HUB TECH IA

Deliverable report 53

AI and IAGEN Application Use Case

Treatment and recycling of fracking water in Vaca Muerta

I. Introduction.

The hydraulic fracturing technique, essential for extracting shale oil and gas in the Vaca Muerta formation, requires the use of vast quantities of water, estimated at around 30 million liters per well. Of this volume injected at high pressure to fracture the rock and release the hydrocarbons, between 20% and 40% returns to the surface in the form of *flowback* .

This flowback fluid not only contains the originally injected water, but also a complex mixture of substances carried over from the geological formation and the chemical additives used in the fracturing process. Due to its volume and composition, *flowback management* represents a significant challenge from both an environmental and logistical perspective.

The increase in activity in Vaca Muerta has led to a proportional increase in the generation of return water.

This situation underscores the critical importance of properly managing *flowback water* in Vaca Muerta. Efficient management would reduce pressure on the region's water resources, minimize adverse environmental impacts, and meet the standards necessary for continued operations.

In this context, the treatment and recycling of return fluid has become a strategic priority for operating companies, where the incorporation of artificial intelligence (AI) emerges as a promising solution. The magnitude of water consumption and the constant increase in *flowback volumes* indicate growing pressure on water resources and waste management infrastructure, making the adoption of efficiency-enhancing technologies, such as AI, a necessity for the long-term sustainability of operations in Vaca Muerta.

II. Challenges in return fluid management

The return water from hydraulic fracturing has a complex and potentially contaminating chemical composition. Upon returning to the surface, the *flowback* carries with it residues of the chemical additives used, such as fracturing gels, as well as elements present in the reservoir rock, resulting in a liquid with high salinity and a high dissolved solids load. Studies and experiments in the basin have detected the presence of hazardous compounds; the returned additives and substances can be toxic, flammable, and even carcinogenic, and warnings have been raised about possible traces of naturally occurring radioactive elements and heavy metals in the *flowback* .

The presence of carcinogenic substances not only poses direct health risks but also increases regulatory scrutiny and public concern regarding *flowback management* , which could affect the social license to operate for businesses in Vaca Muerta. This complex composition classifies flowback fluid as a delicate industrial waste, categorized by regulations as special or hazardous waste.

The potential environmental impacts are considerable if *flowback* is not managed properly. It can contaminate soils and groundwater in the event of leakage or improper disposal, posing health risks to local communities and impacting other economic activities.

Temporary storage in ponds or tanks requires the implementation of specific engineering measures, such as impermeable liners and monitoring systems, to prevent spills. Traditional disposal through sump wells (deep injection) carries its own risks, including increased induced seismicity in areas where no perceptible seismic movements were previously recorded, and the possibility of long-term migration of contaminants into the subsurface.

Furthermore, trucking from oil fields to treatment plants carries risks of accidents and emissions, as well as high costs;

In just one year, 4,800 truck trips transporting contaminated water were recorded in Neuquén.

The logistical burden and risks associated with transporting large volumes of *flowback* highlight the value of on-site or near-site treatment solutions, which can reduce the need for extensive transportation.

Managing the return flow in Vaca Muerta involves technical challenges (due to its polluting composition), operational challenges (increasing volumes, logistics), and regulatory challenges, which require innovative solutions.

III. Application of AI in the treatment and recycling of return fluid

A typical internal treatment scheme begins with phase separation: degassing equipment and liquid-solid separators remove free hydrocarbons and particles (sand, clays) from the return water. Effective phase separation is a crucial first step, as it reduces the load on subsequent treatment stages. Physicochemical processes then adjust parameters such as pH and precipitate metals; for example, the dosing of coagulants or stabilizers helps to aggregate fine solids.

Filtration and centrifugation systems remove remaining suspended solids, while special units can remove volatile organic compounds. To reduce high salinity, desalination technologies such as reverse osmosis or mechanical evaporators are used; these require overcoming problems of scaling and membrane fouling. Finally, the treated water is stored for reuse in new fractures, and the rejected concentrates (brine, sludge) are managed as waste.

The incorporation of AI models into these processes could significantly increase efficiency and controllability. Machine learning techniques can predict the quality of incoming flowback in real time, based on sensor data (pH, conductivity, turbidity, hydrocarbon content) and well operating parameters. This makes it possible to anticipate, for example, a salinity spike or the presence of a certain heavy metal, and proactively adjust chemical dosing or membrane configuration. Artificial neural network (ANN) models have already demonstrated success in optimizing complex water treatment processes, learning from historical data to continuously improve performance.

Algorithms can also be trained to optimize the treatment sequence: deciding the optimal flow rate through each module, when to regenerate or clean filters, or which coagulant mixture removes contaminants at the lowest cost. One applied example is the use of *feedforward networks* with predictive control, which, according to studies, could significantly reduce the costs of desalination and purification of produced water, making recycling not only environmentally attractive but also the most economical option for the company.

Another key area is real-time monitoring and event detection using AI. Traditional SCADA systems already collect data from sensors in operations, but AI allows for going beyond fixed alarms: computer vision algorithms and multivariate analysis can detect subtle patterns that indicate an emerging problem at the treatment plant. For example, cameras and AI could identify changes in water turbidity or color that anticipate solids overload, triggering adjustments before a quality limit is breached. Similarly, AI can recognize risky conditions, such as a tank approaching capacity, and execute automatic actions (closing valves, diverting flows) to prevent spills.

These "virtual operators" work 24/7, complementing human supervision, and have been shown to reduce errors and response times in digital oil operations.

Ultimately, AI can transform water treatment by optimizing processes such as chemical dosing and quality control. It can improve wastewater treatment efficiency by automating processes and predicting problems. It can also help detect pathogens in water and optimize resource recovery, and it can analyze large data sets to understand and predict how treatment plants are performing and make better decisions in real time. The application of this technology has been shown to save 20 to 30% in operating expenses and also reduce raw material costs.

The wide range of successful applications of AI in general industrial water treatment indicates significant potential for similar benefits in the specific context of *flowback water management* in the oil and gas industry.

Today, Generative AI also offers significant opportunities for optimization in this activity. Generative Artificial Intelligence (GENAI) is a branch of artificial intelligence that focuses on creating new content—such as models, images, code, or text—from existing data. 7 This technology uses advanced algorithms to analyze vast amounts of information, identify patterns, and generate new and original content that is often indistinguishable from human-created content.

IV. AI agents and agentic workflows. The evolution of generative AI.

1. IAGEN Agents Concept

In recent years, generative artificial intelligence (GAI) has revolutionized the way we interact with technology, enabling the development of systems capable of generating content, answering complex questions, and assisting with high-demanding cognitive tasks.

Generative Artificial Intelligence (GENI) is a branch of artificial intelligence that focuses on creating new content, such as models, images, code, or text, from existing data. This technology uses advanced algorithms to analyze large amounts of information, identify patterns, and generate new and original content that is often indistinguishable from human-created content.

From this capability, a new technological architecture emerges: IAGen-powered agents. These agents are not simple conversational interfaces, but autonomous systems that can interpret instructions, make decisions, execute tasks, and learn from their interactions with the environment.

An IAGen agent combines large language models with additional components such as external tools, memory, planning, and autonomous execution. This allows them to operate in complex environments, with the ability to break down objectives into steps, coordinate multiple actions, interact with digital systems (such as databases, APIs, or documents), and adapt to context changes in real time. These qualities distinguish them from traditional chatbots and open up a range of more sophisticated and customizable applications.

At the organizational level, these agents are being used to automate processes, generate data analysis, assist in decision-making, and improve the user experience, both internally and externally. For example, they can take on human resources, legal, financial, or logistics tasks, and even tasks linked to the technical areas of production processes, acting as intelligent assistants that collaborate with human teams. This ability to integrate knowledge and execute tasks autonomously transforms the way organizations can scale their operations without losing quality or control.

Furthermore, agentic workflows—structures where multiple agents collaborate to solve complex problems—allow responsibilities to be distributed among different agent profiles, each with specific functions. This creates hybrid work environments where humans and agents coexist, optimizing time, costs, and results. The ability to connect agents with tools such as Google Drive, CRMs, or document management platforms further expands their capabilities.

The development of IAGen-powered agents represents a crucial step toward a new era of intelligent automation.

Among the benefits of authentic workflows powered by generative AI models is the ability to automate entire production processes, end-to-end, and even add value by leveraging the capabilities of language models based on these technologies.

However, its implementation also poses technical, ethical, and legal challenges, ranging from responsible design to human oversight. Therefore, understanding its architecture, operational logic, and potential impacts is critical for its effective and safe adoption in diverse professional contexts.

2. IAGEN-driven agent design proposal applicable to the activity

a. Workflow objective

Maximize the reuse of fracturing water, minimizing risks, costs, and waste, by deploying intelligent agents connected to sensors, SCADA systems, databases, and analysis tools.

b. Workflow

Data Integration and Preprocessing Agent

Role : Collects and normalizes data from multiple sources (IoT sensors, SCADA, laboratory, meteorology, well history).
Connected tools : SCADA APIs, SQL databases, data clouds, spreadsheets.
Functions :

- Detects errors and data gaps.
- Standardizes formats.
- Inform the Predictive Agent.

Flowback Quality Predictive Agent

Role : Predicts return water composition and risks in real time.
Models used : neural networks, multivariate regressions.
Inputs : variables such as pH, salinity, turbidity, heavy metals.
Actions :

- Estimates treatment needs.
- Inform the Process Control Agent.

Treatment Control and Optimization Agent

Role : Adjusts operating parameters in real time to optimize treatment.
Connections : actuators, valves, pumps, chemical dispensers.
Tasks :

- Decide optimal doses of coagulants.
- Adjust treatment sequence (filtering, desalination, etc.).
- Coordinates cleaning and predictive maintenance.

Machine Vision and Security Agent

Role : Detects visual anomalies and triggers automatic responses.
Technology : AI cameras, multispectral detection algorithms.
Functions :

- Alert for abnormal turbidity.
- Detects dangerous tank levels.
- It executes autonomous actions (closes valves, reports faults).

- **Direct benefits and comparison with traditional methods**

The AI-assisted treatment and recycling approach offers tangible benefits over traditional flowback management methods.

In terms of *efficiency and costs* , intelligent process optimization can reduce the cost per cubic meter of treated water, making recycling more cost-effective than conventional disposal. By dynamically adjusting chemical reagent dosage based on actual water quality, excessive input usage is avoided, generating cost savings and fewer byproducts (sludge, salts). Furthermore, maximizing the recovery of reusable water means the operator needs to purchase or extract less fresh water for future fracturing, resulting in cost savings.

A study suggests that implementing AI-powered predictive control in treatment plants reduces operating costs to the point that reuse ceases to be merely an ecological measure and becomes the economically optimal option. This contrasts with traditional methods, where most of the flowback is often disposed of in injection wells, incurring transportation and third-party payment costs, in addition to wasting water resources.

In terms of *operating times* , AI allows for accelerated decision-making and response to changing conditions. In a traditional setup, return water samples could be sent to the laboratory and treatment adjusted days later; with AI models, the system adapts parameters in real time, avoiding delays in subsequent fracturing operations. This means that the time required to condition water for reuse is minimized, potentially reducing the cycle time between fracturing operations on a well pad. Furthermore, intelligent automation reduces unplanned shutdowns: for example, *predictive maintenance algorithms* anticipate pump or filter failures (by analyzing vibrations, pressures, and flow rates) and schedule maintenance at opportune times. This would avoid unexpected interruptions that, under conventional methods, could halt treatment and increase operations costs.

Operational safety and reduced environmental impact are two other areas strengthened. An AI-optimized system requires less continuous manual intervention, which means fewer personnel directly exposed to contaminated water or plant hazards. While it was previously necessary to have operators monitoring tanks and valves to prevent incidents, today much of that monitoring is done by smart sensors; technicians can monitor remotely and only intervene when the system requests it. This reduces the risk of workplace accidents and exposure to hazardous chemicals. From an environmental perspective, the main benefit is that a much larger fraction of the return water can be reused instead of discarding it.

In recent experiences, reuse rates close to 80% of flowback resulted in hundreds of cubic meters of water not being discharged or injected, but rather reincorporated into the production cycle. This not only preserves natural water sources (by reducing extraction from rivers or aquifers), but also reduces the operation's environmental footprint by generating less final liquid waste. Compared with traditional disposal methods (e.g., evaporation in ponds or simple dilution), an optimized process minimizes diffuse emissions, better controls effluents, and ensures greater compliance with regulatory quality limits.

In short, unlike conventional flowback management—characterized by being reactive, resource-intensive, and focused on final disposal—intelligent management with AI is *proactive* , efficient, and focused on the circular water economy.

While traditional methods viewed flowback primarily as a waste to be disposed of, modern practices treat it as a resource: AI makes it easier to extract value (reusable water, even usable byproducts) where previously it was only an environmental liability. This translates into key differences: (1) *Continuous vs. intermittent monitoring* : IoT sensors and AI monitor water quality second by second, versus sporadic manual sampling in classic methods. (2) *Adaptive vs. fixed control* : Algorithms dynamically adjust pumps, valves, and dosing based on conditions, while in traditional plants setpoints are static and require human intervention to change. (3) *Comprehensive vs. segmented optimization* : AI can optimize the entire water management system (treatment, storage, reinjection) as a whole, something that is impractical manually when there are dozens of variables; for example, it can balance in real time how much water to recycle on-site and how much to divert to external disposal so as not to overload any unit. (4) *Traceability and compliance* : A digital system records every liter treated, mixed or disposed of, facilitating automatic reporting to authorities, unlike traditional error-prone paperwork.

Thanks to these differences, operations that adopt AI achieve greater reliability in flowback management, avoiding surprises and optimizing results compared to conventional methodology.

V. Challenges and implementation strategies

Despite the benefits, the adoption of AI in fracking water treatment comes with challenges that require clear strategies for its effective implementation in Vaca Muerta.

From a technical perspective, one of the main obstacles is data availability and quality. AI models are only as good as the data they are trained on; in unconventional reservoirs, flowback composition can vary significantly from well to well and over time, requiring the collection of large amounts of representative data. This entails installing sensors in the field (for physical-chemical variables, flow rates, etc.) and ensuring their calibration and maintenance. Integrating these new data streams with existing systems (SCADA, laboratory history) may require IT infrastructure upgrades and secure communication protocols at remote locations.

Furthermore, developing reliable predictive models requires integrated expert knowledge: applying a generic algorithm is not enough; the model must incorporate the chemical and operational rules specific to flowback treatment. This integration of engineering knowledge with AI is challenging and often requires a multidisciplinary approach, combining data scientists with process engineers and water specialists.

A short-term investment in AI agent implementation teams is recommended, including technology and training. Investment is required in proofs of concept and pilot testing. The focus here must be on developing the talent needed to implement the solution, as there is a trend toward cost reduction in systems that enable "no-code" and "low-code" automation. For the first stage, it is also recommended to recruit teams with experience in AI agent design and implementation. Finally, it is key to form an in-house team to support and foster an agentic culture that redefines human-machine interaction.

There are also regulatory and cultural barriers to the adoption of these technologies. Environmental regulations, while strict in terms of outcomes (effluent quality, traceability), do not always explicitly contemplate the use of AI-based systems. This can create uncertainty about how authorities will accept an automated process: for example, ensuring that an autonomous control algorithm will consistently comply with discharge limits.

Companies must work hand in hand with regulators, demonstrating transparency in the operation of their smart systems (algorithm audits, redundant security measures) to gain trust.

At the organizational level, there may be resistance to change from operators and middle managers accustomed to traditional methods. The introduction of AI often requires staff training to interpret model recommendations and manage exceptions when manual intervention is necessary. Overcoming this cultural gap involves demonstrating *positive results early on* (e.g., a significant reduction in costs or incidents) that help align the entire team with the new way of working.

Economically, the challenge lies in the initial capital and investment justification. Implementing AI in water treatment entails expenses for additional sensors, software platforms, custom model development, and possibly field communications infrastructure (data transmission networks). For some operators, especially mid-sized or new ones in Vaca Muerta, it can be difficult to allocate budget to something they perceive as experimental. Here, it is crucial to develop a gradual strategy: start with low-risk pilot projects that allow for calculating the return on investment. For example, a single on-site treatment plant or a specific module (such as membrane control) could be equipped with AI and the efficiency improvement measured over several months.

If the pilot shows, say, a 15% savings in chemical costs and 10% more reused water, that data helps convince management to scale the solution. Additionally, there are ways to mitigate costs: collaborating with research institutions or technology startups seeking to validate their algorithms in real-world environments, or taking advantage of government incentives.

To address technical barriers, an effective strategy is to build the right team with the relevant skills. This involves having AI experts (data scientists, developers) working closely with the company's water process engineers. Together, they must clearly define the most valuable *use cases* to address with AI—for example, optimizing reuse in consecutive fractures, or minimizing solids in water to protect pumps—so that solutions focus on concrete and measurable business objectives.

Another key aspect is to plan the implementation in phases: first digitize and automate current operations (if a plant still requires a lot of manual actions, equip it with basic sensors and controls), then introduce descriptive analytics (performance dashboards), then predictive analytics (models that recommend actions), and finally prescriptive analytics with autonomous AI. A phased roadmap can facilitate the absorption of change and allows for learning at each stage.

During AI deployment, it's advisable to maintain *redundancies* and contingency plans: for example, if the automated system were to fail, ensure a manual operating mode exists to ensure incident-free continuity. This addresses reliability concerns while the technology matures.

Integration strategies also involve sharing knowledge and standardizing best practices. Since several operators face the same return water challenge, collaborative initiatives (such as industry consortia or pilot projects in conjunction with regulatory bodies) can accelerate the learning curve.

Imagining a *demonstration project* in Vaca Muerta, where multiple companies and the provincial government test different AI solutions for flowback treatment and disseminate results, could generate trust and reduce the perception of risk.

In short, the obstacles to adopting AI—whether technical, regulatory, or economic—can be overcome with careful planning and piloting, with solutions tailored to local realities. The key is to align innovation with business objectives and environmental policies: this way, AI will not be seen as an imposed black box, but as an enabling tool for safer, cleaner, and more efficient water management in Vaca Muerta's unconventional reservoirs.

VI. Conclusion and recommendations

Flowback management in Vaca Muerta represents a critical point where the environmental, operational, and economic dimensions of the unconventional oil industry converge. This report highlights how the treatment and recycling of fracturing water, supported by artificial intelligence tools, can transform a problem—millions of liters of contaminated flowback—into an opportunity for continuous improvement.

Key findings indicate that it is technically feasible and beneficial to reuse a large portion of the return water after proper conditioning, and that AI can boost such reuse to higher levels of efficiency, simultaneously reducing costs and risks. In contrast to traditional "use-it-and-dispose" methods, smart optimization promotes a circular model where water remains within the production cycle for as long as possible, reducing shale's water footprint and waste generation.

Looking ahead, concrete next steps are recommended to capitalize on these opportunities in Vaca Muerta. First, operating companies should identify specific pilot projects for the application of AI in flowback treatment, ideally in collaboration with technology providers and with regulatory support from the outset. These pilot projects will serve to adapt solutions to local specificities (geology, water chemistry, available infrastructure) and generate local data to refine models.

Second, it is advisable for the public sector and local research institutions to actively support these efforts, either by facilitating controlled experimentation (temporary permits, regulatory flexibility for pilots) or through incentives that accelerate private investment in clean technologies.

Third, the industry as a whole must promote training and the sharing of best practices around digitalization and artificial intelligence. Training programs for engineers and operators in data analysis tools, as well as inter-company workshops to discuss the results of different reuse strategies, will help accelerate the adoption curve.

In conclusion, Vaca Muerta has the opportunity to become a benchmark in sustainable water management in unconventional developments. The combination of appropriate environmental policies, advances in AI, and corporate commitment can lead to a model where each barrel of oil produced requires fewer liters of water extracted and less waste generated. Leveraging AI to optimize the flowback cycle will not only help comply with current regulations in Neuquén, but will also prepare the sector for more demanding environmental standards and enhance its public reputation.

The recommendations presented here invite entrepreneurs in the sector to adopt a proactive approach: investing in innovation today to ensure the competitiveness and sustainability of their operations tomorrow.

With firm steps in this direction, the shale oil and gas industry in Argentina will be able to continue its growth while minimizing its water and environmental impact, demonstrating that energy development and water conservation can—and should—go hand in hand.

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