.

A paper presented at GHGT-14 (2018) regarding machine learning came under Session 10F on Mechanical Modelling and was presented by Kristian Gundersen (University of Bergen) on 'Ensuring Efficient and Robust Offshore Storage - Use of Models and Machine Learning Techniques to Design Leak Detection Monitoring'. This work assessed the use of machine learning to identify CO_2 seeps to marine waters, showing that 'Convolutional Neural Networks (CNN) are able to, with high confidence, to classify time series from the model simulations into leak and no-leak situations. CNN in data analysis can increase the detectability of CO_2 seeps, and thus the optimization of sensor deployment and monitoring design'[4].

The US Department of Energy's Office of Fossil Energy (FE) produced a Special Report in 2018 on 'Big Data & Machine Learning for Clean Coal'[5] which recognised the large role that machine learning already play in coal-fired power generation. Recent and relevant efforts in big data and machine learning include in predictive maintenance (with sensor networks and machine learning working to diagnose faults before they occur, and help with upgrading of materials after machine learning has identified operational issues, for example) and with digital twinning, which compliments machine learning involving computational models used alongside visualisation to predict the impacts of changes in an environment before it's applied in the real world, for example NETL's JOULE supercomputer that develops digital twins of coal plants to help in developing future technologies. Sensors and controls are being advanced to improve coal plant efficiency and avoid downtime and subsurface characterisation can be improved by using widespread resources and large amounts of available data to support the development of a virtual subsurface data framework.

Specifically in terms of CCS, the Carbon Capture Program is funding the ongoing Carbon Capture Simulation for Industry Impact (CCSI2) project, employing and refining 'machine learning approaches for optimal experimental data generation and evaluation' by way of an open-source computational toolset for a comprehensive suite of models available to industry end users, computational frameworks that help to generate optimal design of experiments to produce the most impactful results at all stages of commercialisation and techniques for the rational and most efficient design of carbon capture materials. The overall aim is to continue supporting some of the largest CCS demonstration plants by using big data and machine learning to enable carbon storage and improve CO_2 capture and utilisation efforts.

The National Energy Technology Laboratory's (NETL) SMART Initiative specifically looks at science-informed machine learning for subsurface applications by detecting patterns to categorise, predict, identify and detect changes in factors of interest. This leads to control in the subsurface, with real-time visualisation and forecasting, rapid data to knowledge transfer (with autonomous monitoring

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[4] *Gundersen, Kristian and Oleynik, Anna and Alendal, Guttorm and Skaug, Hans and Avlesen, Helge and Berntsen, Jarle and Blaser, Nello and Blackford, Jeremy and Cazenave, Pierre.* **'Ensuring Efficient and Robust Offshore Storage - Use of Models and Machine Learning Techniques to Design Leak Detection Monitoring'**. 14th Greenhouse Gas Control Technologies Conference Melbourne 21-26 October 2018 (GHGT-14). Available at SSRN: https://ssrn.com/abstract=3366095

[5] *US DOE Office of Fossil Energy,* **Special Report: Big Data + Machine Learning For Clean Coal**, 2018, https://www.energy.gov/sites/prod/files/2018/11/f57/FE20SP%20Special%20Report%20BD%2BML_final.docx

and big data management), rapid prediction – this all contributing to virtual learning. Specifically in terms of CCS, real time visualisation could transform reservoir management with improvements in subsurface realisation, visualisation and operations. It would enable operators to explore and test subsurface behaviour prior to field experience, and help to transform reservoir management via real-time forecasts for different operational decisions.

This short Information Paper gives a very brief overview on the potential for artificial intelligence and deep learning in carbon capture and storage. Other emerging and enabling technologies, such as these kind of digital innovations and other technology areas are likely to have an impact in the future deployment of CCS and it will certainly be interesting to see where these technologies come into play in the coming years. For more information on the recent IEAGHG study on the 'Value of Emerging and Enabling Technologies in Reducing Costs, Risks and Timescales for CCS' or to request a copy of the report, please contact tom.billcliff@ieaghg.org

Samantha Neades
28/08/2020