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Using Big Data and Smart Field Technology for Detecting Leakage in a CO_2 Storage Projects

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Abstract

Smart Fields are distinguished with two characteristics: Big Data and Real-Time access. A small smart field with only ten wells can generate more than a billion data points every year. This data is streamed in real-time while being stored in data historians. The challenge for operating a smart field is to be able to process this massive amount of information in ways that can be useful in reservoir management and relevant operations. In this paper we introduce a technology for processing and utilization of data generated in a smart field. The project is CO_2 storage in Citronelle Dome, Alabama and the objective is to use smart field technology to build a real-time, long-term CO_2 Intelligent Leakage Detection System (ILDS).

The main concern for geologic CO_2 sequestration is the capability of the underground carbon dioxide storage to confine and sustain the injected CO_2 for very long time. If a leakage from a geological sink occurs, it is crucial to find the approximate location and amount of the leak in order to take on proper remediation activity.

To help accommodate CO_2 leak detection, two PDGs (Permanent Down-hole Gauges) have been installed in the observation well. A reservoir simulation model for CO_2 sequestration in the Citronelle Dome was developed. Multiple scenarios of CO2 leakage is modeled and high frequency pressure data from the PDGs in the observation well are collected. The complexity of the pressure signal behaviors and the reservoir model makes the use of inverse solution of analytical models impractical. Therefore an alternate solution is developed for the ILDS, based on Machine Learning.

High Frequency Data Streams are processed in real-time, summarized (by Descriptive Statistics) and transformed into a format appropriate for pattern recognition technology. Successful detection of location and amount of CO_2 leaking from the reservoir using the real-time data streams demonstrates the power of pattern recognition and machine learning as a reservoir and operational management tool for smart fields.

Introduction

Geological sequestration of carbon dioxide is one of the most fascinating developing technologies in order to reduce the emission of CO_2 and mitigate greenhouse effects. This technology, which is also named CCS (Carbon Capture and Storage), captures the CO_2 from production sources like the power plants (coal or gas fired) and transfers it to sink or storage site (geologic unit). Hydrocarbon reservoirs, deep saline reservoirs and coal bed formations, are considered different geological CO_2 storages [2]. The last step of the CCS would be injection of the CO_2, preferably in the supercritical phase, into the underground CO_2 storage. It is important to verify that the stored CO_2 remains in the underground storage for a very long time period. However, it is possible that the sequestrated CO_2 could leak back into the atmosphere through some leakage paths, leading to negate the benefits of geologic CO_2 sequestration. The leakage paths can be considered as natural or induced discontinuities in the reservoir's seal (cap rock) like inappropriately cemented wells, unsealed faults, high permeable regions, and fractures [1]. To assure the cap rock integrity, CO_2 storage sites must have active monitoring systems to detect CO_2 leakage and be prepared to take remedial action in the event that leakage occurs. This needs adequate knowledge of the leakage and related factors in order to select appropriate monitoring system [7].

Industry has been experiencing combination of monitoring techniques on the underground geological sites, mainly depending on accessibility and geological characteristics. The monitoring methods can be classified into two different categories: surface and underground measurements. In surface monitoring activities, the presence of CO_2 on the ground can be traced directly. Also, CO_2 related parameter-like ground level or high frequency Electromagnetic (EM) wave are subject to frequent measurements [14]. Satellite –based optical methods, gas sampling, EM and gravity survey are considered the surface or near surface monitoring. The other monitoring method that has been widely implemented by oil and gas industry is underground monitoring. In this method, the main focus is on the underground storages or at the reservoir level where the actual CO_2 sequestration is taking place. Well logs (Pulsed Neutron, RST), 4D seismic, borehole gravity, cross well seismic, brine - gas composition sampling and introduced tracers have been applied to monitor the underground movement of CO_2[6].

Although the mentioned methods have been deployed either in actual projects or research activities, there are still some drawbacks associated with practical application of CO_2 monitoring systems. In the surface monitoring method, the main concern is that it remains essential for CO_2 to appear on the surface. Before that time, even though the leakage could have occurred, it would not be possible yet to detect it [8]. Moreover, in the case of satellite image processing, it would definitely be hard to conclude whether the ground level movement was due to CO_2 leakage or other physical phenomena. Regarding the underground monitoring systems, it is worthy to mention that since most of these methods are implemented periodically, it is not possible to detect any leakage during the time interval that no test or monitoring is offered. Therefore the remediation activity and response to the leakage is considered to be reactive with some time lag. This fact points out the need to have a real time or online monitoring system in order to detect the CO_2 leakage as fast as possible which leads to much more efficient CO_2 leakage risk management.

In the past two decades, Smart Fields have gained advancements and practicality in petroleum industry. Permanent Down-hole Gauges (PDG) and valves have been used for continuous monitoring of pressure, temperature, flow rates, and automatic flow controls [5]. This technology can be used in the underground CO_2 reservoirs to monitor the pressure in real time. The reservoir pressure data provides valuable information in order to history match and update the reservoir simulation model. More importantly, PDGs monitor the pressure changes in the formation and transmit high frequency data streams to the surface. The pressure changes in the reservoir are indications of fluid flow (movement) in the formation which potentially can be due to CO_2 leakage. Therefore, by analyzing the pressure change behavior it might be possible to determine leakage characteristics, such as location and rate [4].

Reservoir Model

The target CO_2 storage in this study is a saline reservoir, located in Citronelle dome (Alabama, US). A twelve-mile pipeline connects Alabama power plant Barry (2,657 MW coal-fired), which is the anthropogenic CO_2 source to Denbury's Southeast Citronelle Unit. A post-combustion capture unit, which uses MHI's advanced Amine (KS-1 solvent) process with a capture rate of up to 650 tons per day, became operational at the power plant. This is the third phase of South Eastern Carbon Sequestration Partnership which aims to demonstrate commercial-scale of a CCS project [6].

Captured CO_2 was planned to be injected at rate of 500 ton per day (for maximum three years) into saline Paluxy sandstones at depths of approximately 9,450 to 10,500 feet (TVD). This inter-bedded shale and sandstone layer is separated by two extensive shale layers from Dantzler sand (saline reservoir) at top and Donovan sand (oil reservoir) at the bottom. Based on well log data from the injection well (D-9-7), 17 sand layers are picked and correlated considering the high resistivity and low SP values. Areal dimensions of some of the thicker sandstones are on the order of 6 square miles or 3,840 acres. The total thickness of sand layers is about 470 feet ranging from 10 to 80 feet. Ten thickest and most extensive sand layers were identified for CO_2 injection. It is worthy to mention that Citronelle anticline provides structural closure to saline reservoir in the Paluxy formation [3].

A reservoir model was built using a commercial numerical reservoir simulator using the results obtained by interpreting geophysical well logs. The geological model of the Paluxy formation consists of 51 simulation layers. This model is divided to 50*50*51 Cartesian grids (Δx and Δy equal to 400 ft; local grid refinement was applied around the injection well). Based on initial core study (taken from injection well), constant values for porosity and permeability were assigned to each layer (Table 1). Relative permeability curves were taken from injection pilot at the Mississippi Test Site. The temperature of the reservoir is 230◦ F. The brine salinity and density values are 100,000 ppm and 62lb/ft^3, respectively. The pressure reference in this model is 4,393 psi at 9,415 feet (TVD).

Table 1: Porosity and Permeability values for different layers in Citronelle reservoir simulation model

Layer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Porosity (%)	19.8	18	18	19.3	21.8	19.3	18.2	17	18.4	16	15.5	19.3	19.3	19.3	19.3	19.3	17.5
Permeability(md)	436	168	168	88	1234	88	191	100	211	59	46	88	88	88	88	88	132

In the Citronelle saline reservoir model, two operational constrains were considered for the injection well (D-9-7), namely: injection rate and maximum bottom-hole pressure. The maximum injection rate was set to be 9.45 MMscf/day. Injection starts at the beginning of year 2012 and lasts for 3 years. The maximum bottom-hole pressure limit is set to be 6,300 psi.

Initial reservoir simulation runs showed that maximum extension of the CO_2 plume takes place in the first (top) layer. This is mainly due to the fact that the top layer represents sand with a higher permeability that causes CO_2 to migrate further from the injection well. As it is shown in Figure 1, the approximate diameter of the plume area in the first layer, reaches to 3900 feet, 25 feet after the injection has stopped.

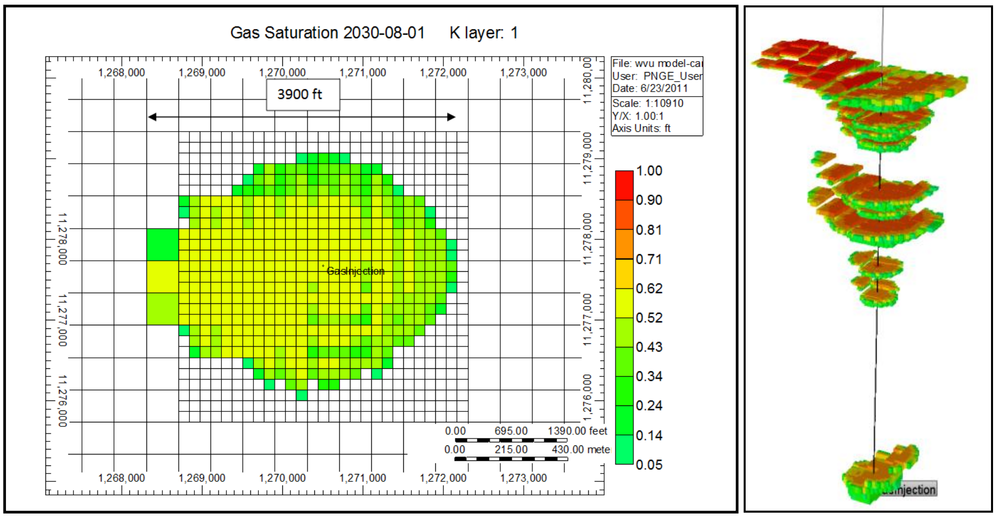

Figure 1: Plume extension in the first layer (left) and all layers 25 years after injection

CO_2 Leakage Modeling

Typically, there are three main sources for the leakage in CO_2 storage reservoirs: faults, wells, and high permeability zones. Based on the geological study, no fault exists in the vicinity of CO_2 injection well. However there are different types of wells in area of review (12 oil producers, 5 water injection and 17 abandoned wells) that could be a pathway for CO_2 leakage, if they do not represent proper integrity mainly due to poor cementing, casing failure, and abandonment failure [8]. Based on the plume extension, some of these wells can be surrounded by CO_2 and consequently prone to leakage. In order to verify the safety of CO_2 storage in Citronelle saline reservoir, different monitoring methods are used: near-surface and deep reservoir fluid sampling, in-zone and above-zone pressure and temperature monitoring, cased-hole neutron logging, cross-well seismic and VSP, and surface soil flux and tracer surveys [6]. The data that are gathered by monitoring process can also be used to history match and update the reservoir simulation models. In this study, the main focus would be on the in zone pressure monitoring. PDGs are installed in the observation well D-9-8. In order to study the pressure behavior in the observation well, several CO_2 leakage rates are assigned to the wells that are located in the area of review (Figure 2a). The pressure behavior in the observation well when CO_2 leakage rate is equal to 40 Mcf/day at well D-9-6 and is illustrated in Figure 2b, as an example. It is worthy to mention that from the beginning of the CO_2 injection until its end, reservoir pressure increases proportionally to the amount of injection and reaches to a maximum value at the end of injection period. When the CO_2 injection stops, there will be a transition time once the reservoir pressure decreases until the brine and injected CO_2 reach to semi-equilibrium. At the end of the transition time, reservoir pressure remains almost constant (or decreases with very slow trend), which can be referred to a steady state period. It is assumed that CO_2 leakage occurs during the steady pressure period (year 2017) resulting in pressure decrease in the observation well (Figure2b).

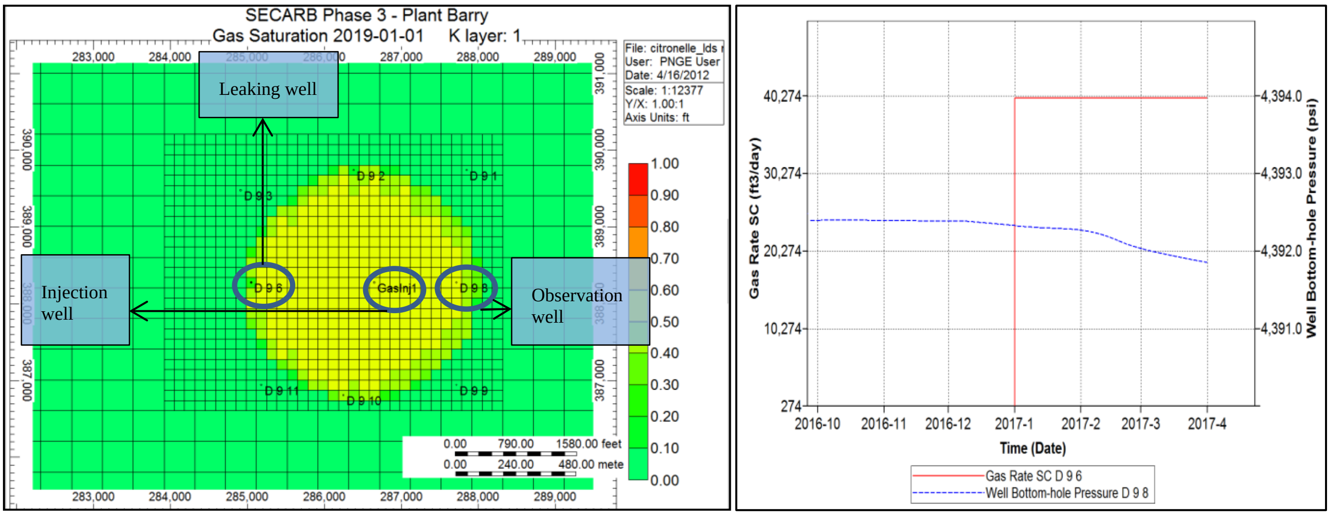

Figure 2 (a): Location of the injection and observation wells in the area of interest (b):pressure behavior in the observation well subject to the leakage rate equal to 40Mcf/day at well D-9-6

Data Summarization

Interpretation of the PDG data can be challenging due to disturbances like noise and outliers. Normally the data that is transmitted from the PDG sensors can be considered as noisy-high frequency data streams [12]. The first step in processing such data streams is removing the noise associated with the data. Noise characteristics, different de-poising methods and their effects on the performance of ILDS will be discussed in other study thoroughly. In this study, a clean pressure signal or the same signal obtained by reservoir simulation model is used. The next step would be summarizing the high frequency PDG data and transforming the data into a format that can be used by the pattern recognition technology. Based on the characteristics of the Δp (pressure change in the reservoir due to leakage) high frequency data streams, Descriptive Statistics was used over a predefined time window (can vary from half a day to weeks) for data summarization. Descriptive statistics quantitatively designates the key features of a group of data and determines informative extractions about the characteristics of the observations that have been made. These summarized data may form the basis of the initial description of the pressure data that represents the specification of each CO_2 leakage scenario and will be used in Neural Network training. The parameters that may represent and summarize a large amount of data can be listed as: Mean, Standard Error, Median, Mode, Standard Deviation, Sample Variance, Kurtosis, Skewness, Range, Maximum, Minimum and Sum.

Intelligent Leakage Detection System (ILDS) Development

In order to make and develop Intelligent Leakage Detection System (ILDS) by use of pressure data that is received in high frequency streams from PDGs, it is required to design a set of simulation runs that provides pressure behavior in the observation well (D-9-8) with respect to leakage rates and locations. The focus was on the different leakage rates that were observed in the real cases all around the world [8]. Different CO_2 leakage rates (starting in 01/01/2017) were assigned to wells D 9-6, D 9-2 and D9-10 (Figure 2a). First of all, the pressure in the observation well is obtained in the case that no leakage occurs in the reservoir. When a CO_2 leakage takes place in one of the wells, it creates a pressure change in the reservoir. This pressure change can be detected in the observation well. Therefore, the difference between pressure in the observation well, in the case that no leakage exists and when a leakage happens, is considered as the leakage indicator. ($\Delta P = P_{No\ leak} - P_{Leak}$). This pressure change (Δp) behavior can characterize the specifications of the leakage specially the location and the amount of CO_2 seepage. For example, the magnitude of Δp is directly proportional to the CO_2 leakage rate. Also, the shape of the Δp as the function of time is related to the location of the leakage. As an illustration, Δp history (high frequency-hourly basis) in the observation well, for the case that well D-9-6 leaks with the rate of 30 Mcf/day is depicted in Figure 3a. High frequency pressure data in observation well were obtained based on twenty different CO_2 leakage rates (from 15 Mcf/day to 110 Mcf/day with 5 Mcf/day increments) in three different locations (wells D-9-2, D-9-6 and D-9-10). At that point, this data was summarized by Descriptive Statistics for neural network training.

In order to predict the leakage location (Latitude and Longitude) and leakage rate, the input dataset will be comprised of the summarized pressure information (PDG readings) after 1 week of leakage in hourly basis. Intelligent data partitioning was used for the segmentation of the dataset. 80% of data were allocated for neural network training, 10% for network calibration and 10% for verification. Error Back-propagation method was used with 10 inputs (Descriptive Statistics parameters) and 3 outputs. There are twelve neurons in one hidden layers and one random seed number (Figure 3b).

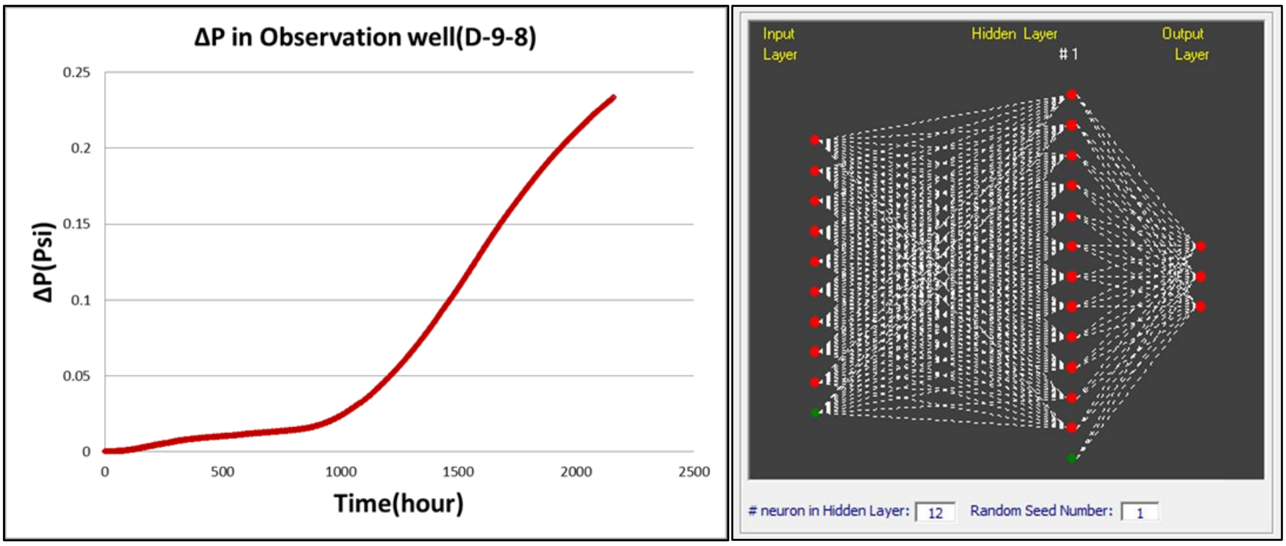

Figure 3a. Pressure change in observation well in the case that well D-9-6 leakage rate is 30Mcf/day (b): Neural Network Design for ILDS

Results and Discussion

The initial results of the neural network training are illustrated in Figure4. This figure compares actual data (Leakage rate and locations) with neural network predictions. The neural network quantifies the location of the leaking well with precise accuracy (R-Square =1). For leakage rates, neural network results cannot predict a few of the actual data correctly (R-Square=.92) specifically the rates belonging to well D-9-6. In order to improve the results for CO_2 leakage rates predictions, we developed a neural network for each leaking well individually. This approach was successful to enhance the prediction performance of the neural network model for the leakage rate which is shown in Figure 5a (R-Square=.96).

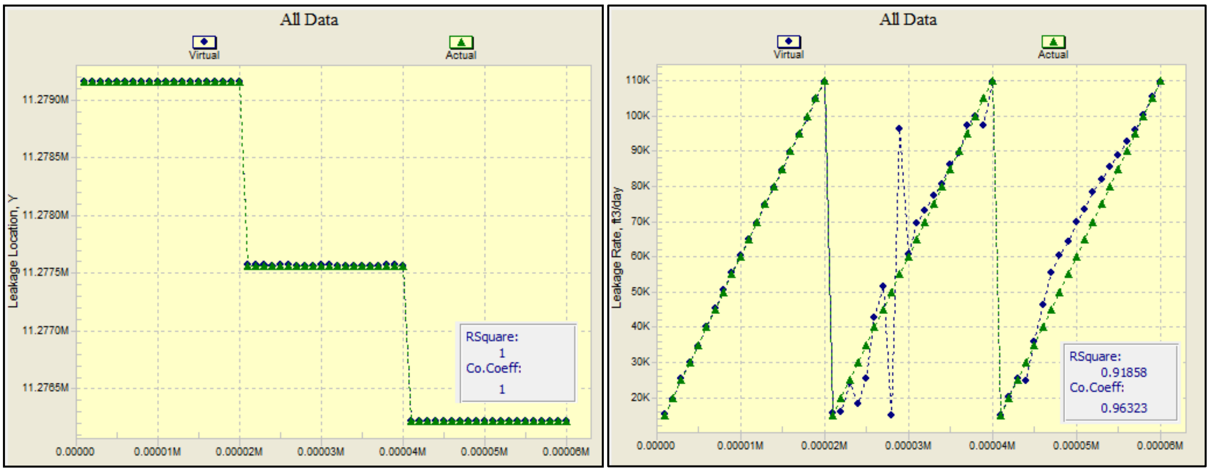

Figure 4: Actual leakage location rates and the corresponding NN predictions (left: leakage latitude, right: leakage rate)

Based on the neural network modeling, results were designed for the ILDS in following manner: initially, the high-frequency pressure data is summarized by descriptive statistics, then summarized features of pressure data are fed to the main neural network that predicts the location of the CO_2 leakage. Afterwards when the location is determined, the pressure data would be fed into the corresponding Neural Network that was designed for that specific location (Figure 6)

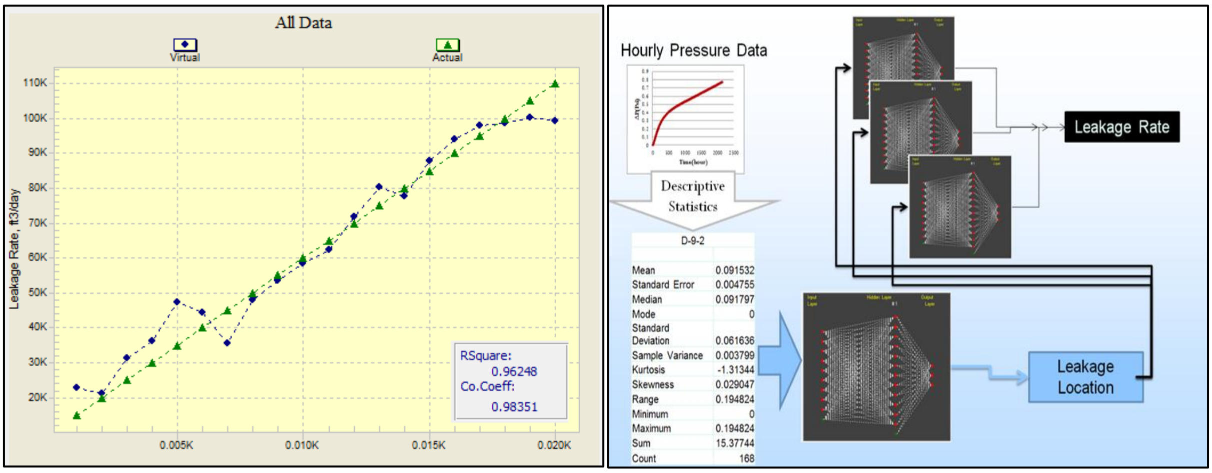

Figure 5(a). Actual leakage rate and corresponding neural network prediction (one network for each well) (b): The workflow for ILDS

In order to validate the performance of the ILDS, three different CO_2 leakage rates not seen by the Neural Network before(25,52,and 88 Mcf/day) were assigned to a possible leakage location (wells D-9-2, D-9-6, D-9-10) as blind runs. Pressure data from these runs were summarized by descriptive statistics and fed into ILDS. The ILDS predications for CO_2 leakage location and rate are shown in Table 2 and Figure 6 respectively. The prediction of the ILDS for the leakage location is highly accurate in a way that the results are almost the same as actual values. For leakage rate predictions, the results are almost accurate as well, although for the low leakage rate (26Mcf/day), they differ minimally with the actual values but still the range of predicted rates is reasonably correct.

Table 2. The actual leakage locations and the ILDS predications

Run	Leakage Location(X) Actual	Leakage Location(X) ILDS	Leakage Location(Y) Actual	Leakage Location(Y) ILDS
1	1268902.53	1268903.05	11277566.74	11277569.97
2	1268902.53	1268902.78	11277566.74	11277565.13
3	1268902.53	1268902.55	11277566.74	11277567.57
4	1270359.37	1270359.03	11279158.24	11279157.46
5	1270359.37	1270359.11	11279158.24	11279157.51
6	1270359.37	1270359.17	11279158.24	11279157.44
7	1270184.29	1270184.53	11276221.98	11276223.47
8	1270184.29	1270185.16	11276221.98	11276224.14
9	1270184.29	1270183.81	11276221.98	11276222.66

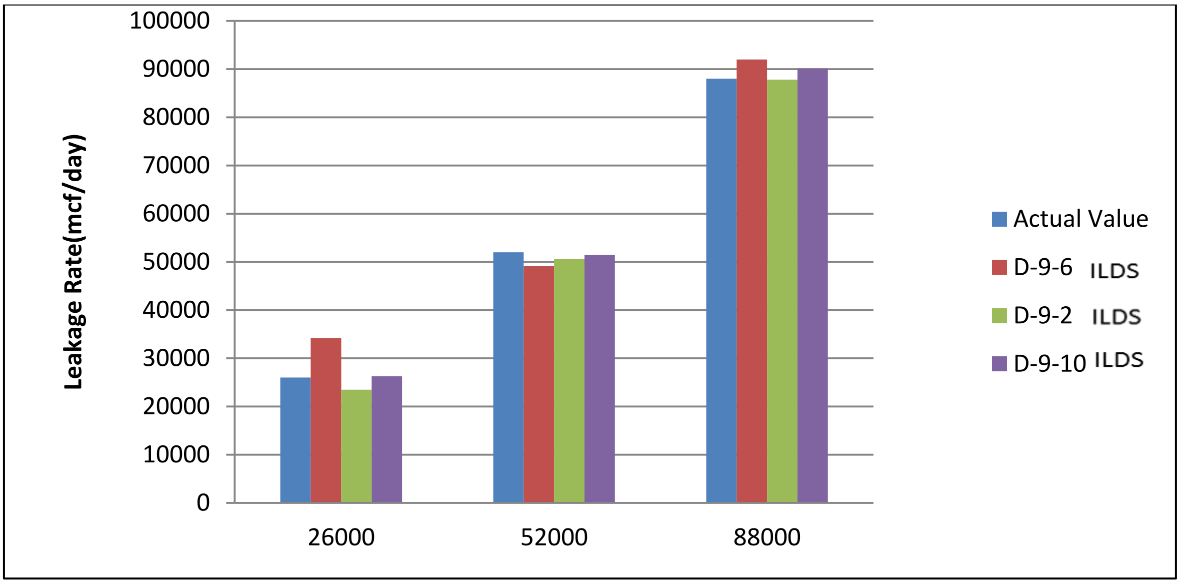

Figure 6: ILDS leakage rate predications

Conclusion

This project is developing the next generation of intelligent software that takes maximum advantage of the data collected using "Smart Field" technology to continuously and autonomously monitor and verify CO_2 sequestration in geologic formations. This technology will provide the means for in-situ detection and quantification of CO_2 leakage in the reservoir.

Injection of CO_2 in a saline reservoir (Citronelle Dome) was modeled and studied in order to predict the performance of reservoir, specifically when CO_2 leakage happens in the reservoir. CO_2 leakage was modeled considering the existence of PDGs in the observation well. High frequency pressure data was processed and summarized by descriptive statistics. Finally, an Intelligent Leakage Detection System (ILDS) was designed, developed, and tested.

The main findings can be summarized as:

- Pattern recognition capabilities of Artificial Intelligence and Data Mining (AI&DM) may be used as a powerful de-convolution tool.
- Locating and quantifying CO_2 leakage in storage sites, using "Smart Field" technology, is a technologically feasible concept.
- ILDS attempts to identify the location and amount of the CO_2 leakage at the reservoir level (long before it reaches the surface). By providing such information to the monitoring team at the surface, ample time is provided for pro-active intervention rather than reactive responses.

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