AUTOMATED SURVEILLANCE AND OPTIMIZATION OF UNDERGROUND GAS STORAGE RESERVOIRS

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1 Introduction/Background (Abstract)
This paper is a collaboration of RWE Gas Storage and Schlumberger. Together an Expert System (ES) for RWE Gas Storage Underground Gas Storage (UGS) systems was established. The paper will explain the system in detail starting with the automated data acquisition from the UGS facilities to the automatic data pre-processing for numerical simulators. Additionally, the automated quality check (QC) and alarming system will be described.

For data cleansing and advanced quality check, intelligent data mining tools were utilized. When automated these tools recognize trends and outliers from those trends are immediately identified. The outliers identification techniques are also applied for proposing missing data and corrected outlier values, whereby the estimates come from the data mining tools. The Expert System is ideal for UGS operations as compared to oil fields one of the advantages is that the UGS’s are highly equipped with meters which provide constant observation of the field.

2 Objectives of the paper (Introduction)
In the UGS business monitoring of the reservoir is crucial. From the companies and dispatchers perspective it is necessary to know the inventory in each UGS for internal planning, as well as to fulfil the requirement set by authorities, which require mandatory monitoring and immediate actions if necessary. The paper will show how continuous awareness of a UGS status can be achieved.

Regularly, engineers spend a lot of time in a low value process, validating the data accuracy before proceeding with the analysis which represents the value for the company. Also engineers, depending on their experience, are not always sure of the parameters that have the most impact on the study objectives. The engineer may spend a disproportionate amount of time on reviewing a non-value adding parameter.¹

Stochastic workflows overcome this problem by assigning an error-margin to a data and propagating the error through the workflow with the objective to minimizing the error-range. With the aid of Experimental Design, Response Surface Models and diagnostic tools such as Pareto charts, it is possible to efficiently and cheaply assess the impact of uncertainties on business decisions and identify the heavy hitters. This approach simplifies the workflow design by arranging tasks in parallel regardless of the proceeding tasks on the condition that the data or interpretation, which the task is based on have boundaries (errors, uncertainty) associated to it. The approach also enables simultaneous handling of the uncertainty reduction process in a so called top-down approach.

3 Development/Methods (Expert System)
The relative intelligence of gas-storage operations can be grouped into three levels:²

1. Level I, automated data flow, is reactive: receive data, analyze data and respond.
2. Level II surveillance and optimization, is reflective but focuses on action: analyze data, compare and validate models, manage models and determine necessary courses of action.
3. Level III can be referred to as the digital oil field: integrate processes, optimize, automate and operate remotely, where it is applicable, in a proactive manner.

Level-I intelligence begins by developing confidence in the data. Supervisory control and data acquisition (SCADA) systems can be found in most UGS operations. These computerized networks remotely acquire well data such as flow rate, pressure and flowing volume, and control transmission of gas throughout a pipeline system. With millions of data points thus acquired, it is impossible to manually validate all information. Automating quality control of the data flow is a necessity.

Software for traditional oil and gas production is often used for UGS applications to identify performance problems as well as monitor individual wells, evaluate completions and characterize the
reservoir. Trend analysis and type-curve matching are frequently used in these programs. However, most petrophysical programs are poorly equipped to handle the huge volume of SCADA data coming from UGS operations. Also, they cannot effectively deal with noisy data resulting from sensor errors and spurious responses. Since proper use of these applications often depends on the ability to identify the onset of linear trends over time or clearly identify subtle features in various type-curves, the data must be cleansed and reduced so that proper identification of such features can be accomplished. Therefore, intelligent data reduction is applied before importing the data into these programs.

The data provide insight for evaluating the relative health of individual wells, as well as that of the producing field. The repeated cycling ability of gas-storage wells – periods of injection followed by periods of production – is a fundamental difference between producing reservoirs and storage reservoirs. Occasionally the storage wells remain static for varying lengths of time and the collected data can be treated as a conventional short-time buildup test. Changes that occur from cycle to cycle can be indicative of problems developing in individual wells, in the reservoir or in the surface equipment. By analyzing these data, the presence of damage can be recognized and remediation plans implemented.

*RWE Gas Storage*, working with *Schlumberger* engineers, began the process of implementing an Expert System (ES) by first developing an integrated platform. A SCADA System was installed to provide continuous high-frequency measurements (on the order of seconds), which are grouped into 15-minute increments and streamed in real time from individual wells, gathering systems and facilities. At this Level I step in the process, the software system checks that a connection to a data stream has been established and generates a notification if there is a failure. If a valid connection is confirmed, the high-frequency data are imported, filtered, quality checked and aggregated over longer time intervals to reduce the size of the dataset. The software filters sensor errors and transmission errors prior the data aggregation and generates statistical reports to allow the engineer to evaluate the reliability of the information. Artificial intelligence has been developed to automate these routine tasks as well as increase the speed of delivery. With the newly acquired data and subsequently automated processing, KPIs (Key Performance Indicators) are available to evaluate the ongoing operations.

![Figure 1: Three levels of automation](image)

At Level II, the cleansed data are fed into software modules to validate proper system performance. The ES integrates external applications that allow data exchange, including reservoir simulation software, production system analysis software and various modules available in the ES itself. The process automatically conducts history-matching for trend analysis, provides individual well status and determines production and capacity constraints. Current and future delivery requests for injection and withdrawal are passed to the system, which provides all the necessary calculations and predictions to verify that the reservoir has sufficient capacity to meet the dispatcher’s requests.

The level beyond monitoring and surveillance is Level III intelligence – an example of the digital oil field. In the system implemented by *RWE Gas Storage*, automated tasks have the following structure: First scheduled tasks (executed based on a periodic/timely recurrence) or trigger automation tasks (executed based on an event) are run. These initiate the workflow in which then predictive data mining proxy models
are run and calculations are applied. Triggering events are either discrepancies from expected trends or violations of predefined constraints. The actions triggered by the alarm include system notification, execution of surveillance software, exchange of data with third-party software, initiation of subordinate tasks and generation of e-mails or text messages to alert the operator of an error condition.

Along with the alarms, the software automatically provides KPIs to the operator at the engineer’s desktop. It formats the data for visualization and provides forecasts based on current performance of the field. Reservoir performance modules identify bottlenecks like facility constraints, and report on optimization opportunities along with recommended courses of action. With dramatically reduced analysis cycle time, the engineer can react almost instantaneously. Automated data flow and transparently updated models allow the engineer to focus on system optimization and problem elimination. Proactive, intelligent reservoir management becomes a reality.

4  Frequent Challenges with monitoring and surveillance in UGS

a. The daily data avalanche
Current levels of reservoir surveillance technology like down-hole gauges and fiber optics coming along with intelligent well completions create an increasing flow of data. Conventional software cannot help the knowledge worker to cope with high-frequency real-time data. Overloaded with data handling work, the knowledge worker in our industry is not capable to reveal the great potential inherent in this data.

The reservoir's response on the applied production strategy is measured with dramatically increasing resolution in time and space. Conventional reservoir modeling techniques like numerical reservoir simulation were developed to predict reservoir performance with a minimum of individual well production information (i.e. monthly data).

While the well-specific performance data become available at a magnitude of 10,000 to 100,000 (10-seconds data) values per day, CPU time consumption and project turnaround time of numerical simulation models do not allow to run these models in real-time.

Conventional E&P software packages and spreadsheet solutions are currently not designed for real-time data as well. Especially the wells for UGS operations are equipped with lots of meters to ensure a constant and effective monitoring of the inventory, pressures and surface facilities.

A data-hub is needed to condition the high-frequency real-time data into a time increment, which can be handled by any commercial petroleum engineering software. Before dispatching data to the pre-defined models and the engineer's desktop, data are automatically analyzed by the Expert System to detect erroneous data.

Erroneous data could be caused by a gauge or reading failure. In this case, an alarm is triggered by the notification system. If data gaps occur, again, an alarm is triggered and the system can automatically suggest a replacement value.

Outliers can be produced by malfunctioning or improper adjusted gauges. The system is able to detect these outliers and remove them. After this extensive data quality check, data are automatically merged to a handy time increment and finally stored on a server in the company's IT-infrastructure. In this way, high quality data are delivered on time at the engineer's desktop.

b. Automation Task Concept
Automating reservoir surveillance requires the proper definition of tasks, which shall be performed by the surveillance software in an automated way. Reservoir surveillance data arrive on a 24/7 basis in the town office. Therefore software solutions are required which process these data also on a 24/7 basis.

SCADA systems are the first step of automation in oil and gas fields, forwarding the raw data into the town office to visualize the data. Conventional reservoir management tools are designed to work in an offline modus, being not prepared to run with real-time reservoir surveillance data.

The core of such a reservoir surveillance system is an expert system, which allows automation of the reservoir surveillance work process. Faster decisions for short-term production optimization through increased productivity of knowledge workers as well as sustainable work process optimization and reduced elapsed time for routine reservoir surveillance can be achieved.
An “automation task” concept allows controlling processes inside and outside of the software. These tasks are scheduled in time – called master tasks - or are triggered by events detected by other master tasks - called slave tasks.

Automation tasks always have the same structure: first schedule tasks (master tasks), or trigger automation tasks (slave tasks), then run the predictive data mining models and apply rules.

Events in general are either discrepancies from expected trends (actual vs. predicted value – predictive data mining models are applied), or violations of defined constraints.

Triggered actions can be of the following types:
- set alarm (information, warning, alert) in notification system
- execute surveillance software module, e.g. database reporting
- exchange data with 3rd party software and/or run this software
- trigger other slave tasks
- send e-mail or text message

**c. Data Acquisition & Data QC**

Data preparation and quality control is the first crucial step in automating reservoir surveillance. Multi-parameter rules and applied neural networks allow complex cross validation of surveillance data, as outliers may be detected only in the context of other measured data.

Additionally, wavelet decomposition can be applied to remove outliers and reduce noise in data. Time delays in receiving the data and different time increments of data makes it necessary to manage automation tasks in order to put certain tasks in waiting loops until data for execution become available. Missing values may be replaced by value estimation models using Artificial Intelligence (AI).

The surveillance system should provide information about the quality of the data, sensor errors and transmission errors. Statistical reports allow the engineer to evaluate reliability of data and sensors. In a last step, data are aggregated to the defined time increment.

After data preparation, data have to be aggregated at a field sample rate - to a rate, which reduces the number of patterns without losing meaningful reservoir behaviour information. Experience has shown that time increments of 15 minutes to 1 day are sufficient for reservoir surveillance data mining models.

Data mining models, like neural networks, are working with patterns, therefore common constant time increments are required for input and output parameters. Raw reservoir surveillance parameters have different
- quality
- frequency
- time delays (transmission)
- ways to be measured (sensors, manually edited)

Therefore, aggregation and interpolation of measured data is required. Better data lead to an increasing utilization of data in the workflow.

The following example shows how quality-control on well production data can be performed using a special type of neural networks, self-organizing maps (SOM). The neural network model can be regarded as a black box, which correlates the relationship between all production parameters – in this example of one well. This type of neural network uses a special architecture without the need to specify an output parameter. All input parameters are reflected on each other and sorted by their similarity. More details about the basic principles of SOM can be found in the literature.
In this example, five parameters in a daily time increment have been used as input for the neural network model:

- Choke size
- Gas rate
- Well head pressure
- Tubing head pressure
- Tubing head temperature

We used those parameters since they are common measurements at the well in an UGS field. Especially the gas rate is necessary to be included in this model since it is frequently changed when different production/injection scenarios are applied.

A time range of one week has been used to train the neural network model. During the training phase, the neural network discovers and captures the non-linear relationship between all input parameters.

If new values are acquired by the automatic data acquisition system, the neural network is triggered by this event to calculate a value for all input parameters using the relationship it has learned from the historic data. In this way, for each input parameter, a calculated value is generated. The comparison of the calculated and the acquired value can detect erroneous values.

As example, the tubing head pressure of the well has been artificially modified to investigate the effect on the neural network model. All other parameters are kept unchanged. Five different cases have been considered. See Table 1 for the manipulated input parameter values and the resulting output values from the SOM.

<table>
<thead>
<tr>
<th>Scenario #</th>
<th>Tubing Head Pressure measured [psi]</th>
<th>Tubing Head Pressure calculated by SOM [psi]</th>
<th>Difference of measured and calculated [psi]</th>
</tr>
</thead>
<tbody>
<tr>
<td>original</td>
<td>578.4</td>
<td>577.3</td>
<td>-1.1</td>
</tr>
<tr>
<td>1</td>
<td>-</td>
<td>577.3</td>
<td>-</td>
</tr>
<tr>
<td>2</td>
<td>400</td>
<td>431.7</td>
<td>31.7</td>
</tr>
<tr>
<td>3</td>
<td>100</td>
<td>385.7</td>
<td>285.7</td>
</tr>
<tr>
<td>4</td>
<td>-200</td>
<td>373.4</td>
<td>573.4</td>
</tr>
<tr>
<td>5</td>
<td>1000</td>
<td>607.9</td>
<td>-392.1</td>
</tr>
</tbody>
</table>

Table 1 –Values and results of the quality control example

In the first case, the value for the tubing head pressure has been completely removed. This scenario represents a total failure of the gauge. The neural network can accurately calculate the original value. The deviation of the calculated and the measured value is very small. As the other parameters are in a normal operational range, the Expert System could detect the source of the problem and send a notification of the gauge failure to the engineer. It even could ask the engineer to replace the gap with the calculated value. If this is done, it is very important, that an annotation for this data point is made, including all information about the replacement (model used to calculate the value, date and time of replacement, engineers ID, etc).

In the second case, the tubing head pressure is set to a lower value (400 psi), keeping all other parameters unchanged. In this case, the SOM calculates a value of 431.7 psi, which shows already a deviation of 31.7 psi from the input value. The SOM tries to raise the value, because it has learned from the historic data, that in a production environment, which is described by all given (and unchanged!) input parameters, the tubing head pressure should be higher. The difference of the actual and the predicted value is not so high that the Expert System could detect this value as an outlier. The reason is that in the history of this well, a couple of times tubing head pressures between 400 and 450 psi have occurred.

In the third and fourth case, the tubing head pressure has been lowered to a value, which is physically not meaningful anymore. In case three, the new value is 100 psi, in case four, the tubing head pressure is even a negative value. The calculated values in both cases (385.7 for case three and 373.3 for case four) are very similar, around 380 psi. This time, the neural network is calculating values, which are substantially higher than the manipulated measured value. The difference between the measured value (100 psi) and the predicted value is 285.7 psi for case three and 573.4 psi for case four. The high differences are indicators for
the expert system to declare the measured values as outliers. Again, the engineer will be proposed to replace these values. In this case, the outlier would be removed first, and then the neural network would be used to calculate the gap value, like in case one. This would ensure a better approximation of the replaced value. Of course, this process can also be done automatically, but considerable problems could occur when a malfunctioning expert system is used.

The last case shows the reaction of SOM on tubing head pressure values, which are higher than they should. The measured tubing head pressure is set to 1000 psi and a neural network calculation is performed. The resulting pressure (607.9 psi) is also higher than the original value (577.3 psi), but still in a physically meaningful range (as can be seen in Figure 3). Nevertheless, the deviation of the two values is -392.1 psi, which is a clear indicator for the expert system, that the tubing head pressure value must be an outlier. The normal procedure as described in the previous cases can be applied.

Such a neural network can be setup for each individual well but also be used in combination with other neural networks or other wells in the same neural network. Together with appropriate rules, which are setup in the Expert System, this approach represents a highly effective and sophisticated quality control tool.

![Frequency Plot](image)

*Figure 3- Frequency distribution of tubing head pressure values*

d. **Event Detection & Key Performance Indicators - KPIs**

Such a process helps to manage assets in the best manner. The engineer is able to react fast on problems occurring. He is able to:

- anticipate the actual reservoir performance and recovery mechanisms which will likely deviate from the planned model
- identify any discrepancies in performance as early as possible
- provide information regarding the cause of these deviations
- use all data available to identify these discrepancies.
Key Performance Indicators are financial and non-financial measures or metrics used to help an organization to define and evaluate how successful it is; typically in terms of making progress towards its long-term organizational goals. A KPI is a measure that represents the condition of factors that directly influence the realization if the organizational strategy.

If a KPI is going to be of any value, there must be a way to accurately define and measure it. Because of the necessity to anticipate quicker to changes in the environment, organizations have to search for KPIs measuring factors that are directly affecting the financial figures. Organizations are not solely steering on financial dimensions, but also on other dimensions like technical issues and internal processes. If the actual value of these KPIs differs from the target, it will always have an effect on the financial performance.

5 Optimization

The SPE Real-Time Optimization Technical Interest Group (RTO TIG) developed a framework to classify the status at a given asset on the seven categories of “Real Time Optimization”:

1. Measurement; all direct or indirect physical measurements.
2. Telemetry; transmitting sensed data over long distances.
3. Data handling and access.
4. Analysis; applications used to model, simulate and predict the field behaviour as well as optimizing the operation.
5. Visualization
6. Automatic control; control engineering
7. Integration and automation; integrating and automating workflows to optimize the operation

Once data preparation and model triggering are automated, it is a small step to automate the use of the models to optimize the current operations. Well set-points (e.g. based on tubing head pressures) can be optimized obeying certain constraints (e.g. maximum gas velocity in the well, maximum bottomhole pressure drawdown).

Very often, the advanced programs used for the reservoir-surveillance models require computer-intensive calculations. Running optimization iterations cannot provide satisfactory results in the required time frame using the large volume of data, even after it has been aggregated and cleansed. Proxy models, although not as accurate, are substituted for full-scale simulations and can provide results in seconds or minutes.
Proxy models mimic large-scale simulators. The models learn to behave like the simulator and, once trained, they can perform a set of calculations in a fraction of a second for a given set of input parameters. This drastically reduces the computation time necessary.

An example use of a NN is a production forecast and optimization simulation. If small changes of the input parameters are involved, such as tubing-head pressure, a forecast can be calculated immediately, rather than waiting for a time-intensive full simulation to be performed. Multiple iterations can also be run quickly to determine the best course of action.

The system implemented by RWE Gas Storage covers five UGS reservoirs. Automation tasks include validation and forecast runs of reservoir simulation coupled with surface models, triggering events based on rules highlighting either discrepancies from expected trends or violations of predefined constraints.

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Figure 5 – Communication between components of the Expert System and the field

Bottlenecks, like facility constraints, are identified, and optimization opportunities are reported along with recommended courses of action. Analysis cycle time is dramatically reduced, allowing the engineer to react almost instantaneously. Because the data flow is automated, the models are updated transparently, and the engineer can focus on system optimization and elimination of problems.

6 Ticketing

When the system identifies variations from actual to optimal statuses it will inform the engineers. In most cases the engineer will react on the alarm and apply changes or updates to the system. Usually those changes will have an effect and no further alarm will occur.

In RWE Gas Storage’s Expert System one of these alarms is for example that the existing reservoir simulation model is not matched any more. Pressure measurements indicate a discrepancy between the modelled pressures. In such a case the engineer will get the message to rematch the model manually. After the re-matching was done the system runs stable again.
A different example of an activity is that the systems presents optimised choke settings for a required production rate. Those settings are applied to the corresponding wells accordingly. Those optimized settings are only based on a software model. Until now there is no feedback from the reservoir if the new choke settings cause the desired effect. A separate workflow will check the changes applied to the system and its consequences to the reservoir. Again alarms and re-optimization workflows are triggered.

a. Process Catalogue

Many processes require manual interaction from the engineer. In such cases computer based, automated workflows are not applicable or not possible. Not all workflows can be done by the computer, also human decisions are necessary.

A Process Catalogue which holds all common manual workflows can be setup. The catalogue holds the standardized workflows, procedures or routines defined by the company or requested by authorities. In a problematic situation the engineer will get an e-mail notification about this situation. In addition the detailed procedure from the process catalogue which explains the required next steps is attached. Figure 7 displays this automated workflow in combination with the process catalogue.

The expert system can also distinguish between different teams. Each team is responsible for a specific UGS. Each team will get only the e-mail notifications of the UGS they are responsible for.

After the manual workflow has been successfully executed the initial notification has to be acknowledged and its status has to be set to “solved”. With this feedback the manual processes can be tracked and reproduced.
7 Business Value

The UGS management cycle is a multidisciplinary practice, which involves in most cases detailed numerical modeling of each system component and analysis of the economic impact of significant changes in the operation strategy. During this cycle, various operational options and strategies are evaluated to determine optimal system design and operation.

Figure 8 presents the three cycles from a time versus (relative) benefits in monetary term. Realizing these benefits requires the application of carefully selected workflows for each cycle. For instance, typical workflows for the fast cycle (focused on the operations) include well and equipment surveillance. For the medium cycle, production loss analysis and management and well optimization workflows are essential. Finally, in the case of the long cycle, reservoir or even company-wide planning & optimization workflows must be used to manage scarce resources and simulate strategic “what if” scenarios for the company, driven by business opportunities and economics.

Traditionally, workflows are run in isolation in the three cycles. Whilst bringing measurable benefits, it is clear, that running those workflows in silos will always lead to a suboptimum solution only.

The three cycles defined above must be performed faster and with less uncertainty to address the current challenges and help maximize the value of existing assets through production optimization and improved recovery. Recently the concept of automating workflows has been introduced in order to accomplish such goals.

Figure 8 presents a hypothetical view of where reservoir management cycles must go when improved by this automation concept. For instance, the operational loop (fast loop) exceptions must be caught within minutes rather than hours to ensure minimal disruption to the operations and losses to production.

The evolution in Figure 8 requires three key components: workflow automation, and breaking (or bridging) the barriers between the cycles through Workflow integration.

Companies benefit from high-level data integration in the business workflow in several different ways. Operating costs can be reduced and production revenues can be accelerated as well as increased.

The monitoring system allows engineers to focus on high-priority tasks. Only exceptions are reported by the notification system. If a process deviates from running economically, the notification system will alert the engineer.
Data are delivered in time - 24/7 – to the desktop of the engineer. Decisions can be made faster and more precise. This accelerates the whole production and injection cycle. Information is always available in time and in perfect condition, which allows full optimization of every asset. Bottlenecks in the production/injection cycle are found and removed.

 Automated processes allow a seamless data flow from the sandface to the desktop of the engineer. Due to previous data conditioning, setting up models to predict and optimize performance is fast and easy.

![Figure 8 - Improved UGS Management Cycles - Benefits vs. Time](image)

8 Conclusions

The Expert System RWE Gas Storage and Schlumberger established benefits from the technology, processes and information in a dynamic, secure and global system to reduce risk, lower cost and enhance rates and active capacities. Cost savings, which are achieved, are related to a high level of automation and continuous optimization of reservoir and surface network management of the UGS.

Overall benefits of the Expert System:

- continual optimization of underground gas storage
- to obtain more detailed information about gas storage behaviour; the information can be used for investment planning of underground gas storage development
- automatic operation with risk decreasing and uncertainty of reservoir estimation and prediction
- to increase operation safety
- to save costs and manpower related to the wells by maximization of the well's operating life, reduction of the well test cost and prompt identification of technical problems with wells
- to save manpower costs related to the surface technology management by direct regulation and automatic control (using the control module of the LS) of individual parts of the surface technology
- to save energy costs spent for compression work
- to save costs for environmental protection
- in the future to add a module of the UGS economics calculating long term and short term direct income / costs of gas storage based on all financial factors

References

